Damage detection in laminated composites by neural networks and high order finite elements

Damage Detection in Laminated Composites by Neural Networks and High Order Finite Elements

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ABSTRACT

In the aerospace industry, machine learning techniques are becoming more and more important for Structural Health Monitoring (SHM). In fact, they could be useful in giving a precise and complete mapping of damage distribution in a structure, including low-intensities or local defects, which cannot be detected via traditional tests. In this work, feedforward artificial neural networks (ANN) are employed for vibration-based damage detection in composite laminates. In the framework of Carrera Unified formulation (CUF), one-dimensional refined models in conjunction with layer-wise (LW) theory are adopted. CUF-based Monte Carlo simulations have been used for the creation of a dataset of damage scenarios for the training of the ANN. Therefore, the latter is fed with the vibrational characteristics of these structures. The trained ANN, given these dynamic parameters, is able to predict location and intensity of all damages in the laminated composite structures.

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INTRODUCTION

Structural health monitoring is assuming a crucial role in several branches of industry, such as civil or aircraft industries. The objective is to overcome the limitations of the Non-Destructive Tests (NDT), which are performed as aircraft maintenance program. The main limitation is the necessity of the operator to know a priori the location of the damage to be analyzed.

Several methods of health monitoring have been developed, such as guided waves [1], Fiber Bragg grating (FBG) sensor [2], and intelligent coating monitoring [3]. In this work, variations in the vibrational characteristics of a structure are studied to predict location and intensity of damages. Thus, the objective of this work is the solution of the so-called “inverse problem”; given the dynamic parameters of the structure (i.e. natural frequencies or mode shapes), the proposed model will be able to detect the location and the severity of damages in the investigated structure.

In this manuscript, Artificial Neural Networks (ANN) are used in combination with one-dimensional refined model, developed through the Carrera Unified Formulation (CUF) [4]. CUF has been recently employed for solving the “direct problem” of vibration-based damage detection [5] : the effect of localized damages on the vibrational characteristics of the structure is studied. Following this research path, this work aims at solving the inverse problem, exploiting the combination of excellent accuracy and low computational cost of CUF formulation for composite materials. The proposed approach has been already employed for metallic structures in [6].

The manuscript is organized as follows: Section 0 describes the finite element models employed. Then, Section 3 presents the layer-wise damage modelling; Section 4 illustrates the ANNs training process. Afterward, the results are shown in Section 5. Finally, conclusions are drawn in Section 6.

UNIFIED FINITE ELEMENTS

In the framework of CUF [4], the 3D field of displacements can be expressed as a summation, of arbitrary expansion functions $F_\tau(x,z)$ and the vector of the generalized displacements $\boldsymbol{u}_\tau(y)$. In the case of one-dimensional beam theories, as in the case of this work, the displacements field is expressed as:

$$\boldsymbol{u}(x,y,z) = F_\tau(x,z)\boldsymbol{u}_\tau(y) \qquad \tau = 1, \dots, M \tag{1}$$

where M is the number of expansion terms. Different expansion functions can be utilized as $F_\tau(x,z)$. In this work, Lagrange expansion (LE) are used in order to adopt a layer-wise (LW) approach for the analysis of laminated parts.

The Finite element method (FEM) is used to study the structures involved in this paper. Therefore, the generalized displacements can be expressed as:

$$\boldsymbol{u}_\tau(y) = N_i(y)\boldsymbol{u}_{\tau i} \qquad i = 1, \dots, n_{nodes} \tag{2}$$

in which n_{nodes} is the total number nodes per element, $N_i(y)$ are the one-dimensional shape functions and $\boldsymbol{u}_{\tau i}$ are the nodal unknowns.

In this work, the undamped dynamic problem is analyzed. Both stiffness and mass matrices are obtained via the application of the virtual displacement principle. After some manipulations, the virtual variation of the internal work reads:

$$\boldsymbol{\delta}(L_{int}) =< \delta\boldsymbol{\varepsilon}^T\boldsymbol{\sigma} >= \delta u_{sj}^T \boldsymbol{k}_{\mathbf{0}}^{ij\tau s} u_{\tau i} \tag{3}$$

where $\boldsymbol{k}_{\mathbf{0}}^{ij\tau s}$ denotes the stiffness matrix in the form of fundamental nucleus, and the <·> operator represents the integral over the volume of the element. The virtual variation of the work of inertial loadings is:

$$\boldsymbol{\delta}(L_{ine}) =< \boldsymbol{\rho}\delta\boldsymbol{u}^T\ddot{\boldsymbol{u}} >= \delta u_{sj}^T \boldsymbol{M}^{ij\tau s} u_{\tau i} \tag{4}$$

where $\boldsymbol{M}^{ij\tau s}$ is the fundamental nucleus of the mass matrix and $\ddot{\boldsymbol{u}}$ the acceleration vector. It should be underlined that no assumption about the approximation order are made for the formulation of both matrices. Thus, any refined beam model can be obtained with this procedure. The assembled global stiffness matrix is obtained by looping through the indices i, j, τ, s.

For the sake of brevity, the governing equations of the undamped dynamic problem are not reported here, but can be found in [4].

LAYER-WISE DAMAGE MODELLING

Layer-wise approach [7] allows an independent formulation for each layer of a laminated composite, while guaranteeing the interlaminar continuity. The derivation of CUF in the LW framework has been introduced for the first time by Carrera in [8] through the adoption of Lagrange expansion (LE). The characteristics of CUF allowed a significant reduction of the computational demand for the LW approach. In the present work, the features of LW formulation have been exploited for damage detection purpose. In fact, each layer can be independently modelled, allowing to introduce a different damage in each layer, or in a reduced portion of one or more layers. This will result in a more localized damage distribution within the laminate and, consequently, to a better localization of the damages via the ANN training. At this stage, an isotropic damage is considered. It is modelled through reduction of the stiffness of the layer involved, with no consequences on its mass. The material properties are modified as follows:

$$E_d = d \times E, \quad with \quad 0 \leq d \leq 1 \tag{5}$$

where E is the Young modulus and d is the damage coefficient. If it is equal to 1, the structure has no damage, while if it is lower than 1, the structure will have a damage with intensity of (1-d). In Fig. 1, an example of damage scenario in a four-layer plate is shown.

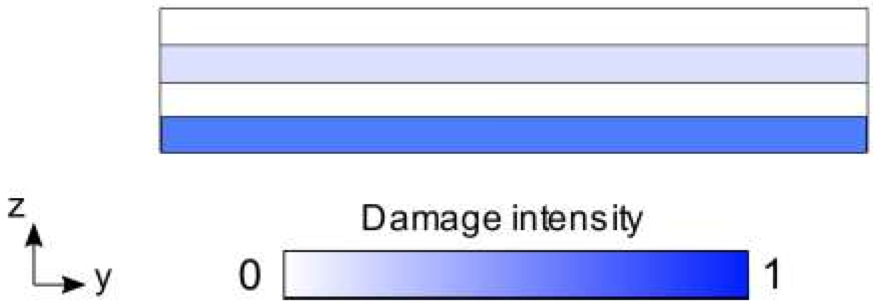


Figure 1. Example of damage introduction in a four-layer plate.

In [5], authors employed natural frequencies and Modal Assurance Criterion (MAC) as parameters for the study of the vibration-based direct problem. MAC is a parameter which quantifies mode-to-mode correlation between, in this case, damaged and undamaged structures. The scalars are computed as follows:

$$\mathrm{MAC}_{ij} = \frac{|\{\phi_{A_i}\}^T\{\phi_{B_j}\}|^2}{\{\phi_{A_i}\}^T\{\phi_{A_i}\}\{\phi_{B_j}\}\{\phi_{B_j}\}^T} \tag{6}$$

where $\{\phi_A\}$ and $\{\phi_B\}$ are the damaged and undamaged modal vector for i^{th} and j^{th} modes, respectively. Thus, the final aim of this research is to build a model which, given natural frequencies and MAC matrix, is able to detect location and intensity of damages in each single layer of the laminate. For this purpose, an ANN has been trained after creation of a database of damage scenarios. This process will be further discussed in the following section.

ANN TRAINING FOR DAMAGE DETECTION

An ANN is a group of interconnected neurons. It is formed by an input layer, one or more hidden layers and an output layer. An example of ANN architecture is shown in Fig. 2. Inputs are the natural frequencies and the MAC matrix, while the outputs of the network will be location and severity of the damage.

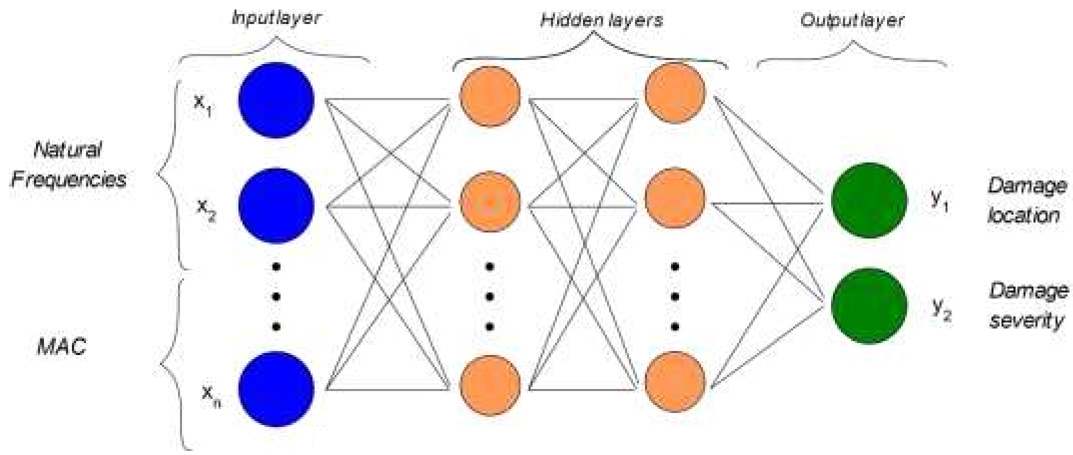


Figure 1. Architecture of an Artificial Neural Network.

The ANN reduces the error in the prediction of the outputs through the training process. A large training database is needed for the quantification and localization of damage. In this work, the database has been created through CUF-based Monte Carlo simulations. Damage intensity was assigned randomly to each component, following a Gaussian distribution, with mean equal to 0 and standard deviation equal to 0.1. The adoption of LW formulation in CUF framework allowed the creation of a database of N structures, providing very accurate analysis with a reduction of the computational cost. Additionally, it allowed a localized damage distribution. An example of database is shown in Tab. I.

Table I. Example of database of N samples for a 4-layers structure. The damage introduced for each component is indicated in terms of stiffness reduction (1-d).

	Layer 1	**Layer 2**	**Layer 3**	**Layer 4**
Sample 1	0.10	0.14	0.01	0.13
Sample 2	0.21	0.04	0.07	0.16
Sample 3	0.17	0.01	0.02	0.17
Sample 4	0.13	0.00	0.04	0.08
…		…	…	
…		…	…	
Sample N	0.03	0.10	0.13	0.09

Once the ANN is well trained, it can be used for investigation of new structures, which are unknown for the network. Hence, the ANN is fed with natural frequencies and MAC scalars of this structure as input, and it will give all damages' location and severity as output. In Fig. 3, a flowchart describing the entire process, from modelling of the structure to the test of the ANN, is shown.

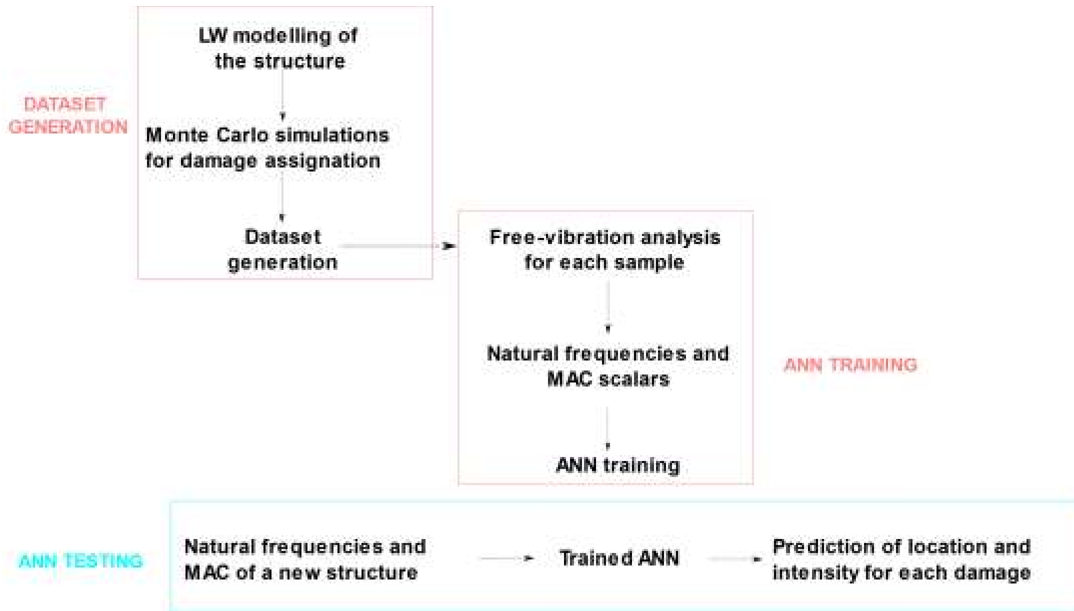


Figure 3. Flowchart representing the entire process for damage detection, from the modelling of the structure to the trained ANN.

NUMERICAL RESULTS

To validate the proposed methodology, a six-layer plate with symmetric stacking sequence $[0_2\text{-}90]_s$ has been studied. This problem has already been treated in [9]. A representative scheme of the plate is shown in Fig. 4.

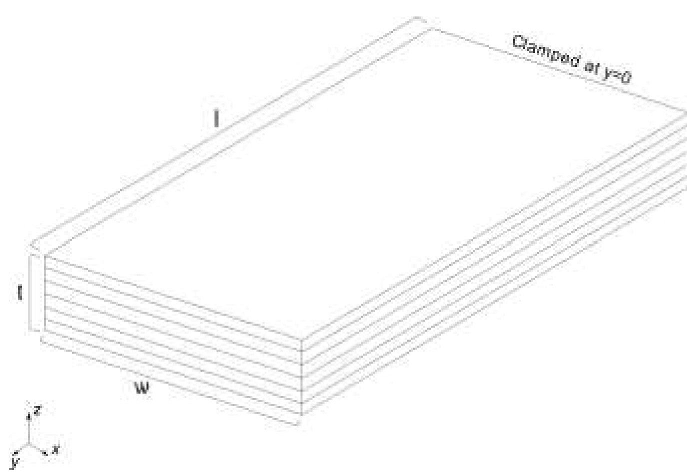


Figure 4. Representative schema of a six-layer plate.

The plies are of equal thickness and they are made of orthotropic material with Young modulus along the fibre direction equal to E_L = 98 GPa, Young modulus along a transverse direction E_T = 7.90 GPa, shear modulus G_{LT} = 5.60 GPa, Poisson ratio υ = 0.28 and density ρ = 1520 Kg/m^3. The length *l*, the width *w* and the total thickness *t* of the structure are equal to 305, 76.2 and 0.804 mm, respectively. Ten 4-node elements (B4) are adopted for the discretization along the beam axis, while quadratic Lagrange polynomials (L9) are employed in the cross-section. The structure is clamped at one end.

Every layer has been divided into two sections: so, each layer will now be described by two L9 elements. In the following discussion, we will refer to each half of each layer with the term "component". Thus, we virtually divided the laminate into twelve components, as illustrated in Fig. 5. Layer-wise approach allows to introduce a different damage in each component. In this case, we choose to damage three components (1, 3 and 6), all in the clamped section.

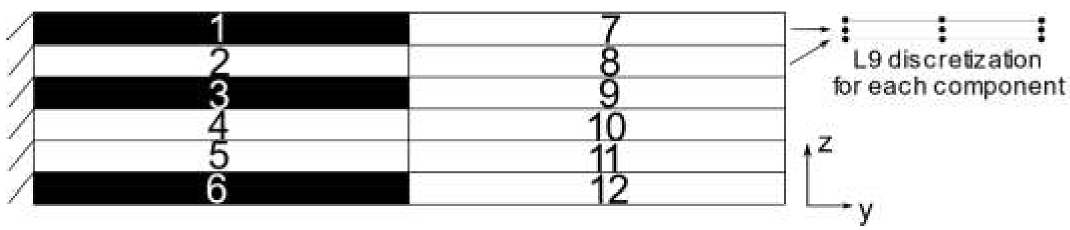
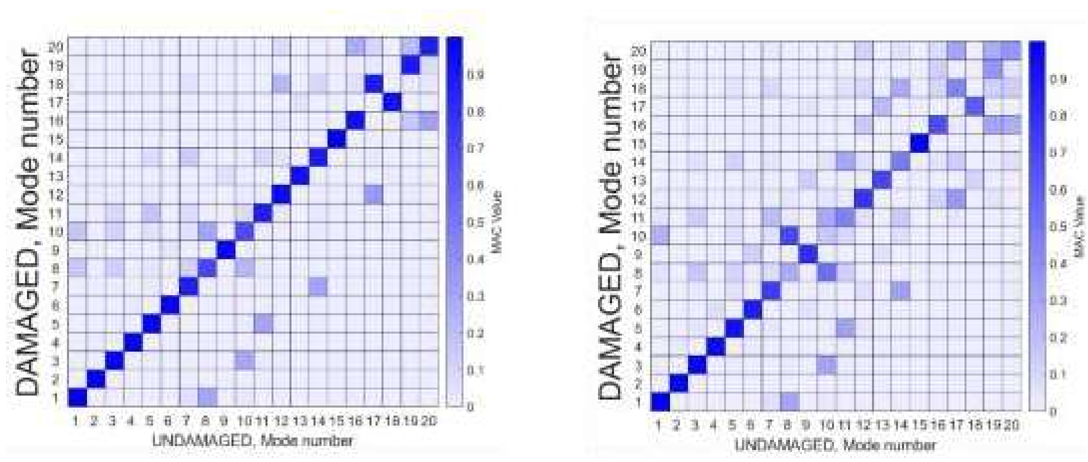


Figure 5. Representation of damage scenario for the laminated composite structure. Highlighted components are randomly damaged.

Firstly, the direct problem is solved: known damages are introduced in the structure and their influence on natural frequencies and mode shapes are investigated. Tab. II shows the variation of natural frequencies when all three components (1,3 and 6 in Fig. 5) are damaged with the same intensities (d=0.5 and d=0.9). Fig. 6 shows the MAC matrix, comparing the mode shapes of the undamaged structure with the two previous damage scenarios.

Table III. First 20 natural frequencies (Hz) of the six-layer plate for the undamaged case and two damage scenarios.

	Undamaged	**d=0.5**	**d=0.9**
f_1	11.23	9.05	6.72
f_2	39.68	33.92	27.08
f_3	70.34	61.26	48.89
f_4	133.85	12.17	107.20
f_5	196.91	177.01	153.53
f_6	269.53	243.33	209.41
f_7	384.66	341.31	283.89
f_8	399.26	369.53	299.51
f_9	461.05	411.29	350.85
f_{10}	462.68	421.60	396.87
f_{11}	589.38	532.86	464.95
f_{12}	638.46	572.59	488.52
f_{13}	713.40	640.71	544.88
f_{14}	777.98	700.21	609.33
f_{15}	882.91	774.53	670.20
f_{16}	952.98	844.28	711.13
f_{17}	1027.51	913.56	776.84
f_{18}	1028.02	923.26	791.47
f_{19}	1330.04	1191.11	1002.45
f_{20}	1339.54	1199.33	1031.38



d=0.5 **d=0.9**

Figure 6. MAC mode-to-mode comparison between undamaged and damaged plate for two damage scenarios.

In order to solve the inverse problem, a large database has to be built for the ANN training process. In this case, training database of 15000 samples has been considered, created as explained in the previous section. The ANN is trained through the MATLAB toolbox [10]. The best ANN architecture in terms of accuracy and computational cost has been found through a trial-and-error approach, where the variables are the number of hidden layers and the number of neurons for each layer. For this problem, a network with a single layer and 16 neurons has been used for the training process. In Fig. 7, the performance of the network is shown. The regression coefficient R is an index of the network accuracy in the output prediction. It can vary from 0 to 1, where a value of 1 indicates that all predicted output match the targets.

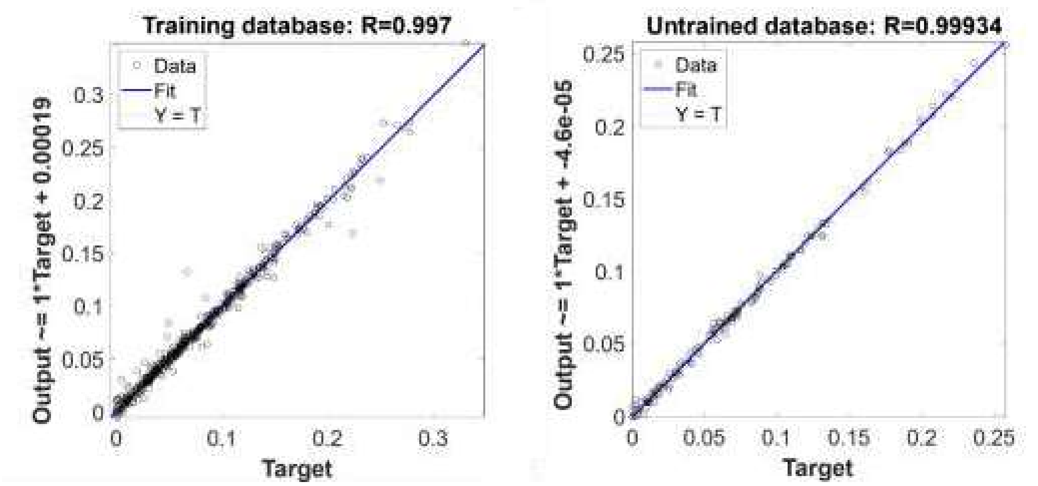


Figure 7. Performance of the ANN with a 16 neurons layer.

Figure 8 shows the comparison between the ANN's guess (Blue Bars) and the solution introduced through CUF-based Monte Carlo simulations (Red Bars). In the horizontal axis, the component's numbering is indicated, according to the structure's repartition shown in Fig. 5. In the vertical axis the intensity of the damage is displayed. This figure shows the accuracy of the network in predicting location and intensity of all damages in the laminate. It should be underlined that these structure were not used for the training of the ANN, so they are unknown for the network.

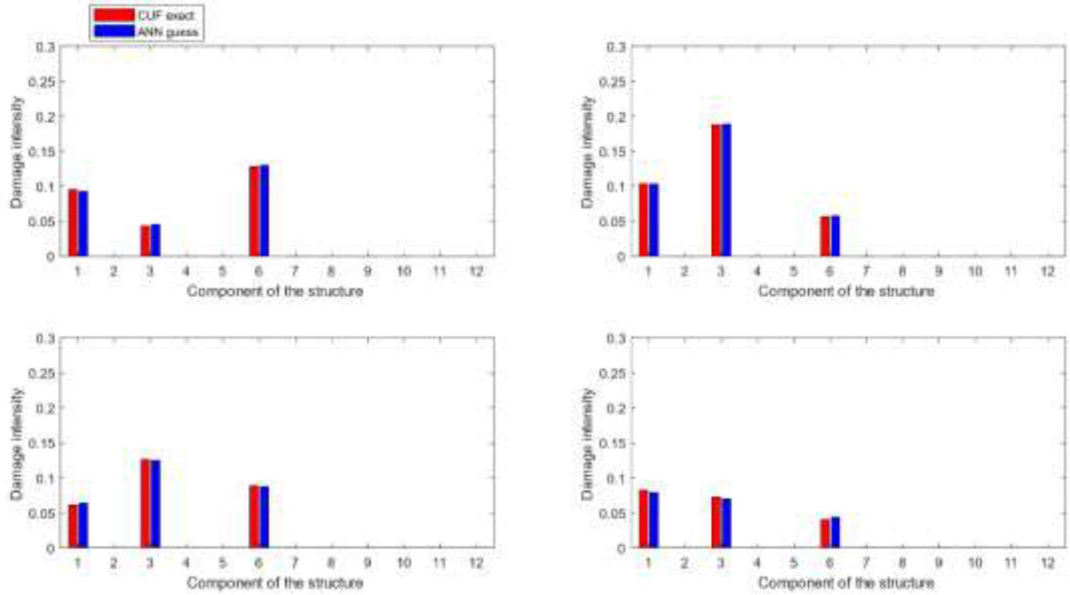


Figure 8. Comparison between the exact CUF solution (Red bars) and the ANN output (Blue bars). Each graph represents a different structure which is unknown for the network.

CONCLUSIONS

In this manuscript, a vibration-based damage detection method is proposed. It combines the Neural network's theory and CUF one-dimensional model. In this framework, the layer-wise formulation has been introduced for the analysis of laminated composite. It allows to carry out free-vibration analysis with high accuracy and low computational cost, characteristics which are essential for the creation of a damage scenarios' database. The proposed model showed to be very accurate for a six-layer plate, whose layers were divided into two halves, for a total of twelve components. The network, after training with the database created via Monte Carlo simulations, was able to predict location and intensity of damages in unknown structures.

Future works will focus on the implementation of a new damage model, which will contemplate a differentiation between damage in the longitudinal and in transversal directions. Moreover, the possibility of detecting delamination between layers will be investigated.

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