An Artificial Neural Network based approach for impact detection on composite panel for aerospace application

M. Viscardi, P. Napolitano

Department of Industrial Engineering, University of Naples "Federico II"
Via Claudio, 21 – 80125 Naples ITALY
massimo.viscardi@unina.it

Abstract: - Fleet maintenance and safety aspects represent a strategic aspect in the managing of the modern aircraft fleets.
The demand for efficient techniques of system and structure's monitoring represent so a key aspect in the design of new generation aircraft.
This is even more significant for composite structures that can be highly susceptible to delamination of the ply, which is often very difficult to detect externally and can lead to a dramatic reduction of design strength and service life, as a consequence of impact damage.
The purpose of the work is the presentation of an innovative application within the Non Destructive Testing field based upon vibration measurements. The aim of the research has been the development of a Non Destructive Test (NDT) which meets most of the mandatory requirements for effective health monitoring systems while, at the same time, reducing as much as possible the complexity of the data analysis algorithm and the experimental acquisition instrumentation.

Key-Words: - SHM, composite materials, piezoelectric materials, impact detection, NDT

1 Introduction to Structural Health Monitoring (SHM)

Structural health monitoring" (SHM) is a collective term for cutting-edge technologies using permanently attached sensor networks to enable the continuous inspection of the reliability of structures. In the last years there has been an increasing interest in structural health monitoring systems for all kinds of aircraft. Beside the expected enhancement of safety and maintenance performance, also economic aspects play an important role. This regards on the one hand the reduction of unnecessary inspection and repair costs and on the other hand, the possible weight reduction of aircraft parts at the designing phase of an aircraft. The main benefits of SHM are:

- Cost saving by reduction of inspection and repair cost and the possibility to reduce the weight at the design phase;
- Enhancement of safety by much more frequently applied automated inspection;
- Enhancement of passenger throughput by reduction of unnecessary maintenance;

The advantages of a SHM system for aerospace applications is that it enables early identification of damage and consequent reduction in the structural performance. Composite materials can often suffer internal damage which vastly reduces the life of the structure; they are also susceptible to flaws within the material being introduced during the manufacturing stage; both these aspects could substantially reduce the life of a component. Moreover composite materials are highly susceptible to impact damage which leads to delamination of the ply, which is often very difficult to detect externally and can lead to a dramatic reduction of design strength and service life. The introduction of structural health monitoring in routine aircraft maintenance seems to be only a question of time. The obstacles, which have so far prevented the earlier introduction of SHM systems, can be avoided by an integrated approach combining modern technical and organizational principles on a large scale. Moreover, end-users such as manufacturers and operators (airlines) must be convinced that a mature SHM concept ensures complete airworthiness. Projects must provide an essential contribution to these objectives. The development of an effective structural health monitoring system must finally be integrated into a structural health management system where the data on structural integrity are classified and where

procedures of maintenance and allocation of resources are organised.
Two fundamental techniques that could be used for a SHM system are Acoustic Emission (AE) and Guided Lamb waves (GLW).

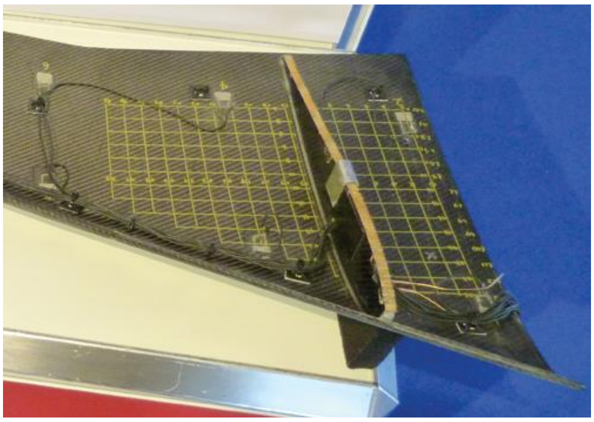

Fig. 1: SHM devices on a wing's panel in composite

2 Impact detection

The safe use of aircrafts can only be guaranteed when appropriate damage assessment is available. Fiber Composite Materials allow to manufacture large and complex structures with minimum weight at relatively low costs. This is a typical material for e.g. aircraft, boats or rotor blades for wind energy plants. However when compared to metal the fatigue behavior of composite material is more complex. Impacts can cause delamination of the individual laminated layers of fiber composite material. This initial delamination slowly grows when alternating or fluctuating mechanical loads stress the structure. The delamination leads to a loss in stiffness. When a part of the structure is finally to weak to withstand the loads a sudden rupture of the fibers in the remaining cross section occurs. This can lead to a chain reaction destroying the whole structure and damaging the others near it. It is therefore important to detect and monitor damages in high loaded safety components made of fiber composite materials to receive an early warning for a well timed shutdown of the facility respectively landing of the aircraft. This kind of application in our study field is in an experimental phase yet because of two main reasons. Lack of technical maturity the first reason, lack of acceptance by end-users the second one. The lack of acceptance by end-users can be overcome by convincing technical solutions that respond to all the challenges inherent to aircraft operations. The major problem already mentioned in the list above is the difficult interpretation of measured data obtained in complex aircraft components. One possibility to detect "barely visible impact damage (BVID)" after impact in aircraft materials is non-destructive testing (NDT) using ultrasound. The ultrasonic waves are usually excited and received by piezoceramic sensors.

2.1 Acoustic method detection based

There are several structural health monitoring concepts for damage detection in fiber composite materials including fiber brag sensors or modal analysis techniques. The first method provides information only when the damage is near the sensor. Traditional vibration-based monitoring techniques provide only global information about a structure under monitoring by identifying and analyzing specific resonance modes. Due to the low frequencies only large defects can be identified and moreover, cannot be precisely localized in general. For crucial parts of a structure, vibration monitoring can be efficiently supplemented by using elastic waves in the kHz frequency regime. These ultrasonic waves have a shorter range but are more sensitive to smaller defects and thus, can serve as an early-warning system raising an alarm long before critical damage occurs. If the wavelengths are of at least the same size or larger than typical dimensions of the structure, the waves are called "guided waves" [7], [8]. In this case geometrical dispersion cannot be neglected in general. If using elastic waves for structural health monitoring purposes two different approaches are possible, a passive and an active approach. In a passive SHM system only sensors are needed and "natural" sources like impact, ambient vibrations or acoustic emission (AE) caused by crack generation and growth are detected (Fig. 2). The AE events can be localized and characterized and can also be used for imaging purposes using acoustic emission tomography. In an active SHM system the transducers are acting as both, sensors and actuators (Fig. 3).
By using pulse-echo or acoustic signature techniques, scattered waves from inside the structure or changes in acoustic signature response can be detected and used as damage indicator.
A set of transducers spans a so-called "synthetic aperture". By temporally delayed excitation and detection by individual actuators and sensors, elasto-dynamic wave fields can be focused to specific control volumes of the structure serving as basis for powerful SHM imaging techniques.

The simplest case of guided waves can be found in plate-like structures where so-called plate waves or Lamb waves can propagate. In general symmetric and anti-symmetric wave modes are being distinguished. In most cases, SHM techniques are working in the low-frequency regime below 500 kHz and thus, only the 0th order Lamb waves are of interest for monitoring applications. In addition to the Lamb waves also horizontally polarized shear waves (SH waves) can be used. In contrast to the Lamb waves the 0th order SH wave is non-dispersive. Numerical and experimental investigations show that each wave mode mentioned above shows different sensitivity to specific kinds of damage. For example the antis-ymmetric mode turns out to be well-suited for detection of delamination.

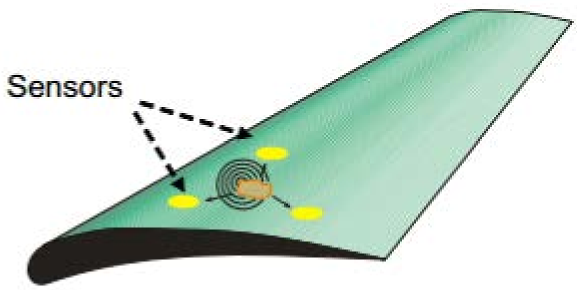

Fig. 2: Passive SHM approach

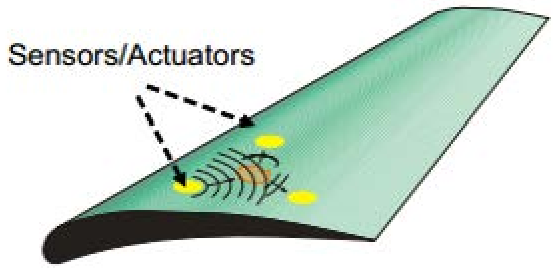

Fig. 3: Active SHM approach

2.2 Fiber Transducer (PZT)

For the SHM-system piezo transducers made of lead zirconate titanate (PZT) are widely used due to their low thickness. Fig. 7 shows the layout of a PZT fiber transducer with corresponding electrode structure. It can be used for both, excitation and detection of elastic waves. The directional characteristic of the PZT fiber transducer depends on its size, the material properties of the structure and the signal frequencies used for monitoring. Therefore, optimized transducers for specific kinds of structures can be designed and applied. Moreover, by using enhanced electrode configurations a wave-mode specific excitation and detection of guided waves is possible. The PZT ceramic is prepared by a special sol-gel process. Gallus PZT-precursors are spun to thin fiber with a diameter of around 30 µm. The endless green fiber is cut into 30 cm long threads to be sintered at 1100 °C in a special gas atmosphere. The sintered piezoceramic fiber threads are embedded in a polymer matrix and electrically connected with silver electrodes in an inter-digital design (Fig. 4). After polarization in an electrical field of 3 kV/mm these thin and flexible transducers (Fig. 5) are ready for use.

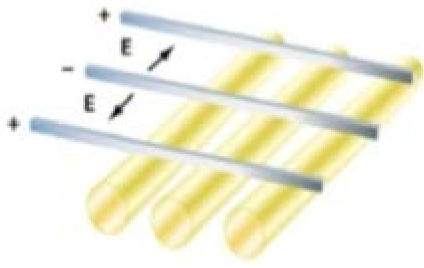

Fig. 4: Inter-digital electrode

Fig. 5: Piezoelectric fiber

Tests on fibre sensors laminated into a glass fiber reinforced plate show a high sensitivity to impact events depending on the orientation of the fibers respectively. For ultrasonic applications the piezoelectric transducers can be manufactured in a special design for frequencies up to more than 10 MHz. Fig. 6 shows a transducer resonance in the impedance spectrum of a piezoelectric fibre composite.

The PZT can be simply applied (using an adhesive film) on the plate or embed into the plate. As the material allows the integration of thin transducers in the structure an ideal acoustic coupling can be achieved. The embedded monitoring device is directly bonded to the fibres.

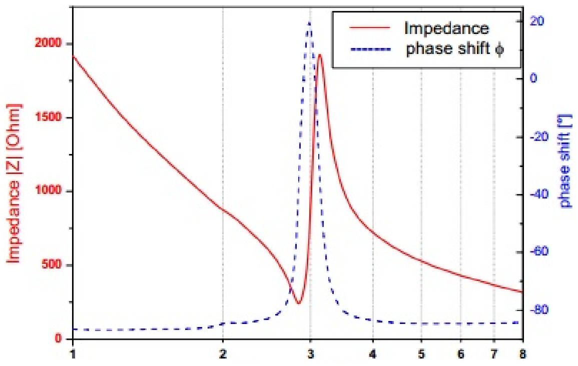

Fig. 6: Resonance phenomena

By avoiding thick adhesive films and using the top and bottom side of the monitoring device a higher acoustic performance can be achieved.

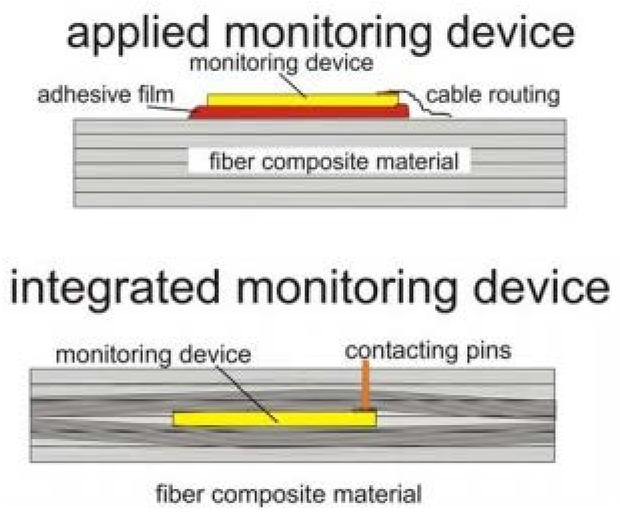

Fig. 7: Applied (up) and integrated (down) device comparison

However, unlike the applied device, it's really important to study influence of the embedded device on the structural durability of the fibre composite material. Fig. 8 shows an aircraft sandwich-wing with embedded PZT fibre transducers. The SHM system can detect impacts, fibre cracks and delamination in this and similar structures. The typical production process for such structures needs only minor changes to ensure reliable electric contacting of the transducers after curing the fibre composite material.

Fig. 8: Embedded PZT fiber transducer

3 Mathematical functions for SHM

All the techniques used for the research of the damage or of the impact on a structure are based on the relation created between a sent signal in the structure and the given response. These functions are then compared, generally in the form of synthetized index, and relative variation can be addressed to the identification of the a damage or an impact.

Main mathematical functions that are widely used for tis purposes, are:

3.1 FRF

The Frequency Response Function represents the relationship between the input and output of electrical systems or structural vibration transmission systems. The Frequency Response Function H(f) can be obtained dividing the cross spectrum for input and output by the power spectrum for input. If the output signal b(t) contains much external noise, random error can be minimized by averaging. Using a random signal as an input signal, a non - linear system can be linearized by averaging. The frequency response function can be represented by the gain and phase characteristics. The gain characteristic indicates the amplitude variation when a signal passes through the system. The X-axis denotes the frequency and the Y-axis decibel based on $10\log_{10}|H(f)|^2$.The phase characteristic is the leading or lagging of the phase between the input and output signals. The X-axis denotes the frequency and the Y-axis the angle in degree or radian. The frequency response function is represented by the ratio of the Fourier spectrum of the input A(f) to the Fourier spectrum of the output B(f). Frequency response function H(f) can be represented by the following expression (1) and Fig. 9. Many methods are based on the acquisition and comparison of Frequency Response Functions (FRFs) of the monitored structure before and after an occurred impact. Structural damage or impact modify the dynamical behavior of the structure and consequently the FRFs, making possible to identify, to localize and quantify a structural damage.

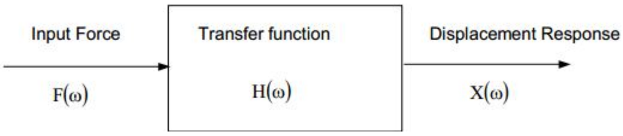

Fig. 9: FRF scheme

$$H(f) = \frac{B(f)}{A(f)} \quad (1)$$

3.2 PSD

Power spectral density function (PSD) shows the strength of the variations as a function of frequency. In other words, it shows the frequencies in which variations are strong and the frequencies in which variations are weak. The unit of PSD is energy per frequency and we can obtain energy within a specific frequency range by integrating PSD within that frequency range. FRF is calculated using autocorrelation and cross correlation function for output and input signals of the structures. Autocorrelation function defined in (2).

$$R_{xx}(\tau) = \lim_{T\to\infty} \frac{1}{T} \int_{-T/2}^{T/2} x(t) \cdot x(t+\tau) \cdot dt \quad (2)$$

The Fourier transform of autocorrelation function is called Power Spectral Density (PSD). Computation of PSD is done directly by the method called FFT or computing autocorrelation function and then transforming it. PSD is a very useful tool if you want to identify oscillatory signals in your time series data and want to know their amplitude. We might be able to get a clue to locate offending machines by looking at PSD which would give us frequencies of vibrations. We quite often compute and plot PSD to get a "feel" of data at an early stage of time series analysis. Looking at PSD is like looking at simple time series plot. PSD tells us at which frequency ranges variations are strong and that might be quite useful for further analysis. The comparison of the function could be done thanks to a lot of methods. The first and the simpler, it’s a simple indexes comparison that allow the observation of function’s changes of the output compared to the input. The most complex methods use the computation networks that allow the comparisons analyzing numerically these functions. An examples are the Neural Networks, that will be described within next paragraph.

4. Introduction to Neural Network

An artificial neural network attempts to reproduce the functioning of biological neural networks, within the human brain (as well as in many other animals) the resolution of cognitive problems is carried out by neural networks, usually consisting of several hundred of neuronal cells. These networks, the extent and magnitude varies depending on the required task, may also involve different brain areas and their development and formation has been crucial in the evolution of the human species. When we speak of artificial neural networks we refer to information processing systems whose purpose is to simulate the functioning of biological networks within a computer system. Artificial neural networks can be considered as a large computer network made up of several dozen units that play the same role that neurons play within biological networks. Each of these nodes (or artificial neurons) is connected to the other nodes of the network through a dense network of interconnections, which also allow the network to communicate with the outside world. The ultimate goal of a well structured network is to acquire information from the outside world, process it and return a result. The transfer function of the signal in the network is not programmed but is obtained through a learning process based on empirical data. This process can be supervised , unsupervised or for reinforcement. In the first case, the network uses a set of training data thanks to which manages to infer the ties that bind these data and to develop a model "general". This model will later be used to solve problems of the same type. In the case of unsupervised learning process, the system refers to algorithms that attempt to group the input data by typology, identifying representative cluster of data typically making use of topological or probabilistic methods. In the process for reinforcement an algorithm aims to find a modus operandi from a process of observation of the external environment. In this process it is the environment itself guides the algorithm in the learning process.

5. Impact detection on a composite panel

The main advantage of current development of SHM systems is their ability to perform automatic signal analysis and damage identification, significantly reducing the human factor. The idea is to use a data set of signal parameters obtained from a reference structure (e.g. undamaged structure, numerical models, laboratory tests) and to use soft computing methods to warn about the damage appearance and predict its type, location and extent. In this manner Neural Networks (NNs) can perform automatic analysis of the elastic waves and accelerate the process of structure diagnosis. A possible use for neural networks is pattern recognition in the development of a physical process. Pattern refers to a kind of model of instruction in which the neural network should attempt to establish the attribute to be supplied to the state of our interest in the physical process under consideration. Specifically, empirical data are provided to our machine as input and as target the state in which our subject matter was when these data were collected, in order to create a relationship of cause and effect between the two sets of data. The first stage use methods which provide a qualitative indication that damage may be present in the structure. It can be accomplished without prior knowledge of how the system behaves when damaged. These methods are referred as novelty detection. Later stage methods of damage detecting provide information about the probable position of the damage and estimate its type or extent. Here the idea of pattern recognition can be used, although it typically requires large amounts of data whose acquisition requires a huge effort in both computational and experimental investigation. A well-defined SHM system should be able to evaluate the damage parameters. However, damage detection and identification are possible only when the measured signals are affected by the presence of damage and its severity, so the application of suitable signal processing techniques is a crucial part of the diagnosis system. The first level identification is performed by the Neural Network(NN) trained for novelty detection. When the signal differs from normal condition, the system will indicate the presence of damage. Then the second identification level can be conducted using the NN trained for damage prediction. The resulting output vector will evaluate the extent of the damage. NNs are used in many interesting areas and tasks. In engineering applications they are especially attractive in solving the so-called inverse problems. The assumption is that NNs are able to learn an unknown relation between input and output data. The learning process consists of minimizing the computed error value between the target and the network outputs obtained for successive iterations. Testing is carried out based on the data that the network has never seen before. What is a crucial issue in damage identification is the correct selection of features that describe the damage and then improving the accuracy of the neural algorithm. NNs consist of an input (first) layer, usually one or two hidden layers and an output layer. The number of elements in the input and output layers is determined by the size of the learning and testing data sets. It is recommended that the training process be started with one hidden layer and a small number of neurons in that layer. When the network is executed, the input variable values are placed in the input units, and then the hidden and output layer's units are progressively executed. Each of them calculates its activation value by taking the weighted sum of the outputs of the units in the preceding layer. The activation value is passed through the activation function to produce the output of the neuron. If the training phase is successful, the network is able to find the common features that samples present in order, to extract few general laws permitting to recognize positive unknown examples. In case of positive samples these are represented by the "healthy" configuration's FRFs. Following the training phase, the auto - encoder will be able to reconstruct more or less accurately on the output layer the positive samples. That implies that a bad reconstruction of the input layer on the output one is a clear symptom of an anomalous dynamic behavior of the monitored structure. Once the auto - encoder has been implemented and trained, in order to use it as a "classifier" for the health status of a structural component, it is necessary to complete the system by another component permitting the determination of a threshold for dividing operatively the two samples classes (positive or "healthy" and negative or "damaged"). The validity of a neural network-based damage detection approach depends on the initial weights and biases, the order of input elements, choice of transfer function, training algorithm, etc. As a convergence precision mean square error (MSE) was introduced to calibrate network performance.

5.1 Used instrumentation and test article

In this chapter the test article and the instruments which have been used for the execution of the experimental tests, will be described.

Test article panel's material consisted of carbon fiber whose main features are listed below:

Size	550x550 mm
Thickness	2 mm
LayUp	[02/±45/0/±45]S

The panel was divided in a grid of 253 square of 0.03x0.03mt (fig 11) .

On the test-article 5 piezoelectric patches have been bonded in order to create an array of sensors and placed in squares 52,61,201,207 and 253 (fig 10). In the square 35 an accelerometer used to calibrate the instrument (fig 12) has been bonded.

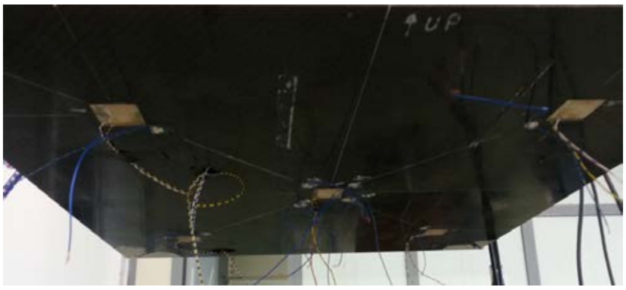

Fig. 10: Piezoceramic patches bonded on the panel

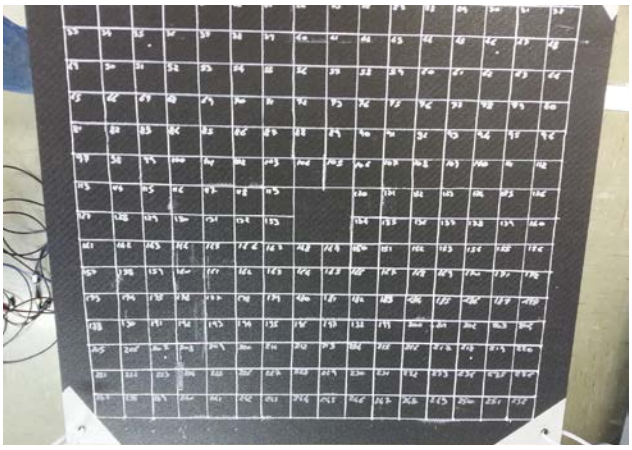

Fig. 11: Test article

Impact signal has been generated by the use of an instrumented hammer, while LMS Test Lab has been used as acquisition environment for simultaneous FRF and PSD function acquisition.

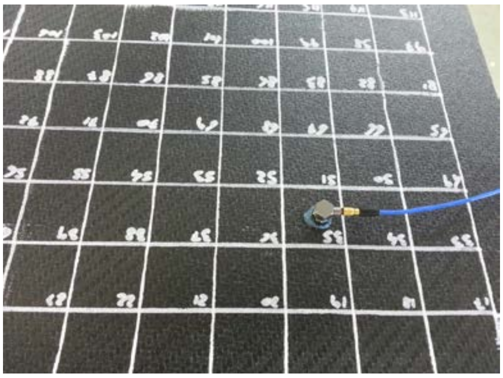

Fig. 12: Detail of Panel and accelerometer

5.2 Experimental data acquisition

After the definition of panel geometry the setting of acquisition parameters, as defined below, has been fixed.

Bandwidth	2049 Hz
Resolution	1 Hz
Sampling	0.01786 KHz

During the next data acquisition step, each point has been impacted and relative Frequencies Response Functions and the Power Spectral Density, have been acquired . In the specific the sub-script *ij*, hase been addressed to single measurements where *i* represent the relative sensor position (=5 piezo sensors) and *j* represent the impact points (=256 possible impact squared areas).

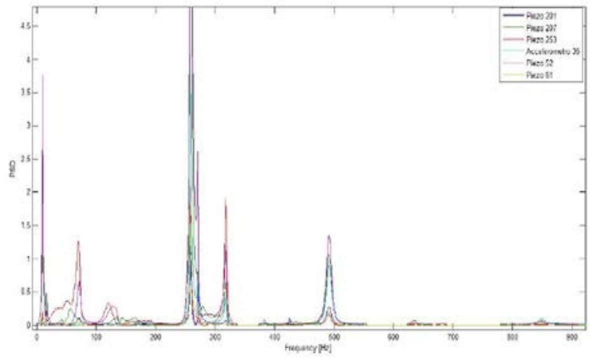

Fig. 133: Examples of acquired FRF

All these data will be in the next stage analyzed using neural networks with the aim to predict the impact location. For this scope, the neural network, needs to be preliminary trained with a set of data as positive examples. During the successive "verification" stage, the network will be able to recognize the similitude of a new response/event with something that has been preliminary recognized or a combination of multiple recognized events.

6 MatLab tool

For the practical implementation of the MatLab tool, the function to be provided is a 1x256 matrix in which each element is a row vector 1x2049 (bandwidth). The first 256 elements of this row vector representing 256 parts into which has been divided by the composite panel, being careful to consider as zero values the four cells that form the square cell in the center of the panel, and therefore does not consider the possible impact in this restricted area.

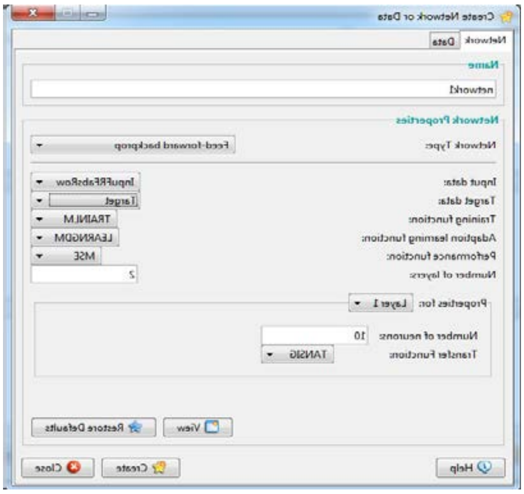

Fig. 14: Nntool configuration form

The vector will be composed of all zeros except for a one in the cell corresponding to the point of impact that we want to represent. The nntool allow us to import the earlier created matrices as Input and Target and, through them, it will produce a network that reconstruct an Output with the same values of the Target. Next step, will be the training of the network utilizing the Open control by the main tool screen, and later the Train Network control.

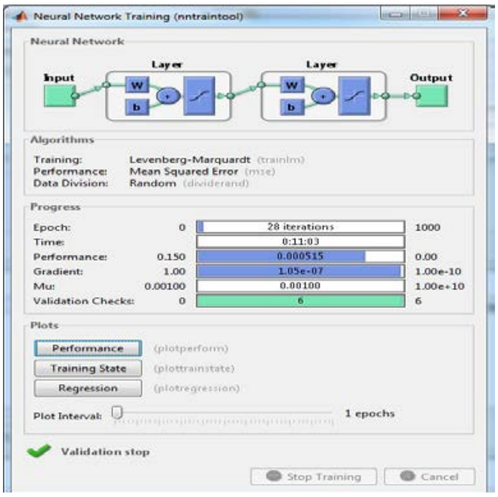

Fig. 15: Nntool validation phase

Once the training step of the neural network has been completed, the next simulation phase has been implemented. During this phase, an unknown set of data has been given to the network, whose output was supposed to be the relative referred impact point.

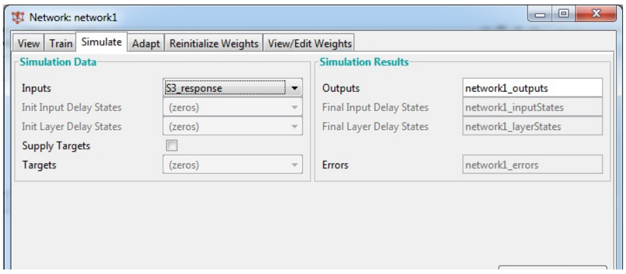

Fig. 16: Nntool simulation phase

Practically speaking, during this stage it is necessary to reorganize the output vector, a row vector 1x2049, inserting its first 256 elements in a 16x16 matrix respecting the indices used on the panel, in order to be able to detect with a good approximation the closest range of the point of impact.

6.1 Results

In the following picture the reconstruction of impact cases have been reported. From the image analysis it can be deduced that, with a good approximation, the impact took place in the range of the cell 132 of the panel because it is in this range that the highest values are concentrated.

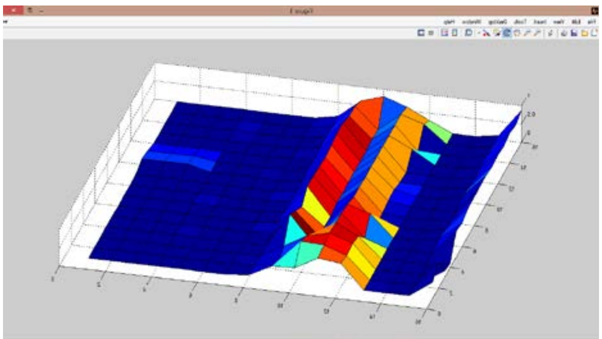

Fig. 17: First case results

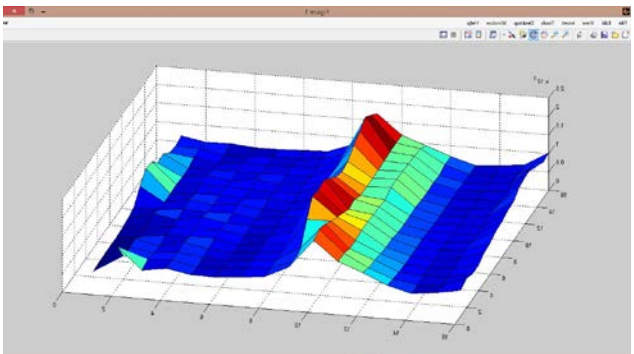

Fig. 18: Second case results

7. Conclusions

The present work presented an innovative technique for impact detection on composite panel by the use of piezoelectric sensor devices and Artificial Neural Network tool for data processing ,

The purpose of the study has been the definition and the verification of the technical feasibility of an impact detection system, that contemporarily could manage the identification of both location and energy related values of a generic impact.

The availability of these information could be of great interest in the direction of more complex SHM techniques set up as well as for predictive numerical models.

The proposed method is based on the acquisition and comparison of the FRFs of the monitored structure for different combination of the impact/sensor point. The focus concept of the method is then based on the idea that a Neural Network tool, once trained, will be able to recognize the real path of an unknown impact and to localize the impact itself.

Preliminary results have confirmed the positive performance of the proposed approach, opening to more extended experimental campaign mainly oriented to the definition of the system precision, possible fault reconstruction and optimization in the data handling and reduction of computational effort.

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