DAMAGE ASSESSMENT OF BEAMS USING AN ARTIFICIAL NEURAL NETWORK AND NATURAL FREQUENCIES

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ABSTRACT: The current paper presents a modal-based damage identification method that uses a one-layer neural network based on Bayesian regularization to estimate the location and severity of transverse cracks present in cantilever beams. A feedforward neural network is created, and it is trained by employing the relative frequency shift curves (RFS) for known damage positions and depths. The RFS values are plotted by using the squared modal curvature for the first eight weak-axis vibration modes and an enhanced method for assessing the severity for cracks of different depths. Training data were obtained for specific damage positions, by removing the transverse crack with a step of 10 mm along the cantilever beam. The ANN system is trained both to depict the location and severity of transverse cracks present in cantilever beams, and the results obtained are evaluated using data generated from FEM analysis.

KEY WORDS: relative frequency shift, severity, neural network, damage detection

1. INTRODUCTION

The essence of the method presented in this paper is characterized by the need to monitor the structural integrity of different installations or structures used in industry today [1]. All structures such as bridges, wind turbines, pipelines, tunnels, oil rigs, rails, or other equipment are subject to various internal and external factors that can cause wear or damage [2]. This can happen, for example, due to deterioration, an incorrect manufacturing process, a lack of quality control, or an extreme situation that results accidentally or due to environmental conditions [3]. To be able to observe these alterations in the material and react appropriately before causing serious harm, the implementation of a damage identification system is crucial [4]. Many damage detection methodologies have sought to identify damage by solving an inverse problem, which centers on the need for an analytical model [5]. Structural integrity monitoring can detect abnormalities over time, allowing maintenance actions to be implemented more efficiently, with a direct impact on reducing operating costs [6]. Replacement of scheduled maintenance with planned maintenance based on monitoring and diagnostics is the main objective of SHM, offering the following benefits: increased safety, continuous monitoring, maintenance automation, the extension of revision cycles, and reduction of costs and downtime [7, 8].

In recent decades, new methods have been used to assess damages using artificial neural networks [9]. Since beam-type structures are used in many applications for which they attain structural consolidation, they have become a crucial component for integrity monitoring [10]. Damages can alter the dynamic behavior of a beam, allowing the severity and position of the damage to be determined by examining this change [11].

The current paper deals with the development and evaluation of a method that uses a neural network with one hidden layer for detecting damages in beams. The first step was to train the neural network in the MATLAB software by generating the RFS values using an original method developed by our research team [12]. After the training stage, modal simulations are performed using the ANSYS software for different damage scenarios present in a cantilever beam [13], and the obtained values are used in order to assess the precision of the developed ANN method.

2. TRAINING DATA

For the one-layer feedforward backprop. network, the training is done by iterative processing of the data.
Training data was generated using an original method, to determine the eigenfrequencies of beam-like structures, developed in the vibro-acustic laboratory of Babes-Bolyai University and presented in the paper [14]:

$$f_D(x,a) = f_U \left\{1-\gamma(0,a)\left[\bar{\phi}_i''(x)\right]^2\right\} \quad (1)$$

In order to evaluate the results, for several scenarios of the damaged beam, the relative frequency shift (RFS) values are used. The RFS's are calculated with the relation (2) contrived by our research group [16].

$$\Delta\bar{f}_i(x,a) = \frac{f_{i-U} - f_{i-D}(x,a)}{f_{i-U}} = \gamma(0,a)\cdot\left[\bar{\phi}_i''(x)\right]^2 \quad (2)$$

In Eq.(1), the terms $\gamma(0,a)$ and $\bar{\phi}_i''(x)$ represent the crack severity and the bending moment, respectively. The bending moments caused by a given crack, with position x along the beam, are given by the following relation [15]:

$$\begin{aligned}\phi''(x) = \cosh(\lambda\frac{x}{L}) + \cos(\lambda\frac{x}{L}) - \\ \frac{\cos\lambda + \cosh\lambda}{\sin\lambda + \sinh\lambda}\cdot\left[\sinh(\lambda\frac{x}{L}) + \sin(\lambda\frac{x}{L})\right]\end{aligned} \quad (3)$$

The next step is to evaluate the effect of transversal cracks on the natural frequencies of cantilever beams by calculating the damage severity $\gamma(a)$ with the method presented in paper [12], using the following relation:

$$\gamma(a) = \left[\sqrt{\delta_D(a)} - \sqrt{\delta_U(a)}\right] / \sqrt{\delta_D(a)} \quad (4)$$

where $\delta_U(a)$ and $\delta_D(a)$ is the deflection determined by the gravity force acting on the cantilever beam when it is in undamaged and, respectively, in a damaged state.
In order to precisely evaluate the severity of different damage depths, we use a theoretical estimation model, developed in paper [17] for calculating the severity of the crack when it is located exactly at the fixed end. The method contains multiple FEM static simulations, for depicting the deflection of the beam in a damaged and undamaged state. By plotting the obtained values with a linear regression curve, the theoretical defection is obtained, as shown in paper [17]. The severity values used for training the network are presented in table 1.

Table 1. Severity values involved in the training process

Crack depth *a/h* [-]	Severity [-]	Crack depth *a/h* [-]	Severity [-]	Crack depth *a/h* [-]	Severity [-]
0.1	0.000866543	0.32	0.009516999	0.56	0.041025088
0.12	0.001191134	0.36	0.012434481	0.6	0.051452517
0.16	0.002140983	0.4	0.016029835	0.64	0.066210046
0.2	0.003345971	0.44	0.020443798	0.68	0.083740071
0.24	0.005123933	0.48	0.026224372	0.72	0.108484839
0.28	0.007104848	0.52	0.032690233	-	-

The training data for the location of the crack is calculated using relation (3), for all combinations of locations x along the beam, with a step of 10 mm starting from the left end. Training consists of the RFS values for the first 8 (eight) weak-axis vibration modes for the input data, and target pairs of data that reflect the outcome of the problem, meaning the position and severity of the crack. We show examples of the introduced input data for the first seven damage locations and smallest severity in figure 1.

The information consists of RFS values obtained, as described earlier, for 17 damage severities using 100 crack locations and 8 modes of transversal vibration, resulting in 8 rows and 1700 columns of data.

The output data consists of 2 pairs of values, one for location and one for severity, meaning the 100 calculated locations of the transversal crack and the 17 severity values corresponding for each set of values given in the input data, as shown in figure 2. The values from figure 1 regarding the input data correspond to the output data in figure 2.

8x1700 double

	1	2	3	4	5	6	7
1	8.6654e-04	8.4285e-04	8.1949e-04	7.9645e-04	7.7375e-04	7.5137e-04	7.2933e-04
2	8.6654e-04	7.8567e-04	7.0876e-04	6.3583e-04	5.6688e-04	5.0194e-04	4.4102e-04
3	8.6654e-04	7.3586e-04	6.1588e-04	5.0668e-04	4.0831e-04	3.2084e-04	2.4428e-04
4	8.6654e-04	6.8646e-04	5.2744e-04	3.8967e-04	2.7329e-04	1.7829e-04	1.0440e-04
5	8.6654e-04	6.3888e-04	4.4611e-04	2.8862e-04	1.6646e-04	7.9072e-05	2.4951e-05
6	8.6654e-04	5.9301e-04	3.7174e-04	2.0327e-04	8.7102e-05	2.0891e-05	1.8386e-09
7	8.6654e-04	5.4887e-04	3.0437e-04	1.3352e-04	3.4215e-05	1.9610e-07	2.0611e-05
8	8.6654e-04	5.0646e-04	2.4398e-04	7.9071e-05	6.1456e-06	1.1795e-05	7.4905e-05

Figure 1. The input data generated with relation (3)

2x1700 double

	1	2	3	4	5	6	7
1	0.0100	0.0200	0.0300	0.0400	0.0500	0.0600	0.0700
2	8.6654e-04	8.6654e-04	8.6654e-04	8.6654e-04	8.6654e-04	8.6654e-04	8.6654e-04

Figure 2. The target data

3. THE ANN MODEL

The feedforward backpropagation neural network is set using a hidden layer with 30 neurons and one processing layer that are separated. Multi-layer networks use a diversity of learning methods, the most popular being back-propagation. Here, the output values are compared with the correct answer to adjust the weights and biases throughout the network, this way the value of the error function is in tune, as shown in figure 3.

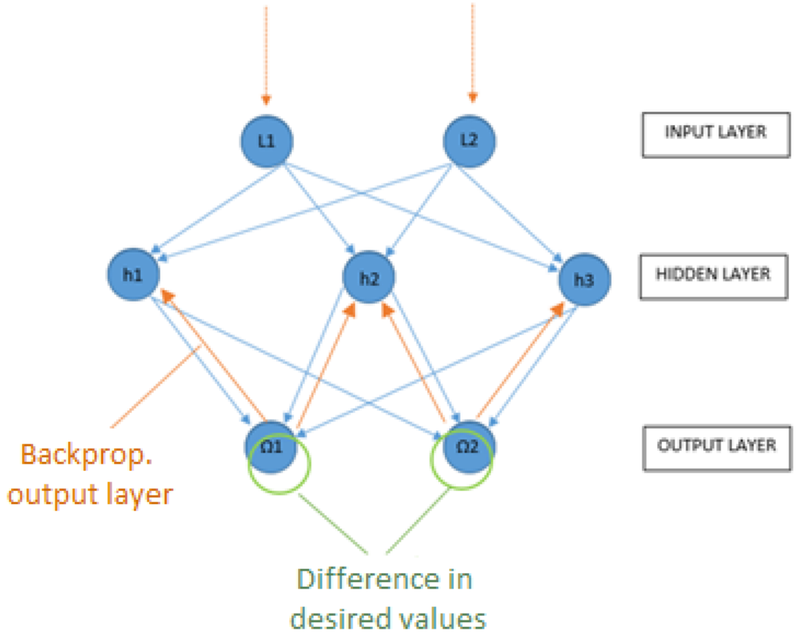

Figure 3. General schematic of a feedforward backpropagation neural network

Due to its good convergence and fast learning capability, the MATLAB training function TRAINBR is used. TRAINBR is a training function based on Levenberg-Marquart optimization, also known as Bayesian Regularisation, shown in figure 4. The function updates the weight and bias values by minimizing a combination of squared errors and weights to determine the correct combination to produce a network that fits the training data.

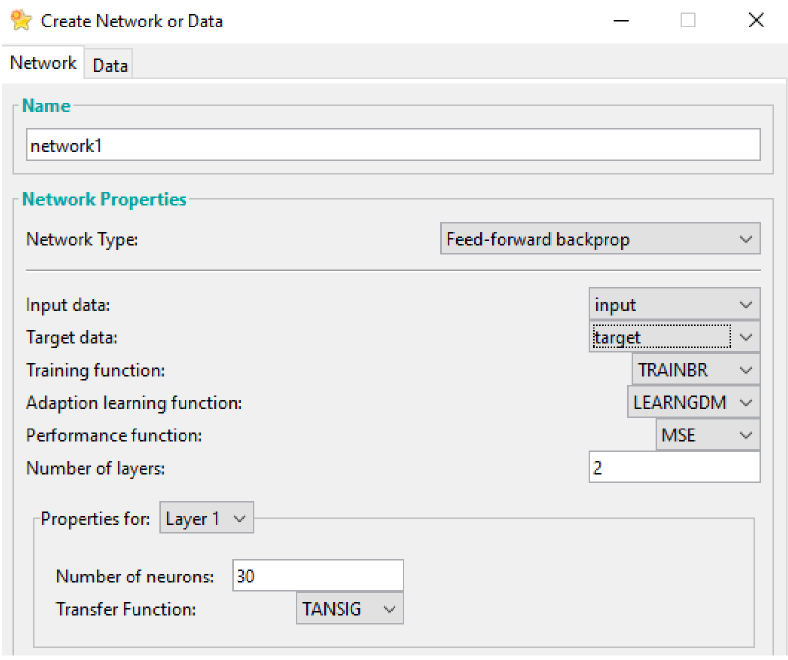

Figure 4. Neural network setup

The validation stops are set to 6 (max_fail = six), as shown in figure 5, so that training can continue until an optimal combination of errors and weights is found.

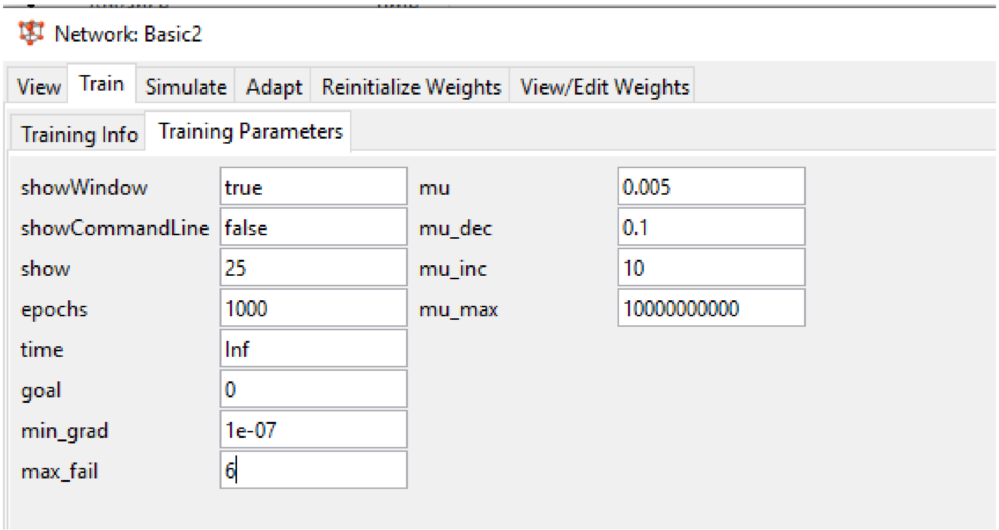

Figure 5. Training parameters

By increasing the number of layers and the number of neurons per layer, the model complexity is increased as it will endow the model the ability to fit more complex functions, but as the complexity of the model increases, it is easy to lead the neural network to overfit.

The training process is started and the workflow is shown in figure 6, where it is also possible to view the status and the validation of the data in the performance window.

The data used for developing the neural network is allocated as follows: 70% for training, 15 % for testing, and for validating 15%. As the network is trained by comparing the output data with the test data the first is adjusted based on the test data and once more with the values used for validation.

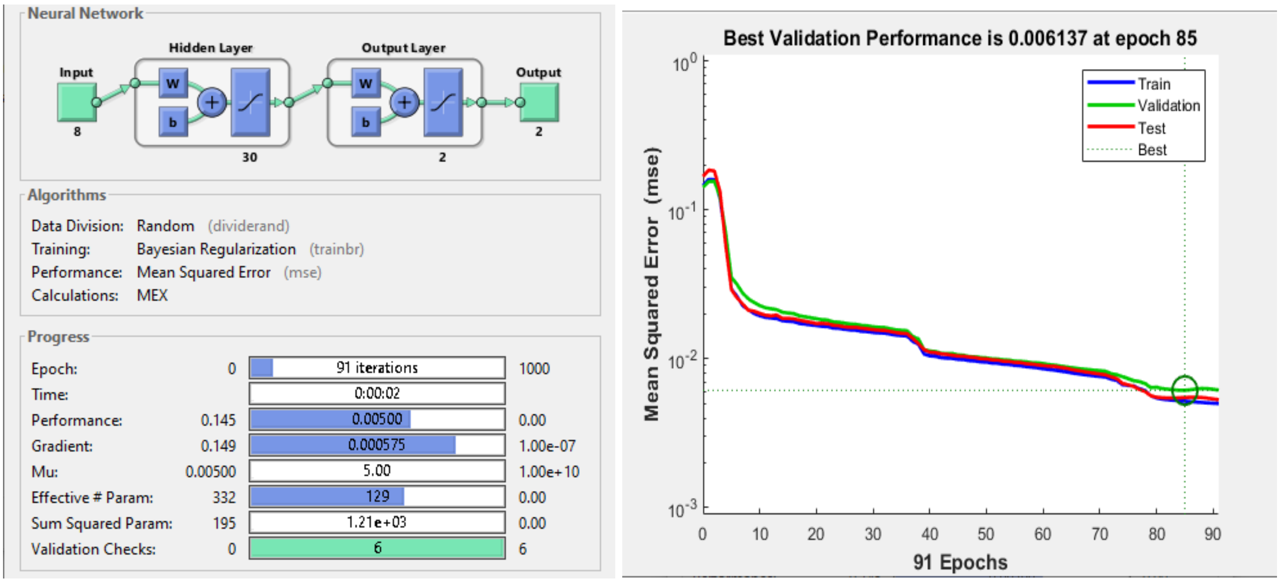

Figure 6. MATLAB window showing the training process

Also, in MATLAB the regression curves with the fitting of the training process, validation, and test data can be seen, as presented in Figure 7.

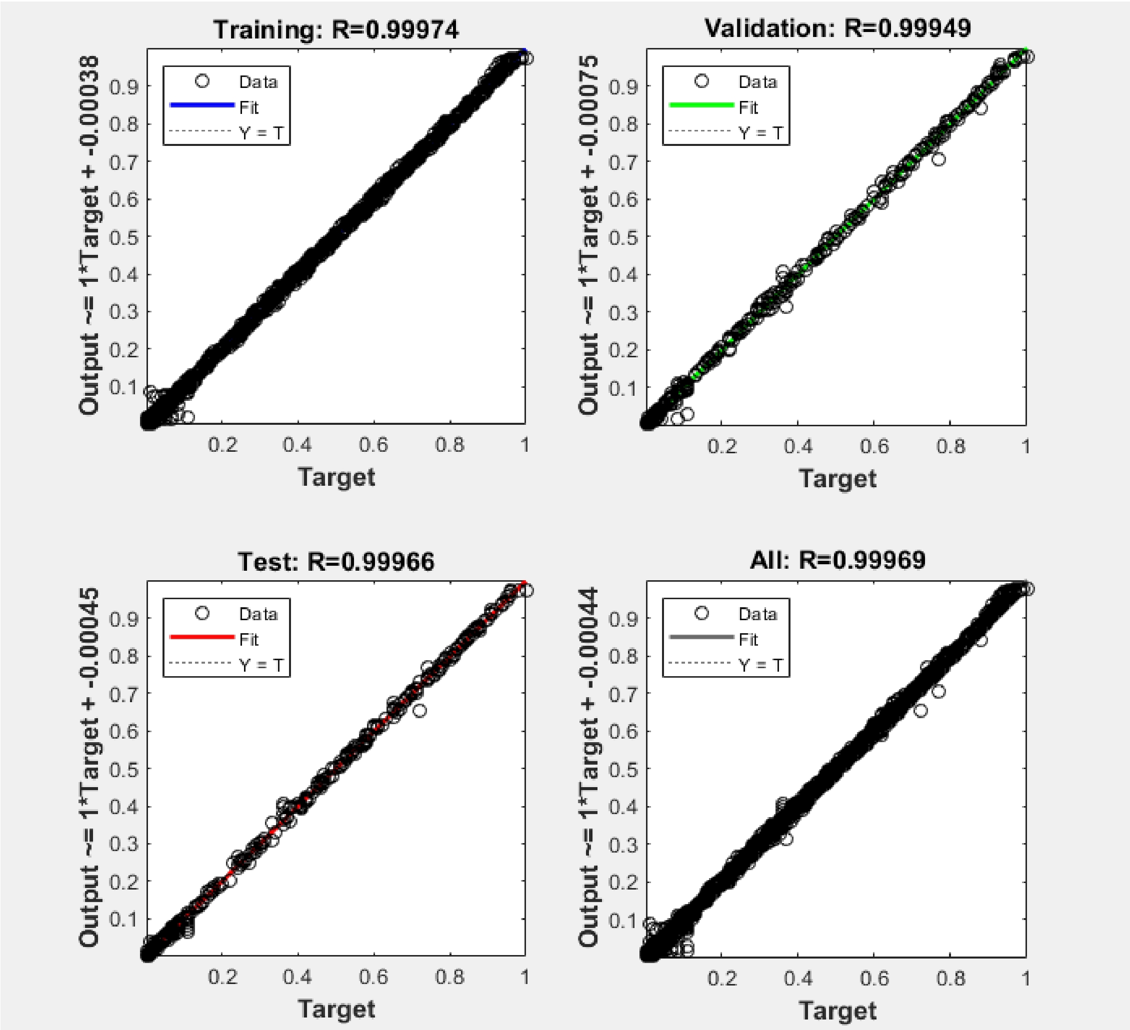

Figure 7. The regression curves with the fitting of the training process, validation and test data

4. RESULTS AND DISCUSSIONS

The precision of detecting the position and severity of transversal cracks present in cantilever beams by using the developed neural network is assessed by performing modal simulations in the ANSYS software for a cantilever beam both in a damaged and undamaged state. The cantilever affected by a transversal crack of different depth *a* and position *x* is presented in figure 8. Simulations are performed for different damage scenarios and from the obtained natural frequencies the RFS values are depicted using relation (3) for the first eight weak-axis bending vibration modes. The FEM RFS for all the damage scenarios are introduced as measured data into the neural network and the position and severity of the transversal crack are depicted.

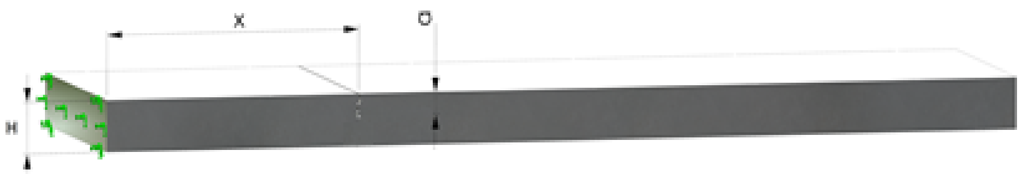

Figure 8. FEM model of the cantilever beam with a transversal crack

After we obtain the crack evaluation from the artificial neural network, the outcome is compared in table 2 for all cases considered in this study.

One can observe that the crack localization is in reasonable limits, the error being at maximum 1.28%, while the severity is found with a maximum error of 8%.

Table 2. Obtained errors using the developed neural network

Known position	Known crack depth	Severity	Neural Network prediction		Position error	Severity error
			Crack position	Severity		
100	1	0.003345	100.6	0.0075	0.96%	0%
150	1		159.2	0.0077	0.92%	0%
400	1		400.7	0.0075	0.07%	0%
75	1		80.1	0.064	0.91%	6%
133	1		131.4	0.072	0.16%	7%
613	1		618.2	0.086	0.52%	8%
550	1		560.9	0.071	1.09%	7%
100	1.5	0.00951	104.9	0.01	0.94%	1%
150	1.5		158.8	0.0099	0.88%	1%
400	1.5		395.6	0.0097	0.44%	1%
75	1.5		79.4	0.0085	0.94%	1%
133	1.5		140.8	0.0099	0.78%	1%
613	1.5		620	0.0101	0.70%	1%
550	1.5		558.2	0.0084	0.82%	1%
100	2	0.01603	101	0.0138	1.00%	1%
150	2		157.3	0.0127	0.73%	1%
400	2		387.2	0.064	1.28%	6%
75	2		78.8	0.0122	0.98%	1%
133	2		140.6	0.013	0.76%	1%
613	2		619.2	0.015	0.62%	1%
550	2		554	0.0132	0.40%	1%

3. CONCLUSION

In this article, a feedforward backpropagation neural network was implemented to perform damage detection in cantilever beams.

The first part presented in this work allowed to prove that the method using the RFS is reliable and straightforward for generating the training data.

After analyzing the obtained differences, it results that the largest error achieved for predicting the location of the crack is 6%, which means that the method used could offer reliable data for evaluating the location of transversal cracks. On the other hand, the error for predicting the severity of the damage is larger, between 2 - 31%, this is caused by the known fact that when a crack is located on an inflection point, it causes a very small frequency drop, making it harder to evaluate the damage severity. This issue could be overcome by training a more complex neural network with several hidden layers and a larger number of neurons.

By evaluating the performance of a basic neural network that is trained with precise calculated data using only one layer of neurons, we can conclude that the method used gives reliable results for detecting transversal cracks in beam-like structures.

Future developments are planned with the upscaling of this study by combining data from different types of neural networks and different damage types in order to have a better assessment of the application potential.

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