APPLICATION OF THE MONTE CARLO METHOD TO REDUCE DATA STORAGE IN SHM

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ABSTRACT

In general, the electromechanical impedance-based SHM method (ISHM) uses a piezoelectric transducer as a sensor/actuator to excite/measure the dynamic response of a mechanical structure under investigation to find incipient damage. The SHM method requires many samples of impedance signatures to analyse the behaviour of the system and draw a diagnostic. This contribution proposes a method to generate new impedance signatures as based on a few measured signatures. The signature generator operates through the Monte Carlo method. This approach proposes drastically reducing the number of measured samples normally used in the ISHM. This reduction can be as large as 93%. For this aim, a case study is proposed using an "I" profile structure with four levels of damage. Moreover, 33 impedance signatures for each level of damage were measured. Then, the Monte Carlo method was used to generate 400 virtual signatures. Finally, the generated signatures were compared with the experimentally acquired ones to measure the error associated with the generated signatures. In conclusion, this contribution presents a method that uses the properties of impedance signatures to store them and, if necessary, uses these signatures to generate numerical signatures, thus reducing the need to store a large amount of data.

KEYWORDS: *Monte Carlo Method, Electromechanical Impedance-based SHM Method, Data Record Reduction, Structural Health Monitoring, Damage Detection*

I. INTRODUCTION

The electromechanical impedance-based method aims to identify the existence of incipient damage in a structure under investigation. The use of structural health monitoring techniques can prevent many of the critical systems from collapsing, thus reducing maintenance costs while ensuring better level of system security.

The lack of maintenance or its insufficient performance can lead to major financial and human life losses, thus justifying the application of SHM methods. Furthermore, in the literature we can find several events of structural failure that could have been prevented through the application of damage detection techniques (the electromechanical impedance-based method is known as a successful SHM approach).

Some incidents of structural failure that could have been avoided by the application of SHM methods became notorious in the literature: the accident of flight Aloha Airlines 243, the collapse of I-35W Mississippi River Bridge (officially known as Bridge 9340) and the widening of hull steel fractures on Liberty's ships during World War II. Incipient damage monitoring would certainly be very helpful both for maintenance and safety issues.

The electromechanical impedance method uses a piezoelectric transducer (such as sensor / actuator) to both excite and collect the dynamic responses of the structure under investigation. Changes in the corresponding dynamic responses can later be quantified by using mathematical and probabilistic techniques. Then, the existence, position and severity of damage can be investigated and identified.

However, SHM techniques currently require large volumes of data for their accuracy, thereby increasing storage costs and subsequently the total computational cost.

In this context, the present contribution aims to present a method for the statistical generation of electromechanical impedance signatures, in which the size of stored data can be reduced. The proposed sample generator is based on the Monte Carlo method, which enables the impedance signatures to be sampled considering a small pre-collected historical database of the structure. The numerical samples generated in the present work were subsequently evaluated for their similarity to the database used for their construction and the corresponding results demonstrate the efficiency of the developed process.

The validation method applied to this contribution is the one-way ANOVA statistical method, which allows for the verification of the variance between two sets, one of them being the test set (generated samples) and the other a reference set (experimentally collected samples).

The purpose of the approach conveyed is to evaluate the possibility of the SHM technique to be further implemented in the context of extreme conditions structural monitoring, such as those that are faced by autonomous SHM in submerse, space and deep forest environments. In such cases, it is very important to have compact systems, including reduced data storage devices.

1.1. Electromechanical Impedance-Based Method

The electromechanical impedance-based monitoring method was initially introduced by Liang et al. [1] and aims to monitor the variation of the mechanical impedance of a structure under investigation as caused by the existence of damage. As it is difficult to measure the mechanical impedance of a structure directly, the method uses piezoelectric materials bonded to or incorporated into the structure to capture the corresponding electrical impedance.

Piezoelectric ceramics are dielectric materials, i.e., they generate an electric charge in response to an applied mechanical stress. Inversely, an electric field applied to the material will strain it. Thus, the direct effect of the piezoelectric material (sensor effect) and the inverse effect (actuator effect) can be used simultaneously as a single component.

From the equation derived by Liang et al. [2], it is possible to find the mechanical impedance variation of a structure by measuring the electrical impedance of a piezoelectric transducer coupled/incorporated to this same structure. In addition, the electrical impedance variation of a transducer coupled to a structure is correlated to the mechanical impedance variation of the structure, thus allowing the diagnostics concerning the existence of damage [3, 4].

Freitas [5] defines damage as an adverse change caused to the structure, which affects its present or future performance. In general, a damage can be represented by changes on stiffness, damping and/or mass characteristics. Consequently, the incipient appearance of structural damage can be monitored and evaluated by using appropriate SHM techniques.

While experimenting, the system undergoes a series of mechanical vibrations generated by the piezoelectric patch (PZT). Simultaneously, the electrical impedance of the system is measured. This procedure allows for acquiring a unique impedance signature that reflects the fundamental mechanical properties of the system under observation.

Figure 1 shows the one-dimensional model of the electromechanical coupling as proposed by Liang et al. [2]. In this model, the modal parameters such as mass, stiffness and damping of the structure under analysis are shown.

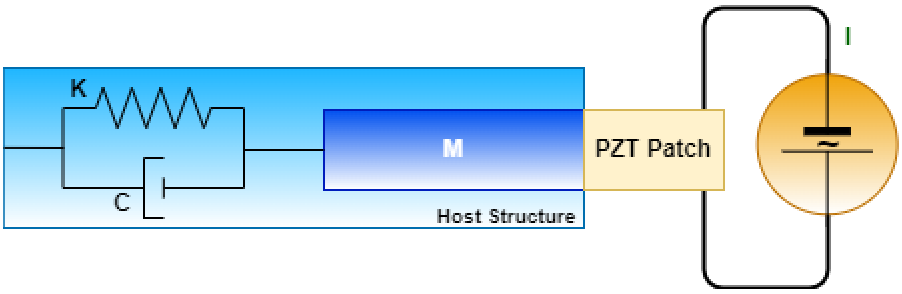

Figure 1: One-dimensional model of the electromechanical coupling.

Equation 1 Liang et al. [2] gives the admittance Equation 1 that models the above system, associating the electrical impedance of the piezoelectric transducer with the mechanical impedance of the structure under study.

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

where Y (ω) represents the electrical admittance, which is the reciprocal of impedance. $Z_a(\omega)$ and $Z_s(\omega)$ denote the mechanical impedance of the PZT patch and the structure, respectively. Furthermore, the complex Young's modulus of the PZT patch at zero electric field is symbolized by $\hat{Y}_{xx}^{E}$, while the piezoelectric coupling constant in the arbitrary x direction at zero stress is denoted as d_{3x}^{2}. Additionally, δ represents the dielectric constant at zero stress, d signifies the dielectric loss tangent of the PZT patch, and a represents the geometric constant of the PZT patch.

To identify early variations in the structure's dynamic behaviour, such as damage, employing a low wavelength for excitation is necessary, leading to using a high-frequency spectrum [6, 7]. Determining the optimal frequency ranges for SHM analysis often involves a trial-and-error methodology, although more advanced approaches, including statistical or optimization methods, can also be employed [8].

After the best frequency range is determined, a damage metric index is usually calculated to quantify the influence/existence of the damage. Although in some cases changes on impedance signatures may be visually observed, it is appropriate to apply statistical techniques to quantify them, especially for characterization purposes (severity and damage location).

According to the literature, the most used damage metric is the RMSD index, which is calculated by Equation 2.

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

where *M* stands for Root-Mean-Square Deviation (a damage metric), $Re(Z_{i,1})$ represents the measured PZT patch under pristine condition in the frequency range *i* and $Re(Z_{i,2})$ represents the signal of the PZT patch for the unknown condition (for comparison purposes) in the frequency range *i*.

In addition, it is noteworthy that the impedance-based structural health monitoring method has been successfully applied to several complex structures as described by [1, 2], and then extended by [9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26].

1.2. Monte Carlo Method

According to Halton [27], the Monte Carlo method is a stochastic technique used for the representation of possible solutions (feasible solutions) of a specific problem, which is of statistical nature. Therefore, in the execution of the method one considers the existence of a hypothetical population, which uses random number sequences to construct the population samples.

The method originated from the use of randomness, encompassing repetitive gambling pro cesses as performed at Monte Carlo casinos, in Monaco. The first study of the Monte Carlo method was applied in 1947 by Jon Von Neuman and Stanislaw Ulam in the Manhattan project during World War II. In this project, the researchers proposed a statistical modelling for the simulation of neutron random diffusion, which proved to be widely usable in other types of stochastic problems [28].

Monte Carlo simulations commonly use mathematical functions and probability distributions to statistically model solutions of complex problems. These problems, according to their characteristics, can be classified either as probabilistic problems (involving the evaluation of complex integrals for the estimation of system parameters) or statistical problems (involving the random sampling of variables correlated to the system parameters).

Furthermore, the Monte Carlo method is currently considered to be one of the most important tools for solving considerable intractable problems, whose solution through experimental tests becomes costly or impracticable. Thus, the application of Monte Carlo simulation enables the reduction of instrumentation costs by creating numerical data that represent the phenomenon under study. Figure 2 illustrates the flowchart of the Monte Carlo method adopted in the present contribution.

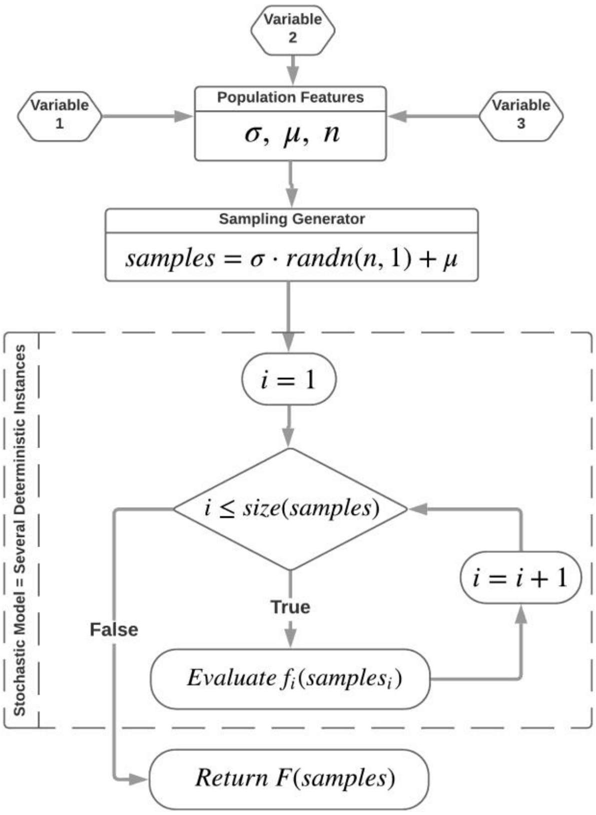

Figure 2: Diagram for sampling by Monte Carlo Method.

According to Figure 2, the variables of the problem need to be identified and their features are to be extracted, such as standard deviation (σ), arithmetic mean (μ), and number of samples (n) to be generated. Samples are then created as based on a given statistical distribution (commonly the normal distribution is chosen).

In this way, the present contribution aims to develop an electromechanical impedance signature generator for structural health monitoring, thus reducing instrumentation and data storage costs. Thus, the goal is to develop a Monte Carlo method that replaces the need for acquiring heavy experimental data by numerically calculated signatures as generated from a small set of experimental impedance responses. The suggested organization includes four main sections: Introduction, Materials and Methods, Discussion and Results, and Conclusions. The Introduction section provides an overview of the electromechanical impedance-based SHM method and related work on data reduction techniques. Also, this section describes the Monte Carlo method for generating virtual data sets based on a small number of experimental measurements. The Materials and Methods section presents a case study to demonstrate the effectiveness of the proposed method in detecting damage in a mechanical structure. The Discussion and Results section discusses the observed results' implications, limitations, and practical considerations. Finally, the Conclusions section produces a summary of the results and their impacts for practical use.

II. MATERIALS AND METHODS

The following subsections describe the experimental acquisition process of impedance signatures together with the characteristics of the specimen and the sensor used and the process of generating new simulated impedance signatures based on the density probability functions calculated from the mean and standard deviation of each group of 33 signatures in the considered dataset. This involves two main steps: sampling and data generation.

2.1. Experimental Acquisition of Impedance Signatures

The experimental setup consists of the following devices: an EVAL AD5933-EBZ board [29] and 132 impedance signatures stemming from an I-shaped profile structure (260x70x100mm) as collected from a PZT patch bonded to the structure at a location 10mm from the tip. According to Figure 3, the PZT patch used in this experiment has the following geometry: diameter of 20mm and thickness of 3mm.

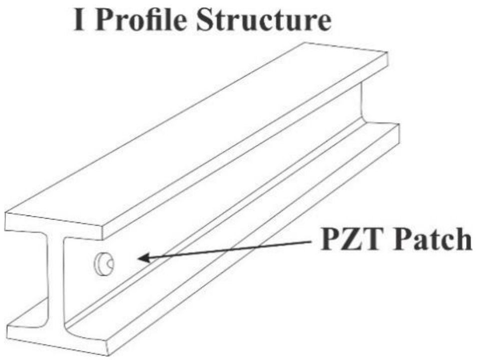

Figure 3: I profile with a PZT patch.

The data acquisition was performed by using the EVAL Board connected to a computer through an USB port and the *AD5933 Evaluation Board Software Rev. B.* Figure 4 presents the experimental setup and the data acquisition system.

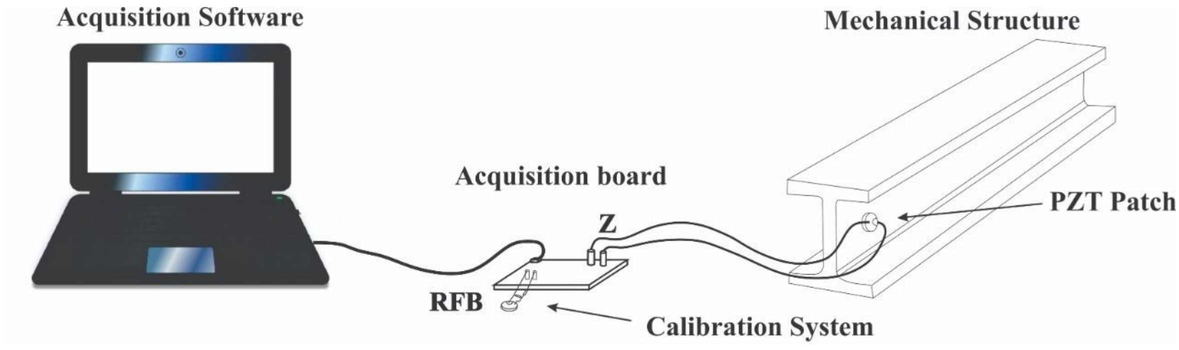

Figure 4: Acquisition system used for collecting the impedance signatures.

In the acquisition system presented in Figure 4, Z represents the connection of the PZT patch to the board while the calibration system is depicted by RFB. Similar schemes are used to acquire electromechanical impedance signals, as found in [8, 30, 31, 32, 33, 34, 35, 36].

The tests considered four damage levels that were inserted by adding masses at different locations along the structure to simulate the increase of damage severity. Then, 33 signatures were collected for each one of the damage levels considered. Figure 5 presents each level of damage and their respective displacements.

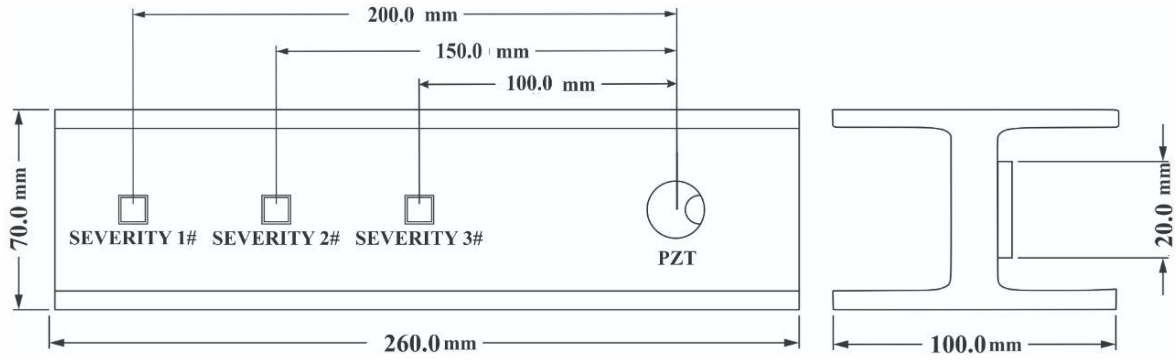

Figure 5: Levels of damage and geometry.

2.2. Test-case Implementation

From the considered dataset, each group of signatures has a mean and a standard deviation that are determined from the sample values of the impedance signatures. Thus, for each group of 33 signatures, the mean and standard deviation of each set of 511 points corresponding to each signature are calculated, leading to 511 density probability functions. Based on these probabilistic functions, new simulated impedance signatures can be generated.

In Figure 6, the generation process adopted is shown according to two main steps: sampling and data generation. In the sampling stage, the mean values of each frequency point and its corresponding dispersion are determined.

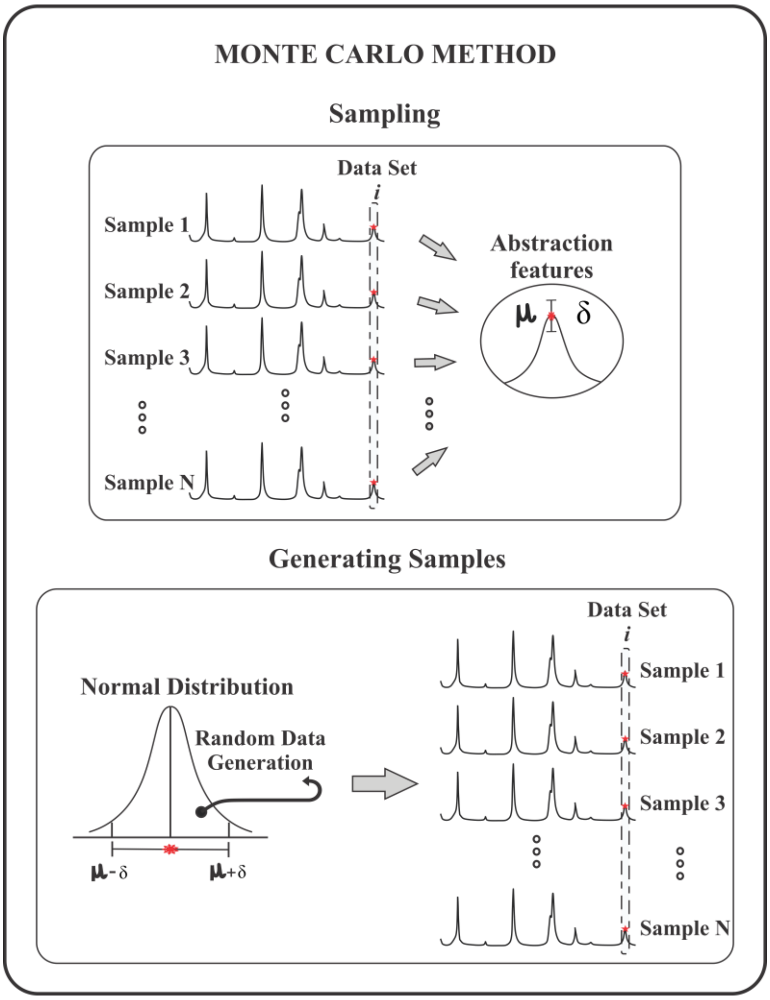

Figure 6: Sampling process.

In the data generation step, the real part of the impedance values of the original system are randomly sampled from the distributions for each frequency point in order to generate samples of impedance signatures which are supposed to be equivalent to those from the experimental procedure. With the reconstructed signals, the RMSD damage metric was applied to check for the correspondence between the experimental and numerical samples.

After applying the damage metric, the Lilliefors parametric test was adopted to verify the normality of the sets of experimental and numerical samples. With the normality verification performed, it was possible to apply the ANOVA (Analysis of Variance) test aiming to identify relevant differences between the means of the independent (experimental and numerical) groups.

III. DISCUSSION AND RESULTS

Only the real parts of the impedance responses are used in the present approach, as justified by the features explained by Moura Júnior, others [17, 37, 38]. For performing the tests, a frequency range of 27 to 32 kHz was obtained by using the trial-and-error method, searching for the region where the highest number of peaks is found. The impedance signatures of each group are represented in Figure 7. Each signature is illustrated by an average of 33 samples.

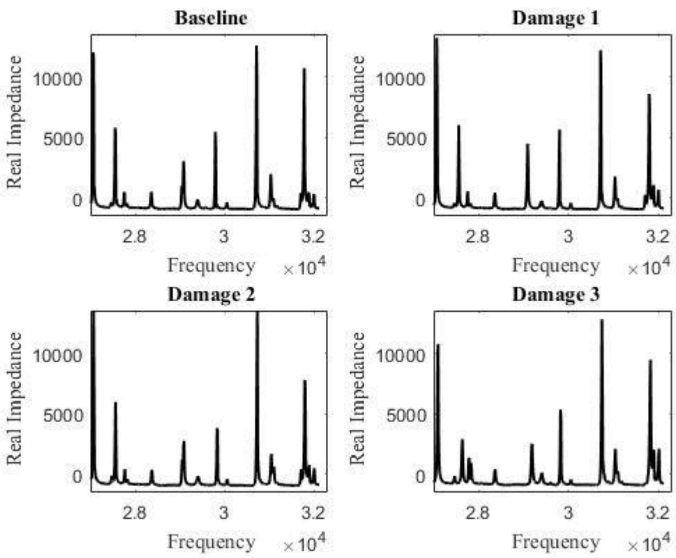

Figure 7: Means of impedance signatures of each damage group

As mentioned above, the Lilliefors test was performed for the damage metrics in order to check for data normality. Considering a 95% level of confidence, the null hypothesis was not rejected, i.e., there is no evidence in the data to conclude that the distribution of the damage metrics is not normal. Consequently, the data can be correctly evaluated by the ANOVA test since the statistical assumptions were met accordingly.

RMSD damage metrics were grouped two by two, so that group #1 includes the metrics of the signatures generated by the Monte Carlo method and group #2 contains the metrics of the signatures experimentally collected by the board AD5933. This procedure was repeated for each of the four considered damage levels.

Then, the one-way ANOVA was used aiming at comparing the mean values of the groups, thus highlighting the homogeneity of the generated signals as compared with the signatures collected. The corresponding results are shown in Tables 1-4 and Figure 8.

In Tables 1-4, the SS parameter stands for the sum of the squares, df represents the degrees of freedom within the group, between the groups and the total number of degrees of freedom, Ms are the average squares, i.e., the value of the F-statistic applied to the groups, and finally Prob > F, which is commonly called a p-value. It corresponds to the probability of the F-statistic to assume a value greater than the value of the computed test.

Table 1: ANOVA results for the Baselines group.

Source	SS	df	Ms	F	Prob>F
Groups	0.00013	1	0.00013	0.2	0.6527
Error	0.08112	131	0.00062		
Total	0.08124	132			

Table 2: ANOVA results for the Damage 1 group.

Source	SS	df	Ms	F	Prob>F
Groups	0.00004	1	0.00004	0.1	0.7544
Error	0.05968	131	0.00046		
Total	0.05973	132			

Table 3: ANOVA results for the Damage 2 group.

Source	SS	df	Ms	F	Prob>F
Groups	0.00004	1	0.00004	0.12	0.7221
Error	0.04285	131	0.00033		
Total	0.04289	132			

Table 4: ANOVA results for the Damage 3 group.

Source	SS	df	Ms	F	Prob>F
Groups	0.00005	1	0	0.79	0.3763
Error	0.00806	131	0		
Total	0.00811	132			

Again, it was considered 95% of significance level and it was proposed four new Hypothesis Test, one for each damage group (baseline and damage levels) so that H0 (null hypothesis) implies that the generated data is not possible to be identified or separated from the experimental data set, i.e., both sets are identical. On the other hand, H1 is the hypothesis assumption implying that both experimental and simulated data sets are completely different from each other.

While the first group of four Hypothesis Tests were performed to conclude about the normality of the damage metrics of each damage level (statistical assumption to apply the ANOVA Test), the second group of four Hypothesis Tests were applied to check for the assumption about the similarity between generated and experimental data sets. Once all p-values (P rob > F) in the ANOVAs were significantly greater than 0.05, all null hypothesis cannot be rejected, i.e., the ANOVAs ensure that the artificial and experimental data sets are statistically the same.

Concluding, this approach can obtain virtual data sets (electromechanical impedance signatures) based on a small amount of experimental measurements. Besides, the present technique does not require the storage of large amount of data along the time.

In descriptive statistics, the boxplot is the box with extreme and quartile diagrams. This is a graphical tool used to represent the variation of observed data of a numerical variable through quartiles To show the adherence of the data generated with respect to the experimental data, four boxplots, representing each damage metric are presented in Figure 8.

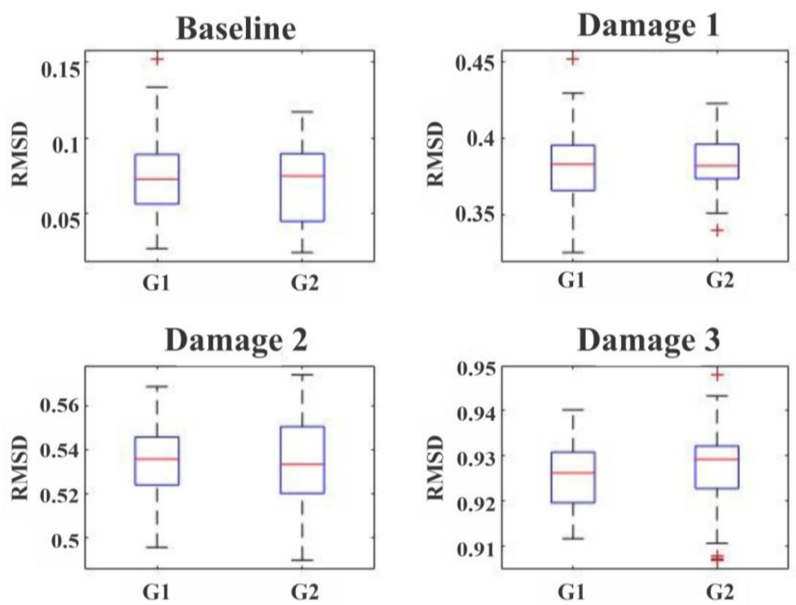

Figure 8: Boxplot of each group of RMSD damage metric

Figure 8 illustrates the proximity between the groups, demonstrating the randomness nature for the generation of samples. Outlier values are identified as individual points (* mark). The spaces between the midlines indicate the degree of dispersion of the data. Although there are outliers in the diagrams, they are very close to the scale of the diagram, i.e., each box is very thin, thus presenting a high proximity between the groups.

IV. CONCLUSIONS

The technique presented leads to a reduction on the amount of data required by the impedance-based SHM. It is well known that a large amount of data is necessary to perform statistical tests, to train artificial neural networks, and to apply other machine learning and heuristics/models based on historic data.

The case-study provided has shown that the statistical tests led to representative results. The use of this technique permitted the reduction of the amount of data by 93\%, since it was necessary to store only the mean and the standard deviation for each level of damage for the construction of the Monte Carlo generator. In the present case, 132 electromechanical impedance signatures were used, as composed of 511 points each signature (a total of 67,452 values).

Then, this approach proposes to substitute these 132 samples with 511 points, corresponding to a total of 67,452 stored values, by an amount of 511 averages and 511 standard deviations for the four conditions of damage (baseline and three damage levels), matching 2044 averages and 2044 standard deviation values (4088 records). This storage of 4088 data corresponds to 6\% of the initial test configuration involving 67,452 records.

In a real autonomous system for remote applications, this method can reduce the need for the associated hardware to permit a high storage capacity as well as the consequent use of memory required for heavy processing of decision-making models. In addition, the analysis procedure is also simplified since the system responsible for performing data generation is easily implemented for signature reconstruction. Besides, the proposed procedure does not include outliers, which is positive, since the outliers might create model divergence.

ACKNOWLEDGEMENTS

The authors acknowledge the financial support given by CAPES.

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