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An Hybrid Real Genetic Algorithm to Detect Structural Damage Using Modal Properties

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Abstract

An hybrid real coded Genetic Algorithm with damage penalization is implemented to locate and quantify structural damage. Genetic Algorithms provide a powerful tool to solved optimization problems. With an appropriate selection of their operators and parameters they can potentially explore the entire solution space and reach the global optimum. Here, the set-up of the Genetic Algorithm operators and parameters is addressed, providing guidelines to their selection in similar damage detection problems. The performance of five fundamental functions based on modal data is studied. In addition, this paper proposes the use of a damage penalization that satisfactorily avoids false damage detection due to experimental noise or numerical errors. A tridimensional space frame structure with single and multiple damages scenarios provides an experimental framework which verifies the approach. The method is tested with different levels of incompleteness in the measured degrees of freedom. The results show that this approach reaches a much more precise solution than conventional optimization methods. A scenario of three simultaneous damage locations was correctly located and quantified by measuring only a 6.3% of the total degrees of freedom.

Key words: Damage Detection, Genetic Algorithm, Modal Analysis, Damage Penalization

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1 Introduction

The early detection of structural damage generates a wide interest in the civil, mechanical and aerospace engineering fields. Many recent studies focus on the application of vibration-based damage detection methods. While visual inspection fails to assess damage at early stages, vibration measurements are sensitive enough to detect damage even if it is located in hidden or internal areas.

Damage detection methods are classified according to the level of identification attempted [1]:

Level 1: Detecting the presence of damage in the structure;
Level 2: Determining the geometric location of the damage;
Level 3: Quantifying the severity of the damage;
Level 4: Predicting the remaining lifespan.

Levels 3 and 4 are the most challenging areas of damage detection, to achieve these levels model-based methods are necessary. These methods correlate a numerical model with measured data from the structure. A set of variables is updated to obtain the minimum difference between the numerical and experimental data. Damage is modelled as a reduction of stiffness in an element, and it is detected by comparing the undamaged and damage state.

A proper selection of the objective function is crucial since it not only modifies the interpretation of the best correlation, but also influences the convergence of the optimization procedure. Several objective functions have been reported

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in the damage detection field. Salawu [2] presents a review of damage detection methods through changes in frequencies. Despite the fact that he emphasizes that damage detection using only natural frequencies is attractive, since it is fast and economical, he concludes that it is not possible to locate and quantify correctly any damage situation by using only frequencies. Hence mode shape data is also necessary.

Many authors discuss the problem of detecting damage using mode shapes and frequencies. Shi et al. [3] present a sensitivity based method to locate and quantify damage. Damage is located using incomplete measured modes and it is quantified using the measured natural frequencies. The method is able to detect the real damage but a significant amount of false damage is also detected. Araujo dos Santos et al. [4] propose a damage detection algorithm based on the orthogonality condition sensitivities, their method produces more accurate results than the mode shape sensitivities method. The same method is implemented later by Ren and De Roeck [5, 6]. Wahab [7] studies the effect of including the modal curvatures in the convergence of a sensitivity based method. He concludes that the addition of modal curvatures does not improve the algorithm convergence. Görl and Link [8] implement a damage detection algorithm based on modes and frequencies sensitivities. Although damage is successfully located and quantified, a careful selection of the regularization parameters is necessary to achieve satisfactory results.

Other objective functions that make use of modal data are strain energy, modal flexibility and residual forces. A disadvantage of these functions is that they need a sufficient fine spatial resolution. Jaishi and Ren [9] update the finite element models of a simulated beam and a real bridge using the strain energy residual. Jaishi and Ren [10] implement a sensitivity based algorithm using modal flexibility residuals. The method is verified on simulated and experimental multi-cracked beams. A sensitivity method based on residual forces is implemented by Kosmatka and Ricles [11]. The method is used to detect damage on an experimental space truss structure.

The use of the Frequency Response Function (FRF) is also an alternative [12, 13]. The advantage is that no modal extraction is necessary, thus contamination of the data with modal extraction errors is avoided. However, complex FRF data with noise can make the convergence process very slow and often numerically unstable as was found by Imregun et al. [[13]. Furthermore, the success of the method is highly dependent on the selection of the frequency points. Lammens [14] addresses how a poor selection of the frequency points can lead to an unstable updating process and inaccurate results. FRFs have also the disadvantage that they can not be identified from output only modal analysis with ambient excitation, thus the excitation by an artificial force is always required.

Conventional optimization techniques used in damage detection or model updating employ sensitivity based searching mechanisms. These searching mechanisms do not assure to reach an unique optimum solution because they are highly sensitive to the initial searching conditions and they usually lead to local minima. Moreover, the ill-conditioned inverse problem leads to instabilities and the convergence is not always assured. According to Natke [15] the only solution to overcome ill-conditioning is the regularization of the equations. However, the regularization parameters must be carefully selected, since the speed of convergence and the quality of the results strongly depends on them [16]. It seems, therefore, that further investigations are needed to implement a robust optimization approach to deal with these problems. Since John Holland first developed the genetic algorithm (GA) in 1975, it has been increasingly introduced in diverse areas such as music generation, genetic synthesis, strategy planning, machine learning and damage detection [17].

The GA is a global searching process based on the Darwin's principle of natural selection and evolution. A simple GA consists in three main operations: selection, genetic operations and replacement. The GA starts with an initial population; the individuals of this population are subjected to the three operators and evolve. The result is a population with a higher fitness than the initial one as in natural selection. This process is iterated for a number of generations until a convergence criterion is achieved. There are three main selection processes: roulette wheel [18], normalized geometric [19] and tournament selection [20]. To increase the speed of convergence an elitist strategy can be adopted. Crossover and mutation are applied randomly with a probability of p_c and p_m respectively. The crossover is considered the main search operator in GAs, as a consequence many types of crossover have been developed. Some of them are: single point crossover, two point crossover [21], uniform crossover [22] , flat crossover [23], arithmetic crossover [24], heuristic crossover [25], blend crossover [26], BLX- crossover [26], and many more. The mutation operation replaces a gene in a chromosome with one chosen randomly from the solution space. In uniform mutation the gene is set equal to a uniform random number, and in boundary mutation it is set equal to either its lower or upper bound. A correct selection of the GA operators and parameters is crucial as they affect the solution and the algorithm runtime [27]. However, there is no general rule to select them; the right decision depends on the number of genes, the objective function and the nature of the problem. This paper studies the problem of selecting the GA operators and parameters during the implementation of a structural damage detection algorithm. This results in guidelines for GA operator and parameter selection in similar damage detection problems.

Binary-coded genetic algorithms (BCGA) were the first GA-methods to be introduced in damage detection [28–33]. Recently, there has been growing interest on implementing real-coded genetic algorithms (RCGA) [34–37], since they work better with continuous variables and require less storage than BCGA. RCGA are inherently faster since decoding the binary variables before each evaluation is not necessary. In addition RCGA do not have a limited precision as do BCGA; this allows a representation to the machine precision [38]. Although RCGAs have already been implemented in damage detection algorithm, they are modern techniques that are still under development. As a consequence, there are still problems to be investigated regarding to their implementation, such as: environmental effect, experimental noise, selection of the objective function, selection of adequate GA parameters and operators, parallelization and hybridization . . . [39].

The performance of BCGA and RCGA in the crack detection of a cantilever beam is studied by Vakil-Baghmisheh et al. [36]. A numerical model of a beam with a single crack is proposed. Numerical and experimental data is used to test the performance. The best average values of location and deep prediction are obtained with the RCGA. Gomes and Silva [37] compared the performance of a RCGA and a sensitivity method for damage detection. They use only natural frequencies in the objective function. The method is tested with noise free simulated data of a simple supported beam and a portal frame. No general conclusions are obtained from the results, since both methods have problems in locating and evaluating the extension of the damage. To improve their results also mode shapes should have been considered, it has already been demonstrated that with only natural frequencies it is not possible to locate and quantified any damage situation [2]. A BCGA with residual forces is implemented by Mares and Surace [28] to detect structural damage. The method is tested with simulated data of a five-bay truss structure and a cantilever beam. Rao et al. [29] also work with force residuals and BCGA optimization to detect damage of simulated truss structures. Ruotolo and Surace [30] describe a damage detection of a multiple cracked beam with both simulated and experimental data. The problem is solved with a BCGA using three fundamentals objective functions based on natural frequencies, modal displacements and modal curvatures. Chou and Ghanboussi [31] use simulated measurements of static displacements and a BCGA to detect damage in two plane truss structures. Asce and Xia [34] implement a damage detection algorithm using a RCGA to minimize an objective function based on natural frequencies and mode shapes. The algorithm is evaluated with an experimental cantilever beam and an experimental portal frame. An algorithm that combines RCGA and simulated annealing is proposed by He and Hwang [35] to detect damage in beam-types structures. A modified GA is developed by Borges et al. [40] to detect damage in framed structures. They proposed: discrete values to represent the damage, a heuristic generation of the initial population, two dynamically varying fitness functions based on modal data and two specialized mutation operators. Kouchmeshky et al. [41, 42] proposed a two stages algorithm to detect structural damage. First the algorithm searches for possible damage scenarios and secondly the algorithm searches for tests that increment the level of information, in both stages GA are used. The feasibility of the method is demonstrated in several examples with simulated data of a four-span bridge truss. This methodology is useful in cases where only a few measurements can be obtained on each test. Perera et at. [33] compared four multiobjective algorithms based on a BCGA for the application of structural damage identification. Two objective functions are considered, the first based on the modal flexibility and the second based on modes and frequencies. The method is tested with numerical and experimental data of a simply supported beam. The best results are obtained with the strength pareto evolutionary algorithm, although considerable false damage is detected.

Genetic Algorithms are inherently slow when they work with complicated or time consuming objective functions. This is partly solved by combining the power of GA with the speed of a local optimizer (hybrid-GA). Thus, the GA finds the regions of the optimum, and the local optimizer finds the minimum. Friswell et al. [31] solve the damage detection problem in two stages. First, the damage is located with a BCGA, and second the eigensensitivity method is used to quantify the damage extend. The method is verified with a simulated cantilever beam and an experimental steel plate. Koh et al. [32] identify damage on a large structure using a hybrid optimization approach. The optimization is handled with a BCGA followed with a least square optimization. Au et al. [43] work with a two step procedure; first the element quotient difference is employed to locate the damage and second a micro-GA is used to quantify it. Simulated beams with multiple damage are use to verified the approach. Raich et al. [44] studied the performance of an hybrid GA in detecting damage of a cantilever beam, a two-spam beam and a steel frame, in the three cases simulated noisy data is used. The performance is evaluated for a fixed representation and an implicit redundant representation, the GA search is followed by local search algorithm to improve the solution accuracy. They concluded that an implicit redundant representation provides a greater accuracy in detecting and locating damage.

Most of the papers cited here focuse on finding a robust optimization procedure that reaches the global optimum using an objective function that is sensitive enough to structural damage. However, little attention has been paid to minimizing the effect of experimental noise or numerical errors in the damage detection procedure. Experimental noise and numerical errors generate differences between the numerical and experimental data that can be interpreted as damage. This false damage causes a minor improvement in the correlation; consequently, a significant amount of false damage can be detected. Ruotolo and Surace [30] introduce a weighting term in the objective function to promote the location of damage at fewer sites. With the introduction of this term, false damage detection was significantly reduced. Friswell et al. [31] add a penalization term in the objective function when there is more than one damage location detected. This penalization works fine when there is only one damage location, but is not intended for multiple damages. Xia et al. [45] study the effect of experimental and numerical noise on false damage detection. They implement a statistical method to define the probability of damage existence.

The present study implements a hybrid-RCGA to detect structural damage. It addresses the set-up of the GA parameters and operators. It studies different objective functions, which are based on frequencies, mode shapes, strain energy and modal flexibility. The chosen objective function is the one that provides both the best convergence and solution. Additionally, the paper proposes a damage penalization term that successfully avoids the problem of false damage detection because of experimental noise or numerical errors. A tridimensional space frame structure with single and multiple damages scenarios provides an experimental framework which verifies the approach. The results are compared with those obtained through conventional methods such as the Inverse Eigen-

Sensitivity Method and the Response Function Method. The accuracy of the method is tested with different levels of incompleteness in the measured data.

2 Damage Detection Procedure

The damage is represented by an elemental stiffness reduction factor β_i, defined as the ratio of the stiffness reduction to the initial stiffness. The stiffness matrix of the damage structure $[K_d]$ is expressed as a sum of element matrices multiplied by reduction factors,

$$[K_d] = \sum_i (1 - \beta_i) [K_i] \tag{1}$$

The value $\beta_i = 0$ indicates that the element is undamaged whereas $0 < \beta_i \leq 1$ implies partial or complete damage. This is the simplest method to model damage. Although this model has problems in matching damage severity to crack depth and is affected by mesh density, Friswell and Penny [46] demonstrated that at low frequencies this method can correctly model a crack. It was shown that a more detailed model does not substantially improve the results from damage assessment

The problem of detecting damage is a constrained nonlinear optimization problem, where the damage reduction factors of each beam β_i are defined as updating parameters. An objective function represents the error between the measured and numerical modal data. To asses the more efficient objective function, five fundamental objective functions have been considered,

(1) The error in frequency,

$$F_1(\{\beta\}) = \sum_i \left(\frac{\lambda_{A,i}(\{\beta\})}{\lambda_{E,i}} - 1 \right)^2 = \sum_i \left(\frac{\omega^2_{A,i}(\{\beta\})}{\omega^2_{E,i}} - 1 \right)^2 \quad (2)$$

The subscripts A and E refer to analytical and experimental respectively.λ_i is the ith eigenvalue and ω_i is the ith natural frequency.

(2) The modal displacements difference,

$$F_2(\{\beta\}) = \sum_i \|\{\phi_{A,i}\} - \{\phi_{E,i}\}\|^2 \quad (3)$$

Where ϕ_i is the ith mode shape. This difference is evaluated only at the measured degrees of freedom. Equation 3 can only be applied if both sets of mode shapes are consistently normalized. Experimental modes shapes are normalized using the modal scale factor MSF [47].

(3) The MAC value,

$$F_3(\{\beta\}) = \sum_i \left(1 - MAC\left(\{\phi_{A,i}\}, \{\phi_{E,i}\}\right)\right)^2 \quad (4)$$

MAC [47] is a factor that expresses the correlation between two modes. A value of 0 indicates no correlation, whereas a value of 1 indicates two completely correlated modes. Scaling of the modes is not required here and the MAC value can be computed using only the measured degrees of freedom.

(4) The strain energy residual [9],

$$F_4(\{\beta\}) = \sum_i \left(\frac{\{\phi_{A,i}\}^T [K] \{\phi_{A,i}\}}{\{\phi_{E,i}\}^T [K] \{\phi_{E,i}\}} - 1 \right)^2 \quad (5)$$

$[K]$ is the analytical stiffness matrix. The normalization of both the analytical and experimental mode shapes must be consistent. Expansion of the measured mode shapes and/or reduction of the numerical model is needed to match the experimental and analytical degrees of freedom.

(5) The difference between experimental and analytical modal flexibility matrices [10],

$$F_5(\{\beta\}) = \left\| [\Phi_A] [\Lambda_A] [\Phi_A]^T - [\Phi_E] [\Lambda_E] [\Phi_E]^T \right\|^2 \tag{6}$$

Where $[\Phi]$ is the eigenvector matrix and $[\Lambda]$ is the eigenvalue matrix. Analytical and experimental modes shapes must be properly scaled. The modal flexibility can be estimated using only the measured degrees of freedom [10].

The objective function J considers some of these five fundamental functions plus a damage penalization term,

$$J(\{\beta\}) = \sum_{j=1}^{5} \delta_j \frac{F_j(\{\beta\})}{F_{j,0}} + \gamma \sum_i \beta_i \tag{7}$$

$F_{j,0}$ refers to the initial values of $F_j(\beta = 0)$, δ_j equals to 1 if the error function F_j is considered and 0 if not. By adding the damage penalization term $\gamma \sum_i \beta_i$, the objective function searches not only for the best correlation, but also the minimum possible damage. Thus, avoiding false damage detection because of experimental noise or numerical errors. The value of γ depends on the confidence in the numerical model and the experimental data. Although a similar damage penalization was proposed by Ruotolo and Surace [30] in 1997 obtaining a significance reduction of the false damage detected, no later references to this penalization have been found.

The optimization problem is defined as,

$$\begin{aligned} & min && J(\{\beta\}) \\ & subject \quad to && F_j(\{\beta\}) \leq F_{j,0} \\ & && 0 \leq \beta_i \leq 1 \end{aligned} \tag{8}$$

The aim is to minimize the objective function J, but GA always maximizes a problem. The minimization problem is transformed into a maximization problem by defining the objective function as a suitable number subtracted by J.

3 Application Case

Figure 1 shows the experimental setup, the structure is a tridimensional statically indeterminate space truss, consisting of 43 members and 20 joins. This configuration has been chosen for the following reasons: First, it provides a reasonable number of global and local modes. Second, it presents a balanced combination of well separated and close modes. Third, it has nodes connecting several elements, which makes the damage identification process [41, 42] more difficult. The dimensions of the structure are: length: $3m$, width: $0.5m$, height: $0.5m$. Each beam has a diameter of $20mm$. The structure is suspended by soft springs to simulate a "free-free" boundary condition.

The Finite Element Model was built on Matlab using $3D$ truss elements for the bars and concentrated inertia elements for the joins. Each bar is modeled with four truss elements as shown in Figure 2. Rotational degrees of freedom were deleted from the FE model using the Guyan reduction technique [48]. As a result, the model has a total of 447 degrees of freedom and 192 elements. A total of 12 global modes are computed with frequencies between $12Hz$ and $125Hz$, subsequent modes are local bar modes. Damage is considered at the bar level, so all elements on each bar are grouped in a single macro-element.

The optimum response configuration is determined by minimizing the MAC off-diagonal values [49]. Thus all the measured modes are independent between each other. For visual representation purposes, all nodes are instrumented with tri-axial accelerometers. As a consequence, a total of 20×3 degrees of freedom are measured; one tri-axial accelerometer per join.

The selection of the excitation and suspension locations is based on the study of the driving point residues (DPR) [50]. The DPR with large values for as many modes as possible indicate good excitation points. In addition, the DPR with lower values indicate good suspension locations.

The frequency range of analysis covers the range from 0 to 256 Hz with a resolution of $0.25Hz$. This range contains all global modes and also a list of local modes. Figure 3 presents the correlation between the numerical and experimental modes in the undamaged state. The maximum frequency difference is 2.3% and the minimum MAC value is 0.86.

3.1 Damage Introduction

Four damage cases are studied. In the first three cases, a few aluminum bars are replaced by plastic bars, thus the stiffness and mass of the replaced bar is reduced. The replaced bars on each case are: ***case 1***: bar 6; ***case 2***: bars 6 and 25; ***case 3***: bars 6, 25 and 43. In ***case 4*** bar 34 was completely removed from the structure. Figure 4 shows the bar numbering.

Figure 5 shows the correlation between the undamaged numerical modes and the damaged experimental modes. In the first case, a new mode is detected at $139Hz$. It is also possible to see a considerable decrease in the correlation of modes 10 and 11. In the second case, a new mode is detected at $135Hz$. In addition, the correlation of modes 10 and 11 is reduced, and the frequency of mode 12 is reduced by 35%. In case 3, two new modes are detected at $135Hz$ and $143Hz$, the correlation of modes 10 and 11 is considerable reduced, and the frequency of mode 12 is reduced by 40%. In case 4 there is a swap of modes 5 and 6, a new mode is detected at $46.7Hz$ and the correlation of mode 11 is reduced.

4 Methodology

4.1 Objective Function

To correctly model the experimental damage, i.e., replacing or removing a bar, a mass reduction factor ρ_i must also be considered. For convenience the mass reduction factor is defined proportional to the stiffness reduction factor, this allows to update only the stiffness parameters as in a general damage detection algorithm,

$$\rho_i = \alpha \cdot \beta_i \tag{9}$$

The ratio of the stiffness reduction to the mass reduction (α) was experimentally determined. When an aluminum bar is replaced by a plastic bar α equals 0.73, whereas when a bar is removed α equals 1.

Five objective functions were evaluated, the one that provided the best performance was chosen. The objective functions are: (1) frequencies, (2) modes and frequencies, (3) MAC and frequencies, (4) strain energy and frequencies and (5) modal flexibility. The first damage case is used to test the different objective functions. The optimization process is performed with the Genetic Algorithm described in section 4.2. To assess the probability that the algorithm would converge to the same solution, each case was run five times during 500 generations. Figure 6 presents the convergence curves and the damage detected for each objective function and run. The left graphs show the evolution of the objective function (J) evaluated for the fitter member of the population. Each objective function is normalized with its global optimum value J_{opt}. On the right a stacked bar plot shows the damage detected at each run with a different color, an arrow indicates the position of the actual damage. By using only frequencies it is difficult to reach the optimum solution, only two of the five runs could reach the optimum in the desired number of generations. This is because the objective function has several local minimums. These local solutions dominate the population and the algorithm relies mainly on mutation which is a slow process. As a consequence, a higher number of generations would be necessary to reach optimum. This problem is partly solved when the modal displacements are added. Here, four of the five runs reach the optimum. The same result is obtained with the modal flexibility. On the other hand, with strain energy and frequencies it was possible to reach the optimum solution in all five runs, but the optimum damage detected does not correspond with the actual damage. Only the objective function MAC and frequencies was able to detect five times the actual damage in the desired number of generations.

The value of the penalization weight was delimited after a sensitivity analysis. The results of this analysis are shown in Figure 7. For values of γ between 0.08 and 2.5 real damage is successfully detected and false damage is avoided. If γ is lower than 0.08 false damage is detected whereas if γ is greater than 2.5 no damage is detected. It should be noticed that the correct values of gamma depend on the structure, level of experimental noise and the errors in the numerical model. Hence, the selected range of gamma is only valid for this particular study case. In other cases a similar sensitivity analysis must be performed.

4.2 Genetic Algorithm

Each chromosome consists of 43 genes. Each gene is the stiffness reduction factor of a beam element. Each chromosome represents one possible damage distribution; the initial population is generated randomly with real numbers between 0 and 1.

Correct selection of the GA operators and parameters is crucial as they affect the solution and the algorithm runtime [27]. However, there is no general rule to select them; the right decision depends on the number of genes, the objective function and the nature of the problem. Here the parameters and operators were selected by optimizing the runtime, i.e., by minimizing the number of function evaluations.

Three selection processes were tested: (1) roulette wheel, (2) normalized geometric and (3) tournament selection. In normalized geometric selection the probability of selecting the best was set to 0.08 and in tournament selection the number of individuals on each tournament was set to two. Figure 8 shows the average convergence curve obtained after running 20 times the algorithm with each selection. The normalized geometric selection gives the best convergence. Once the selection was set, two mutation operators were evaluated: (1) uniform mutation and (2) boundary mutation. Figure 8 shows the average convergence curves: boundary mutation gives the best performance. The last operator is crossover; here five kinds of crossover were studied: (1) single point crossover, (2) double point crossover, (3) uniform crossover, (4) arithmetic crossover (5) heuristic crossover. Arithmetic crossover yields the best performance, as is shown in Figure 8.

Once the GA operators are selected, the method was evaluated with various combinations of mutation and crossover probabilities. For each combination the algorithm was run 20 times, the combination that reached the best average value of the objective function was selected. As is shown in Figure 9 the lowest value of the objective function was reached with a mutation probability of 0.01 and a crossover probability of 0.72. The same procedure was followed to select the population size. The best performance was obtained with a population size of 25 as is shown in Figure 9 .

Hence the best combination of operators and parameters is: normalized geometric selection, arithmetic crossover, boundary mutation, and the following three parameters: population size of 25, $p_m = 0.01$ and $p_c = 0.72$.

4.3 Hybrid GA

The combination of GA's and a local optimizer makes it possible to reach a high level of accuracy in a moderate computational time. In order to reach the same level of accuracy only with GA's, much more generations would be required. Figure 10 illustrates the curve of convergence obtained with a hybrid-GA. The differences in the damage detected using only GA and with hybrid-GA are also given in Figure 10. The Matlab function $fmincon$ was used as a local optimizer. Figure 10 shows that the GA finds the damage locations and a close approximation of their quantity. Then, $fmincon$ starts with the solution given by GA and increases the precision.

5 Results

The damage pattern is obtained through the same procedure on each damage case. The first 12 global modes are used in the objective function. The objective function is based on the frequencies difference and MAC values, including a damage penalization term with a γ value of 0.1. A hybrid-RCGA is used as optimization algorithm. The results are compared with those obtained with two sensitivity based methods, namely, Response Function Method (RFM) and Inverse Eigen-Sensitivity Method (IESM). A description of both methods is found in the paper of Modak et al. [51]. The IESM minimizes the difference between analytical and experimental frequencies and modes, whereas, the RFM minimizes the difference between analytical and experimental frequency response functions.

Figure 11 shows the damage detected in each case (the cases are defined in section 3.1). In cases 1 and 2 the real damage is detected by the three methods. In case 3 only the GA and IESM methods detect the real damage. In case 4 only the GA method detects the damage. As the differences between the damage and undamaged models become higher, the optimization problem becomes unstable and it becomes impossible to reach the optimum solution. On the other hand, the genetic algorithm method is unaffected by these differences, and the optimum solution is always reached as is shown in Figure 11. False damage is detected always with both the IESM and RFM methods; the latter detects a higher quantity.

Figure 12 illustrates the correlation in frequency and modes before and after damage detection. The correlation in frequency is expressed as the relative frequency difference between the numerical and experimental frequencies. The correlation between the numerical and experimental modes is determined with the MAC values. When the numerical model is updated with the damage detected a significant improvement in the correlation is reached. The differences in frequencies after updating are lower than 10% in all cases. And the MAC values after updating are always higher than 75%.

5.1 Incomplete Degrees of Freedom

To define the number of degrees of freedom (DOF) necessary to detect the damage, the method was evaluated with several levels of incompleteness in the measured data. A total of 4 to 32 DOF are considered, these corresponds to 0.9 to 7.2 percent of the total DOF in the numerical model. The locations with a higher sensitivity to damage were chosen as measuring points. To do these, the mode shapes sensitivities were evaluated for each mode shape in all possible damage locations. Then, the first n points with the higher average sensitivity were chosen. The average sensitivity obtained for each DOF is shown in Figure 13. To visualize the most sensitive points in the structure, Figure 14 presents the optimum set of measuring points with 8, 16 and 32 DOF.

Table 1 summarize the damage detected in each case. In the single damage cases, it was possible to locate and quantify correctly the damage measuring only 8 DOF (1.8% of the total DOF). When the number of damage locations increases, the method requires a higher number of measured DOF. For two simultaneous damages the method needs at least 12 DOF (2.7% of the total DOF), and three simultaneous damages locations require at least 28 DOF (6.3% of the total DOF). This indicates that the number of DOF required, depends on the structure and the complexity of the damage situation that needs to be detected.

6 Conclusions

A hybrid real-coded genetic algorithm has been implemented to detect structural damage. A damage penalization term is added to the objective function to avoid false damage detection caused by experimental noise or numerical errors. The algorithm is verified on a tridimensional space frame structure with single and multiple damage scenarios. In addition, the method is tested with different levels of incompleteness in the measured degrees of freedom.

The results show that this Genetic Algorithm approach reaches a more precise solution than conventional optimization methods. Real damage is successfully detected and false damage detection is avoided, even in cases of large or complex damage scenarios on which conventional optimization approaches fail to reach the global optimum. A scenario of three simultaneous damage locations was correctly located and quantified by measuring only 6.3% of the total degrees of freedom.

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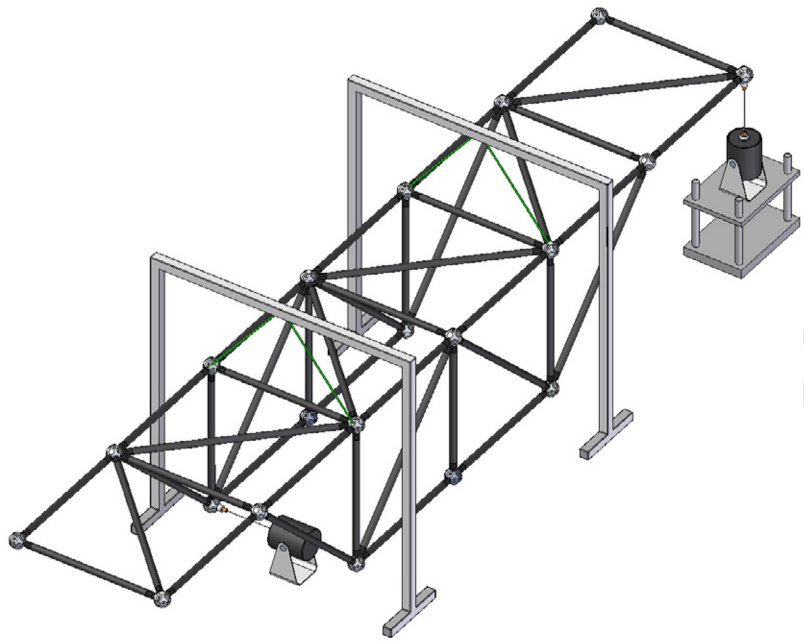

Fig. 1. Experimental Setup

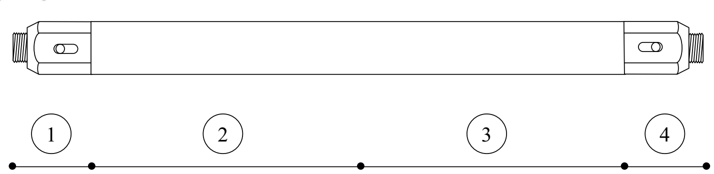

Fig. 2. FE model of each bar

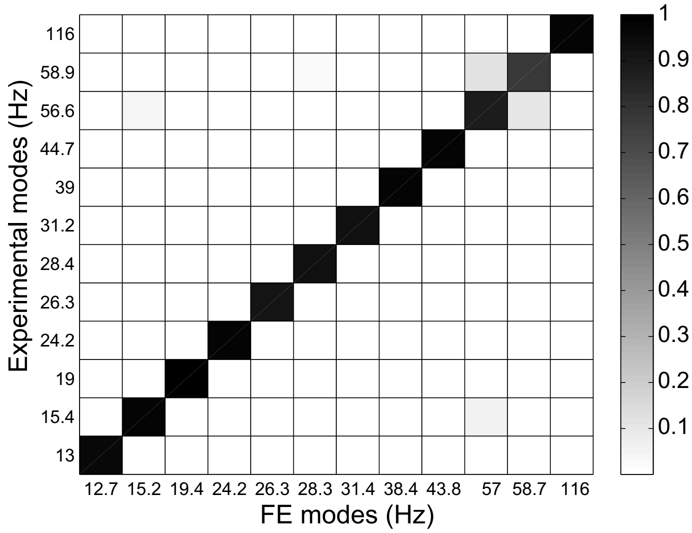

Fig. 3. Initial MAC

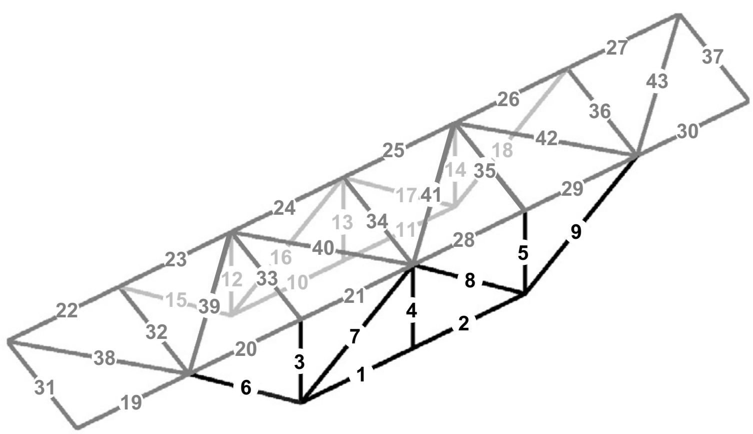

Fig. 4. Bar numbering

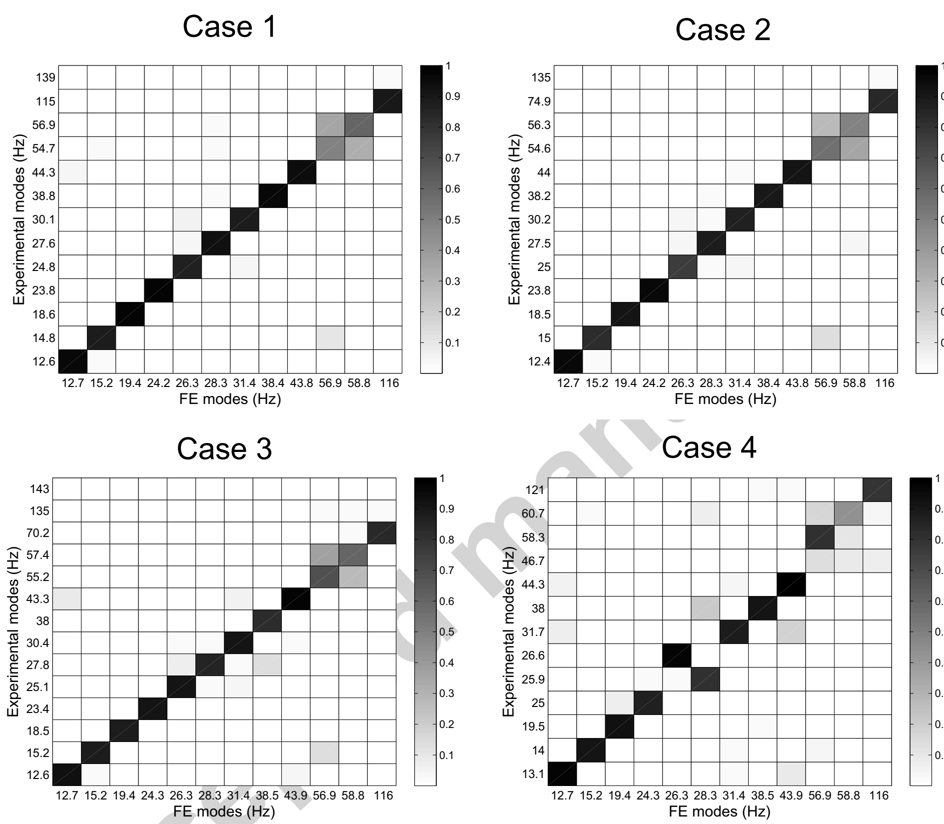

Fig. 5. Correlation between the undamaged numerical and damaged experimental modes

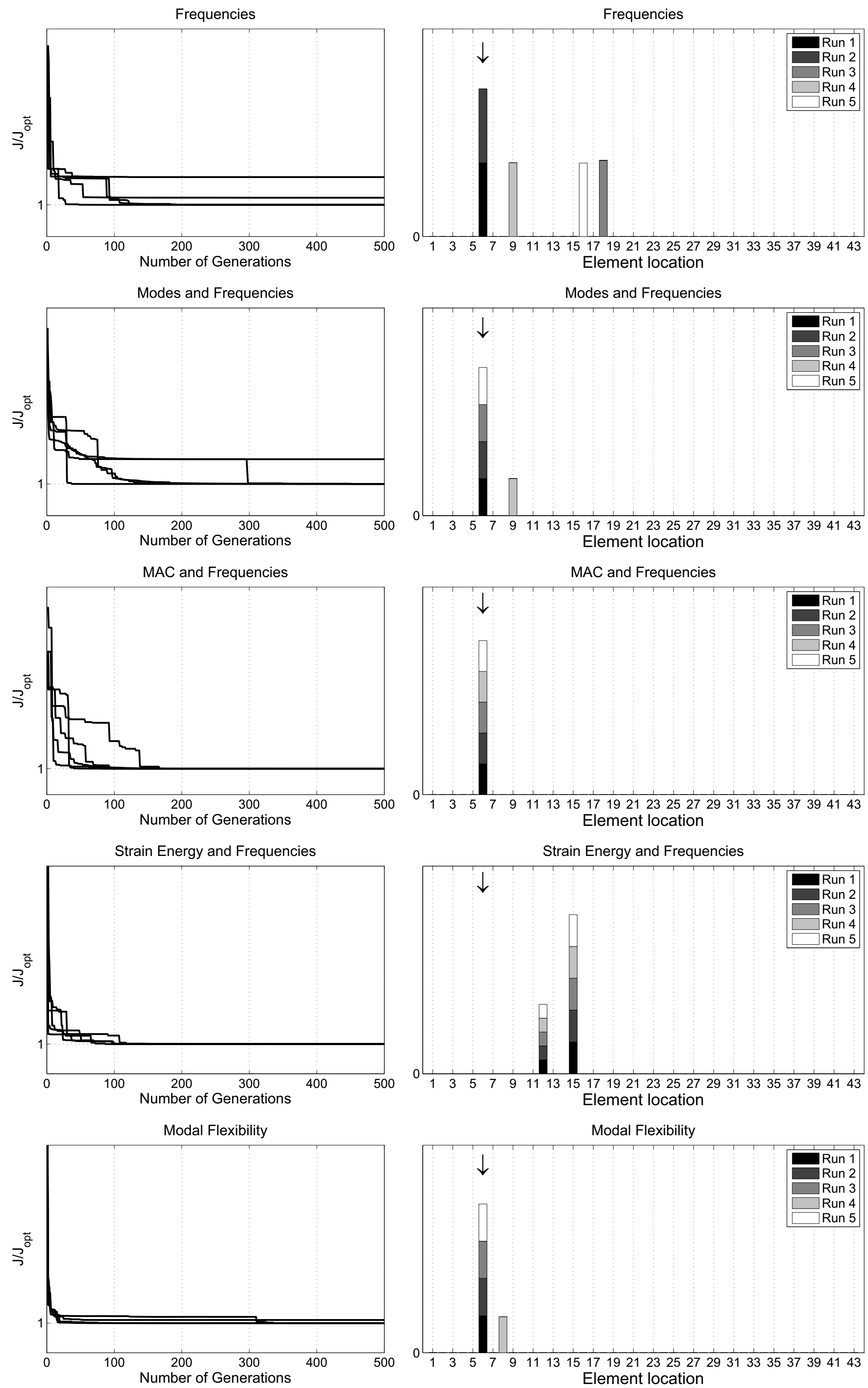

Fig. 6. Convergence curve and solution of different objective functions based on modal data

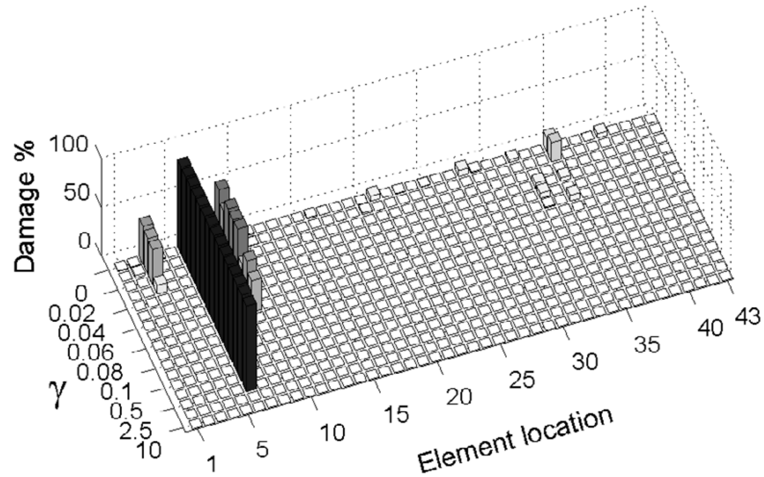

Fig. 7. Effect of on the damage detected

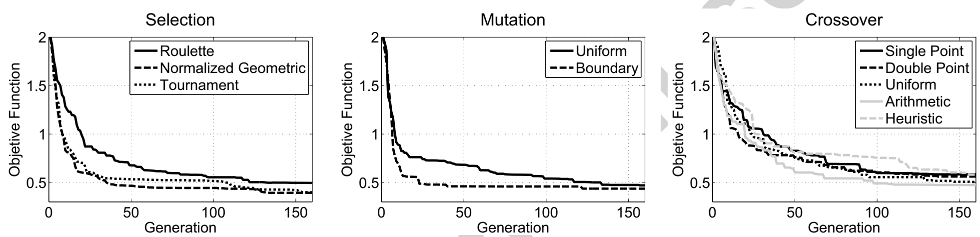

Fig. 8. Average convergence curves after running 20 times for different: left - selection processes, middle - mutation operators and right - crossover operators

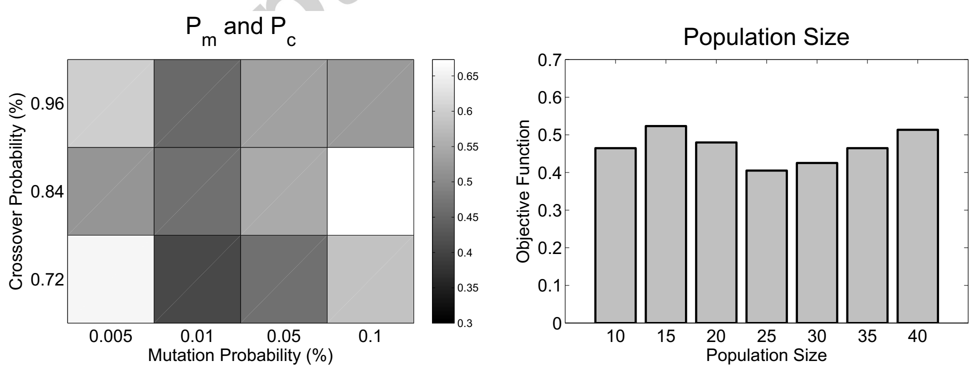

Fig. 9. Average value of the objective function after running 20 times for different combinations of crossover and mutation probabilities (left) and for different population sizes (right)

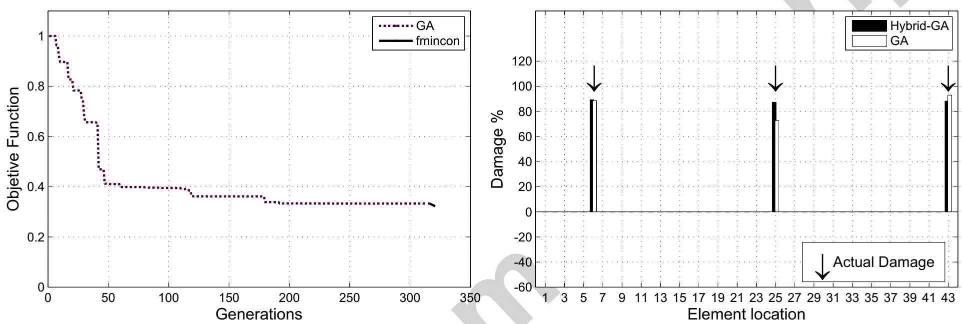

Fig. 10. Right: Curve of converge of the GA followed by a local optimizer. Left: Damage detected with GA and with a hybrid-GA

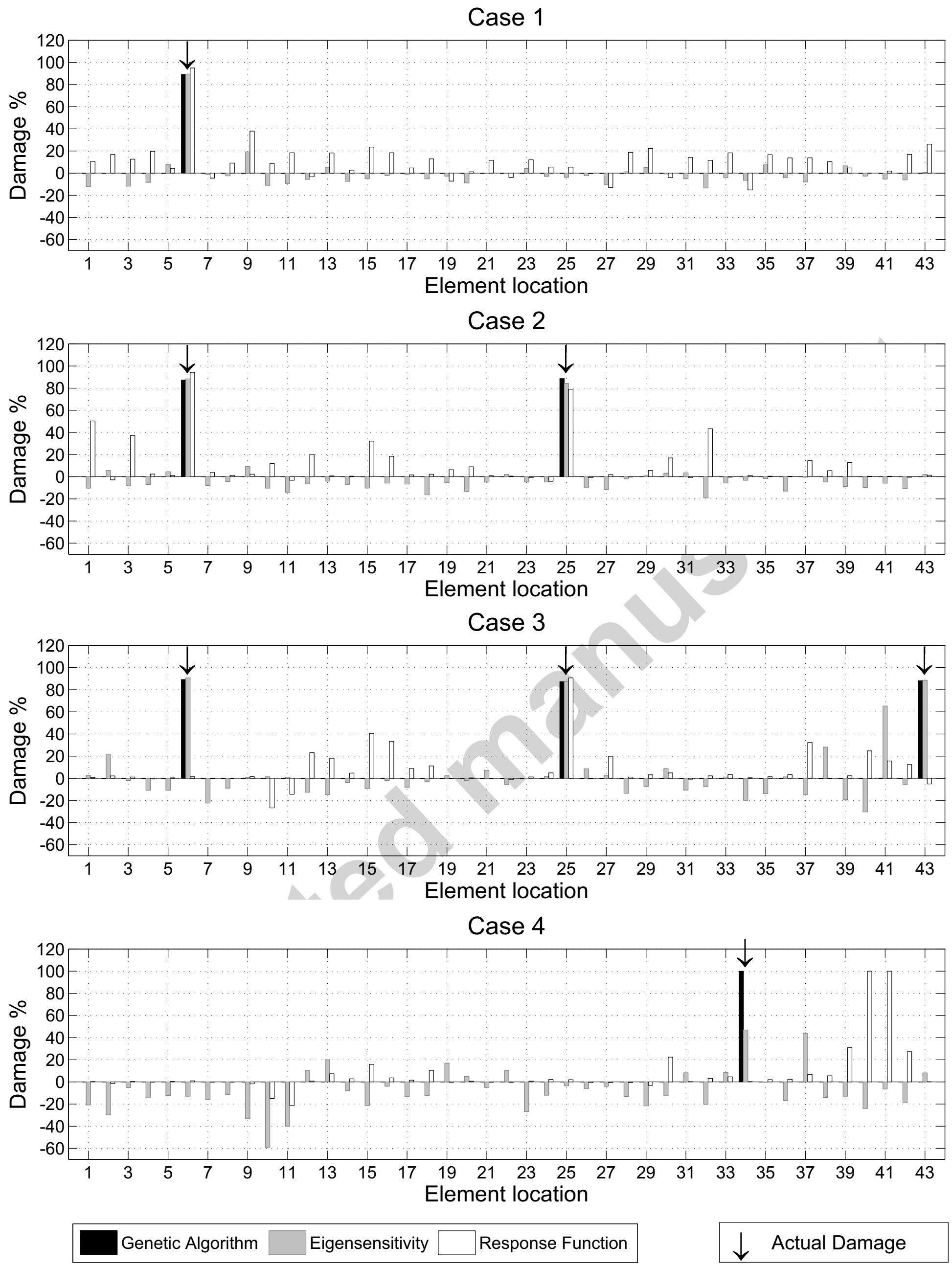

Fig. 11. Damage detected with the proposed algorithm compared to two classical damage detection methods

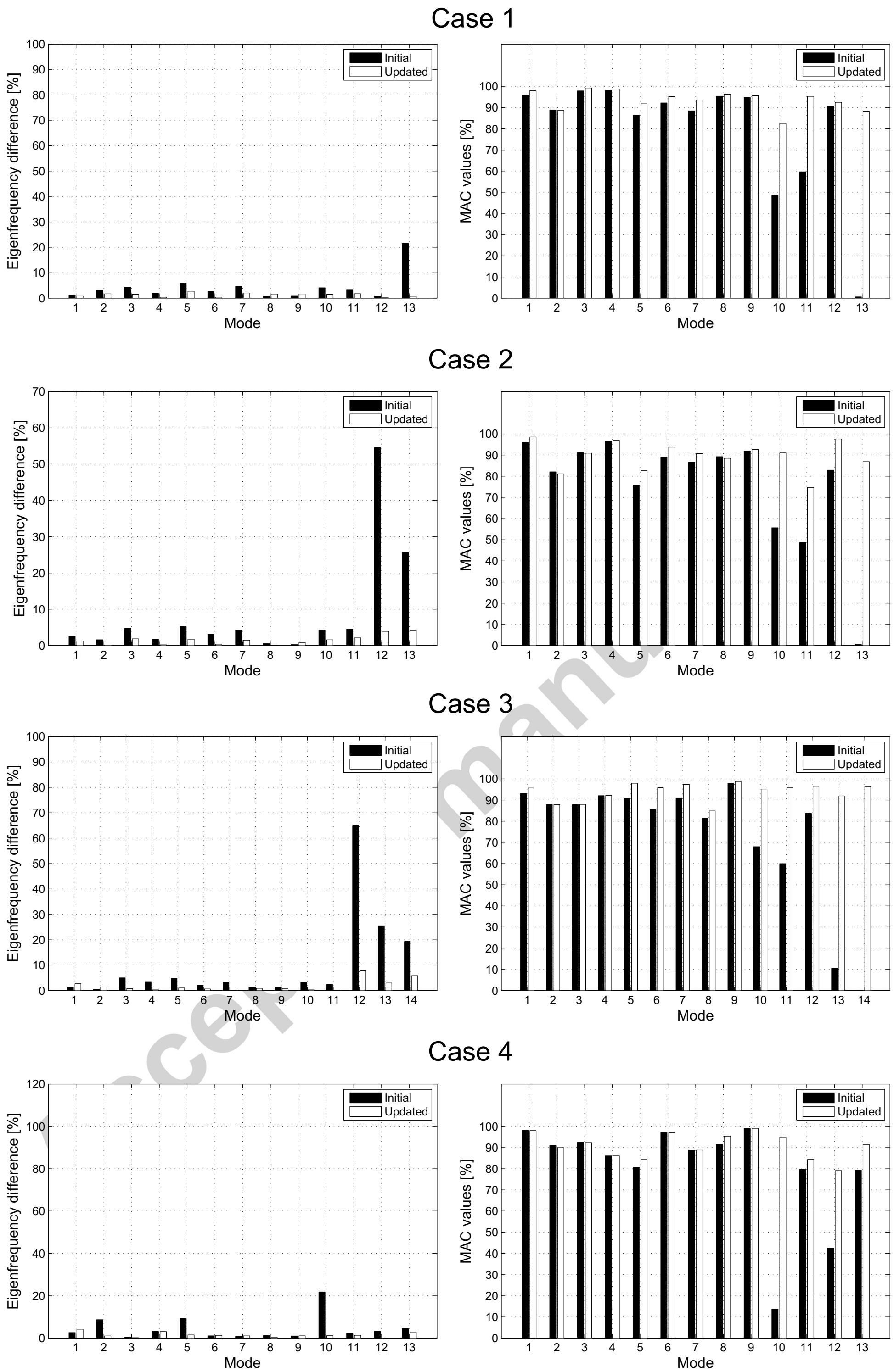

Fig. 12. Improvement in the correlation in frequency and modes after damage detection

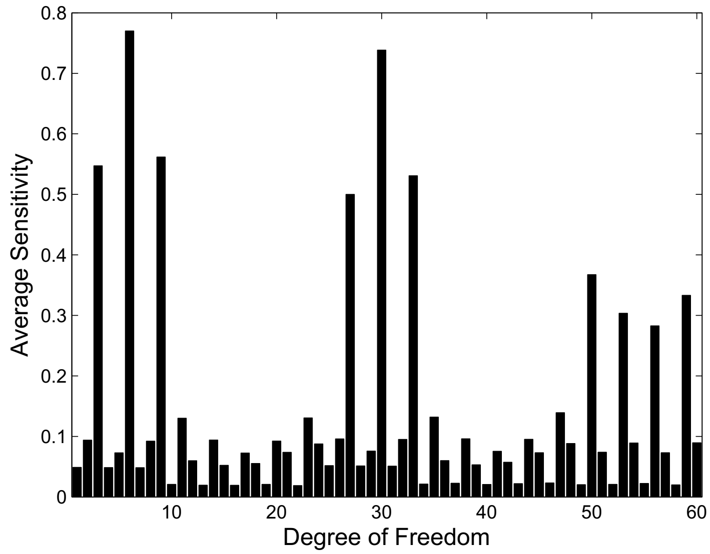

Fig. 13. Average sensitivity to damage for each DOF

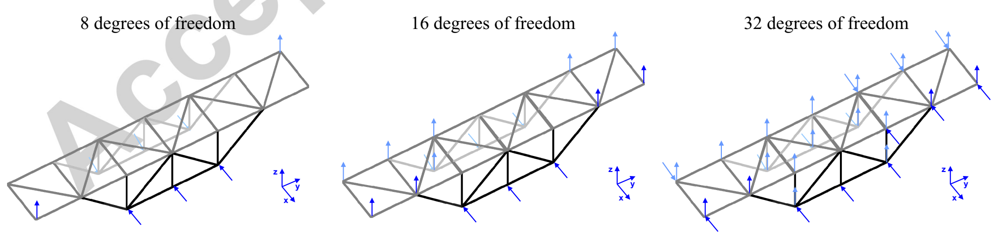

Fig. 14. Optimum set of measuring points

Case	N of measured DOF	Real		Detected	
		Location	Damage %	Location	Damage %
1	4	6	92	3,22	95,21
	6	6	92	3,6	51,93
	8	6	92	6	92
	12	6	92	6	92
	16	6	92	6	92
4	4	34	100	26,34,43	13,100,7
	6	34	100	6,26,34,43	2,19,100,1
	8	34	100	34	100
	12	34	100	34	100
	16	34	100	34	100
2	8	6,25	92,92	6,26	92,92
	12	6,25	92,92	6,25	91,91
	16	6,25	92,92	6,25	92,91
	20	6,25	92,92	6,25	92,91
	24	6,25	92,92	6,25	92,92
3	12	6,25,43	92,92,92	6,42	89,94
	16	6,25,43	92,92,92	6,25,43	89,89,90
	20	6,25,43	92,92,92	6,25,26	89,90,90
	24	6,25,43	92,92,92	6,25,42	89,86,92
	28	6,25,43	92,92,92	6,25,43	89,90,90
	32	6,25,43	92,92,92	6,25,43	89,90,89

Table 1
Damage detected with different number of measured DOF