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Neural Networks in Damage Detection of Composite Laminated Plates

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Abstract: - In this work a methodology for damage detection on laminated composite plates involving the use of piezoelectric sensors and artificial neural networks is present. The presence of damage in the laminated composite plate leads to changes in its structural characteristics, causing variations in electrical potential of sensors. A feed-forward type neural network, trained by Levenberg-Marquardt algorithm is used in order to locate and quantify damage on the laminated plate using data obtained from piezoelectric sensors. A higher order finite element formulation allowing the response of the laminated composite plates is used to obtain the changes on electrical potential. A numerical example shows the feasibility of the proposed procedure.

Key-Words: - Damage Detection, Piezoelectric Sensors, Neural Networks

1 Introduction

The occurrence of damage in a structure causes changes in its response modifying the mass, stiffness or damping properties. Therefore, the correct knowledge of the behavior of the structure can be used to create a damage detection scheme.

The damage identification methods can be categorized based on the type of measured data used and/or the technique used to identify the damage from the measured data [1]. The most common used class of damage identification methods is based on changes in vibration frequencies [2]. However, these methods seem to fail to locate and quantify the damage, since the modal frequencies are a global property of the structure [3].

Another class of damage identification methods uses the mode shape changes. The aim is to compare the mode shapes of the damaged and undamaged structures. These methods are more sensitive to damage than the methods based on modal frequencies. An alternative to using mode shapes to obtain spatial information about vibration changes is using mode shape derivatives, such as curvatures or strain energy [4].

The dynamically measured flexibility matrix is another class of damage identification methods that estimates changes in the static behavior of the structure [5]. These methods are more sensitive to changes in the lower frequency modes of the structure.

Other several damage identification methods can be found in literature, with a special emphasis on neural network based methods [6], [7] and electrical resistance measurement methods [8]. Recently, the development of smart materials and adaptive structures with piezoelectric sensory/active capabilities has improved the performance and reliability of the structural systems, particularly composite materials. However, up to now the great application of these capabilities has been done within the area of control, whereas research in the field of damage identification has been comparatively limited. Since damage is a local phenomenon, it seems that local information provided by sensors is suitable for damage identification. A significant difficulty is that the data obtained from piezoelectric sensors are extremely limited and localized due to the characteristics of strains. The damages generally have very little influence on the strains of areas which are far from damage.

Fukunaga et al. [9] proposed a two-stage damage identification method with data obtained from piezoelectric sensors in a beam example. In the first stage, a first order approximation technique, which separates the effects of damage severity and damage locations, obtains the electrical potential change on sensors. In the second stage, an iterative scheme for solving nonlinear optimization programming problems, based on the quadratic programming technique, was proposed to predict damage extents.

In this work we propose a neural network based methodology to identify and quantify damage using data obtained from piezoelectric sensors as inputs to a feed forward neural network. A higher order finite element formulation allowing the response of the laminated composite plates was used to obtain the necessary electrical potential on sensors [10]. A numerical example of a simply supported laminated composite plate is used to show the feasibility of the method.

2 Problem Formulation

2.1 Laminated Plate with Piezoelectric Sensors

A simulated composite laminated plate, shown in Fig. 1, is employed to describe and investigate the effectiveness of the proposed methodology. The numerical analysis of the plate was done by the finite element method with 36 equal elements [10]. The $1m \times 1m$ composite plate was made with two glass/epoxy layers, both with 4 *mm* of thickness. The plate is simply supported on all sides. In the upper and lower surfaces of the plate, piezoelectric layers acting as sensors can be perfectly bonded. Four pairs of piezoelectric are symmetrically placed (elements shadowed in the Fig. 1). The piezoelectric layers have 1 *mm* of thickness.

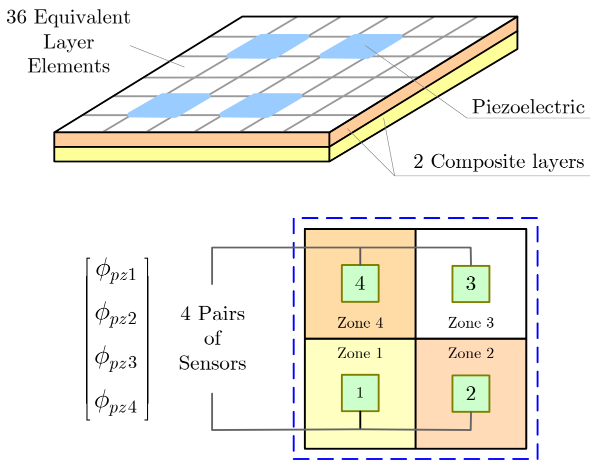

Fig. 1 – Composite Laminated Plate with Piezoelectric Sensors

The mechanical properties for the glass/epoxy layers were obtained from the Halphin-Tsai equations [11] with matrix and fiber properties shown in Table 1.

Table 1 – Properties of Matrix and Fiber

Material	E $[GPa]$	E $[GPa]$	ν	ρ $[Kg/m^3]$
Epoxy Matrix	3.400	1.308	0.3	1200
Glass Fiber	85.000	35.420	0.2	2500

The mechanical properties for an undamaged plate are represented in Table 2. The properties for composite layers are obtained considering 65% of fiber volume fraction. The electric properties considered for the piezoelectric layers are $e_{31} = e_{32} = 0.046 C/m^2$ and $p_{33} = 1.062^{-09} F/m$.

Table 2 – Properties of Composite and Piezoelectric Layers

Material	E_1 $[GPa]$	E_2 $[GPa]$	G_{12} $[GPa]$	ν_{12}
Composite Layer $(65\% V_f)$	56.44	17.358	6.133	0.3
Piezoelectric Layer	2.00	2.00	1.00	0.0

The simply supported plate is charged with a concentrated load of 5N in its center. The mechanical behavior of the piezoelectric material is also considered. The differences among the potentials are obtained with a finite element home made code programmed in Matlab.

More detailed information concerning the analysis of composite laminated plates can be found in [10].

2.2 Damage Simulation

It is assumed that the break of fibers in certain regions of the plate (elements of the plate) can be the damage. The simulation of damage in the plate was considered separately for each element, and refers only to glass/epoxy layers. The break of fibers was simulated by the reduction in the fiber volume fraction of the damaged element. Table 3 shows the percentage values considered for damage simulation. There we can distinguish values used for the training and cross validation of the neural networks and values used for testing the neural network ability to locate and quantify the damage.

For each damage case the differences among the potentials were obtained and normalized between -1 and +1 values.

Table 3 – Percentage Values for Damage Simulation

0	5	6	7	8	9	11	12	13	14	15	16
17	19	20	21	22	23	24	25	27	28	29	30
31	32	33									

Training Test Validation

2.3 Bi-level Algorithm

The two-stage damage identification methodology is proposed using information given from the piezoelectric sensors. The idea of the methodology is to use the fact that the presence of damage in the laminated composite plate causes changes in electrical potential of sensors. The information about these changes can be used to correctly train a neural network.

The plate was divided in 4 equal zones with 9 elements each one, as shown in Fig. 1. The idea consists of using a sensor in each zone of the plate. We have a bi-level algorithm with two steps, schematically shown in figure 2. In the first step a neural network gives the location of the damage on the plate. After recognizing the location of damage, another neural network corresponding to the zone of the damage location is activated and quantifies the damage.

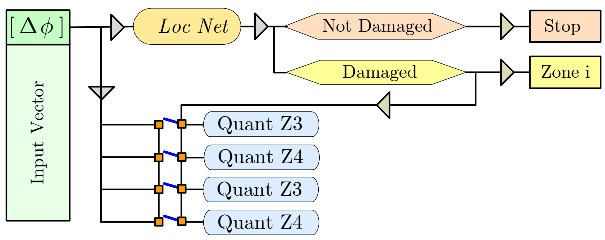

Fig. 2 – Damage Detection Bi-level Algorithm

With this algorithm we need to train a neural network to locate the damage (LocNet 4-X-X-6) and four different neural networks to quantify the damage (QuantNet ZY 4-X-X-1). To train the neural network that made the location of damage, a total of 936 patterns were obtained: 541 for net training, 144 for cross validation and 252 for testing. To train the neural networks that made the quantification of damage we have 135 patterns for net training, 36 for cross validation and 63 for testing each neural network.

Several feed forward neural networks with different dimensions were created. All the networks considered have four layers with hyperbolic transfer function in the hidden layers and sigmoid transfer function in the output layer. The inputs of the networks are the 4 normalized potential differences in the sensors. The outputs are one single value between -1 and +1 for the damage quantification and six binary digits, representing a number between 1 and 36, for the damage location.

The dimensions of the neural networks were obtained by experimentation, knowing that the best neural networks are those ones with fewer dimensions which can generalize well, and that the total number of neurons and bias must be shorter than the total number of patterns [12]. The dimensions considered can be seen in results.

In order to simulate situations in service or experimental conditions, perturbations are added to the testing data. This is done with simulated noise added to the values from neural networks testing, according to

$$\bar{A} = A\left(1 + \frac{\beta}{100} randn\right) \qquad (1)$$

where $\bar{A}$ is the value with noise, A is the value without noise, β is the noise level considered for the piezoelectric sensor readings and $randn$ is a random number with variance and standard deviation 1.

3 Results Obtained

3.1 Damage Location

In Table 4 we present the neural networks trained to make the damage location and the results obtained. There we can see the necessary epochs for training the networks and the number of damage test cases that have not been located (performance of the net). Each neural network was trained 10 times and several levels of perturbation on test data values were considered.

Table 4 – Results Obtained for Damage Location

NET	Epochs	Values of β						
		0	0.5	1	2	4	6	10
4-10-10-6	110	14	-	-	-	-	-	-
4-11-11-6	85	7	-	-	-	-	-	-
4-12-12-6	84	0	0	0	7	35	115	141
4-13-13-6	125	0	0	2	10	37	105	153
4-14-14-6	161	0	0	0	1	48	113	147
4-15-15-6	92	0	0	0	5	89	149	203
4-16-16-6	95	0	0	0	3	44	100	157

From the results obtained we can see that the best network was LocNet4-14-14-6 with only one location error for $\beta = 2$.

As can also be seen in table 4, the increase in the number of neurons in hidden layers does not mean better accuracy. Hence, the results of this net with the ones that have 15 and 16 neurons can be compared.

3.2 Damage Quantification

For damage quantification several neural networks with different number of hidden neurons were tested. The best neural network obtained was QuantNet 4-6-6-1. To train this net we need a mean of 200 epochs and 6 seconds each one.

For this network the results obtained, presented in Table 5, are shown as mean relative errors in each damage case, calculated by

$$error = 100 \times (damage - out) / damage \qquad (2)$$

where $error$ means the relative error, $damage$ is the damage target value and out is the output of the network. The mean relative errors are obtained from the corresponding 9 elements of each zone. The network was tested with a perturbation $\beta = 0.25$ on testing data. It must be pointed out that all networks were trained 5 times, and each result present in the table refers to the best obtained from the ones that were trained.

Table 5 – Mean Relative Errors on Damage Quantification

Damage Target Value	Mean Relative Error				Global Mean Error
	Zone				
	1	2	3	4	
8	1.163	1.312	2.046	1.397	*1.479*
12	0.701	0.626	0.998	1.016	*0.835*
16	0.435	0.550	1.012	0.402	*0.600*
20	0.668	0.489	0.472	0.428	*0.514*
24	1.142	0.774	0.976	1.085	*0.994*
28	0.514	0.445	0.848	0.517	*0.581*
32	0.354	0.433	0.523	0.292	*0.401*

As can be seen in table 5 the mean relative error in quantification is greater, as expected, for greater values of damage. But even for the case of target 8 the global mean error is less than 1.5%.

4 Conclusions

In this paper, a two-stage damage identification method, with a neural network based methodology using information from piezoelectric sensors has been proposed. In the first stage a trained neural network is used to locate the damage and in the second stage another neural network estimates the extension of the damage. A simulated composite laminated plate is employed to illustrate the effectiveness of the methodology. The damage was simulated by the reduction in the fiber volume fraction of an element of the plate. All the necessary data were obtained by the finite element method. From the numerical example, it was found that the accuracy of the technique is high.

The following conclusions can be observed in this study:

a) The neural network model presented can be used in the damage detection of structures with high accuracy. The location and quantification of the damage are determinable if the neural networks are correctly defined and trained;

b) The data collected from the piezoelectric sensors are excellent diagnosis parameters for the detection of the damage and could be used by the neural networks;

c) The neural networks are a promising tool as the non destructive technique for the detection of the damage.

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