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Research Paper

A hybrid heuristic optimization algorithm PSOGSA coupled with a hybrid objective function using ECOMAC and frequency in damage detection

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Presence of damage leads to variation in modal properties of observed structures. The majority of studies use the changes in natural frequencies for damage detection. The reason is that the frequencies are often easily measurable with high accuracy by using reasonable sensors. However, frequencies are more sensitive to environmental effects, such as temperature, in comparison with mode shapes. Besides, defects in symmetric structures can cause the same changes in frequency. In contrast, mode shapes are more sensitive to local damage because they own local information and are independent of symmetric characteristics. These make mode shapes have dominant advantages in detecting nonlinear and multiple damage. ECOMAC is an index derived from mode shapes. It is a fact that these indices are not always possible to detect faults successfully in structures. Therefore, in this paper, a hybrid optimization algorithm, particle swarm optimization – gravitational search algorithm, namely PSOGSA, is used to improve the accuracy of infect detection using a hybrid objective function combined ECOMAC and frequency based on the inverse problem. Numerical studies of a two-span continuous beam, a simply supported truss, and a free-free beam, are utilized to verify the effectiveness and reliability of the proposal. From the obtained results, the proposed approach shows high potential in damage identification for different structures.

1 Introduction

In engineering applications, modal testing approach is employed worldwide as effective non-destructive tools. The approach can be used for different structures due to its simplicity and low cost [1-3]. By means of this approach, damages in tested structures can be detected, localized, and quantified. The changes in natural frequencies are obvious proofs for presence of defects in structures [4]. However, the temperature has a significant effect on these changes. This can lead to misidentifying

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of damage in structures [5]. Another parameter that can be used to identify failures, is the changes in mode shapes. It's stable with temperature changes [6] and more sensitive to local damage. Based on mode shapes, many studies proposed damage indices for damage detection and localization. Authors in [7] developed a new index, namely modal curvature index (MCI) using displacement mode shapes. Location of defect is identified based on differences of curvature of modal data between intact and damaged structures. However, the effectiveness of this method closely related to number of measurement points along structures. Modal flexibility method (*MFM*) is another effective method in damage identification proposed by Pandey and Biswas [8]. Because stiffness matrix is inverse of flexibility matrix, reduction of stiffness leads to an increase of flexibility. The rise of flexibility can point out the damaged location. The point makes this method more attractive is that the method only requires the first few lower modes for accuracy of damage localization. Modal strain energy (*MSE*) is also an effective method for defect identification. In this approach, changes in resonant frequency and strain mode shapes are used to detect damage. In addition, the reduction in modal strain energy between two sets of measurement points can be employed to identify the damage by Stubbs and Kim in [9]. These methods show good performance in defect identification, but they require complex computation.

Some authors proposed simple indices based on directly using displacement mode shapes. Modal assurance criterion, *MAC*, is employed to check the similarity between two mode shapes by using displacements of all measured points in each mode. Orthogonality characteristics of displacement mode shapes are used to determine whether pairs of mode shapes are identical or not. Two different mode shapes, even a small disparity, can cause a change of *MAC* values. Therefore, this index can be used to indicate the presence of damage in the structure, but it fails in damage localization. Coordinate modal assurance criterion (*COMAC*) is an extension of *MAC*, proposed by Lieven and Ewins [10]. Different from *MAC* index, *COMAC* uses displacements of all modes at each measured point to identify mismatching along with the tested structure. This index is calculated at each point in the structure. For this reason, it can be used to localize location of failures. From the study, Hunt proved that his proposed index, enhance coordinate modal assurance criterion (*ECOMAC*) has potential in overcoming the scaling errors or polarity mistakes in measured data [11]. The implementation of this approach for defect presence is simple. However, many studies [12-14] reveal that *COMAC*, and *ECOMAC* often get trouble in damage localization.

Therefore, it is necessary to improve the capacity of failure localization of these indices. Using an artificial neural network is a promising solution that is able to ameliorate their ability [15, 16]. Some authors combined *ANN* and modal damage indicator for damage identification and quantification [17]. Many studies revealed that a combination of *ANN* and optimization techniques can improve the performance of traditional *ANN* [18-20]. However, for an effective network, it requires big data for training related to many scenarios of damage location, single or multiple damage as well as failure quantification. In other words, this method requires more time for collecting the training data. For a real application, the reduction of computation cost and simple implementation is very necessary. Therefore, the inverse problem or model updating method can be employed to enhance effectiveness of these indices. The success of this approach is based on the global optimal search-ability of optimization algorithms. Many well-known algorithms e.g. Genetic algorithm (*GA*), particle swarm optimization (*PSO*), simulated annealing (*SA*), gravitational search algorithm (*GSA*), etc., are applied successfully in many studies of damage detection. Authors in [21] used successfully bird mating optimizer (*BMO*) coupling with a hybrid objective function, derived from frequency and mode shapes. A truss, a planar frame structure, and measurement data of a free-free beam were used to verify the effectiveness of the proposal. Based on errors of frequency, mode shapes, and the relative weighting of the two parameters, Friswell et al. proposed a robust approach for damage detection in a steel cantilever plate. In their study, *GA* combines with Eigen-sensitivity to localize and quantify damage using numerical and experimental data of the steel plate [22]. GA and modified Cornwell indicator confirmed their effectiveness in damage assessment [23]. *XIGA*, Jaya algorithm were also recommended as an efficient approach for inverse problems [24, 25]. Authors in [26, 27] improved significantly capability of failure identification of *COMAC* by coupling with firefly algorithm (*FA*) and Genetic algorithm (*GA*), respectively. A simply supported beam, a truss structure, and a *CFRP* structure were investigated in their study.

Recently, many novel heuristic optimization algorithms, especially hybrid algorithms, have been developing. They were used to solve inverse problems based on vibration measurement of real structures [28, 29]. These algorithms are able to quickly escape from local optima and can find the global optimum faster. Particle swarm optimization-gravitational search algorithm, so-called *PSOGSA* is a promising hybrid algorithm. This hybrid algorithm is developed by Mirjalili and Hashim [30] to improve the exploration of *PSO* as well as speed up the exploitation of *GSA*. From the obtained results, the proposed hybrid algorithm shows a superior performance associated with the convergence rate and the best fitness value of the objective function.

As mentioned above, *ECOMAC* can overwhelm the shortcomings of *COMAC*, but studying on its improvement coupling with an optimization algorithm has not been conducted. Therefore, this study makes use of a hybrid algorithm, *PSOGSA* to intensify *ECOMAC* in damage identification. Two beam-like structures and a truss-like structure are used to evaluate the effectiveness of the proposal.

2 Methodology of proposed approach

2.1 MAC, COMAC, and ECOMAC indices

2.1.1 Modal assurance criterion (MAC)

Modal assurance criterion (*MAC*) is a popular index for correlation checks between mode shapes. The mode shapes can be derived from simulation and measurement, or healthy and damaged structure. Each value of *MAC* can indicate the similarity between two sets of mode shapes. *MAC* values between intact and damaged structure are calculated as

$$MAC_j = \frac{\left|\sum_{i=1}^{nn}(\phi_i^{\text{int}})^{Trans} \times (\phi_i^{dam})\right|^2}{\left(\sum_{i=1}^{nn}(\phi_i^{\text{int}})^{Trans} \times (\phi_i^{\text{int}})\right) \times \left(\sum_{i=1}^{nn}(\phi_i^{dam})^{T} \times (\phi_i^{dam})\right)} \tag{1}$$

where $j = 1 \, to \, nm$, nm is the number of considered modes, $\phi_i^{\text{int}}, \phi_i^{dam}$ are mode shapes of the intact and damaged structure, $i = 1 \, to \, nn$, nn is the number of measured points or degree of freedoms (*DOFs*) along the structure, $(\;)^T$ implies conjugate. When two mode shapes are completely identical, *MAC* value equals 1. *MAC* value of a bad correlation between two mode shapes close to 0. It can be seen that this index only is used to detect the presence of defects without localization.

2.1.2 Co-ordinate modal assurance criterion (COMAC)

Co-ordinate modal assurance criterion (*COMAC*) is developed from *MAC*. However, *COMAC* can point out the location where two mode shapes mismatch. Therefore, *COMAC* value at each measured point (or each *DOF*) can be identified by using all mode shapes data at each point.

$$COMAC_i = \frac{\left(\sum_{j=1}^{nm}\left|\phi_{j,i}^{\text{int}} \times \phi_{j,i}^{dam}\right|\right)^2}{\sum_{j=1}^{nm}\left(\phi_{j,i}^{\text{int}}\right)^2 \times \sum_{j=1}^{nm}\left(\phi_{j,i}^{dam}\right)^2} \tag{2}$$

Same as *MAC*, the best similarity of two mode shapes generates a *COMAC* value of 1. *COMAC* value reaches to 0 for a poor likeness. Therefore, points that have low values of *COMAC* indicate the damaged position. In practical application, values of (1-$COMAC_i$) often are applied to identify failure points.

2.1.3 Enhance Co-ordinate modal assurance criterion (ECOMAC)

Enhance Co-ordinate modal assurance criterion (*ECOMAC*) can indicate the disparity between two sets of mode shapes. Each point (*DOF*) is calculated by using data of all modes obtained at the corresponding sensor. Data of pairs of mode shapes should be on a similar scale before the calculation of *ECOMAC*. *ECOMAC* value of two identical pairs of mode shapes equals 0 and closes to 1 with poor similarity. Therefore, a point, which is near damage position, has a high magnitude.

$$ECOMAC_i = \frac{\sum_{j=1}^{nm}\left|\phi_{j,i}^{\text{int}} - \phi_{j,i}^{dam}\right|}{2 \times nm} \tag{3}$$

2.2 Optimization algorithm PSOGSA

2.2.1 Particle swarm optimization-gravitational search algorithm, PSOGSA

The hybrid algorithm is inspired by particle swarm optimization (*PSO*) and gravitational search algorithm (*GSA*). Mirjalili and Hashim combined the local search capability of *GSA* and social thinking of *PSO*. The combination shows promising performances in exploration and exploitation compared to *PSO*, and *GSA*, respectively.

The algorithm is started by calculation of gravitational forces *F* based on random positions s_i, s_j and Euclidean distances between two agents D_{ij}

$$F_{ij}(t) = G(t) \times \frac{M_{pi}(t) \times M_{aj}(t)}{D_{ij}(t) + \varepsilon} \times \left(s_j(t) - s_i(t)\right) \tag{4}$$

$$D_{ij}(t) + \varepsilon \approx norm\left(s_j(t) - s_i(t)\right) \tag{5}$$

where, M_{aj}, M_{pi}: active and passive gravitational mass of *j* and *i* agents, $G(t)$ is gravitational constant, and α is reducing coefficient. Equations from (6) to (8) are used to calculate $G(t), M_i(t)$ and $m_i(t)$.

$$m_i(t) = \frac{fitness_i(t) - worst(t)}{best(t) - worst(t)} \tag{6}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \tag{7}$$

$$G(t) = G_0 \times e^{\left(-\alpha \cdot \frac{current\_iteration}{\max\_iteration}\right)} \tag{8}$$

Equation (9) computes a total force $F_i(t)$ on agent *i* due to *N* agents. Then, the force divided by the mass of agents M_i as in equation (10) to achieve acceleration of agent *i* at time *t*

$$F_i(t) = \sum_{j=1,\, j\neq i}^{N} rand \times F_{ij}(t) \tag{9}$$

$$a_i(t) = \frac{F_i(t)}{M_i(t)} \tag{10}$$

The social coefficient c_s and cognitive coefficient c_c of *PSO*, and acceleration of agent contribute to the update of agents' velocities

$$v_i(t+1) = \omega \times v_i(t) + c_c \times rand_{(0-1)} \times a_i(t) + c_s \times rand_{(0-1)} \times \left[gbest_i(t) - s_i(t)\right] \tag{11}$$

Then, after each iteration, positions of agents using a correction factor, φ are updated as

$$s_i(t+1) = s_i(t) + v_i(t+1) \cdot \varphi \tag{12}$$

These updated positions are used to evaluate the fitness for all agents in the next iteration. The procedure is repeated until meeting a stopping criterion.

2.2.2 Hybrid objective function

In this study, a hybrid objective function derived from changes in frequencies and *ECOMAC* values is proposed to improve the damage identification capability of *ECOMAC*. These indices are computed by using a set of mode shapes between real and predicted damages. By minimizing the fitness value of the objective function, the predicted damage is close to the real one in terms of damage location and extent.

$$Objective\ function = \sum_{i=1}^{nn}\left(ECOMAC_i\right)^2 + \sum_{j=1}^{nm}\left(\frac{f_j^{real} - f_j^{estimated}}{f_j^{real}}\right)^2 \tag{13}$$

where, *nn* and *nm*: number of DOFs and considered nodes; f^{real}, $f^{estimated}$: frequency values of real and estimated damage.

3 Damage identification based on inverse problem

Three numerical structures are utilized to investigate effectiveness and feasibility of the proposed method. The first is a two-span continuous beam-like structure. The second case is a simply supported truss-like structure. The final study is a free-free beam. These structures are modelled in ANSYS 17 [31] by using beam element (BEAM 188).

3.1 Case study 1: a two-span continuous beam-like structure

3.1.1 FE model and defect cases:

a. FE model of the beam in ANSYS

b. Labelling element numbers

Fig. 1 – FE model of the continuous beam, L=24m

The rectangle-section beam consists of 8 elements as in Fig. 1. Material properties: Young's modulus $E = 2\times10^{11}\ N/m^2$; Density $\rho = 7820\,kg/m^3$, Poisson's ratio $v = 0.3$. Dimension of each element $b\times h = 1\,m\times0.2\,m$, $L_i = 3\,m$. For damage simulation, reductions of Young's modulus of elements are assumed to vary from 0% to 100%. Three damage scenarios, including single and multiple damage in the beam, are investigated in this study.

Table 1 – Summary of damaged elements and corresponding extents of failure

Scenario	Number of damaged elements	Location : Extent (%)			
1	1	6 : 10%			
2	2	3 : 30%		5 : 5%	
3	4	2 : 30%	4 : 40%	5 : 10%	7 : 20%

The first four modes are used to identify the objective function. Summary of the intact and damaged frequencies is showed in Table 2.

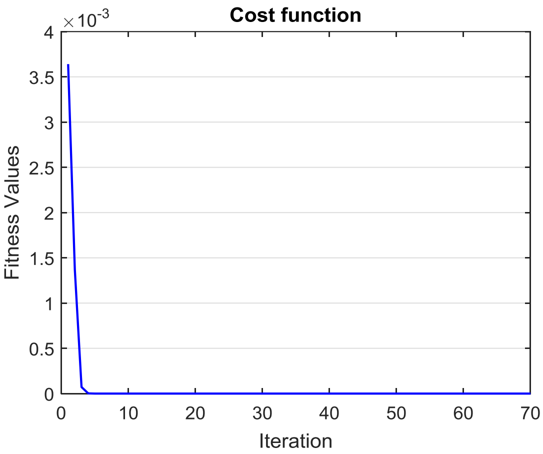
Some initial parameters of the hybrid algorithm are set: population = 200, max iteration = 70, $c_c = 0.5$, $c_s = 1.5$, $\alpha = 20$, $G_0 = 1$, and $\varphi = 1$. To identify the damaged elements as well as severity, all elements are assumed to reduce a random amount in stiffness (in this case, Young's Modulus) in a range of 0%-100%. These reductions of stiffness and corresponding elements are considered as input variables in *PSOGSA*. They are input into the *FE* model to determine sets of frequencies and mode shapes. These modal properties then are used to calculate the objective function. The fitness values of the objective function are evaluated in each loop until obtaining the best value of fitness, close to 0. The final values of these variables are utilized to determine the position and severity of damages in the beam.

Table 2 – The first four healthy and damaged frequencies for the three considered cases

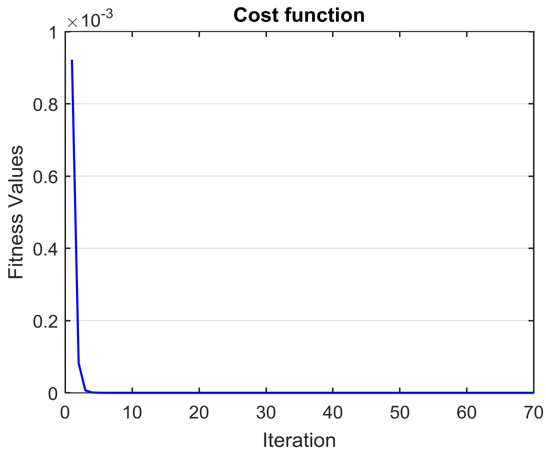
No	Intact beam	Damaged beam		
	f_{intact} (Hz)	$f_{Scenario1}$ (Hz)	$f_{Scenario2}$ (Hz)	$f_{Scenario3}$ (Hz)
1	3.18	3.15	3.05	2.94
2	4.97	4.95	4.89	4.42
3	12.72	12.63	12.36	11.73
4	16.08	15.95	15.62	15.03

3.1.2 Results

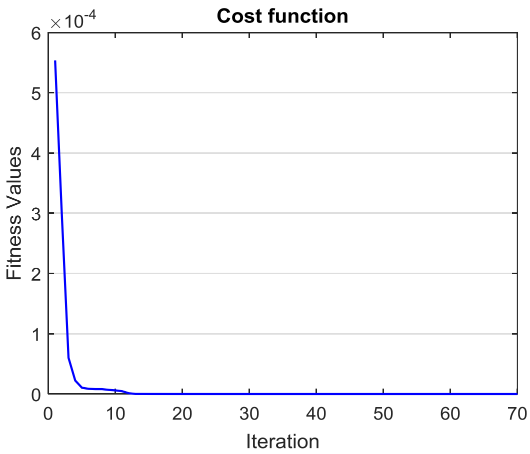
The convergence rate of *PSOGSA* over 70 iterations, the estimated locations and extents of damages in the beam are depicted in Fig. 2 to Fig. 4. It can be observed that the convergence rate of 1st and 2nd damage scenarios are faster compared to the 3rd scenario, as in Fig. 2, and especially in Fig. 3.



a. 1st scenario



b. 2nd scenario



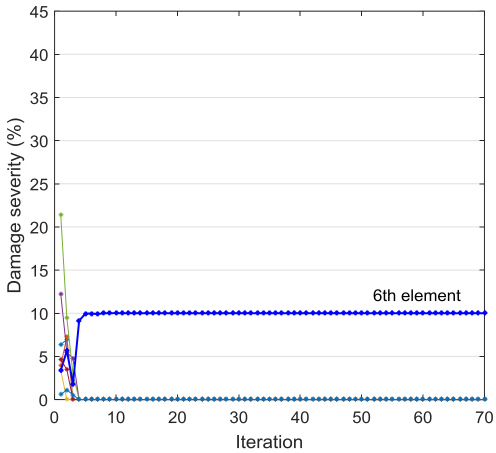
c. 3rd scenario

Fig. 2 – Convergence process of the hybrid objective function using PSOGSA for the beam.

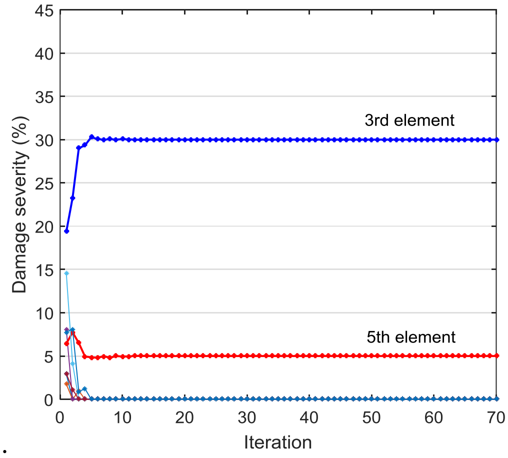
For the first two cases, the damaged elements can be identified after 3 to 5 iterations. Meanwhile, the third case needs more than 25 iterations to determine damaged ones. It is reasonable because the third scenario is considered with four defects in the beam. Therefore, it requires more time for damage identification compared with the other cases. The CPU-time for three cases are 4.70, 5.01 and 5.27 hours, respectively.

For this beam, modal properties of the first five vertical bending modes are collected to calculate *ECOMAC* values and objective function. The purpose of using only a few modes is to investigate the capability of the proposed method for a real application. It is not easy to measure all modes in real structures.

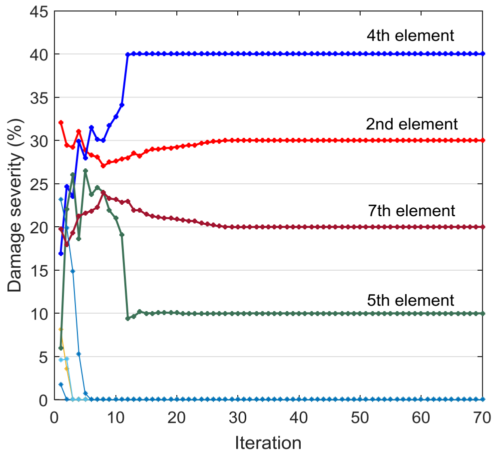
From the obtained results as in Fig. 4, locations of single damage and multiple damage can be identified exactly. Reduction of stiffness at 5%, 10%, 20%, 30%, 40% also are determined successfully.



a. 1st scenario



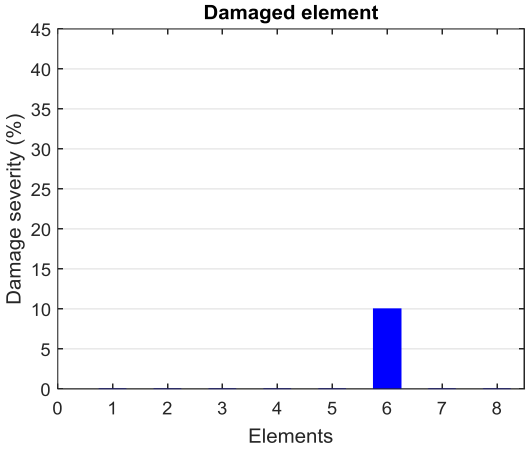
b. 2nd scenario



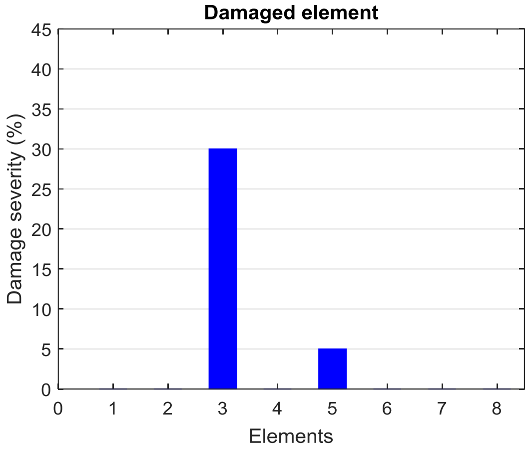
c. 3rd scenario

Fig. 3 – Evolutionary process of damage localization and quantification.

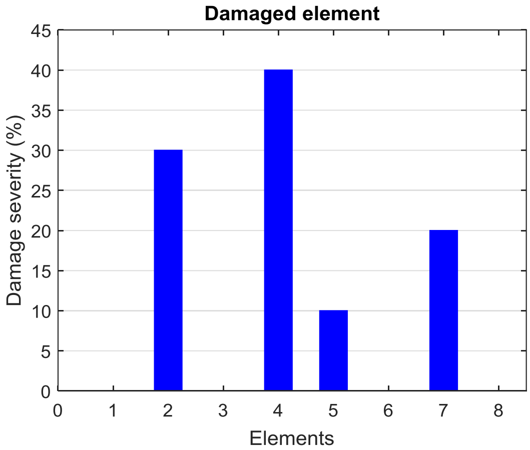
It can be seen that the combination of PSOGSA and *ECOMAC*, frequencies in objective function can overcome the mentioned drawbacks. In other words, *ECOMAC* values are completely improved by using an optimization algorithm, like PSOGSA. For further investigation, this proposed approach is applied to damage identification in a truss-like structure in the next section.



a. 1st scenario



b. 2nd scenario

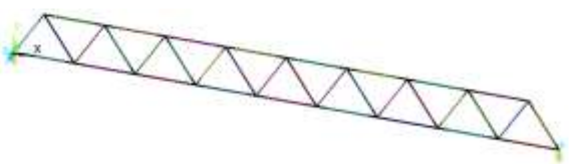


c. 3rd scenario

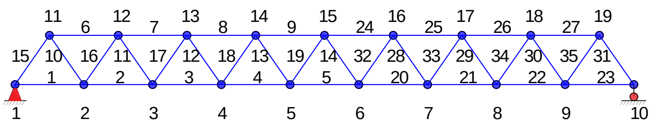
***Fig. 4** – Damage identification associated with the three damage scenarios.*

3.2 Case study 2: a simply supported truss-like structure

3.2.1 FE model and defect cases



a. FE model of the truss in ANSYS



b. Labelling element numbers

***Fig. 5** – FE model of the truss-like structure in ANSYS, L=9x10=90m, H=8m*

A 35-bar truss-like structure is modelled in ANSYS using $I(0.2\times0.1\times0.01)$ cross-section with material properties: Young's modulus $E = 2\times10^{11}\ N/m^2$; Density $\rho = 7850\,kg/m^3$, Poisson's ratio $v = 0.3$. Reductions of Young's modulus of elements also vary from 0% to 100%. Two damage scenarios are generated as listed in Table 3. To guarantee the accuracy of predictions, the first five modes were used to determine the values of the objective function. Frequencies of undamaged and damaged state are performed in Table 4.

Table 3 – Summary of damaged bars and corresponding extents of failure

Scenario	Number of damaged elements	Location : Extent (%)	
1	1	5 : 30%	
2	2	7 : 20%	12 : 30%

Table 4 – The first five healthy and damaged frequencies for the two considered cases

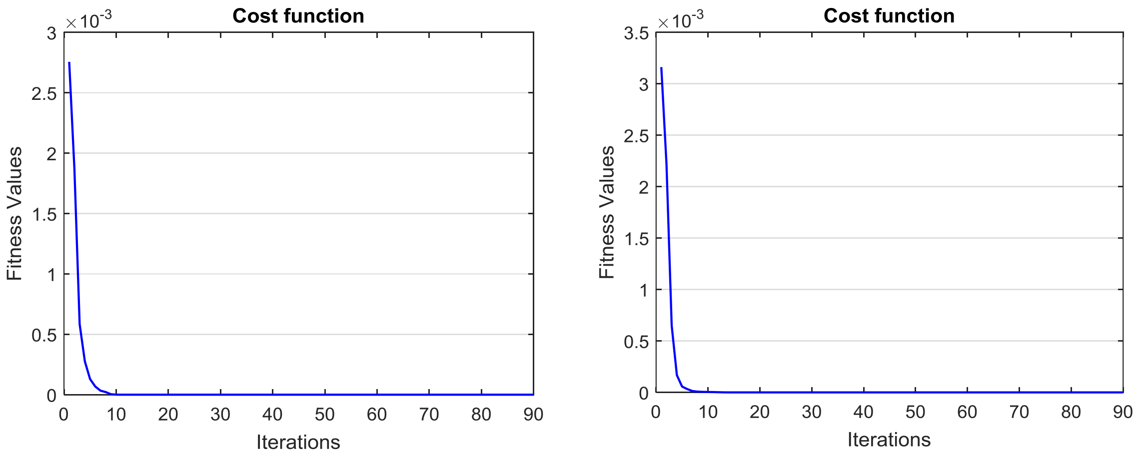
No	Intact truss	Damaged truss	
	f_{intact} (Hz)	$f_{Scenario1}$ (Hz)	$f_{Scenario2}$ (Hz)
1	2.63	2.57	2.55
2	8.24	8.22	7.85
3	10.6	10.57	10.41
4	18.85	18.47	18.65
5	41.09	40.8	39.83

Because the number of elements of truss is higher than that of the beam, a larger number of population and iteration is used. Therefore, population = 250, max iteration = 90, other parameters of *PSOGSA* are set same as previous section, excepting $\varphi = 0.5$.

3.2.2 Results

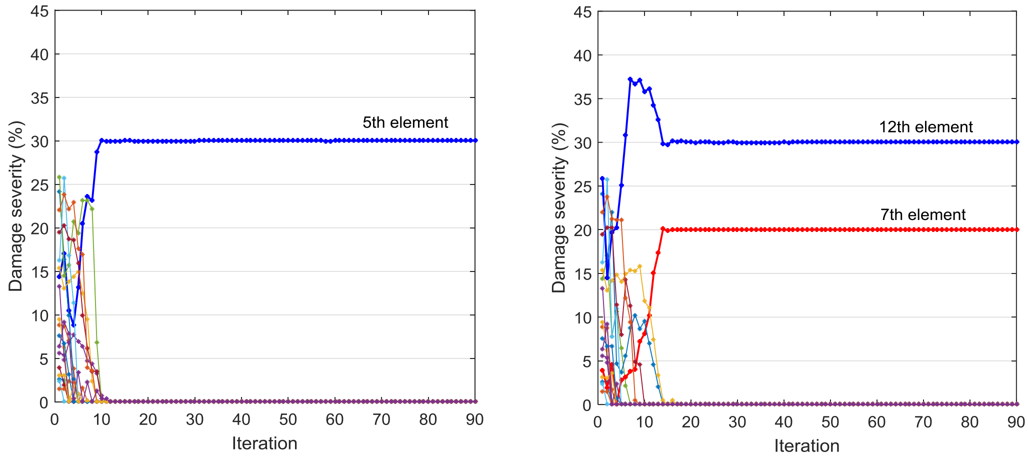
The complex truss structure has 35 elements, 19 nodes. Many elements have to be considered, therefore, the convergence rate is slower and computational time is higher. From Fig. 7, over 10 to 15 iterations, damaged bars can be indicated. In other words, the CPU time is more than that of the beam associated with the same damage scenarios. 8.37 and 8.44 hours are required to idenfity the damaged elements in the second case study.

The first five modes are also used to calculate *ECOMAC* values. Once more time, the proposed approach can localize damages' position and quantify exactly failure severity as in Fig. 8. The high accuracy of the prediction in two damage scenarios regarding the location and extent of damage confirms the reliability of the proposed method.



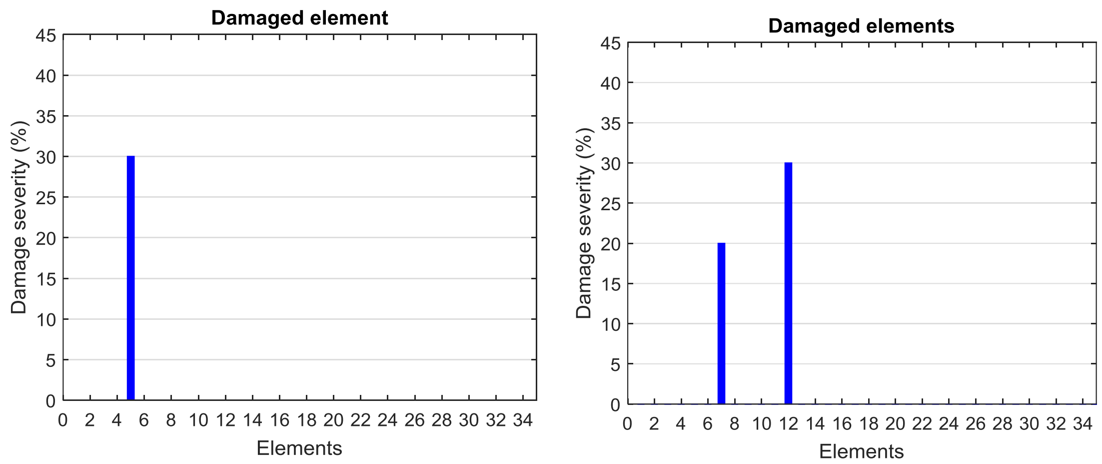
a. 1st scenario b. 2nd scenario

Fig. 6 – Convergence process of the hybrid objective function using PSOGSA for the truss



a. 1st scenario b. 2nd scenario

Fig. 7 – Evolutionary process of damage localization and quantification



a. 1st scenario b. 2nd scenario

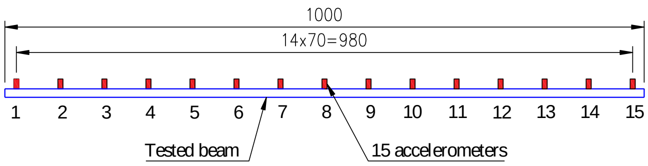
Fig. 8 – Damage identification associated with the two damage scenarios

3.3 Case study 3: a free-free beam-like structure

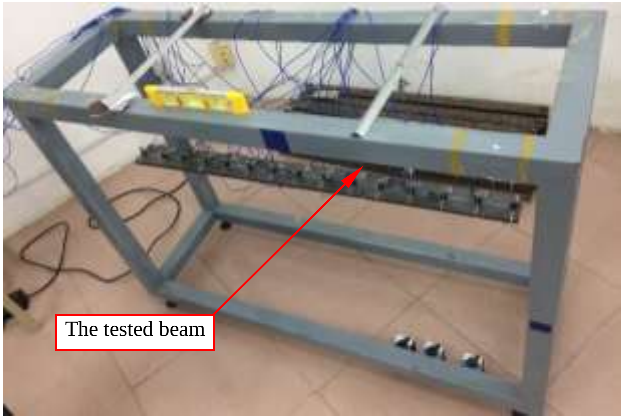
3.3.1 FE model and defect cases

An experiment of the free-free steel beam was conducted in laboratory condition. Fifteen sensors were placed on the top surface to achieve the dynamic response of the beam. Acquisition time is 5 minutes using a sampling rate of 2651 Hz. The beam was excited by striking on the top surface with a hand-hammer. The beam was hung by two wires at points 4 and 12. Measurement grid is depicted in Fig. 9. The interested readers can consult [4] for details of the measurement campaign.

In this paper, a FE model is built based on the vibration data. Beam 189 was used to model the beam in ANSYS. Then this FE model is used to investigate the effectiveness of the proposed approach. Multiple damage with several damage positions and levels are identified using the optimized fitness. Based on the sensor placement in the measurement, the FE model of the free-free beam consists of 16 elements, 17 nodes. The total length of the beam is $L = 0.01 + 14 \times 0.07 + 0.01 = 1m$. Assumed material properties $E = 2 \times 10^{11}\, N/m^2$; $\rho = 7820\, kg/m^3$, Poisson's ratio $v = 0.3$. The dimension of the real cross-section of the beam $b \times h = 0.0714\, m \times 0.0098\, m$. The first five simulated frequencies are compared with the measured frequencies as in Table 5.



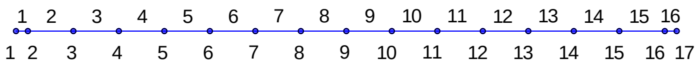
a. The schematic placement of sensors (unit in *mm*)



b. Implementing on the beam

Fig. 9 – Measurement setup.

a. FE model of the beam in ANSYS



b. Labelling the element numbers

Fig. 10 – FE model of the free-free beam.

Table 5 – Discrepancy between computed and measured frequencies

Mode	Measurement (Hz)	Simulation (Hz)	Deviation (%)
1	50.83	51.01	0.35
2	140.4	140.53	0.09
3	274.74	275.23	0.18
4	456.94	454.39	-0.56
5	678.9	677.7	-0.18

All the obtained errors are less than 0.6%. It means that the FE model can represent the behaviour of the real one. Therefore, the FE model can be utilized for damage identification. Damage scenarios are generated by reducing Young's modulus of three elements in a range of 0% to 100% at several positions.

In this case, the number of population and iteration is 200 and 70 respectively. Other hyper-parameters are $c_c = 1$, $c_s = 1.5$, $\alpha = 20$, $G_0 = 1$, and $\varphi = 1$. The first five natural frequencies as in Table 7 and mode shapes are used to calculate the objective function, as mentioned in equation (13). Details of damaged elements and corresponding severity are shown as follows.

Table 6 – Summary of damaged elements and corresponding extents of failure

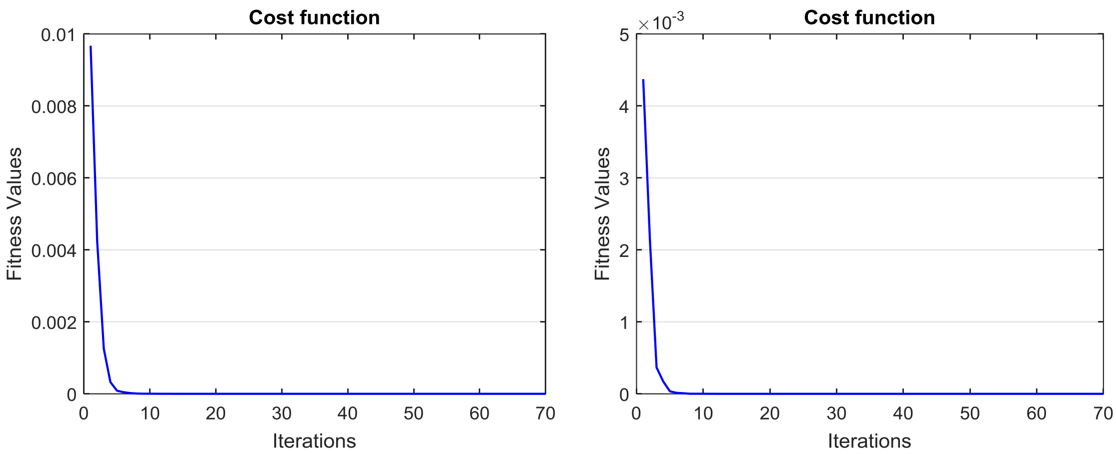
Scenario	Number of damaged elements	Location : Extent (%)		
1	3	8 : 30%	9 : 10 %	10 : 20%
2	3	7 : 12%	11 : 22 %	13 : 32%

Table 7 – The first five healthy and damaged frequencies for the two considered cases

No	Intact beam	Damaged beam	
	f_{intact} (Hz)	$f_{Scenario1}$ (Hz)	$f_{Scenario2}$ (Hz)
1	51.01	48.01	49.58
2	140.53	138.61	134.44
3	275.23	267.19	265.62
4	454.39	443.10	434.20
5	677.7	662.01	656.81

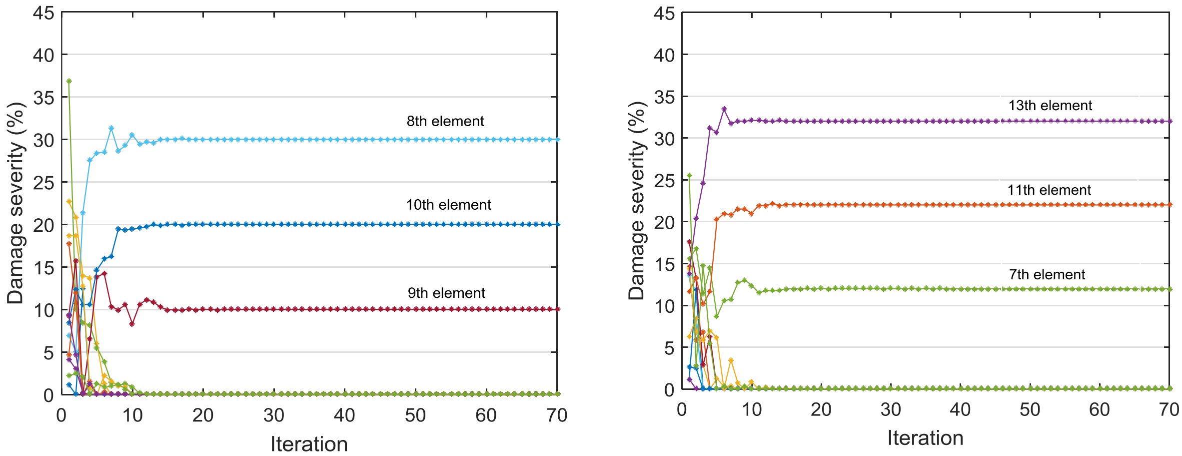
3.3.2 Results

Multiple damage identification is the main objective in this situation. Likewise to the previous section, the changes in frequencies and *ECOMAC* indices are used to compute the fitness function. As can be seen, the proposed approach continues to identify failure as well as the corresponding failure level very quickly, after about 15 loops. (Fig. 11, and Fig. 12). For the first scenario computation time is 5.48 hours. Meanwhile the second one needs 5.28 hours for damage detection. Besides, the chosen hyper-parameters and the objective function using *ECOMAC* index are completely proper for solving this problem.



a. 1st scenario b. 2nd scenario

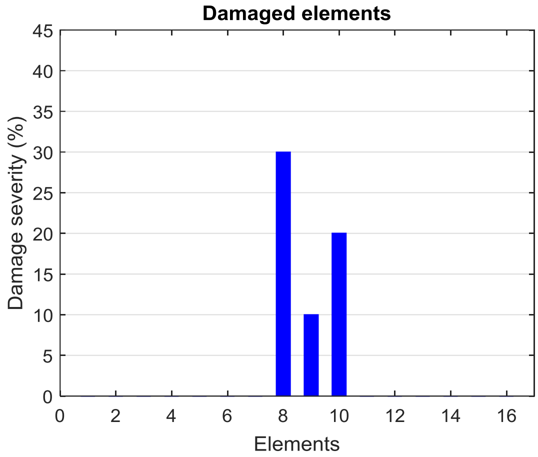
Fig. 11 – Convergence process of the hybrid objective function using PSOGSA for the free-free beam.



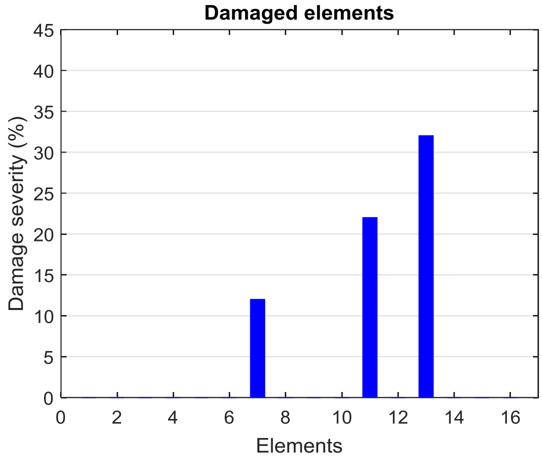
a. 1st scenario b. 2nd scenario

Fig. 12 – Evolutionary process of damage localization and quantification.

The combination of *PSOGSA* and *ECOMAC*, frequency shows high potential in damage identification based on obtained results. Damaged elements are precisely indicated regardless of whether they are successive or apart as in Fig. 13. Besides, this approach also accurately identified the different failure levels.



a. 1st scenario



b. 2nd scenario

Fig. 13 – Damage identification associated with the two damage scenarios.

4 Conclusions

This paper takes advantage of the global optimal search-ability of optimization algorithms in improving damage index, namely *ECOMAC*. The superior identification results in terms of location and quantification, confirm the effectiveness and feasibility of the proposal:

- The proposed approach shows high potential in damage identification for various structures,
- Only the first few modes can be used to determine successfully damaged elements and their extent.
- Simple implementation by using optimization technique coupling with frequency, *ECOMAC*, derived directly from displacement mode shapes.
- Computational time should be considered when the proposed approach is applied to a complex truss structure.

The successful application to the numerical models (two beams and a truss structure) is the promising foundation for the application of the proposal in real structures. However, further works need to be studied, such as using measurement data, considering noise effects.

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