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DETECTION OF TRANSVERSE CRACKS IN PRISMATIC CANTILEVER BEAMS AFFECTED BY WEAK CLAMPING USING A MACHINE LEARNING METHOD

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ABSTRACT

Because our infrastructure is aging and approaching the end of its intended functioning time, the detection of damage or loosening of joints is a topic of high importance 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 that can offer a global evaluation of the structure's integrity. A comparison of using different modal data for training feedforward backpropagation neural networks for detecting transverse damages in beam-like structures that can also be affected by imperfect boundary conditions is presented in the current paper. The different RFS, RFS_{min}, and DLC training datasets are generated by applying an analytical method, previously developed by our research team, that uses a known relation, based on the modal curvature, severity estimation of the transverse crack, and the estimated severity for the weak clamping. The obtained dataset values are employed for training three feedforward backpropagation neural networks that will be used to locate transverse cracks in cantilever beams and detect if the structure is affected by weak clamping. The output from the three ANN models is compared by plotting the calculated error for each case.

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

1. INTRODUCTION

Different types of damages can occur in structures and can be caused by a multitude of factors, such as exceeding the expected operating demands, degradation caused by environmental conditions, material fatigue, loosening of joints due to shocks and excessive vibrations, and improper manufacturing conditions. For a structural monitoring method to be efficient, it is desired to detect invisible damage in the incipient state, preferably by non-invasive methods. Traditional non-destructive detection techniques present the disadvantage that they are limited to an accessible area and require having prior knowledge of the possible location of damage by considering the areas with the highest risk, which in most cases can be erroneous [1]. To increase the operational safety of equipment, installations, and structures, new methods have been developed to monitor structural integrity; these methods can be an integral part of the structure from the design phase or can be mounted retroactively, to assess the condition of the equipment [2].
Promising methods of structural assessment have been developed in recent decades that are based on the use of modal parameters of the structure. Although damage assessment using modal parameters is still under development, over time, many methods of evaluating the integrity of structures, by using the natural frequencies have proven to be reliable [3, 4, 5].
The fundamental starting point of vibration-based damage detection methods starts from the known fact that damages occurring in structures, significantly affect the stiffness and the energy dissipation properties of a system, which in turn will change its dynamic response [6].
The biggest challenge in using detection methods based on modal parameters is the use of a large amount of data, as well as certain disturbances that may occur during signal acquisition caused by environmental conditions and by the improper clamping of structural elements.
To address the shortcomings of current methods of vibro-diagnosis, new techniques have been developed over time, by using artificial intelligent networks which present promising results [7, 8].
In the current paper, we present a mathematical relation used for predicting the natural frequencies of beams affected by transverse breathing cracks and by improper boundary conditions developed in the paper

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[9]. By employing this algorithm, we can easily create different datasets, namely relative frequency shifts (RFS), normalized relative frequency shifts (RFS_{min}), and damage location indicators (DLC) that are later used for training six machine learning models, three models are trained for generating 3 outputs (transverse crack location, transverse crack severity and weak clamping severity if present) and the remaining 3 models are trained to detect only the position of the transverse crack also if the beam is affected by weak clamping.
To evaluate the quality of the developed computational intelligent methods used for damage identification, a set of FEM-generated tests are produced for different damage scenarios. The test natural frequencies are generated by employing the simulation software, ANSYS.

2. MATERIALS AND METHODS

The paper presents the use of a feedforward backpropagation neural network, which is developed in the MATLAB deep learning environment, to detect transverse cracks and also weak clamping in cantilever beams, by using different sets of generated training data.

2.1. Training dataset

The training datasets are generated by using a previously developed method [9] for predicting the natural frequencies for beam-like models affected by cracks, starting from Equations (1):

$$f_{i-D}(x,a) = f_{i-U}\left\{1-\gamma(a)\left[\bar{\phi}_i''(x)\right]^2\right\} \tag{1}$$

In Equation (1), the terms $\gamma(0,a)$ and $\bar{\phi}_i''(x)$ represent the crack severity and the modal curvature, respectively. The transverse crack severity is determined with the model presented in paper [10], using the following Equation (2):

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

In Equation (2), the terms $\delta_D(a)$ and δ_U represent the deflection of the beam with damage, respectively in an undamaged state.
The modal curvature caused by the crack, with a known position x, is given by Equation (3) [11]:

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

To generate the training data, for several scenarios of the damaged beam, the relative frequency shift (RFS) values are used, according to Equation (4) [12, 13]:

$$\Delta\bar{f}_i(x,a) = \frac{f_{i-U}-f_{i-D}(x,a)}{f_{i-U}} = \gamma(0,a)\cdot\left[\bar{\phi}_i''(x)\right]^2 \tag{4}$$

The model shown in equations (1-4) is valid for generating the training data set for the perfect boundary conditions.

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In paper [10] a model that uses the superposition principle is described and the resulting Equation (5) is developed for generating the RFS values for a beam that is affected both by a transverse crack and weak clamping, of known severities.

$$\Delta\bar{f}_{i-D}(0,a_1,x_2,a_2)=\gamma_1(a_1)+\gamma_2(a_2)\left[\bar{\phi}_i''(x_2)\right]^2 \tag{5}$$

where $\gamma_1(a_1)$ is the severity for the weak clamping and $\gamma_2(a_2)$ the severity of the transverse crack.

By using Equation (5), for the research presented in the current paper, we have generated the RFS values, which is the first training dataset used for the ANN models. The RFS values are generated for the first eight weak axis bending vibration modes for several damage scenarios, by considering transverse cracks located on several positions along the beam when the cantilevers clamping is considered to be both in perfect condition and also weak condition. The considered crack position for each set of values is considered starting from *x=2* mm and continuing to *x=998* mm with a step of *s=2*mm. The datasets are generated for a transverse crack depth of *a=1* mm, and for simulating the weak clamping cases a transverse crack at the fixed end of depth *a=1* mm is considered. For both cracks, the severity is calculated using Equation (4).

Furthermore, from the calculated RFS values, we generate a second type of dataset by reducing each value of the RFS series with the minimum value of the series for each damage position, as described in Equation (6):

$$RFS_{\min}=\Delta\bar{f}_{i-D}(0,a_1,x_2,a_2)-\min\Delta\bar{f}_{i-D} \tag{6}$$

In Tab. 1, we present a partial dataset series obtained for a damage scenario where the crack is positioned at x= 510 mm using Equation (5)

The third training dataset is also generated starting from the obtained RFS values by normalizing the dataset according to Equation (7):

$$DLC=\frac{\Delta\bar{f}_{i-D}(0,a_1,x_2,a_2)}{\max\Delta\bar{f}_{i-D}} \tag{7}$$

Table 1. Calculated training values for a cantilever with a crack depth 20% affected by a 10% weak clamping

Damage position x [mm]	Transverse crack severity	Weak clamping severity	Mode no.	Dataset type		
				RFS	RFS_{min}	DLC
510	0.003345971	0.000866543	1	0.001226	0.000341	0.473765
			2	0.002589	0.001703	1
			3	0.000885	0	0.342059
			4	0.002517	0.001632	0.972443
			5	0.000899	1.37E-05	0.347357
			6	0.00249	0.001605	0.961976
			7	0.000935	4.99E-05	0.361338

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			8	0.002448	0.001563	0.945801

The generated data is used for training six ANN models, two for each training dataset, resulting in three models for predicting 3 outputs (transverse crack location, transverse crack severity, and weak clamping severity if present), and the remaining 3 models are trained to detect only the position of the transverse crack also if the beam is affected by weak clamping.
The precision of the developed ANN models is evaluated by comparing the outputs obtained from the considered measured test data generated using the described FEM method.

2.2. Neural network models

The three generated datasets, i.e., RFS, RFS_{min}, and DLC are used for training the six ANN models by using the integrated Deep Learning module of the MatLab software. The training function used is Bayesian regularization, with the parameter sets presented in Fig. 1.

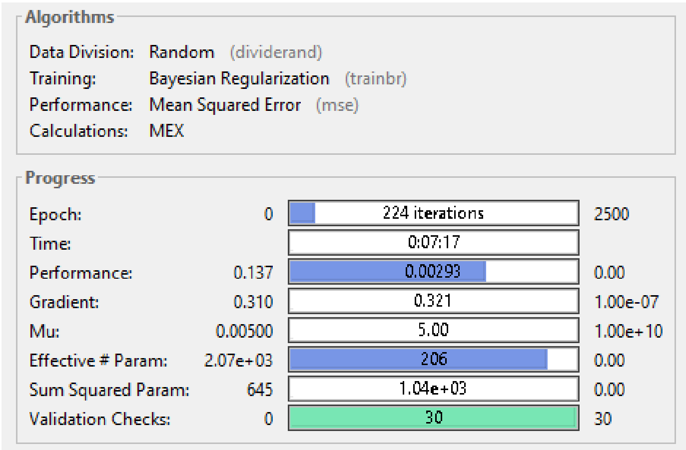

Figure 1. Neural network parameters

Each ANN model is denoted by the name of the dataset type and the number of outputs, resulting in six network names: RFS_1_output, RFS_3_output, RFS_{min}_1_output, RFS_{min}_3_output, DLC_1_output, DLC_3_output.
The Backpropagation algorithm used in the current study learns (finds) the optimal values of the interconnection weights between learning units in a multi-level network with a fixed number of learning units. It uses a gradient slope to try to minimize the error between the value of the network output and the value that is wanted to be obtained for that entry. The problem with learning in this network is to look for the optimal values of the weights in the large space of the hypotheses given by all learning units in the network. The algorithm is described here for a feed-forward network containing three hidden neuron layers, each containing 30 neurons, as shown in Fig.2.

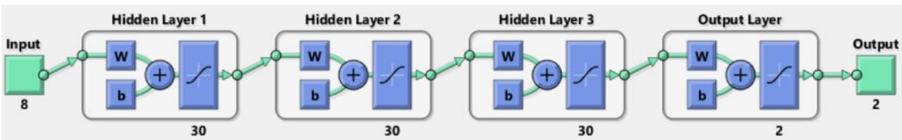

Figure 2. Developed network configuration

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2.3. Test data

The structure considered for the current research is a steel cantilever beam, presented in Fig. 3, with its main dimensions *L=1000* mm, *B=50* mm, and thickness *H=5mm*. The first step for generating the training data was to determine using FEM simulations the natural frequencies for the cantilever in an undamaged state.

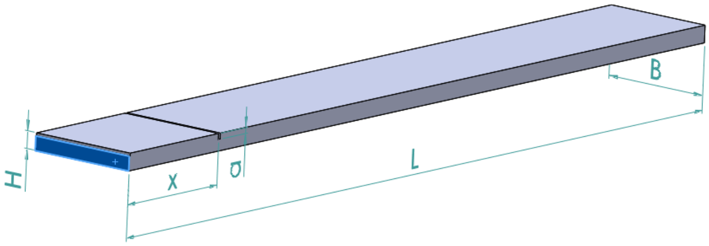

Figure 3. Cantilever beam affected by a transverse crack and weak clamping

The considered beam material, Structural Steel is applied from the ANSYS database with its physical-mechanical properties presented in Tab.2.

Table 2. Physical-mechanical properties of the cantilever beam

Yield strength [MPa]	Ultimate strength [MPa]	Mass density ρ [kg/mm^3]	Young modulus E [N/m^2]	Poisson ratio ν [-]
250	460	7850	$2 \cdot 10^{11}$	0.3

The test data consists of the first eight natural frequencies for the out-of-plain vibration modes, for the healthy beam and the beam with different damage scenarios containing both ideal clamping and non-ideal clamping. The 1 mm depth crack is applied by cutting the 3D model using a rectangle of $1 \cdot 0.04$ mm.
To simulate the weak clamping behaviour, we considered also a 1 mm depth cut on the fixed end of the beam, and by applying the boundary condition only on the remaining surface, as shown in Fig. 3. The severity value for the transverse crack as well as for the weak clamping is determined by performing static simulations under own weight for the beam in undamaged state, damaged state, and with weak clamping. The deflections obtained are used for calculating the severity values using Equation (2).
For the FEM test data, we have considered several damage scenarios, all crack depth (transverse crack and the crack simulating the weak clamping) are considered at depth *a=1* mm. The first 32 scenarios take into consideration the cases where the beam is perfectly clamped, and the only variable considered is the crack location, which is considered one by one at *x*= 56, 73, 81, 120, 165, 173, 210, 233, 255, 290, 325, 347, 360, 414, 466, 489, 516, 560, 563, 590, 660, 687, 690, 760, 796, 810, 820, 876, 896, 906, 946, 980. The next 32 damage scenarios take into consideration the same crack positions but also consider the weak-clamping scenario at the fixed end.

3. RESULTS AND DISCUSSION

The frequencies obtained from the FEM simulations for the undamaged and the 64 damaged beam cases are used for calculating the test data, meaning the RFS, $RFS_{min,}$ and DLC measured values, which are later introduced correspondingly in each of the 6 developed ANN models, depending on the data type.

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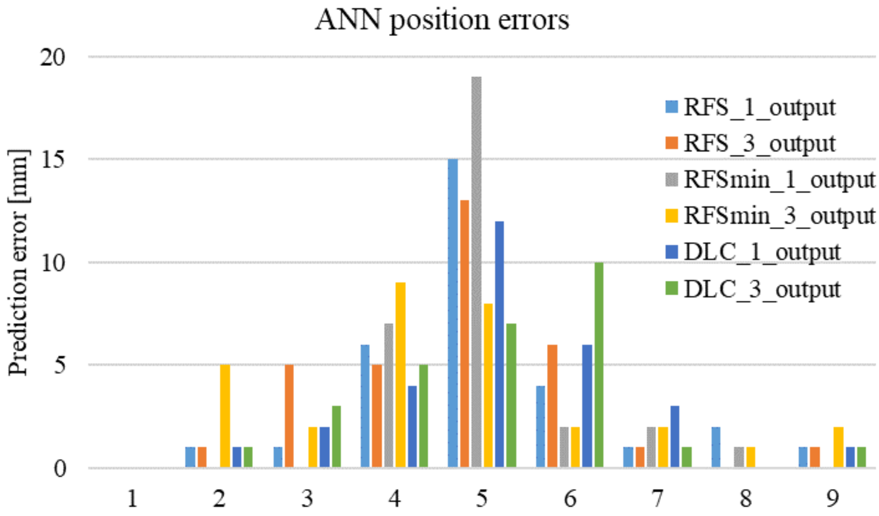

Figure 4. Graphical representation of the obtained errors for the 6 ANN models

The precision of predicting the position of a transverse crack present in cantilever beams by using the developed neural networks trained with different data types is assessed by comparing the prediction of each ANN model. The obtained errors are graphically plotted and illustrated in Fig. 4.

4. CONCLUSIONS

In the current study, six feedforward backpropagation neural networks are trained, using different datasets, for predicting the damage location for several scenarios, including the case where the cantilever is affected by weak clamping.
After analyzing the obtained differences, it results that the largest error achieved for predicting the location of the crack is 19 mm for the network that is trained using the RFSmin_1_output dataset. The largest prediction error is obtained for the scenario where the crack is closer to the free end, i.e., x=980 mm.
The ANN models with the best performance considering the crack position between x=2 mm and x=906 mm is the RFS_1_output and DLC_1_output models, the first being the more precise one.
The ANN models with the best performance considering the crack position starting from x=906 are DLC_3_output and RFS_{min}_3_output models.
From the obtained prediction values, we can conclude that the method used could offer reliable data for evaluating the location of transversal cracks, even if the crack is located near the free end of the beam where the frequency drop due to the presence of damage is very small. The described algorithm can easily be applied for generating any of the three presented dataset types for training ANN models.

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REFERENCES

[1] A. Khajeh, A. Y. Koma, Suitable Frequency of Structural Health Monitoring, 7th International Conference on Mechanical Engineering, Dhaka, Bangladesh, December 29-31 2007.
[2] J. R. Casas, J. J. Moughty, Bridge Damage Detection Based on Vibration Data: Past and New Developments, Frontiers in Built Environment 3, DOI:10.3389/fbuil.2017.00004, February 2017.
[3] Y. Yang, Y. Zhang, X. Tan, Review on Vibration-Based Structural Health Monitoring Techniques and Technical Codes, Symmetry 13(11):1998, DOI:10.3390/sym13111998, October 2021.
[4] C. P. Fritzen, Vibration-Based Structural Health Monitoring-Concepts, and Applications, Key Engineering Materials 293, DOI:10.4029/www.scientific.net/KEM.293-294.3, September 2005.
[5] A. Guechaichia, I. Trendafilova, A simple method for enhanced vibration-based structural health monitoring, Journal of Physics Conference Series 305(1):012073, DOI:10.1088/1742-6596/305/1/012073, July 2011.
[6] M. I. Friswell, Damage identification using inverse methods, Phil. Trans. R. Soc. A. 2007, 365 (1851), (2007), pp. 393-410.
[7] L. Nguyen-Ngoc, H. Tran-Ngoc, T. Bui-Tien, A. Mai-Duc, M. A. Wahab, H. X. Nguyen, G. De Roeck, Damage detection in structures using Particle Swarm Optimization combined with Artificial Neural Network 28(1), (2021), pp.1-12.
[8] N. Gillich, C. Tufisi, C. Sacarea, C. V. Rusu, G. R. Gillich, Z. I. Praisach, M. Ardeljan, Beam Damage Assessment Using Natural Frequency Shift and Machine Learning, Sensors 22(1118), 2022.
[9] G. R. Gillich, D. Frunzaverde, Z. I. Praisach, F. P. Minda, A new method to detect, locate and evaluate the severity of damages using natural frequencies, SISOM 2011 and Session of the Commission of Acoustics, Bucharest, May 25-26 2011.
[10] G. R. Gillich, N. M. Maia, M. A. Wahab, C. Tufisi, Z. I. Korka, N. Gillich, M. V. Pop, Damage Detection on a Beam with Multiple Cracks: A Simplified Method Based on Relative Frequency Shifts, Multidisciplinary Digital Publishing Institute, 2021.
[11] G. R. Gillich, C. Tufisi, M. A. Wahab, C. O. Hamat, Crack Assessment Based on the Use of Severity-Adjusted Modal Curvatures of the Healthy Beam. Proceedings of the 15th AVMS, Timisoara, 2019.
[12] G. R. Gillich, J. L. Ntakpe, M. A. Wahab, Z. I. Praisach, M. C. Mimis, Damage detection in multi-span beams based on the analysis of frequency changes. Journal of Physics: Conference Series 842(1):012033, May 2017.
[13] G. R. Gillich, C. Tufisi, Z. I. Korka, C.O. Hamat, N. Gillich, Automatic detection of L and T shaped cracks in semifinished casting products, IOP Conference Series: Materials Science and Engineering 393(1):012016, 2018.

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