

# DAMAGE IDENTIFICATION USING ARTIFICIAL NEURAL NETWORK-AIDED AIMED MULTILEVEL SAMPLING METHOD

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DOI: 10.35181/tces-2023-0017

**Abstract.** *Structural health monitoring is extremely important for sustaining and preserving the service life of civil structures. Research to identify the damage can detect, locate, quantify and, where appropriate, predict potential structural damage. This paper is about damage identified by non-destructive vibration-based experiments, which uses the difference between modal frequencies and deflection of an initial and damaged structure. The main objective of this paper is to present a hybrid method for structural damage identification combining artificial neural network and aimed multilevel sampling method. The combination of these approaches yields a more efficient damage identification in terms of time and accuracy of damage localization and damage extent determination.*

## Keywords

*Damage identification, artificial neural network, aimed multilevel sampling, inverse analysis.*

## 1. Introduction

Monitoring the condition of structures provides the possibility of early detection of damage that would lead to structural collapse or can be an indicator for planning preventive action. One of the main objectives of structural monitoring is to minimise the time and scope of maintenance and possible shutdown of operations due to major failures, as well as collect data providing valuable information that can be used to modify the structure or optimise the design of future structures. Another advantage is to allow maintenance to be resumed based on operating conditions, rather than

periodic maintenance actions that may be unnecessary [1, 2].

Structural monitoring itself does not provide solutions to structural problems. However, when combined with computational and optimization methods, it provides the necessary data for successful damage identification. The identification methods being developed work with the static and especially dynamic response of the structure. A structure that is in some way damaged exhibits a different mechanical behaviour than an intact structure. Various response indicators can be used to identify damage. Popular ones are those obtained from dynamic measurements. These indicators are easy to use, but there are areas where they need to be improved. Many indicators have sensitivity issues, need to know the original condition and are unable to determine the probability of false damage identifications, which reduces their reliability [3].

Most structural assessment procedures use numerical modelling techniques such as the finite element method (FEM) [4]. Popular damage identification techniques include the FE model updating method, where certain design parameters (directly related to damage) are defined as optimization variables [5]. Then, based on the differences between the expected and actual values of these variables, it is possible to construct objective functions to be minimised or maximised according to a predefined criterion. In this way, detection is implemented as an optimization problem, which is currently most often solved using stochastic methods [6]. Genetic algorithms are a popular and robust optimization method because they provide solutions to complex optimization problems. Due to the way the genetic algorithm searches the design space, there is no risk of getting stuck in a local minimum, i.e. non-optimal solution to the problem [7].

The disadvantage of the above genetic algorithms is their extreme computational complexity, which, in con-

junction with FEM design analysis, makes them difficult to use. Thus, the current trend in the development of damage identification methods is the search for an optimal method that is both sufficiently accurate and less time-consuming. Well-known optimization methods are often used with various improvements applied to help increase accuracy, convergence speed, and most importantly, to reduce time required to evaluate the results. This paper presents a new hybrid FE model updating method for structural damage identification that effectively combines artificial neural network and aimed multilevel sampling method.

## 2. The methodology

### 2.1. FE model updating

The damage identification method works with a computational model of the structure. Thus, in the first step of the identification, an accurate FE model is created, which allows for static and dynamic analysis of the structure under consideration. In accordance with the required accuracy of damage localization, the structural model is divided into several regions for which the stiffness parameters are changed during the optimization process. A probability distribution is assigned to the stiffness parameters to create an initial design space. Subsequently, the stiffness parameters of each region of the structure are randomly generated in FReET software [8] using the Latin hypercube sampling method (LHS, [9]) and a static analysis is performed to determine the deflections of the structure and a modal analysis to determine the eigenfrequencies and mode shapes. This results in random input data in the form of stiffnesses of each region and output data in the form of static and dynamic response parameters for each simulation. These data are then used to determine the location and extent of damage to the structure. In this paper, the identification is performed using a metaheuristic optimization algorithm combined with inverse analysis using artificial neural networks.

### 2.2. Aimed multilevel sampling optimization method

The optimization method used in this paper is the Aimed Multilevel Sampling (AMS) [10, 11], which due to its concept offers a significant reduction in computational complexity. Its basic idea is to divide the simulation run into several levels. Advanced sampling within a defined design space will be performed at each level. Subsequently, the sample with the best properties concerning the definition of the optimization problem will

be selected. There are two methods to obtain the design vector  $\mathbf{d}_{i,best}$ . It can be obtained as (a) the best realization generated at the  $i$ th level corresponding to the minimum of the objective function, or (b) the best realization can be obtained using an artificial neural network trained from the data of the corresponding level. The resulting vector is then used as a vector of mean values of random variables for simulation at the next level of the AMS algorithm. Subsequently, the design space for generating samples is shrunk around this best sample. The next LHS simulation is then performed in this reduced space. This leads to a more detailed search in the region around the best-performing samples for the extreme value function. The general algorithm of the presented method is described in the flowchart in Fig.1.

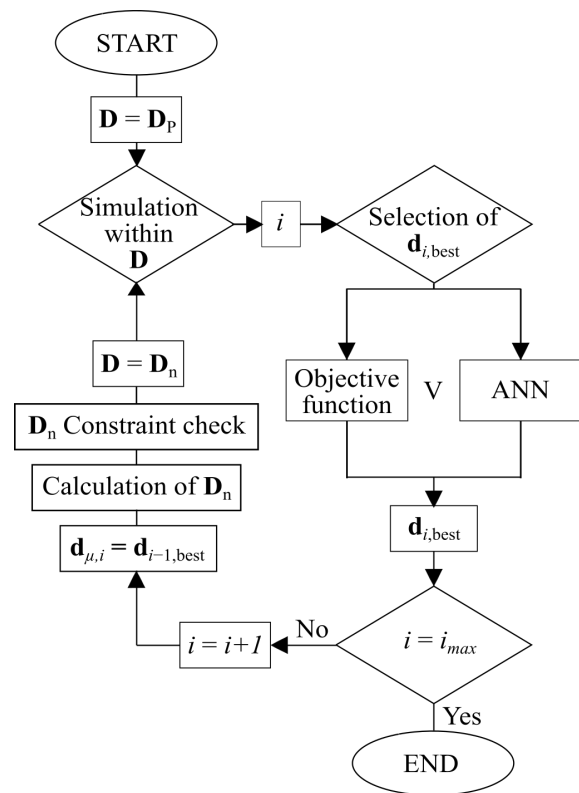


Fig. 1: Algorithm of AMS method.

The value  $\mathbf{D}$  in Fig.1 represents the design space of  $n$  dimensions.  $\mathbf{D}_p$  is the initial design space of the optimization problem.  $\mathbf{D}_n$  is the scaled design space at the next level. The levels are computed using the value of the index  $i$ , where  $i_{max}$  is the maximum level representing the termination criterion. The design vector  $\mathbf{d}_{i,best}$  corresponds to the best realization generated at the  $i$ th level,  $\mathbf{d}_{\mu,i}$  is a vector of mean values of the random variables of the  $n$ -dimensional design space  $\mathbf{D}$  for a simulation at a given level  $i$ . The reduction of the sample space is based on heuristic assumptions and is a key point for the accuracy and performance of the AMS method.

### 1) Objective function

The term FE model updating refers to the procedure to calibrate the FE model to match the experimental and numerical static and dynamic properties of the structure. The objective is to determine the optimum value of the vector of structural parameter vector  $\mathbf{d}$  that minimizes the objective function  $\phi(\mathbf{d})$  defined as:

$$\phi(\mathbf{d}) = \sum_{i=1}^n \left[ \frac{e_i - m_i(\mathbf{d})}{e_i} \right] \quad (1)$$

where  $e_i$  denotes the  $i$ th experimental static or dynamic response parameter of the structure to be compared with the response parameter  $m_i(\mathbf{d})$  produced by the FE model.

### 2) Artificial neural network

In the case of using an artificial neural network (ANN), the problem can be viewed as an inverse problem where the static and dynamic response of the structure  $\mathbf{e}$  is used to find its design parameters  $\mathbf{d}$ . In the case of the above-mentioned AMS optimization method, the relationship between the input design parameters and the real (experimental) response parameters  $\mathbf{d} \xrightarrow{f} \mathbf{e}$  is replaced by a computational FEM model that provides the simulated response  $\mathbf{d} \xrightarrow{f_{FEM}} \mathbf{m}$ . On the other hand, for the inverse analysis, the inverse relation  $\mathbf{m} \xrightarrow{f_{FEM}^{-1}} \mathbf{d}$  is needed. Since this relationship cannot be found for complex structures, it is convenient to define it using a surrogate model, for example in the form of an artificial neural network  $\mathbf{m} \xrightarrow{f_{ANN}^{-1}} \mathbf{d}$ . Such a machine learning-based model is very robust and efficient in mapping different damage scenarios and structural response parameters. For a proper approximation of the inverse function, the artificial neural network needs to be first trained using a suitable training set. Such a training set consists of ordered input–output pairs  $[\mathbf{m}, \mathbf{d}]$ . Fig.2 shows a scheme of a general feed-forward two-layered neural network [12, 13].

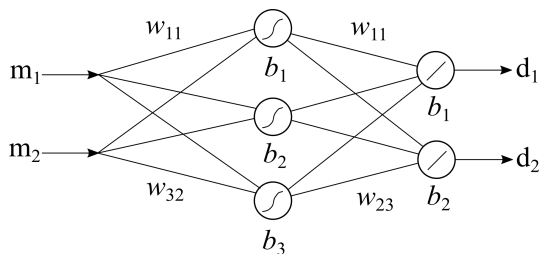


Fig. 2: Scheme of a general feed-forward layered artificial neural network.

The third alternative is the hybrid method that combines the above-mentioned approaches. The reason

for this method is that the objective function-based method is not as accurate as the ANN-based method, but the ANN-based method is more complex and time-consuming due to the network training. This hybrid method starts at the first level with ANN and then uses the objective function at each level, but at every fifth level, it uses the ANN with the data from five previous levels. Thus, the ANN refines the level for which it is used. This method is less time-consuming and sufficiently accurate.

## 3. Application

The methods were applied individually and in combination to a single-span steel truss structure ten meters long. The computational model was created using the finite element method in ANSYS. The structure was divided into ten sections, where one section is shown in the Fig. 3. A different material model was created for each section. The damage was modelled by reducing the stiffness by reducing the modulus of elasticity. The modulus of elasticity was multiplied by the coefficient  $\mathbf{k}$ . If the coefficient is equal to 1, the structure is undamaged, any smaller value indicates a reduction in stiffness, i.e. theoretical damage to a section of the structure.

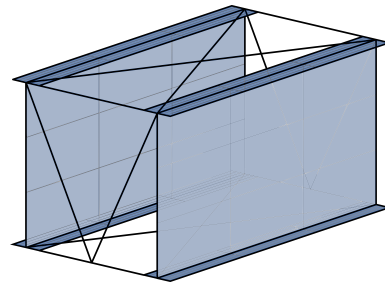


Fig. 3: Scheme of one section of the structure

First, static and dynamic analyses were performed on the damaged structure to determine the eigenfrequencies, mode shapes, maximum displacements, and multi-point displacement vectors of the structure, which in practice represent the measured response parameters of the damaged structure.

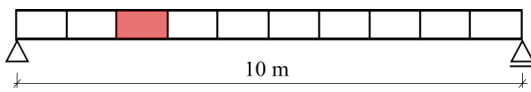
This was followed by a procedure of randomly damaging the structure according to the LHS sampling scheme and determining its dynamic and static response. This response, in the case of the AMS, which was based on an objective function Eq.(1), was compared with the response of the damaged structure and by minimizing the objective function, the damage to the structure was detected. In the case of AMS, which determines the best realization using the ANN, the ANN is first trained using all realizations of the damage on a given level or five levels (hybrid method) and the

corresponding responses, and then the damage of the structure is determined by inversion from the response of the damaged structure.

## 4. Results

### 4.1. Structure damaged in one location

The first analyzed case is a structure asymmetrically damaged in one location. Damage is in section 3 (the third section from the left support), see Figure 4, i.e. the stiffness  $k_3$  was reduced to  $k_3 = 0.9$ .



**Fig. 4:** Scheme of a structure asymmetrically damaged in one location

At the beginning of the damage identification process, the size of the initial design space was the same for all  $\mathbf{k}$  parameters, with evenly distributed values from 0.95 to 1.05. Simulations were performed at 30 levels and 200 simulations were performed at each level. Three types of methods showing the evolution of the error at each level during the optimization process are presented in Figure 5. The total error  $E_r$  of identification is calculated as:

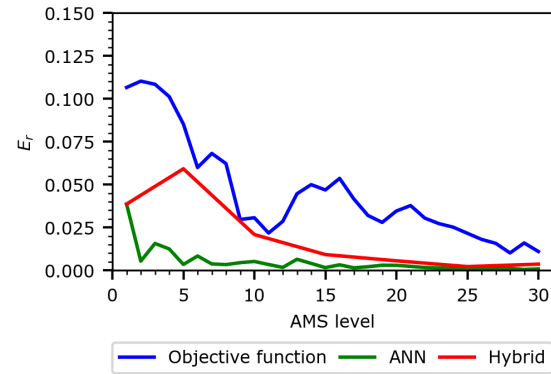
$$E_r = \sqrt{\sum_{i=1}^n (k_i^e - k_i^d)^2}, \quad (2)$$

where  $k_i^e$  is experimental stiffness of  $i$ th section,  $k_i^d$  is estimated stiffness of  $i$ th section,  $n$  is number of sections.

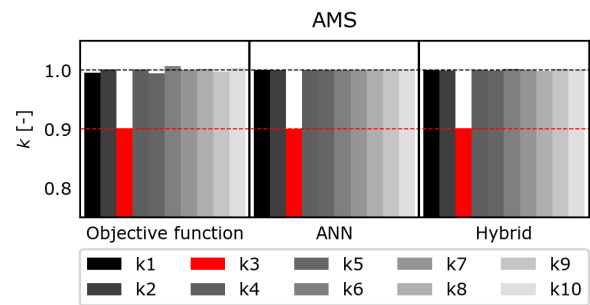
The first method (see blue line in Figure 5) uses the minimum of the objective function as the best realization, the second (green line) uses ANN to identify the best realization. The third method (red line) is a hybrid method combining both approaches. Figure 6 depicts the final stiffnesses identified by all three methods in the last 30th level.

### 4.2. Symmetrically damaged structure

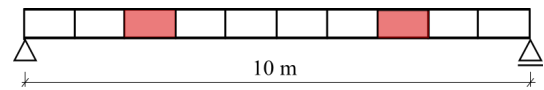
The second analyzed case is a structure symmetrically damaged in two locations. Damage is in sections 3 and 8 (the third section from the left support and third section from the right support), see Figure 7, i.e. the stiffness  $k_3$  and  $k_8$  were reduced to  $k_3 = 0.9$ .



**Fig. 5:** Comparison of the methods – error progress during optimization

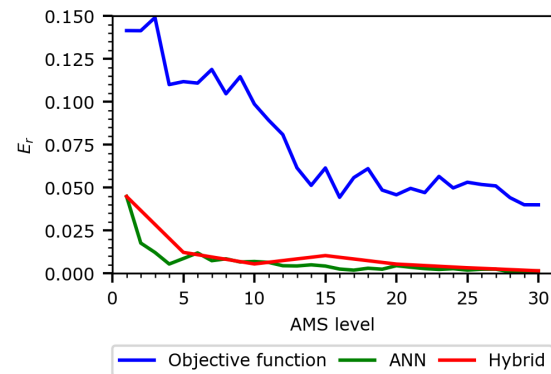


**Fig. 6:** Comparison of the methods – the resulting stiffness in individual beam sections

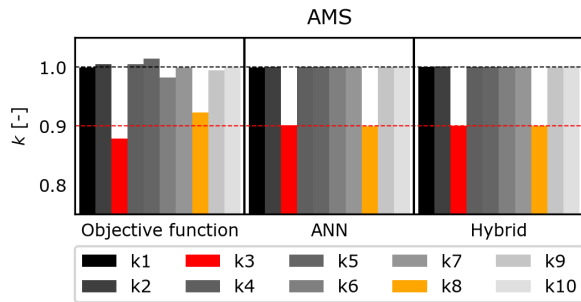


**Fig. 7:** Scheme of a structure damaged in two locations

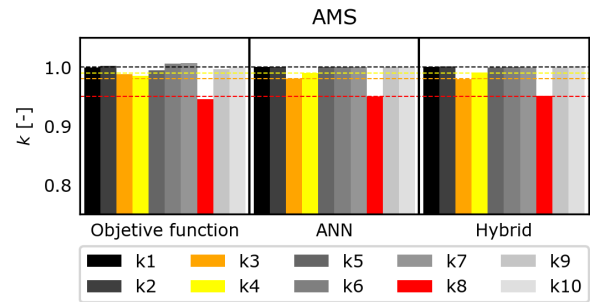
Figure 8 shows the evolution of the error  $E_r$  at each level during the optimization process for all three methods. Figure 9 depicts the final stiffnesses obtained at the last optimization level. Note that damaged sections with reduced stiffness are in red and orange colour.



**Fig. 8:** Comparison of the methods – error progress during optimization



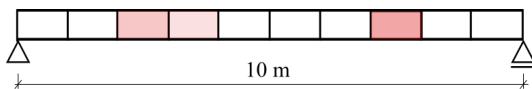
**Fig. 9:** Comparison of the methods – the resulting stiffness in individual beam sections



**Fig. 12:** Comparison of the methods – the resulting stiffness in individual beam sections

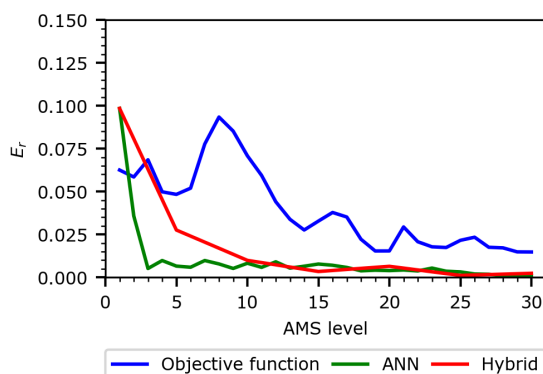
### 4.3. Asymmetrically damaged structure in multiple locations

The last analyzed case is an asymmetrically damaged structure in three locations with different levels of damage. Damages are in sections 3, 4 and 8 (the third and fourth section from the left support and the third section from the right support), see Figure 10, i.e. the stiffness  $k_3$  is reduced to 0.98,  $k_4$  is reduced to 0.99 and  $k_8$  is reduced to 0.95.



**Fig. 10:** Scheme of a structure damaged in multiple locations

Figure 11 shows the evolution of the error  $E_r$  at each level during the optimization process for all three methods. Figure 12 depicts the final stiffnesses obtained at the last optimization level. Note that damaged section three, which is reduced to 0.98 is in orange, section four reduced to 0.99 is in yellow and the most damaged section eight reduced to 0.95 is in red color.



**Fig. 11:** Comparison of the methods – error progress during optimization

## 5. Conclusion

From the results of all three analyzed damage cases, it can be concluded that all presented methods can correctly identify the given structural damage. When comparing the individual methods, it can be seen that the ANN method gives the best convergence and accuracy of the resulting damage identification. The advantage of ANN is its robustness and ability to generalize so it can provide satisfactory results even with a relatively small number of samples at each level. However, creating, training and simulating ANNs brings increased computational demands. The AMS method, on the other hand, due to the layering principle, progressively targets the correct solution using a limited number of simulations at each level. The proposed hybrid method, which combines the advantages of both approaches, appears from the results to be a suitable compromise between accuracy and speed of convergence on the one hand and time and computational complexity on the other. From the results, it can be seen that the inclusion of ANNs at every fifth level of the AMS significantly speeds up the convergence and accuracy of the solution compared to the original AMS, where the best realization is selected as the minimum of the objective function.

## Acknowledgment

This work was supported by specific university research project No. FAST-J-23-8267 granted by Brno University of Technology and the project No. TM04000012 supported by the Technology Agency of the Czech Republic.



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