Cover page

Title: Damage Detection in FRP Laminated Beams Using Neural Networks

Authors: Melin Sahin
R. Ajit Shenoi

ABSTRACT

This paper presents a technique to predict the severity and the location of the damage in beam-like composite laminates by using modal parameters as input for an artificial neural network. A laminated cantilever beam is modelled using ANSYS 5.6© finite element software. Normal mode dynamic analyses have been performed for the first three natural modes of intact and damaged beams to find the modal parameters. Damage has been modelled as a local reduction in stiffness of the selected elements in the finite element model. Considering various stiffness reductions at different locations along the beam, a variety of damage scenarios have been created. Natural frequencies and corresponding displacement mode shapes have been obtained from finite element analyses and the curvature mode shapes of the beam have been calculated from the normalised displacement mode shapes by using finite difference method. Following the sensitivity analyses aimed at finding the necessary parameters for the damage detection, different input-output sets have been introduced to various artificial neural networks for training. Finally, a trained feed-forward backpropagation artificial neural network is tested using new damage cases and checks are made for severity and location prediction of the damage.

INTRODUCTION

Composite laminates have damage that mostly initiates at fibre/matrix level. These micro-level local failures could be fibre fracture, fibre buckling, fibre splitting, fibre pullout, fibre/matrix debonding and matrix cracking. Damages at the laminate level can be considered as delamination between the layers of the laminate, transverse cracks leading lamina failure and fibre-dominated failures. All these different types of damage affect the life of the structure and they must be carefully investigated.

Melin Sahin, University of Southampton, School of Engineering Sciences,
Highfield, Southampton, SO17 1BJ, United Kingdom – melin@ship.soton.ac.uk
R. Ajit Shenoi (address as above)

The effects of the common damage on the structure are changes in the natural frequencies, mode shapes and structural damping. Therefore, damage detection techniques based on measuring changes in the structural dynamic characteristics have been studied by several researchers [1, 2, 3, 4, 5, 6].

From previous research, it is seen that change in natural frequencies helps to characterise the severity of the damage. However, locating the damage from the changes in natural frequencies alone is difficult as modal frequencies are global properties of the structure and hence cannot provide spatial information about structural changes. In order to overcome this drawback additional features (such as displacement or curvature mode shapes) that provide spatial information about the damage are needed. Moreover, for better estimation of severity and location of the damage, multiple modes need to be considered. Since each natural frequency and the corresponding mode are affected to different extents depending on the location of the damage, analyses become too complicated to be handled. Therefore, artificial neural network (ANN) can be used in the post processing of vibration-based data to extract the patterns and to detect the trend.

ANN is an information-processing paradigm that is inspired by the way the brain processes information. The brain has multiple neurons working together in parallel to process information; similarly an ANN can be configured and trained through a learning process by non-linear parameterised mapping between the input and the output sets via their neurons (i.e. highly interconnected processing elements). The main advantages of ANNs are their applicability to problems that do not have an algorithmic solution or for which an algorithmic solution is too complicated to be found. Besides this, ANN offers other capabilities like self-adaptiveness, generalisation, abstraction capabilities and suitability for real-time applications. Therefore, in recent years ANNs have been widely used to characterise damage in monotonic [7, 8, 9] and composites structures [10, 11].

The approach adopted here aims to utilise features extracted from the changes in natural frequencies in the first three natural modes and the corresponding curvature mode shapes as input to the multi-layer perceptron model using feed-forward backpropagation algorithm to detect severity and location of the damage. In order to generate these features that serve as input to ANN, the dynamic behaviour of the undamaged and damaged composite beams were simulated by finite element method.

FINITE ELEMENT MODELLING

A one-dimensional composite beam is modelled in this paper since the primary purpose here is to demonstrate the feasibility of the proposed approach.

Cantilever composite beam model (Figure 1.) used in the analysis is made up of four-layer, equal thickness, symmetric cross-ply $[0^\circ/90^\circ/90^\circ/0^\circ]$ laminae with following normalised geometrical properties.

$$\frac{L}{w}=10, \quad \frac{L}{t}=100 \tag{1}$$

L, w and t are the length, width and total thickness of the beam respectively. Dimensionless elastic properties [12] of the high modulus single fibre lamina are as follows:

$$\frac{E_1}{E_2} = \frac{E_1}{E_3} = 40 \qquad \frac{G_{12}}{E_2} = \frac{G_{13}}{E_3} = 0.6 \qquad \frac{G_{23}}{E_3} = 0.5 \qquad \upsilon_{12} = \upsilon_{23} = \upsilon_{13} = 0.25 \tag{2}$$

where E's, G's and υ's are elastic moduli, shear moduli and the Poisson's ratio respectively.

MODELLING OF THE DAMAGE

Severity of the Damage

Structural damage causes a local reduction in stiffness and increase in damping. Since later has a relatively small effect in laminae with high modulus fibres, damage is modelled as a local reduction in stiffness of the selected elements by changing the modulus of elasticity to different values. Since damages having a severity of less than 25% reduction in stiffness are of primary interest, a 2.5% incremental reduction is used between the undamaged and the damaged beam up to 25% stiffness reduction. For more severe damages, the incremental reduction in stiffness is chosen as 5% from 25% local damage to 80%.

Location of the Damage

Six different locations have been selected along the beam span for introduction of damage. These locations are 0.2L, 0.35L, 0.45L, 0.55L, 0.65L and 0.8L away from the fixed end. For example, in Figure 1, the location of damage (grey area) has been taken as 0.55L. The width and the length of the damage are kept constant during the analyses as 0.1L that corresponds to four elements in the finite element model.

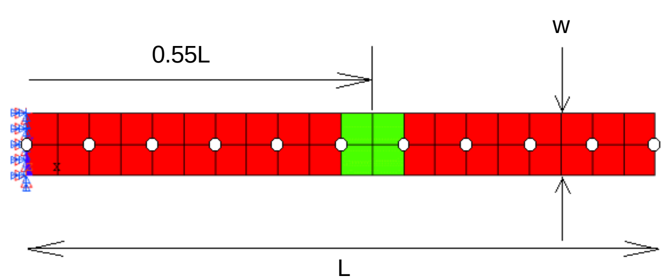

Figure 1. Finite Element Model of the Cantilever Composite Beam

Analytical Procedure

Modal analysis is performed to find the first three natural frequencies and corresponding displacement mode shapes of the cantilever beam. Eleven points along the centre line of the beam are selected to obtain one-dimensional displacement mode shapes. In Figure 1, the white dots show the locations of these points along the beam.

Since absolute differences in displacement mode shapes are not a good indicator for the damage detection, absolute differences in curvature mode shapes [5] are used as a damage index in the analysis. Curvature mode shapes, the function of the second derivative of the deflected shapes, can be obtained from the normalised displacement mode shapes with a central difference approximation.

SENSITIVITY ANALYSIS OF FEATURES

In order to investigate the effect of the severity (percentage reduction in local stiffness) and the location of the damage on natural frequencies in the first three natural modes, variations of the percentage reduction in the frequencies should be considered. Figure 2 shows the percentage reduction in natural frequencies with different severities of the damage in different modes at different locations along the beam. From the trends in this figure, it can be concluded that the reduction in natural frequencies increases with the increasing severity and depending on the location of the damage, different natural modes of the beam are affected to different extents in frequency reduction.

As can be seen in Figure 2a, there is a higher reduction in natural frequency in Mode 1 when the damage is near the root of the beam (0.2L). On the other hand, in Figure 2b, Mode 2 is much more influenced when the damage is located around mid-span (0.55L) of the beam. This shows that it is important to consider more than one mode of the beam (first three modes) for better prediction of the severity of the damage.

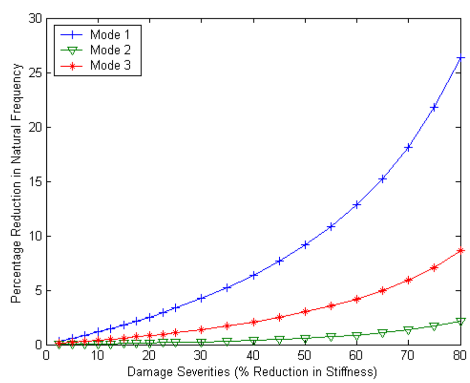

Figure 2a. Percentage reduction in natural frequencies (Damage located at 0.2L)

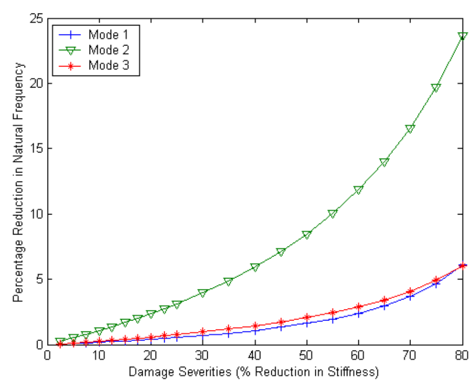

Figure 2b. Percentage reduction in natural frequencies (Damage located at 0.55L)

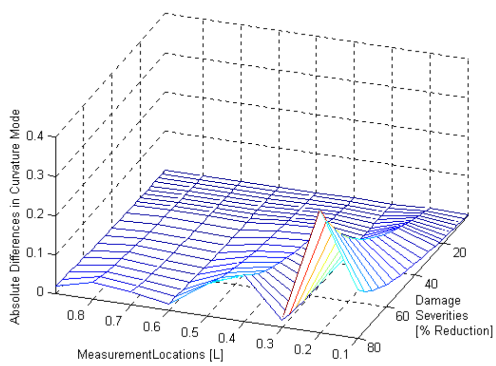

Figure 3a. Variation of the magnitude of the absolute differences along the beam with different severities (Damage located at 0.2L)

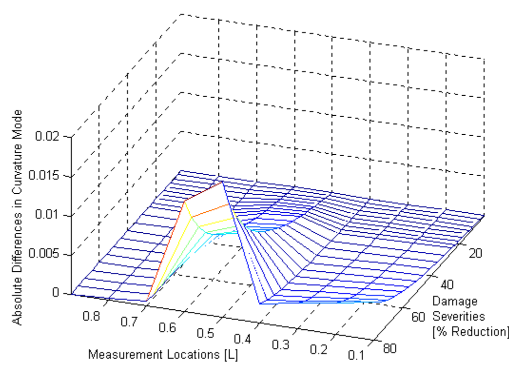

Figure 3b. Variation of the magnitude of the absolute differences along the beam with different severities (Damage located at 0.55L)

After considering the effects of natural frequency reduction, the effectiveness of maximum absolute differences in curvature mode shape is investigated to predict the location of the damage. In Figure 3a, Mode 3 is considered with a damage located at 0.2L. It can be seen from the figure that the maximum absolute difference occurs near the damage location, which is 0.2L. If another damage located at 0.55L in Mode 1 is considered, it can be observed from Figure 3b that the maximum absolute difference still gives the information close to the damage location.

Therefore, the maximum value of the absolute difference in curvature and its corresponding location along the beam coming from three different modes would be additional information serving as input to ANN.

ANN FOR DAMAGE DETECTION

In this study, supervised feed-forward multi-layer back-propagation ANN in MATLAB© Neural Network Toolbox [13] is used to estimate the severity and location of the damage in beam-like composite structures.

Training Samples and Validation

The most important criterion in the selection of the training samples is to find the ideal set that can represent all possible samples in the total space. In this analysis, 126 different damage scenarios are generated by using 21 different reductions in stiffness at 6 different locations throughout the beam. 100 input-output pairs are given to the ANN for training and the rest of the input-output pairs are used to check the generalisation of the learning. Input-output pairs are randomly distributed before introducing them to neural network in order not to affect the learning process and normalised [11] to avoid numerical difficulties.

The size of the ANN is very important since small networks cannot represent the system while larger networks can be over-trained. Hence optimisation in size of the network is crucial. Therefore, different neural networks with one hidden layer are designed to maximise performance in the prediction of the severity and location of the

Table I. ANNs used in the analyses

Artificial Neural Networks			
	Input	**Output**	**Architecture**
1	RNF	DS	3:6:1
2	MADC	DS	3:6:1
3	RNF&MADC	DS	6:9:1
4	RNF	DL	3:6:1
5	MADC	DL	3:6:1
6	RNF&MADC	DL	6:9:1
7	MADC&LOC	DL	6:9:1
8	MADC	DS&DL	3:8:2
9	RNF	DS&DL	3:8:2
10	RNF&MADC	DS&DL	6:12:2
11	RNF&MADC&LOC	DS&DL	9:18:2

Table II. Test cases for ANNs

Reduction (%)	Location (L)
8	0.55
14	0.20
21	0.80
37	0.45
42	0.35
53	0.65
8	0.50
14	0.60
21	0.30
37	0.75
42	0.25
53	0.40

RNF: Reduction in natural frequency, MADC: Maximum absolute differences in curvature mode shapes, LOC: Location where the maximum absolute difference occurs, DS: Severity of the damage, DL: Location of the damage.

damage using input data considering the first three natural modes of the beam. Table I shows all the ANNs designed and used in the analyses with a variety of input and output pairs. Values (separated with semicolon) used in the architecture column of Table I show the total number neurons in the input, hidden and output layers respectively.

Test Samples and Simulation

Twelve different cases (Table II) are used to test the trained neural networks. In the first six cases, the damage locations are selected from training sets while in the other six cases, new locations are considered. In both cases, six new reductions in stiffness are introduced to ANN. After completing simulations with different ANN architectures, the best three networks (first, seventh and eleventh ANNs in Table I) are selected on the basis of minimal error and better convergence.

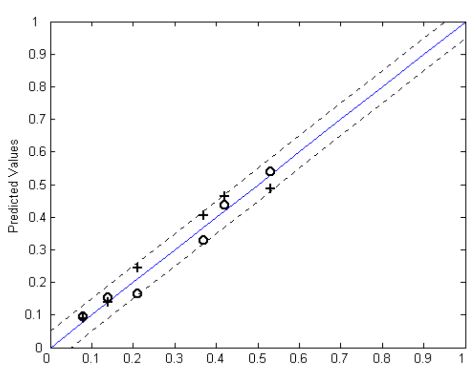

Figure 4. ANN results for severity prediction (Input: RNF)

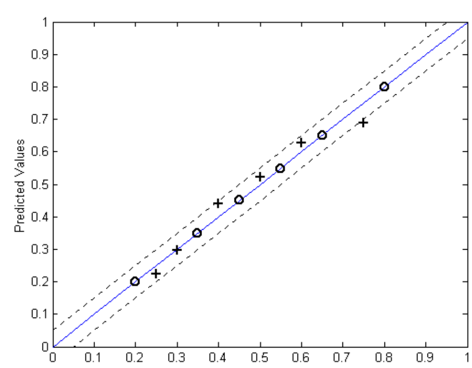

Figure 5. ANN results for location prediction (Input: MADC&LOC)

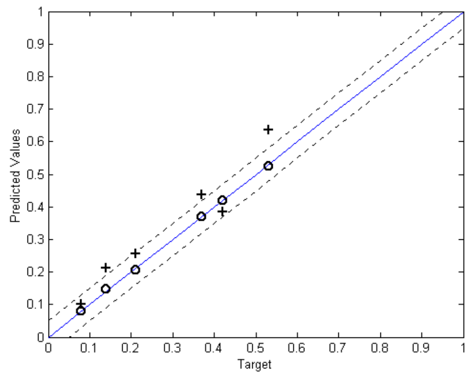

Figure 6a. ANN results for severity prediction (Input: RNF&MADC&LOC)

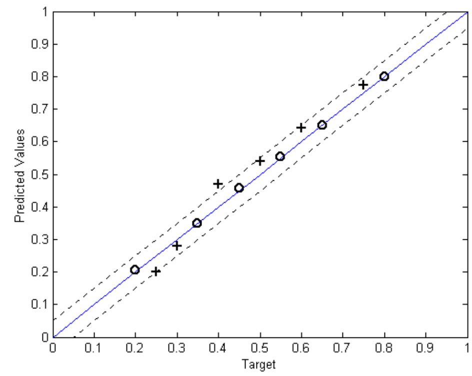

Figure 6b. ANN results for location prediction (Input: RNF&MADC&LOC)

In the first ANN, the reduction in natural frequencies is given as an input and the severity of the damage is predicted as an output. After training and validation runs, the first test with three inputs (reduction in natural frequencies from three natural modes) is performed on 12 different cases. Figure 4 shows the results of neural network regarding prediction of the severity of the damage. The symbols, circles and crosses, indicate the first and the last six test cases used in Table II respectively. The dotted lines lying on both sides of the centre line indicate a 5% deviation from the target values.

The seventh ANN test run is for the prediction of location of the damage. In this case, the maximum absolute differences in curvature mode shape and their corresponding locations along the beam in the first three natural modes are given as an input to the ANN. The prediction of this ANN can be seen in Figure 5. Although almost all the predictions are within 5% limits, first six predictions (shown with circles) are quite accurate when compared to the last six test case predictions. This means better generalisation is needed for higher accuracy.

The eleventh ANN test run performed with nine inputs namely: reduction in natural frequencies, maximum absolute differences in curvature mode shapes and their corresponding locations along the beam from the first three natural modes. In this case, the severity and the location of the damage are predicted at the same time. Since the input and output pairs are larger in size and the association between the features is much more complicated compared to previous runs, results show that there is slight overestimation in the prediction of severity (Figure 6a). On the other hand, in the prediction of location of damage, the outputs are closer to target values with acceptable deviations (Figure 6b).

CONCLUSIONS

In this study, features extracted from vibration-based analysis on beam-like composite laminate were used as input to feed-forward backpropagation neural network in order to predict the severity and location of the damage. Different input-output pairs have been generated from various damage scenarios and used for the training and validation of different types of ANNs. The results obtained using new test cases show that selection of features considered as an input data is crucial in accuracy of prediction of damage. It can be concluded that although reduction in natural frequencies is considered as an indicator for the existence of the damage and its severity, it did not provide any useful information about the location of the damage. On the other hand, maximum absolute differences in curvature mode shapes and their corresponding locations along the beam served as better indicators for the location of the damage. Therefore, these features were used in the ANN as a separate input.

The combination of these three features i.e. reduction in natural frequencies, maximum absolute differences in curvature mode shapes and their corresponding locations when introduced to ANN show that the results regarding severity and location of the damage are not as promising as the ones obtained with individual inputs. Moreover, considering the computational time aspect, the trained ANN gives quick response to online applications. Hence it can be concluded that two separate ANNs function more efficiently than one trained ANN using all the combined inputs. Finally, in order to achieve more accurate predictions in the damage detection, better features providing additional information related to damage characteristics are needed.

REFERENCES

1. Salawu, O. S. 1997. "Detection of Structural Damage Through Changes in Frequency: A Review," *Engineering Structures*, Vol. 19, No.9: 718-723.
2. Zou, Y., L. Tong, and G.P. Steven. 2000. "Vibration-Based Model-Dependent Damage (Delamination) Identification and Health Monitoring for Composite Structures - A Review," *Journal of Sound and Vibration*, 230(2): 357-378.
3. Cawley, P. and R. D. Adams. 1979. "The Location of Defects in Structures from Measurements of Natural Frequencies," *Journal of Strain Analysis*, 14 (2): 49-57.
4. Yuen, M. M. F. 1985. "A Numerical Study of The Eigenparameters of a Damaged Cantilever," *Journal of Sound and Vibration*, 103(3): 301-310.
5. Pandey, A. K., M. Biswas, and M. M. Samman. 1991. "Damage Detection from Changes in Curvature Mode Shapes," *Journal of Sound and Vibration*, 145(2): 321-332.
6. Ratcliffe, C. P. 1997. "Damage Detection using a Modified Laplacian Operator on Mode Shape Data," *Journal of Sound and Vibration*, 204(3): 505-517.
7. Kudva, J.N., N. Munir, and P. W. Tan. 1992. "Damage Detection in Smart Structures using Neural Networks and Finite-Element Analyses," *Smart Materials and Structures*, (1): 108-112.
8. Worden, K. and G. R. Tomlinson. 1994. "Damage Location and Quantification using Neural Networks," in Engineering Integrity Assessment, J. H. Edwards, J. Kerr and P. Stanley, eds. pp.11-31.
9. Zapico, J. L., K. Worden and F. J. Molina. 2001. "Vibration-based Damage Assessment in Steel Frames using Neural Networks," *Smart Materials and Structures*, (10): 553-559.
10. Okafor, A.C., K. Chandrashekhara, and Y. P. Jiang. 1996. "Delamination Prediction in Composite Beams with Built-In Piezoelectric Devices using Modal Analysis and Neural Network," *Smart Materials and Structures*, (5): 338-347.
11. Xu, Y. G., G. R. Liu, Z. P. Wu, and X. M. Huang. 2001. "Adaptive Multilayer Perceptron Networks for Detection of Cracks in Anisotropic Laminated Plates," *International Journal of Solids and Structures*, (38): 5625-5645.
12. Mallikarjuna and T. Kant. 1989. "Free Vibration of Symmetrically Laminated Plates using Higher-Order Theory with Finite Element Technique," *International Journal for Numerical Methods in Engineering*, Vol. 28: 1875-1889.
13. Demuth, H. and M. Beale. 2000. "Neural Network Toolbox, User's Guide, Version 4," The Math Works, Inc.