Identification of stiffness reduction in beams using parameter-dependent frequency changes and neural networks

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Abstract

This paper presents the application of artificial neural networks (ANN) in the identification of damage in simple engineering structures. Three numerical examples are presented considering the identification of damage in a cantilever beam with and without an additional support. The application of ANNs expands the nondestructive damage identification method using an additional parameter introduced to the structure. The input vector of the ANNs consists of the dynamic responses of a structure with additional mass. The output vector is composed of the position of damage and, in the last example, the extent of damage.

Keywords: Artificial neural networks; Identification; Dynamics; FEM

1. Introduction

Nowadays the understanding of a structure's condition is considered to be more and more important. The state of the structure and its safety strongly depend on the degradation of the structural elements (beams, supports, etc.). New methods, able to identify the degradation of a structure, are expected by inspectors and structures maintainers. Some methods require the introduction of external perturbations to the structure. Nondestructive methods predict the location and the extent of damage in existing engineering structures. Publications on the identification of damage mainly present the approach that implies the knowledge of eigenfrequencies and eigenmodes of an undamaged structure. The damage is identified on the basis of the variations of dynamic parameters with respect to the initial values Doebiling et al. [1]. Friswell et al. [2] show the application of a model updating method to damage identification; they discuss in detail the application of incomplete measurement data. Some authors apply mode curvature or variation of positions of node lines; see Cawley at al. [3] and Friswell et al. [4].

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2. Identification method

The detection method, which provides the global assessment of damage, is usually not sensitive to the degree of the damage. In a paper by Dems et al. [5], to increase the accuracy of identification, an additional parameter is introduced, namely concentrated elastic or rigid support, an additional mass elastically or rigidly attached to the structure, boundary constraint or prestress. In that paper, apart from mechanical examples, the mathematical explanation of the proposed method has been presented. This paper intends to provide an analysis of eigenvalues with respect to the additional mass and the application of artificial neural networks (ANNs) Waszczyszyn et al. [6] to the identification of damage. An ANN is applied to the analysis of the dynamic response of a structure and for the assessment of the structure's condition. This approach was also presented by Ziemiański et al. [7]. Herein three examples are discussed, in all of which ANNs are applied to develop a new method of identification. The assessment of the state of a structure relies, in the case of the application of the proposed extended identification method, on the comparison of structure eigenfrequencies obtained from the systems with additional masses placed at different nodes. The differences in the sources of information were employed to identify the location and the extent of the damage.

3. Numerical examples

The numerical models of the considered beams were built using the ADINA [8] finite element (FE) system. All the beams were modeled using one-dimensional two-node beam elements. Every beam had an IPE200 cross-section, and the material properties were as follows: Young's modulus E = 2.0×10^5 MPa, mass density ρ = 7800 kg/m^3. In all the examples, only one damage at a time was considered. During the research, the damage was located in each element of the FE model in turn. The damage of the beam was simulated by the progresive reduction of the flexural stiffness in one finite element first by 20% then 30%, 40%, 50%, 60% and 70%. The reduced stiffness EI equalled, respectively, 0.8EI, 0.7EI, 0.6EI, 0.5EI, 0.4EI or 0.3EI, where EI is the initial stiffness of an undamaged element. Changes to the eigenfrequencies were observed after the addition of mass and a reduction in stiffness. An additional mass of M = 8.5 kg (it was 10–16% mass of models) was placed at each node of the FE model in turn. An ANN was applied to identify the location and the extent of the damage. In each example some patterns used to train and test the ANN were obtained by changing the damage location and/or its extent. In each case 40% of patterns were selected as testing ones, the remaining 60% of patterns were considered as training ones. In the presented examples the optimal architecture was determined by checking a number of different architectures. All neural networks computation were performed using Neural Network Toolbox for Matlab [9].

3.1. Cantilever beam

In this example, a cantilever beam of length l = 2m (Fig. 1a) was considered. The FE model was composed of 21 finite elements. In one of them the stiffness was reduced to 80% of the initial stiffness (0.8EI). An ANN was applied to identify the location of the damage. Twenty-one different locations of damage and 21 locations of added mass were considered, and in total 441 patterns were obtained; some of them created the training set, the others created the testing set. The input vector consisted of two ($\mathbf{x}$ = $\{\omega_1, \omega_2\}$) or three ($\mathbf{x}$ = $\{\omega_1, \omega_2, \omega_4\}$) eigenfrequencies, where ω_i is the ith eigenvalues. A number of network architectures were tried out, the best results being obtained from one hidden ANN layer with six or eight neurones. The output vector ($\mathbf{y}$ = $\{x_D\}$) had only one element, which described the location of damage. The network was able to locate the damage; the optimal architecture was found to be 3–8–1. The results of identification are presented in Table 1. In the table, MSE is the mean square error and R^2 is the correlation coefficient. The analysis was repeated with other damage extent. The ANN was able to identify the location of all damages, but better results were obtained for higher reductions of flexural stiffness.

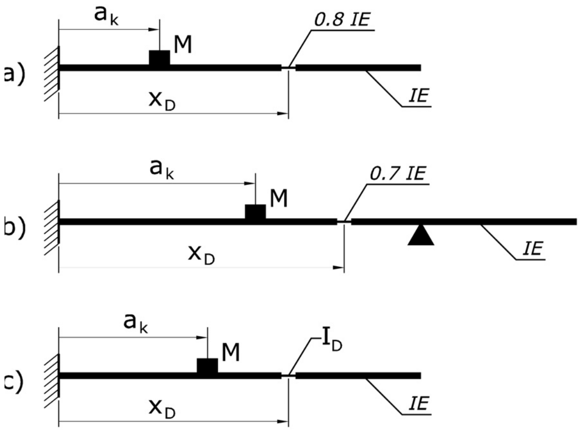

Fig. 1. Models considered: (a) cantilever beam (Example 3.1); (b) cantilever beam with intermediate support (Example 3.2); (c) cantilever beam (Example 3.3).

3.2. Fixed beam with intermediate support

In the second example, a fixed beam (with intermediate support) of length l = 3m (Fig. 1b) was considered. The FE model was composed of 31 elements. The stiffness of one of them was reduced to 70% of the initial stiffness (0.7EI). Thirty-one different

Table 1
Comparison of the results of Example 3.1

Error parameters	Network 2–8–1			Network 3–8–1			
	Input eingenvalues			Input eingenvalues			
	1 and 2	1 and 4	1 and 5	1, 2 and 4	1, 2 and 5	1, 4 and 5	2, 4 and 5
MSE $\times 10^{-4}$	0.338	0.322	0.483	0.202	0.272	0.332	117
R^2	0.999	0.999	0.999	0.999	0.999	0.999	0.803

locations of damage and 31 locations of additional mass were considered, and in total 961 patterns were obtained. In this case, in order to locate the damage, the input vector was obtained from the model with additional mass located in three different nodes in turn. The first and second eigenvalues for each location of the mass were taken into account. The input vector (say: $x = \{\omega_1^1, \omega_2^1, \omega_1^{11}, \omega_2^{11}, \omega_1^{25}, \omega_2^{25}\}$) consisted of six elements, where ω_i^k is the ith frequency computed when the additional mass was attached to the kth node. The ANN had one hidden layer with six or eight neurones. The output vector ($\mathbf{y} = \{x_D\}$) had only one element, which described the location of damage. The accuracy of the identification employing the ANN was very high (see Fig. 2). The best architecture was found to be 6–8–1 where MSE $= 7.66 \times 10^{-5}$.

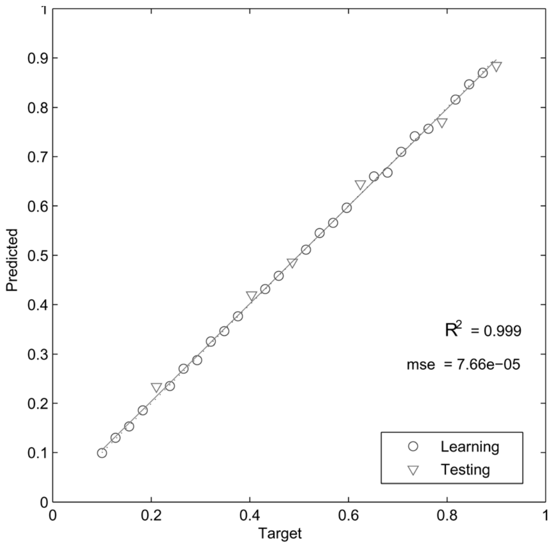

Fig. 2. The results of the identification of the localization of damage.

3.3. Cantilever beam continued

In the third example, the first model was considered again (Fig. 1c). Twenty-one different locations of damage, 21 locations of additional mass and six values of the extent of damage were considered. Altogether 2646 patterns were obtained. In this case not only the location but also the extent of the damage was identified, so the networks had two outputs. The network of architecture 6–8–2 was applied. The input vector of the ANN, as in the previous example ($x = \{\omega_1^1, \omega_2^1, \omega_1^{11}, \omega_2^{11}, \omega_1^{25}, \omega_2^{25}\}$), consisted of two frequencies (first and second) obtained for three different locations of the additional mass. The output vector ($\mathbf{y} = \{x_D, I_D\}$) was composed of the position and extent of the damage. The accuracy of the identification was also very high. The results for localization of damage are shown in Fig. 3 (MSE $= 4.28 \times 10^{-5}$). The results for the extent of damage are shown in Fig. 4 (MSE $= 12.21 \times 10^{-5}$).

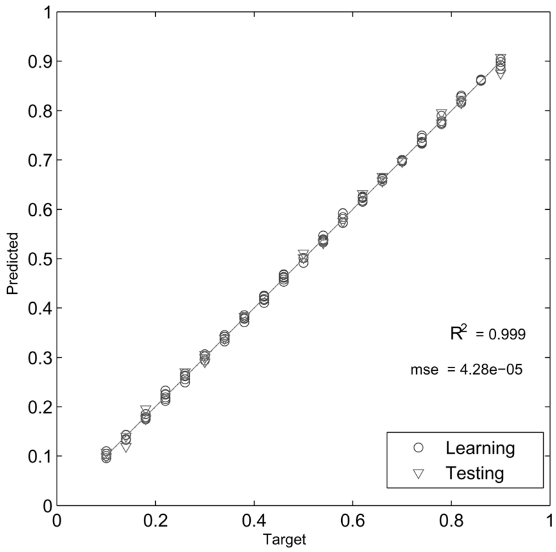

Fig. 3. The results of the identification of the localization of damage.

4. Final remarks

The additional parameter introduced to the structure increases the identification accuracy. The artificial

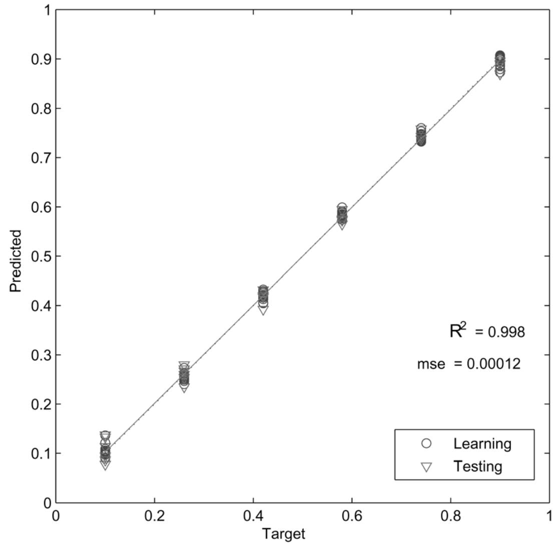

Fig. 4. The results of the identification of damage extent.

neural networks are able to locate the damage and determine the extent of the structured degradation. The obtained results show that it is possible to identify the damage using the dynamic responses of the structure. The results presented in this paper are very promising; the next step will be to consider more complicated structures. Moreover, other perturbations should also be considered.

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