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DETERMINING THE POSITION AND SEVERITY OF A TRANSVERSE CRACK IN COMPOSITE STRUCTURES USING MACHINE LEARNING

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Abstract: *Currently, composite materials are used more often in engineering constructions in fields such as aerospace, energy, and military as well as in the car manufacturing industry. For ensuring the safe operation of structures produced from multilayered materials, it is good practice to apply Structural Health Monitoring (SHM) methods. In the current paper, we present an SHM method based on modal analysis, for evaluating open transverse cracks that can be present in a 5-layered composite cantilever beam. To achieve the proposed objectives of the research, we use a method for calculating the Relative Frequency Shifts (RFS) caused by the damage, by expressing the severity of the crack as a function of the stored energy. The obtained RFS's values are used as input data for training an artificial neural network (ANN), which can determine the crack's position and severity.*

Keywords: fatigue *cracks, damage detection, artificial neural networks, natural frequencies*

1. INTRODUCTION

Multilayer materials, most consisting of soft and hard components, are used in a wide range of engineering applications, including in aerospace, civil,

extraction industry, and automobile production [1]. Composites can be affected by damage, transverse cracks, and delamination being the most common forms [2-4]. Due to their non-linear behavior, it is difficult to detect the presence of cracks in multi-layer materials [5]. Evaluating the structure's integrity by using modal parameters, mainly the natural frequencies or modal shapes has been proven to be reliable in detecting and evaluating damages present in beam-like structures [6, 7]. Numerous research [8-10] are concerned with the detection of damages in composites by using modal parameters, but few studies present a mathematical model for predicting the frequency shift caused by damages.
In the current research, we aim to develop a damage detection method for evaluating transverse cracks present in multi-layer cantilever beams by developing a Machine Learning model using the analytical method presented in [11]. For this purpose, we calculate the relative frequency shift (RFS) values using an algorithm developed by our research team, see [11]. These values are used to train an Artificial Neural Network (ANN) in the MATLAB program for locating and determining the severity of a transverse open crack that affects a 5-layer composite cantilever beam and test if the network is able to detect damages with accuracy.

2. MATERIALS AND METHODS

The 5-layer composite beam we involve in this study has the two exterior and the inner layers made of carbon steel, and the two intermediate layers made of PVC. The main dimensions and the relevant material properties of the layers are given in table 1.

Table1. Dimensions and material properties layers of the composite beam

Beam's dimensions			**PVC**		**Steel**	
Length L	**Width B**	**Thickness H**	**Mass density**	**Young's modulus E**	**Mass density**	**Young's modulus E**
[mm]	[mm]	[mm]	[kg/m3]	[N/m2]	[kg/m3]	[N/m2]
1000	50	1	1300	$2.41\cdot10^{9}$	7850	$2.1\cdot10^{11}$

The severity values, as these are defined and determined in [11], are shown in figure 1. One can easily observe the evolution of the damage severity relative to the transverse crack propagation.

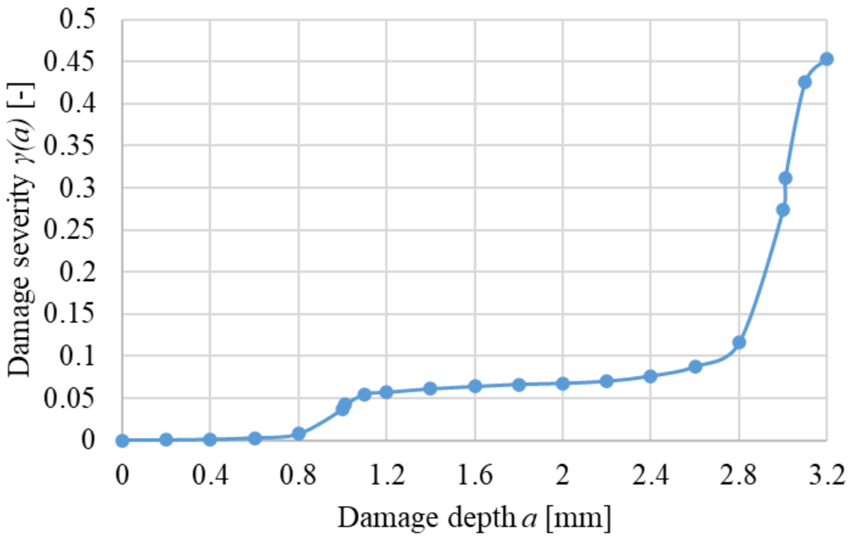

Figure 1: Damage severity evolution with the crack depth

By employing the damage severity $\gamma(a)$ and the normalized modal curvature $\bar{\varphi}''(x)$, we can calculate the relative frequency shift (RFS) involving the method presented in [12]. The relation proposed there is described in equation (1):

$$RFS_i(x,a) = \frac{f_{i-U} - f_{i-D}(x,a)}{f_{i-U}} = \gamma(a) \cdot \left[\overline{\varphi_i''}(x) \right]^2 \tag{1}$$

In the above relation x is the crack's position, a is the crack depth, f_{i-U} and f_{i-D} is the undamaged and respectively damaged beam's natural frequency.

3. DEVELOPING THE ANN MODEL FOR DAMAGE DETECTION

To detect the damages in the 5-layer composite beam we use the calculated RFSs for the first five transverse vibration modes (i=1…5) as the input for an ANN, and the damage parameters x and a as the target. The intelligent model is trained to detect damages. The ANN is developed in MATLAB, using as input data the RFS values calculated with relation (1). The severities considered in the calculus correspond to cracks with the width 0.04 mm and the depth between a_1=0.2 mm and a_{17}=3.2 mm. For all these damage severities we calculate the RFSs at 500 positions along the beam, thus the crack is iteratively removed with a step s=2 mm. It resulted in a total of 8500 damage signatures.

The chosen ANN is a feedforward backpropagation network that use the Bayesian Regularization as the training function. The ANN is trained to generate two outputs, respectively the damage location and the damage depth, containing one hidden layer of 20 neurons; its architecture is shown in figure 2.

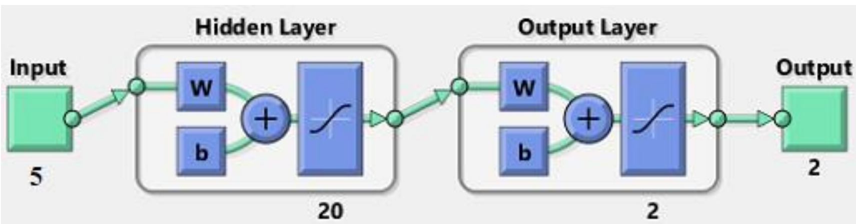

Figure 2: ANN architecture

After the ANN is trained, its performance is evaluated using the regression curves plotted figure 3.

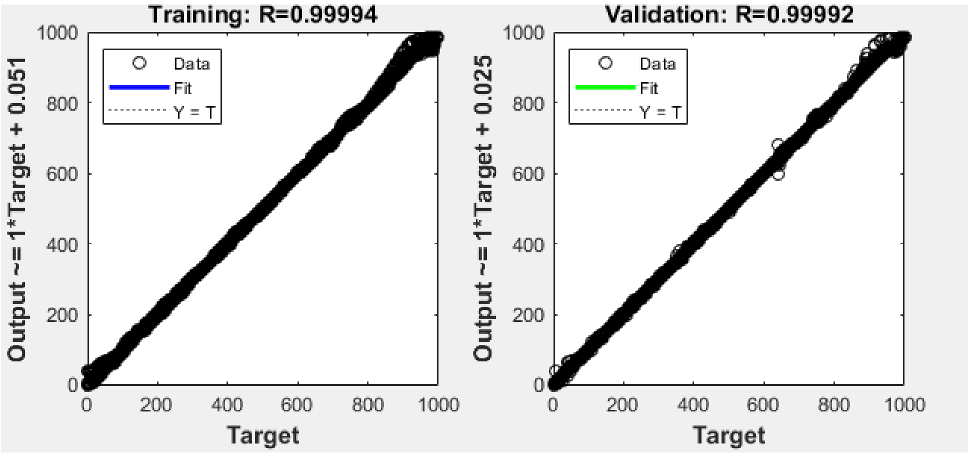

Figure 3: ANN performance

The regression curves show a good training performance, with slight validation error leading to R very close to 1.

Furthermore, to test the accuracy of the developed ANN model we make use of the natural frequency values for several damage scenarios determined by FEM methods taken from [11]. The RFS values needed for testing the ANN are calculated using relation (1), considering the natural frequency of the beam in undamaged f_{i-U} and damaged state f_{i-D} obtained for FEM simulation. The RFS for the FEM damage scenarios are shown in table 2. The crack's position is considered for all scenarios at x=274 mm.

Table 2. RFS values for FEM damage scenarios

Mode no.	Damage depth *a* [mm]							
	0.4	0.8	1.2	1.6	2	2.4	2.8	3.2
1	0.00087	0.00283	0.02642	0.00335	0.00196	0.00714	0.01554	0.15237
2	0.00006	0.00031	0.00329	0.00040	0.00023	0.00080	0.00175	0.01643
3	0.00076	0.00268	0.02486	0.00297	0.00171	0.00611	0.01289	0.09851
4	0.00054	0.00187	0.01606	0.00180	0.00103	0.00359	0.00734	0.04494
5	0.00001	0.00000	0.00003	0.00002	0.00001	0.00001	0.00002	0.00010

4. RESULTS AND DISCUSSIONS

The obtained results are shown in table 3. As it can be observed from table 4, the results in most cases are not very accurate, the position error being contained between 8.32% and 26.69% which can leave to false diagnostics if applied on real structures.

Table 3. Damage parameters predicted by the ANN for the FEM data

Defined scenario			Predicted values			
Damage scenario	**Damage location [m]**	**Damage depth [mm]**	**Damage location [m]**	**Location error [%]**	**Damage depth [mm]**	**Depth error [%]**
1	0.274	0.4	0.180	9.36	0.2	50.00
2	0.274	0.8	0.379	10.57	0.9946	24.33
3	0.274	1.2	0.190	8.32	2.274	89.50
4	0.274	1.6	0.181	9.27	2.506	56.63
5	0.274	2	0.176	9.73	2.5643	28.22
6	0.274	2.4	0.167	10.65	2.801	16.71

7	0.274	2.8	0.188	8.58	2.8452	1.61
8	0.274	3.2	0.71	26.69	2.4964	21.99

Regarding the depth prediction of the crack, the error is comprised between 0.21% and 9.98%. The results show that even if the performance tests made in the training phase show good results when dealing with noisy data, like the ones generated in FEM simulations, the overall performance of the network is not satisfactory. To achieve better results, we generate a new network architecture based on an empirical equation (2) proposed in [14]. It considers the relation between the number of samples and the number of neurons. For this specific application, the number of hidden neuron layers was set to two. Previous research has shown that if we use more than two hidden neuron layers L_h it only leads to an increased computation time without increasing the precision of the network.

$$N_h > \frac{\sqrt{(L_h + N_i + N_o)^2 + 4(L_h - 1)(N_s - 1)} - (L_h + N_i + N_o)}{2(L_h - 1)} \tag{2}$$

where: N_h represents the total number of neurons needed, L_h the number of hidden layers, N_i the number of input neurons, N_o – number of output neurons and N_s the number of input samples. By applying relation (2) we obtain the total number of neurons needed in the hidden layers N_h>73. Because 80% of the total number of input samples is used for training, 15% for validating and 5% for testing, the input sample size is N_s=6800. We train a new artificial neural network considering 80 neurons in the hidden layers, i.e., 40 neurons per layer as shown in figure 4.

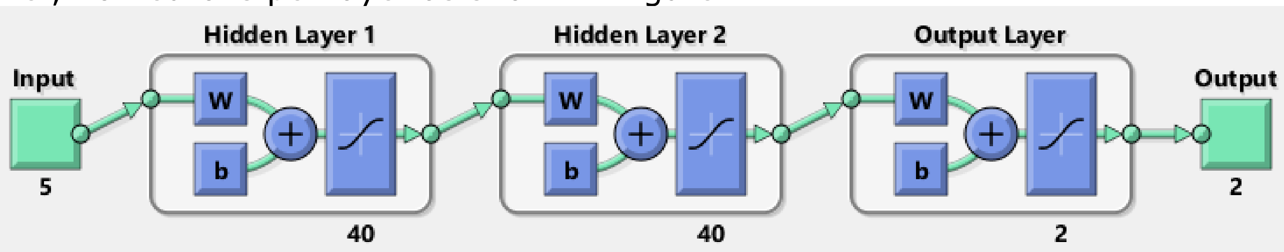

Figure 4: Improved ANN architecture

After training the network we performed the validation tests using the same FEM data and obtained the results shown in table 4.

Table 4. Damage parameters predicted by the enhanced ANN for the FEM data

Defined scenario			Predicted values			
Damage scenario	**Damage location [m]**	**Damage depth [mm]**	**Damage location [m]**	**Location error [%]**	**Damage depth [mm]**	**Depth error [%]**
1	0.274	0.4	0.244	2.94	0.377	5.65
2	0.274	0.8	0.214	5.96	0.786	1.65
3	0.274	1.2	0.322	4.88	1.209	0.77
4	0.274	1.6	0.326	5.21	1.759	9.98
5	0.274	2	0.334	5.99	1.955	2.25
6	0.274	2.4	0.356	8.17	2.420	0.83

7	0.274	2.8	0.343	6.93	2.794	0.21
8	0.274	3.2	0.248	2.60	3.216	0.50

It is easy to observe from table 4 that the precision of the network has increased by adjusting the number of hidden layers and neurons. The largest error obtained for the location is 8.17% and for the damage depth 9.98%.

5. Conclusions

The research presented in this paper compares two Artificial Neural Networks regarding the accuracy of the predicted values for the position and the depth of transverse cracks in 5-layer prismatic composite beams. Both networks use as input the RFSs calculated with an original relation derived by our research group, and as target the crack parameters. For the specific case we treat in this study we found out that the larger network provides better results and does not request much more computational effort compared to the simple network.

The biggest error in assessing the position of the cracks was found to be 8.17%, and for the depth of the crack is 9.98%. The errors are reasonable and show that the network can assess the integrity of composite beams as those used for training.

REFERENCES

[1] Maiboroda V. P., Kopan V. S., Properties of thin-layer steel-copper rolled stock, Izv. Akad. Nauk SSSR, Met., No. 3, pp. 132–136, 1973

[2] He M., Yang T., Du Y., Nondestructive identification of composite beams damage based on the curvature mode difference, Compos. Struct. 2017;176:178–186, doi: 10.1016/j.compstruct.2017.05.040

[3] Gillich G. R., Samoilescu G., Berinde F., Chioncel C. P., Experimental determination of the rubber dynamic rigidity and elasticity module by time-frequency measurements Materiale Plastice, Vol. 44 No. 1, pp. 18-21

[4] Iancu V., Vasile O., Gillich G. R., Modelling and characterization of hybrid rubber-based earthquake isolation systems, Materiale plastice, vol. 49, No. 4, pp. 237-24

[5] Zhang Z., Pan J., Luo W., Ramakrishnan K.R., Singh H.K., Vibration-based delamination detection in curved composite plates, Compos. Part A Appl. Sci. Manuf. 2019;119:261–274. doi: 10.1016/j.compositesa.2019.02.002

[6] Gillich, G.R., Abdel Wahab, M., Praisach, Z.I., Ntakpe, J.L., The influence of transversal crack geometry on the frequency changes of beams, Proceedings of International Conference on Noise and Vibration Engineering (ISMA2014) and International Conference on Uncertainty in Structural Dynamics (USD2014): 485-498, 2014

[7] Chinka S.S.B., Putti S.R., Adavi B.K. Modal testing and evaluation of cracks on cantilever beam using mode shape curvatures and natural frequencies, Structures, 2021, 32:1386–1397, doi:10.1016/j.istruc.2021.03.049

[8] Manoach E., Samborski S., Mitura A., Warminski J., Vibration-based damage detection in composite beams under temperature variations using Poincaré maps, International Journal of Mechanical Sciences, Volume 62, Issue 1, 2012, Pages 120-132, ISSN 0020-7403, https://doi.org/10.1016/j.ijmecsci.2012.06.006.

[9] Yang Z., Wang L., Wang H., Ding Y., Dang X., Damage detection in composite structures using vibration response under stochastic excitation, Journal of Sound and

Vibration, Volume 325, Issues 4–5, 2009, Pages 755-768, ISSN 0022-460X, https://doi.org/10.1016/j.jsv.2009.03.040

[10] Krishna O, Mohammad M, Sabu J., Herszberg, Damage Detection in Composites Using Vibration Signatures, Proceedings of the 2008 International Conference on Scientific Computing, CSC 2008. 16-22, Israel 2008

[11] Gillich G. R., Maia M.M.N., Mituletu I. C., Tufoi M., Iancu V., Korka Z., A New Approach for Severity Estimation of Transversal Cracks in Multi-layered Beams, Articles Lat. American journal solids structures, vol. 13 (8), 2016, https://doi.org/10.1590/1679-78252541

[12] Gillich G. R., Tufisi C., Wahab M. A., Hamat C. O., Crack Assessment Based on the Use of Severity-Adjusted Modal Curvatures of the Healthy Beam, Acoustics and Vibration of Mechanical Structures—AVMS 2019, pp. 499-504 Springer, Cham

[13] Tufisi C., Gillich G. R., Vasile O., Korka Z. I., Hamat C. O., Identification of delamination in multilayered composites IOP Conference Series: Materials Science and Engineering, vol. 416, Issue 1, pp. 012045

[14] Minda A., Burtea D. G., Gillich G. R., Tufisi C., Gillich N., Praisach Z. I., Accurate Frequency Estimation using DFT and Artificial Neural Networks, Eusipco 2022, pp. 1551-1555, ISBN: 978-1-6654-6798-8.