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Multi-swarm fruit fly optimization algorithm for structural damage identification

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Abstract. In this paper, the Multi-Swarm Fruit Fly Optimization Algorithm (MFOA) is presented for structural damage identification using the first several natural frequencies and mode shapes. We assume damage only leads to the decrease of element stiffness. The differences on natural frequencies and mode shapes of damaged and intact state of a structure are used to establish the objective function, which transforms a damage identification problem into an optimization problem. The effectiveness and accuracy of MFOA are demonstrated by three different structures. Numerical results show that the MFOA has a better capacity for structural damage identification than the original Fruit Fly Optimization Algorithm (FOA) does.

Keywords: damage identification; multi-swarm fruit fly optimization algorithm; non-destructive techniques; frequency domain

1. Introduction

Structural damage identification has drawn increasing attention from the scientific and engineering communities. Non-destructive damage identification has a very broad perspective and promising application in structural damage detection due to its non-destructive property, satisfying effectiveness and low cost. In the last three decades, extensive research on vibration-based damage identification has been studied and significant progress has been made in this area (Fan and Qiao 2011).

From a mathematical view, structural damage identification can be considered as an optimization process using an objective function in order to make the calculated results of a given model of a system as close as the measured results of the real one. Many intellectual algorithms are utilized in this area, such as Genetic Algorithm (GA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Artificial Neural Network (ANN), Charged System Search (CSS), etc. Friswell *et al*. (1998) applied a genetic and eigensensitivity algorithm to the problem of damage detection using vibration data. Tsou and Shen (1994) detected and identified damage characteristic (location and severity) of the system from its dynamic properties through a backward-propagation neural network. Majumdar *et al*. (2013) proposed a method that can detect and assess structural damages from changes in natural frequencies using ACO. Dackermann *et al*.

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(2014) used the cepstrum analysis and ANN for damage identification of a structure based on response-only measurements. Abolbashari *et al*. (2014) presented two ANNs for the prediction of Functionally Graded Beam Cracks' location and depth. Kaveh and Zolghadr (2015) presented an improved CSS for damage detection of truss structures using changes in natural frequencies and mode shapes. Charalampakis and Dimou (2010) applied two variants of the PSO to the identification of Bouc-Wen hystereic systems. Kang *et al*. (2012) proposed an immunity enhanced PSO which is efficient on damage identification based on vibration data. Guo and Li (2014) used PSO to identify the extent of structural damage after the damaged locations are determined. Begambrea and Laiera (2009) identified accurately damaged elements in the truss and beam using a hybrid PSO – Simplex algorithm. Mohan *et al*. (2014) compared the efficiency of PSO and GA on structures like beam, planar truss and spacial truss. Maresa and Suraceb (1996) applied GA to detect damage in elastic structures. Chou and Ghaboussi (2001) also presented a method that is capable of successfully detecting the location and magnitude of the structural damage using GA. Yi *et al*. (2015) implemented a novel collaborative-climb monkey algorithm (CMA) as a effective strategy for optimal placement of a predefined number of sensors in high-rise structural health monitoring. Kwon *et al*. (2008) utilized the fine-tuning and small-digit characteristics of the successive zooming genetic algorithm (SZGA) to propose a method of structural damage detection in a continuum structure.

Fruit Fly Optimization (FOA) is a novel evolutionary computation and optimization technique based on the swarm behavior of fruit fly, which was developed by Pan (2011). Pan (2012) took the financial distress model as an example to demonstrate the accuracy and stability of FOA. Li *et al*. (2014) used FOA to solve the steelmaking casting problem and the results indicate FOA is more effective than other four presented algorithms. However, this kind of swarm behavior FOA might be trapped in local optimal and result in an unexpected optimization consequence. A modification on the original FOA technique named Multi-Swarm Fruit Fly Optimization Algorithm (MFOA) is introduced by Yuan *et al*. (2014). They illustrated that the application of MFOA shows an effective improvement in its performance over the original FOA technique.

As both the original FOA and MFOA methods have not yet been applied in the area of structural damage identification. We attempt to apply these optimization methods to structural damage identification in this study. In the process of damage identification, we established an objective function based on the changes in the first several natural frequencies and mode shapes of the structure. The application of FOA and MFOA method on three different structures shows MFOA has marked and significant performance to identify damage of a structure.

The rest of the paper is organized as follows: in Section 2, damage detection method is introduced, followed by the basic FOA and MFOA method in Section 3. Section 4 includes test examples of three typical structures. Finally, Section 5 gives concluding remarks.

2. Damage detection method

2.1 Parameterization of damage

The equation of free vibration for a basic structure with an undamped *n* degrees-of-freedom given by

$$[\mathbf{M}]\{\ddot{x}\} + [\mathbf{K}]\{x\} = 0 \tag{1}$$

where matrices M and K are the $n{\cdot}n$ global mass and stiffness matrices, and $\{x\}$ and $\{\ddot{x}\}$ are the $n{\cdot}1$ displacement and acceleration vectors, respectively.

The eigenvalue equation is expressed as

$$([\mathbf{K}]-\omega_j^2[\mathbf{M}])\,\phi_j=0 \tag{2}$$

where ω_j is the j^{th} natural frequency and ϕ_j is the j^{th} mode shape of the structure.

In this study, damage is modeled as a reduction in the elemental stiffness parameter, for instance elemental Young's modulus, namely, $E_{jd}=(1-\alpha_j)\cdot E_{j0}$, E_{j0} is the Young's modulus of the j^{th} element of the intact structure, α_j represents the damage extent of the j^{th} element. $\alpha_j=0$ denotes the j^{th} element has no damage and $\alpha_j=1$ means fracture of the element.

2.2 Objective function

The fundamental law of structural damage identification is that damage will affect and change mass, stiffness, and damping properties of a structure. We assume damage is only defined as changes in elemental stiffness. The decrease of stiffness would lead to changes of natural frequencies and mode shapes. Therefore, the problem can be transformed to find damage location and size by detecting the change of stiffness parameter.

Modal assurance criteria (MAC) and frequency residual are introduced to identify the damage by comparing responses between damaged and undamaged states. The objective function f in terms of frequency residual and MAC is expressed as

$$\Delta\omega_j=\frac{\left|\omega_j^q-\omega_j^r\right|}{\omega_j^r} \tag{3a}$$

$$MAC_j=\frac{\left|\phi_j^{rT}\cdot\phi_j^q\right|^2}{\left|\phi_j^{rT}\cdot\phi_j^r\right|\left|\phi_j^{qT}\cdot\phi_j^q\right|} \tag{3b}$$

$$f=\sum_{j=1}^{N}w_{\omega j}\cdot\Delta\omega_j^2+w_{\phi j}\cdot(1-MAC_j) \tag{3c}$$

where ω_j^r and ϕ_j^r are the analytical natural frequency and mode of j^{th} element, respectively. ω_j^q and ϕ_j^q are the test natural frequency and mode of j^{th} element, respectively. The $w_{\omega j}$ and $w_{\phi j}$ are weighting coefficients of the objective function.

3. Optimization algorithm

3.1 The original FOA technique

The Fruit Fly Optimization Algorithm (FOA) was introduced by Pan (2011), as a new approach to seek global optimization based on the food finding behavior in swarms of fruit fly. The fruit fly itself is superior to other species in sensing and perception, especially in osphresis and vision. The osphresis organs of fruit can find all kinds of scents floating in the air; it can even smell food source from 40 km away. Then, after it gets close to the food location it can also use its sensitive vision to find food and company's flocking location, and fly towards that direction too (Pan 2012).

This FOA technique can be divided into several necessary steps and the main steps are described as follows:

Step 1. Randomly initialize fruit fly swarm location

$$Init\ X\_axis$$

$$Init\ Y\_axis \tag{4}$$

Step 2. Give the random direction and distance for the search of food using osphresis by an individual fruit fly.

$$X_i = X\_axis + Random\,Value$$

$$Y_i = Y\_axis + Random\,Value \tag{5}$$

where i is the population size of fruit flies, i=1,2,3...*Popsize*.

Step 3. Since the food location cannot be known, the distance to the origin is thus estimated first $Dist_i$, then the smell concentration judgment value S_i is calculated, and this value is the reciprocal of distance.

$$Dist_i = \sqrt{X_i^2 + Y_i^2} \tag{6a}$$

$$S_i = 1/Dist_i \tag{6b}$$

Step 4. Substitute smell concentration judgment value S_i into smell concentration judgment function (or called Fitness function) so as to find the smell concentration $Smell_i$ of the individual location of the fruit fly.

$$Smell_i = Function\,(S_i) \tag{7}$$

Step 5. Find out the fruit fly with maximal smell concentration (finding the maximal value) among the fruit fly swarm.

$$[bestSmell\ bestIndex] = \max(Smell) \tag{8}$$

Step 6. Keep the best smell concentration value and x, y coordinate, and at this moment, the fruit fly swarm will use vision to fly towards that location.

$$Smellbest = bestSmell$$

$$X\_axis = X(bestIndex)$$

$$Y\_axis = Y(bestIndex) \tag{9}$$

Step 7. Conduct iterative optimization to repeat the implementation of **Step 2-Step 5**, then judge if the smell concentration is superior to the previous iterative smell concentration, if so, implement **Step 6.**

3.2 MFOA technique

The Multi-Swarm Fruit Fly Optimization Algorithm (MFOA) was introduced by Yuan *et al*. (2014), based on the Fruit Fly Optimization Algorithm (FOA). MFOA has been proved to enhance accuracy and speed up convergence rate of the original algorithm. The implement procedure of the proposed MFOA is summarized as follows.

Consider the optimization problem for nonlinear function with boundary constraints

$$\min\ f(X),\ \ X \in [a,b] \tag{10}$$

Step 1. Initialization. Set the max iteration times $k_{\max}$, let k=1, population size of fruit flies i=1,2,3...*Popsize*. Initialize fruit fly swarm location *Init X_axis*.

Step 2. Give the random direction and distance for the search of food using osphresis by an individual fruit fly, each swarm is conducted independently as

$$X_{i,m} = X\_axis_m + R(k) \cdot Random\,Value \tag{11}$$

$$\text{with}\quad R(k) = \frac{b-a}{2}\left(\frac{k_{\max}-k}{k_{\max}}\right)^{\varphi}$$

where φ=2~6, $R(k)$ with big value in early iterations may increase the diversity of solution vectors for global exploration, while in final iterations $R(k)$ with small value may enhance the fine-tuning of solution vectors by local exploitation.

Step 3. Substitute decision variable value X_i into fitness function or objective function so as to find the fitness $Semll_i$ function value of the individual location of fruit fly.

$$Smell_i = Function\,(S_i) \tag{12}$$

Step 4. Find out the fruit fly with the minimum value or the best fitness value among each sub-swarm.

$$[bestSmell_m\ \ bestIndex_m] = \min(\,Smell) \tag{13}$$

Step 5. Judge if the fitness of each sub-swarm is superior to the previous iterative fitness, if so, update the best fitness value of each sub-swarm, and at this moment, each sub-swarm will use vision to fly independently towards that location.

$$Smellbest_m = bestSmell_m$$

$$X\_axis_m = X\left(bestIndex_m\right) \tag{14}$$

Step 6. Update the global fitness Smellbest and best position *X_axis* among multi-swarm by:

If $Smellbest_m < Smellbest$, then $Smellbest = Smellbest_m$, $X\_axis = X\_axis_m$.

Step 7. Perform cooperative local search method by

$$X\_new = \frac{1}{M}\sum_{m=1}^{M} X\_axis_m \tag{15}$$

If *Function*(*X_new*)<*Smellbest*, update the global fitness and best position as: *Smellbest*=*Function*(*X_new*), *X_axis*=*X_new*.

Step 8. If $k \geq k_{\max}$, stop the MFOA search; otherwise, go to **Step 2.**

The flow chart of FOA and MFOA are shown in Fig. 1.

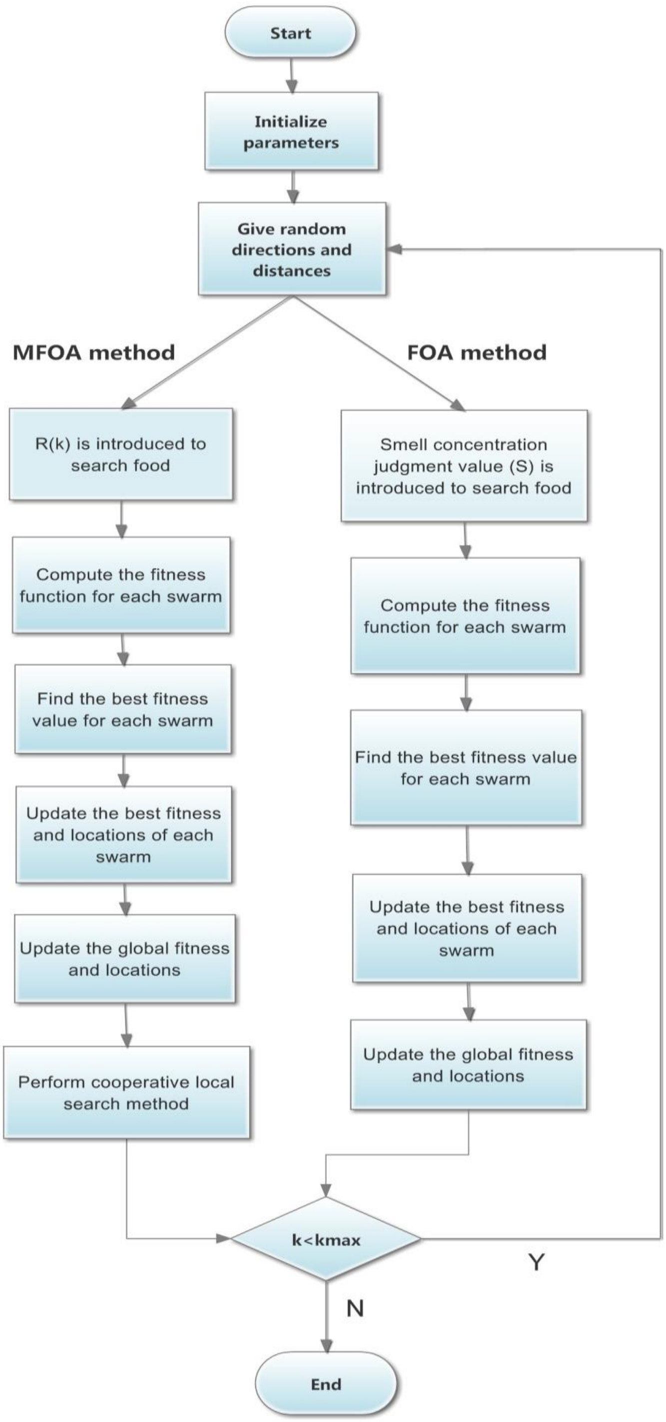

Fig. 1 Flow chat of FOA and MFOA method

4. Numerical simulation

Three numerical examples are chosen to illustrate and compare the reliability, accuracy and efficiency of structural damage identification using FOA and MFOA methods.

Because of unavoidable errors in instrumentation and measurements, natural frequency and mode shape data are often contaminated with noise. The measurement noises are also considered here. Numerically, noises are added to the natural frequencies and mode shapes to simulate the noisy data with

$$\omega_{noise,i} = \omega_i + E_{p1} \cdot N_{noise} \cdot \omega_i \tag{16a}$$

$$\phi_{noise,i} = \phi_i + E_{p2} \cdot N_{noise} \cdot \phi_i \tag{16b}$$

where $\omega_{noise,i}$ and ω_i are the natural frequency components of the i^{th} order with noise and without noise, respectively; $\phi_{noise,i}$ and ϕ_i are the mode shape components of the i^{th} order with noise and without noise, respectively; E_{p1} and E_{p2} are the percentage noise level for natural frequencies and mode shapes, respectively; $N_{noise}$is a uniformly distributed pseudorandom number in the interval $[-1,1]$.

The effect of artificial measurement noise on the identified extent results is studied. In all examples, the coefficients $w_{\omega j}$, $w_{\phi j}$ and c are set to 1, 1 and 4, respectively. The Popsize equals 200 and the max iteration $k_{\max}$=1800. In order to consider the stochastic nature of the optimization-based damage detection problem, five independent optimization runs are performed to decrease the influence of randomness and the average values are shown in the following cases. In the experiments, we detect the damage coefficient α which varies from 0 to 1. The initial fruit fly locations mean that the structure has no damage at the beginning.

4.1 A simply supported beam

A simply supported beam as shown in Fig. 2 is considered as the first example. It is discretized into 10 Euler beam elements in the finite elements. The length, thickness, and width of the beam are 2.1 m, 0.025 m, 0.019 m, respectively. The mass density is 7832 kg/m^3. And the elasticity modulus is 207 GPa.

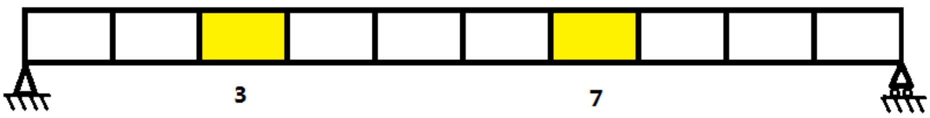

Fig. 2 A simply supported beam

4.1.1 Case1: Multiple damages identification using different number of frequencies and mode shapes

Damages in the structure, as shown in Table 1, are introduced by reducing the elemental Young's modulus by 8% and 14% at the elements 3 and 7, respectively. The artificial measured noises are considered here as E_{p1}=1% and E_{p2}=5%. The first three natural frequencies and mode

Table 1 Damage settings in the numerical simulation

Type	Scenario	Damage Location		
Beam	Young’s modulus reduction (elements)	3rd element 8%	7th element 14%	
Truss	Young's modulus reduction (elements)	2nd element 10%	8th element 15%	
Discrete System	Stiffness coefficient reduction	15th spring 28%	16th spring 26%	56th spring 20%
		57th spring 18%	springs from 17th to 21st 10%	

Table 2 Identified results of the damage elements in case 1

Assumed value		Identified value			
	α_3	MFOA		FOA	
case 1	8%	mean 7.52%	std. 0.032	mean 6.39%	std. 0.038
	α_7 14%	mean 13.52%	std. 0.019	mean 12.6%	std. 0.030

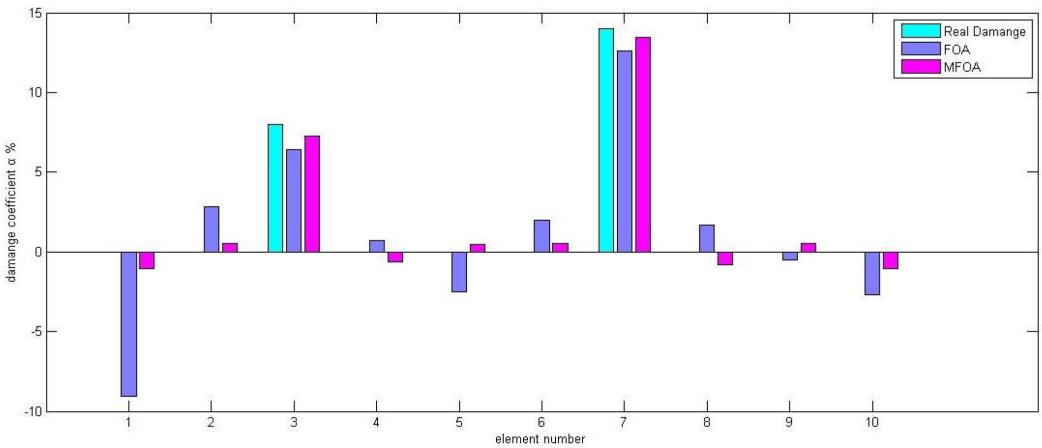

Fig. 3 Identified results using the first three natural frequencies and mode shapes

shapes of the simply supported beam are adopted in the identification. The detection results using FOA method and MFOA method are illustrated in Fig. 3 and Table 2. The iteration process of FOA and MFOA is shown in Fig. 4.

The figures and the table give the comparison of capacity of detecting damage for FOA and MFOA methods. From the figures, one can find that both FOA and MFOA are able to detect location and severity of damaged elements. FOA has a relatively worse ability of detecting location and severity of undamaged elements than MFOA does. The detection result from MFOA

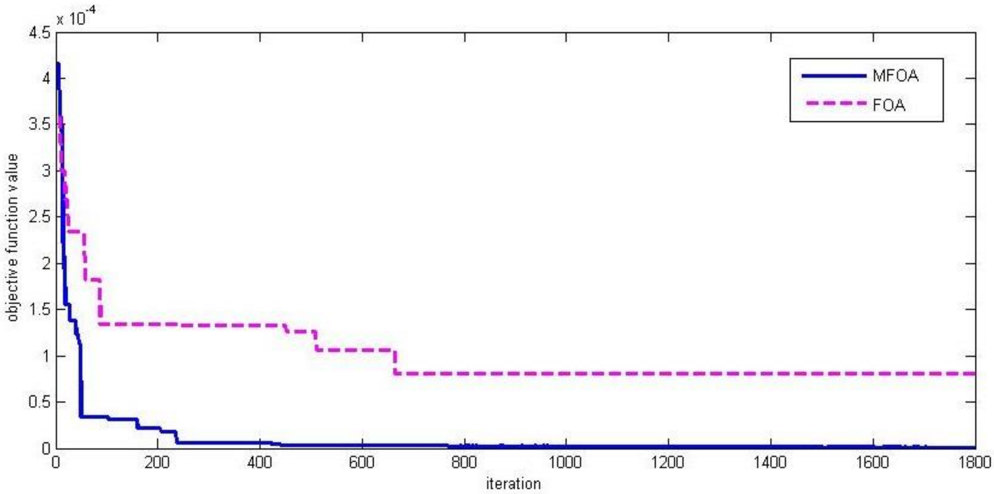

Fig. 4 Iteration process of FOA and MFOA in case 1

Table 3 Identified results of the damage elements in case 2

Assumed value		Identified value					
	α_3	MFOA1		MFOA2		MFOA3	
	8%	mean	std.	mean	std.	mean	std.
case 2		7.52%	0.032	7.38%	0.080	3.18%	0.083
	α_7	mean	std.	mean	std.	mean	std.
	14%	13.52%	0.019	13.17%	0.044	15.8%	0.136

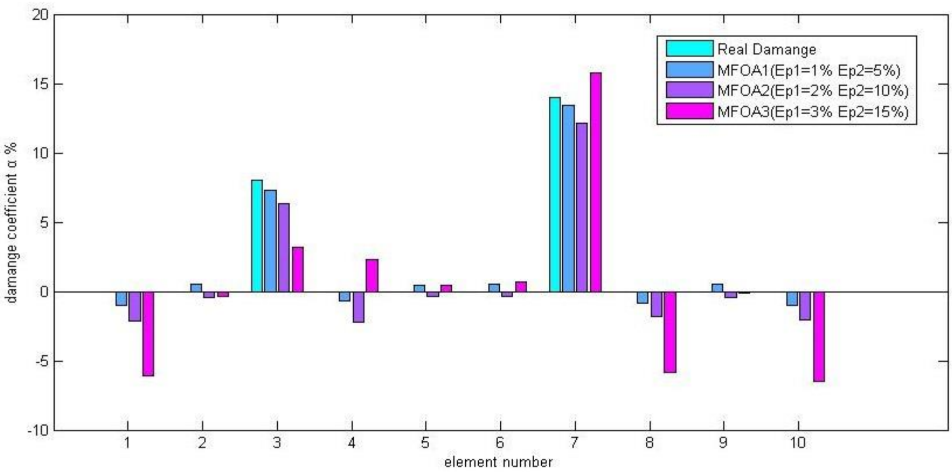

Fig. 5 Identified results with different level of artificial noises

is always stable and accurate using the first three natural frequencies and mode shapes. Hence, MFOA has a better capacity of identifying damaged elements than FOA.

4.1.2 Case 2: Multiple damages with different level of artificial noises

Three different level of noise are presented in this example. The first level noise is introduced as E_{p1}=1% and E_{p2}=5% (denotes by MFOA1), the second E_{p1}=2% and E_{p2}=10% (denotes by MFOA2) and the third E_{p1}=3%and E_{p2}=15% (denotes by MFOA3). The identified results through MFOA using only the first three natural frequency and mode shape are illustrated in Fig. 5 and Table 3.

From Fig. 5, one can find that with the level of noise increasing, the results are becoming increasingly less accurate. Most identified results are a little bit smaller than the real damage extents according to Table 3. MFOA can locate the damaged elements successfully with acceptable identified errors in the damage extent in the MFOA1 and MFOA2 situations. However, in the MFOA3 situation, MFOA almost loses the ability to identify damage. Hence, the result from MFOA can be easily affected by severe noise.

4.2 A 31-bar planar truss

The same truss structure studied by Shiraz *et al*. (2014) is considered as the second example. The length of a bar is shown in the Fig. 6. The cross-sectional area, mass density and the elasticity modulus is 0.0025 m^3, 7860 kg/m^3 and 200GPa, respectively. In this example, only the first five natural frequencies and mode shapes are used to identify damage. Damages in the structure, as shown in Table 1, are introduced by a reduction in the elemental Young's modulus by 10% and 15% at the elements 2 and 8, respectively. The artificial measured noises are considered here as E_{p1}=1% and E_{p2}=5%.

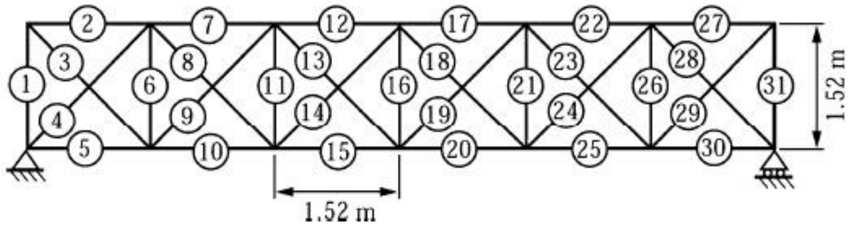

Fig. 6 A 31-element truss system

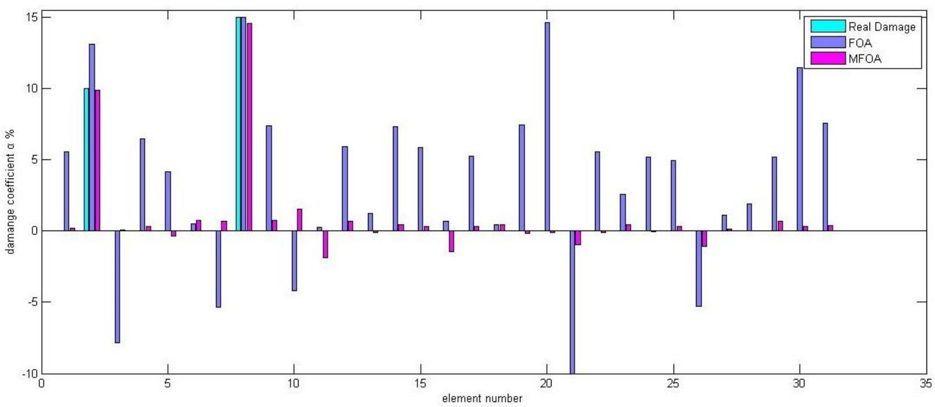

Fig. 7 Identified results in a 31-element truss using FOA and MFOA

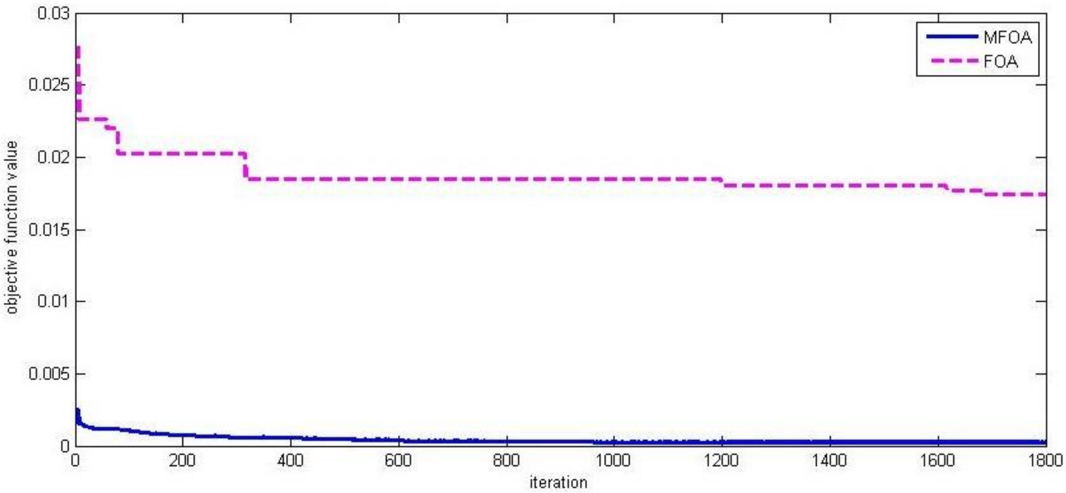

Fig. 8 Iteration process of FOA and MFOA in case 3

Table 4 Identified results of the damage elements in case 4

Assumed value		Identified value					
	α_2	3 modal data		4 modal data		5 modal data	
case 4	10%	mean	std.	mean	std.	mean	std.
		9.76%	0.005	10.02%	0.004	9.86%	0.004
	α_8	mean	std.	mean	std.	mean	std.
	15%	12.44%	0.067	15.21%	0.012	14.57%	0.009

4.2.1 Case 3: Identification of multiple damages

The detection results using FOA and MFOA are shown in Fig. 7 and Fig. 8. MFOA can accurately locate the damaged elements and identify the severity of damaged elements with very few false alarms. On the contrary, FOA almost fails to identify the damages in such a relatively complex truss structure. There are many large false alarms when the FOA are used. This may due to the reason that FOA is trapped into a local optimum which is far away from the real damage.

4.2.2 Case 4: Multiple damages with different number of frequencies and mode shapes

Different number of modal data is studied in this case, namely, the first three, four and five natural frequencies and associate mode shapes are examined. The results from MFOA using these modal data are shown in Fig. 9 and Table 4. When the less number of modal data are used in the identification, the damaged elements can still be identified successfully. But there are some false alarms in the identified results. This case further illustrates the effectiveness of present methods as only the first few modal data are needed in the identification.

4.3 Case 5: A discrete spring-mass system with 100 degrees of freedom

A discrete spring-mass system with 100 degrees of freedom as shown in Fig. 10 is studied as the last test example. The stiffness of all the springs is 2×10^5 N/m and the mass of each M is 78 kg.

Damages in the structure, as shown in Table 1, are introduced by reducing stiffness coefficients of the 15th, 16th, 56th and 57th spring by 28%, 26%, 20% and 18%, respectively. And a zone damage from the 17th spring to 21st spring by 10% reduction in the spring coefficient. The artificial measured noises are considered here as E_{p1}=1% and E_{p2}=5%. The FOA completely fails to identify damage in this example. The identified results and iteration process with and without artificial noises using MFOA are illustrated in Fig. 11 and Fig. 12, respectively. The complex damage scenario has been identified successfully with few small false alarms using the first thirteen natural frequencies and mode shapes. All of the damaged spring elements have been located successfully and the damage extents also identified accurately.

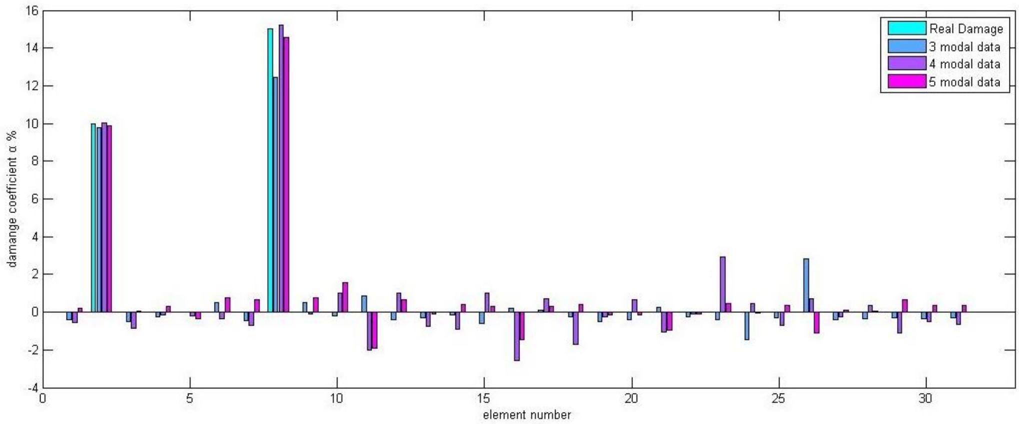

Fig. 9 Identified results in a 31-element truss using different number of modal data

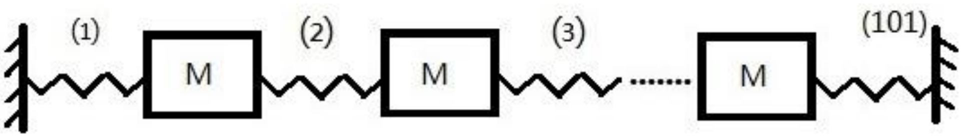

Fig. 10 A discrete spring-mass system with 100 DOFs

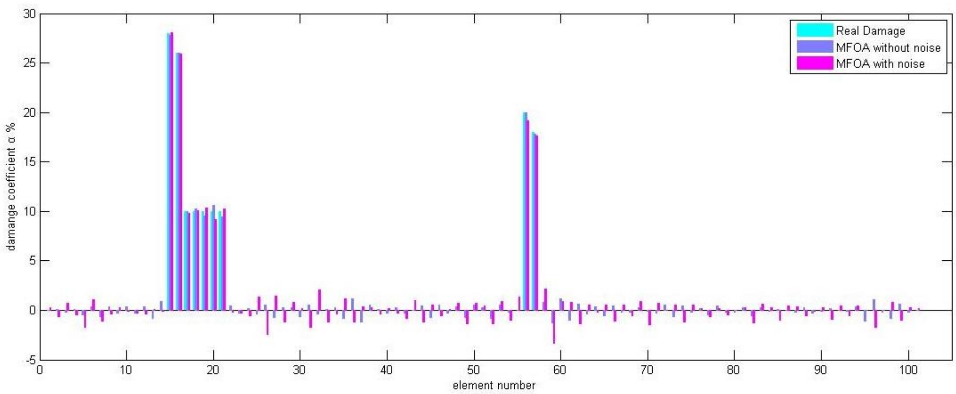

Fig. 11 Identified results using the first thirteen natural frequencies and mode shapes

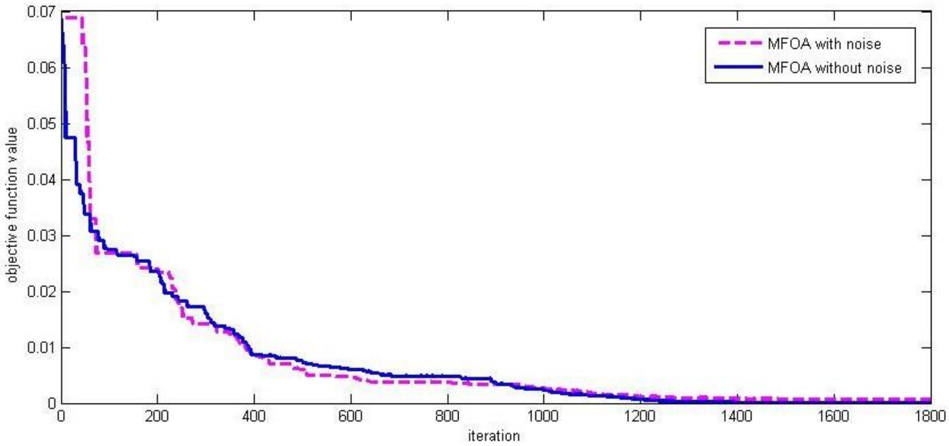

Fig. 12 Iteration process of MFOA in case 5

5. Conclusions

In this study, FOA and MFOA method are introduced for structural damage identification. Three different structures are studied as the numerical example to illustrate the correctness and effectiveness of the present methods. Studies show that MFOA method is a powerful search algorithm and can identify damage using the first few natural frequencies and mode shapes. And the present method is not very sensitive to the artificial measurement noise.

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