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PREDICTION OF FATIGUE CRACKS IN BEAMS USING ARTIFICIAL NEURAL NETWORKS

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Abstract: In their functioning time, most engineering structures are subjected to cyclic loading which can lead to the development of fatigue cracks that can propagate in time until the structure fails. Fatigue cracks in metals usually start from the surface of a structure, where the damage initiates as shear cracks. In the current paper, we demonstrate the possibility of evaluating two transverse cracks present in a steel cantilever beam by applying an intelligent algorithm with the help of MatLab software. The research demonstrates the possibility of detecting and locating the damages by employing the natural frequencies of the structure.

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

INTRODUCTION

Structural failure is often caused by material fatigue, which can occur not only after a long operation period but also at the beginning of functioning caused by fabrication errors [1]. Usually, fatigue cracks occur on the surface of the structure, are more than one and if not detected in the incipient state, they can propagate, leading to structural failure [2]. To ensure the safe operation of structures, it is important to develop reliable methods for detecting damages in the initial state. Vibration-based methods, relying on the changes in the natural frequency of the evaluated structure have proven to be reliable for detecting and evaluating damages, even in the early stage [3]. Furthermore, by coupling Artificial Neural Networks (ANN) with vibration-based methods, more advanced and precise structural evaluation techniques can be produced [4]. ANN methods for damage identification and evaluation have been developed by many researchers [5, 6], but few studies deal with the possibility of detecting two cracks as well as establishing the position and the surface on which they are located. In paper [7] the authors apply the natural frequencies for training a feed-forward backpropagation artificial neural network for detecting, locating, and evaluating of multiple cracks in a cantilever beam of 300 mm length, obtaining an error smaller than 5%. The predictions of multicracks by using an artificial neural network in shaft geometries are presented in [8], and the predictions are verified by using FEM and experimental analysis. In the current research, we aim to prove the accuracy of detecting and locating two cracks present in cantilever beams using an ANN method developed in MatLab by using as training data the results obtained from FEM modal simulations. By using the phenomenon of interference when the cracks are close to each other [9], we demonstrate that the model is also capable of determining the surface on which the cracks occur.

1. GENERATING THE TRAINING DATA

The analyzed structure is a steel cantilever beam which is generated with the help of the Ansys design modeler, having its main dimensions length L=1 m, width B=0.05 m, and thickness H=0.005 m. The material is Structural Steel chosen from the Ansys library. Cantilever steel beams have a wide range of applications and are used in engineering products as fundamental structural elements, they can be affected by cyclic loading during the functioning time, thus the possibility of multicrack occurrence can be very high.

Modal studies are performed for determining the first six weak-axis natural frequencies for specific damage scenarios. The transverse breathing cracks are modeled by removing material with a width of 0.04 mm and 1 mm depth. The beam is fixed on the left end and a fine mesh of hexahedral elements of 2 mm maximum size is applied. The modal simulations are run, and the first six natural frequencies are recorded. The damage configuration is presented in figure 1.

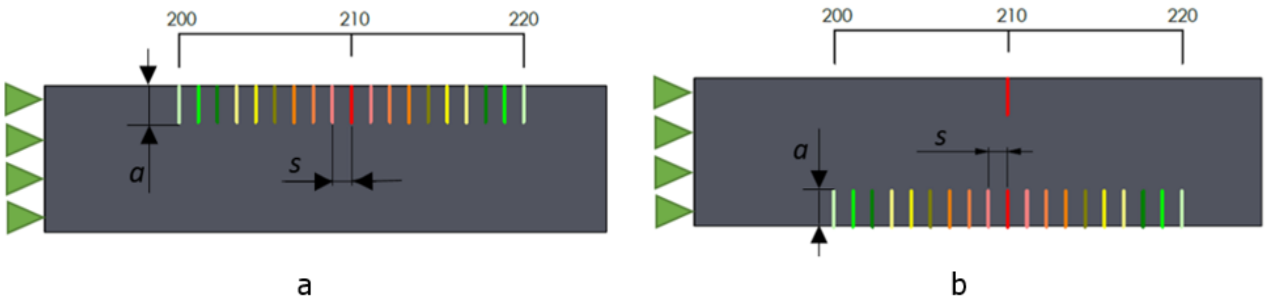

Figure 1: The analyzed structure; a) two cracks on the same face, b) cracks on opposite faces

The location of the first crack x_1 is at 210 mm and the second crack position x_2 is shifted iteratively with a step of s=1 mm relative to the first, in the interval of 200-220 mm.
After the modal simulations are performed, the natural frequency values are plotted and presented in figure 3.

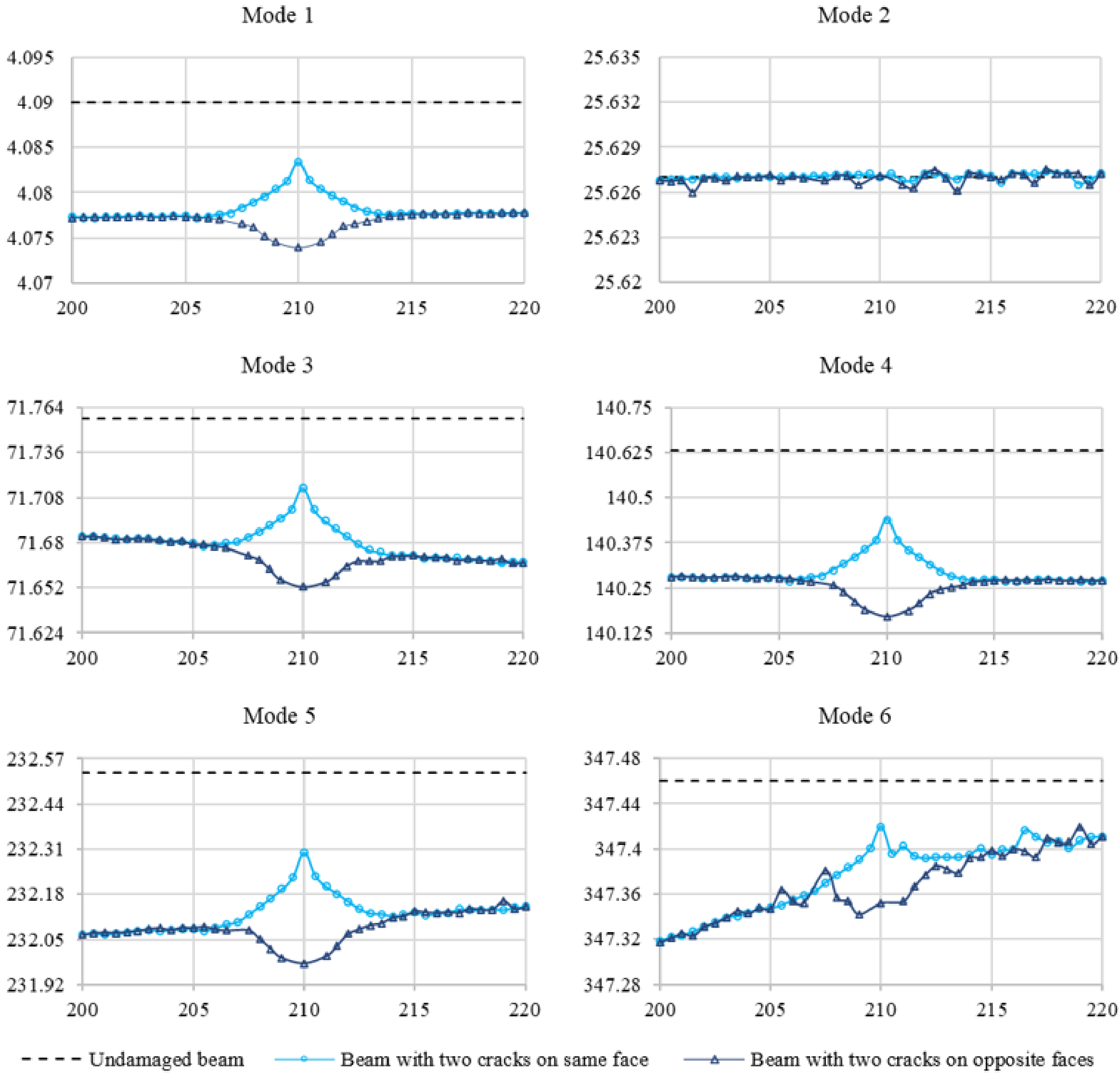

Figure 2: Obtained natural frequencies from FEM simulations

From the plotted results, one can observe that in a narrow location, where the cracks are close to each other, the superposition principle does not apply because the crack's effects interfere. In the case where the cracks are on the same face, the frequency increases, and in the cases where the two cracks are on opposite faces, the effect is the opposite, and the natural frequency values decrease.
The results presented in figure 2, i.e., the first six natural frequency values are used for training the ANN mode. Furthermore, for testing the developed intelligent model we have performed modal simulations for intermediate crack positions, with a step of s=0.5 mm.

2. DEVELOPMENT OF THE ARTIFICIAL NEURAL NETWORK

The purpose of automatic learning algorithms is to allow computing systems to make decisions or make certain forecasts. For this, there is a training stage, which involves entering a volume of data to adjust the algorithm's parameters, so that the desired task is performed with high accuracy. Artificial neural networks represent advanced learning techniques that can also be used in the assessment of structural integrity. In the current paper, we developed a Feed Forward Backpropagation neural network by using MatLab software for detecting and evaluating two cracks present in a steel cantilever beam. For training the ANN we use the first 6 transverse vibration natural frequencies of the structure which are generated through FEM simulations with the help of the ANSYS software.

At this moment there is a multitude of neural architectures used in various machine learning tasks. Feed Forward Networks are a set of neural networks in which to acquire the signature of a sample, the information must always be propagated to the upper layers of the network's hierarchical structure. This type of neural network is constructed by an input layer, a hidden layer, and an output layer. The functioning of an ANN assumes that each neuron in the current layer influences each neuron in the next layer. The obtained result is passed through an activation function, which decides, based on the required output, whether the information should be propagated or not. The information is propagated through the network and based on the neuron with the highest value in the output layer, it is checked whether the prediction is good or not. If the prediction is wrong, then based on the error the weights in the network are readjusted through the backpropagation algorithm.

We indicate as output the location of the two cracks and the surface on which the cracks are positioned for a limited zone, where the cracks interfere [9], resulting in three possible outputs: the position of the first crack in mm, the position of the second crack in mm, and the surface on which the cracks are located. For the third output, there are three possible outcomes, i.e., The ANN will output the value 1 when the cracks are on the same face, the value -1 when they are on opposite faces, and the value 0 when the output is outside the interference range and the natural frequencies are similar, regardless of the surface on which the crack resides. For the current research, the best results were obtained for a network containing two hidden layers, each having 10 neurons, according to relation 1, where N_h is the number of hidden neurons, N_s – number of samples (N_s=40), N_i – number of inputs and N_t number of target values. The network's architecture is presented in figure 3 [10].

$$N_h = \frac{N_s - N_i - N_t}{\sqrt{N_i + N_t}} \tag{1}$$

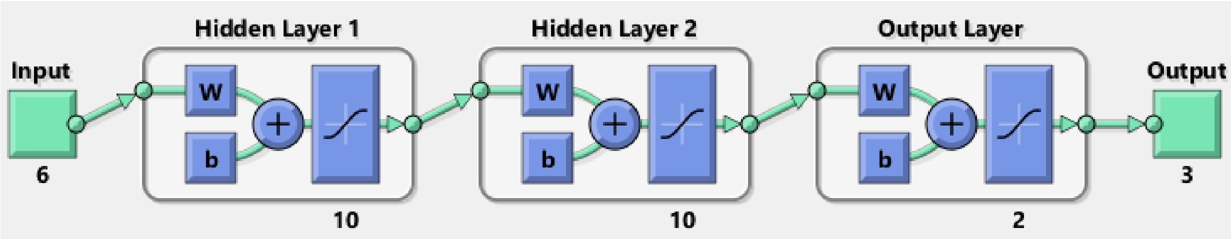

Figure 3: Network architecture

For training the network we employ the trainbr function, which applies the Bayesian Regularization algorithm for avoiding overfitting.

After the ANN is trained MatLab can automatically plot the performance and regression curves, offering the possibility to evaluate the performance of the network. The plotted curves are shown in figure 4.

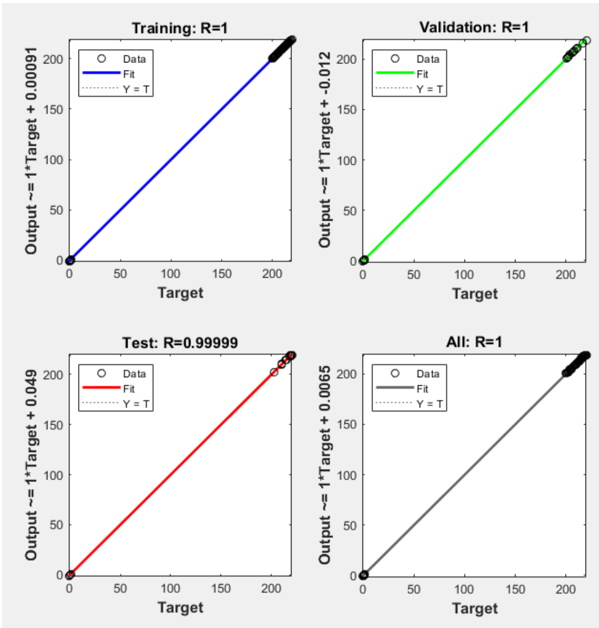

Figure 4: Trained ANN performance

The regression curves show the output error obtained for the training stage with a blue line, validation phase with green line, and with red line the testing phase. The plotted graph show that the developed ANN is very accurate [10].

3. RESULTS AND DISCUSSIONS

After the ANN model is trained, to test its accuracy we employ the intermediate values for the crack scenarios defined in the previous chapter from the FEM simulations. After the test values are introduced in the network the predictions are provided and the results consisting of the two cracks positions x_1 and x_2 and the surface on which the cracks are located are shown in table 1.

Table1. Results obtained

Expected values			Predicted values			Expected values			Predicted values		
Face	$\mathbf{x_1}$	$\mathbf{x_2}$	**Face**	$\mathbf{x_1}$	$\mathbf{x_2}$	**Face**	$\mathbf{x_1}$	$\mathbf{x_2}$	**Face**	$\mathbf{x_1}$	$\mathbf{x_2}$

0	210	200.5	0	210	200.6437	0	210	219.5	0	210	218.4525
0	210	202.5	0	210	202.1243	0	210	200.5	0	210	200.6243
0	210	203.5	0	210	203.4419	0	210	202.5	0	210	202.1827
0	210	204.5	0	210	204.5398	0	210	203.5	0	210	204.025
0	210	205.5	0	210	205.6423	0	210	204.5	0	210	204.496
0	210	206.5	0	210	206.4003	0	210	205.5	0	210	205.7285
1	210	208.5	1	210	208.6485	0	210	206.5	0	210	206.039
1	210	209.5	1	210	209.4833	-1	210	208.5	-1	210	208.7001
1	210	210.5	1	210	209.5737	-1	210	211.5	-1	210	211.5161
1	210	211.5	1	210	211.3955	0	210	213.5	0	210	213.9151
0	210	213.5	0	210	212.97	0	210	214.5	0	210	214.3803
0	210	214.5	0	210	214.5165	0	210	216.5	0	210	216.2027
0	210	216.5	0	210	216.4675	0	210	217.5	0	210	217.6852

4. CONCLUSIONS

In the current research an ANN model for determining the positions of two cracks and the surface on which the cracks are located is developed through the help of the MatLab software. The training data is obtained using the FEM software ANSYS by performing modal simulations for determining the natural frequencies of a steel cantilever beam having two cracks.

From the results shown, we conclude that the intelligent model very reliable for locating the two cracks, with a high precision and for the interference zone it can establish the face on which the crack's occur. The model could be furthermore trained for the whole beam's length.

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