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Machine Learning and Electromechanical Impedance Applied in the Structural Health Monitoring

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Abstract. *The advancement of industrial systems, machine learning techniques to monitoring and damage diagnosis have attracted much attention and are widely used in engineering projects. The development of smart systems provides real-time analysis of large volumes of data and important insights to optimize, reduce costs and improve product quality. The objective of this study is to propose a smart system to assess structural integrity using electromechanical impedance. This model is constituted by supervised and unsupervised machine learning tools. The strategy adopted for the choice of resources for the data matrix and the data pre-processing step play an important role in the modeling process and, consequently, have a direct impact on the performance of the clustering and classifier algorithms. Primary a fitted Gaussian Mixture Model is applied to divide the samples into two main clusters: normal or damage. Then a Support Vector Machine classifier was used in the damage cluster to identify the different types of damage. Metrics such as Recall, Accuracy and F1 Score were used to evaluate the model performance. Preliminary results enable the use of the proposed model as a promising methodology for monitoring structural integrity.*

Keywords: *smart system, electromechanical impedance, Gaussian Mixture Model, Support Vector Machine, damage diagnosis.*

1. INTRODUCTION

Nowdays, the constant advancement of industrial processes supports the development of intelligent solutions that drive increased efficiency, quality, cost reduction and innovation. In this scenario, data collection has become increasingly easier due to technological advances and connectivity.

The development of smart devices, sensors and Internet of Things (IoT) aliens make it possible to collect real-time data from a variety of sources, create and manipulate large shared databases. These data collection facilities provided a solid foundation for the development and improvement of intelligent diagnostic systems (Liu *et al.*, 2018).

The application of machine learning tools brings numerous advantages, allowing the analysis of a large volume of data, driving strategic decision-making quickly and accurately. In addition, machine learning tools can be employed in early detection of failures and predictive maintenance, avoiding unexpected production line stops, catastrophic failures or structural collapse.

According to Liu *et al.* (2018), an intelligent monitoring and diagnostic system comprises several steps, which include data acquisition, feature security, normalization, dimensionality reduction, identification and diagnosis. Furthermore, these systems can incorporate statistics covering a variety of optimization methods and self-adaptive systems in pattern recognition, as discussed by (Bishop, 2006). This remarkable versatility makes it possible to apply it in different areas of knowledge.

Machine learning techniques also play a crucial role in the field of SHM. In the context, these techniques enable the collection, analysis, and interpretation of data from sensors installed in structures such as bridges, buildings, and critical infrastructure. The use of clustering algorithms (Saxena *et al.*, 2017; Xu and Tian, 2015) helps identify behavior patterns that may indicate the presence of structural anomalies, while classifiers (Alpaydin, 2020; Liu *et al.*, 2018) assist in data categorization and the detection of potential issues.

SHM benefits from machine learning by allowing early detection of structural damage, ensuring the safety and durability of infrastructures. The continuous development of algorithms and the application of data-driven predictive models contribute to preventive maintenance, cost reduction, and ultimately public safety. Therefore, machine learning plays an essential role in advancing SHM, ensuring the integrity of critical structures and effective asset management.

Due to the versatility of these diagnostic systems, they are widely applied in various areas, including the electromechanical impedance (EMI) technique for structural health monitoring (SHM), theme explored in this study. EMI has been used in the detection of structural failures due to its efficiency and cost-effectiveness. It has non-destructive property and ease of implementation of small and inexpensive piezoelectric transducers that are attached to structures, which leads to cost reduction as well as less dependence on manual inspection methods (Batista da Silva *et al.*, 2018).

In recent studies the electromechanical impedance technique has been applied successfully to detect damage civil and mechanical engineering structures. For the most part, these studies use those in reinforced concrete (RC). Thick steel structures are still little explored.

In Bansal *et al.* (2021), the authors used autoregressive integrated moving average (ARIMA), an effective machine learning (ML) time series prediction algorithm to predict the baseline/healthy electromechanical data and futuristic data of corroded in RC samples. In Li *et al.* (2023) was showed a new method to predict and monitor the strength development of concrete using smart embedded aggregates (SAs), combining EMI electromechanical technology and machine learning to monitor the strength development of early-age concrete.

In Bento *et al.* (2017) the authors identified frequency ranges with greater sensitivity for monitoring structural damage using the impedance-based monitoring technique. The study employed bioinspired optimization methods, such as Bee Colony Optimization and Ant Colony Optimization, to enhance damage detection.

In this context, the present study aims to develop an intelligent damage detection and diagnosis system based on machine learning models. For this proposed methodology, the Bee Colony Optimization was applied to the electromechanical impedance signatures in order to find the most sensitive frequency range for damage monitoring. Statistical features are extracted to obtain the dataset for the machine learning model. Through similarity, the Gaussian Mixture Model will allow the model to identify two main clusters, normal or damaged instances. Subsequently, a Support Vector Machine is applied to the cluster containing the damaged instances in order to classify the type of damage.

2. SMART MONITORING AND DIAGNOSIS MODEL

2.1 Bee Colony Optimization (BCO)

Using the entire frequency spectrum is an expensive undertaking. Therefore, the objective is to identify a more sensitive frequency range for damage monitoring. Optimization algorithms like Bee Colony Optimization can be employed for this purpose. This algorithm can explore and search for an optimal subset of frequencies within the entire spectrum that provides the most relevant information for damage detection.

The BCO Algorithm (Lucic and Teodorovic, 2001), is a bioinspired optimization algorithm used to solve combinatorial optimization problems. This method is based on the foraging behavior of bees in search of raw materials for honey production. After observing nature, the autors noticed that bee colonies could fly over long distances in various directions simultaneously in search of food sources. Thus, the Bee Colony Algorithm is based on this phenomenon, incorporating methods of communication, information sharing through sound, pheromones, touch, dances, and electromagnetic stimulation (Lucic and Teodorovic, 2001; Serapião, 2009).

The BCO process involves creating a population of potential solutions to a combinatorial optimization problem, where each solution is represented as a virtual bee. These "bees" explore the search space of the problem, searching for promising solutions. As they find better solutions, they share this information with other bees in the colony, akin to real bee communication. The interaction among the virtual bees often leads to some form of collective intelligence, with the colony converging toward better solutions over time. The idea is that this process of distributed search and information sharing enables the discovery of solutions that are close to optimal for the optimization problem.

The sum of RMSD and CCD damage metrics was used in the objective function as the quantitative index (Bento *et al.*, 2017; Tsuruta *et al.*, 2017).

The equation that mathematically describes the RMSD damage metric is given by Eq. 1:

$$RMSD = \sqrt{\sum_{i=1}^{n}\left(\frac{(R_e(Z_{b,i}) - R_e(Z_{t,i}))^2}{(R_e(Z_{b,i}))^2}\right)}, \tag{1}$$

where n is the number of samples, $R_e(Z_{b,i})$ and $R_e(Z_{t,i})$ are, respectively, the real parts of the measured impedance for the normal and damage conditions, being collected at the sweep frequency i.

The damage metric based on the correlation coefficient being used especially in temperature compensation algorithms. The equation that describes the CCD damage metric is given by Eq. 2:

$$CCD = 1 - \frac{1}{n}\sum_{i=1}^{n}\left(\frac{(R_e(Z_{b,i}) - R_e(\overline{Z}_{b,i}) * (R_e(Z_{t,i}) - R_e(\overline{Z}_{t,i}))}{S_{Z_{b,i}} * S_{Z_{t,i}}}\right), \tag{2}$$

where $R_e(\overline{Z}_{b,i})$ and $R_e(\overline{Z}_{t,i})$ represent the means of the real parts of the measured impedance for the normal and damage conditions, respectively.

2.2 Feature Extraction and Dimensionality Reduction by PCA

Monitoring through electromechanical impedance signatures can provide relevant information about health of the structure. This way, the present study explored a comprehensive set of statistics frequently used in the existing literature as mean, standard deviation, RMS (Root Mean Square), peak value, asymmetry, kurtosis, energy and entropy.

A fundamental tool for machine learning models is dimensionality reduction. The larger the number of features, the more challenging it becomes to visualize the training dataset, and in some cases, many of these features are correlated or redundant. According Brito *et al.* (2022), dimensionality reduction can be done keeping only the most relevant features from the original dataset (generally called feature selection) or reducing the original dataset into a new one through analysis/combinations of the input variables, where the new dataset basically contains the same information as the original (generally called dimensionality reduction).

Different techniques can be used to reduce the dimensionality of the data obtained, such as: Principal Component Analysis (PCA). This technique is widely used in the field of data analysis and machine learning for dimensionality reduction. It is applied when there is a set of data with many variables, which can make analysis and computational processing complex. According Jolliffe (2002), PCA is a linear transformation that seeks to find the low-dimensional subspace within the data that maximally preserve the covariance up to rotation. This maximum covariance subspace encapsulates the directions along which the data vary the most.

PCA works by transforming the original variables into a new set of variables, called principal components, that are predominantly linear from the original variables. These new variables are ordered so that the first principal component explains the most variability in the data, the second principal component explains the second most variability, and so on. This allows you to reduce the dimensionality of the data, keeping most of the information relevant and simplifying the interpretation of the results.

2.3 Gaussian Mixture Model Clustering (GMM)

Data clustering is an unsupervised analysis technique that aims to group similar objects into sets called clusters. This approach seeks to identify intrinsic patterns in the data, where objects within the same cluster are more similar to each other than to objects in other clusters. The objective is to automatically group N database instances into k disjoint clusters according to some similarity measure (Alpaydin, 2020; Bishop, 2006).

According to scheme of the Fig. 1, clustering algorithms based on mixture model the data are generated by a mixture of underlying probability distributions. The clustering process is transformed into a parameter estimation problem, since all data can be modeled by a mixture of distributions of k components. Each distribution defines the degree of similarity of an observation to each of the clusters.

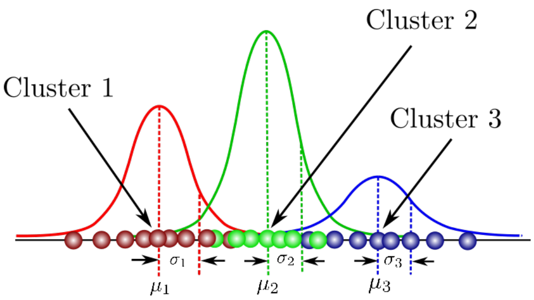


Figure 1. Formation of clusters based on probability distribution.

Usually, when estimating the GMM parameters, the *Expectation Maximization* (EM) algorithm is considered, summarized in two steps that are repeated iteratively until convergence (Bishop, 2006).

First, in step E (*Expectation*), the expected responsibilities $\gamma(z_{nk})$, according Eq. 3, from each observation to each component are evaluated.

$$\gamma(z_{nk}) = E[z_{nk}] = \frac{\pi_k N(X_n \mid \mu_k, \Sigma_k)}{\sum_{j=1}^{K} \pi_j N(X_n \mid \mu_k, \Sigma_k)}, \tag{3}$$

where E denotes the *expected value*, generally seen as the *responsibility* of the *k*th component in explaining the observation X_n.

Based on these responsibilities, the expected value of the log-likelihood function that allows evaluating the models can be obtained according Eq. 4.

$$log(X_n, \Psi) = \sum_{n=1}^{N} \sum_{k=1}^{K} \pi_k N(X_n \mid \mu_k, \Sigma_k), \tag{4}$$

where $\Psi = \left\{ \{\pi_k\}_{k=1}^K, \{\mu_k\}_{k=1}^K, \{\Sigma_k\}_{k=1}^K \right\}$ is the set of model parameters proposed; K is the number of components in the mixture; $\{\pi_k\}_{k=1}^K$ are the mixing coefficients, also called probabilities, subject to: $0 \leq \pi_k \leq 1$ e $\sum_{k=1}^K \pi_k = 1$ and $N(X_n \mid \mu_k, \Sigma_k)$ is the multivariate gaussian distribution.

Second, in the step M (*Maximization*), the model parameters are adjusted in order to maximize the likelihood function. To find maximum likelihood solutions that are valid at local maxima, we estimate the derivatives of $log(X_n, \pi, \mu, \Sigma)$ with respect to the parameters π_k, μ_k and Σ_k. After algebraic manipulations, the updates of the parameters referring to each k component are carried out according to parameters Eq. 5, 6 and 7.

$$\pi_k = \frac{\sum_{n=1}^N \gamma(z_{nk})}{N}, \tag{5}$$

$$\mu_k = \frac{\sum_{n=1}^N \gamma(z_{nk}) X_n}{\sum_{n=1}^N \gamma(z_{nk})}, \tag{6}$$

$$\Sigma_k = \frac{\sum_{n=1}^N \gamma(z_{nk})(X_n - \mu_k)(X_n - \mu_k)^T}{\sum_{n=1}^N \gamma(z_{nk})}. \tag{7}$$

2.4 Support Vector Machine Classifier (SVM)

The SVMs are usually used to solve classification and linear regression problems. This method have attracted a lot of attention in recent years due to their efficiency when compared to other more complex approaches, such as neural networks, in applications that require machine learning and because they are well founded in statistical learning theory (Géron, 2019).

Computational learning of an SVM is based on obtaining an ideal separation hyperplane between data sets, as illustrated in Fig. 2, solving a constrained quadratic optimization problem based on structural risk minimization (Liu *et al.*, 2018).

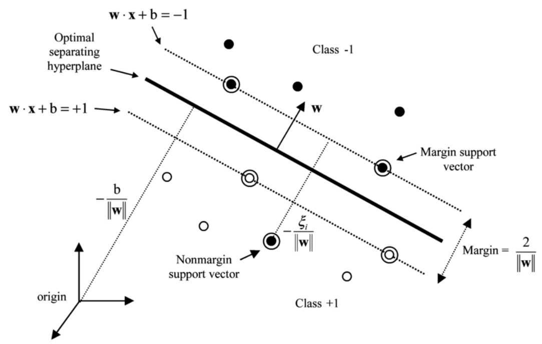


Figure 2. Optimal separating hyperplane in SVMs for a linearly nonseparable case. Support vectors are indicated by an extra circle. Adapted Melgani and Bruzzone (2004)

In agreement with Fig. 2, consider a data set $D = \{(x_1, y_1), (x_2, y_2), \cdots, (x_n, y_n)\}$ where the point $x_i \in R^d$ is the ith entry observation and $y_i \in \{-1, 1\}$ is the ith output pattern, indicating class membership. The optimal separation hyperplane is represented by the equation $w^T x + b = 0$ with $w \in U$ and $b \in R$. The hyperplane determines a maximum margin of separation between the classes, white and black circles refer to the classes "+1" and "-1," respectively.

To prevent the model from overfitting to noisy data, slack variables ξ_i are introduced to allow some data points to fall within the margin. The constant $C > 0$ is the trade-off factor between maximizing the margin and the number of training data points within the margin.

The minimization problem, see Eq. 8, is solved by Lagrange multipliers and the use of the Kuhn-Tucker condition allows obtaining the classifier according to the support vector.

$$min_{w,b,\xi_i} \frac{\|w\|^2}{2} + C \sum_{i=1}^n \xi_i \qquad \text{subject to:} \qquad y_i \left(w^T \Theta(x_i) + b \right) \geq 1 - \xi_i \tag{8}$$

for $i = 1, \ldots, n$ and $\xi_i \geq 0$.

The decision function rule for a data point x is given by Eq. 9:

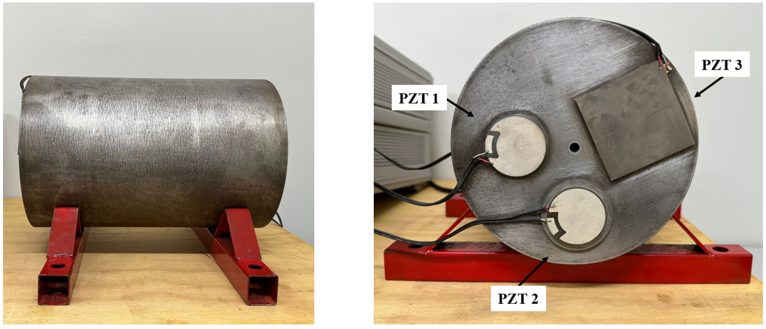
$$f(x) = sgn\left(\sum_{i=1}^n \alpha_i y_i K(x, x_i) + b \right), \tag{9}$$

α_i are the Lagrange multipliers; every $\alpha_i > 0$ is weighted in the decision function and acts as a backer for the machine. SVMs are sparse there will be relatively few non-zero lagrange multipliers.

An SVM model has the property of creating a non-linear decision boundary that projects the data through a non-linear function Θ to a higher dimensional space. The function $K(x, x_i) = \Theta(x)^T\Theta(x_i)$ is the kernel function whose choice directly influences the separability of the samples and the class classification performance. The most popular ones for the kernel function are linear, polynomial, sigmoidal and mainly the gaussian radial basis function (*rbf*).

3. EXPERIMENTAL TEST

For the experimental test, a steel dowel with $300mm$ in length and $200mm$ in diameter was considered, supported by two square steel bases and four angle brackets to support the structure, see Fig. 3(a). It was instrumented with three piezoelectric transducers at one of its ends, named PZT 1, PZT 2 and PZT 3, see Fig. 3(b).



(a) Bench. (b) Piezoelectric transducers.

Figure 3. Thick steel structure with piezoelectric transducers.

For damage simulation, masses have been added in structure. The *damage type A* corresponds to four threaded bars mounted on the dowel using nuts and washers totalizing 369,5g, see Fig. 4(a). In the *damage type B* the nuts were tightened and a steel disc with mass of 4163,5g was added in structure, see Fig. 4(b). The impedance signatures were obtained using the SySHM impedance analyzer, Fig. 4(c), developed by the LMEst researchers. It is an innovative, low-cost, versatile, fast-processing technology that operates at frequencies from 0 to 400kHz (Finzi *et al.*, 2010).

(a) (b) (c)

Figure 4. Masses added to the structure for damage simulation and SySHM impedance analyzer.

4. RESULTS AND DISCUSSION

There weren't efforts for the compensation of temperature because was considered the same temperature during the measurement. According Park *et al.* (2003) the structural stiffness, mass, or damping change directly affects the electrical impedance of the PZT patches due to the electromechanical coupling. Thus, it was considered only the real part of the impedance signatures due to the mechanical properties were associated to them. In total, 150 samples were collected, 50 for each of the conditions presented. The impedance signatures collected by the SySHM analyzer comprise a frequency range of 0 to 250 kHz in a step of 10 Hz. The average impedance signature for PZT1 can be seen in Fig. 5.

Using the entire frequency range available in Fig. 5 is possible but unfeasible. In addition, up to 175 kHz the impedance signatures are visibly discrepant. Therefore, a frequency range of 175 to 250 kHz was chosen to apply the methodology. The BCO is applied to identify the frequency range most sensitive to damage, avoiding loss of accuracy due to information that isn't relevant. 120 candidates were considered in the population, with a crossover rate of 0.875 and a maximum limit of 500 iterations, although a stopping criterion was established based on a population variance of less than 0.01.

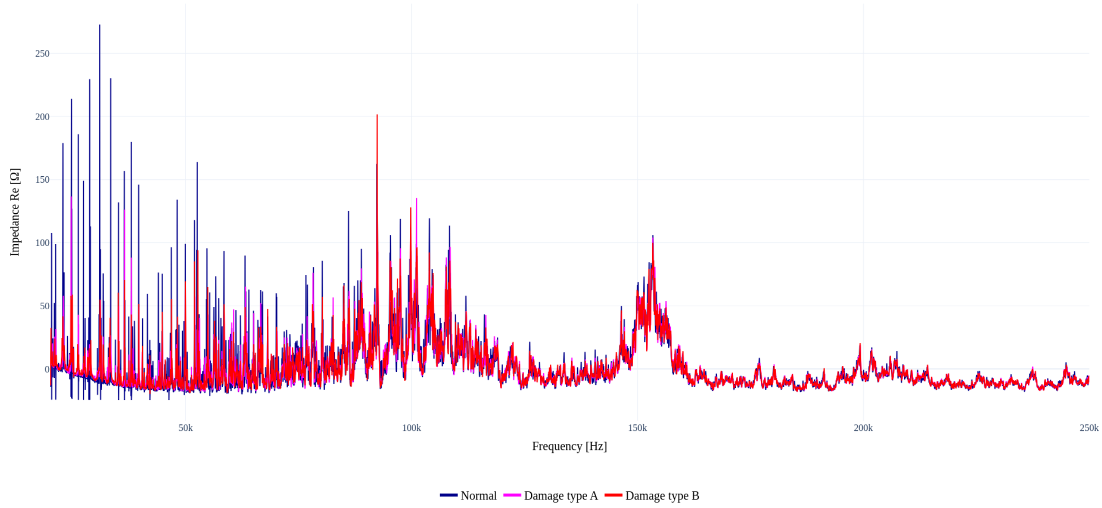


Figure 5. Complete signature of the structure.

According to the BCO algorithm, the ideal frequency range to evaluate the impedance signatures under study was 219459 to 224489 Hz, shown in Fig. 6 to 504 points and with an objective function value of approximately 2,764 and standard deviation of the population of 0,0073.

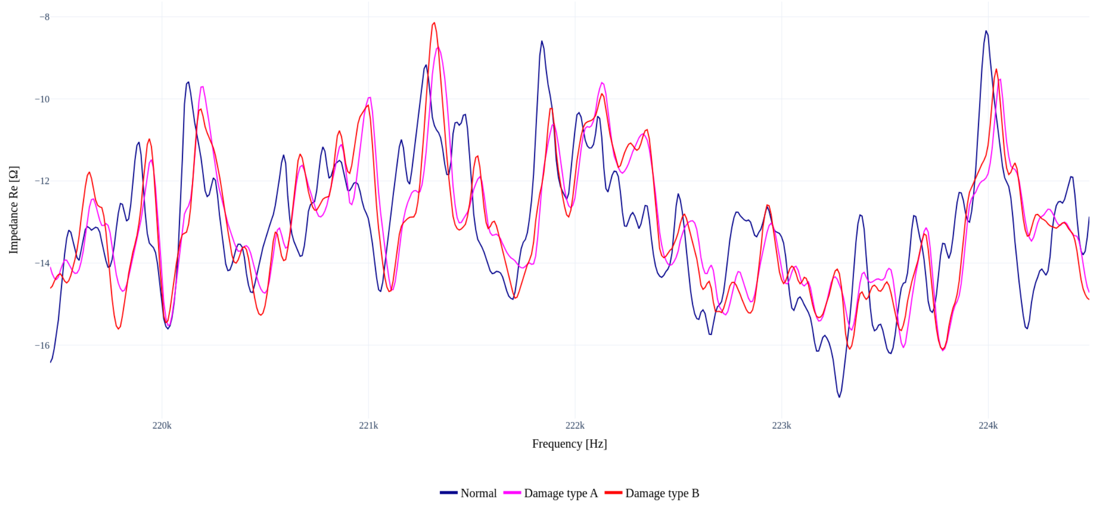


Figure 6. Zoom of the best frequency range.

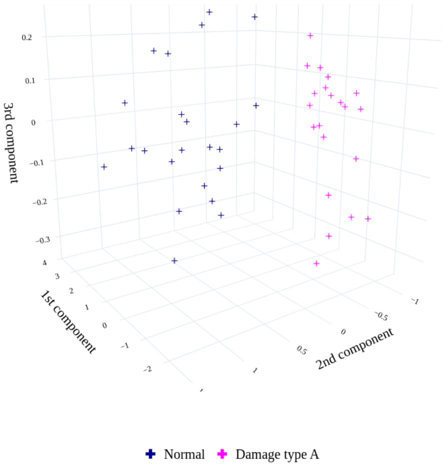
The features were extracted from the scikit-learn library (Pedregosa *et al.*, 2011) and used for transforming the data to have zero mean and unit variance. PCA was employed for dimensionality reduction. The training and testing sets were split into percentages of 80% and 20%, respectively.

Subsequently, the GMM clustering was applied to the test set to identify normal and damaged samples based on their similarity according to the probability of belonging. In this approach, each Gaussian distribution represented a distinct cluster. The outstanding performance of the clusterizer in identifying normal samples and those with damage of both type A (as shown in Fig.7(a)) and type B (as depicted in Fig. 7(b)) can be observed in Fig. 7.

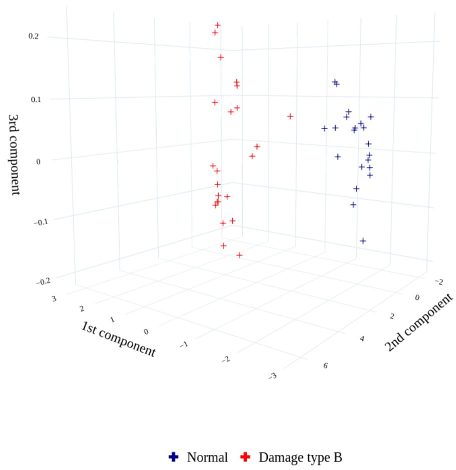
In the next step, a new dataset was created, comprising only those samples identified as damaged. The primary aim here was to categorize these samples based on the type of damage they exhibited. To achieve this, an SVM classifier was employed, which was trained with 20% of the data using a linear kernel and a regularization parameter (C) set to 0,01.

Table 1 and Figure 8 showcase the exceptional performance of the SVM classifier in classifying different types of damage. Notably, the model exhibits complete sensitivity to the integrity classes defined in this specific case study, achieving a 100% accuracy, recall, and F1-score.

The utilization of cross-validation further enhances the reliability of the model, mitigating potential overfitting and



(a) 3D PCA projection of clusters for Normal and Damage Type A.



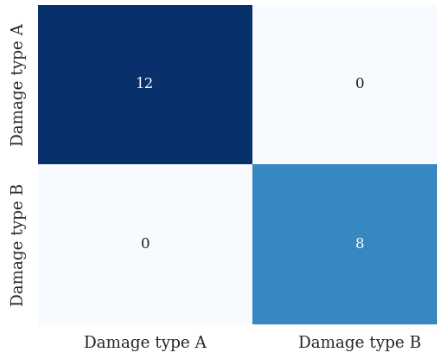
(b) 3D PCA projection of clusters for Normal and Damage Type B.

Figure 7. visualization of the performance to GMM clustering.

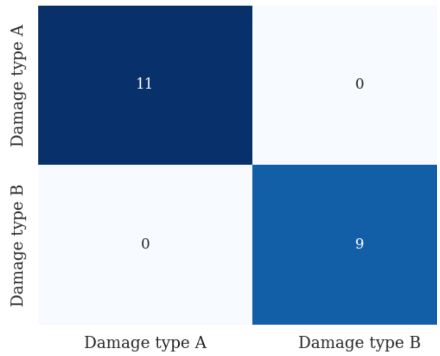
underfitting concerns. This approach ensures that the model's performance is robust across various test datasets in all the k-folds considered during cross-validation.

Table 1. Performance Indicators for SVM classifier.

	Accuracy	**Precision**	**Recall**	**F1-Score**
1	1,0	1,0	1,0	1,0
2	1,0	1,0	1,0	1,0
3	1,0	1,0	1,0	1,0
4	1,0	1,0	1,0	1,0
Mean	1,0	1,0	1,0	1,0
SD	0,0	0,0	0,0	0,0



(a)



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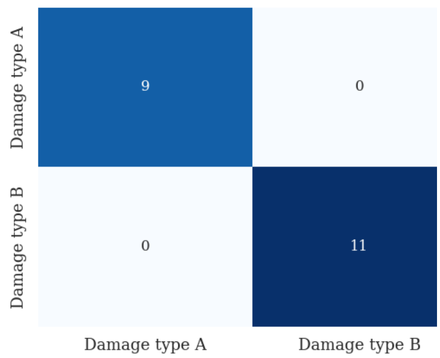
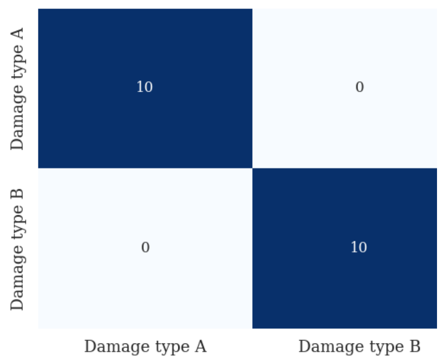


(c)



(d)

Figure 8. Confusion matrix of values predicted by the SVM classifier at various folds.

5. CONCLUSIONS

In this study, an intelligent diagnostic system for Structural Health Monitoring (SHM) was implemented and evaluated, incorporating machine learning and Electromagnetic Impedance (EMI) techniques. The evaluation involved a detailed analysis of a substantial steel structure, where simulated mechanical damages were used to assess the system's effectiveness.

The BCO algorithm was used to determine the optimal frequency range for monitoring, highlighting the maximum difference between normal and damaged signatures. The result of the optimization process identified a frequency range spanning from 219459 to 224489 Hz, a range that clearly highlighted the distinctions between damaged and undamaged states. After the extraction of statistical features and dimensionality reduction through PCA, the GMM clustering was applied to distinguish normal samples from the damaged ones. After, the SVM classifier was used only in the cluster those samples identified as damaged. This further enhanced the accuracy of the classification process, enabling a more effective differentiation between samples in different states.

Importantly, both the SVM and GMM achieved 100% accuracy in this classification task, underscoring the remarkable efficacy of these models in detecting structural alterations and the presence of damage within thick metallic structures. It's worth noting that the high accuracy achieved by both the SVM and GMM further emphasizes the promising potential of this proposed model for future applications in damage diagnosis across various structural contexts.

6. ACKNOWLEDGEMENTS

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