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# Vibration Parameters for Impact Detection of Composite Panel: A Neural Network Based Approach

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**Abstract:** The need for reliable methodologies for structural monitoring is certainly a current line of research in many engineering sectors. The detection of the impact on composite materials is in fact a recent subject of study, aimed at safeguarding the mechanical integrity and improving the useful life of structural components. In such a context, the work deals with evaluation of the use of neural algorithms for localizing the position of the impacts on composite structures. Starting from FE (finite element) simulations, representative of the dynamic response of a CFRP (Carbon Fiber Reinforced Polymer) panel as a benchmark, the approach has been finally validated experimentally by modal parameters identification.

**Keywords:** impact detection; modal analysis; neural network; vibrations



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## 1. Introduction

The aim of the current lines of research in the structural field is the development of “intelligent” systems with fully integrated sensor networks to constantly monitor their operational functioning [1,2]. The system should be able to recognize external events of various nature (temperature, pressure, and vibrations) in order to quickly identify possible inspection actions for safeguarding structural integrity [3]. Consequent main benefits would be a broad cost-saving which lies in the reduction in inspections and needless maintenance tasks, ref. [4]. Impact localization is a common problem in many transport systems, especially in aviation: the impacts often occur within airports during take-off and landing. Generally, dropping debris or tools leads to high-frequency vibrations predictable by ultrasonic techniques. On the other hand, impacts due to bird strike could represent a dynamic source exciting the modal vibrations in the low-frequency range. Composite based structures are greatly vulnerable to impact damage, which could lead to delamination of the ply, which is often very difficult to detect externally and can lead to a dramatic reduction in design strength and service life. Several non-destructive techniques (NDT) can be employed, but are expensive, in addition to requiring advanced skills for their application in situ. The most common methods are based on ultrasonic wave inspection thermography, visual inspections, x-ray radiography, penetrant liquids, magnetoscopy, and eddy current techniques. The present paper aims to investigate the potential possibility for predicting stochastic events such as impacts with an artificial neural network (ANN) capable of recognizing variations and events in its own status. An ANN based algorithm has been implemented to assess the impact position on a composite panel. The adoption of genetic algorithms in the reconstruction of digital signals has been extensively studied, in particular on the investigation of impact detection and consequent damage [5–9]. Studies [10–13] made it possible to estimate the position of the impact and the extent of the load. An ARX (self-regressive with exogenous input) algorithm has been developed in relation to finite element analysis on a stiffened composite panel, refs. [14,15]. Analyses on more complex systems were conducted by LeClerc et al. [16]: the localization problem was managed by sub-structuring the entire system into fewer control actions. ANN is essentially

a machine learning inspired tool which adapts its weights during the training phase. Neural algorithms make it possible to reconstruct identification paths relying on a set of reference data (i.e., undamaged structure, numerical models, and experimental measurements) [17,18]. The main advantage therefore lies in the greater automation of structural diagnosis processes. More accurately, data sets are supplied to the machine as input while the objective function represents the current state in which the system learns. A perfect correspondence between input and target is a necessary condition for a complete training of the algorithm: the system would be therefore capable to recognize itself. The crucial step that verifies the robustness of the algorithm consists in the recognition of data never observed by the system; if the new signal differs from the former condition, the system will indicate the presence of events. The resulting output vector will evaluate the new version of target set. The assumption is that ANNs could learn an unknown relationship between input and output data. The learning process consists of minimizing the calculated error value between the target and the network outputs obtained for subsequent iterations. ANNs consist of a (first) input layer, usually one or two hidden layers, and an output layer. The number of items in the input and output layers is determined by the size of the learning and testing datasets. The training preliminarily process is initiated with a hidden layer and a small number of neurons in that layer. When the network is performed, the values of the input variable are inserted into the input units, then the cells of the hidden layer and the output are progressively calculated. If the training phase is successful, the network is able to find the common characteristics that the samples present, in order to extract some general assumptions which allow the recognition of unknown paths. After the training phase, the algorithm will be able to reconstruct the positive samples more or less accurately on the output layer. This implies that an improper reconstruction of the input layer on the output layer is a clear symptom of an anomalous dynamic behavior of the monitored structure. The validity of an event detection approach based on the neural network depends on the initial weights and biases, the order of the input elements, the choice of the transfer function and the training algorithm. The approach proposed by the authors lies on the implementation of modal parameters for the impact localization on orthotropic structures with the use of a small amount of sensors. A CNN (Convolutional Neural Network) method, based on the real-time vibration acquisition, was assessed for the structural damage detection, ref. [19,20]. Such a method allowed for using only raw signals for the optimum damage-sensitive feature identification. Similarly, CNN-based techniques were developed for damage detection in metallic structures [21] and rotating machines [22–26]. These strategies were, however, supported by the considerable growth of sensing technologies [27,28]. The applicability of CNN in impact recognition of complex laminate structures, such as aircraft stiffened panels, has been widely discussed in [29]. In the present work, starting from a FE representation of a laminated panel, an ANN has been trained in Matlab<sup>®</sup> (MathWorks<sup>®</sup>, Natick, MA, USA) based on the vibration response of the same structure under impact loads. The neural system was precisely trained through in-plane velocity spectra performed by numerical analyzes. The robustness of the method was then validated by experimental investigations, inserting in the neural network some spectral functions measured by a PZT-array arranged on the structural surface. The appreciable results obtained on a composite structure encourage the further development of such detection means, extending the field of application to geometrically even more complex structures. The novelty of this research consists in adapting existing models for forecasting the impact (feedforward) using operating parameters of the structures. In this case, the vibration data measurements (resonance frequencies, mode shapes, frequency response) made it possible to build data sets for properly training the ANN. The solidity of the approach was also checked with respect to experimental measures. In such perspective, the correlation has been proven on two sides: first of all, the correspondence with the representative FE model; secondly, with respect to the level of precision of the algorithm in identifying the impact case.

## 2. Materials and Methods

### 2.1. Composite Panel Description and Modal Characterization

An orthotropic carbon fiber panel of 12 plies  $((0^\circ/90^\circ))$ ,  $((0^\circ/90^\circ), (\pm 45^\circ))_{2s}$ , and  $((0^\circ/90^\circ))$  with the following mechanical properties:  $E_{11} = E_{22} = 62.6$  GPa;  $\nu_{12} = 0.068$ ;  $G_{12} = 3.45$  GPa, was chosen as reference test article. The considered composite panel is square in shape (550 mm  $\times$  550 mm in dimensions) with a thickness of about 3.43 mm. A numerical mesh comprising 441 grid points and 400 four-node reduced integration shell elements (CQUAD4, ref. [30]) was used to analyze its dynamic response in Nastran<sup>®</sup> (sol 108) (MSC Software, Newport Beach, CA, USA). The same scheme has been replaced on the actual composite panel. The experimental protocol consists of several phases aimed at determining the structural response and the vibration modes of the panel under examination. For the modal analysis purpose, an excitation by a piezoelectric actuator (PI ceramic, [www.piceramic.com](http://www.piceramic.com), 6 July 2021) in the center of the panel has been applied, Figure 1. The transfer functions were obtained as a complex ratio between the vibration speed (mm/s) in the grid points measured by laser vibrometry (Figure 2) and the piezoelectric voltage (mV) in the driving point previously described. A quick frequency analysis is first carried out in order to identify the main resonant frequencies participating in the global structural response. Then, the most suitable bandwidth interval is selected for the acquisition of experimental data. In addition to the transfer functions, particular attention should be paid to the stability of the coherence functions; a very high coherence index (close to 1) denotes a low influence of the boundary conditions and of any background noise. A white noise signal has been provided to the piezo actuator by a signal generator in the bandwidth (0, 500 Hz).

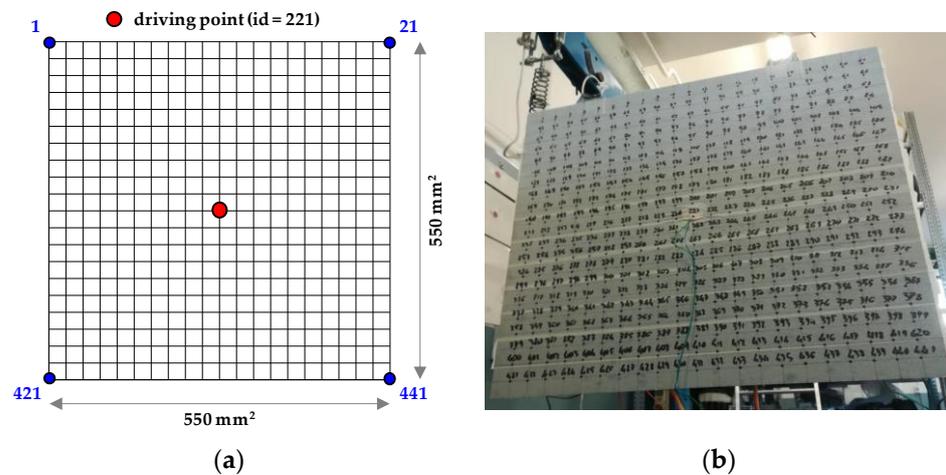


Figure 1. Discretization of composite panel in 441 grid points: (a) mesh with details of size and driving point; (b) acquisition mesh for laser vibrometry test.

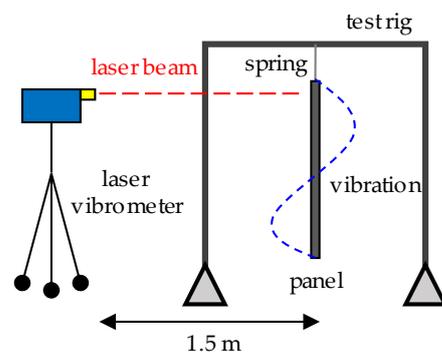


Figure 2. Experimental setup for laser vibrometry test: panel boundary conditions.

### 2.2. ANN Matrixes and Setup

The proposed approach is based on the acquisition and comparison of the FFTs of the monitored structure for different combinations of the impact/sensor point. The focus concept explains that an ANN, once trained, will be able to recognize the actual path of an unknown impact. The RMS (Root Mean Square) of out-of-plane velocities calculated by the FE analyses, and experimental measurements were also used as input data for the ANN definition. Several data clusters have to be applied to train the network for performing some particular tasks. In particular, the following matrixes should be conceived:

- the *input matrix* has dimensions  $(9 \times 49)$ : it comprises the RMS values of the vibration velocity FFT (Parseval’s theorem) following the 49 impacts considered on the panel with respect to the 9 acquisition points ( $C_1$  to  $C_9$ ), Figures 3 and 4a. The coordinates of these field points also represent the positions of the piezo sensors during the experimental calibration;
- the so-called *target matrix* has dimensions  $(2 \times 49)$  that provide the in-plane cartesian coordinates of the 49 impacts considered on the panel: basically, it constitutes the loaded nodes of FE mesh, Figure 4b;
- the *output matrix* represents the new points cloud returned by the ANN following training steps.

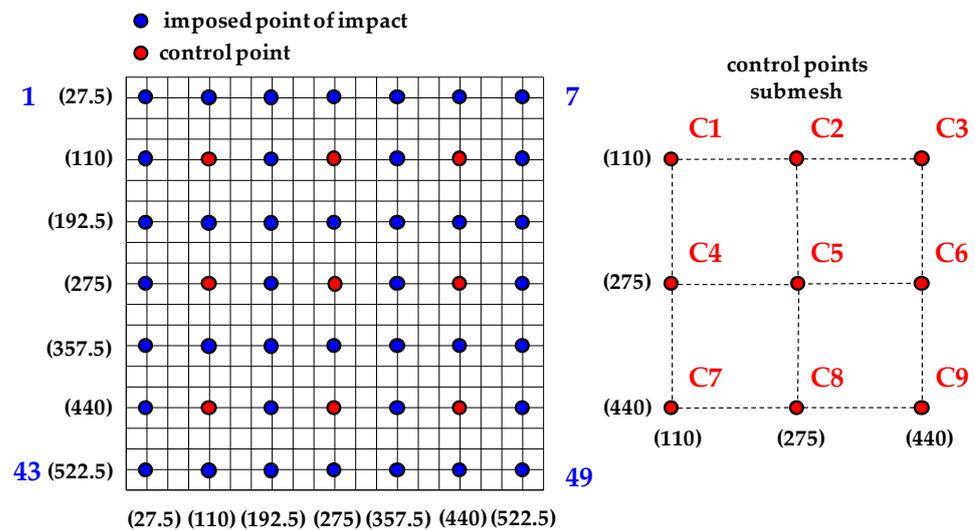


Figure 3. Matrixes for the construction of the ANN: 49 impact and 9 detection points (numbers in brackets are in millimeters).

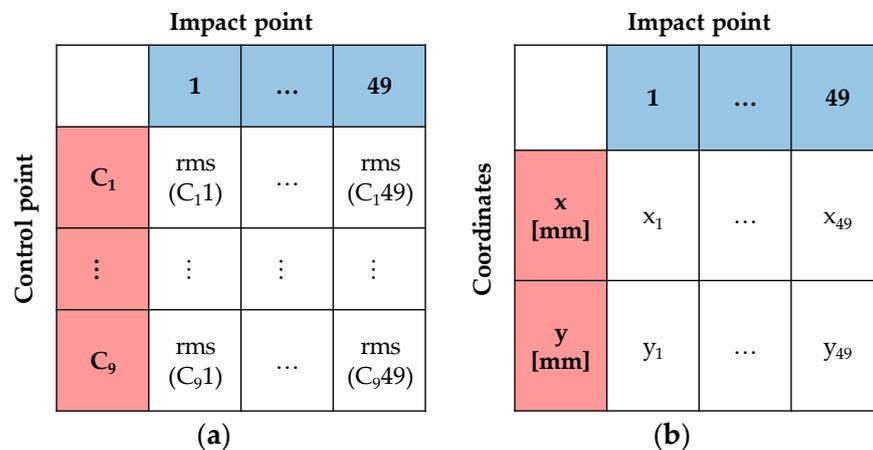


Figure 4. Architecture of training matrixes: (a) input matrix; (b) target matrix.

Training represents a central step for controlling the degree of uncertainty of the network, as a direct comparison between the output and the target data. In such circumstances, using the RMS vibration parameter made it possible to considerably optimize the size of the involved matrices. Each cell of the input matrix would have had to contain the entire spectrum, so the frequency would have been a third variable giving rise to a three-dimensional matrix with a high computational weight. The RMS index, compared to other statistical parameters such as the mean, the median, etc., comes very close to the spectral content, especially at low frequency, where a low modal density generally occurs. In the low frequency region, the modal density is poorer and the resonance peaks are very far apart, so an acceptable approximation error may occur on the RMS application. At high frequencies, on the other hand, the square mean could underestimate the energetic contribution of a greater number of mode shapes participating in the structural response. For this reason, the ANN-based approach was preferred in the modal vibration regime.

2.3. Computational Aspects of ANN Code

The development environment follows a block logic where the user can structure the neural network data in compact and tabular form, Figure 5. All building phases were performed within the Matlab® environment, in particular by Neural Network Toolbox, refs. [31,32]. The workflow aimed at the ANN design process comprises the following logical steps:

- 1 Data collection (theoretical, numerical, and empirical);
- 2 Network structure arrangement (multilayer and feedforward);
- 3 Input-output configuration (processing functions);
- 4 Weights and biases initialization;
- 5 ANN training;
- 6 ANN validation;
- 7 Application and errors detection.

The properties of ANN setup are listed in Table 1.

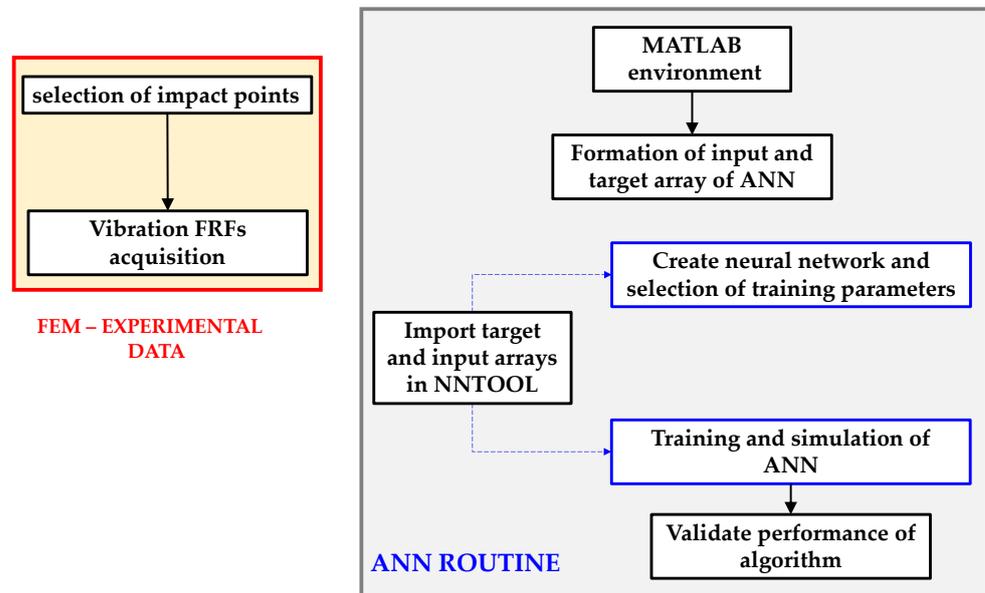


Figure 5. Block diagram of simulation processes—nested structure.

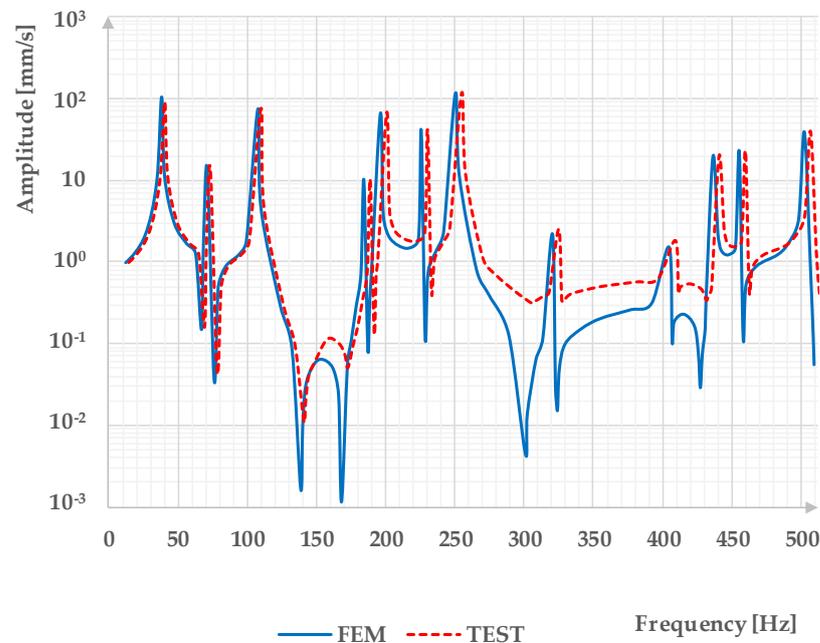
**Table 1.** ANN properties setup, (MathWorks®, Natick, MA, USA) [32].

Network Type	Feed-Forward Backpropagation
Input data	RMS of out-of-plane velocities
Training function	Levenberg-Marquardt (TRAINLM)
Adaption learning function	Gradient descent with momentum weight and bias learning function (LEARNGDM)
Performance function	Mean squared normalized error (MSE)
Number of neurons	20
Transfer function	TANSIG

### 3. Results

#### 3.1. FE Model Validation Based on Modal Analysis

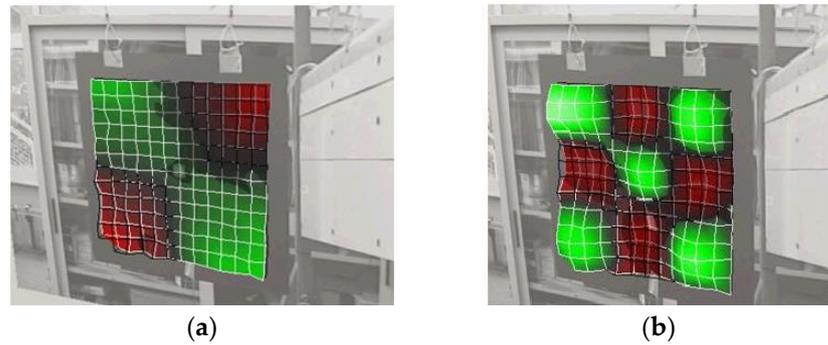
The objective of the study is to assess the applicability of the ANN to reconstruct the position of a generic impact event. The robustness of the procedure was evaluated using both numerical data deriving from both FEM analyses and experimental measurements. Therefore, it is essential that the numerical model representative of the structure in question should be well correlated with the real dynamic response. Figure 6 compares the velocity spectra according to the scheme illustrated in the Section 2.2 (Figure 1). The curves are obtained from the sum of the single frequency spectra obtained in the 441 points of the mesh. The numerical curve has been updated considering the structural damping value—approximately 2%—estimated within the modal test; the FE based response is well correlated, apart from a slight deviation in the range between 300 and 450 Hz where it is more rigid (more sharp resonance peaks and less uniform curve). The set of first ten resonance frequencies are listed in Table 2. The FE based mode shapes are compared with ODS (Operational Deflection Shapes) estimated by means of laser vibrometry technique, Figure 7. Additional consistency index among numerical and testing eigenvectors was provided by calculation of the MAC (Modal Assurance Criterion) matrix, Figure 8: value next to 1.0 along the main diagonal denotes a high-correlation level.



**Figure 6.** Frequency response function: experimental-numerical comparison.

**Table 2.** Natural frequencies comparison among first 10 mode shapes.

ID Mode	FEM Frequency (Hz)	Experimental Frequency (Hz)
1	37.9	40.0
2	70.9	73.0
3	107.4	109.6
4	183.9	188.6
5	195.9	200.5
6	225.4	230.0
7	250.0	254.6
8	320.2	324.8
9	404.5	409.0
10	436.1	440.7



**Figure 7.** Operational Deflection Shapes (ODS) by laser vibrometry technique: (a) basic and (b) more complex shape.

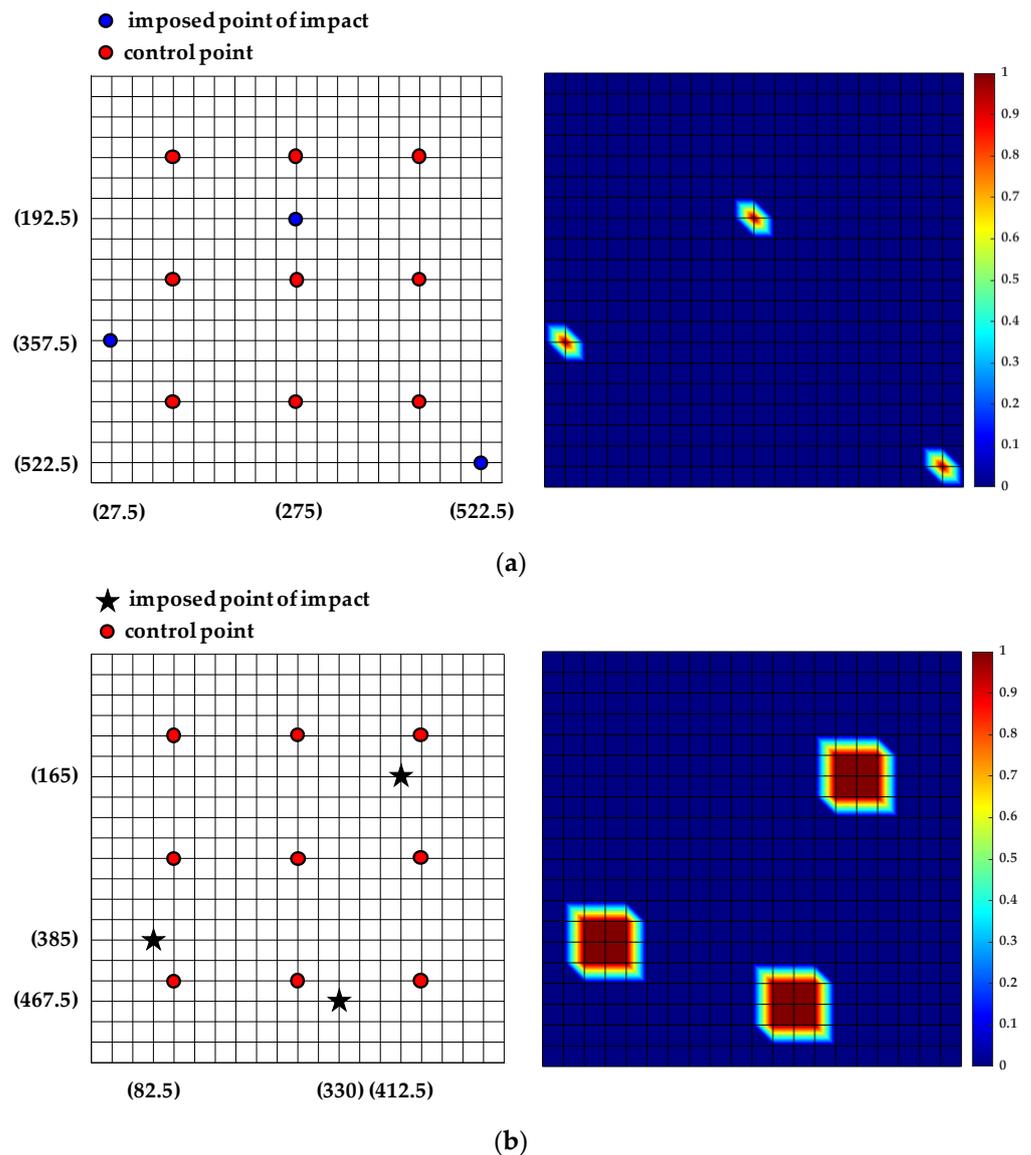
		EXPERIMENTAL EIGENVECTORS										
		40.0	73.0	109.6	188.6	200.5	230.0	254.6	324.8	408.0	440.7	
FEM EIGENVECTORS	ID	1	2	3	4	5	6	7	8	9	10	
	37.9	1	0.98									
	70.9	2	0.00	0.97								
	107.4	3	0.20	0.10	0.97							
	183.9	4	0.20	0.22	0.10	0.96						
	195.9	5	0.10	0.21	0.12	0.10	0.97					
	225.4	6	0.19	0.19	0.20	0.20	0.15	0.96				
	250.0	7	0.00	0.24	0.20	0.18	0.29	0.11	0.96			
	320.2	8	0.20	0.20	0.10	0.28	0.20	0.24	0.27	0.95		
	404.5	9	0.20	0.20	0.30	0.20	0.10	0.19	0.21	0.27	0.95	
436.1	10	0.20	0.20	0.30	0.27	0.24	0.18	0.22	0.30	0.26	0.95	

**Figure 8.** MAC matrix: mode shapes comparison.

3.2. ANN Reliability: Impact Detection Considering FEM Based Data

The first step in verifying the training of the network consists in requesting, as output, the recognition of Cartesian coordinates already known in the target data group. Strictly speaking, this test would allow us to check if the network is able to recognize itself. As an example, the probability distribution maps returned by the network are shown in

Figure 9, once the plate has been excited at nodes 18, 29, and 49. The well concentrated distribution of color denotes that the impact at one point known to the neural network was perfectly recognized by it. The map evolves towards dark blue where no events are recognized. In terms of length and width of the impact area, the percentage errors were equal to 0% for all three nodes considered. These results indicate that the network could accurately detect the impact region. Subsequently, the detection check is performed in points not belonging to the ANN. Considering in particular the nodes with 2D Cartesian coordinates (82.5, 385), (330, 467.5), and (412.5, 165), the algorithm makes an error of approximately 27.5 mm: the identification area is much wider than in the first case but is, however, uniformly circumscribed with respect to the point of interest.

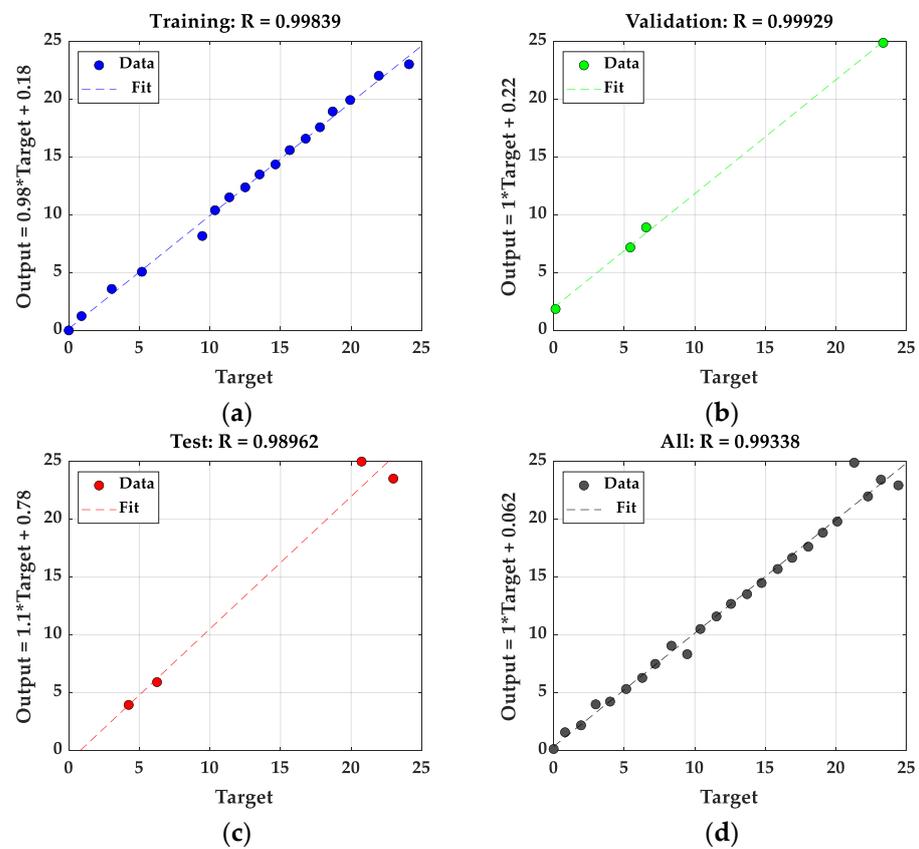


**Figure 9.** Impact position detection on a FE based ANN: (a) autocorrelation with points 18, 29, and 49; (b) verify of geometric coordinates (x, y) with data unknown to the ANN (82.5, 385), (330, 467.5), and (412.5, 165).

For evaluating the efficacy of the ANN, it is possible to train it to control the trend of the performance and regression curves. The more the curves tend to converge, the more effective the training. The following regression curves in Figure 10 report the ANN outputs with reference to targets for training, validation, and test sets. If a good training threshold occurs, the data cloud should fall along a 45-degree line, where the ANN outputs

fit with the targets. Such a relationship represents a way to evaluate the efficacy of the ANN training: the more these two curves tend to converge, the more effective the training. The three plots represent the training, validation, and testing data. The last summarizes all results. The dotted line in each figure denotes the best correlation between output results and targets. The solid line, on the other hand, represents the best fitting for linear regression approximation between outputs and targets. The R-value (regression coefficient) is an indicator of the relationship between these data.  $R = 1$  implies an exact linear match is achieved. If R is close to zero, then the two fields (output and targets) are not at all related. In order to achieve more accurate results, following actions could be performed:

- reset the initial network weights and biases;
- increase the number of hidden neurons;
- increase the number of training vectors;
- increase the number of input values;
- implement different training algorithm.

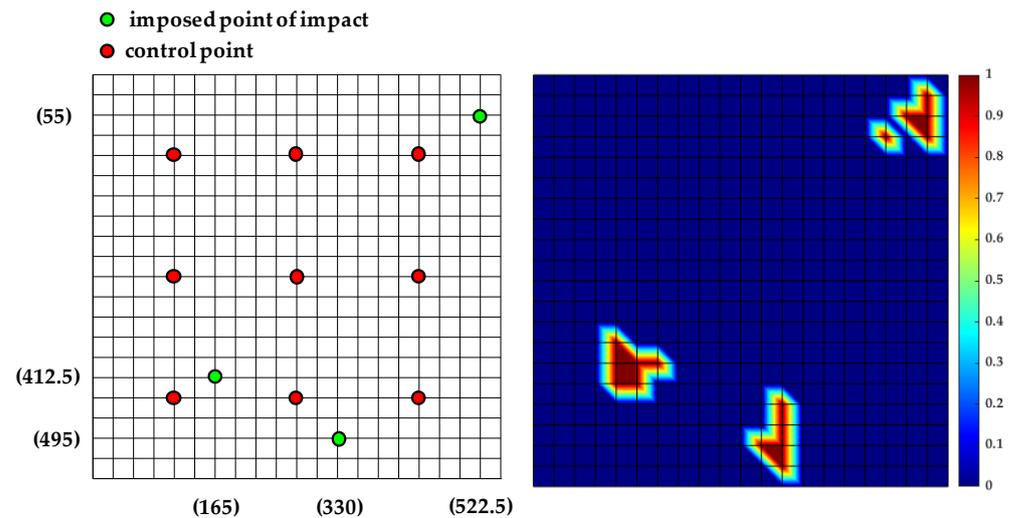


**Figure 10.** ANN training regression trend: (a) training; (b) autovalidation; (c) test with external data; (d) results combination (MathWorks®, Natick, MA, USA) [32].

### 3.3. ANN Reliability: Impact Detection Considering Experimental Data

In order to validate the rational procedure implemented through numerical modeling, an experimental verification was performed using the frequency responses obtained on the real panel. The approach serves to demonstrate whether the ANN algorithm is able to still recognize impact stations by using vibration responses determined this time experimentally. The testing data obviously bring with them possible measurement errors, mainly related to the boundary conditions (the sample panel is not in ideal free–free conditions but suspended by soft springs) and to the inaccuracy of the position of the excitation source, etc. Therefore, with the exception of these concerns which would have influenced the experimental–numerical modal basis correlation, the algorithm however revealed good detection performance. In particular, the RMS values representative of three experimental

spectra—impacts on points (165, 412.5), (330, 495), and (522.5, 55)—were assigned to the ANN trained with FEM data; the outcomes are represented in Figure 11. The lower performance for detecting the impact at node (522.5, 55) may be due to the nearness to the structure boundary, which can significantly affect the overall dynamic characteristics of the system. Taking into account that the ANN has been trained with an approximation of the spectra, that is, the respective RMS, the error is acceptable. In this context, the authors are not so much interested in the precise geometric location, as in the area affected by the event. The ANN is, in fact, used to identify low frequency impacts in which modal forms with greater generalized displacements of the structure are expected.



**Figure 11.** Impact position detection on experimental test-based ANN: verify of geometric coordinates (x, y): (165, 412.5), (330, 495), and (522.5, 55).

#### 4. Conclusions

The present work presents an innovative method for detection of impacts on composite structures by combining the laser vibrometry technique, FE modeling, and an ANN algorithm for data processing. In this view, this multi-disciplinary approach is innovative with respect to the literature applications. The forecast algorithm can use measurable operative data, even characterized by a lower signal-to-noise ratio: dynamic parameters as resonance frequencies, mode shapes, and modal response are in fact often available during the testing and commissioning phases of prototype systems. Once the numerical model representative of the structure under examination has been validated, the algorithm allows for tracing the same information obtained experimentally. Therefore, the proof of the whole algorithm can be performed on two sides: first through the correlation of the relative FE model (for example, comparing frequencies, MAC, etc.) and subsequently with the direct output provided by the neural network. The key-concept of the method is then based on the idea that an ANN tool, once trained, will be able to recognize the real path of an unknown impact and to localize the event itself. Another consistent advantage of the suggested methodology is the use of a very limited number of sensors with respect to numerical/experimental acquisition grid. This aspect meets the requirements of integration simplicity and low weight relative to industrial standard. The results carried out on a standard composite plate have confirmed the positive performance of the proposed approach. The “neural” system was trained with the transfer functions (vibration speed/actuation voltage) obtained from a dynamic FE model. Subsequently, robustness was proven, also considering experimental data measured on the current composite panel. In addition to a good structural correlation—in terms of resonance frequencies and eigenvectors—the neural network could estimate the position of the impact with a maximum error of 27.5 mm with FEM values, and about 50 mm in the case of testing data. At this stage, the error is acceptable, given the interest in the area rather than the precise grid point.

These results can be further improved with more neurons and more iterations during the training process; however, a higher computational effort would follow. The development of robust predictive models would open the interest to in-depth studies, mainly oriented to the definition of the system precision, possible fault identification, and computational cost optimization.

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**Conflicts of Interest:** The authors declare no conflict of interest.

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