COBEM UBERLÂNDIA 2019

ABCM Associação Brasileira de Engenharia e Ciências Mecânicas

25th ABCM International Congress of Mechanical Engineering
October 20-25, 2019, Uberlândia, MG, Brazil

COB-2019-1437
DAMAGE DETECTION ON COMPOSITE BEAMS USING COMPUTATIONAL VIBRATION MODEL WITH UNCERTAINTIES AND ARTIFICIAL NEURAL NETWORKS

Pedro Almeida Reis
Luisa Rosenstock Völtz
Eduardo Lenz Cardoso
Ricardo de Medeiros
Santa Catarina State University, Department of Mechanical Engineering, Joinville, Brazil.
email: pedro.reis@edu.udesc.br, luisa.voltz@gmail.com, eduardo.cardoso@udesc.br, ricardo.medeiros@udesc.br

Abstract. *All engineering structures are subject to variations in their mechanical properties associated with damages, such as time of use, misuse, design errors, assembly and fabrication failures, climate change and other factors related to the environment. However, reliable tools that permit monitoring damage, calculating the residual resistance of the structure, allowing for possible failures to be foreseen have been sought for years by researchers and engineers. In this context, Structural Health Monitoring (SHM) is already highlighted with some applications around the world, through the identification of damage by non-destructive testing (NDT), among them, models based on the vibration response applied to Artificial Neural Network (ANN). However, as this method is quite sensitive to the type, quantity, and treatment of data inserted in the network, some applications are implemented using finite element (FE) methods, which, however, offer limitations on the uncertainties in the real model. Considering the scenario pointed above, this work proposes a methodology to evaluate uncertainties contained in a real model and to insert them into the computational one. After that, it is treated by Principal Component Analysis (PCA) to serve as the input of Neural Network, which has its topology determined via Particle Swarm Optimization (PSO). Thus, a multi-layer neural network was developed for detecting damage in composite beams made of Glass Fiber Reinforced Polymer (GFRP). Finally, it is discussed the potentialities and limitations of the methodology for use in damage detection systems.*

Keywords: *Artificial Neural Networks(ANNs), Composite beam, Damage detection, Structural Health Monitoring (SHM), Vibration-based method.*

1. INTRODUCTION

Composite materials are obtained by a combination of two or more different materials, such that there must be at least one continuous medium known as a matrix and another part called reinforcement inserted in the form of the fibers, particles or flakes. Thus, different properties of two or more materials may be associated with a new one, which has led to the creation of lighter and stronger structures such as fiber-reinforced plastics, for example (Kaw, 2005). In this context, they have been increasingly used in detriment to the traditional ones in the industry, with great emphasis on aeronautics and aerospace, due to its structural performance that provides high strength and rigidity, minimizing the mass of the system. However, during their service, they may present faults associated with damages such as cracks in the matrix, fiber rupture, and delamination. The latter being considered as the greatest "weakness" of composite materials. The delamination can easily be understood as the separation between two laminates of the laminate due to shear stresses, which can lead to catastrophic failure (Gomes *et al.*, 2018).

Damage, therefore, can be related to variations in the physical properties of the structure such as mass and rigidity that occur over time, either due to design problems, climatic conditions, accidents, or effects of adverse agents (De Medeiros *et al.*, 2018). By Kessler *et al.* (2002), Structural Health Monitoring (SHM) is defined as the acquisition, validation, and analysis of generated data that allow to evaluating the residual resistance of the structures during their life from the changes that occur in their properties, providing information so that it is used more reliably. In this way, several non-destructive techniques are being implemented to identify damages that are not visible to the barely visible, such as acoustic methods, by magnetic field and radiography. However, they are sometimes inconclusive and require a priori knowledge about the location and existence of the damage. Knowing that the physical properties of the structure are modified, including damping, rigidity, and mass, methods based on vibrational characteristics have been widely used (Humar *et al.*, 2006). Ewald *et al.* (2019) suggested that the implementation of non-destructive techniques (NDT) for monitoring damage to structures makes it possible to save resources on aircraft maintenance, representing a significant share of the total cost of service to airlines.

Even SHM has been used in the worldwide to offer more security in engineering structures by evaluating data of their structural loads, responses and real time-performance, generating a large amount of data as Sutong bridge in China (Tang *et al.*, 2019). However, the robustness of damage detection has the sensibility to a data treatment, which could add or remove information, influencing the accuracy to recognize the differences between intact and damaged structure responses, which still generates several studies in search of better results for its consolidation. In this context, Allemang (2003) used a Modal Assurance Criterion (MAC), correlating vibration modes (MAC) to identify the damage. Tang (2005) applied the Principal Component Analysis (PCA) for Frequency Response Functions (FRFs), which reduces noise and increases the detectability of damage more efficiently. Recently, computational intelligence algorithms have been used in recognizing and patterns classification, in this line Alves *et al.* (2015) purpose Symbolic Data Analysis (SDA) as technique to filter the acquired data and after apply it in some techniques as: Bayesian Decision Trees (BDT), Support Vector Machine (SVM) and Artificial Neural Network (ANN), where the (ANN) verified most satisfactory. In sequence, Piazzaroli (2019) proposed an alternative using response on time-domain and statistical indicators from fourth-order as input, where it can be seen that the difference in the input data influences the final result. This can be made clearer through the work done by Völtz *et al.* (2018) that used Principal Component Analysis (PCA) to reduce data via FRFs.

In addition to treatment, the amount of data used in machine learning-based methods is also relevant, since large quantities may be necessary in some cases. Thus, an economical way of acquiring them is through the use of finite element discretized models (FE). Regardless of, the existence of errors in the computational model due to the inaccuracy of the physical parameters, non-ideal contour conditions, discretization, and nonlinear structural properties can measure errors that hinder ANNs efficiency in the identification of damages (Bakhary *et al.*, 2007). A strategy already used by some researchers to solve this problem is through the modeling of uncertainties that allow adding noises that can approximate the numerical model to the real one (Padil *et al.*, 2017). This work proposes the implementation of the addition of uncertainties in the data generated by a computational model, aiming to improve the efficiency of the neural network for damage identification, functioning as a more reliable tool for SHM techniques.

2. METHODOLOGY

During the manufacturing process, the composite laminated beams present dimensional changes such as thickness, fiber orientation, and the total length, that cause a shift in its mechanical properties, modifying the dynamic responses of structure. In this work, a methodology is applied to represent uncertainties of an experimental model in a numerical one, though work of dos Santos Souza *et al.* (2019) where the main design variables were identified for unidirectional plies with $[0]_8$ stacking. In the sequence, responses collected in the first step will serve as a reference for the detection of damage using Artificial Neural Network (ANNs) the application of the Principal Component Analysis (PCA) to treat the corresponding data.

2.1 Vibration Based Model

Vibration can be understood as an oscillating movement of a certain object around an equilibrium position, and these oscillations can be periodic, non-periodic and transient. Two elements are fundamental for vibration occur, mass or inertia and the spring, that corresponds to the stiffness of the system. However, when a system is shifted out of from its equilibrium position, the component responsible for mass generates kinetic energy, while the elastic part stores this energy and then establishes a cycle between the conservation of these plots culminating in the occurrence of oscillations. However, as can be observed experimentally or in the most diverse models of vibrations, there is a dissipation of energy associated with damping, which tends to make the oscillation cease (Rao, 1995).

Therefore, the differential equation governing the motion of a body subjected to vibration for one or more degrees of freedom is,

$$\mathbf{M}\ddot{x}(t) + \mathbf{C}\dot{x}(t) + \mathbf{K}x(t) = \mathbf{F}(t), \tag{1}$$

where (**M**) corresponds to equivalent mass, (**C**) damping, stiffness (**K**), and the exciting force (**F**). With this general equation to vibration systems, many types of the computational analysis may be improved as *implicit*, *explicit* and *modal*. In this study, FRF Analysis was used. This approach is based on the reciprocity between the excitation point (j) and the response (i), being evaluated through of a matrix $H_{ij}(\omega)$, which due to this property has symmetry (Fu and He, 2001). Thus, the response of a structure via FRF can be measured as

$$\mathbf{H}(\omega) = \frac{\mathbf{X}(\omega)}{\mathbf{F}(\omega)}, \tag{2}$$

where $F(\omega)$ is the excitation force and $X(\omega)$ the response.

2.2 Numerical Model using (FEM)

A numerical example using a finite element method (FEM) of a simple composite beam in free-free boundary condition is selected. The geometrical and mechanical properties are shown in Tab 1, and they are chosen according to the Völtz (2019).

Table 1. Geometrical and mechanical properties Völtz (2019).

Property	**Value**
Length	227 mm
Width	28.35 mm
Thickness	3.00 mm
Longitudinal elasticity modulus - E_{11}	30.00 GPa
Transversal elasticity modulus - E_{22}	15.00 GPa
Composite density - ρ_c	1260 kg/m^3
Shear modulus - G_{12}	5.9 GPa
Shear modulus - G_{13}	5.9 GPa
Shear modulus - G_{23}	4.0 GPa
Poisson ratio - ν_{12}	0.18
Stacking orientation	$[0]_{12}$

In addition to geometry and mechanical properties, to create the beam computational model it is necessary to represent its equivalent structural damping. Thus, through the experimental FRF analysis (Völtz, 2019), the peak-picking method was used and parameters (α and β) correspondents the Rayleigh damping obtained to be introduced on the numerical model. Figure 1 corresponds to the schematization of the numerical model, referring to the positions in which excitation force, accelerometer, and damage (5 mm) were applied. The frequency range studied is 1500 Hz using direct steady-steady dynamic analysis analysis. The FEM model is done in ABAQUS 6.12 and consists of 25938 quadrilateral continuum shell elements (SC8R), with eight nodes and three degrees-of-freedom (displacement).

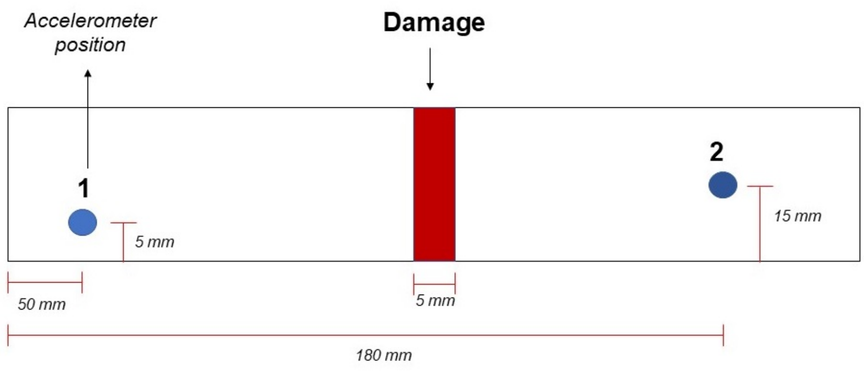

Figure 1. Accelerometer and excitation position.

The responses of the dynamic models, based on vibration analysis are extremely sensitive to variations in the mechanical properties of the material and geometry. Thus, dos Santos Souza *et al.* (2019) presented an alternative to represent those uncertainties that may be due to the limitations of the manufacturing processes, evaluating which design variables were most influential in each vibration mode. Therefore, this work shows that for the composite laminates with unidirectional fibers that have orthotropic characteristics, the properties that most influence the response are the elasticity and shear modulus. However, when the directions of the fibers were modified, the parameters related to geometry were more sensitive.

In this study, different dynamic tests are simulated for each stage of damage, varying the mechanical properties and the stacking orientation as presented in Tab 2. The values are chosen to vary the properties between 10% according dos Santos Souza *et al.* (2019). The procedure is implemented in a Python script to automate the process. For example, varying the longitudinal modulus from 27.0 GPa to 33.0 GPa at 0.5 GPa step gets in total 26 FRFs for position H_{11} and H_{21}. In total 94 FRFs are simulated for each state conditions.

Table 2. Geometrical and mechanical properties: numerical simulation. Source: Author

Property	Minimum Value	Maximum Value	Step
E_{11}	27.0 GPa	33.0 GPa	0.5 GPa
E_{22}	13.5 GPa	16.5 GPa	0.5 GPa
ρ_c	1160 kg/m^3	1380 kg/m^3	20 kg/m^3
G_{12}	5.3 GPa	6.2 GPa	0.3 GPa
Stacking orientation	$[-5]_{12}$	$[+5]_{12}$	1

2.3 Artificial Neural Networks (ANNs)

Artificial neural networks (ANNs) are a powerful tool for solving nonlinear problems. According to Haykin *et al.* (2009), they should work as a "black box", where input data is entered and corresponding output data is collected to solve a specific problem. However, for this process to happen effectively it is necessary to subject it to a learning stage that will be described further.

To understand how a neural network works, the Fig. 2 illustrates the basic architecture of a neuron, which is the processing of information.

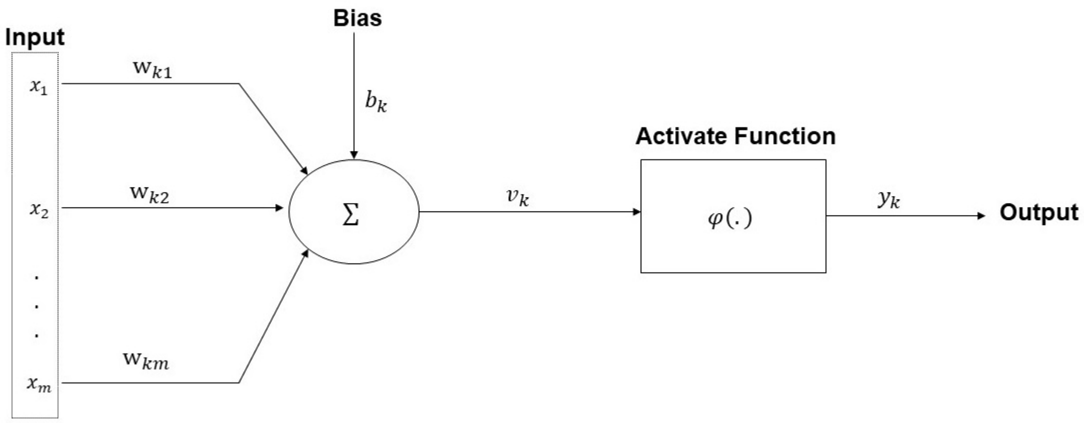

Figure 2. A simple perceptron model

Considering the example that a model containing only one layer and a neuron (known as perceptron), it follows that weights are assigned w_{km} to an input data $[x_1, .., x_m]^T$, so the adaptive function ($\sum$) represents a linear combination obtained from the input data, as

$$v_k = \sum_{j=1}^{m} w_{kj} x_j. \tag{3}$$

Then, this result follows an activation function $\varphi(.)$. Which presents the output results (y_k), and in this stage the so-called bias (b_k) can be incremented to shift the hyperplane

$$y_k = \varphi(v_k + b_k). \tag{4}$$

It is worth mentioning that there are different types of activation functions such as heavyside functions, linear functions, hyperbolic functions, gaussian functions and logistic functions, each with its specific properties. In this work, the activation function used was the logistic function as follows

$$\varphi(v_k + b_k) = \frac{1}{1 - e^{-(v_k + b_k)}}. \tag{5}$$

However, for more complex problems like what will be presented by this work, it is necessary to apply a network with more than one layer and more than one neuron per layer, called by "Multilayer Perceptron", where the intermediate layers are defined as hidden layers (Völtz *et al.*, 2018).

As previously mentioned, neural networks work through learning and this process can happen through the insertion of input data which, generating corresponding output data has an error e_k associated with the desired reference value(target) z_k and the output y_k as

$$e_k(t) = z_k(t) - y_k(t). \tag{6}$$

Thus, the learning process used in this work follows the Haykin proposal of minimizing the following objective function that corresponds to the mean square error, comparing the result obtained by the network the target as

$$E(t) = \frac{1}{2}e_j^2(t). \tag{7}$$

Therefore, for the minimizing process, optimization algorithms can be used. In this work were applied the Steepest Descent that determines a search direction through the derivative of $E(t)$ relative to the weights (w) e bias (b), and at the end of (t) times or iterations, the resulting direction is found (Arora, 2004) as

$$\vec{d}^t = -\vec{\nabla}E, \tag{8}$$

$$x^{t+1} = x^t + \alpha^t d^t. \tag{9}$$

Where

$$\vec{\nabla}E = \begin{Bmatrix} \frac{\partial E}{\partial b} \\ \frac{\partial E}{\partial w} \end{Bmatrix}. \tag{10}$$

The gradients were evaluated using automatic differentiation, following the work of Kedem (1980), applying the chain rule. In a process of optimization using descent direction, an important parameter is the step (α), called learning rate on machine learning approach that express how fast the networking training process is being conducted towards its convergence (Völtz *et al.*, 2018). The learning rate was calculated using Backtracking line-search (or Armijo-Goldstein). Assuming that large variations may make the network unstable. The momentum term (γ) is added with values $0 \leq \gamma \leq 1$. For calculation of weights and bias to t iterations we are used

$$\vec{\Delta}w^t = \gamma\vec{\Delta}w^{t-1} + \alpha^t d_w^t \qquad and \qquad w^t = w^{t-1} + \vec{\Delta}w^t. \tag{11}$$

$$\vec{\Delta}b^t = \gamma\vec{\Delta}b^{t-1} + \alpha^t d_b^t \qquad and \qquad b^t = b^{t-1} + \vec{\Delta}b^t. \tag{12}$$

It is worth noting that for the FRF in terms of $H_{ij}(\omega_j)$ brings information about a lot of points, demanding more computational cost. Thus, applying all of them as input to the neural network could be extra inefficient because a much more robust topology might be required. Then, a pre-processing step was imposed using the Principal Component Analysis (PCA). This technique consists in taking a raw containing data obtained from the FRF of a space *n*-dimensional with the data set $[x_1, ..., x_n]$ and map to another orthogonal vector z_p at the *p*-dimensional, such that $p << n$, where the elements $[z_1, ..., z_p]$ correspond to the main components (Zang and Imregun, 2001). Considering a FRF matrix H_{mn}. To evaluate the PC's is necessary firstly find the mean vector response $\overline{H}_j$ using Eq. (13), and evaluating standard deviation $\overline{S}_j$ from Eq. (14). Thus each element of FRF matrix H_{ij} can be rewritten in terms of $\widetilde{H}_{ij}$ by Eq. (15). So that, correlation Matrix $[C]$ is obtained, where their eigenvalues (λ_l) are the PC's and eigenvectors (ϕ_l) their correspondents directions

$$\overline{H}_j = \frac{\sum_{i=0}^{n} H_{ij}}{m}, \tag{13}$$

$$\overline{S}_j = \frac{\sqrt{\sum_{i=0}^{n}(H_{ij} - \overline{H}_j)^2}}{m}, \tag{14}$$

$$\widetilde{H}_{ij}(\omega) = \frac{h_{ij} - \overline{H}_j}{S_j\sqrt{m}}, \tag{15}$$

$$[C] = [\widetilde{H}(\omega)]^T[H(\omega)], \tag{16}$$

$$[C]\{\phi_l\} = \lambda_l\{\phi_l\}, \tag{17}$$

$$([C] - \lambda_l[I])\{\phi_l\} = 0. \tag{18}$$

However, another common problem encountered when working with ANNs is to determine the number of layers and number of neurons to be used without the problem of oversizing or sub-dimensioning. Therefore, the Particle Swarm Optimization (PSO) method was applied. This technique is based on the behavior of colony or swarm of insects, where they behave as a "particle" in search of food for example, having a relation between them and the medium that influences this search (Rao, 2009). The particles assuming a position (X) and a velocity (V). The parameters (W), ($C1$) and ($C2$) measure inertia weight, self confidence factor and swarm confidence factor, respectively. The algorithm works generating a population randomly with candidate solutions, leading to a local minimum which is the best objective function of ($pBest$) and the group of ($gBest$) as

$$V(t) = WrandV(t-1) + C_1rand(pBest - X(t-1)) + C_2rand(gBest - X(t-1)), \tag{19}$$

$$X(t) = X(t-1) + V(t). \tag{20}$$

3. RESULTS AND DISCUSSIONS

The first four modes corresponding to a healthy beam are shown in Fig. 3, and the frequencies are Mode 1: 224.76 Hz; Mode 2: 650.78 Hz; Mode 3: 889.73 Hz and Mode 4: 1226.20. Modes 1,2 and 4 are flexural modes and 3 is a torsional mode.

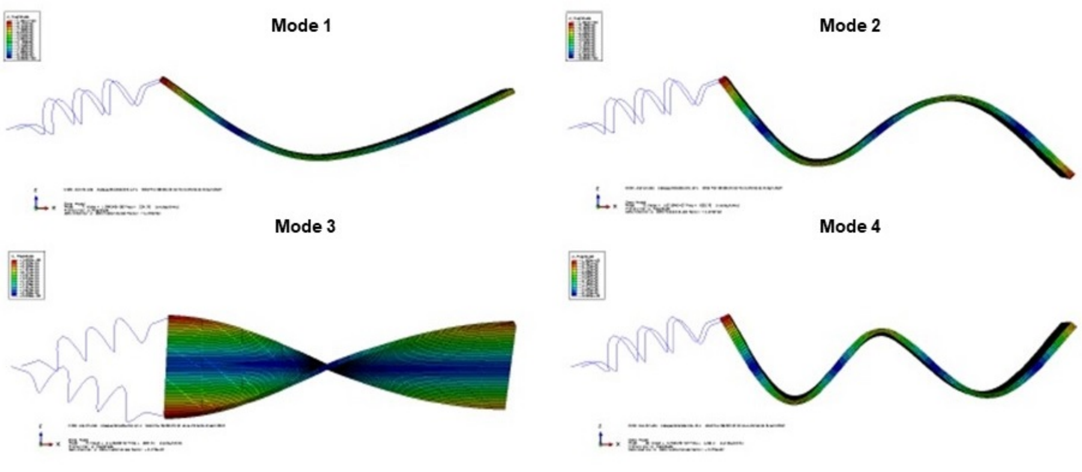

Figure 3. Modes shapes.

The H_{11} - FRFs can be seen in Fig. 4 and H_{21} - FRFs in Fig. 5, both using accelerance values. The range between the minimum frequency and maximum frequency for the first four modes shapes from two states conditions (healthy and damaged) are shown in Fig. 6. It may be noted that interval of each mode for a particular state is large. And when compared to the mode and the states it is noted that many samples within the same range. So the two scenarios are very similar when comparing the resonant frequencies.

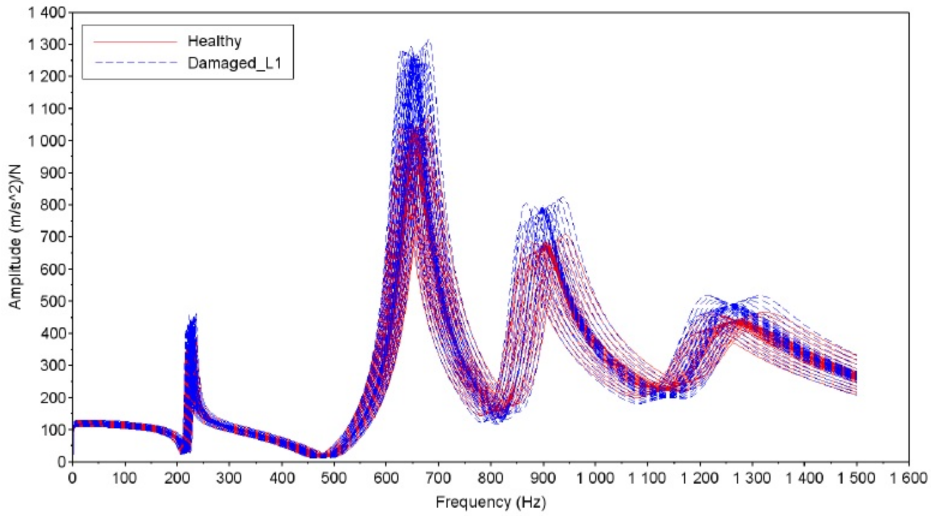

Figure 4. H_{11} - Numerical FRFs curves (accelerance values).

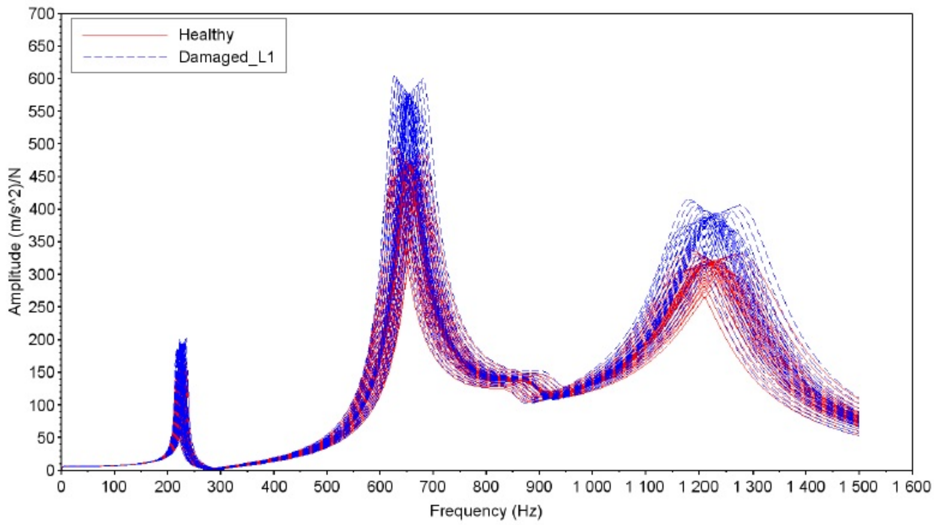

Figure 5. H_{21} - Numerical FRFs curves (accelerance values).

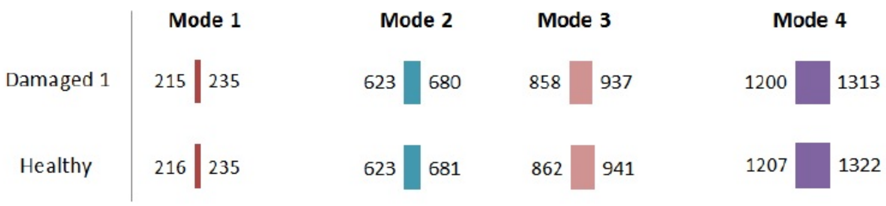

Figure 6. A simple perceptron model.

To define how much data would be allocated for the corresponding training and testing steps, the subroutines *kfold.jl*, *stratifiedobs.jl* and *stratifiedobs.jl* were used. Using *kfold.jl*, initially, if the dataset is composed by 90 observations, 18 observations go to the testing set and 72 go to the training set. After that, each 5-fold of the training sets are again split by 85 % for a new training set and 15% for validation set using *stratifiedobs.jl* subroutine. The use of *stratifiedobs.jl* will try to make sure that both subsets are both appropriately distributed.

After PCA calculations on the training set, the change of space of the validation and the testing sets are performed by multiplying the eigenvectors (which means the new base) found during PCA calculations using only the training set. The PCA is performed and total variance for each 5-folds, 10 and 20 PCs, where the results shown in the Table 3 presents results.

Table 3. The variance for each 5 folds 10 and 20 PCs.

Set	**10 PCs (%)**	**20 PCs (%)**
1	99.817	99.993
2	99.808	99.992
3	99.808	99.993
4	99.816	99.993
5	99.811	99.992

The case studied is when the dataset is composed of two-state conditions: healthy and damaged, with 2 output neurons (healthy and damaged). Thus, applying the Particle Swarm Optimization with parameters shwon in Tab 4, we have found two types of topology for ANN1 and ANN2 (Tab 5), correspondent to 10 PC's and 20 PC's of input data, respectively.

Table 4. Parameters used on Particle Swarm Optimization (PSO).

Parameter	**Value**
C_1	1.2
C_2	1.2
W	0.5
Iterations	10
Particles	10
Variables	3
Lower bound	[1;1;1]
Upper bound	[2;24;24]

Table 5. ANNs simulations.

ANN	**Topology**	Activation	Cost function	Step Size	γ
ANN1	20-[15]-2	tanh	quadratic	Backtracking	0.3
ANN2	10-[3,4]-2	tanh	quadratic	Backtracking	0.3

Tables 6 and 7 shows the results for the all 5-sets (after 150 times runs). It can be noted that both simulations present very good results, with almost all accuracies averaging more than 90%. The best set is set 4. It can be observed that there is no link between maximum variance acquired in PCA and the ANN results since the largest variance is found in set (for 10 and 20 PCs) and this one obtained the maximum accuracy of 94.7%.

Table 6. ANN 1 simulation with different parameters - accuracy results (Sets 1,2,3,4 and 5) - 150 times run - Numerical.

Set	**Dataset**	**Mean - %(mean deviation)**	**Maximum**
1	Training	100.00 (0.003)	100.00
	Validation	91.30 (0.027)	100.00
	Testing	94.74 (0.015)	100.00
2	Training	100.00 (0.006)	100.00
	Validation	100.00 (0.020)	100.00
	Testing	100.00 (0.014)	100.00
3	Training	100.00 (0.006)	100.00
	Validation	100.00 (0.011)	100.00
	Testing	94.74 (0.016)	100.00
4	Training	100.00 (0.000)	100.00
	Validation	100.00 (0.021)	100.00
	Testing	100.00 (0.000)	100.00
5	Training	100.00 (0.023)	100.00
	Validation	100.00 (0.027)	100.00
	Testing	97.30 (0.000)	97.30
Total	Training	100.00 (0.000)	100.00
	Validation	100.00 (0.028)	100.00
	Testing	97.30 (0.027)	100.00

Table 7. ANN 2 simulation with different parameters - accuracy results (Sets 1,2,3,4 and 5) - 150 times run - Numerical.

Set	**Dataset**	**Mean - %(mean deviation)**	**Maximum**
1	Training	100.00 (0.014)	100.00
	Validation	91.30 (0.034)	100.00
	Testing	94.74 (0.019)	100.00
2	Training	99.21 (0.030)	100.00
	Validation	95.65 (0.052)	100.00
	Testing	94.74 (0.041)	100.00
3	Training	100.00 (0.023)	100.00
	Validation	95.65 (0.027)	100.00
	Testing	92.10 (0.027)	97.37
4	Training	100.00 (0.024)	100.00
	Validation	100.00 (0.034)	100.00
	Testing	100.00 (0.025)	100.00
5	Training	97.67 (0.049)	100.00
	Validation	90.91 (0.063)	100.00
	Testing	89.19 (0.073)	97.30
Total	Training	100.00 (0.014)	100.00
	Validation	95.65 (0.029)	100.00
	Testing	94.74 (0.028)	100.00

The worst mean accuracy obtained with numerical study for the testing set is 89.19 %. This response may be due to the increase in the number of samples with a greater representatively for each condition. In a numerical study, it can be noted there are not large discrepancies between the FRFs of the same state condition case, eliminating the problem of having atypical samples, which do not represent the state condition group. One point to note is that the methodology works very well with samples that have small differences between them. Since healthy FRFs have values very close to FRFs damaged by 5mm.

4. CONCLUSION

It is possible to conclude that, the methodology for damage detection in composite beams considering uncertainties can be applied into Structural Health Monitoring (SHM) solutions. It has been shown that the variations in mechanical and geometrical properties that may occur during the manufacturing and assembly process, for example, are represented, which resulted in a certain variability of FRF responses for intact and damaged samples. However, even using the damage of 5mm that do not show large variations in its FRF compared to intact, when 20 PCs were used, the worst result obtained to identify the damage was 94.74 %, proving the robustness of the technique.

Therefore, with this work development, it is perceptible that parameters associated with the Artificial Neural Network as the number of layers, neurons, activation function, cost function to evaluate the error on training phase, being one of the more difficult parts of work. Thus, Particle Swarm Optimization worked well in direction to determine these hyper-parameters. This work can be improved in further projects, studying another's techniques to treat the data of vibration model and other uncertainties approach, compared with experimental results.

5. ACKNOWLEDGE

The authors acknowledge the financial support of the State Research Founding Agency (FAPESC process number: 2017TR1747 and 2017TR784). As well as, Coordination for the Improvement of the Higher Level Personnel (Finance Code 001) and National Council for Scientific and Technological Development (CNPq). The authors also would like to thank Prof. Joel Martins Crichigno Filho (Santa Catarina State University – Brazil) for kindly providing the use of the ABAQUS^{TM} license.

6. REFERENCES

Allemang, R.J., 2003. "The modal assurance criterion–twenty years of use and abuse". *Sound and vibration*, Vol. 37, No. 8, pp. 14–23.

Alves, V., Cury, A., Roitman, N., Magluta, C. and Cremona, C., 2015. "Structural modification assessment using supervised learning methods applied to vibration data". *Engineering Structures*, Vol. 99, pp. 439–448. ISSN 1873-7323. doi:10.1016/j.engstruct.2015.05.003. URL `http://dx.doi.org/10.1016/j.engstruct.2015.05.003`.

Arora, J.S., 2004. *Introduction to optimum design*. Elsevier.

Bakhary, N., Hao, H. and Deeks, A.J., 2007. "Damage detection using artificial neural network with consideration of uncertainties". *Engineering Structures*, Vol. 29, No. 11, pp. 2806–2815.

De Medeiros, R., Vandepitte, D. and Tita, V., 2018. "Structural health monitoring for impact damaged composite: a new methodology based on a combination of techniques". *Structural Health Monitoring*, Vol. 17, No. 2, pp. 185–200.

dos Santos Souza, L.F., Vandepitte, D., Tita, V. and de Medeiros, R., 2019. "Dynamic response of laminated composites using design of experiments: An experimental and numerical study". *Mechanical Systems and Signal Processing*, Vol. 115, pp. 82–101.

Ewald, V., Groves, R.M. and Benedictus, R., 2019. "DeepSHM : A Deep Learning Approach for Structural Health Monitoring Based on Guided Lamb Wave Techniques DeepSHM : A Deep Learning Approach for Structural Health Monitoring Based on Guided Lamb Wave Techniques". , No. March.

Fu, Z.F. and He, J., 2001. *Modal analysis*. Elsevier.

Gomes, G.F., Mendéz, Y.A.D., da Silva Lopes Alexandrino, P., da Cunha, S.S. and Ancelotti, A.C., 2018. "The use of intelligent computational tools for damage detection and identification with an emphasis on composites âĂŞ A review". *Composite Structures*, Vol. 196, No. April, pp. 44–54. ISSN 02638223. doi:10.1016/j.compstruct.2018.05.002. URL https://doi.org/10.1016/j.compstruct.2018.05.002.

Haykin, S.S. *et al.*, 2009. *Neural networks and learning machines/Simon Haykin*. New York: Prentice Hall,.

Humar, J., Bagchi, A. and Xu, H., 2006. "Performance of vibration-based techniques for the identification of structural damage". *Structural Health Monitoring*, Vol. 5, No. 3, pp. 215–241.

Kaw, A.K., 2005. *Mechanics of composite materials*. CRC press.

Kedem, G., 1980. "Automatic differentiation of computer programs". *ACM Trans. Math. Softw.*, Vol. 6, No. 2, pp. 150–165. ISSN 0098-3500. doi:10.1145/355887.355890. URL http://doi.acm.org/10.1145/355887.355890.

Kessler, S.S., Spearing, S.M., Atalla, M.J., Cesnik, C.E.S. and Soutis, C., 2002. "Damage detection in composite materials using frequency response methods". *Composites Part B:Engineering*, Vol. 33, No. 1, pp. 87–95. ISSN 13598368. doi: 10.1016/S1359-8368(01)00050-6.

Padil, K.H., Bakhary, N. and Hao, H., 2017. "The use of a non-probabilistic artificial neural network to consider uncertainties in vibration-based-damage detection". *Mechanical Systems and Signal Processing*, Vol. 83, pp. 194–209.

Piazzaroli, R., 2019. "An SHM approach using machine learning and statistical indicators extracted from raw dynamic measurements". Vol. 16, No. 1998, pp. 1–17.

Rao, S.S., 1995. "Mechanical vibrations(laboratory manual)".

Rao, S.S., 2009. *Engineering optimization: theory and practice*. John Wiley & Sons.

Tang, J., 2005. "Frequency response based damage detection using principal component analysis". In *2005 IEEE International Conference on Information Acquisition*. IEEE, pp. 6–pp.

Tang, Z., Chen, Z., Bao, Y. and Li, H., 2019. "Convolutional neural network-based data anomaly detection method using multiple information for structural health monitoring". *Structural Control and Health Monitoring*, Vol. 26, No. 1, pp. 1–22. ISSN 15452263. doi:10.1002/stc.2296.

Völtz, L., Lenz Cardoso, E. and De Medeiros, R., 2018. "Damage Detection on Aluminum Beams Using Vibration-Based Method and Artificial Neural Networks." doi:10.26678/abcm.cobem2017.cob17-0583.

Völtz, L.R., 2019. *Fault Diagnosis in composite structures using Artificial Neural Networks and Principal Component Analysis*. Master's thesis, State University of Santa Catarina, Joinville, Santa Catarina, Brazil.

Zang, C. and Imregun, M., 2001. "Combined neural network and reduced frf techniques for slight damage detection using measured response data". *Archive of Applied Mechanics*, Vol. 71, No. 8, pp. 525–536. ISSN 1432-0681. doi:10.1007/s004190100154. URL https://doi.org/10.1007/s004190100154.

7. RESPONSIBILITY NOTICE

The authors are the only responsible for the printed material included in this paper.