

# The identification of the load causing partial yielding on the basis of the dynamic characteristics

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(Received in the final form October 18, 2006)

Possible yielding of the cross-section of a structure, which may arise as a result of external actions or the (micro)defects, might significantly decrease the safety margin of the considered structure [2]. Since the cross-section yielding affects the structure stiffness, the dynamic characteristics (eigenvalues and eigenvectors) might be significantly different than the ones of the original structure. The measurement of the changes of the dynamic parameters may provide the information necessary to identify the load causing the yielding of the cross-section and further the yielding index (which may be calculated when the load causing the yielding is known) enables the evaluation of the structure safety margin. This paper presents the application of Artificial Neural Networks (ANN) [4, 9] in the identification of the load causing partial yielding of simply-supported beam and one- or two-column frames.

**Keywords:** finite element method, identification, dynamics, artificial neural networks

## 1. INTRODUCTION

Plastic deformation of a structure may arise as a result of external actions and/or as a result of section defects (microdefects) [1]. Determination of section yielding index (possible when the load affecting the structure is known) enables the evaluation of the safety margin of the structure [10]. The identification of the yielding load can be performed by modal analysis of the object dynamic response and by structure dynamic characteristics estimation.

The term dynamic characteristics of a structure refers in this paper to the eigenfrequencies and eigenvectors of a mathematical model, both of them represent modal parameters of the structure [3]. The structure state changes, e.g. yielding zones development, lead to the structure stiffness changes and further to modal parameters changes. Information on dynamic characteristics changes during the yielding process may be used for the structure state evaluation [6]. By measuring the dynamic response changes the structure state might be assessed and load causing the partial yielding may be identified.

This paper presents some new results of application of ANN in load identification based on modal properties changes [5]. The assessed problem is of the Load Simulation type in which the response and features of a Mechanical Structure (MS) are given and the identification of the load is the expected result. Simply-supported beam and one- or two-column frames with loads exceeding the yielding load have been analysed. The load location and resultant have been obtained on the basis of the structure eigenfrequencies and eigenvectors changes. ANNs recognising load parameters have been constructed. The minimum number of eigenfrequencies and elements of eigenvector for proper network operation and the optimum network architecture have been found. All neural network calculation were performed in Matlab environment, using the NNet toolbox.

## 2. PROBLEM DESCRIPTION

The measurable quantities adopted herein are up to the first 10 eigenfrequencies  $f_1, \dots, f_{10}$  and the selected elements of the first 10 eigenvectors  $v_1^i, \dots, v_j^i$ , where  $i$  is the number of the appropriate eigenvector and  $j$  is the number of the elements in one selected eigenvector ( $j$  equals 61, 482 or 662, depending of the structure investigated — see Fig. 1). Those data were obtained from numerical simulations (forward analyses) involving finite element commercial code ADINA.

Let the vector  $\mathbf{x} = \{ \Delta f_1, \dots, \Delta f_n, v_k^1, v_m^1, \dots, v_k^n, v_m^n \}^T$  gather the measurable quantities involved in the identification process (for simplicity the assumption was made herein, that for each considered eigenfrequency — 1st, 2nd,  $\dots$ ,  $n$ th — only two elements of the corresponding eigenvector were taken into account), where  $\Delta f_i$  is the relative change of the  $i$ th eigenfrequency in comparison to the same eigenfrequency calculated for the structure without yielding,  $v_k^n$  is the  $k$ th element of  $n$ th eigenform. Let vector  $\mathbf{y} = \{ l, r, w \}$  gather the location  $l$  of the center, the resultant  $r$  and the width  $w$  of the load causing partial yielding in the cross-section.

The dependence of the measurable quantities gathered in vector  $\mathbf{x}$  on the parameters of the load (gathered in vector  $\mathbf{y}$ ) causing partial yielding will be referred to as forward operator  $\mathbf{x} = H(\mathbf{y})$ . The task of the ANNs is to perform the inverse operation  $\mathbf{y} = H^{-1}(\mathbf{x})$ , namely to identify the elements of vector  $\mathbf{y}$  on the basis of known vector  $\mathbf{x}$ . The Backpropagation ANNs trained using Resilient Backpropagation (Rprop, see [4]) algorithm were used. The decision on application of such networks has been based on authors experience and on publications on ANNs in civil engineering, especially in structure mechanics [7, 8].

## 3. INVESTIGATED STRUCTURES

Three structures were investigated: simply supported beam (see Fig. 1a), one-column frame (see Fig. 1b) and two-column, portal frame (see Fig. 1c). The load causing partial yielding was applied to the upper, horizontal surface of each structure. The load had constant quantity and was spread over either one selected finite element or consequent two, four, six, eight, ten or twelve elements. In case of both frames an additional, small horizontal load was applied to columns in order to obtain the yielding of a horizontal beam cross-section instead of the yielding of a beam-to-column connection. The investigated structures were modelled using 4-node 2-dimensional elements, each beam and column was modelled using 10 layers of elements.

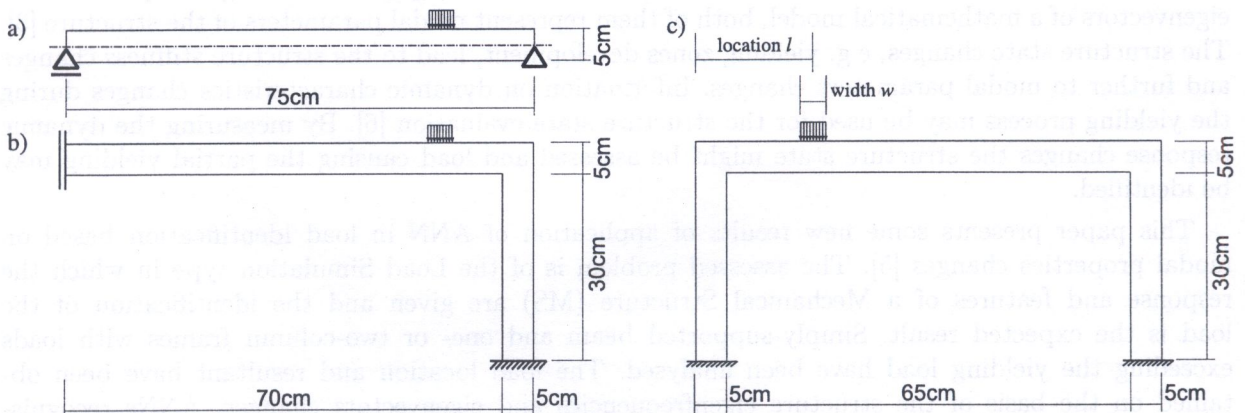


Fig. 1. FE models of investigated structures: a) beam, b) one-column frame, c) two-column, portal frame

4. THE IDENTIFICATION OF THE LOAD

In order to find the optimal input vector a variety of its definitions have been tried out. There were tested the input vectors consisting of the changes of two, three, four or five eigenfrequencies as well as of the elements of corresponding eigenvectors (two, three, four or five selected values). Some results of preliminary calculations for simply supported beam are shown in Figs 2a,b. The identified values were the location of the load and its resultant (the output vector was as follows:  $y = \{l, r\}$ ), the ANN architecture was 6- $h$ -2, where  $h$  was the number of hidden neurones, the number of learning and testing patterns (the same in all investigated examples) was 803 and 802 respectively. The inputs were the first two eigenfrequencies and two elements of the first and the second eigenvectors.

Figures 2a,b (as well as Figs 3 through 4) show the Mean Square Error (MSE) over the testing patterns versus the number of hidden neurones in the only hidden layer. The outer lines in the figure present the maximal and minimal MSE error from among errors obtained from 50 separate runs of learning (with the same input definition and architecture), the central line shows the average MSE, the remaining two lines between the average and maximal (minimal) values show the average error increased (decreased) by the value of standard deviation. The diamonds show the value of the median for each number of hidden neurones.

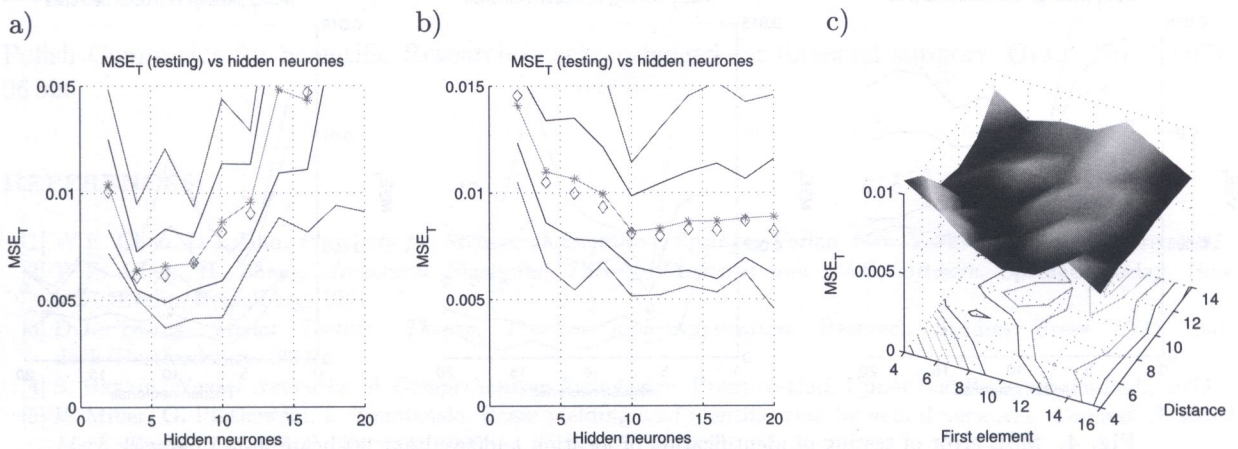
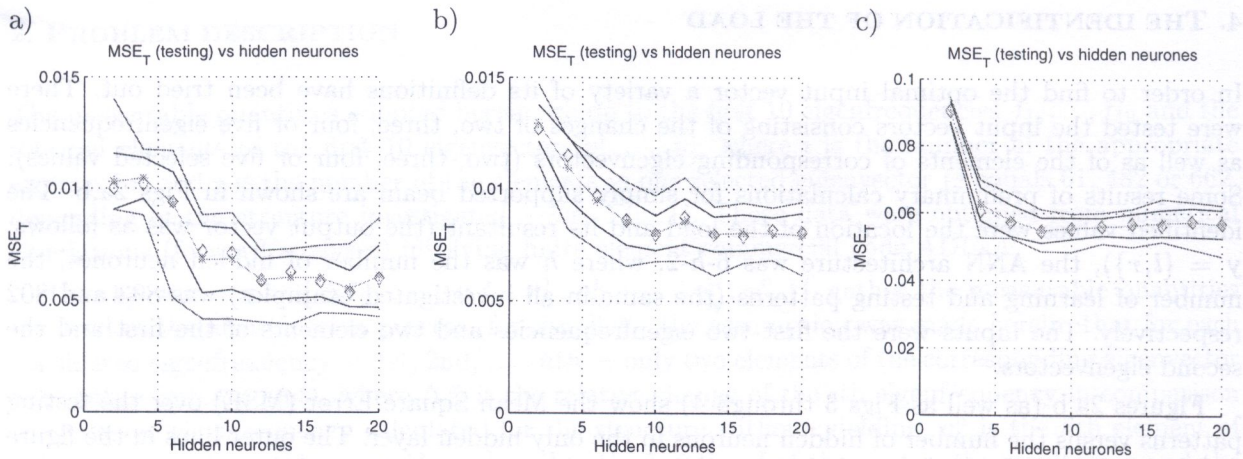


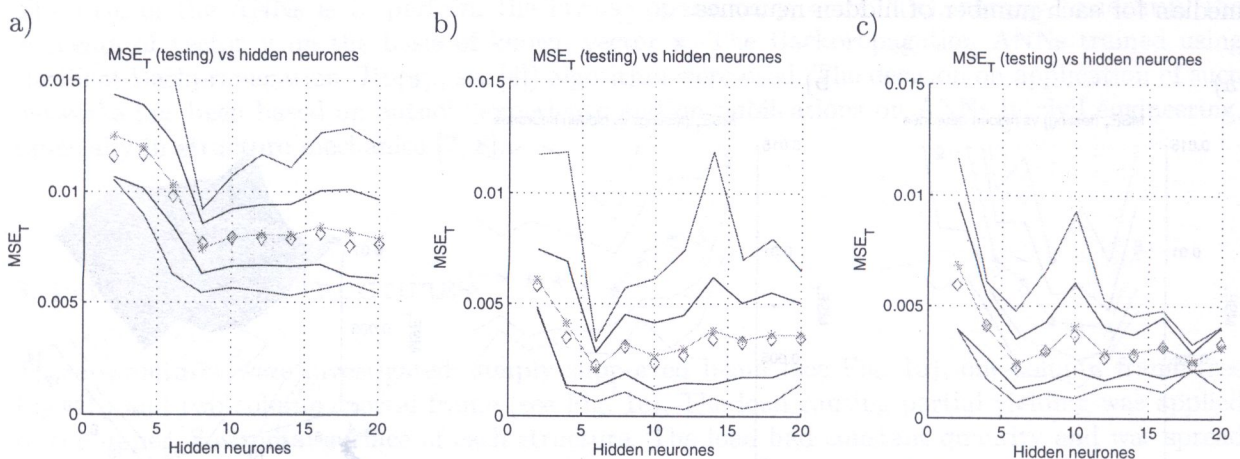
Fig. 2. MSE error of testing of identification of the location and resultant for beam (see Fig. 1a) by 6- $h$ -2 network on the basis of a) 10 eigenfrequencies or b) 2 eigenfrequencies and 2 elements of two eigenvectors, c) MSE error versus the coordinates of the eigenvectors elements

The results shown in Figs 2a,b prove that it is possible to identify the load causing partial yielding using the information obtained only from the first two eigenfrequencies and two elements of corresponding eigenvectors. Although the best results obtained from 10-input network (with ten first eigenfrequencies on input) are slightly better it would be very difficult or even impossible to measure ten eigenfrequencies in a real situation.

Fig. 2c shows the MSE testing error versus the data describing two elements of the first and the second eigenvectors taken into account during the identification. The X-axis shows the number of the first element, the Y-axis shows the distance between the first and the second element ( $x = 10$  and  $y = 4$  mean that the elements number 10 and 14 —  $10 + 4$  — were taken into account). The architecture of the networks applied here was 6-10-2 (the inputs are two first eigenfrequencies and two elements of the first and the second eigenvectors). This figure enables the assessment of the optimal location of the accelerometers during the measurements of a real structure — one of them should be located in the point number 8 (1/8 of the beam length), the second one in the point number 16 (1/4 of the beam length). The eigenvectors elements used in further calculation were the ones described above (points number 8 and 16).



**Fig. 3.** MSE error of testing of identification (beam, see Fig. 1a) of a) location, b) resultant, c) width of the load



**Fig. 4.** MSE error of testing of identification of location and resultant: a) beam, 6-h-3 network, b) one-column frame, 12-h-2 network, c) two-column, portal frame, 15-h-2 network

The next figure (Fig. 3, for description of the figure see the description of Fig. 2) shows the best results obtained from the 6-h-3 network after an analysis involving different architectures, numbers of epochs and learning algorithms. The additional, third output was the width of the distributed load causing the cross-section yielding ( $\mathbf{y} = \{l, r, w\}$ ). Each of the diagrams in Fig. 3 shows the results separately for each parameter (location, resultant and width of load), although the identification of all of them was done by the same network. The accuracy of the identification of the width of the load is not as high as in case of location and resultant identification (please note the difference in vertical axis range in Figs 3a,b and Fig. 3c). The identification of the width of the load was given up, since using the presented procedure and the input data including eigenvalues and selected elements of eigenvectors it was impossible to improve the accuracy of identification of this parameter.

In order to compare the results obtained from 6-h-2 networks (Fig. 2) and the results obtained from 6-h-3 networks (Fig. 3) in the next figure, namely Fig. 4a (for description of the figure see the description of Fig. 2), the network errors of identification of location and resultant by 6-h-3 networks are presented in the same manner as in Fig. 2 (errors of identification of location and resultant together on one diagram). The other diagrams in Fig. 4 show the results of identification of location and resultant of the load causing cross-section yielding in one-column frame (Fig. 4b) and in two-column, portal frame (Fig. 4c). The identification of the load was done using as input information the first three eigenfrequencies and three selected elements of the first three eigenvectors

(one-column frame) or the first three eigenfrequencies and four selected elements of the first three eigenvectors (portal frame).

## 5. FINAL REMARKS

The paper shows that it is possible to identify the load causing partial yielding in a cross-section of simply supported beam on the basis of the data which may be obtained from the measurements gathered from only two accelerometers. Two first eigenfrequencies and two elements of the first and the second eigenvectors provide the information sufficient to precisely identify the location and resultant of the load. It is impossible to identify the load width (the results are not presented here for brevity), some other data would be necessary to identify this parameter. In case of both considered frames the identification involves three eigenfrequencies and three eigenvectors.

Further studies should involve additional input data to enable the identification of the load width and then to identify possible defects (cracks or the areas with decreased stiffness). Besides dynamic characteristics also other sources of information should be investigated, for example the data which could be obtained from the measurements of the propagation of elastic waves.

## ACKNOWLEDGMENTS

Polish Committee for Scientific Research is acknowledged for financial support, Grant No. 4T07E 06 526

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