IMPEDANCE-BASED STRUCTURAL HEALTH MONITORING AND KOHONEN NETS FOR DAMAGE DETECTION

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ABSTRACT

Several expensive structures have been developed in the past century. Thus, corrective, preventive, and predictive maintenance techniques were proposed based on the ability to investigate a monitoring parameter up to the inflection point of the component's useful life. Consequently, several structural health assessment methodologies have been implemented using smart sensors. In general, damage classification models in this kind of monitoring have a limitation due to the influence of temperature on piezoelectric sensors, requiring a temperature compensation step (normalization). In this work, a Kohonen map is used with a Principal Component Analysis to demonstrate the potential of this kind of model in eliminating the compensation step and classifying the damage correctly. For the case study, an aluminum beam instrumented with a PZT (Pb-lead Zirconate Titanate) patch was used and subjected to different temperatures in a climatic chamber in 11 levels of temperature. The test structure had thickness removals with seven levels at the opposite end of the beam with the sensor. Several parameters of the models were changed and demonstrated the availability to use the proposed methodology as an approach to the temperature-independent damage model. In conclusion, this type of result enables the use of this model in real structural monitoring.

KEYWORDS: *Structural health monitoring, Self-organizing maps, Artificial neural networks.*

I. INTRODUCTION

Over the last few decades, before the current understanding of maintenance was developed, corrective actions were already in place to keep structures or equipment functioning [14]. Thus, corrective, preventive, and predictive maintenance techniques arise based on the ability to investigate a monitoring parameter up to the inflection point of the component's useful life. Among the predictive maintenance techniques, Impedance-based Structural Health Monitoring (ISHM) aims to identify the damage, whether in real-time or not [3, 9, 10, 13]. This non-destructive method uses the piezoelectric property of specific materials such as sensors/actuators that, when they suffer some damage, produce a change in the electrical potential difference [25]. The method consists of fixing a Pb-lead Zirconate Titanate (PZT) sensor/actuator in the investigated structure, which, after being excited at high frequency, promotes the excitation and the corresponding measurement of the structural vibration signature [9, 10, 13, 25]. This excitation enabled by the patch causes the structure to undergo deformation, consequently generating a vibration in the system. With impedance being considered as resistance to movement, the electrical measurement of the PZT patch incorporates both the electrical impedance aspect of the component and mechanical impedance due to the structure [13, 14].

On the other hand, methods based on machine learning and artificial neural networks have grown over the last few years. One of these methods is the unsupervised network called Self-Organizing Maps (SOM), and the answers are not known but are deduced by their similarities. When requested, the algorithm only extracts knowledge from the input data [8]. Another statistical and machine learning technique is Principal Component Analysis (PCA) which aims to reduce the dimensions of a dataset to reveal information that may be hidden [24].

In their study, Buethe, Kraemer, and Fritzen [4] employed Self-Organizing Maps (SOM) in the field of Structural Health Monitoring (SHM) to discern between data obtained from piezoelectric sensors in their pristine condition and the presence of damage under varying environmental conditions. In addition, the authors specifically examined two failure modes: degradation and sensor breakage. However, as highlighted in this research, addressing the complexities associated with changes in environmental conditions remains a challenge.

Angulo-Saucedo *et al.* [2] proposed a monitoring system for damage classification using normalization techniques, PCA, and supervised Self-Organizing Maps in two aluminum plates with different characteristics and a composite material plate (CRFP). First, different masses were attached to the aluminum plates in the structure to simulate damage conditions. Then, the real damage was done on the composite material plate as delamination and cracking. Due to the excellent results, validating the techniques, supervised Kohonen and X–Y fusing Kohonen about damage classification was possible.

Abdeljaber and Avci [1] presented a non-parametric algorithm for anomaly detection that combines SOM with a pattern recognition neural network in a finite element model (FEM) for the grid structure constructed using Abaqus software. As damage conditions, stiffness losses in the transverse beams, changes in boundary conditions, and noise-contaminated data were considered. It was shown that the algorithm could locate several damage cases, including noise effects.

Tibaduiza *et al.* [26] used SOM with the Multiway Principal Component Analysis (MPCA), Discrete Wavelet Transform (DWT), Squared Prediction Error (SPE) to detect and classify damage conditions on an Airbus A320 aircraft fuselage and multilayer carbon fiber reinforced plastic (CFRP) plate. As a result, all cases of simulated damage were detected.

Oliveira Jr *et al.* [12] used a method based on electromechanical impedance (ISHM) damage classification and self-organized maps (SOM) on a diamond grinding tool. Even though the application was made on a small dataset, they still significantly improved the classification of anomalies, demonstrating the effectiveness of this technique.

This work aims to use Kohonen's maps to obtain estimates of faults and their severity through data obtained from tests carried out by ISHM. To resolve the problem of data presented as false-positive about temperature variation, PCA was applied to reduce the dimensionality of the dataset to reduce errors.

This article is organized as follows. Section II presents the theoretical framework for ISHM, SOM, and PCA and ends with the experiment developed. Then, in section III, it was shown how the temperature variation affected the collected data and a comparison between the results obtained from applying the SOM in the original dataset and the modified by the PCA. Finally, in section IV, final considerations are presented.

II. METHODOLOGY

Several studies and research have been conducted during the last two decades on ISHM (Impedance-based Structural Health Monitoring). According to these studies, the methodology can prevent situations with high maintenance costs and damage that can lead to fatal accidents. Such occurrences can be avoided by implementing a monitoring system, avoiding unnecessary maintenance, and increasing safety [18]. Furthermore, the ISHM technique has a high significance level due to its sensitivity in detecting initial damage, relative cost, and low need for component customization [5, 13, 14, 22, 23, 25].

2.1. Impedance-based structural health monitoring

Piezoelectric materials are essential for performing the ISHM technique due to their conversion between electrical and mechanical properties. Since these conversions occur in two directions, two effects are considered, the direct and the inverse principle. In the direct principle, an electrical potential is generated at the terminals due to mechanical strain in the transducer. In the inverse principle, mechanical strain occurs when applying an electrical voltage to the transducer terminals. These effects are applied to the structure to obtain a response in electromechanical impedance values. Equations 1 and 2 represent, respectively, the direct and inverse principles [5].

$$D = d\sigma + \varepsilon E_1 \tag{1}$$

$$S = s\sigma + dE_1 \tag{2}$$

where D is the strain vector, E_1 is the electric field vector, S is the strain tensor, σ is the stress vector, d is the voltage tensor piezoelectric, ε is the dielectric tensor of the material and s is the elastic property of the piezoelectric material.

In view of this, Liang, Sun, and Rogers formulated a model to characterize the measurement process of electromechanical impedance in systems with one degree of freedom. This model utilizes the inverse of impedance, known as electromechanical admittance. By combining the mechanical impedance function of the PZT patch, denoted as $Z_a(\omega)$, with the structural impedance of the system, denoted as $Z(\omega)$, the admittance function $Y(\omega)$ can be obtained as shown in equation 3 [16, 17].

$$Y(\omega) = \frac{I}{V} = i\omega a\left(\bar{\epsilon}_{33}^{T}(1 - i\delta) - \frac{Z(\omega)}{Z(\omega) + Z_a(\omega)} d_{3x}^{2}\hat{Y}_{xx}^{E}\right) \tag{3}$$

where Y is the electrical admittance, V is the input voltage of the PZT actuator, I is the output current of the PZT patch, a is the geometric constant of the PZT patch, d_{3x}^2 is the coupling constant PZT patch in an x direction with zero strain, $\hat{Y}_{xx}^{E}$ is the Young's complex modulus of PZT patch with zero electric field, $\bar{\epsilon}_{33}^{T}$ is the complex dielectric constant of PZT patch at zero voltage, ω is the angular frequency, Z is the complex impedance of the structure, Z_a is the complex impedance of the PZT patch and δ is the tangential dielectric loss factor of PZT patch.

Impedance signatures do not provide data about damage to the structure. However, when observing a structure's signature without damage and after, one can qualitatively perceive the occurrence of the failure through its structural changes (local stiffness, mass, and damping). Therefore, to carry out a quantitative procedure, a damage index for identifying damages, also called damage metrics, is necessary. The most used of these indices is the Root Mean Square Deviation (RMSD), a scalar value that provides quantitative information, shown in equation 4 [17, 18, 21].

$$M = \sum_{i=1}^{n} \sqrt{\frac{[Re(Z_{i,1}) - Re(Z_{i,2})]^2}{[Re(Z_{i,1})]^2}} \tag{4}$$

where M is the failure measure, $Re(Z_{i,1})$ represents the real part of the PZT patch measured under healthy conditions, $Re(Z_{i,2})$ represents the real part of the signature to be compared and i is the frequency point.

If the RMSD index has a significant value, the signals measured in the damaged and undamaged structure indicate a larger difference, therefore, a significant defect. Even though many SHM studies have been carried out on this index, a problem is challenging to solve: the effects not related to the damage, such as temperature variations, which affect the frequency influencing the value of the index [21, 22].

At the same time, another damage metric is the correlation coefficient deviation (CCD). This assigns a value to the difference between two data sets. To obtain this value, it is necessary to calculate the correlation coefficient (CC) shown in equation 5 [22].

$$CC = \frac{1}{n}\sum_{i=1}^{n}\frac{(Re(Z_{i,1}) - Re(\bar{Z}_1))(Re(Z_{i,2}) - Re(\bar{Z}_2))}{S_{Z_1}S_{Z_2}} \tag{5}$$

where S_{Z_1} is the standard deviation of the impedance signal of the reference and S_{Z_2} is the standard deviation of the impedance signal to be compared. After calculating equation 5, equation 6 is intended to calculate the CCD.

$$CCD = 1 - CC \tag{6}$$

As the CC metric approaches +1, it indicates that the peaks of the input signal closely match those of the reference signal, suggesting that the structure is in good condition. However, as the CC values deviate from +1, it may signify damage, with lower CC values indicating more pronounced deviations in the signal and, thus, more significant damage [21, 22].

2.2. Kohonen's maps

Teuvo Kohonen, a prominent figure in the field of neurocomputing, is credited with pioneering the development of Self-Organizing Map (SOM) networks. With extensive research in self-organization theory, associative memories, neural networks, and pattern recognition, Kohonen has authored over 200 articles and four books on these subjects [4, 20].

In this sense, Teuvo Kohonen's research on self-organizing maps began in 1981 to develop an efficient algorithm that would map similar patterns given as vectors next to each other in the input space into continuous locations in the output space [4, 20].

The SOM algorithm was one of the factors in the resumption of the popularity of artificial neural networks (ANNs). It is the most used ANN learning rule in unsupervised algorithms. Moreover, it has been implemented in many public and commercial neural network software packages [20].

SOM produces a similar plot of the input data in its basic form. Non-linear statistical relationships between extensive data are converted to simple geometric relationships on a smaller screen, usually a two-dimensional image of nodes [15].

The network employs a competitive and unsupervised learning algorithm wherein neurons in the output layer compete for activation. As a result, only one output neuron is activated for each input pattern, following the "winner takes all" principle. To facilitate this competition, inhibitions on the lateral connections between the output neurons in the same layer are implemented, as illustrated in Figure 1 [6].

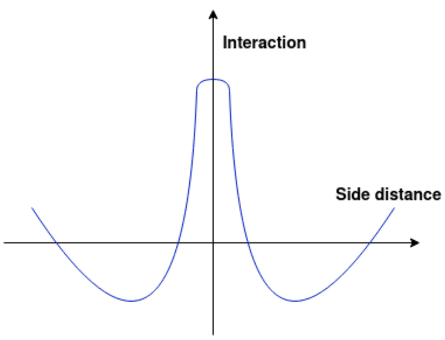

Figure 1 - Representation of the neighborhood interaction between the neurons of a SOM network.

In this type of topology, each output neuron is connected to all neurons in the input layer, also called the fully connected layer. As shown in Figure 2, this network represents a feedforward structure with a single computational layer after the input layer [12].

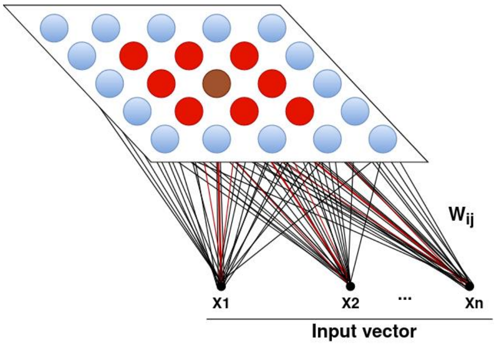

Figure 2 - Representation of a Kohonen neural layer.

Once a Kohonen networks construction starts, the connections' weights will have random values. After applying these weights, each node will calculate the function in equation 7 [1, 11].

$$v = argmin_j \left| x - w_j \right|; \qquad j = 1,2,\dots,l \tag{7}$$

In the SOM network, the input vector is represented by *x*, the weights are denoted by *w*, and *l* represents the number of neurons in the network [1]. The winning neuron is determined based on the criterion of maximizing the inner product, which is equivalent to minimizing the Euclidean distance between *x* and *w*, as described by equation 7 [1].

Furthermore, to ensure cooperative behavior among neurons, it is crucial to establish a relationship between the lateral distance separating winning and excited neurons. This connection can be quantified differently depending on the network configuration. For instance, in a one-dimensional network, the lateral distance can be represented by |j-1|. On the other hand, in a two-dimensional grid, the lateral distance is defined by equation 8 [1, 11].

$$d_{j,i}^2 = |r_j - r_i|^2 \tag{8}$$

where r is the discrete vector of the positions of neurons excited j and winning i [1].

Then the topological neighborhood process will take place. At this point, the winning neuron will excite the closest compared to the farthest. The Gaussian function can be used to model the lateral interaction, as shown in equation 9 [1, 11].

$$h_{j,i(x)} = exp(\frac{-d_{j,i}^2}{2\sigma^2}) \tag{9}$$

where $h_{j,i(x)}$ is the topological neighborhood, $d_{j,i}^2$ is the lateral distance, σ is the effective width of the topological neighborhood, i is the winning neuron, and j is the excited neuron [1]. The next and last step is to update the weights using equation 10 [11].

$$\Delta w_{ji} = (\eta(t))(T_{j,I(x)}(t))(x_i - w_{ji}) \tag{10}$$

where t is the number of epochs, $\eta(t)$ is the learning rate over time and $T_{j,I(x)}$ is neighborhood region [1]. In the output layer, in two-dimensional cases, there can be two types of grids, hexagonal, as shown in Figure 4, or rectangular, as shown in Figure 3.

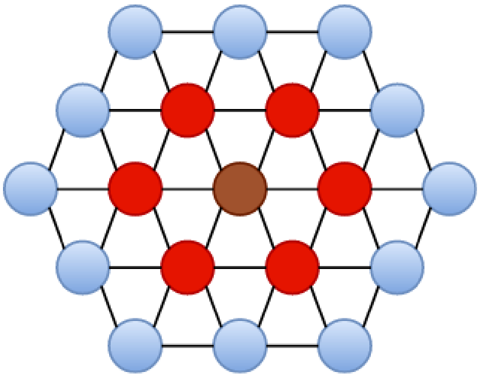

Figure 3 – Hexagonal map.

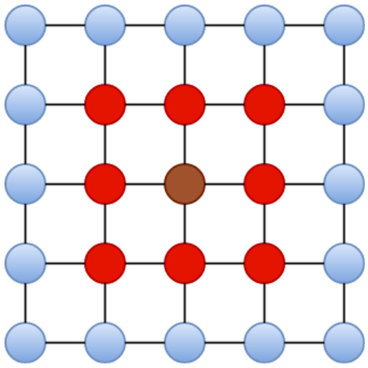

Figure 4 - Rectangular map.

As can be seen, in the hexagonal topological map, each neuron is surrounded by six neighboring neurons, determined by the number of faces of the element. In contrast, the rectangle has four neighbors. In the rectangular topology, the neighborhood calculation is done with the four neighbors, creating distortions in the network and causing accumulated errors. However, in the hexagonal topology, the behavior is similar in the six directions, making the visualization more pleasing.

2.3. Implementation of Kohonen Maps

In this work, the Python language was used to implement Kohonen's self-organizing maps due to its dynamic nature and object-oriented capability, which makes it suitable for a wide range of applications, including scientific and non-scientific purposes [7]. Furthermore, the decision to use Python was motivated by its extensive collection of libraries and straightforward syntax. Table 1 provides an overview of the libraries that will be used to implement the Kohonen maps, along with a brief description of their functionality.

Table 1. Available libraries in Python for implementing SOM networks, with their respective descriptions.

Libraries	Description
Numpy	Extensive collection of functions for math operations.
Pandas	Data manipulation and analysis functions.
MiniSom	Minimalist implementation of Self-organizing maps.
Matplotlib	Creating graphs and visualizing data in general.
Scikit-learn	Machine learning.

As evidenced in Table 1, the MiniSom library stands out as a major Python library for implementing Kohonen's self-organizing maps, making it a good choice for the current study's structural integrity monitoring needs. In addition, this library, available in a GitHub repository developed by Giuseppe Vettigli, serves as a valuable resource for students seeking to understand the complexities of the Kohonen network and allows researchers to build their applications quickly [27].

To develop applications using the MiniSom library, the collected data set must be a matrix, where each line refers to an observation [27]. After loading the dataset using the Pandas library, the next step is to initialize the self-organized map by executing the *MiniSom* command. Regarding the parameters that can be used in the previous function, *x* and *y* represent the dimensions of the resulting map, *input_len* is the number of elements of the input vector, *sigma* represents the propagation of the neighborhood function, *learning_rate* is the initial learning rate, *decay_function* means the function that reduces *learning_rate* and *sigma* parameters at each iteration, *neighborhood_function* is the function that weights the neighborhood of a position on the map, *topology* is the topology type of the map and *activation_distance* represents the distance used to activate the neurons of the map [27]. Table 2 shows some items available by default for each parameter.

Table 2. Examples of default values for the initialization parameters of the self-organizing map via the MiniSom library.

Neighborhood function	Topology	Activation distance
gaussian	rectangular	euclidean
mexican_hat	hexagonal	cosine
bubble		manhattan
triangle		chebyshev

The *values of the x, y, input_len, learning_rate, and sigma parameters* are contingent upon the specific data set being utilized. While the *decay_function* parameter normally employs the asymptotic decay function, as described in equation 11 [27].

$$asymptotic\_decay = \frac{2(learning\_rate)}{(max\_iter) + t(max\_iter)} \quad (11)$$

where *learning_rate* is the current learning rate, t is the current iteration, and *max_iter* is the maximum number of iterations performed during the neural training process [29].

Following the initialization of the self-organizing map (SOM), the subsequent step entails initializing the connection weights with random data samples, accomplished by employing the *random_weights_init* command. Subsequently, the training process is carried out using the *train* function. Upon completion of training, the *winner* function can be utilized to determine the position of the winning neuron for a given sample [27].

The main evaluation method of the SOM network is topological error quantization. The average distance between each input vector and its best corresponding unit is calculated in the quantization error, shown in equation 12 [27].

$$E_q = \frac{1}{n}\sum_{1}^{n} |v_n - w_{win}| \quad (12)$$

where v_n is the input vector, w_{win} is its best matching unit, and n is the total of samples [11].

The topological error is calculated by finding the first and second best-matching neurons in the map for each input and then evaluating the positions. A sample where these two nodes are not close means an error has occurred. Therefore, the topographic error is given by the total number of errors divided by the number of samples shown in equation 13 [27].

$$E_q = \frac{1}{n}\sum_{1}^{n} u(v_n) \quad (13)$$

where $u(v_n)$ represents the occurrence of the error and n is the total number of samples [11].

2.4. Principal Component Analysis

The primary objective of the PCA (Principal Component Analysis) normalization technique is to achieve a unit variance in the data, thereby eliminating redundancies and improving results. This is achieved by transforming the main components into a new set that is initially uncorrelated, with the first component accumulating the highest variance. Ultimately, this process helps to reduce dimensions and mitigate redundancies in the data, as supported by references [2, 19, 23].

With the dataset organized in a matrix form, the first step is calculating covariance using equation 14.

$$C = \frac{1}{n-1} X^T X \tag{14}$$

where n represents the number of lines, X^T is the transverse matrix and X is the matrix. The next step is to calculate the subspaces defined by the eigenvalues and eigenvectors of the covariance matrix using equation 15 [2, 23].

$$C\tilde{P} = \tilde{P}A \tag{15}$$

where A is a diagonal matrix of eigenvalues and $\tilde{P}$ are the eigenvectors of the covariance, called principal components. Since the most important patterns are defined according to the eigenvalues of eigenvectors, the structure is constructed by the transformation matrix, where the number of principal components with the least number of trials is chosen. Thus, the PCA model is formed, representing a reduced and better version of the original data [2, 23].

2.5. Induced failure in an aluminum beam

The experiment utilized an aluminum beam with specific dimensions (500mm in length, 38mm in width, and 3.2mm in thickness) coupled to a PZT patch (1mm in thickness and 20mm in diameter). The PZT patch was affixed 100mm away from one edge of the beam. Then, impedance signatures data was measured and analyzed to determine the health condition of the beam. The data was acquired in a controlled environment with temperature and humidity maintained using a Platinous EPL-4H series climatized chamber, as illustrated in Figure 5. This chamber is installed in the Structural Mechanics Laboratory of the School of Mechanical Engineering at the Federal University of Uberlandia.

Figure 3 - Platinous EPL-4H series climatized chamber.

The failure mechanisms used were surface grinding on one of the faces of the 30mm width beam at 70mm from the opposite end of the PZT patch but on the same face. Figure 6 illustrates an image of one of the machined states.

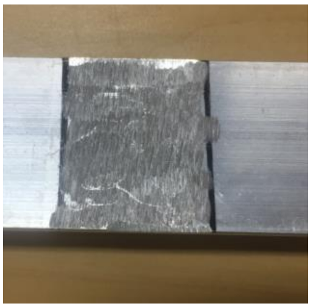

Figure 4 - Beam in the machined state.

Eleven temperature levels were selected, ranging from 10º C to 40º C, in the increasing form of 3º C in 3º C, as shown in Table 3.

Table 3. Temperature values in this case study.

Levels	Temperature (ºC)
1	10
2	13
3	16
4	19
5	22
6	25
7	28
8	31
9	34
10	37
11	40

Impedance data was collected in intervals, with the chamber temperature gradually rising during the data collection process. After each temperature cycle, the chamber was held steady for 30 minutes to allow the new temperature to stabilize, and data was collected in a new cycle. This process was repeated for 11 temperature cycles, with nine different levels of damage induced in the samples. In total, 30 repetitions were performed, resulting in 2970 collected signatures. The first two levels of damage served as reference signals, representing the original beam in a controlled environment. The remaining seven levels of damage were intentionally induced to study the behavior of a specific flaw in the collected signatures.

Regarding the 2970 observations collected, each cycle had 4000 attributes that are not in a multivariate situation. Therefore, the variables cannot be interpreted in isolation, being related to each frequency point from 30000 Hz to 70000 Hz, with a step of 10 Hz. Figure 7 illustrates the plot of 4 signatures collected referring to baseline conditions without temperature variation for better visualization.

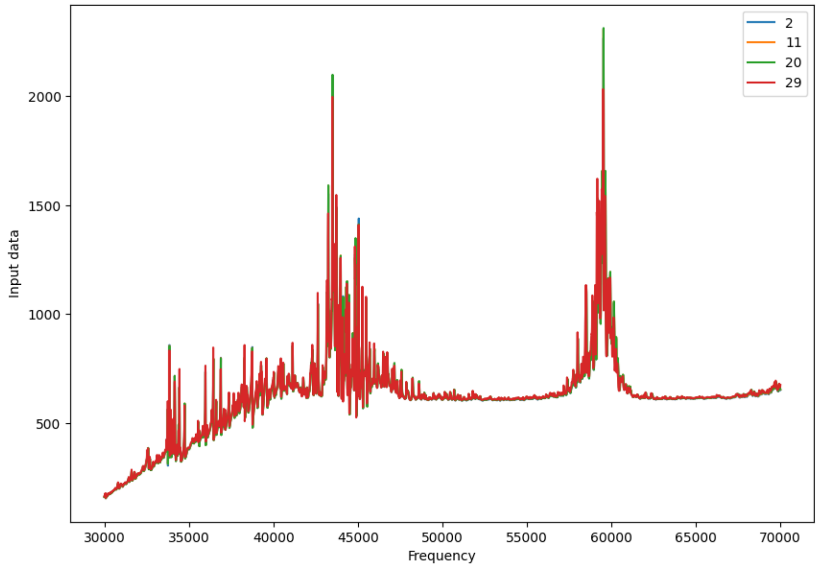

Figure 5 - Baseline without temperature variation.

As mentioned, the EPL-4H chamber was utilized to simulate temperature variations. In Figure 8, the plot showcases four collected signatures, which serve as a reference to the baseline, but with varying temperatures of 10°C, 22°C, 31°C, and 40°C.

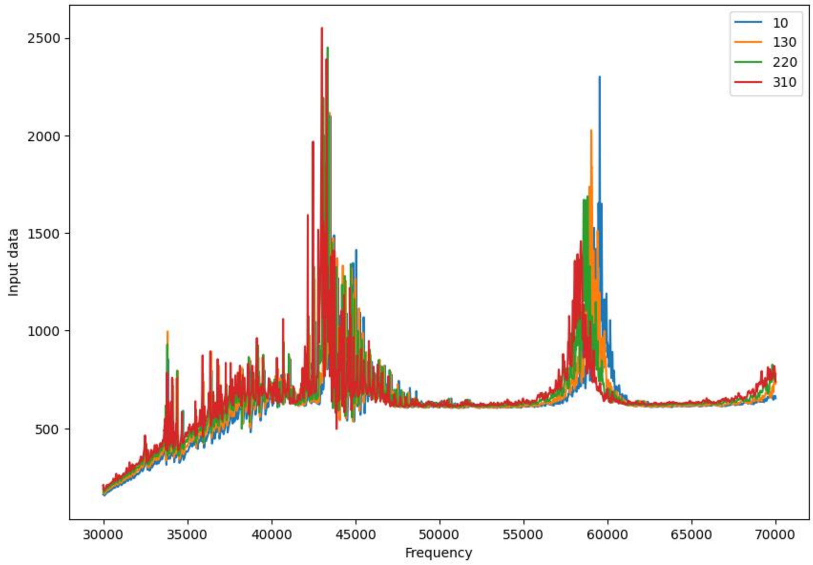

Figure 6 - Baseline with temperature variation.

As evident from Figures 7 and 8, both depict plots of signature data obtained from the same baseline condition. However, in Figure 8, the temperature variation resulted in a shift of the signals in the horizontal direction, potentially leading to false alarms in anomaly detection.

III. Results and Discussion

After processing the data, this is one of the most critical steps in any application, using the dataset with 4000 attributes and the MiniSom library with the parameters defined as *dimensions=200x200*, *topology=hexagonal*, *neighborhood_function=gaussian*, *learning_rate=0.5* and *sigma=10*. Figure 9 illustrates this map.

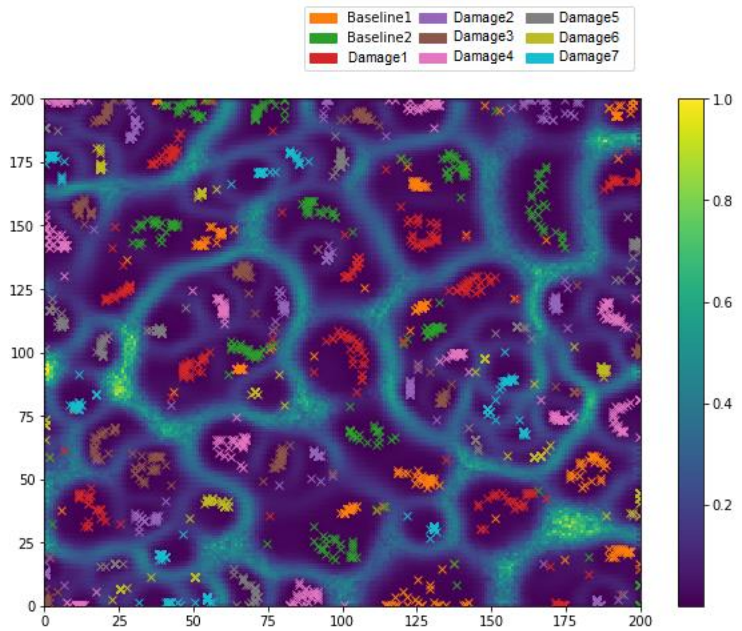

Figure 7 - Kohonen map for dataset with 4000 attributes.

In Figure 9, the map is designed with a bar on the right side representing the neighborhood's distance of neurons. Each bar number is color-coded on the map for better visualization. The legend includes two baseline levels and seven damage levels, denoted by the "×" marker, each represented by a distinct color indicating the position of the winning neuron. As mentioned, the topology parameter was set to hexagonal to exclude topological errors, making the quantization error evaluation method the sole approach. However, this method revealed an error of 183.80. Therefore, the PCA method was applied to reduce the dataset of 4000 attributes to 20 principal components to mitigate this error. The MiniSom library was then utilized with the following parameters: *dimensions* = 300x300, *topology* = *hexagonal*, *neighborhood_function* = *gaussian*, *learning_rate* = 0.5, and *sigma* = 10. The result of this step is shown in Figure 10.

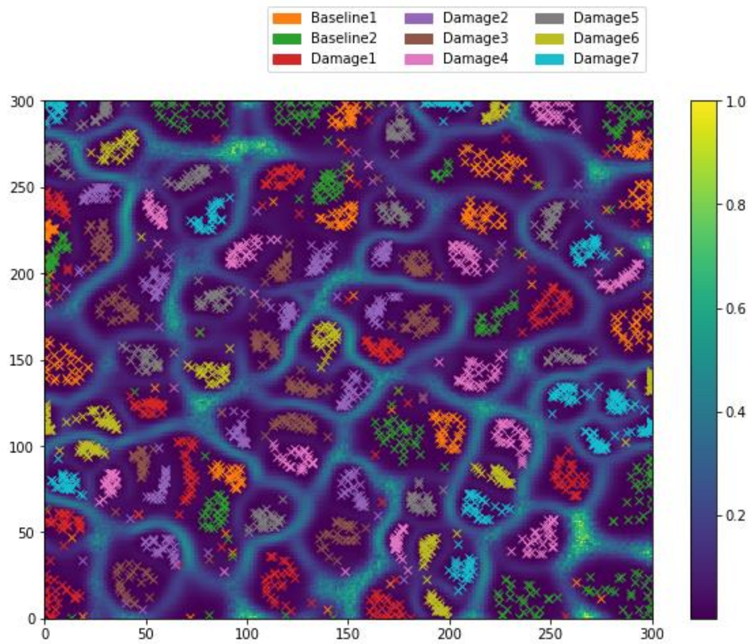

Figure 8 - Kohonen map for Dataset with 20 principal components.

As shown in Figure 10, it was possible to disturb the mesh more to reduce false classifications. Nevertheless, compared with the previous output map, it is possible to verify that there was a greater dispersion of the data concerning the increase in the neighborhood adjustments and that, due to the application of the PCA method, the value of the quantization error was reduced to 31.54. It was also possible to observe that, in Figures 9 and 10, the variation in the same type of damage comes from the difficulty of Kohonen's self-organizing maps in analyzing temperature variation.

IV. CONCLUSIONS

This contribution demonstrated the utility of the Self-organized Maps (SOM) and the Principal Component Analysis (PCA) for the structural health monitoring of aluminum beams. Specifically, the electromechanical impedance technique, a non-destructive testing approach, was employed. In addition, the SOM facilitated data grouping and classification using artificial neural networks, making it a valuable tool in structural health monitoring (SHM).

One of the main benefits of employing the SOM network is its easy implementation. Once the weights are defined, matrix multiplication based on the specified number of iterations is all that is needed. This efficient approach results in clear separation and identification of classes, as evidenced by the output maps presented in the previous section. However, the main disadvantage of SOM networks is the variation of the same class due to temperature changes, which can confuse damage that is just a temperature variation, which is the main problem when analyzing real-world practices.

Regarding the proposed application, the deformations in the aluminum beam caused by the temperature variation greatly impacted the detection of anomalies. To reduce the quantization error value found in this problem, the PCA method with 20 principal components was used, making it possible to reduce the quantization error from 183.80 to 31.54.

Hence, the efficacy of utilizing Kohonen networks in conjunction with PCA for classifying distinct damage conditions experienced by the selected aluminum beam structure was demonstrated. This highlights the potential of this unsupervised network as an efficient tool in the structural health monitoring process.

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