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FAULT ANALYSIS IN COMPOSED MATERIAL: A NEURAL NET APPLICATION USING ACOUSTICAL SIGNAL

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Abstract. Since '80 an increasing interest in Global Faults Determination is developing. Here, we are interested in non destructive analysis. Non destructive analysis is applied to detect and to localize structure faults by using a signal with a wavelength smaller than the detecting fault. To detect the fault, this type of analysis requires the evaluation of the object in numerous small sections. In Global Faults Determination the fault detection procedure requires only a global measurement in the structural component in operational conditions, which decreases the cost considerably since do not require very large number of measurements. In this effort a neural network as a global fault diagnosis detector for structural mechanical components will be applied. The research is applied in structures such as composite beams. The composite material is epoxy reinforced with fiber glass. Those beams have saw cuts with different deepness in order to simulate possible faults. Acoustic signals, based on signals captured by a microphone, are used as neuronal network input. A Levenberg-Marquardt backpropagation algorithm is used for training a supervised fully connected feedforward neural network.

1 INTRODUCTION

The use of acoustic monitoring probably dates from ancient times, since hitting an object can generate sounds whose differences can be heard when an object is defective. The use of sound and human hearing to make the transfer and recognition depends on a sophisticated natural system whose duplication artificial is only recently being considered. One of the first monitoring systems was to analyze the acoustic signal emitted by the bearing of a shaft rotating at a certain speed. The knowledge of the lack of rolling depends on the amplitude of the signal exceeding a predetermined acoustic level (Finch, 2005). In general non destructive evaluation is used to detect and locate structural defects using signals with a wavelength less than or equal to the defect to be detected. Currently, ultrasound techniques are commonly used in engineering for the determination of material defects, thickness measurement, presence of adhesion on layers, and in metallurgy for the determination of the welds quality on metallic parts. But this technique requires the object to be analyzed in many small sections. The flaws in metallic structures cause small changes in resonance. Conventional techniques require through usual methods of observation long intervals or the use of very powerful mechanisms to impose movement in the structure. On the other hand, previous experiences show that small changes in resonance produce variations in the dynamic properties. Therefore, neural networks can be used to distinguish adequately between structures with and without flaws. Analysis in the frequency domain is performed to determine the Frequency Response Function (FRF) of the structure thus characterizes its dynamics. Using error functions in the result of comprehensive estimates of the structural dynamics can characterize the faults. In this work global non destructive testing can analyze experimentally the complete structure with only a single measurement. The proposed methodology is able to reduce the cost of structural monitoring. Moreover, the technique is easily applied when the fault is located in inaccessible places.

In more advanced systems an analysis in the frequency domain is performed to determine the Frequency Response Function (FRF) of the structure. The FRF characterizes the dynamics of the structure i.e. natural frequencies and mode shapes. The monitoring of railway wheels is an example of this kind of research (Nagy et al. (1978)). The main failure in the rail wheels are cracks on the wheel plate and upon the edge. The detection was performed through comparison of FRF of wheel pairs subjected to the same railway services. In those wheels in which a significant resonance shifts were found, a defective classification was assigned by using qualitative statistical methods. In the 80's this type of monitoring was common usage to get qualitative data to detect this sort of faults in the train service. In Zapico and Molisani (2009) is shown that a neural network trained with the FRF classifies successfully the steel beams between undamaged and damaged. The problem is the expensive equipment required to perform the measurements, which is not available to every research team or engineers. The main idea of this research is to develop a strategy in order to drastically decrease the cost of structural fault analysis.

In next Section, Sound Pressure Level is introduced. In Section 3, a neural network applying acoustical signal to Fault Analysis in Composed Material GRP is developed. Finally, we summarize some concluding remarks in Section 4.

2 ACOUSTIC SIGNALS: SOUND PRESSURE LEVEL

Acoustics signal are usually captured by using a pressure transducers. In this work the Sound Pressure Level (SPL) is measured by a microphone. The microphone is used instead of an accelerometer because of the accelerometer added mass effect. The composite material sample used in this effort weights 25 grams. Usually an accelerometer could weights between 8 and

10% of the sample weight. Therefore the sample material dynamic behavior is going to be influenced by the accelerometer weight. The sound radiated from the beam is carrying its dynamical properties. A typical microphone used in the measurements is shown in Figure 1. The SPL is defined by Equation 1 as

$$L_p = 10\log_{10}\left(\frac{P_{rms}^2}{P_{ref}^2}\right) \tag{1}$$

Where Lp is the SPL, P_{rms} is the root mean square acoustic pressure and the P_{ref} is the reference pressure. The P_{ref} is the minimum pressure difference that a human being can hear, which is $20\mu Pa$ (Finch, 2005). The SPL is the response of impulsive load acting upon the beam sample.

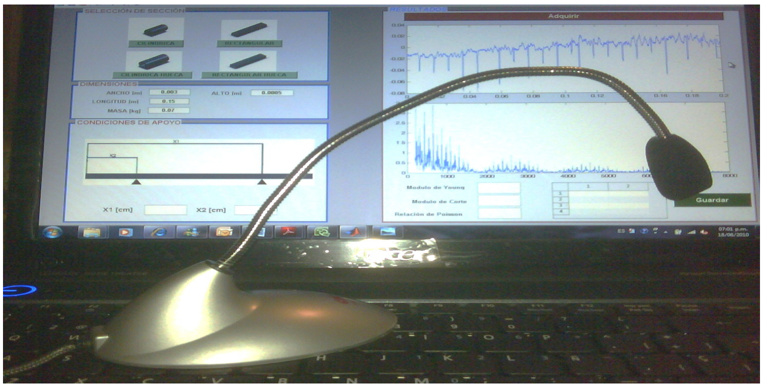

Figure 1: Typical microphone used for the measurements

Since the impulsive load is not acquired for different measurements the SPL magnitude is different. The proposed methodology uses error function acting upon the SPL signal to evaluate the shift on the natural frequencies. Therefore a normalization is introduced in the SPL signals to establish a uniqueness in the signal amplitudes. The normalization is computed relative to the first resonance of the first measurement set. The first measurement set is always the reference sample in this work. The SPL normalized data is shown in the Figure 2.

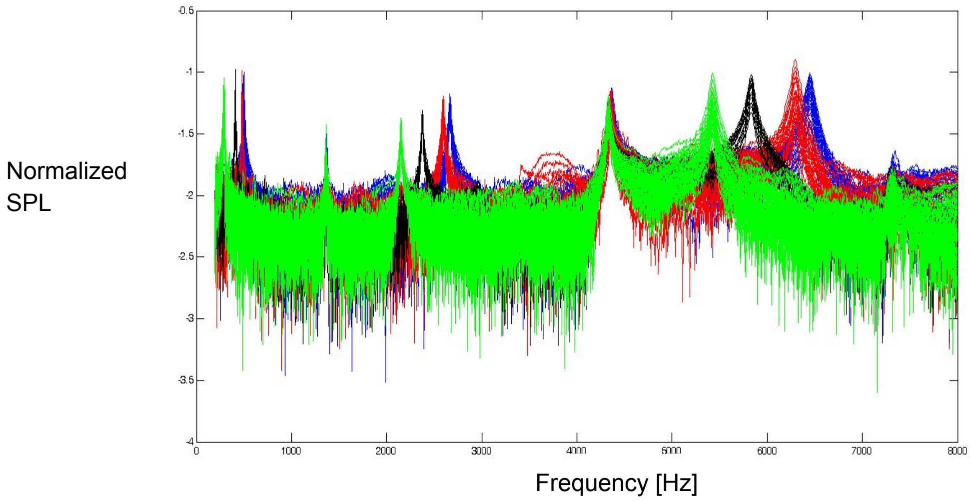

Figure 2: Normalized Sound Pressure Level(SPL)

3 FAULT ANALYSIS: A NEURAL NETWORK APPLICATION

One of the goals of neural networks is to develop methodologies that can deal with abstract and poorly defined problems. The use of neural networks is common, particularly for classification, i.e. character recognition, oil exploration, classification of radar signals radar, automatic control, doped of semiconductors, photocopiers, control and prediction of faults in electric motors and prediction such as financial operations, market predictions, development of sunspots, weather forecasts. As shown the application area covers a very wide range from medicine (cellular analysis of breast cancer, design prosthesis, hospital expense reduction, modeling of schizophrenia), Industry predicting gas furnace output, prediction and optimization of issuers and consumption in electric motors, the image processing, internet searches) to prediction of hourly electricity demand.

A neural network definition given by Haykin (2009) states: “A neural network is a massively parallel distributed processor made up with simple processing units, which has a natural propensity for storing experiential knowledge and making this knowledge available for use. It resembles the human brain in two aspects:

1. Knowledge is acquired by the network from this environment through a learning process.

2. Interneuron connections strengths, known as synaptic weights, are used to store the acquired knowledge.”

Neural networks advantage is the capacity of solve problems without having a complete problem description.

It is possible to recognize acoustic patterns for monitoring purposes using neural networks. In some experiments developed at the University of Houston vibration signals were obtained for a steel beam with rectangular cross section (Man (1996); Man et al. (1994.)). The beams had saw cuts to simulate damage. The digital data were used to train an artificial neural network to produce future analysis of the vibration signal. In other approach the measured vibration signal was the Frequency Response Functions on steel beams (Zapico and Molisani (2009)).

This method use the analysis of the FRF measurements to estimate the depth of saw cuts. The analysis was enough sensitive to detect the deepness of the cuts up to 2.54 mm. This novel technique is capable to solve problems of determining fault in structures with low-cost global assessments and working in real time. The experimental measurement setups are not accessible to project with small budgets. In this research a universal wire support (see Figure 3) and a low cost microphone are combined to obtain the experimental data.

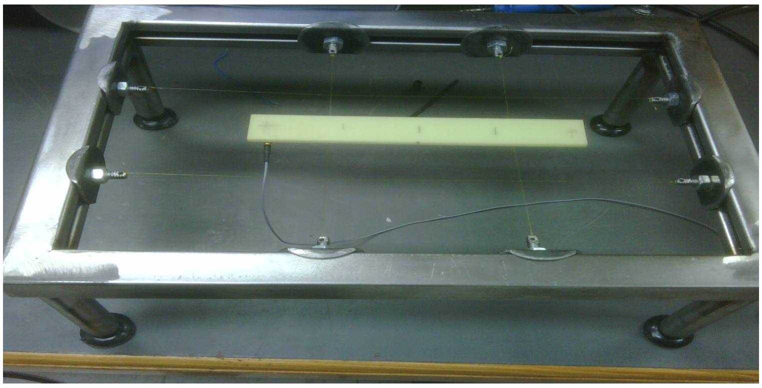

Figure 3: A universal wire support

The previous works applying neural networks for recognizing fault in beams are based in Frequency Response Functions measurements. The main interest of this work is the development of a fault analysis detector. The fault analysis detector is designed to have low cost and the capability to work in real time. The capability to work in real time is interesting in industrial application i.e. rotating machinery and structural components. Nowadays new materials are used in different structural components and its dynamic behavior could change in operational conditions. Therefore systems with fast response are needed to prevent severe structural damage and collapse.

The main research topic is fault analysis applied to composite material beams. The composite material samples are made of epoxy reinforced with fiber glass (GRP). The samples are supported with a free-free condition. The beams geometrical properties are 175 mm of length, 25 mm of width and 4 mm of thickness. The faults are simulated by using saw cuts with different deepness, which are 1.2 mm, 2.1 mm, 3.1 mm (see Figure 4)

A microphone is applied to obtain in the universal wire support the Sound Pressure Level (SPL), which is used as the neural network input. The neural network is able to detect the different type of faults, which are simulated by saw cuts with different deepness. Therefore low cost resources are applied to global faults determination.

The artificial neural network is a feedforward configuration trained with a backpropagation algorithm. The network architecture has one hidden layer and the corresponding input and output layers. The number of neurons in the input layer is two hundred, seven in the hidden layer and two in the output layer.

The first transfer function applied is the sigmoid and the second is the lineal function. The network converge with an small mean square error (mse) with the purpose to detect the damage deepness. The mse in average is between 1.45% and 1.70 %. Since the classification error is negligible, the analysis gives total confidence in the detection of sample beam damage. The simplest net classification is just damage or undammed.

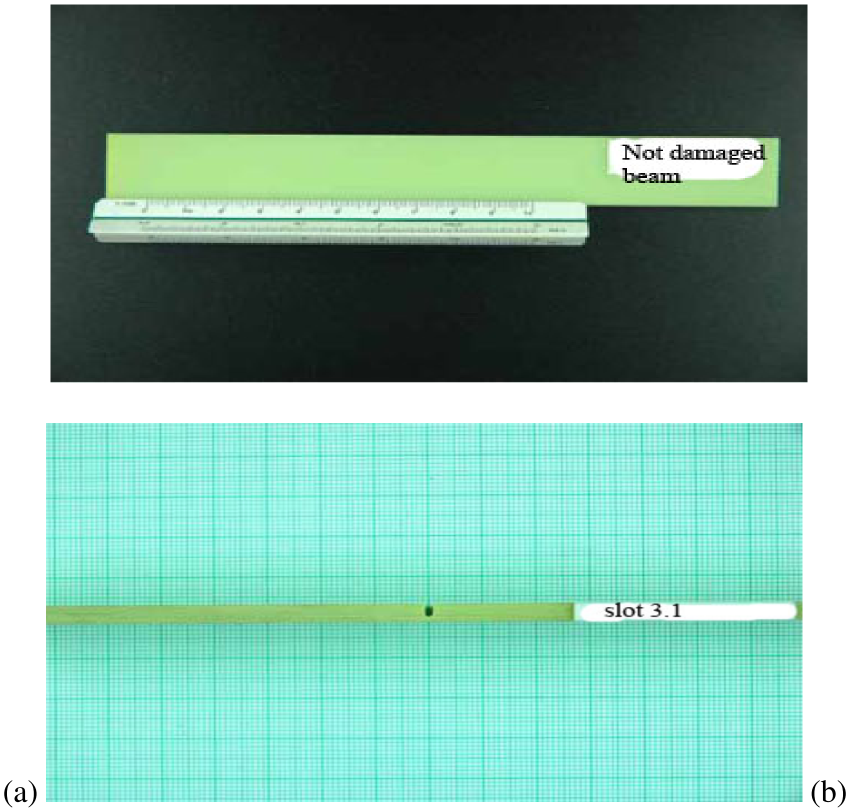

Figure 4: (a) A not damage beam of GRP, (b) a beam of GRP with a saw cut of 3.1 mm of deepness to simulate fault.

4 CONCLUDING REMARKS

In some experiments developed at the Houston University (Man et al. (1994.)), vibration signals were obtained from steel beams of rectangular cross section. Several beams had saw cuts in order to simulate faults. In this work saw cuts are also considered to simulate structural damage. Experimental data were used to train an artificial neural network to analyze and classify future signal information. It is known that Pattern Recognition is a usual application for neural networks (Bishop (1995)). There are several works in the open literature applying neural networks as classifier in fault detection Chang et al. (2000); Chen and Wang (2002); Sun and Chang (2002); Zang and Imregun (2001), but not in beams with free supported boundary conditions. Free support conditions were used in Zapico and Molisani (2009). Steel beams of rectangular cross section and saw cuts of different deepness were employed to simulate structural damage.

In previous developments the authors worked with aluminum alloy beam samples. The samples are two beams adhered at the end with epoxy. The research consisted in detecting faults using vibration signals. The faults consisted in adhesion surface completeness. If the adhesion is only partial the adhered joint was supposed to be damaged. The adhesion surface may be of 25%, 50% 75% (damaged) or totally adhered (undamaged). The research work is promising in the fault detection of adhered joints. There is a previous work with composite beams of epoxy reinforced with fiber glass with a similar technique. In this research, the authors present a novel technique with a significant low cost in a way that the measurement requires very few resources and is amenable to be applied in real time.

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