Coupled evolutionary algorithm and artificial neural network in defects identification

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Abstract

This paper is devoted to a method based on computational intelligence for non-destructive defect identification. In the paper an elastic body with an unknown number of internal defects is considered.

The Evolutionary Algorithm (EA) is combined with the Artificial Neural Network (ANN) into one computational intelligence system. The EA is applied to identify the number of defects and their parameters by minimizing the fitness function, which is expressed as a difference between measured and computed displacements on the boundary and a difference between measured and computed eigenfrequences of the investigated structure. The fitness function is computed by means of a Fuzzy-Artificial Neural Network (FANN).

Keywords: Identification; Evolutionary algorithm; Fuzzy artificial neural network; Boundary element method; Finite element method; Internal defect

1. Introduction

There are several approaches to identification. One group of methods is based on sensitivity analysis [1]. This approach is very refined and strict from a mathematical point of view but sometimes it fails because the minimization of identification functions leads to a local minimum.

Another group of methods is based on techniques which try to simulate (or imitate) biological systems. One approach concerns ANNs [2,3]. In such a method there is a problem with identifying a large number of different defects, especially when the number of defects is unknown. Another very common approach is to use evolutionary algorithms in identification tasks [4,5]. The EA enables us to find multiple defects. It can distinguish different kinds of defects as voids and cracks, and a number of defects can be considered as a design variable. The EA minimizes the fitness function, which is formulated as a weighted sum of the difference between the measured boundary displacements and eigenfrequences of the examined body and the computed displacements and eigenfrequences for the numerical model of the body with an assumed number and shapes of defects:

$$\min_{ch} F(ch), F(ch) = w_1 \cdot \left\{ \frac{1}{2} \sum_{i=1}^{N} [\hat{u}(x_i) - u(x_i)]^2 \right\} + w_2 \cdot \left\{ \frac{1}{2} \sum_{j=1}^{M} \left(\hat{\omega}_j - \omega_j\right)^2 \right\} \quad (1)$$

where $\hat{u}(x_i)$ and $u(x_i)$ are the measured and computed displacements at sensor point x_i; $\hat{\omega}_j$ and ω_j are the measured and computed eigenfrequences of the body; N is the number of sensor points; M is the number of eigenfrequences taken into account; ch is a vector of defect parameters which plays the role of a chromosome in EA; and w_1 and w_2 are the weights.

In order to evaluate the field of displacement $u(x)$ and eigenfrequences, one should solve a boundary-value problem using the boundary element method (BEM) or the finite element method (FEM). This part of the identification process is very time consuming because the fitness function has to be computed for each chromosome in every generation. The second disadvantage of such an approach is that the time needed for solving the

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identification problem depends on the geometry of the model [6,7]. One way to speed up the identification process is to improve the fitness function evaluation by replacing the BEM or FEM solution by an approximate solution which is obtained by using the ANN. As a result, by coupling of the EA and the ANN a computational intelligence system (CIS) is obtained.

2. Approximation and identification

2.1. Approximation

In order to approximate the boundary displacements and eigenfrequences, the Fuzzy-Artificial Neural Network (FANN) with gaussian description of a membership function is taken into account [7]. The network is trained by means of the back propagation method with a momentum. In such a method the learning process depends on minimizing of a square error:

$$E = \frac{1}{2}[y - d]^2 \tag{2}$$

where x is the input vector, y is the value approximated by FANN, and d is the desirable answer of FANN for input vector x. In order to avoid local minima during the training process the simulated annealing, the 'jog of weight' technique and learning using EA were used.

2.2. Identification

A two-dimensional elastic body with $D \leq D_{max}$ internal defects in the form of circular holes is considered. D_{max} means the maximum number of defects that can be expected in the body. The EA should identify the actual number of defects D and their parameters based on information about M eigenfrequences and displacements in N sensor points on the boundary of the body. The unknown parameters of the defect are the coordinates of the hole's centre (X_z, Y_z) and its size R_z ($z = 1,2, \ldots, D_{max}$).

Defects are specified by a chromosome:

$$ch = [X_1, Y_1, R_1, X_2, Y_2, R_2, \ldots, X_z, Y_z, R_z, \ldots, X_{D\max}, Y_{D\max}, R_{D\max}] \tag{3}$$

where X_z, Y_z and R_z play the role of genes. The EA sends the chromosome with the suggested values of positions and of radii of defects to the approximation block. When $R_z < R_{min}$, the program assumes that genes X_z, Y_z, R_z are inactive genes and:

$$R_z = 0 \quad \forall \quad (R_z < R_{\min}) \tag{4}$$

The condition (4) controls the number of defects. Genes with information about the position and shape of defects are sent to inputs of the FNNs. Approximated displacements in several sensor points on the boundary of the model and eigenfrequences are obtained on the outputs of the ANNs. They are sent back to the EA where the fitness function of each chromosome is computed.

3. Numerical examples

A two-dimensional elastic rectangle in plane stress under static load is considered (Fig. 1). The body contains one or two defects in the form of a circular hole. The geometrical and material parameters are presented in Table 1. One should find the number, position and size of the internal defects. To solve the problem the EA coupled with the FANN is applied. The FANN is chosen because of its good approximation abilities [8], and the short time needed for learning [7].

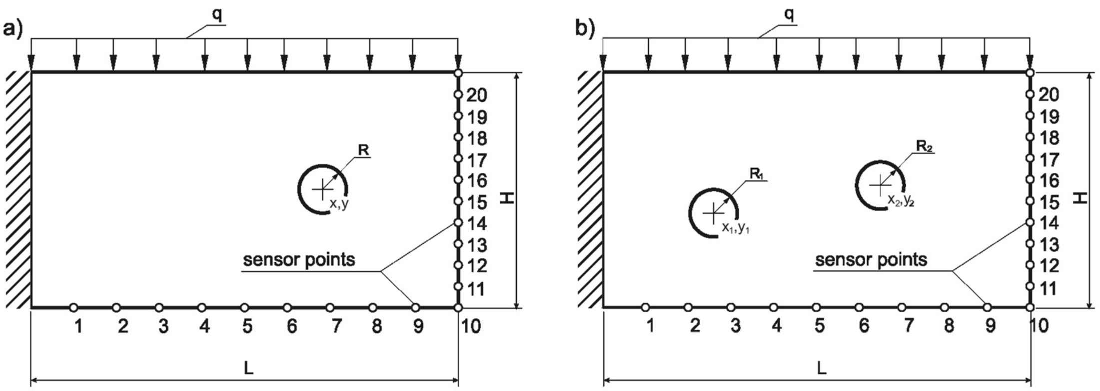

Fig. 1. An elastic body with one (a) and two (b) internal defects.

Table 1
The geometrical and material parameters of the plate

Geometrical and material parameters	A structure with one defect	A structure with two defects
L [cm]	4.0	4.0
H [cm]	2.0	2.0
q [N/m]	3750	3750
E [MPa]	2.e5	2.e5
ν	0.3	0.3
$R_{\min}$ [cm]	0.0314	0.0314

Table 2
The parameters of the EA

Number of chromosomes	300
Number of iterations	100
Number of design parameters	6
Probability of uniform mutation	0.25
Probability of arithmetic crossover	0.25
Probability of cloning	0.05
Selection coefficient	0.75

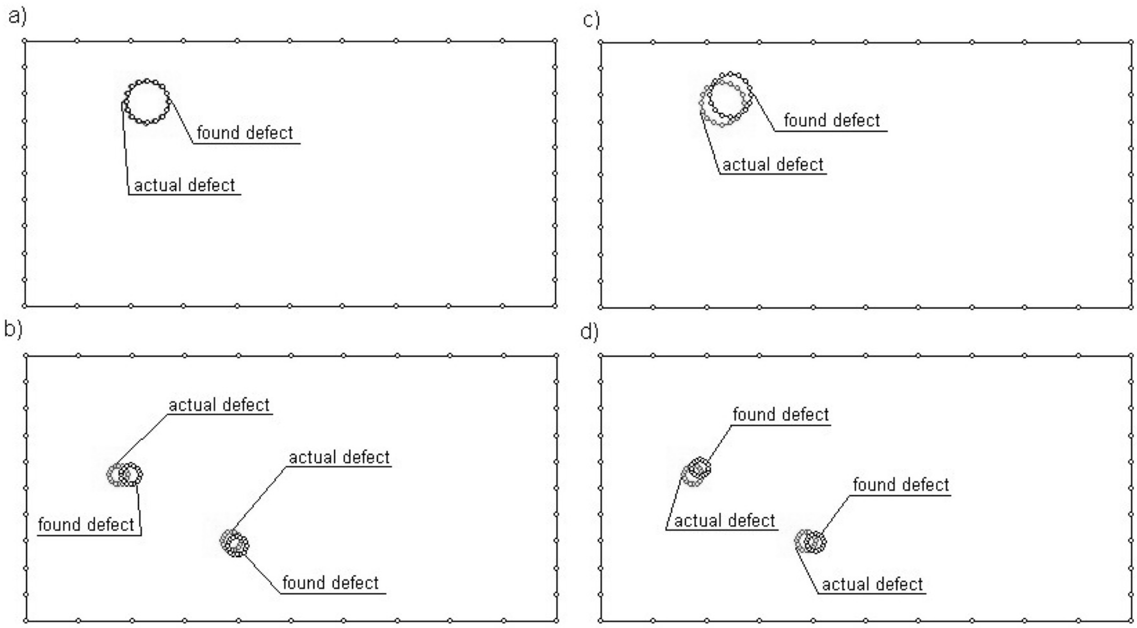

Fig. 2. Defect: actual and found by means of the EA with the BEM: (a) one defect (b) two defects; using the EA with the FANN: (c) one defect, (d) two defects.

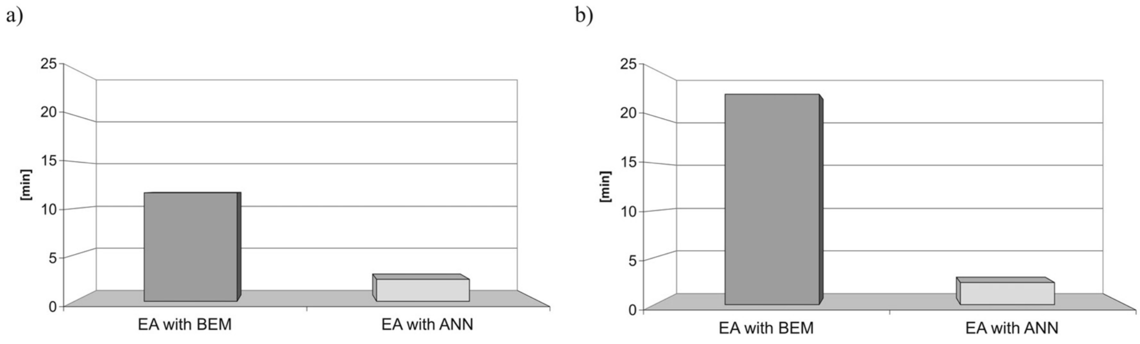

Fig. 3. CPU time using the EA with the BEM or the FANN for a body with (a) one defect (b) two defects.

The EA parameters are presented in Table 2. The learning and testing data were obtained using the BEM and the FEM. The example of the results of the identification using the EA are presented in Fig. 2. The CPU time of the identification is shown in Fig. 3.

4. Conclusions

The presented tests confirm that the EA coupled with the ANN identifies the number, positions and radii of circular holes in the 2D body under static load.

This approach is less accurate but much faster than EA coupled with the BEM. In the case of the identification of two internal defects the computing time using the CIS is more than 90% shorter than the computing time using the EA with the BEM. The more complicated geometry of the examined body, the longer time for identification using EA with BEM is needed. In the approach proposed the time of computations does not depend on the geometry of the body.

The time of computation using the EA with the FANNs, presented in this paper, does not take into account the time needed to prepare the learning and testing data, and to learn the FANNs. This approach is worth using when the defect identification in many structures with the same shape has to be done. In such a case the time needed to prepare learning and testing sets and to train the ANN is not significant.

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