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Application of the Monte Carlo Method to Reduce Data Storage in SHM

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Summary

In general, the electromechanical impedance-based SHM method uses a piezoelectric transducer as a sensor/actuator to excite/measure the dynamic response of a mechanical structure under investigation in order to find incipient damage. The SHM method requires many samples of impedance signatures to analyze the behavior of the system and draw a diagnostic. This contribution proposes a method to generate new impedance signatures as based on a number of measured signatures. The signature generator operates through the Monte Carlo method. Thus, this approach proposes to drastically reduce the number of measured/recorded samples that are normally used in the impedance-based SHM. This reduction can be as large as 93%. For this aim, a case study is proposed, namely, an "I" profile structure with four levels of damage (mass addition). 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 in order to measure the error associated with the generated signatures. In conclusion, this contribution presents a method that uses the properties of the impedance signatures to store them and, if necessary, to use these signatures to generate numerical ones, thus reducing the need for storing a large amount of data and lessen the number of experimental impedance signatures acquired over time.

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

1 | INTRODUCTION

The electromechanical impedance-based method aims to identify the existence of incipient damage in a structure under investigation. The use 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 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.

2 | ELECTROMECHANICAL IMPEDANCE-BASED METHOD

The electromechanical impedance-based monitoring method was initially introduced by [12] and aims to monitor the variation of the mechanical impe- dance 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 [13], 1, 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.

[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.

During the test preparation phase, a high frequency mechanical oscillation is applied to the system by the piezoelectric patch (PZT) and the corresponding electrical impedance is measured simultaneously. Thus, an impedance signature is obtained, which represents the main mechanical characteristics of the monitored system.

Figure 1 shows the one-dimensional model of the electromechanical coupling as proposed by [13]. In this model, the modal parameters such as mass, stiffness and damping of the structure under analysis are shown.

Equation 1 [13] gives the admittance equation that models the above system, associating the electrical impedance of the piezoelectric transducer with the mechanical impedance of the structure under study.

$$Y(\omega) = i\omega a \left(\varepsilon_{33}^{-T} (1 - i\delta) - \frac{Z_s(\omega)}{Z_s(\omega) - Z_a(\omega)} d_{3x}^2 \hat{Y}_{xx}^E \right) \tag{1}$$

where $Y(\omega)$ is the electrical admittance (inverse of impedance), $Z_a(\omega)$ and $Z_s(\omega)$ are the PZTs and the structure's mechanical impedance, respectively, $\hat{Y}_{xx}^E$ is the complex Young's modulus of the PZT patch at zero electric field, d_{3x} is the piezoelectric coupling constant in the arbitrary x direction at zero stress, δ is the dielectric constant at zero stress, d is the dielectric loss tangent of the PZT patch, and a is the geometric constant of the PZT patch.

In order to detect incipient changes on the dynamical behavior of the structure (damage), the wavelength of the excitation should be small; therefore, a high frequency range is used[19]. The best frequency ranges for SHM analysis can be determined by using a trial-and-error approach. However, more sophisticated techniques (either statistical or optimization methods) can also be used[1].

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 2.

$$RMSD = \sum_{i=1}^{n} \sqrt{\frac{[Re_{i,1} - Re_{i,2}]^2}{[Re_{i,1}]^2}} \tag{2}$$

where RMSD stands for Root-Mean-Square Deviation (a damage metric), $Re_{i,1}$ represents the measured PZT patch under pristine condition in the frequency range i and $Re_{i,2}$ 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[12,13], and then extended by[2,3,6,7,9,10,11,14,17,20,21,22,23,24,25,27,28].

3 | MONTE CARLO METHOD

According to[8], 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 processes 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 modeling for the simulation of neutron random diffusion, which proved to be widely usable in other types of stochastic problems[29].

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).

Futhermore, 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.

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.

4 | EXPERIMENTAL PROCEDURE

4.1 | Experimental Acquisition of Impedance Signatures

The experimental setup consists of the following devices: an EVAL AD5933-EBZ board[4] 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.

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.

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 [1,15,16,18,26,30].

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.

4.2 | 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.

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.

5 | DISCUSSION AND RESULTS

Only the real parts of the impedance responses are used in the present approach, as justified by the features explained by [17]. 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.

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.

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 H_0 (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, H_1 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 ($Prob > F$) 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 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.

6 | CONCLUSION

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.

References

1. Bento J P M (2018) Uso das cadeias de Markov associado ao monitoramento da integridade estrutural baseado em impedância eletromecânica. Dissertation, Universidade Federal de Goiás.

2. Chaudhry Z A, Joseph T, Sun F P and Rogers C A (1995a) Local-area health monitoring of aircraft via piezoelectric actuator/sensor patches. Smart Structures and Materials 1995: Smart Structures and Integrated Systems (Vol. 2443, pp. 268-276). International Society for Optics and Photonics.

3. Chaudhry Z A, Lalande F, Ganino A, Rogers C A and Chung J (1995b) Monitoring the integrity of composite patch structural repair via piezoelectric actuators/sensors. 36th structures, structural dynamics and materials conference (p. 1074).

4. Devices A (2011) High Accuracy Impedance Measurements Using 12-Bit Impedance Converters. AD5933 Datasheet. https://pdf1.alldatasheet.com/datasheet-pdf/view/532232/AD/AD5933.html. Accessed 23 October 2019.

5. Freitas E S D (2016) Análise experimental de diafragmas piezelétricos comerciais para detecção de dano estrutural baseada na impedância eletromecânica. Dissertation, Universidade Estadual Paulista.

6. Giurgiutiu V, Zagrai A and Jing Bao J (2002) Piezoelectric wafer embedded active sensors for aging aircraft structural health monitoring. Structural Health Monitoring, 1(1), 41-61.

7. Giurgiutiu V, Zagrai A, Bao J, Redmond J, Roach D and Rackow K (2003) Active Sensors for Health Monitoring of Aging Aerospace Structures. International Journal of the Condition Monitoring and Diagnostic Engineering Management, 6(1), 3-21.

8. Halton J H (1970) A retrospective and prospective survey of the Monte Carlo method. Siam review, 12(1), 1-63. https://doi.org/10.1137/1012001.

9. Hoshyarmanesh H and Abbasi A (2018) Structural health monitoring of rotary aerospace structures based on electromechanical impedance of integrated piezoelectric transducers. Journal of Intelligent Material Systems and Structures, 29(9), 1799-1817.

10. Jung H K, Jo H, Park G, Mascarenas D L and Farrar C R (2014) Relative baseline features for impedance-based structural health monitoring. Journal of Intelligent Material Systems and Structures, 25(18), 2294-2304.

11. Koo K Y, Park S, Lee J J and Yun C B (2009).Automated impedance-based structural health monitoring incorporating effective frequency shift for compensating temperature effects. Journal of intelligent material systems and structures, 20(4), 367-377.

12. Liang C, Sun F and Rogers C A (1996) Electro-mechanical impedance modeling of active material systems. Smart Materials and Structures, 5(2), 171.

13. Liang C, Sun F P and Rogers C A (1997) Coupled electro-mechanical analysis of adaptive material systems-determination of the actuator power consumption and system energy transfer. Journal of intelligent material systems and structures, 8(4), 335-343.

14. Martowicz A, Sendecki A, Salamon M, Rosiek M and Uhl T (2016) Application of electromechanical impedance-based SHM for damage detection in bolted pipeline connection. Nondestructive Testing and Evaluation, 31(1), 17-44.

15. Mascarenas D L, Todd M D, Park G and Farrar C R (2007) Development of an impedance-based wireless sensor node for structural health monitoring. Smart Materials and Structures, 16(6), 2137.

16. Min J, Park S, Yun C B and Song B (2010) Development of multi-functional wireless impedance sensor nodes for structural health monitoring. Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2010 (Vol. 7647, p. 764728). International Society for Optics and Photonics.

17. Moura Júnior J R V (2008) Uma contribuição aos sistemas de monitoramento de integridade estrutural aplicada a estruturas aeronáuticas e espaciais. Dissertation, Universidade Federal de Uberlândia.

18. Na S, Tawie R and Lee H K (2012) Electromechanical impedance method of fiber-reinforced plastic adhesive joints in corrosive environment using a reusable piezoelectric device. Journal of Intelligent Material Systems and Structures, 23(7), 737-747.

19. Nokes J P and Cloud G L (1993) The application of interferometric techniques to the nondestructive inspection of fiber-reinforced materials. Experimental Mechanics, 33(4), 314-319.

20. Park G, Cudney H H and Inman D J (1999) Impedance-based health monitoring technique for massive structures and high-temperature structures. Smart Structures and Materials 1999: Sensory Phenomena and Measurement Instrumentation for Smart Structures and Materials (Vol. 3670, pp. 461-469). International Society for Optics and Photonics.

21. Park G, Cudney H H and Inman D J (2000a) Impedance-based health monitoring of civil structural components. Journal of infrastructure systems, 6(4), 153-160.

22. Park G, Cudney H H and Inman D J (2000b) An integrated health monitoring technique using structural impedance sensors. Journal of Intelligent Material Systems and Structures, 11(6), 448-455.

23. Park G, Cudney H H and Inman D J (2001) Feasibility of using impedance-based damage assessment for pipeline structures. Earthquake Engineering and Structural Dynamics, 30(10), 1463-1474.

24. Park G, Kabeya K, Cudney H H and Inman D J (1999a) Impedance-based structural health monitoring for temperature varying applications. JSME International Journal Series A Solid Mechanics and Material Engineering, 42(2), 249-258.

25. Park G, Sohn H, Farrar C R and Inman D J (2003) Overview of piezoelectric impedance-based health monitoring and path forward. Shock and Vibration Digest, 35(6), 451-464.

26. Rosiek M, Martowicz A and Uhl T (2012) An overview of electromechanical impedance method for damage detection in mechanical structures. 6th European Workshop on Structural Health Monitoring – Fr.1. B.4. Germany.

27. Song H, Lim H J and Sohn H (2013) Electromechanical impedance measurement from large structures using a dual piezoelectric transducer. Journal of Sound and Vibration, 332(25), 6580-6595.

28. Sun F, Chaudhry Z, Liang C and Rogers C A (1995) Truss structure integrity identification using PZT sensor-actuator. Journal of Intelligent material systems and structures, 6(1), 134-139.

29. Ulam S, Richtmyer R D and Von Neumann J (1947) Statistical methods in neutron diffusion. LAMS-551, Los Alamos National Laboratory, 1-22.

30. Wandowski T, Malinowski P and Ostachowicz W (2014) Calibration problem of AD5933 device for electromechanical impedance measurements. EWSHM-7th European Workshop on Structural Health Monitoring.

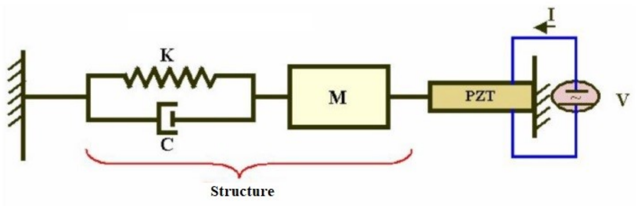

FIGURE 1 One-dimensional model of the electromechanical coupling.

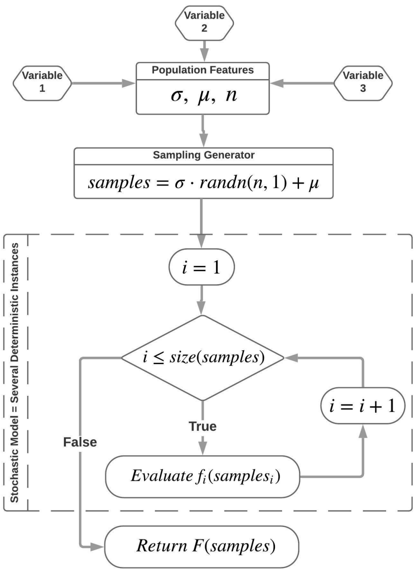

FIGURE 2 Diagram for sampling by Monte Carlo Method.

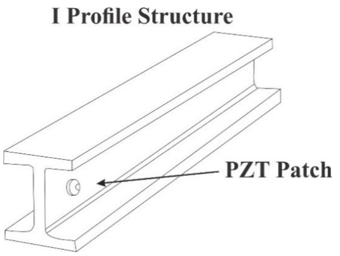

FIGURE 3 *I* profile with a PZT patch.

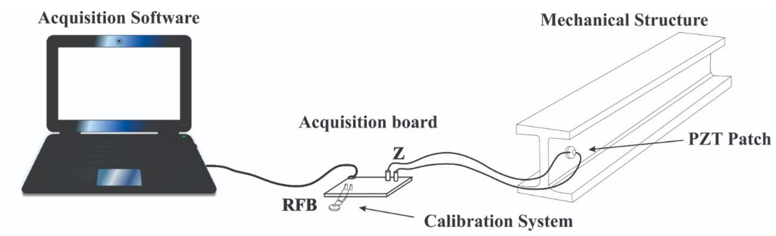

FIGURE 4 Acquisition system used for collecting the impedance signatures.

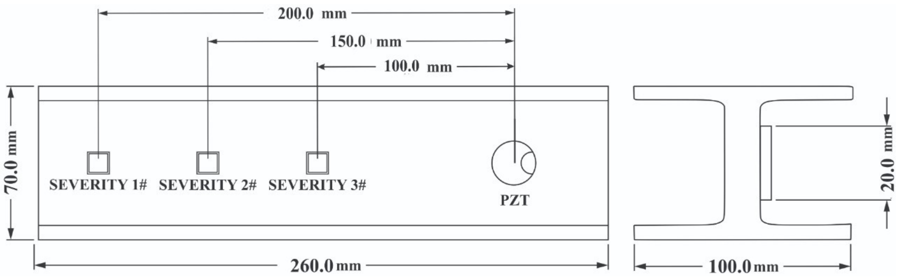

FIGURE 5 Levels of damage and geometry.

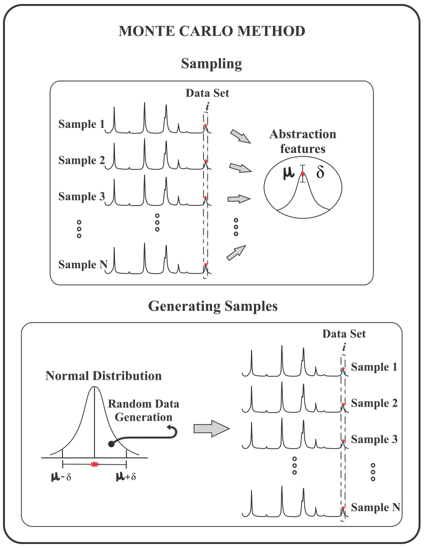

FIGURE 6 Sampling process.

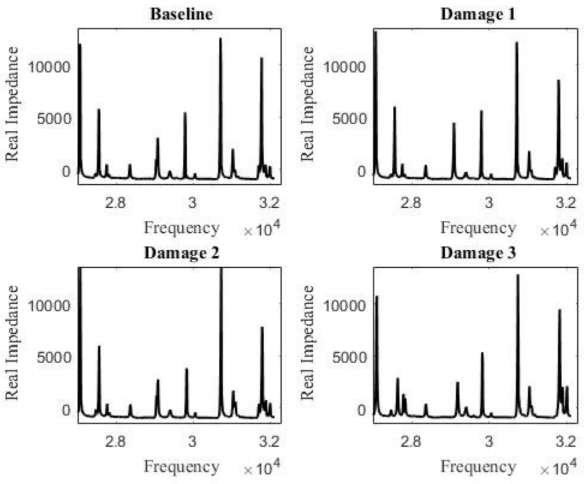

FIGURE 7 Means of impedance signatures of each damage group.

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	0.7271
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			

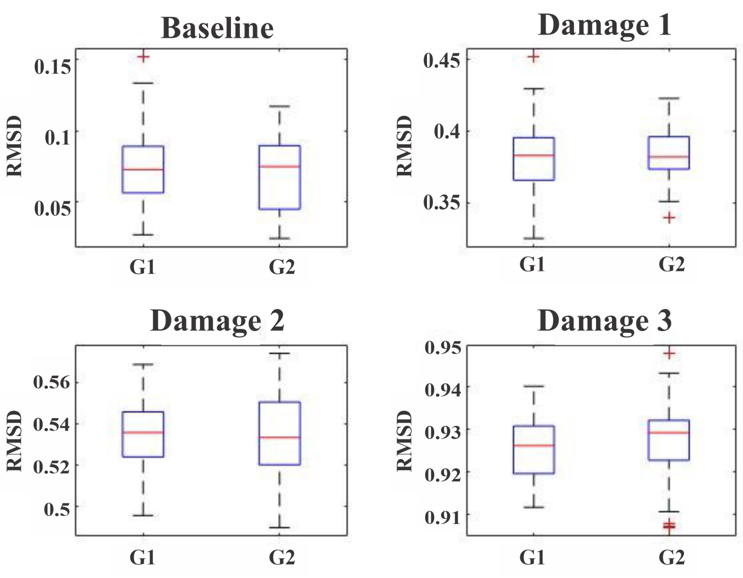

FIGURE 8 Boxplot of each group of RMSD damage metric.

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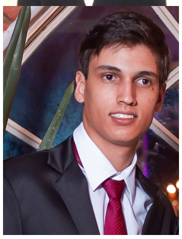

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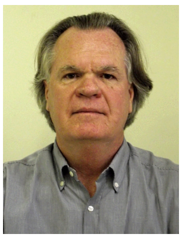

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