

# STUDY ON OPTIMAL SETUP OF THE ANN-AIDED AIMED MULTILEVEL SAMPLING OPTIMIZATION METHOD

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## Abstract

This paper deals with the application of Aimed multilevel sampling metaheuristic optimization method supported by an artificial neural network. The main aim is to study the optimal parameter settings of this method for damage identification on a two-span steel truss using a limited number of simulations. The convergence rate is tested as a function of the number of simulations and the choice of the parameter that controls the resizing of the design space. The results are summarized and discussed with respect to their practical applicability in bridge damage identification using structural health monitoring data.

## Keywords

Aimed multilevel sampling, artificial neural network, damage identification, model updating

## 1 INTRODUCTION

The growing occurrence of bridge and footbridge collapses underscores the critical importance of early detection of structural damage in aging structures through the analysis of structural health monitoring, which is important in maintaining reliability of structure. Numerous methods for monitoring and detecting structural issues have been developed to provide early warning signs of potential damage. Among these, vibration-based techniques, which rely on the vibrational response of the monitored structure to assess its condition and detect structural damage, have gained popularity [1], [2].

Damage, in this context, can be defined as difference in the geometric or physical properties of the structure. A structure afflicted by damage exhibits distinct mechanical responses compared to an undamaged structure. The response parameters are directly affected by changes in the physical properties of the structure, particularly its mass and stiffness. The identification of damage is subsequently accomplished through a mathematical process known as finite element (FE) model updating. This process involves modifying the original model of the undamaged structure to closely match the characteristics of the damaged structure. Once a suitable match is achieved, the damage is identified [3],[4].

This paper describes the Aimed multilevel sampling (AMS) optimization method used for model updating [5], which is aided by an artificial neural network. The following section presents the main aspects of the AMS method and its application to a two-span steel truss. This is followed by a presentation and discussion of the results of the FE model updating process for different settings of the method.

## 2 METHODOLOGY

### AMS aided ANN method

In this section, the above mentioned artificial neural network-aided AMS method is briefly introduced. The method belongs to the category of simulation techniques and, thanks to its concept, reduces often undesirable computational complexity. The main idea of this method is to divide optimization process into several levels. At each level, advanced sampling is performed within the defined design space using Latin hypercube sampling method. The best realization of the structural parameter vector  $\mathbf{d}$  is then determined. This is done by inverse analysis using an artificial neural network. The obtained best realization  $\mathbf{d}_{i,best}$  at a given level  $i$  is then used as the mean value of the design space for the next level  $i + 1$ , as shown in Fig. 1.

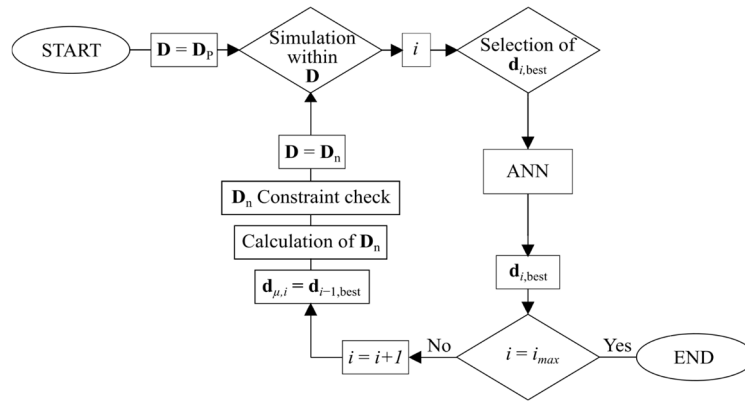


Fig. 1 Scheme of ANN-aided AMS method.

In Fig. 1,  $\mathbf{D}_p$  represents an initial design space of the optimization problem,  $\mathbf{D}_n$  is the scaled design space at the next level and  $\mathbf{D}$  is the design space of  $n$  dimensions. The index  $i$  denotes the current level,  $i_{max}$  is the maximum (final) level, whose achievement represents the termination criterion of the optimization process.

At the beginning of the process, the user have to define the initial size  $a_1$  and final size  $a_{i,max}$  of the design space at the last level. Note that  $a_{i,max}$  represents the accuracy of the obtained solution. It is also necessary to define the total number of simulations  $N_{tot}$  and the final level index  $i_{max}$ . The value of coefficient  $q$ , which drives the reduction of the design space at each level, is obtained as:

$$q = \frac{i_{max}^{-1} \sqrt{a_{i,max}}}{a_i} \quad (1)$$

Ignoring the initial and final size of the design space and the total number of simulations, which are often predetermined, the accuracy of the solution and the rate of convergence of the AMS method is controlled by the number of levels  $i_{max}$ , the related value of the parameter  $q$ , and the number of simulations at each level  $N_{sim}$ . In the following application, the setting of these parameters on the optimization results is investigated.

## Application

The AMS method is employed to identify damage to a two-span steel truss. The numerical model of the structure is made of twelve sections. Each section is 1 m long and is made of two I-beams with a height of 0.5 m, L-section stiffeners were added in the transverse and horizontal direction, see in Fig. 2. Each section has its linear elastic material model. Damage is modelled by the reduction of stiffness, specifically the modulus of elasticity  $E$ , which initial value is 210 GPa.

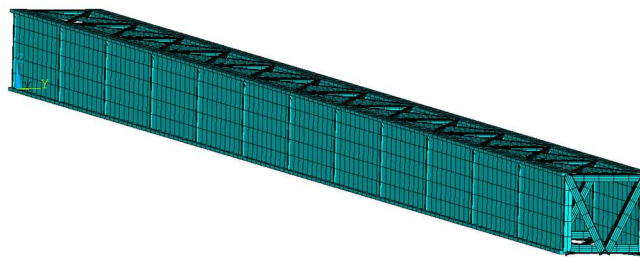


Fig. 2 Scheme of the FE model.

The structure is damaged in three places. The first damage is in section 3 where the stiffness is reduced by 5%, the second and third locations are above the middle support and the damage represents a 10% reduction in stiffness, see in the Fig. 3.

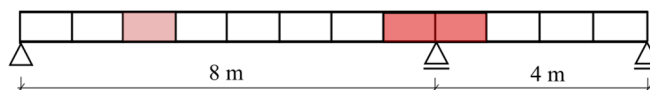


Fig. 3 Side view of the damaged structure with colour indication of damaged sections.

### 3 RESULTS

In this section, optimization results for different settings of the AMS method are presented. The total number of simulations  $N_{tot} = 600$  remains the same for all test cases, but the number of levels  $i_{max}$  changes. The initial space size  $a_1 = 0.1$  and the final space size  $a_{i,max} = 0.01$ , see equation (1). Eight combinations of the number of simulations at each level vs. the number of levels ( $N_{sim} \times i_{max}$ ) were analysed, ranging from a combination of  $25 \times 24$  to  $600 \times 1$ , see the x-axis in Fig. 4. The vertical y-axis gives the error between the damaged and identified stiffness of the structure, which is calculated as:

$$Error = \sqrt{\sum_{i=1}^m (k_i^e - k_i^d)^2} \quad (2)$$

where  $m$  represents the number of structure sections, in our case, it is 12,  $k_i^e$  is the experimental (real) stiffness of the  $i$ th section and  $k_i^d$  is estimated (identified) stiffness of the  $i$ th section.

Note that in the last combination ( $600 \times 1$ ) AMS targeting was not used at all because there is only one level, so all samples were generated at once. Since stochastic optimization is performed, five calculations were performed for each combination of settings. The results of each calculation are shown in Fig. 4, where each black point represents the resulting optimization error and the dashed line connects the mean values of the five samples.

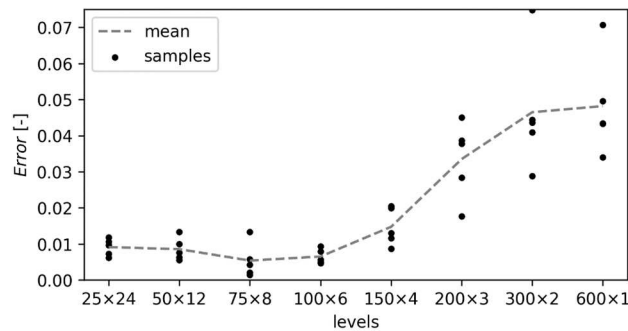


Fig. 4 Graph of resulting optimization errors for different setup of the AMS method.

Instead of using the number of levels and simulations, the above graph can be transformed to use the value of the coefficient  $q$  from equation (1), which determines how much the design space at the next level is reduced. See Fig. 5. Correct setting of the  $q$  parameter is important to ensure the accuracy of the solution and the convergence speed of the optimization process.

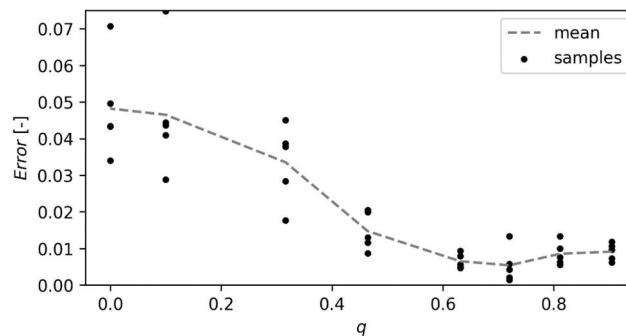


Fig. 5 Graph of resulting optimization errors for different  $q$  values of the AMS method.

Fig. 6 shows eight graphs that depict the evolution of the error (2) during the optimization process for eight combinations of AMS method setup. The mean error for each combination are then compared with each other in Fig. 7, where the difference between setups can be better seen.

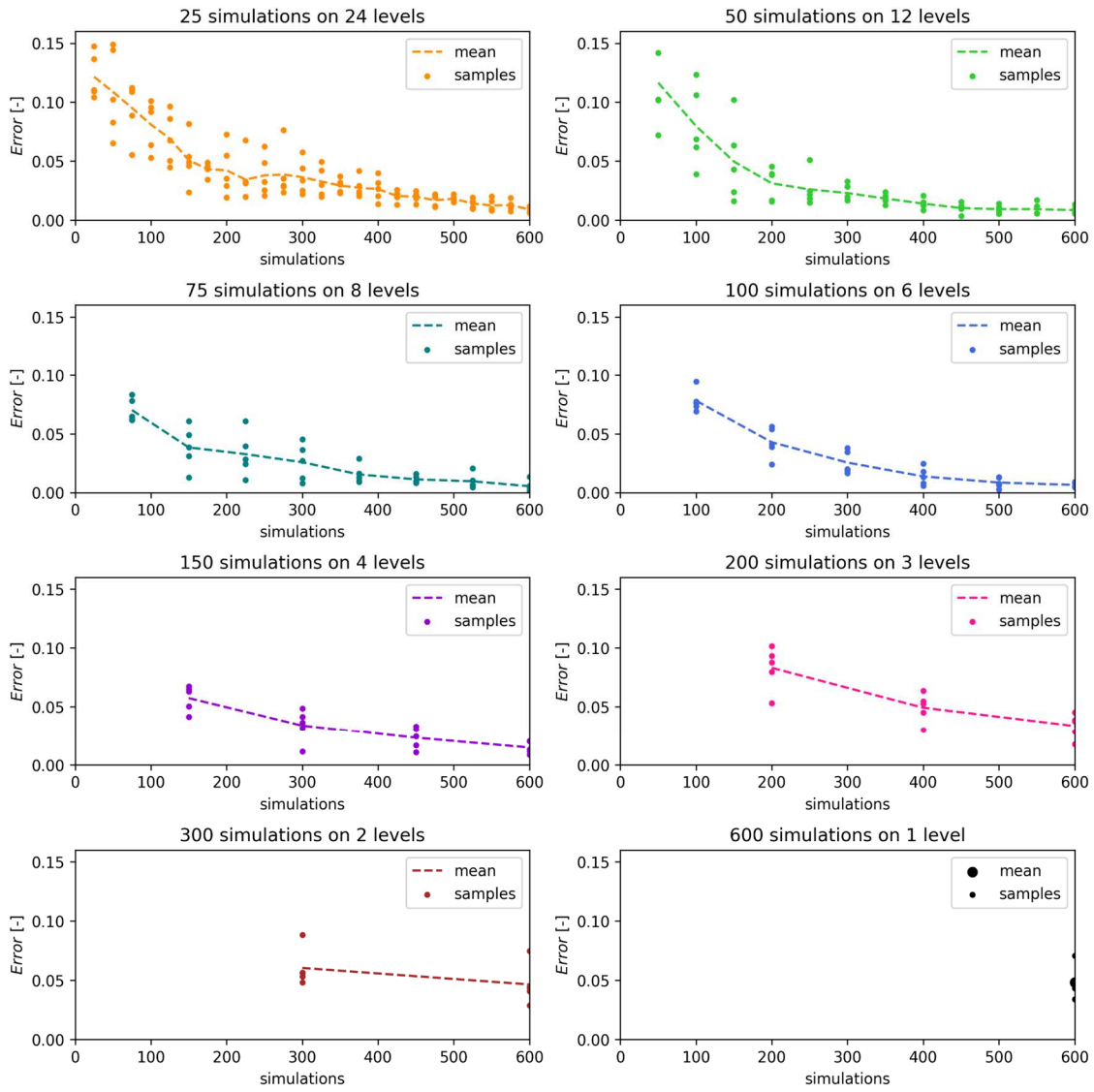


Fig. 6 The evolution of the error during the optimization process for eight combinations of AMS method setup.

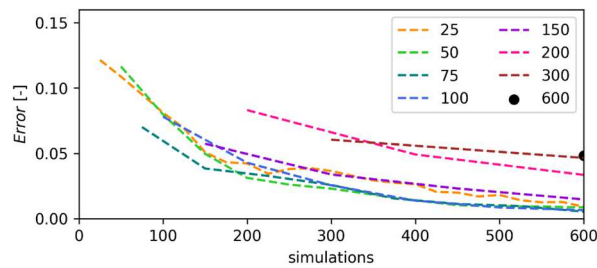


Fig. 7 The mean error evolution during the optimization process for eight combinations of AMS method setup.

## 4 DISCUSSION

As can be seen in Fig. 6, in the first two setup cases, where 25 simulations on 24 levels and 50 simulations on 12 levels are used, the optimization error on the first couple of levels is high because the ANN cannot map the design space well due to the small amount of training data (25 and 50 simulations). On the contrary, the final result obtained on the last level is really good because the design space has enough time to be properly targeted by dividing the process into a relatively large number of levels. The disadvantage of this setup is that the network must be trained 24 and 12 times respectively.

In the case of 300 simulations on two levels, it can be observed that there is not so much difference between the first and second level, which is due to the fact that on the second level, the simulations are performed on a small final design space (0.01), which prevents a significant change in the values of the parameters. Thus, the ANN is trained on similar data as at the first level, leading to similar results.

The last case, where 600 simulations are used on one level, represents the case of using ANN without AMS targeting. That is, 600 simulations are generated over the entire initial design space, and the ANN is trained on all this data and then picks the best realization from the entire design space. The advantage is the mapping of the design space using a large number of realizations, the disadvantage is not taking advantage of the targeting provided by the AMS method.

## 5 CONCLUSION

As can be seen in the results section, the low error values in Fig. 4 are between 25 simulations on 24 levels and 100 simulations on 6 levels. From Fig. 5, it is obvious that the value of parameter  $q$  must be at least 0.6 for the analysed structure, the initial and final design space and the total number of simulations. Considering not only the lowest value of error but also the time used to train neural network, the best setup seems to be 100 simulations on 6 levels, where the value of error is still small and the ANN only needs to be trained six times.

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