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DYNAMIC DAMAGE IDENTIFICATION BASED ON ARTIFICIAL NEURAL NETWORKS, SARA – PART IV

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Abstract

The paper is focused on damage identification of dynamically loaded structures using methods of artificial intelligence, the damage and variability of material properties (stiffness) along the structure will be studied. The identification method based on coupling of artificial neural networks and stochastic analysis of structure for preparation of appropriate training set is used. Sensitivity analysis of the input parameters is the integral part of the method. The proposed methodology is extended towards the dynamic response of structures when results of modal analysis are the input parameters (frequencies, mode shapes).

Damage parameters play the role of basic random variables, with the scatter reflecting the physical range of possible values. A random response is obtained from generated basic random variables. This set of data is used for the training of a suitable type of neural network. Once the network is trained, it represents an approximation which can be used in a way that ensures that for given experimental data, the best input parameters are provided, so that the calculation may result in the best agreement between experimental and numerical results.

The verification of the proposed methodology is carried out using experimental data from measurements of Z24 Bridge in Switzerland and using virtual simulation of concrete beam.

INTRODUCTION

Continuous health-monitoring of structures (bridges) is an essential part of its maintenance. Therefore damage localization and its level is the subject of research of both academic and industrial research groups during the last decade. Non-destructive testing – vibration measurements to get modal data (frequencies, modal shapes) is the most promising technique as it can be performed using a structure in usage. The task is based on the fact that a damaged structure has smaller stiffness in some parts – and this difference will affect vibration (modal data). The comparison of vibration of virgin (undamaged) structures and damaged structure can be used for the detection of damaged parts (localization of damage), e.g. Bonfiglioli et al. (2004). “The model updating method” is the term frequently used in identification (Huth et al., 2005, Fang et al., 2005, Deix and Geier, 2004, Teughels et al., 2002, Link, 1999, Wenzel, 2005). "Updating" means that individual parameters of FEM model are iteratively changed in order to minimize the difference between experimentally measured and calculated response. A sensitivity of the response on model parameters is frequently used and can be directly utilized for efficient identification (Strauss et al., 2004a, 2006).

The aim of this paper is to describe a methodology of dynamic damage identification based on the coupling of Monte Carlo type simulation and artificial neural networks (ANN). It extends a methodology of inverse analysis developed and applied for fracture-mechanical parameters identification (Novák and Lehký, 2004, 2005, 2006, Lehký and Novák, 2004, 2005, Strauss et al. 2004b). Applications to dynamic damage identification are presented in the paper. The methodology belongs to "Structural Analysis and Reliability Assessment" (SARA) project, Bergmeister et al. (2007).

ARTIFICIAL NEURAL NETWORK-BASED DAMAGE IDENTIFICATION METHOD

The proposed inverse analysis technique is based on the combination of the statistical simulation and ANN. The procedure can be itemized as follows:

- The computational model of a particular problem has to be first developed using the dynamic FEM software. In case of dynamic damage identification identified parameters (IP) are usually values of stiffness varied along the structure, often Young modulus of elasticity. Measured data (MD) are modal parameters (eigenfrequencies, mode shapes). IP have to be selected carefully to capture MD as close as possible.
- IP of the computational model are considered as random variables described by a probability distribution; the rectangular distribution is a "natural choice" as the lower and upper limits represent the bounded range of the physical existence of IP. However, other distributions can be used, e.g. the Gaussian one. IP are simulated randomly based on the Monte Carlo type simulation, the small-sample simulation LHS is recommended. The results are random realizations of IP (vector $\mathbf{y}$, see Figure 1). A statistical correlation between some parameters may be taken into account too.
- A multiple calculation (simulation) of FEM model using random realizations $\mathbf{y}$ of IP is performed, a statistical set of the virtual response $\mathbf{p}$ (see Figure 1) is obtained. The selection of number of simulations is driven by many factors, mainly by complexity of the problem (computational demand), structure of ANN and variability of IP.
- Random realizations $\mathbf{y}$ (outputs of ANN) and the random responses from the computational model $\mathbf{p}$ (inputs of ANN) serve as the basis for the training of an appropriate ANN. This key point of the whole procedure is sketched in Figure 1 (here for the FEM model response in the form of eigenfrequencies).
- The trained neural network is ready to give an answer to the key task: To select the best parameters IP so that the calculation may result in the best agreement with MD, which is performed by means of the network simulation using MD as an input. This results in an optimal set of parameters $\mathbf{y}_{opt}$.
- The last step is the results verification – the calculation of the computational model using optimal parameters $\mathbf{y}_{opt}$.

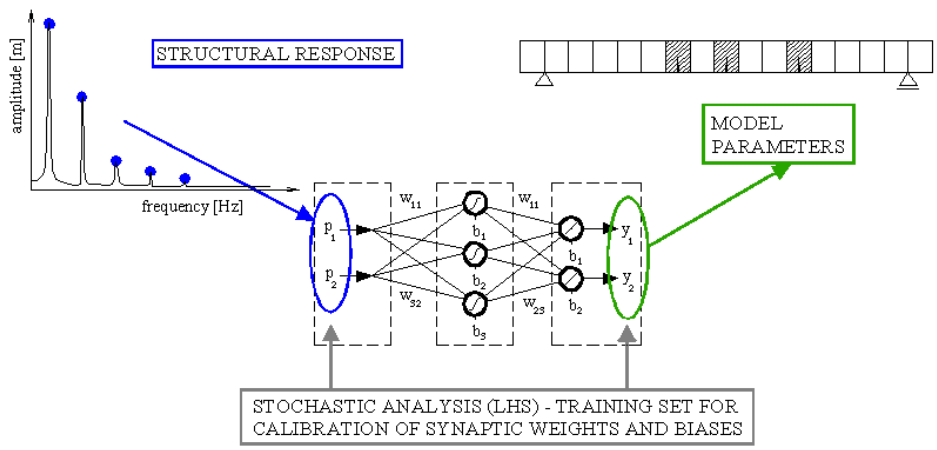

Figure 1. A scheme of stochastic training of ANN for dynamic damage identification

METHODS AND SOFTWARE TOOLS

The problem of inverse analysis and damage identification is integral part of SARA project. The methods and software tools are described in SARA Part I paper (Bergmeister et al., 2007). Here only methods and tools relevant for ANN-based dynamic damage identification are highlighted more. Basic methods are: simulation of Monte Carlo type called Latin Hypercube Sampling (McKay et al., 1979), sensitivity analysis based on non-parametric rank-order correlation (Iman and Conover, 1980), ANN – classical feed-forward neural network, multi-layer-perceptron (MLP) (e.g. Cichocki and Unbehauen, 1993).

Multi-purpose software for any user-defined problem of the inverse analysis has been developed. It is based on the integration of software for statistical, sensitivity and reliability analyses FReET (Novák et al., 2007), and a neural network software DLNNET (Lehký, 2007). SOFiSTiK FEM software (SOFiSTiK AG, 2004) was used for dynamic analysis providing frequencies and mode shapes for identification purposes.

NUMERICAL EXAMPLES

Concrete Beam

The beam tested by Bonfiglioli (2004) was considered for the numerical verification, see Figure 2. The beam was damaged in three stages. After each stage, dynamic measurement was carried out and eigenfrequencies of the beam were evaluated, they are summarized in Table 1. The first three frequencies served as input parameters (IP) for identification of damages along the beam. Figure 1 shows locations of the cracks experimentally obtained. At the first stage, the first crack at the midspan occurred (location **a1** which is 1.1m from left support). At the second stage, the second crack occurred (location **a2**). Finally, the third crack occurred at location **a3**. The beam was divided into 19 elements with different stiffness (MD). The aim of the procedure was to identify a decrease of stiffness in elements where cracks had been localized.

ANN consists of 1 hidden layer with 12 nonlinear neurons and an output layer with 19 linear neurons (19 parts with different stiffness). The normalized stiffness has been taken into account, so the stiffness range was from 0.1 to 1.5 (stiffness 1 means referenced stiffness level for undamaged beam). There are also 3 parameters as input to the network (3 frequencies corresponding to the first three modeshapes of the beam). A training set is generated using 500 simulations of the LHS method. The training set was divided into two parts, 450 simulations were used directly for training the network, while 50 simulations served for testing of network overfitting.

Table 1. Eigenfrequencies evaluated from experiments at particular stages

Damage stage	First frequency	Second frequency	Third frequency
0 (undamaged)	66.0	270	612
1	58.0	270	556
2	52.2	259	560
3	47.8	230	544

After the network was trained, the first three frequencies from experimental testing were used for the simulation of ANN. The output of ANN is a spatial distribution of stiffness along the beam (19 values). A final dynamic analysis (SOFiSTiK software) was performed using these values to obtain simulated mode shapes and corresponding frequencies. Figure 3 shows stiffness distribution along the beam for stage 1.

From the results it is visible that the identification procedure was successful and that the decrease of stiffness at the damaged elements was captured satisfactorily. It is necessary to mention that only first three frequencies were used as an input data for identification. Area with reduced stiffness is wider than one element where the crack is localized, the real experiment exhibits also wider fracture process zone.

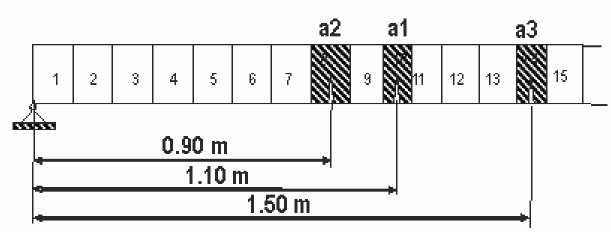

Figure 2. Damage locations after last damage state (Bonfiglioli, 2004)

Because damage at each stage of experimental testing is significant, another study was focused on identification using smaller damage. For that reason we prepared a simulated experiment by SOFiSTiK software. At each stage we decreased the stiffness of the element corresponding to location of damage during the experiment. The simulated experiment used in that study makes it possible to take more frequencies into account. From the experiment of the simple supported beam only the first three frequencies are available. The aim of the study was to find out if consideration of more frequencies (here 5) will improve identification results. Because of the size of the paper the detailed results of both studies are not described here and can be found in Lehký and Novák (2006). We can shortly say that localization of small damage is problematic using only the first few eigenfrequencies as an input for identification. In the case of testing more eigenfrequencies the damage was localized slightly well if five eigenfrequencies were considered instead of three. Also, results of the beam with the smaller damage are a little bit better in comparison with the previous study with only 3 eigenfrequencies.

An example of damage identification using a simple supported beam has shown the potential of proposed identification technique based on an artificial neural network in combination with stochastic analysis of a structure to detect damage along the structure. Note that when using only a few frequencies, results cannot be absolutely perfect; they are, however, sufficient for detection.

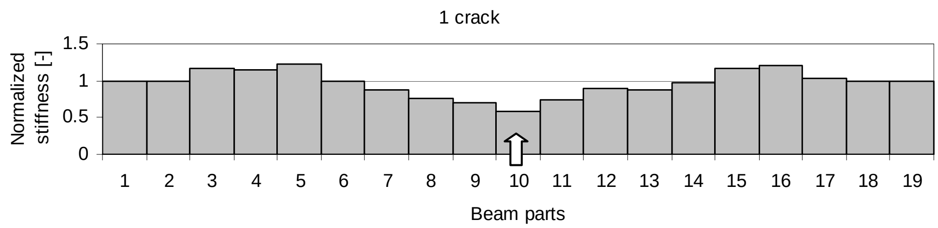

Figure 3. Stiffness distribution along the beam at stage 1 obtained using first three frequencies evaluated from experiment (location of crack is highlighted by arrow)

Bridge Z24

Currently, the technique described and verified above is applied for damage identification of the bridge Z24 (Huth et al. 2005, Teughels et al. 2002). The scheme of the bridge is shown in Figure 4. This bridge was subjected to different damage scenarios in 1999. Modal data are very well known and identification can be applied and verified with the good knowledge of damage from experiment. Tests employing different techniques of identification on this bridge have shown that by considering several structural responses like frequencies, mode shapes and displacements, the identification approach can yield fruitful results. This is a very well documented example of bridge dynamic testing and therefore very suitable for verification of the proposed approach.

First, computational model in SOFiSTiK has been developed and tuned according to experimental measurements (stiffness, eigenfrequencies and modeshapes). Equivalent values for the cross-section area, the bending and torsional moment of inertia of the box section of the main girder were calculated. For identification purposes, the girder was divided into twenty parts with different bending and torsional stiffness. The girder has higher stiffness above the supporting piers because of higher thickness of the bottom and top slab. Examples of modeshapes are in Figure 5, comparison of eigenfrequencies for undamaged state obtained from experiment and numerical model is in Table 2.

For damage identification the scenario with the inner right pier lowering was used (see Figure 4). Corresponding experimental eigenfrequencies are in Table 2. As a first step after the experiences with beam in previous example, only eigenfrequencies were considered as an input for identification (see Table 2). Because of troubles with symmetry and a high number of unknowns (20 parts with 2 stiffness values) the identification was restricted to the right half of the bridge where pier lowering was done. Finally, 18 stiffness values were identified (9 parts with bending and rotational stiffness).

The neural network used for identification consists of 1 hidden layer with 8 nonlinear neurons and an output layer with 18 linear neurons (18 stiffness values). The stiffness range was from 25 % to 125 % of original stiffness (undamaged girder). There are also 4 parameters as an input of the network (4 eigenfrequencies). In the example presented, a training set is generated using 500 simulations of the LHS method.

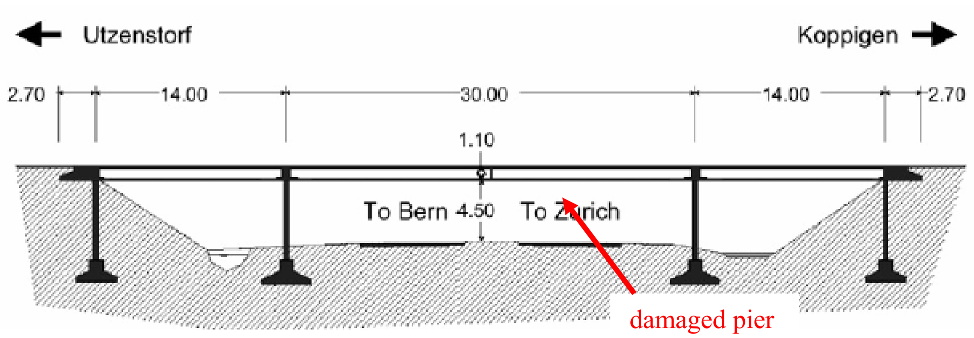

Figure 4. Scheme of bridge Z24

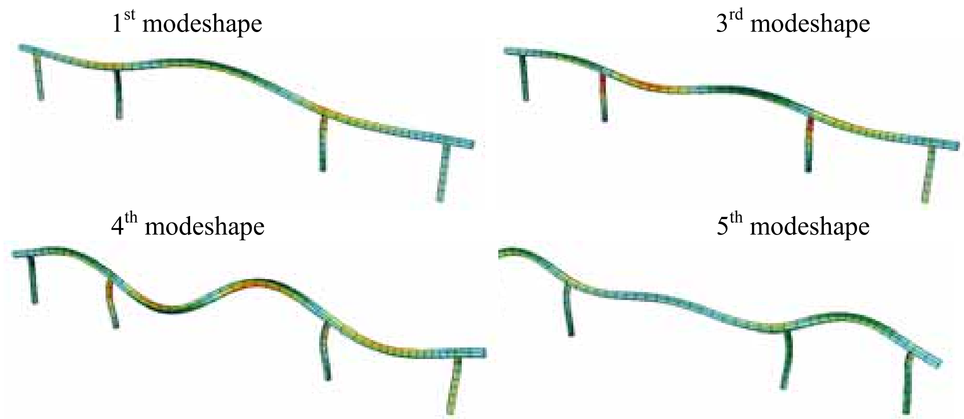

Figure 5. Four modeshapes which are considered for identification – first and fifth are pure bending, third and fourth are combination of bending and torsion (second modeshape is horizontal bending and it was not considered for identification)

Table 2. Eigenfrequencies for undamaged and damaged state

Modeshape	Undamaged		Damaged	
	Experiment	Model	Experiment	Model
1st	3.89	3.87	3.67	3.75
3rd	9.80	9.81	9.21	9.38
4th	10.30	10.42	9.69	9.95
5th	12.67	12.03	12.03	12.26

The training set was divided into two parts, 450 simulations were used directly for training the network, while 50 simulations served for testing the network over fitting. After the network was trained, the frequencies from the experimental testing for damage state were used for the simulation of ANN. The output of ANN is a spatial distribution of stiffness along the girder (18 values, one half of the girder). The final analysis by SOFiSTiK was performed using these values to obtain mode shapes and frequencies.

Figure 6 shows bending and rotational stiffness distribution along the girder for undamaged (reference) and damaged (after pier lowering) stages. Stiffness for damaged stage is a result of identification. Final eigenfrequencies are presented in Table 2. An example of comparison of experimental and numerical modeshape (here 4^{th}) is shown in Figure 7. The results of identification using four eigenfrequencies have again shown potential of proposed identification technique and this type of input information. But to be honest, it is necessary to say, that the damage of the girder in the region of pier lowering was quite big which caused high relative changes of eigenfrequencies. With smaller changes the identification will be more difficult.

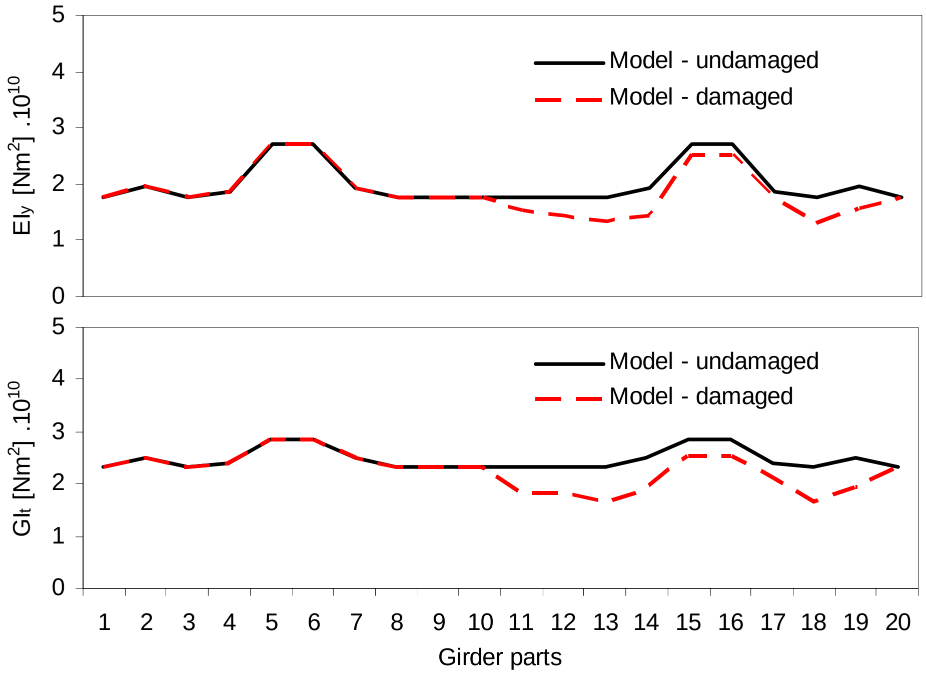

Figure 6. Bending and torsional stiffness for undamaged and damaged beam

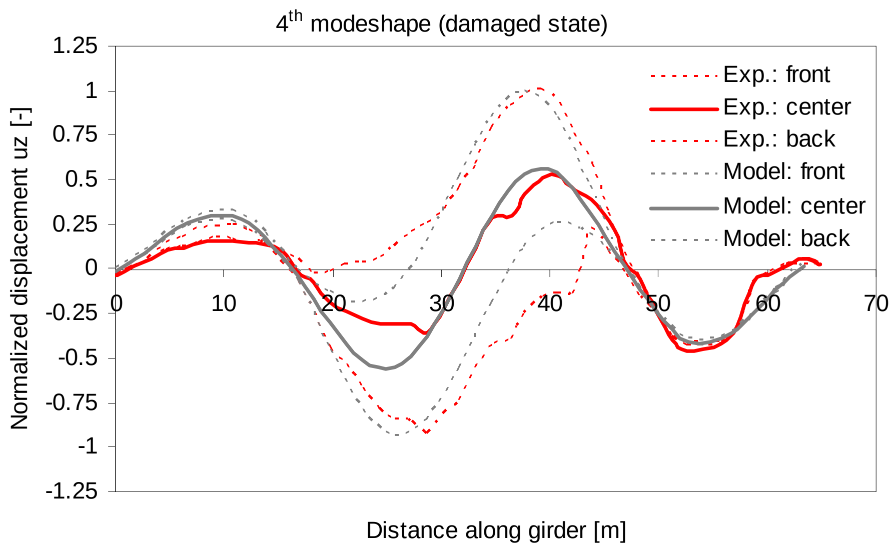

Figure 7. Experimental and numerical 4th modeshape (combined bending and torsion)

CONCLUSIONS

The identification of locations and the levels of damage are very important for the assessment of residual capacity of structures. This is important especially in the case of concrete bridge structures. Dynamic measurements are performed in order to answer the questions on damage, but without robust and sophisticated numerical inverse analysis procedures they can provide only partial answers to damage levels and locations. The proposed approach of inverse analysis using virtual statistical simulation and artificial neural networks appeared to be a very promising technique, the efficiency was documented by numerical examples.

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