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Damage detection of riveted truss bridge using ANN-aided AMS optimization method

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ABSTRACT: Aging transport infrastructure brings increased economic burden and uncertainties regarding the reliability, durability and safe use of structures. Early damage detection to locate incipient damage provides an opportunity for early structural maintenance and can guarantee structural reliability and continuing serviceability. This paper describes the use of the hybrid identification method, which combines a metaheuristic optimization technique aimed multilevel sampling with an artificial neural network-based surrogate model to approximate the inverse relationship between structural response and structural parameters. The method is applied to identify damage in existing riveted truss bridge. The effect of the damage rate and location on the identification speed and the accuracy of the solution is investigated and discussed.

1 INTRODUCTION

The increasing frequency of bridge and footbridge collapses highlights the critical importance of early detection of damage to ageing structures through structural health monitoring data. This plays a key role in maintaining the reliability of structures and ensuring the safety of people and property. Various monitoring and detection approaches have been proposed for practical early warning of structural damage (Gomez et. al. 2019, Avci et al. 2021). Among them, vibration-based methods, which use the vibration response of the monitored structure to evaluate its condition and identify damage, have gained wide popularity.

Damage means a change in the geometric or physical properties of the structure. A damaged structure exhibits a different mechanical response compared to an intact structure, with response parameters directly affected by changes in physical properties such as mass and, in particular, stiffness. Damage identification involves a mathematical process known as finite element (FE) model updating. This process modifies the original intact model to accurately match the damaged structure. Once a match is achieved, local adjustments to the model pinpoint the presence of damage.

Minimizing the residuals between the static and dynamic characteristics of the FE model and the characteristics of the damaged structure is an optimization problem that can be solved either directly or in conjunction with a sensitivity-based method (Jung & Kim 2013, Mordini et al. 2015, Zheng et al. 2015). In the methods presented in this paper, sensitivity analysis is used to normalize the effect of response parameters with different sensitivities on the extent and location of damage. This increases the convergence and refinement of the results. Another group of methods directly addresses the inverse relationship between the static and dynamic characteristics of the FE model and its response parameters. This relationship is often represented by a surrogate model such as an artificial neural network, Kriging, etc. (Lehký & Novák 2009, Yin et al. 2019).

In this paper, three methods are used to detect structural damage. The first method uses a metaheuristic optimization technique called aimed multilevel sampling (AMS) to efficiently

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explore the design parameter space, achieving the best match between the deformed structure and its model. This method is enhanced by involving an artificial neural network (ANN) in finding the best realizations during the optimization process. In this paper, the method is referred to as ANN-aided AMS. The second method is a modification of the first method where, in order to reduce the computational complexity, ANN is used in only a limited number of iterations and in the remaining iterations the selection of the best sample is driven by the minimum value of the objective function. The last method treats model updating as an inverse problem and utilizes an ANN metamodel to approximate the inverse relationship between structural response and parameters. All methods are employed to identify damage in single-span riveted steel truss bridge. The study investigates the effect of damage rate and location on the identification speed and solution accuracy.

2 DAMAGE IDENTIFICATION

2.1 *FE model updating*

The method for identifying damage operates through a computational model of the structure. Consequently, the initial step in the identification process involves creating a precise Finite Element model and performing static and dynamic analyses of the considered structure. To meet the required accuracy for damage localization, the structural model is segmented into multiple regions, with stiffness parameters varied during the optimization process. A probability distribution is assigned to these stiffness parameters to establish an initial design space.

Following this, the stiffness parameters for each region are randomly generated in FReeT reliability software (Novák et al. 2014) using the Latin Hypercube Sampling method (LHS), (Stein 1987). Subsequently, modal analysis is performed to ascertain eigenfrequencies and mode shapes. This generates random input data in the form of stiffness values for each region and output data consisting of static and dynamic response parameters for each simulation. These data are then utilized to identify the location and extent of damage within the structure. In this paper, the identification process is carried out using a metaheuristic optimization algorithm coupled with inverse analysis employing artificial neural networks.

2.2 *Aimed multilevel sampling optimization method*

The AMS optimization technique employed in this paper was chosen for its capacity to significantly reduce computational complexity (Lehký 2018). The fundamental concept involves breaking down the simulation process into multiple levels. At each level, advanced LHS sampling is conducted within a predefined design vector $\mathbf{d}$. The sample with the most favorable properties, addressing the optimization problem definition, is subsequently chosen.

Following this, the design space for generating samples is narrowed down around this best sample $\mathbf{d}_{i,\text{best}}$. The next LHS simulation is executed *within* this reduced space. This process facilitates a more detailed exploration in the vicinity of the best-performing samples for the extreme value function. The reduction of the sample space is executed based on heuristic assumptions, constituting a pivotal aspect influencing the accuracy and performance of the AMS method.

There are two approaches to obtaining the best realization for the given design vector, $\mathbf{d}_{i,\text{best}}$. The basic approach is, that it can be derived as the optimal realization generated at the *i*th level for the structural vector $\mathbf{d}$, corresponding to the minimum of the objective function $\phi(\mathbf{d})$, defined as:

$$\phi(\mathbf{d}) = \sum\nolimits_{j=1}^{n} w_i \left[\frac{e_j - m_j(\mathbf{d})}{e_j} \right] \tag{1}$$

where, the term e_j represents the *j*th experimental static or dynamic property, serving as a structural response parameter to be aligned. Meanwhile, $m_j(\mathbf{d})$ represents the equivalent response parameter generated by the FE model. The parameters w_i are weight coefficients associated with the response parameters. Their role is to offset the influence of response parameters with lower sensitivity, which is crucial for accurately identifying the location and extent of damage. These parameters ensure that even though some response parameters may have lower sensitivity, their contribution is considered in the identification process, preventing their neglect in the presence of more dominant response parameters.

An alternative approach is to view the problem as an inverse problem, where the inputs are the eigenfrequencies and mode shapes and the outputs are the stiffness values. However, for complex structures, this inverse relationship is impossible to find and the FE model must be replaced by a surrogate model, in our case the ANN. The neural network is trained using input–output pairs and then the best realization of the vector $\mathbf{d}_{i,\mathrm{best}}$ is predicted. The basic idea of this method is to perform a large number of simulations using LHS on the initial design space, map the inverse space using a robust ANN, and then use it to predict the best realization. This method is hereinafter called "pure ANN".

The flagship of this paper is a method using ANN at each level of AMS. This method is called the ANN-aided AMS method. This method is the most complex of all the methods in this paper because it requires creating, training and simulating an ANN at each AMS level. Due to the time-consuming nature of the method, there is an alternative approach called here as the "hybrid method" that combines two approaches to estimate the best realization, namely using an ANN at every third level and using the minimum of the objective function at the other levels (Eq. 1).

3 REVITED TRUSS BRIDGE

Figure 1. Sideview of a riveted truss bridge in Trnovec nad Váhom (Slovakia).

The methods were applied to a steel railway bridge over the Váh River in Trnovec nad Váhom (Slovakia) (Figure 1). The steel bridge consists of 28 simply supported bridge objects, 14 on each of the two tracks. One of the tracks consists of truss bridges and the other is a combination of truss and box bridges. The total span of the bridge is 455.8 m. Objects are placed on concrete pillars (four on each pillar). This paper will focus on one of the truss bridges. The span of the selected bridge object is 31.3 m.

3.1 *Measurement of the dynamic response of the bridge*

A large part of the bridge passes through an inundation area, so access to individual objects was relatively easy. The dynamic response of individual bridge objects was measured using several measuring devices. The measurements were made during full operation without traffic restrictions. The displacements of the structure caused by passing trains were measured using the IBIS-S interferometric radar. From the time records of the displacements, it was also possible to determine the natural frequencies of the structure. In addition, appropriately spaced accelerometers were used to accurately determine the eigenfrequencies and mode shapes. The measured data were used to verify the correctness of the FE model.

3.2 *FEM model*

A detailed FEM model of the bridge was created (Figure 2). Almost all structural elements (except for the lateral and transverse bracing) were created using shell elements. To better capture the response of the bridge when trains pass by, non-load-bearing parts, such as wooden sleepers and steel rails, were also modelled. The bridge was supported by a fixed bearing on one side and a sliding hinged bearing on the other side.

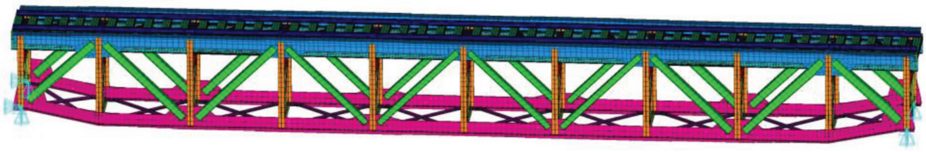

Figure 2. FEM model of the bridge.

The methods were applied to identify damage in three different cases – damage at one location, at three locations with the same and different levels of damage. The damage was modelled by reducing the Young's modulus of selected diagonal members. The original (undamaged) model was made of steel with a modulus of elasticity E = 210 GPa. A separate material model was created for each diagonal member, and the original modulus of elasticity E was multiplied by the coefficient k, which expressed how severe the damage to the member was. If the coefficient is equal to 1, the section was without damage (the coefficient less than 1 indicates damage). The coefficients k represent random variables for the FE model updating.

4 RESULTS

4.1 *Structure damaged in one location*

4.1.1 *Damage description*

The first analyzed case is the structure damaged in the fifth diagonal member, see Figure 3, where the damaged member is marked in red.

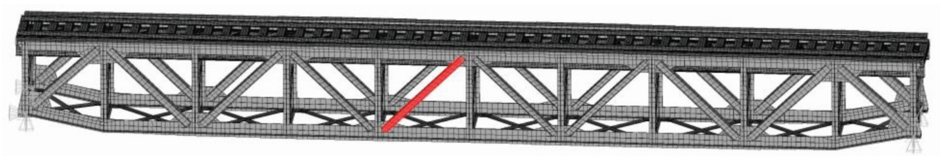

Figure 3. FEM model of the bridge with the damaged fifth diagonal member marked.

At the beginning of identification process, the initial design space was chosen in the range of 0.85-1.05 for all stiffnesses k. The total number of simulations was 1200, which for the AMS method was divided into 12 levels each of 100 simulations. The performance of each method is further compared in terms of error, which is calculated as:

$$Error = \sqrt{\sum\nolimits_{i=1}^{n} \left(k_i^e - k_i^d\right)^2}, \tag{2}$$

where k_i^e is experimental stiffness of ith section, k_i^d is estimated stiffness of ith section, n is number of diagonals.

4.1.2 *ANN-aided AMS*

The first employed method is ANN-aided AMS method, where the best realization $\mathbf{d}_{i,\text{best}}$ at each AMS level is selected by an artificial neural network. The course of identification is shown in Figure 4, where on the left side is the evolution of the stiffness values during the optimization process and on the right side is the evolution of the error (Eq. 2).

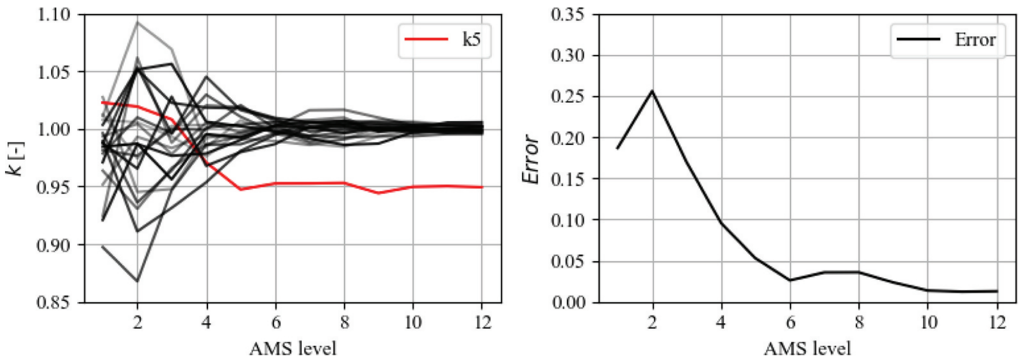

Figure 4. Case 1 optimization by the ANN-aided AMS: evolution of the stiffness values, with damaged segment k_5 in the red (left) and the evolution of the error (right).

4.1.3 *Hybrid method (ANN at every 3^rd^ level)*

The second method is the hybrid method, which uses a combination of the objective function and artificial neural network. Compared to the first method, ANN is used only at every 3^{rd} level, and the objective function is used at the other levels. The ANN helps to improve solution convergence while maintaining the speed of the classical AMS optimization method, see vertical changes in Figure 5.

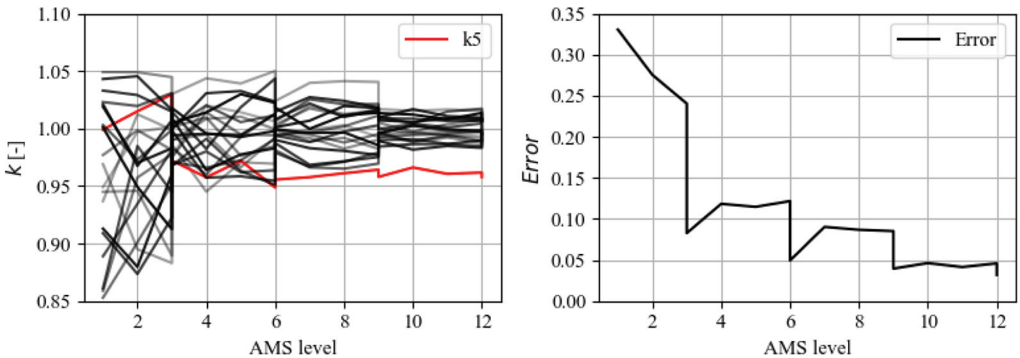

Figure 5. Case 1 optimization by the hybrid method: evolution of the stiffness values with damaged segment k_5 in the red (left), and the evolution of the error (right).

4.1.4 *Pure ANN*

The last method approaches optimization as an inverse analysis and uses ANN to replace the inverse relation. First, all 1200 simulations are calculated at once using the LHS method. The artificial neural network is then trained on all simulations and one prediction is provided. The method is not iterative and there is no sequential aiming. Figure 6 depicts the resulting stiffnesses of the diagonal members using a bar graph, with the damaged fifth member in red, and other undamaged members in shades of grey. The left side of the figure shows the best realization at the last AMS level (12^{th}) provided by the ANN-aided AMS method, the middle is the best realization at the last AMS level (12th) calculated by the hybrid method, and the right-hand side is the damage prediction for the pure ANN. The results show that splitting the simulations into several levels using AMS brings better results than using ANN once for all available simulations.

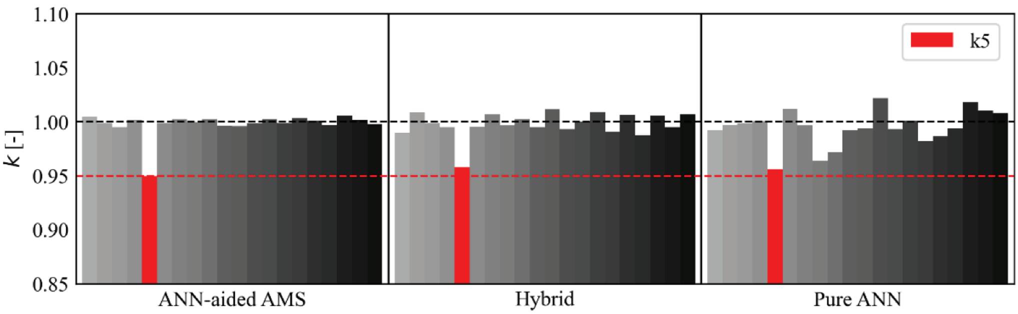

Figure 6. Comparison between ANN-aided AMS, Hybrid and Pure ANN methods.

A comparison of the errors for the first damage case for all methods is shown in Figure 7. The first column of the graph represents the ANN-aided AMS method, where the artificial neural network is used at each level, the error value is 0.0128. The second column represents the hybrid method, where ANN is used at every 3rd level, the error value is 0.0319. The last column belongs to the pure ANN method, where only one ANN is used for all simulations, the error value is 0.0635.

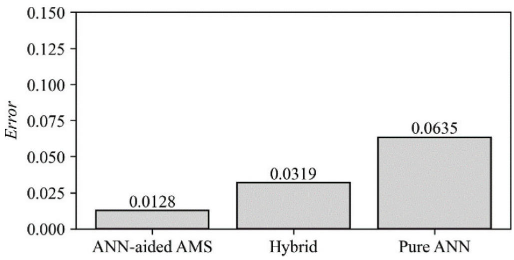

Figure 7. Comparison of the final optimization errors for the first damage case.

4.2 *Structure damaged in three locations with the same level of damage*

4.2.1 *Damage description*

The second case analyzed is the damage to the fifth, eighth and eighteenth diagonal members, as can be seen in Figure 8, where damaged members are marked in red. The damage magnitude is the same for all members and corresponds to a 5% reduction in stiffness.

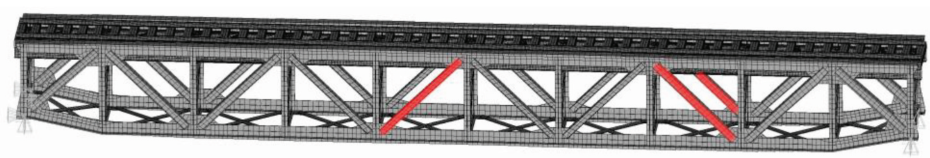

Figure 8. FEM model of the bridge with the damaged fifth, eighth and eighteenth diagonal member marked.

4.2.2 *ANN-aided AMS*

Given the best performance, only the ANN-aided AMS method was used, which uses an ANN to select the best realization at each AMS level. From the results depicted in Figure 9, it can be seen that all three damaged locations as well as the damage level were correctly identified.

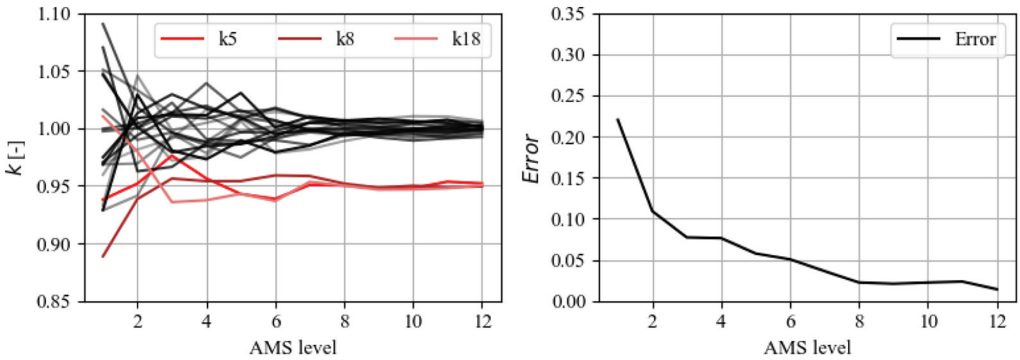

Figure 9. Case 2 optimization by the ANN-aided AMS: evolution of the stiffness values, with damaged segments in shades of red (left), and the evolution of the error (right).

4.3 *Structure damaged in three locations with different level of damage*

4.3.1 *Damage description*

The last case presented in this paper is a structure damaged in three different locations, each location having a different level of damage. The least damaged diagonal member is the eighth member (stiffness is reduced to 0.97), marked in light red, as shown in Figure 10. The most damaged member is the eighteenth member (stiffness is reduced to 0.93), the location is opposite to the eighth member, marked in dark red in the figure. In the fifth member, the stiffness is reduced still to 0.95, marked in red.

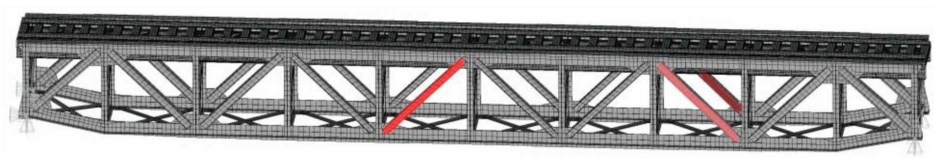

Figure 10. FEM model of the bridge with the damaged fifth, eighth and eighteenth diagonal member marked.

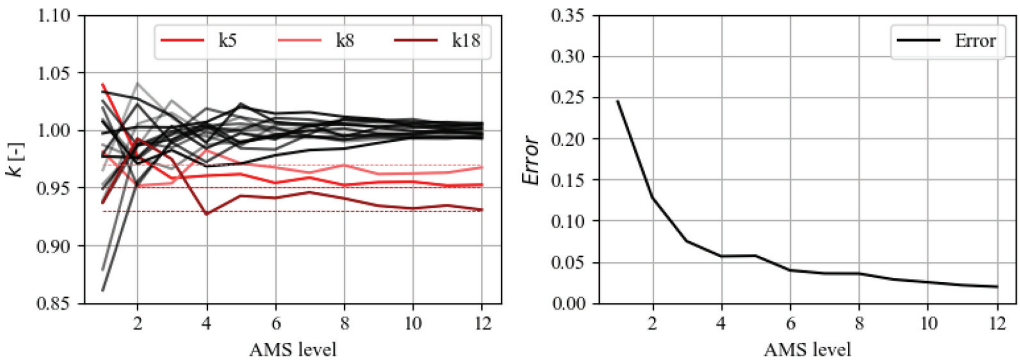

Figure 11. Case 3 optimization by the ANN-aided AMS: evolution of the stiffness values, with damaged segments in shades of red (left), and the evolution of the error (right).

4.3.2 *ANN-aided AMS*

As in the previous case, the ANN-aided AMS method was used. As can be seen in Figure 11, this method dealt with this problem really well. All damaged members were detected correctly, including an accurate estimation of the damage level.

5 CONCLUSION

The results of the analyzed damage cases show that the use of the AMS method in combination with an artificial neural network represents the most accurate approach to the task of damage identification. However, this method is the most time-consuming and computationally demanding of all the methods, since an ANN has to be created, trained, and simulated at each AMS level. An alternative is to use the classical AMS method, where the minimum of the objective function is used to select the best realization. This is a computationally relatively fast solution, but the disadvantages tend to be lower accuracy and slower convergence. A compromise between accuracy and time is the hybrid method, which combines the advantages of the classical AMS method and the use of ANNs at selected levels to improve convergence. When computational time is not an issue, the most efficient and accurate solution is the ANN-aided AMS method.

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