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Damage detection in simply supported beams using machine learning

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Abstract. *The more our infrastructure is aging, the risk of structural failure is higher, making the detection of damage using modal parameters a very important factor that can be applied in structural health monitoring. The most desired way to assess the health of engineering structures during operation is to use non-destructive vibration-based methods. In the current paper, a modal approach using a machine learning technique by training a feedforward backpropagation neural network for detecting transverse damages in simple supported beam-like structures is presented. A method for analytical determination of the training data is used and the obtained dataset values are employed for training an ANN that will be used to locate and evaluate the severity of transverse cracks in cantilever beams. The output from the ANN model is compared by plotting the calculated error for each case in comparison with FEM results using the SolidWorks simulation software.*

Keywords: *damage detection, machine learning, natural frequency, structural health monitoring*

1. Introduction

Engineering systems rely on effective damage detection techniques to ensure their safe operation over time. In case of damage occurrence, the dynamic and static behavior of structures, such as natural frequencies, modal shape, stiffness, and the degree of damping are affected [1]. The development of the modern aeronautical industry, mechanical systems, and the civil industry generated a new trend for a more rigorous analysis of structures. The recent orientation in the development of damage detection methods in structures is characterized by using high-performance computers that engage numerical methods, including the finite element method, comparing the results with experimental data, and with different analytical methods [2].

The use of modal parameters in early-stage damage detection techniques has gained much attention in the last decades, as of the promising results obtained by several research [3]. Paper [4] presents a method to detect the location and severity of transverse cracks in a simply supported beam that uses the first three natural frequencies, and the method is validated through FEM, analytical and experimental data. The authors in paper [5] illustrate a damage detection method, capable of locating a crack in beams with any boundary conditions by considering the changes of the modal curvature. Because the computation performance of computers has increased, new methods that rely on intelligent algorithms that can handle large amounts of data, mainly by using modal parameters, have been developed for the detection of damages. In the paper [6], the authors present a method for detecting damages in cantilever beams by using artificial neural networks (ANN) that are trained using the mode shape displacements. In article [7], the authors successfully developed an ANN algorithm for detecting the presence of one or multiple cracks in structures using a metaheuristic training algorithm, and paper [8] demonstrates the possibility of locating and evaluating cracks by using ANN's even when the boundary conditions are uncertain. In the current research, we extend the method presented in [8] for developing an ANN using the MATLAB software that is capable of detecting, locating, and evaluating breathing transverse cracks, present along the whole width, in simply supported steel beams by employing the Relative Frequency Shifts (RFS).

2. Analytic approach

Damages decrease the overall capacity of a structure to retain energy, thus impacting its dynamic parameters. By using the RFS values caused by the occurrence of a crack, depending on its location and severity, a database of damage signatures can be easily created by analytical approaches.

In the current research, we utilize the methods shown in paper [9] to calculate the RFS values, for the first six weak-axis vibration modes, by considering the severity $\gamma(a)$ for a crack of depth a and the squared normalized modal curvature $\left[\overline{\phi''}(x)\right]^2$ for a known position x along the beam [10]. The RFS values for any crack severity can be found with the following relation (1) [10]:

$$\Delta_{fi-D} = \gamma(a) \cdot \left[\overline{\phi''}(x)\right]^2 \tag{1}$$

By using the stiffness decrease method presented in paper [11], the severity for a certain crack depth can be calculated from the beam's deflection both in undamaged δ_u and damaged state δ_d, with the following relation (2):

$$\gamma(a) = \frac{\sqrt{\delta_D} - \sqrt{\delta_U}}{\sqrt{\delta_D}} \tag{2}$$

The normalized modal curvature is determined using eq. (3):

$$\varphi''(x) = -\sin(\alpha x) \tag{3}$$

In the present paper, the training dataset represents the RFS values calculated for the first six natural frequencies of the damaged beam, considering only the transverse vibration modes. The RFS values generated for training the ANN model are calculated using relations (1) to (3) for a transverse breathing crack that is present on a simply supported steel beam with its considered dimensions presented in mm in Figure 1.

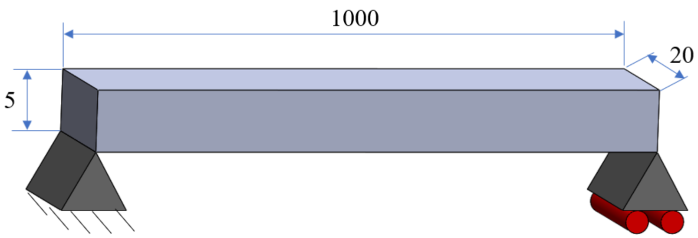

Figure 1. Main dimensions of the simply supported steel beam

The severity *γ(a)* of the transverse crack is considered for a crack depth *a* between $a = 0.1...0.28 \cdot H$, where *H* represents the beam's thickness as presented in Table 1. The ANN is trained to output the percent of the damage depth.

Table 1. Severity values used for calculating the RFS's

Severity *γ(a)* [-]	Crack depth [mm]	Crack depth [%]
0.00086654	0.5	10.00%
0.00119113	0.6	12.00%
0.00214098	0.8	16.00%
0.00334597	1	20.00%
0.00512393	1.2	24.00%
0.00710485	1.4	28.00%

The RFS's are calculated, for the six vibration modes, iteratively for all defined severity values considering several positions of the crack along the beam, starting from the left end with a step of 10 mm, thus obtaining 600 possible damage scenarios. The calculated RFS's for the six vibration modes are plotted and presented in Figure 2.

Because of the nature of the boundary conditions, as can be observed from Figure 2, the modal curvature will be symmetric relative to the axis of the beam, therefore the developed neural network will always output two possible damage locations, from which one location is the mirrored value of the true one.

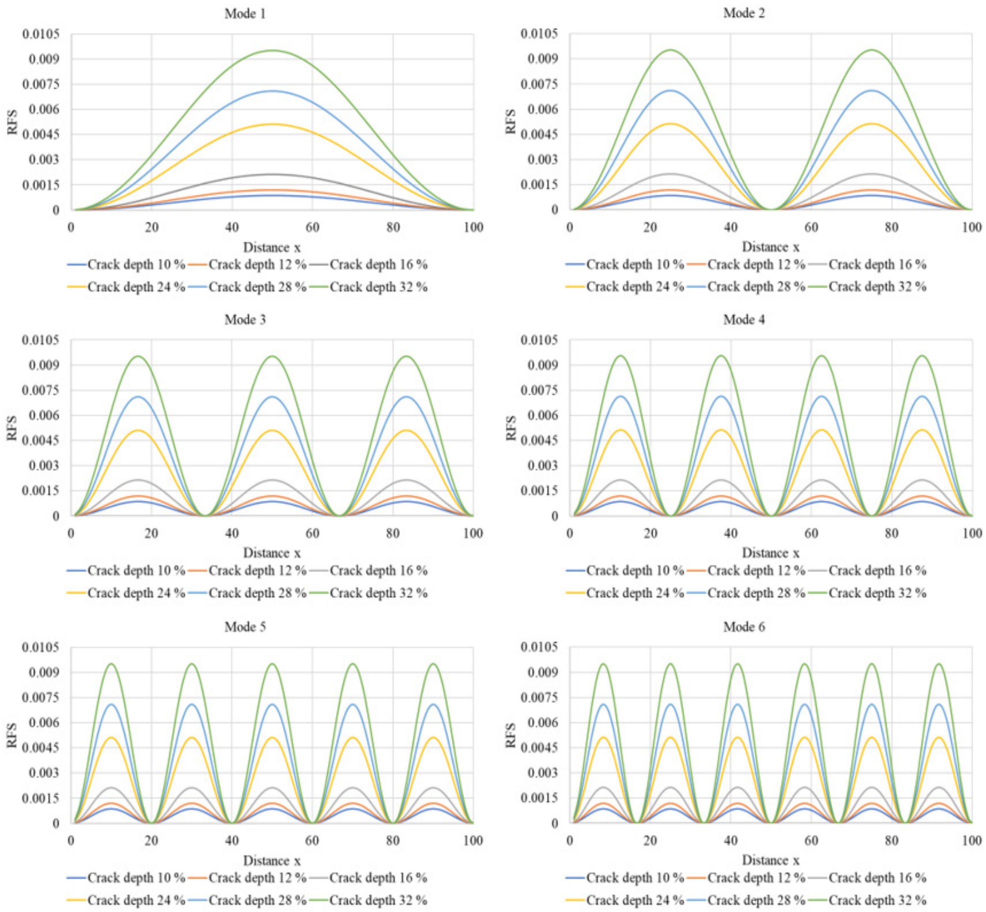

Figure 2. Plotted RFS curves for the defined damage scenarios

3. Training the ANN model

After the RFS values are calculated for the first six modes of transverse vibration, they are imported into a MATLAB database and used to train a Feedforward Backpropagation Neural Network with six inputs. As the target value for the ANN we introduce the position of the crack and the corresponding severity value which is equated with the percentage depth of the transverse crack. For the given training and output data we have considered a network architecture of one hidden layer with the number of neurons $N_h=25$ according to relation (4):

$$N_h = \frac{N_s}{\alpha \cdot (N_i + N_t)} \tag{4}$$

where:

N_s – number of scenarios; N_s=600; α – coefficient dependent of the ANN's complexity; α=3; N_i – number of inputs; N_i=8; N_t – number of targets; N_t=2.

The network is trained by applying the Bayesian Regularization algorithm [13] and considering 70% of the data for training, 15% for validation and 15% for testing. The architecture of the ANN is presented in Figure 3, where the input layer contains 6 neurons representing the 6 RFS values, the hidden layers contain 25 neurons according to Eq. (4) and the output layers contain 2 neurons for predicting two parameters i.e., crack location and depth. The terms *w* and *b* represent the considered weights and bias values used in each iteration for defining the activation function of the network [14].

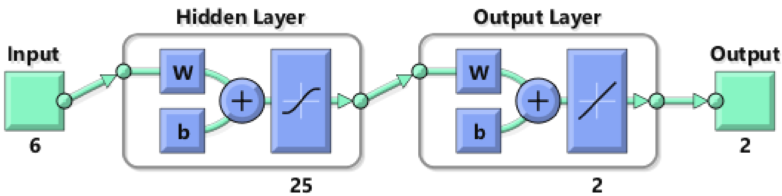

Figure 3. Developed ANN architecture

The performance of the ANN is evaluated based on the 15% test data directly from the MATLAB interface by plotting the regression curves, as shown in Figure 4.

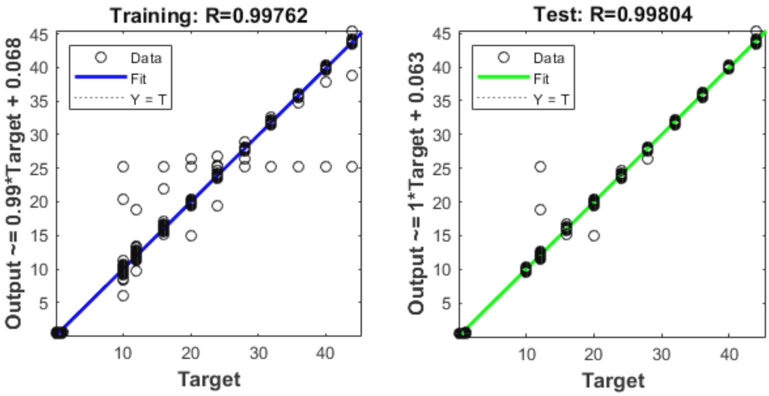

Figure 4. ANN plotted performance

4. Evaluating the accuracy of the ANN model

To test the accuracy of the ANN developed using MATLAB, we performed FEM modal simulations considering several damage scenarios to extract the natural frequency values for the simply supported steel beam of a constant section, both in an undamaged and damaged state, with the dimensions presented in Figure 1 and physical-mechanical properties of the Plain carbon steel material chosen from the SolidWorks library presented in Table 2.

Table 2. Physical-mechanical properties of the material

Physical-mechanical properties of the material					
Density [kg/m3]	Young modulus [N/m2]	Poisson criterion [-]	Tensile strength [MPa]	Yield strength [MPa]	Elong. [%]
7800	$2 \cdot 10^{11}$	0.3	470-630	355	20

The beam and crack geometry were generated also using SolidWorks. The crack is generated by removing material, with its width being defined as a maximum of 0.04 mm, and its location as the distance from the left end of the beam to the damage. Fine meshing was calculated for all cases, applying elements with a maximum edge size of 3 mm. After meshing, the healthy beam consists of 44587 elements and 241639 nodes. For the damaged beam, due to the crack, a larger number of elements is required. The simulation configuration as well as the vibration analysis is shown in Figure 5 for the case where a 1 mm crack is present at position x=250 mm. To achieve the required boundary conditions for the simply supported beam, we have considered the bottom edge of the left face as fixed, allowing only the rotation along its transverse axis (axis y) and for the right face of the beam we have constrained the bottom edge by fixing the translation along the y and z axis, allowing only the rotation along the y axis and translation along the x axis.

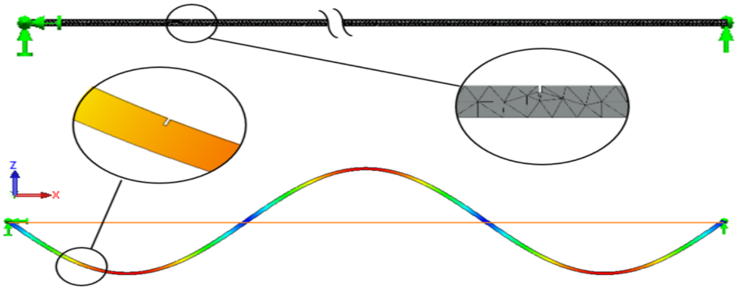

Figure 5. FEM frequency simulation for the simply supported beam

After the results are acquired, the RFS's are calculated and introduced as test data into the developed ANN. The damage scenarios as well as the prediction errors obtained from the neural network are presented in Table 3. Because of the symmetry of the mode shapes caused by the boundary conditions, FEM tests were performed for damage scenarios considering the crack position in the interval from 0 to 500 mm.

Table 3. Defined damage scenarios and obtained results

Defined simulation values			Predicted values			
Damage scen.	Crack position [mm]	Crack depth [%]	Crack Position [mm]	Position error [%]	Crack depth [%]	Severity error [%]
1	50	12	43.00	0.70%	12.33	0.33%
2	150	12	168.2	1.82%	14.36	2.36%
3	365	12	350.6	1.44%	13.85	1.85%
4	458	12	462.0	0.40%	12.35	0.35%
5	50	20	56.50	0.65%	20.00	0.00%
6	150	20	143.4	0.66%	22.71	2.71%
7	365	20	377.4	1.24%	23.54	3.54%
8	458	20	470.2	1.22%	23.095	3.10%
9	50	28	50.10	0.01%	28.00	0.00%
10	150	28	150.6	0.06%	28.38	0.38%
11	365	28	364.2	0.08%	29.10	1.10%
12	458	28	458.1	0.01%	29.27	1.27%

5. Conclusion

In the current research, we have tested the accuracy of a Feedforward Back-propagation ANN to locate and evaluate transverse cracks occurring in steel simply supported beams. The study demonstrates that by using the RFS determined analytically with the presented methods, one can train precise intelligent algorithms for damage identification and evaluation. The accuracy of the presented ANN can be furtherly enhanced by dividing the training data into sectors [8].

References

[1] Choi S., Park S., Stubbs N., Nondestructive damage detection in structures using changes in compliance, *International Journal of Solids and Structures*, 2005, 42(15), 2005, pp. 4494-4513.

[2] Wahab M.A., De Roeck G., Damage detection in bridges using modal curvatures: Application to a real damage scenario, *Journal of Sound and Vibration*, 226, 1999, pp. 217-235.

[3] Kenley R.M., Dodds C.J., *West Sole we platform: detection of damage by structural* response *measurements,* 12th Annual Offshore Tech. Conf., 1980, pp. 111–118.

[4] Sharma U., *Damage Detection in a Steel Beam using Vibration Response*, Youngstown State University, Aug., 2020.

[5] Pooya S.M.H., Massumi A., A novel and efficient method for damage detection in beam-like structures solely based on damaged structure data and using mode shape curvature estimation, *Applied Mathematical Modelling*, 91, 2021, pp. 670-694.

[6] Kumar G.S., Das S., Damage detection in a cantilever beam using noisy mode shapes with an application of artificial neural network-based improved mode shape curvature technique, *Asian Journal of Civil Engineering*, 22, 2021, pp.1671-1693.

[7] Tran-Ngoc H., Khatir S., Le-Xuan T., Tran-Viet H., De Roeck G., Bui-Tien T., Wahab M.A., Damage assessment in structures using artificial neural network working and a hybrid stochastic optimization, *Sci Rep*., 23:12(1):4958, 2022.

[8] Gillich N., Tufisi C., Sacarea C., Rusu C., Gillich G.R., Praisach Z.I., Ardeljan M., Beam Damage Assessment Using Natural Frequency Shift and Machine Learning, *Sensors,* 22, 1118, 2022.

[9] Gillich, G.R., Praisach, Z.I., Robust method to identify damages in beams based on frequency shift analysis, *Health Monit. Struct.Biol. Syst*., 2012, 8348, 83481D.

[10] Gillich N., Tufisi C., Vasile O., Gillich G.R., Statistical Method for Damage Severity and Frequency Drop Estimation for a Cracked Beam using Static Test Data, *Rom. J. Acoust. Vib.,* 16, 2019, pp. 47–51.

[11] Gillich G.R., Tufoi M., Korka Z.I., Stanciu E., Petrica A., The relations between deflection, stored energy, and natural frequencies, with application in damage detection, *Rom. J. Acoust. Vib.,* 13, 2016, pp. 87–93.

[12] Praisach Z.I., Gillich G.R., Protocsil C., Muntean F., *Evaluation of crack depth in beams for known damage location based on vibration modes analysis*, Applied Mechanics and Materials, 430, 2013, pp. 90-94.

[13] https://www.mathworks.com/help/deeplearning/ref/trainbr.html;jsessionid=b6ad10a78b987242c7c285ce1596 – accesed 12.10.2022.

[14] Fauselt L., *Fundamentals of Neural Networks, Architectures, algorithms and applications*, Prentice-Hall, Inc.Division of Simon and Schuster One Lake Street Upper Saddle River, NJ United States.

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