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# Global Fault Detection in Adhesively Bonded Joints Using Artificial Intelligence

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**Abstract**

In general, non-destructive evaluation is applied to detect and localize structural faults using a signal with a wavelength smaller than the detected fault. But the method requires analyzing the object in numerous small sections to detect the damage. Non-invasive diagnosis methods for fault detection are used in different industrial sectors. In this work, the main focus is on global fault detection for structural mechanical components such as a bonded beam using artificial intelligence, i.e., neural nets. Therefore, the fault detection procedure requires only a global measurement in the structural component in operational conditions. An experimental setup using two aluminum beams bonded with an adhesive was used to simulate a bonded joint. Different sizes of adhesive surface simulate faults in the original adhesive joint. Thereafter, resonance frequency shifts in the Frequency Response Functions (FRFs) were used to detect structural faults. Damage in structures causes small changes in the structural resonances. Then, the FRFs were used as an input into an artificial supervised neural network. This work considers global non-destructive tests focused only on the soundness estimation of the system. The neural network involved is a supervised feed-forward network with Levenberg–Marquardt backpropagation algorithm, which classifies the beams in four clusters. The classification consists in beam damaged or not damaged. If the beam is damaged the intensity of the fault is established.



**Keywords**

Neural networks, fault diagnosis, Frequency Response Functions (FRFs), bonded joints

## 1. Introduction

Generally, non-destructive evaluation is applied to detect and localize structural faults using signals with a wavelength less than or equal to the defect to be detected. One of the first monitoring systems was made for analyzing the acoustic signal

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emitted by the bearing in a shaft rotating at a certain speed. The lack of balance detection depends on the amplitude of the signal exceeding a predetermined vibration level. Currently, ultrasound techniques are commonly used in engineering for the determination of defects, adhesive layer, thickness measurement and in metallurgy, for determining the quality of welds performed on metal parts. But this technique requires the object to be analyzed in small sections and, therefore, increases considerably its cost and difficulty. The flaws in metallic structures cause small changes in their dynamic properties, i.e., in natural resonance frequencies. This fact requires for the conventional methods the usage of a large number of small intervals of measurements or the use of powerful and expensive mechanisms, to impose movement in the structure. Previous experiences show that flaws in structures produce small changes in their dynamic properties. According to [1] the nature of defects in adhesive joints is concerned with the adhesive itself and the adhesive–adherend interface zone. Reference [1] presents a table with defect types and possible non-destructive techniques for composites and bonded joints. Also several comprehensive reviews of the techniques available for the NDT of composites and bonded joints are available [2, 3]. In this study a global method to find and classify the faults in bonded beams is developed by applying neural networks.

Modal Analysis in the frequency domain is performed to determine the Frequency Response Function (FRF). An FRF characterizes the structure unequivocally like a fingerprint. FRF measurements are used in error functions, which characterize the faults in a bonded structure.

Non-destructive global tests focus only on estimating the integrity of the system. Longer wavelengths than the size of the defects can be used. In this way, non-destructive global tests can analyze experimentally the whole structure with only one testing measure.

In advanced systems, an analysis in the frequency domain is performed for the estimation of the FRF of the structure. Then, the dynamics of the structures is unequivocally characterized. The monitoring of railroad wheels is an example of this type of procedure. The main problem in the railroad wheels are the cracks in the wheel plate and edge. The detection was carried out by comparison of pairs of wheel FRFs subjected to the same operational service. Those in which a significant resonance shift was found were classified as defective. The classification used was based on statistical techniques. This kind of monitoring was used for several years in the 1980's to detect faults in the wheels employed in the train service [4]. It is possible to recognize acoustic patterns for monitoring purposes using artificial neural networks. In some experiments carried out previously, vibration signals were obtained for a steel beam of rectangular section where faults were simulated by saw cuts of different depths [5–7].

Neural networks [8] have a broad application field, which includes Pattern Recognition. Pattern Recognition has been used in engineering works for a long time. At the beginning, Pattern Recognition had low applicability due to the hardware requirements for data acquisition and computing [9–11]. Then, hardware and software improvements had a significant impact in the Pattern Recognition field by using neural nets. One of the benefits of neural networks is that a specific model of the problem does not necessarily have to be totally known.

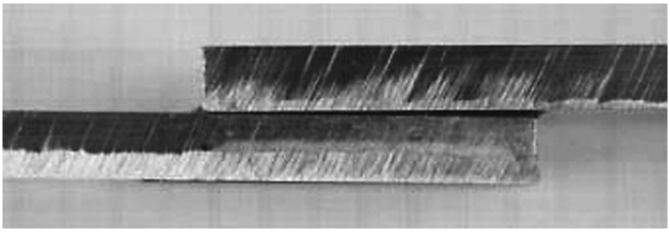
Neural networks are applied for different purposes within the field of adhesive bonding. These, for example, are used to recover the elastic constants of a fiber-reinforced composite plate from experimental measurements of ultrasonic Lamb waves generated and detected with lasers [12] or for predicting the adhesive tensile capacity [13]. It is also capable of predicting the ultimate bending capacity of steel circular tubes with a high degree of accuracy, and outperform most available codes and standards [14].

There are various approaches for training the neural network. One is the wavelet packet transform (WPT) which adopts redundant basis functions and hence can provide an arbitrary time–frequency resolution. First dynamic signals measured from a structure are decomposed into wavelet packet components. Component energies are then calculated and used as inputs into neural network models for damage assessment [15]. Another approach is the Principal Component Analysis applied to FRF in order to reduce the signal dimensionality [16]. Moreover, the structural response variance could be inputted into the neural net system as a fault analysis tool. The neural net output is capable to identify the beam damage [17].

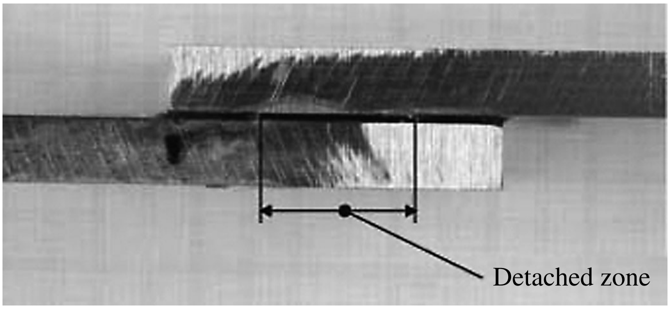
In this research, the technique of Artificial Intelligence is proposed as a method for global estimation for faults diagnosis to detect faults in structural joints using acoustic data. Different adhesive surface sizes simulate faults in the original adhesive joint. Thereafter, resonance frequency shifts in the Frequency Response Functions (FRFs) were used to detect structural faults. Damage in structures causes only small changes in the FRF resonances. Then, the FRFs were used as an input into an artificial supervised neural network [18]. This work considers global non-destructive tests focused only on the estimation of the integrity of the system. The neural network involved is a supervised feed-forward network with Levenberg–Marquardt backpropagation algorithm, which classifies the beams in four clusters, distinguishing damage and the intensity of the damage.

## 2. Experimental Details

In the present experiments, rectangular beams of aluminum were used. The faults in bonded joints were simulated using different amounts of bonded surfaces adhered, i.e., between 25 and 100% of the total surface as shown in Fig. 1. The dimensions of the bonding area were 30 mm long by 25 mm wide. The adhesive thickness was 0.5 mm (the simulated bonded faults were 75, 50 and 25% of the total surface (see Fig. 2)). The aluminum EN AW 7075 beam size was 225 mm by 25 mm by 6 mm. The surface treatment used for the aluminum alloy was a solvent degreasing with a lanolin-free tissue soaked in methyl ethyl ketone (MEK) followed by abrasion with a ScotchBrite® scouring pad containing alkaline detergent and debris removal with a lanolin-free tissue soaked in MEK. The adhesive used was Loctite Hysol 9483,



(a)




(b)

**Figure 1.** (a) Aluminum alloy beams EN AW 7075 completely bonded with epoxy, (b) aluminum beams EN AW 7075 bonded at 50% with epoxy.

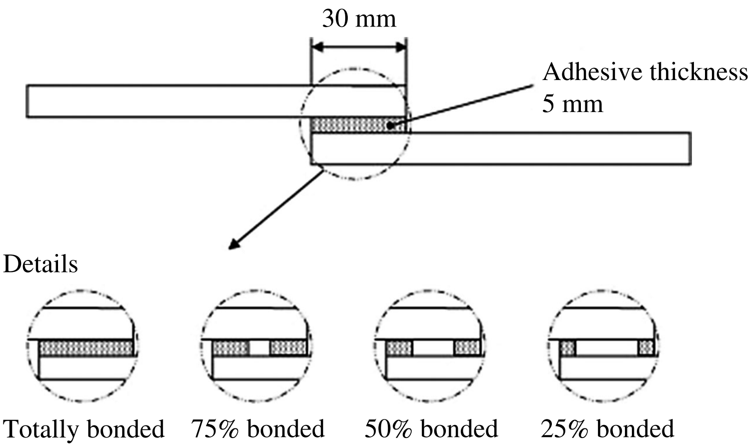



**Figure 2.** Examples of aluminum alloy beams EN AW 7075 totally or partially bonded with epoxy.

which is a two-part epoxy adhesive that cures at room temperature and was supplied by Henkel Loctite Corporation. The components were mixed in a 2:1 volume ratio using a disposable mixer syringe. The beams sections were bonded together with an overlap length of 30 mm. During bonding, the beams were kept in a jig in order to obtain a uniform bondline of 0.5 mm. The average bondline thickness was 0.5 ±

0.1 mm. After 24 h of curing at room temperature in a jig, the specimens were stored in a desiccator for a week at $24 \pm 1$°C.

The neural network is first trained with beams with 100% bonded surfaces of the joint. This case corresponds to the structure without faults. Later, beams with less bonded surfaces were considered simulating different fault sizes.

In this way an artificial neural network [8] is used to adequately differentiate between structures with structural joints containing faults or not by distinguishing their respective signal patterns [18, 19].

## 3. Frequency Response Function (FRF) Estimation

Acoustic monitoring has been performed for many years since man had the capability to distinguish between different sounds. If an acoustic radiating object suffers from structural damages its radiated sound undergoes frequency changes, i.e., bells. Moreover, damages in structures cause changes in the object resonances. The changes in the resonances affect the object dynamical properties. In this endeavor, analysis in the frequency domain was performed to obtain the dynamical properties of the structures under analysis by measuring the FRF. (The test conditions given in this work are between the start to the end of the test.) The temperature was from 16 to 22°C, the relative humidity was from 94 to 83% and the atmospheric pressure was from 1015 to 1006 mbar. The FRF obtained is the so-called accelerance $\alpha(\omega)$ [20, 21]. The $\alpha(\omega)$ is defined as the ratio between the acceleration $A(\omega)$ and the external force $F(\omega)$ in the frequency domain as shown, in equation (1).

$$\alpha(\omega) = \frac{A(\omega)}{F(\omega)}. \tag{1}$$

The FRF were obtained using the state-of-the-art modal analysis kit (see Fig. 3).

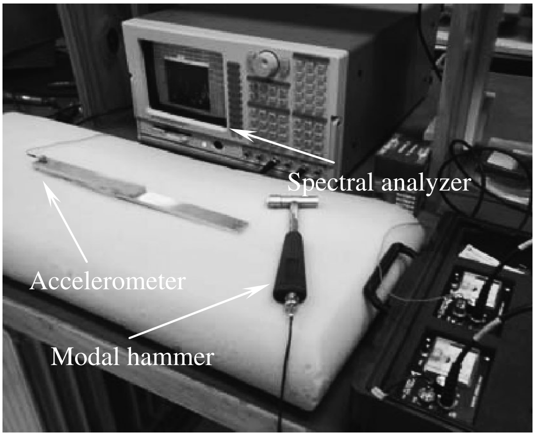



**Figure 3.** Vibration measurements setup including a modal analysis kit.

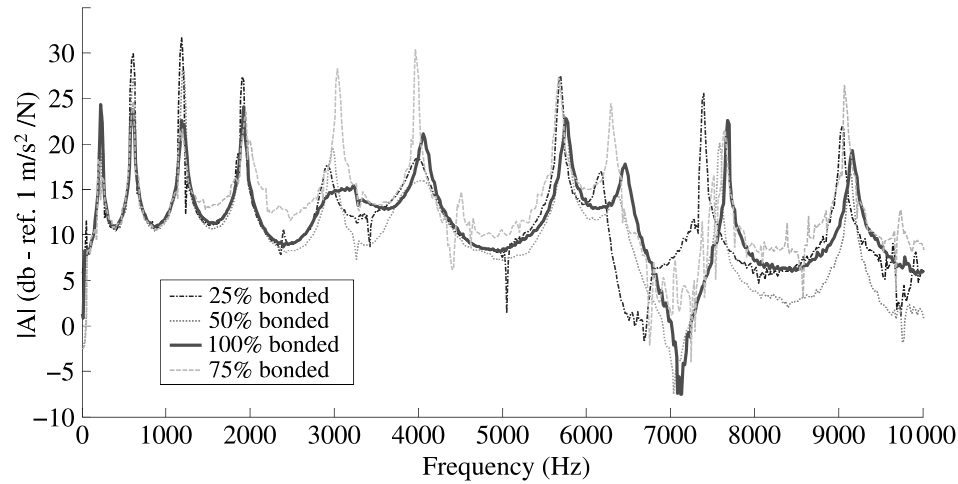



**Figure 4.** FRF accelerance curves for different amounts of bonded surfaces.

The input force was an impulsive load type provided by a modal hammer with a sensitivity of 44.0 mV/N. The response was measured by an accelerometer with a sensitivity of 10.6 mV/g. The response and the impulsive force were inputted in a two-channel spectral analyzer. The spectral analyzer provides a vector average FRF. Each modal analysis test was performed using 5 averages per measurement in order to diminish the signal uncorrelated content. The coherence value was used in the test to ensure the quality of the measurements. Only tests with a coherence value greater than 99% were used in this study. The test boundary condition was free–free in nature. The free–free condition was achieved by placing the system under a very flexible foam. The force impulse and acceleration measurements were performed in opposite beam ends. The FRF magnitude measurements are shown in Fig. 4.

The 100% bonded surfaces correspond to the FRF curve as solid line. The solid line curve is taken as reference for the undamaged bonded structure. The curves correspond to 75, 50 and 25% bonded surfaces.

The curves with incomplete bonded surfaces are used as damaged structures. The reference and damaged joints show noticeable differences in the accelerance magnitude around 2500 Hz. The differences are not only in magnitude but also in the natural frequency positions. Since the only difference between the four tested points is the size of the bonded surface, the tests are used to simulate damage in bonded beam structures. The noticeable shift in resonance frequencies could be explained due to the decreasing stiffness of the joint. The decrease in stiffness of the joint is due to the decrease in the bonded surface size. The bonded surface sizes were used to simulate faults in the bonded joints. (The bonded surfaces failures were simulated using 75, 50 and 25% of the total bonded surfaces.)

## 4. Detecting Faults Using Artificial Intelligence: Neural Networks

A supervised fully connected neural network can be seen in Fig. 5. That is, the procedure is based on a set of given example pairs and the aim is to find a function that matches well the provided samples. Namely, the purpose is to infer what will be the output for a known input.

The output is being provided with a set of training patterns including not only their inputs but also their targets. The capability of generalization is one of the benefits of neural networks. The neural nets have the capability of generalizing the results to cases that have not been involved in training steps, i.e., to learn outputs for inputs that have not been previously considered. A feed-forward neural network is an artificial network in which connections between the units do not form a directed cycle (recurrent neural network).

A set of learning numbers is stored in the net system. A single number is obtained as the sum of the weighted inputs (see Fig. 6). Later, this number is evaluated by a nonlinear mathematical function called the transfer function. Examples of transfer functions are the sigmoid function (which is generally used), the step or hard limit function, and the linear function.

A special class of multilayer networks is the feed-forward representation with backpropagation as learning algorithm. The backpropagation algorithm is used to minimize the simulation error until the network converges to the expected function. The neural net converges on applying the gradient descent method when the error function achieves a minimum in the weight space [8]. The combination of weights which minimizes the error function is considered to be the solution of the learning problem.

A requisite for this method is the continuity and differentiability of the error functions since they are involved in each iteration step. A supervised feed-forward neural network with Levenberg–Marquardt backpropagation algorithm [23] was

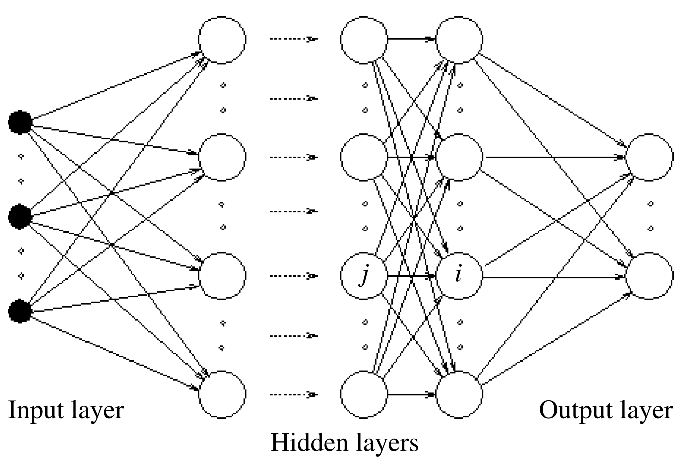



**Figure 5.** A fully connected neural network structure.

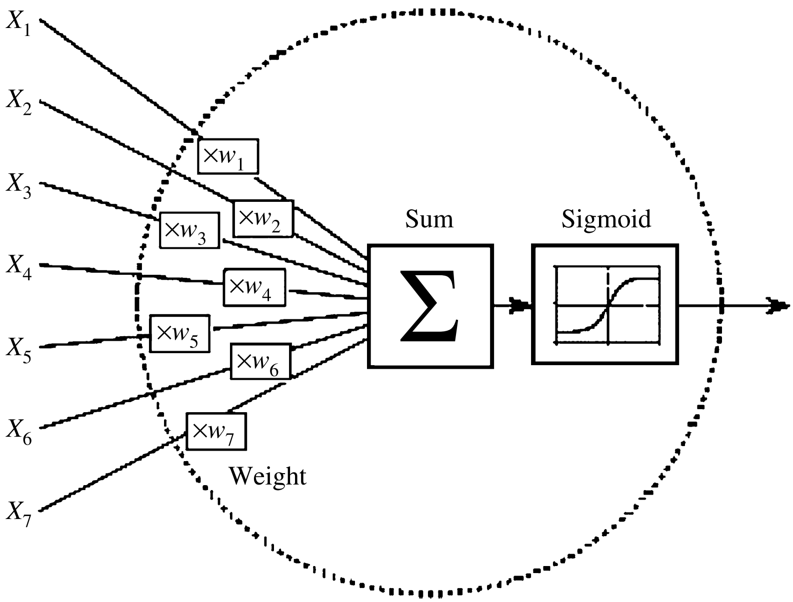



**Figure 6.** Neural network's configuration viewed from a hidden neuron (see [22]).

used in this work. The neural net structure chosen had a hidden layer. The output level has two neurons for distinguishing damage and its intensity while the input level has seventy five neurons. The neural net classifies the beams in four clusters according to the beam damage. The network converges with an approximate mean square error (mse) of 2%. In this effort, the neural net approach was capable of detecting the presence of a bonded beam fault. Once the joint damage was detected the neural net classified the damage intensities of the four simulated cases.

## 5. Conclusion

A novel technique using neural net to detect faults in bonded aluminum beams with free–free support was developed in this work. Adhesive joints with faults were simulated by partially bonded surfaces. The neural network used FRF signals as the system input. The artificial neural network specially designed and trained classifies the beam structures taking into account that the beam joints may be partially or totally damaged. The simulated joint faults were successfully detected and classified in four clusters. The quality parameter used in this effort was the Mean Square Error (MSE). The average MSE achieved was 2%. Next, the research will focus on the case of beams of composite material, e.g., epoxy reinforced with glass fibers and epoxy reinforced with carbon fibers. The faults will be simulated by saw cuts of different depths. Again, an FRF signal will be used as the input in a neural network. Clearly, the Global Fault Detection Using Artificial Intelligence is a promising tool to detect faults with low cost.

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