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Procedia Structural Integrity 5 (2017) 107–114

Structural Integrity Procedia

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2nd International Conference on Structural Integrity, ICSI 2017, 4-7 September 2017, Funchal, Madeira, Portugal

Impact force reconstruction in composite panels

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Abstract

Passive sensing is a branch of structural health monitoring which aims at detecting positions and intensities of impacts occurring on aeronautical structures. Impacts are one of the main causes of damage in composite panels, limiting the application of these modern components on aircraft. In particular, impacts can cause the so called barely visible impact damage which, if not detected rapidly, can grow and lead to catastrophic failure.
The determination of the impact location and the reconstruction of impact force is necessary to evaluate the health of the structure. These data may be measured indirectly from the measurements of responses of sensors located on the system subjected to the impact. The impact force reconstruction is a complex inverse problem, where the cause is to be inferred from its consequences. Inverse problems are in general ill-posed and ill-conditioned. Therefore, several techniques have been employed in the last four decades and have proven to be effective within certain limitations. Among these methods, transfer function based methods have been mainly validated for low-energy impact where the linear assumption should be valid. Nonlinearities may affect the accuracy in the reconstruction process and thus in the evaluation of damage other techniques have been adopted, such as artificial neural networks (ANN) or genetic algorithms (GA).
In this study, a stiffened panel model developed in Abaqus/CAE is first validated, then numerical simulations are used to obtain data for several impacts, characterized by different impact locations and different energy (by changing the impactor mass and/or velocity). Geometrical nonlinearities of the dynamic system are considered in order to represent accurately the mechanics of the composite panel. Then the complex nonlinear behavior will be modeled through a nonlinear system identification approach, such as ANN, and an intelligent algorithm with global search capabilities, such as GA, will be used in sequence to accurately recovery the impact force peak and, therefore, properly evaluate the health status of the structure.

Keywords: impact force reconstruction; neural networks; genetic algorithms; stiffened composite panel.

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2452-3216 © 2017 The Authors. Published by Elsevier B.V.
Peer-review under responsibility of the Scientific Committee of ICSI 2017
10.1016/j.prostr.2017.07.075

1. Introduction

Structural health monitoring is a key component of a damage prognosis system as pointed out in Raghavan and Cesnik (2007) and it has to deal with new safety requirements related to the increasing use of composite materials for aerospace structures. Composite materials are more vulnerable to defects related to the production process or incurred during service because they are unable to redistribute stresses by plastic deformation as explained in Wiggenraad et al. (2000). Impacts may cause the barely visible impact damage which may reduce drastically the residual strength of the flawed structure and eventually lead to the catastrophic failure of the system. During an impact, the critical parameter ruling the occurrence of damage initiation is the peak force as pointed out in Wiggenraad et al. (2000).

As listed in Inoue et al. (2001) and Sanchez and Benaroya (2014), several methods have been employed for modeling dynamic system response, but most of them are based on the assumption of a linear time-invariant system. Kerschen et al. (2006) and Thiene et al. (2014) highlight that nonlinear effects cannot be neglected for an accurate prediction of the impact force reconstruction because the use of the linear theory results in an overestimation of the deflection of the structure, as shown in Wiggenraad et al. (2000).

Recently, Artificial Neural Network (ANN) based approaches have been employed for this purpouse. ANN are computational systems that are meant to simulate the structure of a biological nervous system as reported in Yegnanarayana (2009) and, therefore, suitable to describe complex nonlinear systems. They have been used for the reconstruction of the contact force of the impact, the recovery of the impact location, and therefore for recovering information about the possible presence of damage, as presented in Sharif-Khodaei et al.(2012), Ghajari et al. (2013) and Greenhalgh et al. (2003).

Another approach used to solve similar kind of complex problems is genetic algorithm (GA) based techniques, which are inspired by the process of natural selection as described in Davis (1991). The inverse problem of force reconstruction from data related to the structure response is formulated as an optimization problem and solved by GA thanks to its global search capability. GAs have been used for the impact load identification in Yan and Zhou (2009), for determining the location of the impact in Doyle (1994) and for investigating the optimal number of sensors in Worden and Staszewski (2000).

In this study, the location of an impact and the impact peak force are recovered through the use of multi-layered ANNs, trained with data from a structure in which nonlinearities due to large deformations are taken into account. Differently from previous works on the topic, the weights of a trained ANN employed for the evaluation of the peak force of an impact onto a composite stiffened panel are optimized through a GA.

2. Methodology

It is rather difficult to find an accurate solution to the inverse problem of force reconstruction in nonlinear systems, such as composite panels subjected to impact loads by employing mathematical approaches. Mathematical models are mainly developed for linear systems. Therefore, other techniques are commonly employed to approximate the multi-dimensional generalized response of a nonlinear dynamic system. One of these techniques consists in the use of ANNs, that are able to learn from experience and find solutions to multi-dimensional functional problems, establishing complex, nonlinear relationships between input and output (Fig. 1). For training an ANN, an initial set of data where a particular input to the system leads to a specific output is required. The network adjusts the connections between input and output (connections based on interpolation factors named weights) until the network output matches the target. In this study, ANNs are created and trained by the Neural Network Toolbox of Matlab®, where feed-forward networks with sigmoid hidden neurons can be built and trained by several types of back-propagation algorithms.

The weights obtained for the ANN for the peak force evaluation are subsequently optimized by a GA: a cost function based on the mean square error of the output of the ANN with respect to the target is built. While the ANN algorithm does not guarantee that this cost function is minimized, GAs are optimization algorithms based on evolution theory and genetic principles able to find the optimal solution even in large domains, as explained in works such as Huang et al. (2015).

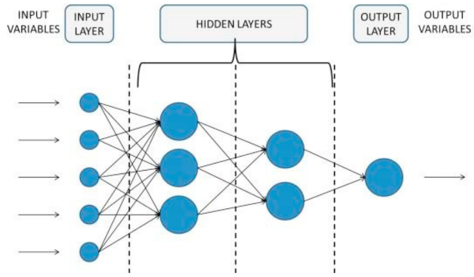

Fig. 1 Structure of a ANN.

3. Numerical simulations

The system under study is a CFRP (carbon fiber-reinforced polymer) stiffened panel subjected to a low-velocity impact as in Faggiani and Falzon (2010). The panel is 450 x 375 x 3 mm^3 and has three I-stiffeners (see Fig. 2). The numerical simulations have been performed using the commercial software Abaqus/CAE.

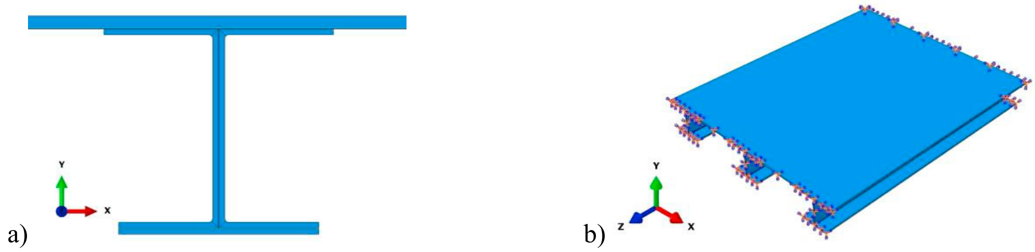

Fig. 2 Model of the stiffened panel: a) zoom of the cross section of a stiffener and b) the complete panel with its boundary conditions.

It was manufactured from laminas of Fribredux HTA/6376C and tested within the EDAVCOS program as explained in Greenhalgh et al. (2003). The property of each lamina is shown in Table 1.

Table 1 Material properties of HTA/6376C reported in Faggiani and Falzon (2010).

E_1 [GPa]	E_2 [GPa]	G_{12}=G_{13} [GPa]	G_{23} [GPa]	ν_{12}	ρ [kg/m^3]
145	10.3	5.3	3.95	0.301	1590

The skin has a quasi-isotropic layup of $[+45°/-45°/0°/90°]_{3S}$, while each stiffener is made up of three laminates (two bent in a C shape and the third on top of them as shown in Fig. 2a) with a layup of [+45°/-45°/0°3/90°/0°3/-45°/+45°]. The laminates were bonded by using Cytec FM 300-2M adhesive whose data can be found in Cytec (2011). The panel is clamped at two ends and free at the other edges (Fig. 2b).

The panel was modeled by 72210 linear hexahedral elements (SC8R, which is an 8-node quadrilateral in-plane general-purpose continuum shell). The adhesive is modeled by 14886 cohesive elements (COH3D8, an 8-node three-dimensional cohesive element).

The impactor is a cylinder with a hemispheric head of 12.7 mm of radius and it was simulated as a rigid body with 372 linear quadrilateral elements (R3D4, a 4-node 3D bilinear rigid quadrilateral element) and 31 linear triangular type (R3D3, a 3-node 3D bilinear rigid triangular element) for the tip. The impactor can move only in the Y direction (all the other degrees of freedom are constrained) and the impact is defined by a hard contact penalty formulation. Its mass and velocity were varied for collecting response data of the system: the simulations were carried out with 0.5, 1.0, 2.0 kg masses and speeds equal to 0.6, 0.8, 1.0 m/s.

A first simulation was carried out to verify the validity of the model: the impact force obtained by the FEM model was compared to that of the experimental impact test analyzed in Faggiani and Falzon (2010). The predicted impact force is in good agreement with the experimental one (see Fig. 3a, where the peak force value is properly captured).

However, the validation model was used for impact cases that induced only geometric nonlinearities, therefore, the allowed maximum force was computed as the delamination threshold force evaluated in Olsson (2001):

$$F_d = \pi\sqrt{16D^*G_{IIc}} \quad (1)$$

where D^* is the effective stiffness computed as the sum of the stiffness contributions of bay, ribs and flanges as explained in Seydel and Chang (2001) and G_{IIc} is the mode II interlaminar toughness. To speed up the simulations, the model was simplified by defining a coarser mesh whose results were compared to those of the complex FEM model previously validated (Fig. 3b). This analysis was carried out for a lower value of initial velocity, value for which the peak force is below the delamination threshold computed by equation (1).

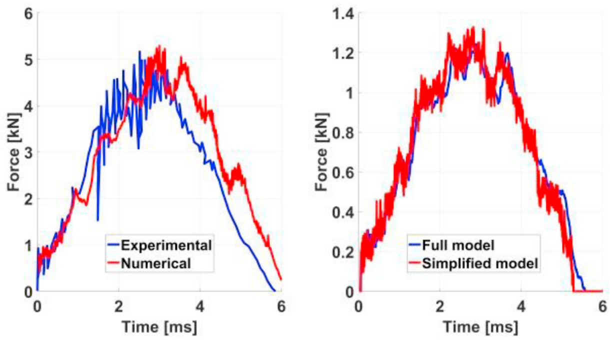

Fig. 3 a) Comparison between numerical and experimental forces (the impact energy is equal to 15 J); b) comparison between the complex and simplified FEM models employed in the analysis (the impact energy is equal to 1 J).

For reconstructing the impact force using ANNs, a series of impacts were simulated to train the net. For this reason, 689 impacts were simulated and the sensor signal data (displacements in the cross section direction) were collected with a sampling frequency of 200 kHz. Different sets of impacts were used for training the ANNs for the peak force evaluation and for the impact localization.

3.1. Peak force evaluation

For the peak force evaluation ANN, the positions of the impacts are shown in Fig. 4 and 585 simulations were performed: for each impact location, nine simulations with different initial velocities (0.6, 0.8, 1.0 m/s) combined with different mass values (1.0, 1.5, 2.0 kg) of the impactor were carried out.

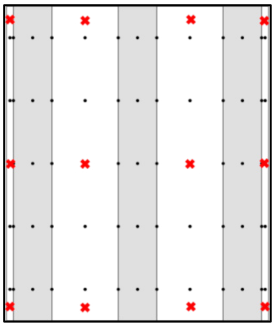

Fig. 4 Scheme of the positions for the impacts for training the ANN for the peak force evaluation procedure: the grey areas identify the position of the stiffeners, the black dots are the positions of the impact, the red crosses are the positions of the sensors.

The inputs of the ANN for the peak force evaluation are the maximum values of the recorded displacement signals from the sensors (the common type of sensors used in literature for impact simulations on composite structures), while the targets are the peak values of the impact force. The feed-forward network is composed of three hidden layers of 20, 15 and 10 neurons respectively and one linear output layer made of 1 neuron (see Fig. 5).

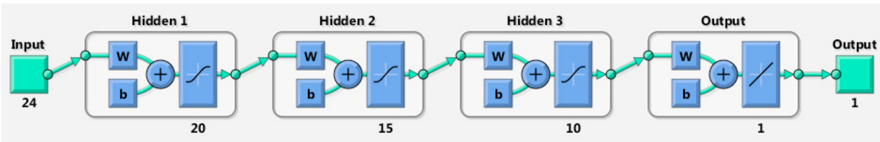

Fig. 5 Peak evaluation ANN Diagram.

The training was done with 96% (561) of the samples, while the validation and test sets are made of 2% (12) of the samples each. The training of the net is made by Levenberg-Marquadt back-propagation algorithm, as explained in Beale et al. (2017).

The performance of the ANN is evaluated by using the mean square error and the regression analysis which shows the correlation between output and targets. Since the peak of the impact force is directly related to the occurrence of damage in a composite, particular attention is paid to the accurate recovery of its value. Therefore, the weights obtained by the ANN were optimized by a GA implemented with the Global Optimization Toolbox of Matlab®. This task was performed by providing the nonlinear constraints related to the known impact data used for training the ANN and parallelizing the code to decrease the computational time.

3.2. Impact location

For recovering the impact location, 169 impacts for training the ANN were located as shown in Fig. 6, the simulations were carried out with a 2 kg impactor with an initial velocity equal to 1 m/s.

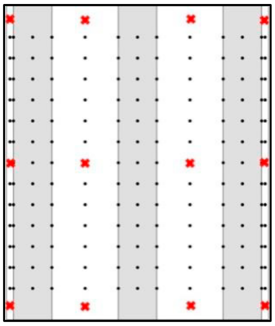

Fig. 6 Scheme of the positions for the impacts for training the ANN for the impact location procedure: the grey areas identify the position of the stiffeners, the black dots are the positions of the impact, the red crosses are the positions of the sensors.

The inputs of the ANN are the time delays of the displacement signals with respect to a reference sensor signal and the maximum displacement recorded by each sensor; the targets are the X and Z components of the impact location on the panel. The network employed for this purpose is made of three hidden layers of 50, 40 and 60 neurons respectively, while previous works employed only one hidden layer ANN, and one linear output layer of 2 neurons (see Fig. 7). The training of the net is made by Levenberg-Marquadt back-propagation algorithm, as explained in Beale et al. (2017).

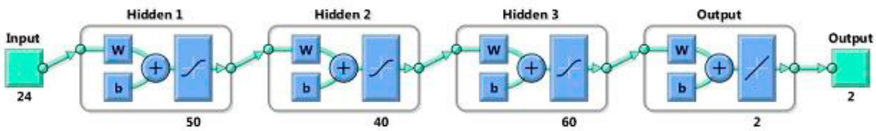

Fig. 7 ANN Diagram for the recovery of the impact location.

The training was done with 96% (162) of the samples, while the validation and test sets are both made of 2% (3) of the samples each. The performance of the ANN is evaluated by using the mean square error of the recovered positions with respect to the expected ones (the targets with which the ANN training was fed) and the regression analysis which shows the correlation between output and targets.

4. Results

As for the peak force reconstruction, three impact peaks were recovered, as shown in Fig. 8 and reported in Table 2. The last column lists the improvement in the algorithm performance by computing the decrease in the percentage error between the algorithm employing only the ANN and that employing it combined with a GA: the improvement in the accuracy of the reconstructed results reaches 6%.

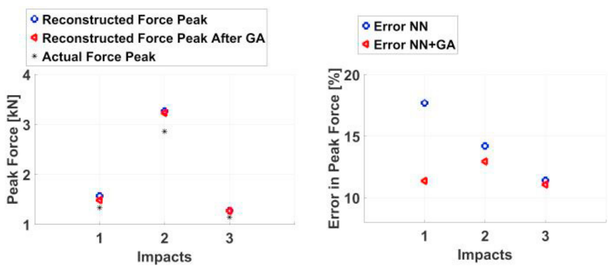

Fig. 8 Peak forces recovered (left) and correspondent percentage error (right) with the ANN and the ANN+GA techniques.

Table 2 Impact peak forces simulated and evaluated with ANN and ANN+GA, and the relative change in percentage error.

Impact	Expected Peak [kN]	ANN Reconstructed [kN]	ANN+GA reconstructed [kN]	Decrease in Percentage Error [%]
1	1.33	1.57	1.48	6.77
2	2.86	3.26	3.23	1.05
3	1.15	1.28	1.27	0.87

The ANN for recovering the impact positions has been employed for recovering four different impact locations as listed in Table 3.

Table 3 Locations of the reconstructed impacts.

Impact	X [mm]	Z [mm]
1	350	300
2	120	400
3	350	400
4	250	50

The reconstructed positions can be seen in Fig. 9a. The detection error is computed as the distance between the known and the reconstructed positions and it is plotted in Fig. 9b for each impact.

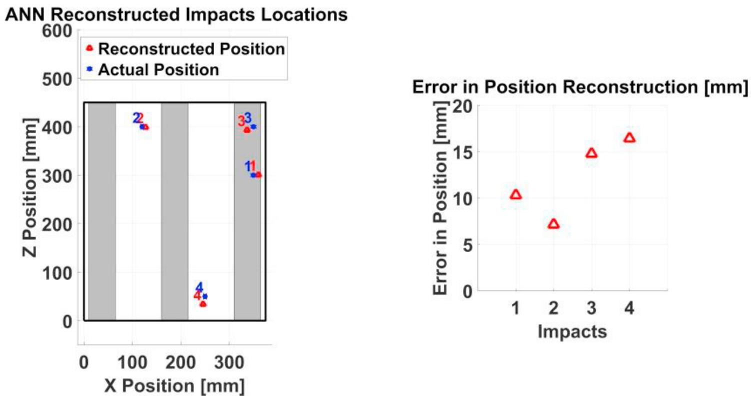

Fig. 9 a) Positions of reconstructed impacts: ANN reconstructed impact locations (red triangles) are compared to FE simulated locations (blue stars); b) Detection error in position reconstruction.

4. Conclusions

For the study of the recovery of the impact location, a multi-layered ANN was employed for the first time and proved to give accurate results even for a complex structural component such as a stiffened composite panel: the recovered positions are in good agreement with the real ones (the mean detection error is 12.16 mm).

For the evaluation of the impact peak force, this study results show that combining ANNs with GAs is a promising approach. The accurate evaluation of the peak force is possible thanks to the combination of the two techniques and therefore the health status of the structure may be properly assessed. In particular, this combination method can be investigated by changing the topology of the ANN (number of hidden layers and neurons per layer) and exploiting other evolutionary algorithms, such as bees and swarm particle optimization techniques.

Acknowledgements

The financial support of the University of Padova - Department of Industrial Engineering project "PASIS" is gratefully acknowledged.

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