mathematics

MDPI

Article

Location of Multiple Damage Types in a Truss-Type Structure Using Multiple Signal Classification Method and Vibration Signals

Carlos A. Perez-Ramirez [1], **Jose M. Machorro-Lopez** [2], **Martin Valtierra-Rodriguez** [1], **Juan P. Amezquita-Sanchez** [1,*], **Arturo Garcia-Perez** [3], **David Camarena-Martinez** [3] and **Rene de J. Romero-Troncoso** [4]

1 ENAP-Research Group, CA-Sistemas Dinámicos, Facultad de Ingeniería, Universidad Autónoma de Querétaro (UAQ), Campus San Juan del Río, Río Moctezuma 249, Col. San Cayetano, San Juan del Río, Querétaro C. P. 76807, México; carlos.perez@uaq.mx (C.A.P.-R.); martin.valtierra@enap-rg.org (M.V.-R.)
2 Cátedras CONACYT-Instituto Mexicano del Transporte, km 12 Carretera Estatal No. 431 "El Colorado-Galindo" San Fandila, Pedro Escobedo, Querétaro C. P. 76703, México; jmachorro@imt.mx
3 Departamento de Electrónica, División de Ingenierías Campus Irapuato-Salamanca (DICIS), Salamanca, Guanajuato C. P. 36885, México; agarcia@hspdigital.org (A.G.-P.); david.camarena@enap-rg.org (D.C.-M.)
4 Facultad de Ingeniería, Universidad Autónoma de Querétaro (UAQ), Campus San Juan del Río, Río Moctezuma 249, Col. San Cayetano, San Juan del Río, Querétaro C. P. 76807, México; troncoso@hspdigital.org
* Correspondence: jamezquita@uaq.mx

Received: 14 May 2020; Accepted: 28 May 2020; Published: 7 June 2020

check for updates

Abstract: A new multiple signal classification (MUSIC)-based methodology is presented for detecting and locating multiple damage types in a truss-type structure subjected to dynamic excitations. The methodology is based mainly on two steps: in step 1, the MUSIC method is employed to obtain the pseudo-spectra of vibration signatures, healthy and damaged, to be used for damage detection. In step 2, a new damage index, based on the obtained pseudo-spectra, is proposed to measure the structure condition. Furthermore, the damage location is estimated according to the variation in the amplitudes of the estimated pseudo-spectra. The presented results show that the proposed methodology can make an accurate and reliable estimation of the condition and location of three specific damage conditions, i.e., loosened bolts, internal corrosion, and external corrosion.

Keywords: structural health monitoring; multiple signal classification technique; vibration signals; multiple damage types; damage location

1. Introduction

In recent years, the monitoring of civil infrastructure, e.g., buildings and bridges, has attracted the interest of many researchers, engineers, and governments around the world, because it is of paramount importance to ensure its optimal or healthy condition, via a research field known as structural health monitoring (SHM), or, if necessary, to perform the reparations required to restore its structural functionality and integrity [1–4]. In particular, truss-type structures are widely used for developing civil infrastructure, i.e., building skeleton towers, cranes, bridges, or roof supports, among other designs, because of their (1) ease of assembly and (2) light weight. These great advantages allow them to be employed in many applications [5,6]. Despite these great benefits and their robustness, they are exposed to diverse physical phenomena, e.g., corrosion, constant cycles of high-temperature operation, cumulative crack growth, degradation of columns, missing elements, fatigue, loosened bolts, joint–beam deterioration, wind-induced vibrations, and impacts by extern objects that can damage them [7–15]. Therefore, the development of reliable strategies for evaluating the health condition of a civil structure is of great interest for the academic and industry communities.

SHM is defined as the design and implementation of a strategy to detect damage types in a civil structure through the features identified from the measurements recorded in civil infrastructure [16–18]. In this regard, damage produces alterations in the structural operation parameters, such as stiffness, damping, natural frequencies, among other parameters, which can lead to the degradation of its service life and might yield economic losses or, even worse, human lives might be threatened [16,17]. In order to identify these alterations, diverse SHM schemes based on local procedures such as ultrasound [19], X-ray [20], laser scanning [21], acoustic emission [22], GPS signals [23], and image processing [24], have been mainly employed for evaluating the health condition of a civil structure. However, to fully exploit these procedures, they require the temporary closure of the structure and a priori knowledge of the damage location, which is not always possible to achieve in real-life conditions [25]. These reasons have led to the development of novel SHM strategies based on other physical properties of the civil structures, such as their vibrations [25–28]. The basic idea of a vibration-based SHM is that even slight damage modifies the physical properties of civil structures, such as their mass, stiffness, damping, and mode shapes, affecting their vibrational response [25,29,30]. Therefore, a signal processing technique, with the capability of detecting subtle changes or features produced in the measured vibration signal, becomes a potential solution for SHM.

Fast Fourier transform (FFT) is without a doubt the most widely used signal processing technique for evaluating the vibration signals in order to determine the health condition of a civil structure [10,31,32]. FFT is an adequate method to analyze time signals with stationary and linear properties embedded in a high signal-to-noise ratio (SNR) levels (low-level noise) [25]. Unfortunately, the vibrational responses acquired in a civil structure generally present nonlinear and non-stationary properties, besides having a low SNR (high-level noise), compromising negatively the results obtained by FFT to evaluate the health condition of a civil structure [25]. For this reason, in recent years, diverse methods have been proposed in the literature such as Kalman filter approaches [33], Hilbert–Huang transform (HHT) [34–36], time series autoregressive (AR) models [10,37–39], wavelet transform-based algorithms (WT) [40,41], artificial neural networks (ANN) [11,28,42–44], probabilistic-based approaches [15,18,45,46], subspace methods [12,47,48], WT-NN [49–52] and deep learning methods [53–56], among other methods or strategies. Although they have shown promising results in evaluating the condition of civil structures, these methods also present problems in identifying reliable features in noisy signals when associating them to the structure condition; in addition, some of them require repeated processing and modeling, the hand-crafted selection of the best-suited parameters, a large database, and multiple indices to detect different types of damage [57]. Therefore, it is necessary to propose an algorithm with the capability of monitoring the structure dynamics accurately, without requiring pre-processing stages nor extensive training stages and a tolerance to the noise-corrupted signals. To achieve these goals, it should be desirable to consider that time series signal can be modeled as a sum of harmonic components that are embedded in noise, as this will allow us to obtain its frequency content using matrices operations. In this regard, the multiple signal classification (MUSIC) algorithm is an algorithm that fulfills the aforementioned features. MUSIC assumes that a time series signal is a sum of complex exponentials that are defined in a noisy environment [58]. The frequency estimation of the exponentials is done using an eigenvector decomposition; in consequence, a high-resolution spectral estimation, even for data with a low SNR, is obtained. It is worth noticing that signals with a low SNR are measured in SHM schemes [40,41]. Further details about the MUSIC method are described in the next sections. In addition, it should be noted that the MUSIC method displays increased detectability of weak-amplitude frequencies, which has been a great advantage in identifying the natural frequencies of civil structures [59], as well as determining if a building presents cracks or not [60], but not to perform both damage detection and localization. These advantages make MUSIC a suitable alternative that must be explored to design a methodology that can detect and locate damage in civil structures.

In this work, the evaluation of the MUSIC method, a high-resolution spectral method, for detecting and locating multiple damage types in a five-bay truss-type structure exposed to forced dynamic excitations is presented. These excitations are produced by an electrodynamic shaker in a controlled way. MUSIC method is employed to obtain the pseudo-spectra of vibration signatures, healthy and damaged, in order to identify and locate the damage zones by comparing them. In other words, the pseudo-spectrum of each healthy bay is compared with the pseudo-spectrum of each damaged bay in order to locate the damage zone. In order to evaluate the proposal performance, the data experimentally obtained by four conditions: healthy, loosened bolts, and internal and external corrosion are analyzed. The obtained results demonstrate that the proposal can carry out a correct and reliable evaluation of the health condition of truss-type structures and locate the three specific damage conditions.

2. Theoretical Background

This section briefly presents the concepts and mathematical definitions used in the proposed methodology.

2.1. Truss-Type Structure

The truss or triangulated structure evaluated in this work employs flexible truss members that are pin connected at joints. Since their components are axial members, structural stability is guaranteed in the presence of tension or compression forces [59,61]. The triangulated structure under investigation, shown in Figure 1a, has the following dimensions: 3.535 m length and 1m height. It is composed of five bays made of aluminum, where each assembled bay has the following dimensions: 0.7 m in length and $0.7\sqrt{2}$ m for diagonal members. Each node is bolt-connected with the bar element as shown in Figure 1b, where the nodes and bar elements present diameters of 0.055 m and 0.019 m respectively.

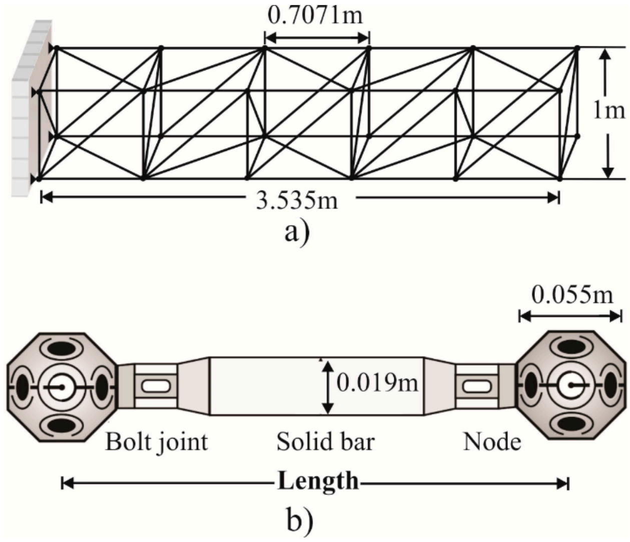

Figure 1. (**a**) Truss structure under test and (**b**) typical assembly of a bar element.

2.1.1. Joint Failure

Joint failure or loosened bolt (JF) is a typical type of damage encountered in the truss-type structures [62]. It is generally produced by excessive or constant vibrations (e.g., wind, earthquakes, traffic, among others) imposed on the truss structure, resulting in the separation of the elements which conform it [63]. In order to simulate a JF, one side of the bar element is separated from the bolt connector, as shown in Figure 2a.

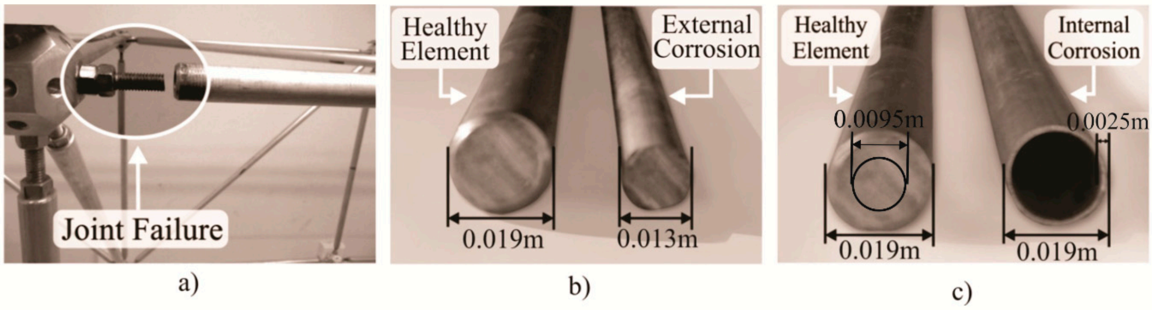

Figure 2. Simulated elements damaged by: (**a**) joint failure, (**b**) external corrosion, and (**c**) internal corrosion.

2.1.2. External and Internal Corrosion

Corrosion is an important problem for many civil structures, especially truss structures, since it is characterized by producing the deterioration of materials, mainly metals, which conform the structure. Corrosion reduces the lifetime of the material; thus, it loses mass and, consequently, the stiffness is reduced, endangering the structure's capacity to support forces or displacements [64]. Two types of corrosion produced in a truss-type structure with bar or tube elements are studied in this work: external (EC) and internal (IC) (a fault produced by water filtration and humidity, among other factors) corrosion [64]. To simulate the EC condition, a bar element with a reduced diameter of 0.013 m is used (see Figure 2b), resulting in a reduction of 30% in comparison with the healthy bar. On the other hand, the IC test is carried out using a tube element with an external diameter of 0.019 m and thickness of 0.0025 m (see Figure 2c). It is important to mention that the healthy bar element is perforated with a drill to generate a hole with a dimeter of 0.0095 m to connect it with the node; therefore, the reduction in material to simulate the IC is 0.007 m.

2.2. Multiple Signal Classification (MUSIC) Algorithm

MUSIC algorithm is a subspace-based method that manipulates a time series signal to determine its frequency components [65]. MUSIC considers a time series signal, $x[n]$, as a harmonic model represented by:

$$x[n] = \sum_{i=1}^{m} |B_i| e^{j\varphi_i} e^{j2\pi f_i n} + e[n] \tag{1}$$

where m is the number of complex exponentials, i.e., the frequencies contained in the signal, $|B_i|$ is the i-th complex sinusoid magnitude of $e^{j\varphi_i}$, f_i represents the frequency value, and $e[n]$ is the white noise that any measured signal has.

Later, an eigenvector decomposition is computed for obtaining two orthogonal subspaces (R_s and R_n, respectively), which represent the signal and noise autocorrelation matrices, respectively. The sum of both R matrices is an autocorrelation matrix estimated as follows:

$$R = R_s + R_n = \sum_{i=1}^{P} |B_i|^2 e(f_i) e^H(f_i) + \sigma_n^2 I \tag{2}$$

where P represents the number of frequencies to encounter in the time signal, the operator $(.)^H$ is the Hermitian transpose, I is the identity matrix, and $e^H\,(f_i)$ is a vector constructed as:

$$e^H(f_i) = \begin{bmatrix} 1 & e^{-j2\pi f_i} & \cdots & e^{-j2\pi f_i (N-1)} \end{bmatrix} \tag{3}$$

The orthogonality property of both subspaces (R_s and R_n) simplifies the estimation of the pseudo-spectrum (Q), which is defined by:

$$Q^{MUSIC}(f) = \frac{1}{\left|e(f)^H V_{m+1}\right|^2} \tag{4}$$

where V_{m+1} is the noise eigenvector. The waveform generated by the pseudo-spectrum shows response peaks at f_i that indicate the frequency components contained in the time signal, but the magnitude of the estimated frequency components does not relate to the magnitude of real power spectrum.

3. Proposed Methodology

The goal of a signal processing technique is to detect changes, alterations or patterns in any signal that can be associated with the studied phenomenon [66]. Regarding the vibrations in structures, it is important to mention that, to measure the vibrational responses of civil structures, they need to be exposed to diverse dynamical excitations such as natural alternatives (e.g., wind, traffic load, low-amplitude earthquakes, etc.) or artificial approaches (e.g., shakers, hammers, drop weights, etc.), resulting in a low-amplitude vibration response with a high level of noise [6,25]. Thus, an adequate signal processing technique to correctly evaluate this type of signal is of paramount importance. In this regard, the capabilities of the MUSIC method, i.e., high frequency resolution and high immunity to degrade its performance under signals with a low SNR, are evaluated to determine variations in the vibrational responses with the aim of associating them with the truss-type structure condition, which is exposed to forced dynamic excitations generated by an electrodynamic shaker.

Figure 3 presents a schematic diagram of the proposed methodology for detecting and locating damage in a truss-type structure by using the MUSIC method. It is based on three main steps, which are described as follows:

1. Vibration signal acquisition: firstly, the vibrational responses of the truss-type structure for each condition, healthy and damaged (JF, EC, and IC), are measured through five sensors located in each bay of the structure. It is important to mention that each damage type was introduced to the structure in an independent manner (one by one). In addition, when damage is introduced in the first bay, the others are healthy, and vice versa;
2. MUSIC method: then, the measured vibrational signatures for each condition and bay of the truss structure are analyzed by means of the MUSIC method in order to estimate their pseudo-spectra (PS), which will be associated with the structure condition and taken as references;
3. Condition evaluation: finally, the obtained pseudo-spectra are used for (1) determining the structure condition through a damage index (DI) and (2) locating the damaged zone according to a detectability value (DV), which will be explained in the following sub-sections.

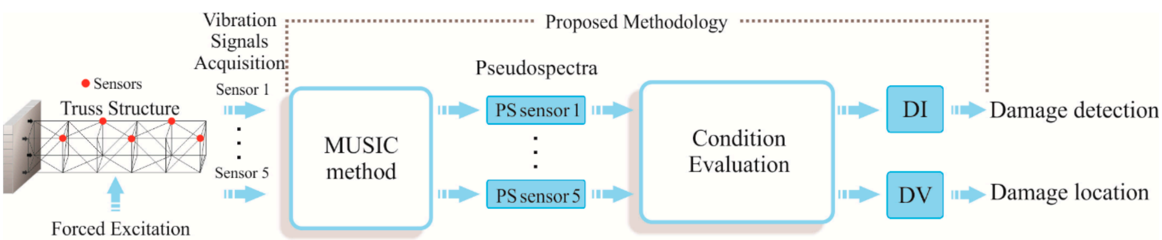

Figure 3. Schematic diagram of the proposed methodology.

3.1. Experimental Setup

Figure 4 shows the proposed experimental setup, where a 3D five-bay truss structure is employed to validate the proposal. It is exposed to forced dynamic excitations, i.e., a sinusoidal sweep whose frequency range varies from 15 to 150 Hz during 15 s as shown in Figure 5, produced by an electrodynamic shaker from Labworks (model ET-127), which is powered by a linear amplifier from Labworks (model PA-141). This frequency range is employed because it allows for the excitation of the structure's natural frequencies of interest. The amplifier is fed by using a proprietary digital waveform synthesizer system that has a high-speed 14-bit digital-to-analog converter DAC2904 from Texas Instruments. In order to measure its vibrational responses, each bay is instrumented with a tri-axial accelerometer from STMicroelectronics model LIS3L02AS4, which has a user-selectable full scale of ± 2 g/± 6 g and a 5×10^{-4} g resolution over a 100 Hz-bandwidth. The measured signals are digitalized using a proprietary data acquisition system (DAS) with a 12-bit four-channel ADS7841 ADC from Texas Instruments; then, the measured signals are sent to a personal computer (PC) by means of a universal serial bus (USB) protocol. It operates to a sampling frequency of 300 Hz to obtain 4500 samples during the time window of excitation.

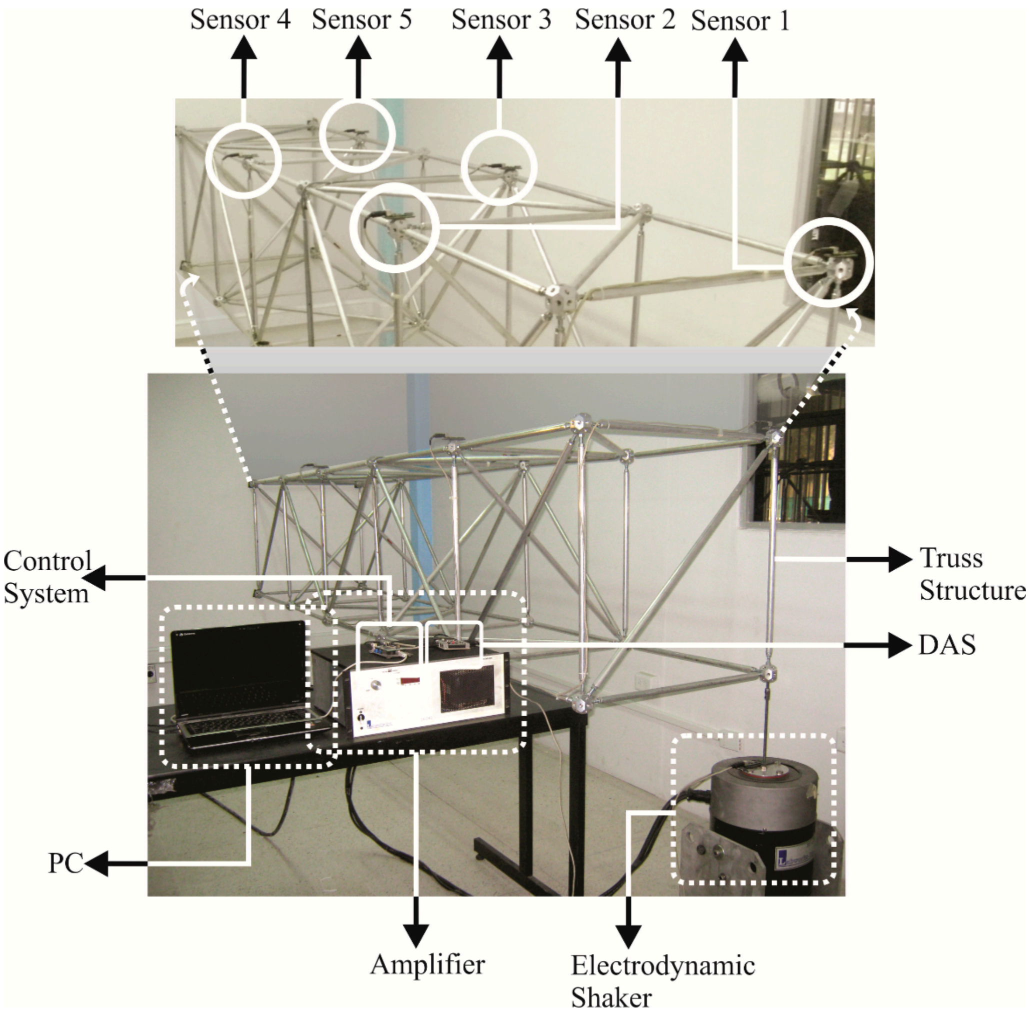

Figure 4. Experimental setup.

To generate statistical information, 10 tests are carried out for the healthy condition and 10 tests for each damage condition (JF, EC, and IC) at each bay, resulting in 160 tests. It should be noticed that each damage type is applied to the truss structure one by one, replacing a healthy bar element with another one (EC or IC). For example, when a damaged bar element is introduced in the first bay, the other ones are healthy and vice versa. The location of the damaged bar elements is designated randomly in each bay (see Figure 6), but the same location is used to place another damaged element. On the other hand, the JF is introduced in the truss structure by separating one of the extremes in each bay, one by one.

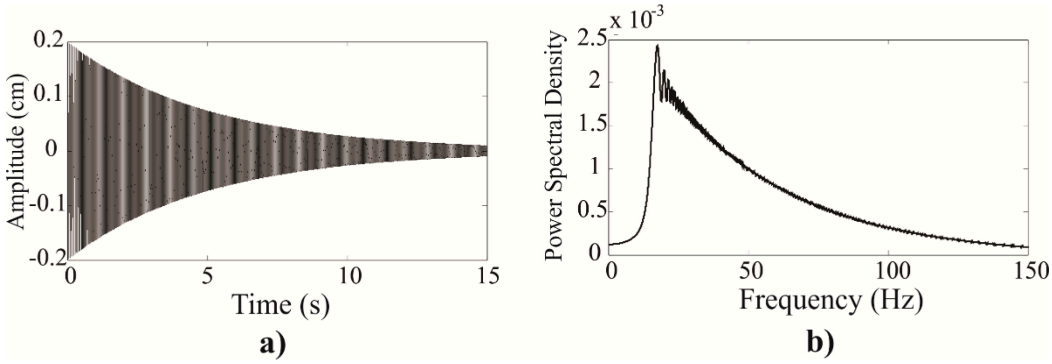

Figure 5. (**a**) Sinusoidal sweep excitation and (**b**) synthesized signal spectrum.

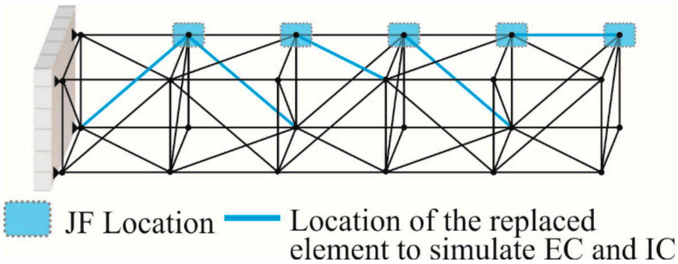

Figure 6. Location of different damage types applied to the truss-type structure.

3.2. Vibration Signature Analysis

Commonly, a healthy structure will produce a vibration signature that has a constant and small magnitude [66]; but, if damage appears, the structure's physical properties (e.g., damping, mass, stiffness, among other properties) will be modified according to the damage level [67], leading to the apparition of changes in the vibration signature. Therefore, if a frequency analysis is performed, the vibration signature spectrum of both will reflect differences which can be associated to the changes in the structure mechanical conditions, allowing to perform a fault diagnosis.

To demonstrate the improved detection capabilities that a MUSIC pseudo-spectrum has over a FFT spectrum, Figure 7 shows a comparison between the FFT spectrum and MUSIC pseudo-spectrum for a healthy bay and a damaged bay in a truss-type structure. From the figure, it is observed that the FFT-spectra for both the healthy and the damaged cases are not capable of detecting frequencies or signatures useful to verify the structure condition because the analyzed signals present a low amplitude and a high level of noise, limiting the correct identification of their frequency components [25]. On the contrary, the MUSIC pseudo-spectrum, with an order of 15, shows that the signatures for both cases are different, demonstrating that it is capable of determining the frequency components encountered in both noisy signals [58]. It is important to mention that further processing stages can be added to the FFT results to improve its performance; however, the goal is to demonstrate that MUSIC can provide more suitable results without the need for further stages. On the other hand, it is worth noting that the frequency band from 40 to 60 Hz is selected in this work because this region contains the frequency components or natural frequencies with the highest amplitude or energy, which can be more susceptible to changes in vibration signals produced by damage [67].

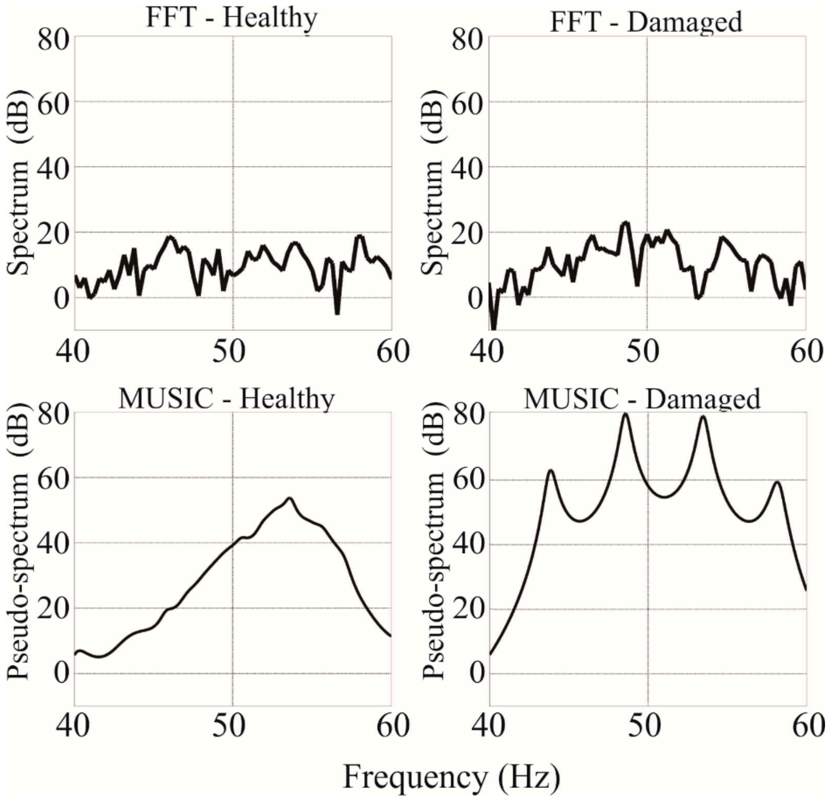

Figure 7. Comparison between healthy bay and damaged bay spectra using fast Fourier transform (FFT) and multiple signal classification (MUSIC) methods.

3.3. Damage Detection

To determine whether the truss-type structure presents damage or not, a damage index (DI) based on the average of the highest amplitudes in decibels for the main frequency components encountered in a frequency band or region, which contains successive frequency components with high magnitudes in each sensor, is proposed. It is defined mathematically as:

$$\mathrm{DI} = \frac{\sum_{i=1}^{N} A_i}{N} \tag{5}$$

where A_i is the amplitude value of the selected frequency component at location i and N represents the total of locations. Employing the available data, a threshold is established for the DI value, where a value inferior to 60 indicates that the truss structure is healthy. This value is obtained from the experimental data. It is important to mention that the proposed value depends on the configuration and material of the structure.

In order to illustrate how to estimate the DI value, the pseudo-spectra of the healthy condition for the five sensors are employed (see Figure 8). Firstly, the frequency component with the highest amplitude in the region of interest (denoted by a rectangular region marked in dark gray in each pseudo-spectrum) is located in the pseudo-spectrum of each sensor. The region of interest is determined experimentally according to the frequency peak values found in the pseudo-spectrum of each sensor and damage condition. This region slightly changes in each sensor because each type of damage has a different impact on the overall structure; moreover, the damage location also modifies the measured response at each sensor. Once the frequency component with the highest amplitude for each frequency region and sensor is determined, the amplitudes of the selected frequencies are averaged to obtain the DI value using Equation (5). For example, the amplitude values of the identified frequency components in each pseudo-spectrum and sensor are: 58, 52, 59, 54, and 70, resulting in a DI value of 58.6, which is inferior to the estimated threshold with all the experimental data.

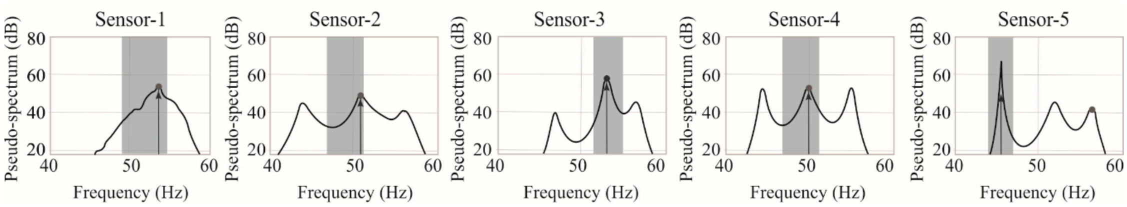

Figure 8. Pseudo-spectra estimated by using the MUSIC method for the healthy condition and five sensors and damage index (DI) estimation.

3.4. Damage Location

The damage location is based on a proposed detectability value (DV), which is calculated as the absolute value for the amplitude difference (in decibels) between the frequency peak of the spectrum of a damage condition (Dd) (this frequency presents the most abrupt change in amplitude) and the frequency peak of the spectrum of a healthy condition (Dh). Therefore, DV is computed as follows:

$$DV = |Dd\text{-}Dh| \tag{6}$$

From this definition, the damage location consists of the following steps: (1) locate the frequency peak values (Dh) from the pseudo-spectra for a healthy condition in each sensor (see Figure 9), (2) for the damage condition (unknown frequency content), compute the pseudo-spectrum for each sensor and locate the frequency peak values (Dd) in the region of interest, which is determined according to the damage condition of structure, (3) compute the DV for each sensor, i.e., DV_{S1}, DV_{S2}, DV_{S3}, DV_{S4}, and DV_{S5}, using Equation (6), and (4) find the damage location according to:

$$\text{Damage location} = \max(DV_{S1}, DV_{S2}, DV_{S3}, DV_{S4}, \text{and } DV_{S5}) \tag{7}$$

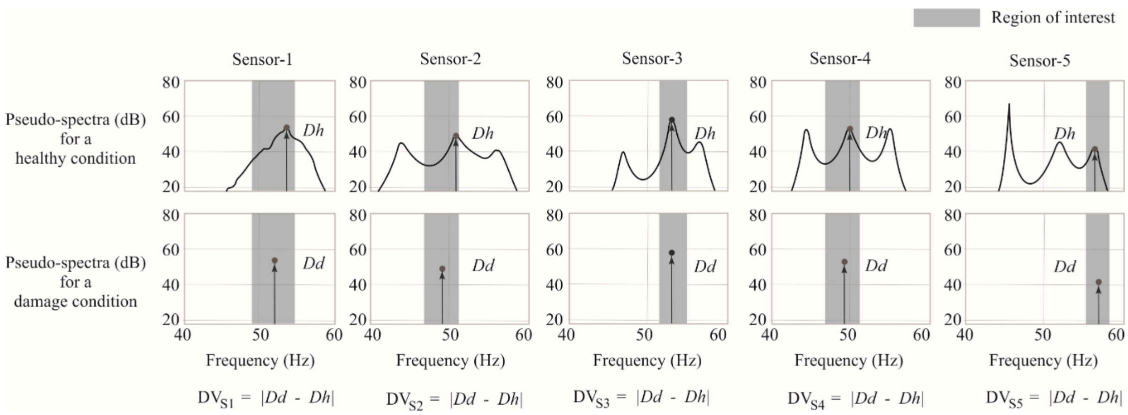

Figure 9. Pseudo-spectra analyses for DV computation and, consequently, damage location.

4. Obtained Results

Following the proposed methodology steps and MATLAB software, the vibration signals for a healthy condition and the other three damage conditions (JF, EC, and IC) are analyzed by means of the MUSIC method in order to determine the structure condition through the estimated pseudo-spectra. Figure 10 presents an example of the vibration signals in the three axes (X, Y, and Z), which are measured by the third sensor for the healthy condition and the three studied damage types: joint failure, external corrosion, and internal corrosion. The damage is located in the third bay (damage located next to the third sensor). When observing this figure, both conditions (healthy and damaged ones) present similar vibration signatures, indicating the need for an additional method for identifying reliable differences between them in order to detect and locate damage in the truss-type structure. It is important to mention that the vibration signals measured in the vertical axis, the *Z*-axis, presented better results than the other two axes (X and Y); therefore, the obtained results from the vertical axis to determine the health condition of the truss-type structure are presented in this work.

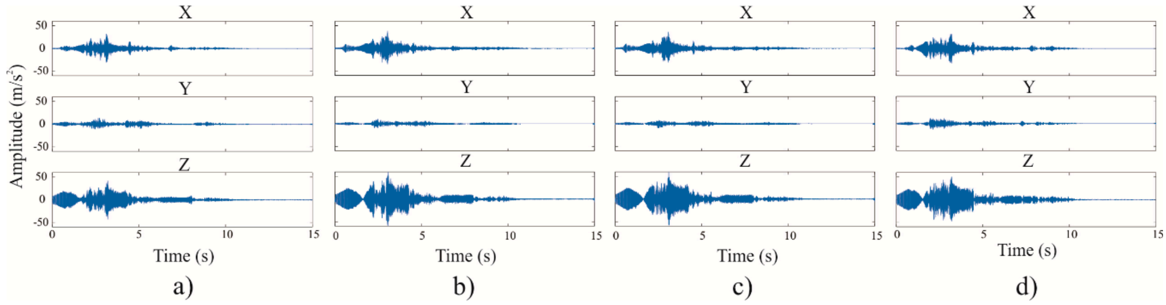

Figure 10. Measured vibrational signals in X, Y, and Z axes for (**a**) a healthy structure, (**b**) joint failure, (**c**) an external corrosion, and (**d**) an internal corrosion in the third bay.

Once the pseudo-spectra for all conditions have been estimated, the amplitudes of the frequency components in the frequency region from 40 to 60 Hz with the highest amplitude in all sensors are averaged by using Equation (5) in order to determine the structural condition. It is important to mention that, when the structure is healthy, the identified frequency component values present a close range or similar values and, hence, the DI value will be lesser than the set threshold. On the other hand, when the truss-type structure presents a damage, the DI value becomes larger than the set threshold. In this regard, the ten tests measured for each condition, healthy and damaged, are evaluated by DI for determining the structure condition, meaning that the proposed index is capable of determining the structure condition with an accuracy of 100%.

Once the structure condition is estimated, the damage location is performed by using the abrupt changes encountered in the amplitudes of the frequency components estimated into the frequency region by means of the MUSIC method. To perform this task, it is first necessary to find the common frequency peak among the healthy pseudo-spectrum and the damaged pseudo-spectrum in the same bay, which means that the pseudo-spectrum of healthy first bay is compared with the spectrum of damage in the first bay, second bay, third bay, fourth bay, and fifth bay in order to obtain the Dh and Dd values of Equation (6). Therefore, the highest DV value, from the five sensors, indicates the bay with the damage. Figures 11–13 present the obtained pseudo-spectra estimated for the five sensors and the three damage types studied, JF, EC, and IC, respectively, in comparison with the healthy condition located in the first row of the figures. The lines introducing the regions highlighted in dark gray are the selected frequency peaks (Dh and Dd), where the frequency peak (Dh) from the healthy spectrum was taken as a reference. Table 1 summarizes the selected frequency peak values for each sensor or bay to locate the damaged zone (bay) according to the damage condition (JF, EC, and IC).

Table 1. Selected frequency peak regions for each sensor to locate the damaged bay for the conditions joint failure (JF), external corrosion (EC) and internal corrosion (IC).

Condition	Frequency (Hz)				
	Sensor 1	Sensor 2	Sensor 3	Sensor 4	Sensor 5
JF (see Figure 11)	53	51	47	50	56
EC (see Figure 12)	53	51	53	50	53
IC (see Figure 13)	53	51	53	50	56

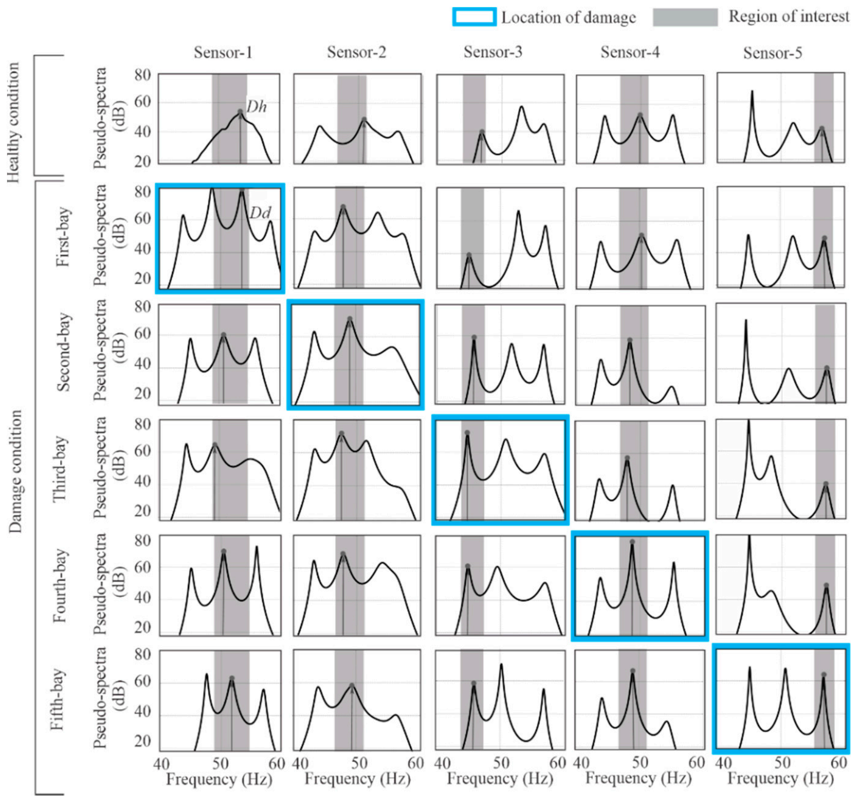

Figure 11. Pseudo-spectra obtained from the JF scenario and used to identify condition–location of damage.

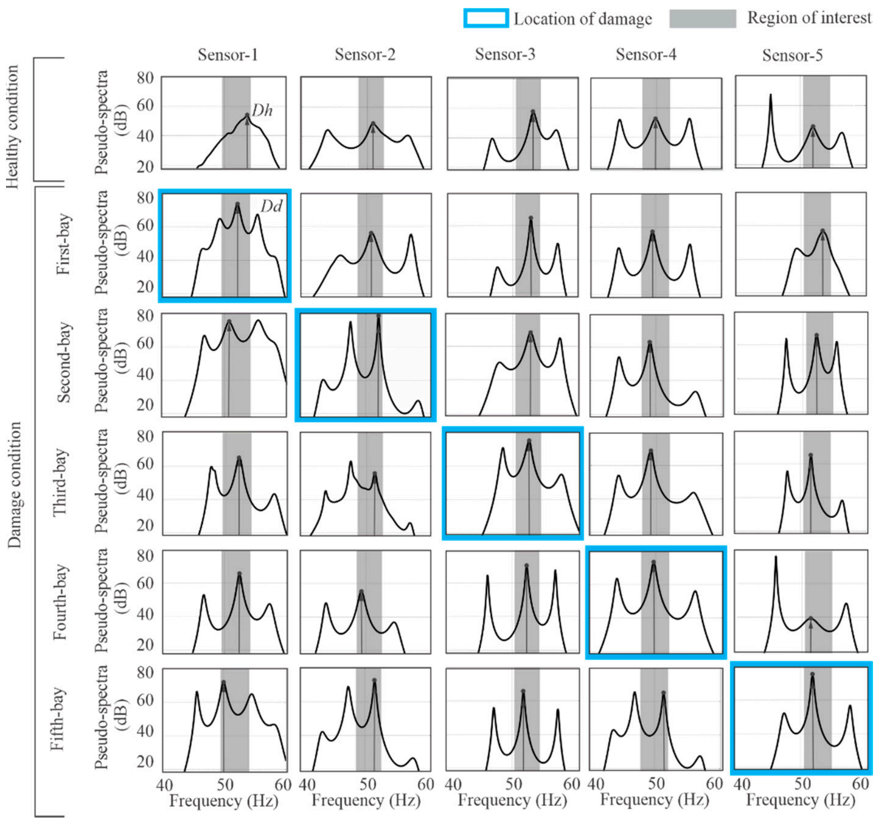

Figure 12. Pseudo-spectra obtained from the EC scenario and used to identify condition–location of damage.

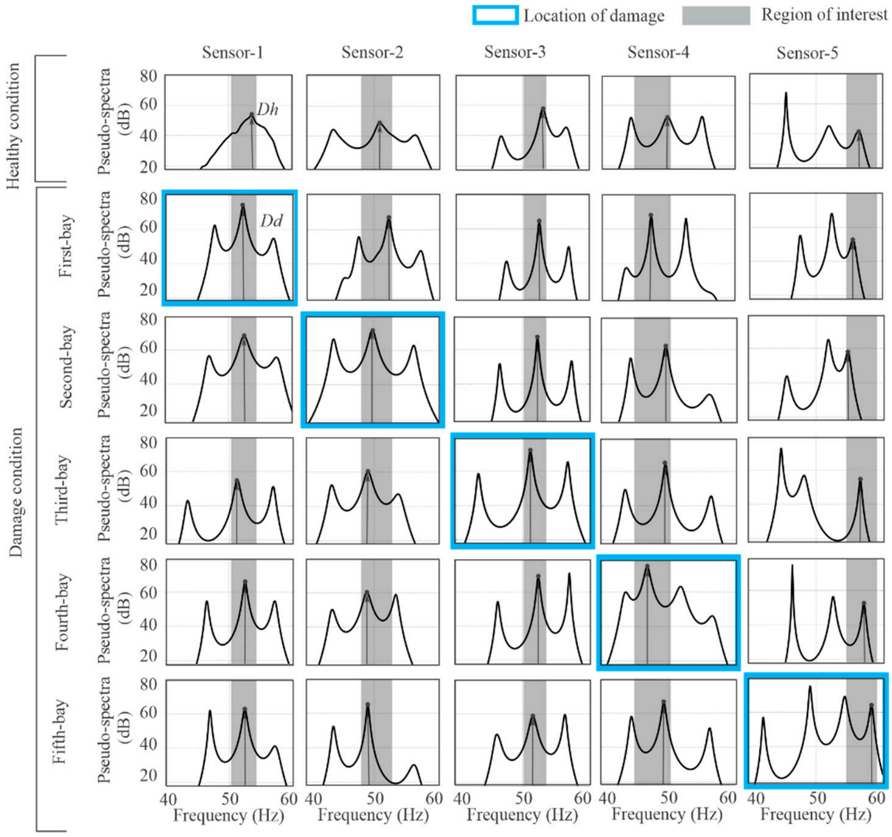

Figure 13. Pseudo-spectra obtained from the IC scenario and used to identify condition–location of damage.

Tables 2–4 summarize the mean of DV values obtained for the five sensors and the three damaged conditions: JF, EC, and IC, respectively, where ten tests for each condition are analyzed. Therefore, the damage location is obtained according to the highest detectability values, DV, from the five sensors, which indicates the bay with the damage. For example, using the results shown in Figure 11, the healthy and damaged frequency peaks (Dh and Dd) of sensor 1 are 54 dB and 79 dB, respectively, resulting in DV values of 25 dB. For sensor 2, Dh and Dd are 49 dB and 67.5 dB; thus, DV is 18.5 dB. For the rest of the sensors, DV values of 0.5 dB, 1.5 dB, and 6.8 dB are obtained, respectively. Thus, the 25 dB-value in sensor 1, which is the highest in the row, indicates that the damage location is in the first bay according to Equation (7). This procedure is repeated for all the remaining sensors and bays. The same procedure is applied for the values presented in Tables 3 and 4.

Table 2. Detectability in decibels for the JF damage analysis (DV values).

Damage Location	Sensor 1	Sensor 2	Sensor 3	Sensor 4	Sensor 5
Bay 1	25	18.5	0.5	1.5	6.8
Bay 2	6	22	20.5	6	0.7
Bay 3	10.5	22.5	33	5	2.7
Bay 4	16	19.5	21.5	23	2.7
Bay 5	9.5	9	19	13.5	22.3

Table 3. Detectability in decibels for the EC damage analysis (DV values).

Damage Location	Sensor 1	Sensor 2	Sensor 3	Sensor 4	Sensor 5
Bay 1	20	7.5	6.5	4	11.5
Bay 2	20.5	26.5	10.5	10	20.5
Bay 3	11	14	33	16	20
Bay 4	12	6.5	12.5	23	6.5
Bay 5	18	20.5	8	12	30

Table 4. Detectability in decibels for the IC damage analysis (DV values).

Damage Location	Sensor 1	Sensor 2	Sensor 3	Sensor 4	Sensor 5
Bay 1	20	18.5	7	15	11.3
Bay 2	14	23	9	9	16.3
Bay 3	1	11.5	14.5	11.5	12.3
Bay 4	12	11.5	11	22	10.8
Bay 5	8.5	16	1	13.5	22.3

5. Conclusions

This paper presents a methodology based on the MUSIC method and vibration signals for detecting and locating three types of damage (joint failure, external corrosion, and internal corrosion) in a five-bay truss-type structure subjected to forced dynamic excitations. The experiments performed in this paper show that the MUSIC algorithm and the proposed indices, i.e., DI and DV, allow for the identification and location of damage with an accuracy of 100%.

Finally, it is important to mention that the obtained results are possible since the MUSIC method considers the measurement of background noise in the signal model. Therefore, the amplitude of frequency components in each bay correctly indicate the damage detection and location in the three types of damage studied. Therefore, the proposed MUSIC-based methodology provides an easy procedure to detect and locate three different damage types, which will help to maintain the structure integrity. In addition, in a future work, diverse levels of damage, other type of damage and other civil structure configurations will be investigated in order to evaluate and calibrate the performance of the proposed methodology under these new circumstances, as this will offer a complete solution that is desirable for any SHM scheme.

Author Contributions: Conceptualization, C.A.P.-R. and J.P.A.-S.; investigation, resources, and visualization, A.G.-P., D.C.-M., and R.d.J.R.-T.; funding acquisition and formal analysis, J.P.A.-S., J.M.M.-L. and M.V.-R.; writing—original draft, review, and editing, all authors. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partially funded by the National Council of Science and Technology by project SEP-CONACyT 254697 and project Cátedras CONACyT 34/2018.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Park, H.S.; Lee, H.M.; Adeli, H.; Li, I. A new approach for health monitoring of structures: Terrestrial laser scanning. *Compt. Aided Civ. Infras. Eng.* **2007**, *22*, 19–30. [CrossRef]
2. Kralovec, C.; Schagerl, M. Review of Structural Health Monitoring Methods Regarding a Multi-Sensor Approach for Damage Assessment of Metal and Composite Structures. *Sensors* **2020**, *20*, 826. [CrossRef] [PubMed]
3. De, S.; Gupta, K.; Stanley, R.J.; Ghasr, M.T.; Zoughi, R.; Doering, K.; Van Aken, D.C.; Steffes, G.; O'Keefe, M.; Palmer, D.D. A comprehensive multi-modal data fusion approach for failure assessment in aircraft lap-joint mimics. *IEEE Trans. Instrum. Meas.* **2013**, *62*, 814–827. [CrossRef]
4. Das, S.; Dutta, S.; Putcha, C.; Majumdar, S.; Adak, D. A Data-Driven Physics-Informed Method for Prognosis of Infrastructure Systems: Theory and Application to Crack Prediction. *ASCE-ASME J. Risk Uncer. Eng. Sys.* **2020**, *6*, 04020013. [CrossRef]

5. Poulsen, P.N.; Olesen, J.F.; Baandrup, M. Truss optimization applying finite element limit analysis including global and local stability. *Struct. Multidiscip. Opt.* **2020**. [CrossRef]
6. Jiang, S.; Zhu, S.; Guo, X.; Li, Z. Full-scale fire tests on steel roof truss structures. *J. Construct. Steel Res.* **2020**, *169*, 106025. [CrossRef]
7. Sousa, H.; Rozsas, A.; Slobbe, A.; Courage, W. A novel pro-active approach towards SHM-based bridge management supported by FE analysis and Bayesian methods. *Struct. Infras. Eng.* **2020**, *16*, 233–246. [CrossRef]
8. Sony, S.; Laventure, S.; Sadhu, A. A literature review of next-generation smart sensing technology in structural health monitoring. *Struct. Control Health Mon.* **2019**, *26*, e2321. [CrossRef]
9. Mishra, M.; Barman, S.K.; Maity, D.; Maiti, D.K. Performance Studies of 10 Metaheuristic Techniques in Determination of Damages for Large-Scale Spatial Trusses from Changes in Vibration Responses. *J. Compt. Civ. Eng.* **2020**, *34*, 04019052. [CrossRef]
10. Riasat Azim, M.; Gül, M. Damage Detection of Steel-Truss Railway Bridges Using Operational Vibration Data. *J. Struct. Eng.* **2020**, *146*, 04020008. [CrossRef]
11. Mousavi, A.A.; Zhang, C.; Masri, S.F.; Gholipour, G. Structural Damage Localization and Quantification Based on a CEEMDAN Hilbert Transform Neural Network Approach: A Model Steel Truss Bridge Case Study. *Sensors* **2020**, *20*, 1271. [CrossRef] [PubMed]
12. Aloisio, A.; Di Battista, L.; Alaggio, R.; Fragiacomo, M. Sensitivity analysis of subspace-based damage indicators under changes in ambient excitation covariance, severity and location of damage. *Eng. Struct.* **2020**, *208*, 110235. [CrossRef]
13. Shahsavari, V.; Mehrkash, M.; Santini-Bell, E. Damage Detection and Decreased Load-Carrying Capacity Assessment of a Vertical-Lift Steel Truss Bridge. *J. Perform. Construct. Facil.* **2020**, *34*, 04019123. [CrossRef]
14. Han, Y.; Li, K.; Cai, C.S.; Wang, L.; Xu, G. Fatigue Reliability Assessment of Long-Span Steel-Truss Suspension Bridges under the Combined Action of Random Traffic and Wind Loads. *J. Bridge Eng.* **2020**, *25*, 04020003. [CrossRef]
15. Long, L.; Döhler, M.; Thöns, S. Determination of structural and damage detection system influencing parameters on the value of information. *Struct. Health Mon.* **2020**. [CrossRef]
16. Fan, G.; Li, J.; Hao, H. Vibration Signal Denoising for Structural Health Monitoring by Residual Convolutional Neural Networks. *Measurement* **2020**, *157*, 107651. [CrossRef]
17. Zonzini, F.; Malatesta, M.M.; Bogomolov, D.; Testoni, N. Vibration-based SHM with up-scalable and low-cost Sensor Networks. *IEEE Trans. Instrum. Meas.* **2020**. [CrossRef]
18. Agis, D.; Tibaduiza, D.A.; Pozo, F. Vibration-based detection and classification of structural changes using principal component analysis and -distributed stochastic neighbor embedding. *Struct. Control Health Mon.* **2020**, *27*, e2533. [CrossRef]
19. Chang, M.; Yuan, S.; Guo, F. Corrosion Monitoring Using a New Compressed Sensing-based Tomographic Method. *Ultrasonics* **2019**, *101*, 105988. [CrossRef]
20. Moosavi, R.; Grunwald, M.; Redmer, B. Crack detection in reinforced concrete. *NDT E Int.* **2020**, *109*, 102190. [CrossRef]
21. Li, J.; Xie, B.; Zhao, X. A Method of Interstory Drift Monitoring Using a Smartphone and a Laser Device. *Sensors* **2020**, *20*, 1777. [CrossRef]
22. Ma, G.; Du, Q. Structural health evaluation of the prestressed concrete using advanced acoustic emission (AE) parameters. *Construct. Build. Mat.* **2020**, *250*, 118860. [CrossRef]
23. Yu, J.; Meng, X.; Yan, B.; Xu, B.; Fan, Q.; Xie, Y. Global Navigation Satellite System-based positioning technology for structural health monitoring: a review. *Struct. Control Health Mon.* **2020**, *27*, e2467. [CrossRef]
24. Li, G.; Liu, Q.; Zhao, S.; Qiao, W.; Ren, X. Automatic crack recognition for concrete bridges by fully convolutional neural network and Naive Bayes data fusion based on visual detection system. *Meas. Sci. Tech.* **2020**. [CrossRef]
25. Amezquita-Sanchez, J.P.; Adeli, H. Signal Processing Techniques for Vibration-Based Health Monitoring of Smart Structures. *Arch. Compt. Meth. Eng.* **2016**, *23*, 1–15. [CrossRef]
26. Huang, C.S.; Le, Q.T.; Su, W.C.; Chen, C.H. Wavelet-based approach of time series model for modal identification of a bridge with incomplete input. *Compt. Aided Civil Infras. Eng.* **2020**. [CrossRef]
27. Azimi, M.; Pekcan, G. Structural health monitoring using extremely compressed data through deep learning. *Compt. Aided Civ. Infras. Eng.* **2019**. [CrossRef]

28. Bao, Y.; Guo, Y.; Li, H. A machine learning–based approach for adaptive sparse time–frequency analysis used in structural health monitoring. *Struct. Health Mon.* **2020**. [CrossRef]
29. Park, H.S.; Oh, B.K. Damage detection of building structures under ambient excitation through the analysis of the relationship between the modal participation ratio and story stiffness. *J. Sound Vib.* **2018**, *418*, 122–143. [CrossRef]
30. Sivori, D.; Lepidi, M.; Cattari, S. Ambient vibration tools to validate the rigid diaphragm assumption in the seismic assessment of buildings. *Earthq. Eng. Struct. Dyn.* **2020**, *49*, 194–211. [CrossRef]
31. Huynh, T.-C.; Park, J.-H.; Kim, J.-T. Structural identification of cable-stayed bridge under back-to-back typhoons by wireless vibration monitoring. *Measurement* **2016**, *88*, 385–401. [CrossRef]
32. Wickramasinghe, W.R.; Thambiratnam, D.P.; Chan, T.H.T. Damage Detection in a Suspension Bridge Using Modal Flexibility Method. *Eng. Fail. Anal.* **2020**, *107*, 104194. [CrossRef]
33. Zhang, C.; Gao, Y.-W.; Huang, J.-P.; Huang, J.-Z.; Song, G.-Q. Damage identification in bridge structures subject to moving vehicle based on extended Kalman filter with l1-norm regularization. *Inv. Probl. Sci. Eng.* **2020**, *28*, 144–174. [CrossRef]
34. Delgadillo, R.M.; Casas, J.R. Non-modal vibration-based methods for bridge damage identification. *Struct. Infras. Eng.* **2020**, *16*, 676–697. [CrossRef]
35. Celik, O.; Dong, C.-Z.; Catbas, F.N. Investigation of Structural Response under Human-Induced Excitations Using Noise-Assisted and Adaptively Transformed Multivariate Empirical Mode Decomposition. *J. Struct. Eng.* **2020**, *146*, 04020019. [CrossRef]
36. Moreno-Gomez, A.; Amezquita-Sanchez, J.P.; Valtierra-Rodriguez, M.; Perez-Ramirez, C.A.; Dominguez-Gonzalez, A.; Chavez-Alegria, O. EMD-Shannon Entropy-Based Methodology to Detect Incipient Damages in a Truss Structure. *Appl. Sci.* **2018**, *8*, 2068. [CrossRef]
37. Gharehbaghi, V.R.; Nguyen, A.; Noroozinejad Farsangi, E.; Yang, T.Y. Supervised damage and deterioration detection in building structures using an enhanced autoregressive time-series approach. *J. Build. Eng.* **2020**, *30*, 101292. [CrossRef]
38. Zhu, H.; Yu, H.; Gao, F.; Weng, S.; Sun, Y.; Hu, Q. Damage identification using time series analysis and sparse regularization. *Struct. Health Mon.* **2020**. [CrossRef]
39. García-Macías, E.; Ubertini, F. MOVA/MOSS: Two integrated software solutions for comprehensive Structural Health Monitoring of structures. *Mech. Sys. Signal Proc.* **2020**, *143*, 106830. [CrossRef]
40. Yazdanpanah, O.; Mohebi, B.; Yakhchalian, M. Seismic damage assessment using improved wavelet-based damage-sensitive features. *J. Build. Eng.* **2020**. [CrossRef]
41. Yazdanpanah, O.; Mohebi, B.; Yakhchalian, M. Selection of optimal wavelet-based damage-sensitive feature for seismic damage diagnosis. *Measurement* **2020**, *154*, 107447. [CrossRef]
42. Gordan, M.; Ismail, Z.; Abdul Razak, H.; Ghaedi, K.; Zhi, Z.; Haider, X.; Ghayeb, H. Data mining-based damage identification of a slab-on-girder bridge using inverse analysis. *Measurement* **2020**, *151*, 107175. [CrossRef]
43. Tan, Z.; Thambiratnam, D.; Chan, T.; Gordan, M.; Abdul Razak, H. Damage detection in steel-concrete composite bridge using vibration characteristics and artificial neural network. *Struct. Infrastruct. Eng.* **2019**. In Press. [CrossRef]
44. Gordan, M.; Abdul Razak, H.; Ismail, Z.; Ghaedi, K. A hybrid ANN-based imperial competitive algorithm methodology for structural damage identification of slab-on-girder bridge using data mining. *Appl. Soft Compt.* **2020**, *88*, 106013. [CrossRef]
45. Murali Krishna, B.; Guru Prathap Reddy, V.; Shafee, M.; Tadepalli, T. Condition assessment of RC beams using artificial neural networks. *Structures* **2020**, *23*, 1–12. [CrossRef]
46. Kullaa, J. Robust damage detection in the time domain using Bayesian virtual sensing with noise reduction and environmental effect elimination capabilities. *J. Sound Vib.* **2020**, *473*, 115232. [CrossRef]
47. Chen, Z.; Zhang, R.; Zheng, J.; Sun, H. Sparse Bayesian learning for structural damage identification. *Mech. Syst. Sig. Proc.* **2020**, *140*, 106689. [CrossRef]
48. Bhowmik, B.; Tripura, T.; Hazra, B.; Pakrashi, V. Real time structural modal identification using recursive canonical correlation analysis and application towards online structural damage detection. *J. Sound Vib.* **2020**, *468*, 115101. [CrossRef]

49. Cancelli, A.; Laflamme, S.; Alipour, A.; Sritharan, S.; Ubertini, F. Vibration-based damage localization and quantification in a pretensioned concrete girder using stochastic subspace identification and particle swarm model updating. *Struct. Health Mon.* **2020**, *19*, 587–605. [CrossRef]
50. Yapar, O.; Basu, P.K.; Volgyesi, P.; Ledeczi, A. Structural health monitoring of bridges with piezoelectric AE sensors. *Eng. Failure Anal.* **2015**, *56*, 150–169. [CrossRef]
51. Dai, H.; Zhang, H.; Wang, W. A Multiwavelet Neural Network-Based Response Surface Method for Structural Reliability Analysis. *Compt. Aided Civ. Infras. Eng.* **2015**, *30*, 151–162. [CrossRef]
52. Jiang, X.; Mahadevan, S. Bayesian wavelet methodology for structural damage detection. *Struct. Control Health Mon.* **2008**, *15*, 974–991. [CrossRef]
53. Turkan, Y.; Hong, J.; Laflamme, S.; Puri, N. Adaptive wavelet neural network for terrestrial laser scanner-based crack detection. *Auto. Construct.* **2018**, *94*, 191–202. [CrossRef]
54. Lee, K.; Byun, N.; Shin, D.H. A Damage Localization Approach for Rahmen Bridge Based on Convolutional Neural Network. *KSCE J. Civ. Eng.* **2020**, *24*, 1–9. [CrossRef]
55. Li, S.; Sun, L. Detectability of Bridge-Structural Damage Based on Fiber-Optic Sensing through Deep-Convolutional Neural Networks. *J. Bridge Eng.* **2020**, *25*, 04020012. [CrossRef]
56. Truong, T.T.; Dinh-Cong, D.; Lee, J.; Nguyen-Thoi, T. An effective deep feedforward neural networks (DFNN) method for damage identification of truss structures using noisy incomplete model data. *J. Build. Eng.* **2020**, *30*, 101244. [CrossRef]
57. Ma, X.; Lin, Y.; Nie, Z.; Ma, H. Structural damage identification based on unsupervised feature-extraction via Variational Auto-encoder. *Measurement* **2020**, *160*, 107811. [CrossRef]
58. Amezquita-Sanchez, J.P.; Adeli, H. A new music-empirical wavelet transform methodology for time–frequency analysis of noisy nonlinear and non-stationary signals. *Digit. Signal Proc.* **2015**, *45*, 55–68. [CrossRef]
59. Gkoktsi, K.; Giaralis, A. A compressive MUSIC spectral approach for identification of closely-spaced structural natural frequencies and post-earthquake damage detection. *Prob. Eng. Mech.* **2020**, *60*, 103030. [CrossRef]
60. Jiang, X.; Adeli, H. Pseudospectra, MUSIC, and dynamic wavelet neural network for damage detection of highrise buildings. *Int. J. Numer. Meth. Eng.* **2007**, *71*, 606–629. [CrossRef]
61. Vaez, S.R.H.; Mehanpur, H.; Fathali, M.A. Reliability assessment of truss structures with natural frequency constraints using metaheuristic algorithms. *J. Build. Eng.* **2020**, *28*, 101065. [CrossRef]
62. Schumacher, A.; Nussbaumer, A. Experimental study on the fatigue behaviour of welded tubular K-joints for bridges. *Eng. Struct.* **2006**, *28*, 745–755. [CrossRef]
63. An, Y.; Li, B.; Ou, J. An algorithm for damage localization in steel truss structures: Numerical simulation and experimental validation. *J. Int. Mat. Sys. Struct.* **2013**, *24*, 1683–1698. [CrossRef]
64. Fisher, J.W.; Yen, B.T.; Wang, D. Corrosion and its influence on strength of steel bridge members. Transportation Research Record (No. 1290, p. 1). In Proceedings of the 3rd Bridge Engineering Conference, Denver, CO, USA, 10–13 March 1991.
65. Zamudio Ramirez, I.; Ramirez-Nunez, J.A.; Antonino-Daviu, J.A.; Osornio-Rios, R.; Lopez, A.Q.; Razik, H.; Romero-Troncoso, R.J. Automatic diagnosis of electromechanical faults in induction motors based on the transient analysis of the stray flux via MUSIC methods. *IEEE Trans. Ind. Appl.* **2020**. [CrossRef]
66. Entezami, A.; Shariatmadar, H. An unsupervised learning approach by novel damage indices in structural health monitoring for damage localization and quantification. *Struct. Health Mon.* **2017**, *17*, 325–345. [CrossRef]
67. Salawu, O.S. Detection of structural damage through changes in frequency: A review. *Eng. Struct.* **1997**, *19*, 718–723. [CrossRef]