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A novel WOA-based structural damage identification using weighted modal data and flexibility assurance criterion

Zexiang Chen[a] and Ling Yu*

MOE Key Laboratory of Disaster Forecast and Control in Engineering, School of Mechanics and Construction Engineering, Jinan University, Guangzhou 510632, China

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Abstract. Structural damage identification (SDI) is a crucial step in structural health monitoring. However, some of the existing SDI methods cannot provide enough identification accuracy and efficiency in practice. A novel whale optimization algorithm (WOA) based method is proposed for SDI by weighting modal data and flexibility assurance criterion in this study. At first, the SDI problem is mathematically converted into a constrained optimization problem. Unlike traditional objective function defined using frequencies and mode shapes, a new objective function on the SDI problem is formulated by weighting both modal data and flexibility assurance criterion. Then, the WOA method, due to its good performance of fast convergence and global searching ability, is adopted to provide an accurate solution to the SDI problem, different predator mechanisms are formulated and their probability thresholds are selected. Finally, the performance of the proposed method is assessed by numerical simulations on a simply-supported beam and a 31-bar truss structures. For the given multiple structural damage conditions under environmental noises, the WOA-based SDI method can effectively locate structural damages and accurately estimate severities of damages. Compared with other optimization methods, such as particle swarm optimization and dragonfly algorithm, the proposed WOA-based method outperforms in accuracy and efficiency, which can provide a more effective and potential tool for the SDI problem.

Keywords: structural damage identification; whale optimization algorithm; constrained optimization problem; objective function; flexibility assurance criterion

1. Introduction

Structural damages affect structural performance and lead to structural collapse in even extreme conditions, which cause human and economic losses. Hence, structural damage identification (SDI), as a crucial step in the field of structural health monitoring (SHM), it is particularly important to assess the reliability, integrity and safety of bridge structures in real time through the SHM technologies (Seo *et al*. 2016).

Most of the existing methods are based on the recognition of changes in the structural characteristic properties. In the SHM field, SDI and quality assessment can usually be divided into four stages (Zhu and Wu 2014): detecting presence or absence of structural damages, determining locations of structural damages, identifying damage severities, and estimating remaining life of structures. In order to make SDI theory and technology better applicable to practical engineering, a number of investigations have been conducted over the past decades, and some fruitful results produced (Cha 2015, Su *et al*. 2016, Huang and Lu 2017, Gao and Khalid 2018, Zheng *et al*. 2018, Huang *et al*. 2018, Ghannadi and Kourehli 2019, Huang *et al*. 2019). For example, SDI methods based on neural networks (Kao 2003), wavelet analysis (Chang and Chen 2003), Bayesian (Hou *et al*. 2019), finite element model updating (Yuen 2010), genetic algorithms (Perera and Torres 2006), and sparse regularization (Ding *et al*. 2019) have been extensively studied. However, the SDI methods based on dynamic fingerprints have disadvantages, such as poor robustness to noise and weak ability to recognize small damage. The neural network-based SDI method is an effective SDI method for bridges, but the neural network theory is not perfect yet, and there are still some difficulties in damage identification of bridge structures in practice.

Beginning in the 1990s, the meta-heuristic methods, as a promising method in SDI optimization problems, have been developed rapidly, and achieved valuable research results. Among them, swarm intelligence (SI) optimization algorithms, such as ant colony optimization (ACO, Yu and Xu 2010), particle swarm optimization (PSO, Kang 2012, Huang *et al*. 2019), global artificial fish swarm algorithm (GAFSA, Li and Yu 2014), and cuckoo search (CS, Xu *et al*. 2016), are adopted in the SDI area. For example, Yu and Xu (2011) proposed an ACO-based algorithm for continuous optimization problems on SDI in the SHM field. Li and Yu (2014) verified the effectiveness and feasibility of applying GAFSA to damage detection based on model updating through numerical simulation of two-story rigid frame under different damage conditions and experimental verifications on three-story frame structure. Xu *et al*. (2016) proposed an approach for SDI based on modified cuckoo search (MCS). Meanwhile, they take frequency residual error and the modal assurance criterion (MAC) as indexes of damage detection in view of the crack damage, and the

*Corresponding author, Professor
E-mail: lyu1997@163.com
[a] Post-Graduate Student

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MCS algorithm is utilized to identify structural damages. However, there are some shortcomings in these algorithms, such as local optimum and slow convergence rate, and their robustness under noise effects are not so good.

As a novel strategy, so called hybrid algorithm, is proposed to improve the performance of the existing methods, such as self-adaptive firefly–Nelder–Mead (SA-FNM) algorithm (Pan *et al*. 2016), PSO-improved Nelder-Mead (PSO-INM, Chen and Yu 2017), hybrid PSO (HPSO, Chen and Yu 2018), and PSO–CS algorithm (Huang *et al*. 2019). For example, Pan *et al*. (2016) proposed a hybrid SA-FNM algorithm as an exploring attempt to the SDI problem. Some new strategies on information exchange, random walk and self-adaptive method were then used to improve the performance of SA-FNM for solving the SDI problem. The Nelder-Mead (NM) algorithm was incorporated into the basic firefly algorithm (FA) for improving the local searching ability. A new strategy for exchanging the information was used to reduce the computation cost of FA. The illustrated SDI results show that the SA-FNM can effectively identify both damage location and damage extent with a better noise immunity. Chen and Yu (2017) proposed a PSO-INM algorithm, which combined PSO algorithm and an improved NM method to solve the multi-sample objective function based on Bayesian inference. The illustrated results show that the proposed method can provide a reliable SDI tool for the ASCE benchmark frame structure. Moreover, Chen and Yu (2018) proposed a new SDI strategy of HPSO combining PSO with NM method, and used the new strategy to embedding the powerful local search NM algorithm into PSO to enhance the global search capability of PSO. The effectiveness of the method was verified by Monte Carlo simulations and a series of experiments in laboratory. To perform SDI considering temperature variations and noises, Huang *et al*. (2019) proposed a damage identification method using PSO–CS hybrid algorithm, which applied the updated mechanism of PSO in CS, blind-searching was improved in PSO and the global search in CS was enhanced. It is validated with a numerical example of a simply supported beam, and the performance of PSO-CS is better than PSO and CS. And the robustness and practicability of the algorithm was verified by the damage identification of ASCE Benchmark frame. The abovementioned hybrid algorithms show a bright prospect in the SDI problems under environmental conditions.

Although these hybrid methods have achieved fairly satisfactory SDI results, there still remain some challenges because the inherent shortcomings are still involved in the basic SI-based algorithms. For example, PSO is easy to fall into the local optimum in the later stage. ACO has a problem of instability in solving the high-dimensional objective optimization function. The AFSA efficiency is not high enough (Guo 2017). The Big Bang and Big Crunch optimization algorithm provides a good detection result only for structures with severe damage (Huang and Lu 2017).

Apart from trying to improve the insufficient accuracy and lower efficiency of existing SDI methods, the scholars never stop to explore new methods. As one of leading inventors in optimization algorithms, Australian scholar Mirjalili and his research group have proposed a large number of new algorithms, such as grey wolf optimizer (GWO, Mirjalili *et al*. 2014), moth-flame optimization (MFO, Mirjalili 2015), dragonfly algorithm (DA, Mirjalili 2016), and whale optimization algorithm (WOA, Mirjalili and Lewis 2016). These algorithms have been widely and successfully applied in diverse engineering field (Precup *et al*. 2016, Alireza *et al*. 2018, Mafarja and Mirjalili 2018). And as a new meta-heuristic optimization algorithm for solving optimization problems, WOA simulated solutions of 29 mathematical benchmark functions and 6 structural engineering optimization problems, and demonstrated excellent performance of WOA algorithm in terms of convergent rate and avoidance of local optimal solutions (Mirjalili and Lewis 2016). The main difference between WOA and some of the previously proposed algorithms is the simulated hunting behavior with random, the best search agent to chase the prey and the use of a spiral to simulate bubble-net attacking mechanism of humpback whales. In the past years, WOA has been successfully applied in many fields and has shown good performance (Oliv *et al*. 2017, Mafarja and Mirjalili 2018), but to the knowledge of authors, it has not been applied to the SDI problem yet.

On the other hand, the dynamic characteristics of structures will change due to structural damages. The structural modal parameters, such as frequency, damping and mode shapes will also change with structural damages. In the process of SDI, an objective function needs to be defined in order to evaluate the changes in modal properties because of the occurrence of damages. Most of existing SDI methods employed frequencies and mode shapes to define the objective function, which is also the most common practice (Ding *et al*. 2016). However, modal frequencies and mode shapes are not much sensitive to structural damages, especially for some minor damage cases, it is difficult to identify well if frequencies and mode shapes are used only. To this end, the flexibility matrix is introduced to the traditional objective function to improve the sensitivity of the objective function to structural damages as well as improving the accuracy of SDI methods. In addition, multiple weight strategies can provide a good way to balance the contribution of different parameters defined in the objective function (Chen and Yu 2020).

The main contribution of this paper is to propose a new WOA-based SDI method and to define a new objective function related to SDI problem by weighting both modal parameters and flexibility assurance criterion so as to improve the SDI accuracy and efficiency for different structures. The probability thresholds of different predator mechanisms in WOA are reset to improve the iterative speed and optimization ability of the algorithm. Finally, under different noise levels and various structural damage conditions, numerical simulations on SDI problem are performed on simply-supported beam and a 31-bar planar truss structure to verify the effectiveness and feasibility of the proposed WOA-based SDI method. A comparison with PSO and DA is conducted as well.

2. Theoretical background

2.1 Damage model

The structural modal parameters will obviously change as structural damages occur. These modal parameters can be used to establish the objective function, and then the parametric difference between calculated and measured results is minimized. Finally, the minimum value of the objective function is solved to perform the SDI. In general, the global stiffness and mass of a structure are divided into numerous element stiffness and masses, and the structural damage is simulated by reducing the element stiffness and masses. The stiffness reduction due to damage will be mainly considered. And the change in mass will be ignored as it makes less influence to modal parameters compared with stiffness reduction. The linear relationship between the global stiffness matrix and the element stiffness matrix of the structure is expressed as:

$$\mathbf{K} = \sum_{i=1}^{N}(1-\alpha_i)\mathbf{K}_i \tag{1}$$

where $\mathbf{K}$ and $\mathbf{K}_i$ denote global stiffness matrix and the i-th element stiffness matrix of the structure, respectively; N is the total number of elements; α_i denotes the damage factor of the i -th element and its range is from 0 to 1, $\alpha_i = 0$ means that the i -th element is undamaged.

Traditionally, the changes in modal parameters, such as natural frequencies and mode shapes, are used to realize SDI, and these changes are related to the stiffness. An objective function based on frequencies and mode shapes is established, and the damage identification of the structure is achieved by finding the minimum value of the objective function. In other words, the SDI problem is converted to an optimization problem, which can be expressed as:

$$\begin{aligned} &O(\alpha_i) = \min f(\alpha_i) \\ &s.t.\ \ 0 \le \alpha_i < 1 \end{aligned} \tag{2}$$

where $f(\alpha_i)$ is objective function. When it reaches the minimum value, a series of related parameters α_i can reflect the damage severities of the structure.

2.2 Objective function

For the SDI problem, most investigations define objective functions by natural frequencies and mode shapes of the structure. The expression is usually as follows:

$$f = \sum_{i=1}^{s}[(1-MAC(\Phi_i^h, \Phi_i^d)) + ER(\omega_i^h, \omega_i^d)] \tag{3}$$

In Equation (3), *MAC* and *ER* are modal assurance criterion and frequency percentage error, respectively. Their expressions are as follows:

$$MAC(\Phi_i^h, \Phi_i^d) = \frac{\left|(\Phi_i^h)^T \Phi_i^d\right|^2}{\left|(\Phi_i^h)^T \Phi_i^h\right|\left|(\Phi_i^d)^T \Phi_i^d\right|}\ ,\quad i = 1, 2, ..., s \tag{4}$$

$$ER(\omega_i^h, \omega_i^d) = \left|\frac{\omega_i^h - \omega_i^d}{\omega_i^h}\right| \times 100\% \tag{5}$$

where s represents the considered modal number; (ω_i^h, Φ_i^h) denotes the i-th frequency and mode shape of healthy structure; (ω_i^d, Φ_i^d) denotes the i-th frequency and mode shape of damaged structure.

This study ignores the influence of mass change when the structural damages are simulated. According to structural mechanics, stiffness and flexibility are inversely related. Decreasing the stiffness of the structure will make the corresponding flexibility to increase, and the flexibility matrix will be more sensitive to damage. For SDI, they have different changes in frequencies, mode shapes and flexibility sensitivity of structures, so they are weighted in the objective function respectively to achieve their balance.

The objective function is defined as:

$$f = \sum_{i=1}^{s}[\alpha(1-MAC) + \beta ER + \lambda(1-F_{le})] \tag{6}$$

where α, β and λ are all weight coefficients. F_{le} denotes flexibility assurance criterion, and its expression is:

$$F_{le} = \frac{\left|(F_i^h)^T \cdot F_i^d\right|^2}{\left|(F_i^h)^T \cdot F_i^h\right|\left|(F_i^d)^T \cdot F_i^d\right|} \tag{7}$$

where F_i^h and F_i^d denote the flexibility matrix before and after structural damage, respectively, which is expressed as follows:

$$[F] = \sum_{i=1}^{s}\frac{1}{\omega_i^2}\{\Phi_i\}\{\Phi_i\}^T \tag{8}$$

In Equation (6), the relationship of the weight coefficients is $\alpha+\beta+\lambda=1$. Among them, the frequencies are less affected by noise, it is easy to be measured and the measurement accuracy is higher, so β takes a larger value. The flexibility matrix is inversely proportional to ω^2, so its sensitivity is also higher, and λ takes a larger value. The measurement error of mode shapes is larger than the frequencies and the sensitivity is lower, so α is smaller. As a result, these weighted coefficients are determined as α=0.01, β =0.79 and λ =0.20 in this study, which also refers to the weighting method on frequencies and mode shapes by Chen and Yu (2020).

2.3 Whale Optimization Algorithm (WOA)

For WOA, a random or best search agent is used to track the prey's simulated hunting behavior, and a spiral is used to simulate the humpback whale's bubble net attack mechanism. The whole process of predation is mainly divided into three different stages: encircling prey, bubble-net attack method and searching for prey.

2.3.1 Encircling prey

The process of surrounding the prey is expressed as follows:

$$D = \left|C \cdot X^*(t) - X(t)\right| \tag{9}$$

$$X(t+1) = X^*(t) - A \cdot D \tag{10}$$

where t denotes the current iteration, both A and C are coefficient vectors, X^* is the position vector of the optimal solution obtained so far, X is the position vector of the whale, and " · " is the product of the corresponding elements of the vector. A and C are defined as:

$$A = 2a \cdot r_1 - a \tag{11}$$

$$C = 2r_2 \tag{12}$$

where r_1 and r_2 are random vectors in [0, 1], and a is linearly decreased from 2 to 0 as the number of iterations increases, which can be expressed as:

$$a = 2 - \frac{2t}{Max\_iter} \tag{13}$$

where Max_iter is the maximum number of iterations.

2.3.2 Bubble-net attack method

In order to simulate the bubble-net behavior of humpback whales, two mechanisms were designed: shrinking encircling mechanism and spiral updating position. In order to simulate the behavior of humpback whales contracting and spiraling at the same time, the algorithm assumes that the probability that the whale choosing the two mechanisms is the same. The mathematical model is:

$$X(t+1) = \begin{cases} X^*(t) - A \cdot D & if\ p < 0.5 \\ D' \cdot e^{bl} \cdot \cos(2\pi l) + X^*(t) & if\ p \geq 0.5 \end{cases} \tag{14}$$

where p is a random number in [0, 1], b is a constant used to define the logarithmic spiral shape, l is a random number in [-1, 1], and D' is the distance between the whale and its prey (the best solution obtained so far), which can be expressed as:

$$D' = \left| X^*(t) - X(t) \right| \tag{15}$$

2.3.3 Search for prey

In the prey search stage, the whales randomly search for prey according to each other's position. A whale is randomly selected in the group as the current optimal solution to update its position, forcing the whale to stay away from its prey. The mathematical model can be expressed as:

$$D = |C \cdot X_{rand} - X| \tag{16}$$

$$X(t+1) = X_{rand} - A \cdot D \tag{17}$$

where X_{rand} is the position vector of the whale randomly selected from the current population.

2.4 Choose probability threshold

In the prey phase, in order to simulate the simultaneous implementation of the two mechanisms, the probability that each mechanism is selected by the whale during the predation process is set to be 50%. However, this equal probability selection mode will make the whale unable to choose the most suitable predator mechanism, which will cause the algorithm to slow down the convergent rate and fall into a local optimal solution. Therefore, the selecting method for the probability threshold is as follows:

$$p' = \left(\frac{2}{\pi}\right)^{\lambda} . \arccos^{\lambda}\left(\frac{t}{Max\_iter}\right) \tag{18}$$

where λ is determined in the following form,

$$\lambda = \frac{2Max\_iter}{t'} \tag{19}$$

where t' is the number of iterations at convergence. At the beginning of the iteration, the value of p' is relatively large, and the whale has a high probability to choose the shrinking enclosing mechanism. When it is close to convergence, the value of p' is relatively small, and the whale has a high probability to choose the spiral update position mechanism to improve the iterative speed and global optimization ability.

The flowchart of WOA-based SDI method is shown in Figure 1.

3. Numerical simulations

In order to assess the performance of the proposed WOA-based method for SDI problem, some numerical simulations on two structures, i.e., 10-element simply supported beam and 31-bar planar truss structure are carried out, some SDI results are illustrated in the following sections.

3.1 A 10-element simply supported beam

Figure 2 is a finite element model of a simply supported beam. The beam is 3m long and it is divided into 10 elements with same element length. Each element has 2 nodes and 4 degrees of freedom. The numbers above and below the beam are the node number and element number, respectively. The parameters of the beam are shown as follows: elastic modulus E=2.1×10^{11}Pa, structural density ρ =7850kg/m^3, area of cross section A=1.164×10^{-3}m^2 and moment of inertia I= 7.617×10^{-7}m^4.

The simulated damage cases are shown in Table 1, which includes single damage, double damage and multiple damage conditions. The finite element analysis to damaged beam model is performed to obtain the modal parameters under each damage condition. The first five natural frequencies and corresponding mode shapes of the structure in the vertical degrees of freedom of each node are adopted. The influences of measurement noise on modal parameters are considered in the following form,

$$r_{noise} = r\left(1 + L \cdot R_n\right) \tag{20}$$

where r_{noise} and r denote the modal parameters with and without noise, respectively; L is the noise level; Rn

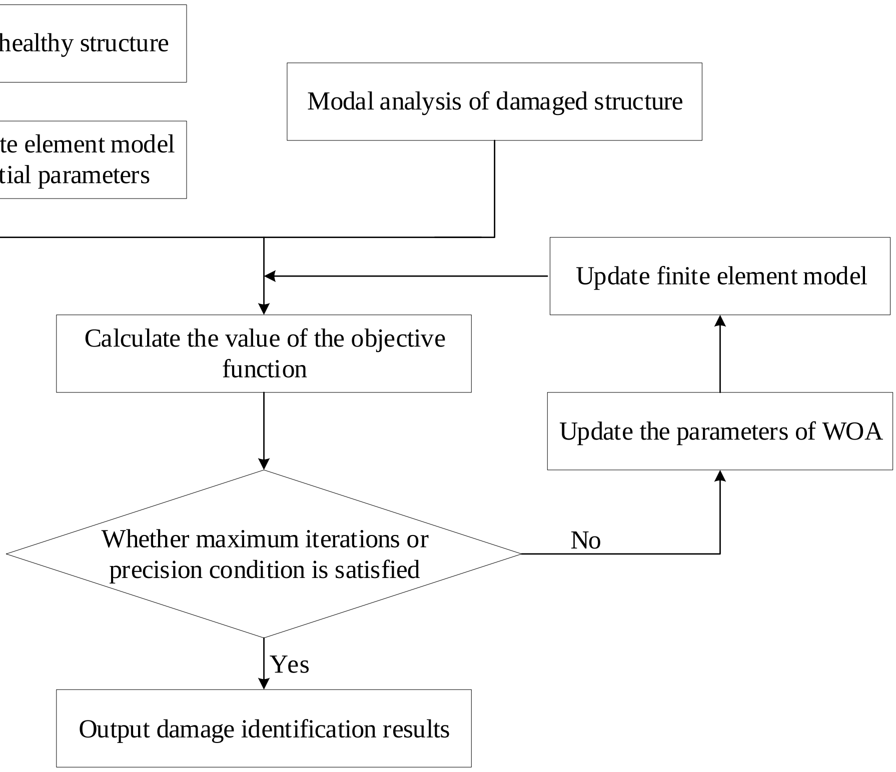

Fig. 1 Flowchart of proposed WOA-based SDI method

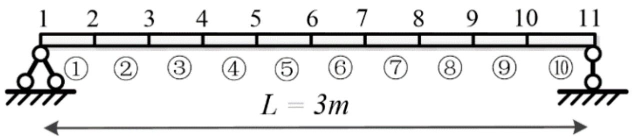

Fig. 2 Finite element model of simply supported beam

Table 1 Damage cases for 10-element simply supported beam

Damage type	Scenarios	Damage severity @ damage element
Single damage	1	15%@1
	2	10%@6
Double damages	3	15%@6 & 10%@10
	4	15%@5 & 15%@6
	5	10%@1 & 8%@9
	6	15%@3 & 15%@9
Multiple damages	7	15%@4 & 15%@5 & 15%@6
	8	12%@3 & 15%@5 & 10%@9

represents a random matrix where each element is a random number in [0, 1].

The numerical simulation process is completed by software MATLAB2016b. The parameters of WOA are set as: the number of whale populations *SearchAgents*=80; the maximum number of iterations *Max_iter* = 200; the variable dimension *dim*=10; the lower bound of the domain *lb*=*zeros*(1, *dim*); the upper bound of the domain *ub*=*ones*(1, *dim*).

The SDI results by the WOA-based SDI method are listed in Table 2 in eight damage conditions. In these scenarios, the occurrence of damage near the support and the span of the beam was simulated in scenarios 1 and 2. Damage at the symmetric and asymmetric positions of the structure was simulated in scenarios 3-6, and the same and different damage levels were considered as well. Multiple damages with same and different damage levels in the structure are simulated in scenarios 7 and 8. Figures 3 to 4 show the SDI results in partial damage conditions under different noise levels. In addition, under the same noise level, the partial SDI results based on the WOA and other optimization algorithms, i.e., particle swarm optimization (PSO) and dragonfly algorithm (DA) are compared in Figures 5-6.

It can be seen from Table 2 that at the same noise level, the accuracy of SDI with slight damage is lower than that with severe damage, and the accuracy of SDI with symmetric damage is higher than that with asymmetric damage. In the case of multiple damages under the same noise level, the identification accuracy of the structure with slight damage is higher than severe damage. Under the same noise level, the continuous multi-damage identification accuracy is higher than the decentralized type. In summary, the SDI accuracy decreases with increasing complexity of the scenarios.

It can be clearly seen from Figures 3-4 that in the cases of double and multiple damages, regardless of the presence or absence of noise, the damage locations and severities of the structure can be well identified, while in scenario 8, although the damage can be accurately located and quantified, some identification errors have increased significantly. Figures 5 and 6 show the comparison of the WOA-based SDI method results and other methods (PSO,

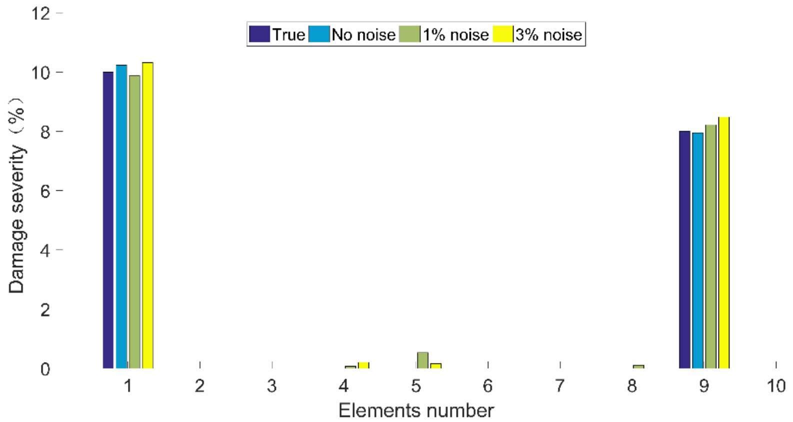

Fig. 3 SDI result of double damage in Scenario 5

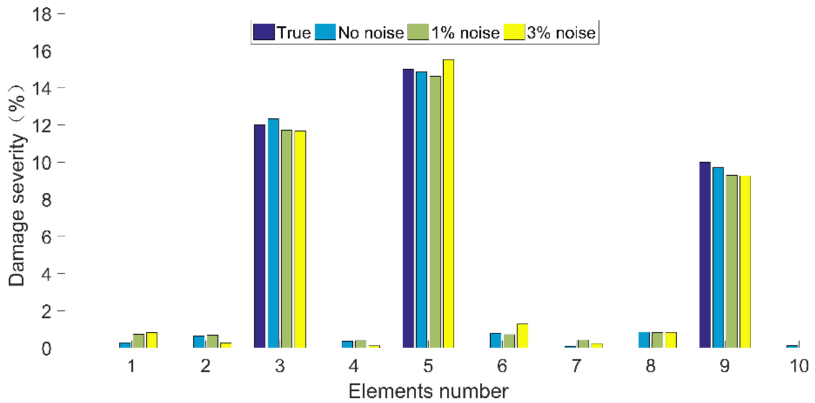

Fig. 4 SDI result of multi-damage in Scenario 8

Table 2 SDI results of 10-element simply supported beam by WOA-based method

Damage type	Scenarios	Simulated damage	Identified damage (%) under different noises		
			No noise	1% noise	3% noise
Single damage	1	15%@1	15.01@1	15.32@1	15.60@1
	2	10%@6	10.03@6	10.22@6	10.38@6
Double damages	3	15%@1 & 10%@10	15.25@1 & 9.75@10	14.90@1 & 10.90@10	15.67@1 & 8.72@10
	4	15%@5 & 15%@6	15.10@5 & 14.76@6	14.18@5 & 15.53@6	14.40@5 & 14.45@6
	5	10%@1 & 8%@9	10.23@1 & 7.95@9	9.87@1 & 8.22@9	10.32@1 & 8.48@9
	6	15%@3 &15%@9	14.72@3 & 15.14@9	14.6@3 & 14.43@9	16.27@3 & 14.12@9
Multiple damages	7	15%@4 & 15%@5 & 15%@6	14.66@4 & 14.47@5 & 15.86@6	15.61@4 & 13.93@5 & 14.43@6	14.30@4 & 16.17@5 & 14.16@6
	8	12%@3 & 15%@5 & 10%@9	12.33@3 & 14.86@5 & 9.70@9	11.72@3 & 14.63@5 & 9.29@9	11.68@3 & 15.53@5 & 9.26@9

DA) under double and multiple damage conditions, it can be seen that the WOA-based SDI method is obviously better than both of PSO and DA methods. The results show that at the same noise level, the WOA-based SDI method can provide the highest SDI accuracy, the DA-based method is next, and the PSO-based method has the worst accuracy among them.

In addition, in order to assess the convergent rates of three methods, a comparison on convergence for different identification algorithms under 1% noise level is shown in Figure 7 in double damages condition. It can be found that the WOA-based method is the fastest SDI method among the three methods. Moreover, Table 3 listed the detailed executing time required to identify damages based on the WOA and other optimization algorithms (PSO, DA) in the same computer, the same noise levels and the same damage conditions. Obviously, the proposed WOA-based SDI method is the fastest one in three methods.

The illustrated SDI results show that the WOA-based SDI method can not only effectively locate structural damages, but also quantify damages more accurately with a good robustness to noise. In a word, the WOA-based SDI method is significantly better than both PSO and DA methods.

3.2 A 31-bar planar truss structure

In order to apply the proposed WOA-based SDI method to a more complicated structure, some further numerical simulations on a 31-bar planar truss structure are conducted to assess the performance of the proposed SDI method. There are three main reasons. Firstly, in terms of the dimension of the FEM, since the FEM of the simply supported beam was divided into 10 elements in the

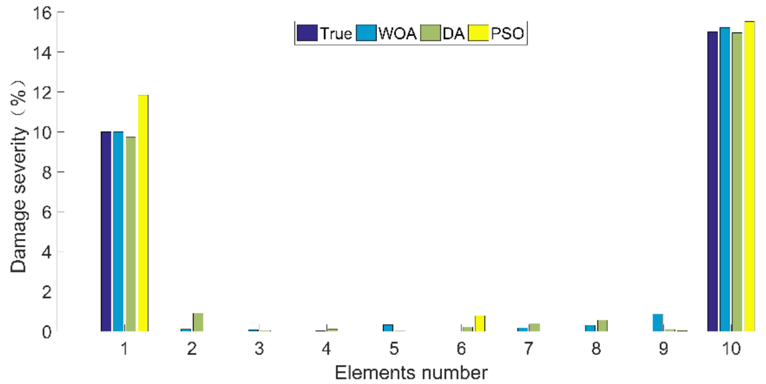

Fig. 5 Double damages SDI results by different identification algorithms

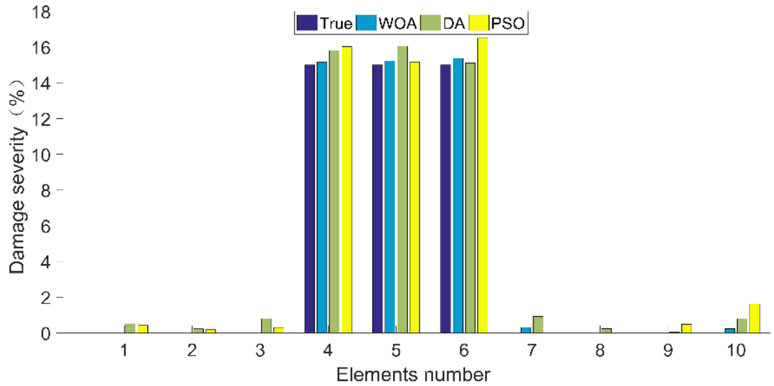

Fig. 6 Multiple damages SDI results by different identification algorithms

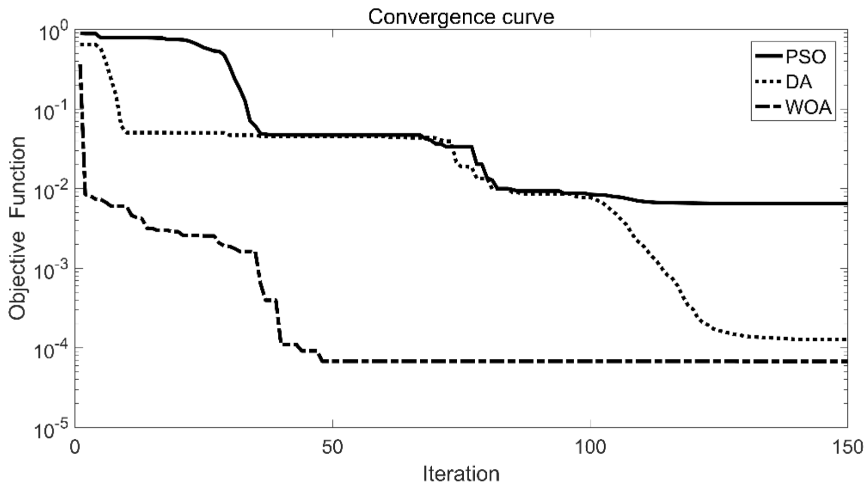

Fig. 7 Convergence curves of different identification algorithms

Table 3 Executing time for different methods under different damage cases

Damage type	SDI method	Time(s)	parameters
Double damages	PSO	51.99	1% noise Windows10 i5-3230M CPU@2.60Hz RAM@8.0GB $SearchAgents = 80$ $Max\_iter = 200$
	DA	44.73	
	WOA	10.69	
Multiple damages	PSO	53.24	
	DA	47.65	
	WOA	10.76	

abovementioned simulation cases, it means that the search dimension in the recognition process is 10. There are 31elements in the FEM of the truss structure, which means that the search number is increased to 31, and the multi-dimensional feasibility of the proposed method can be studied. Secondly, in terms of structural dimensions, the simply supported beams are regarded as one-dimensional structure, while the truss is a two-dimensional structure. The numerical simulation of SDI problem in the two structures can further verify that the WOA is feasible and

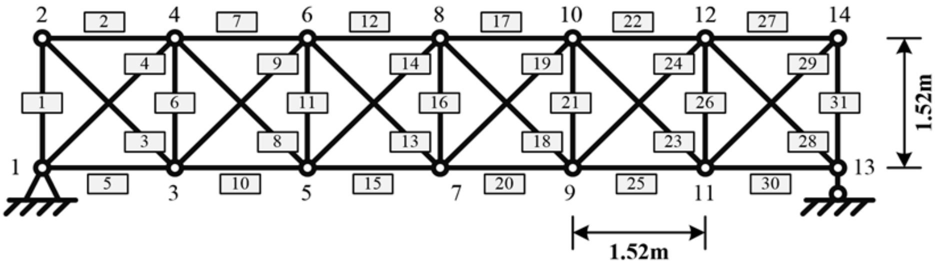

Fig. 8 Finite element model of 31-bar planar truss structure

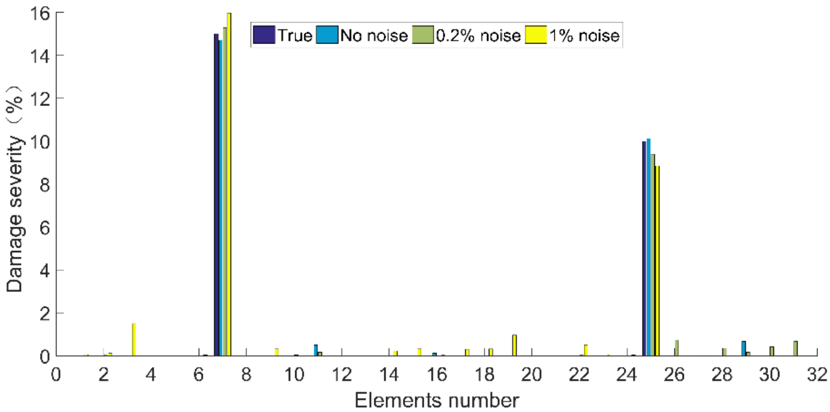

Fig. 9 SDI result of double damages in Scenario 10

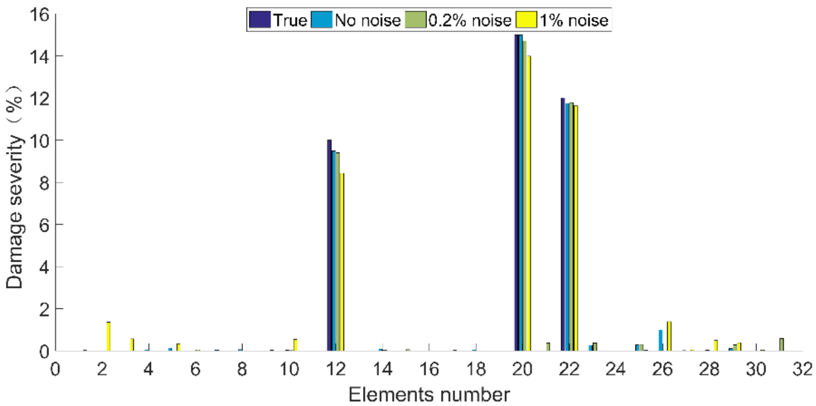

Fig. 10 SDI result of multiple damages in Scenario 11

effective for structures of different dimensions. Finally, in terms of the complexity of the structure, the truss structure is more complicated and closer to the practical bridge than the simply supported beam. The numerical simulations on the planar truss structure can verify the feasibility of the proposed WOA-based method to identify the structural damages in more complicated structures.

The finite element model of 31-bar planar truss structure is shown in Figure 8. The span of structure is 9.12m long and 1.52m high. The structure is divided into 31 elements, and each element has 2 nodes and 4 degrees of freedom. The specific parameters of the structure are shown as follows: elastic modulus E=7.0×10^{10}Pa, structural density density ρ =2770kg/m^3, area of bar cross section A=0.01×0.01(m^2) and moment of inertia I= 0.01×0.01^3/12(m^4). The SDI results are listed in Table 4, and some of them by the WOA-based method are shown in Figures 9-10.

Table 4 SDI results of 31-bar planar truss structure by WOA-based method

Damage type	Scenarios	Simulated damage	Identified damage (%) under different noises		
			No noise	0.2% noise	1% noise
Single damage	9	8%@20	8.03@20	7.92@20	7.83@20
Double damages	10	15%@7 & 10%@25	14.71@7 & 10.12@25	15.29@7 & 9.40@25	15.97@7 & 8.85@25
Multiple damages	11	10%@12 & 15%@20 & 12%@22	9.48@12 & 14.99@20 & 11.75@22	9.41@12 & 14.71@20 & 11.78@22	8.43@12 & 14.00@20 & 11.63@22

In a similar way as in the first simulation example, the single damage, double damages, and multiple damages are considered separately in these three scenarios. The difference is that there is an increased complexity of the structure, and the noise levels are reduced in all the simulation cases. In Scenario 10, the damage is set in the 7th and 25th elements, which are located on the upper and lower chord rods on both sides of the mid-span. The multiple damage locations in Scenario 11 are also located at the upper and lower chord rods.

Figures 9 and 10 show that the WOA-based SDI method can locate and quantify the damage of the two-dimensional 31-bar planar truss structure. Although there are some identification errors occurred in health elements, they do not affect the SDI results, even more do not lead to misjudgments, because they are too small to be considered.

4. Conclusions

A novel whale optimization algorithm (WOA) based structural damage identification (SDI) method is proposed by weighting modal data and flexibility assurance criterion in this study. The SDI problem is first converted into a constrained optimization problem in mathematics. Unlike traditional objective function defined using frequencies and mode shapes, a new objective function on the SDI problem is formulated by weighting both modal data and flexibility assurance criterion. Then, the WOA method with good convergent performance and global searching ability is adopted to provide an accurate solution to the SDI problem. Numerical simulations on a simply-supported beam and a 31-bar truss structures are conducted to assess the performance of the proposed WOA-based SDI method. Meanwhile, the particle swarm optimization (PSO) and dragonfly algorithm (DA) are used to compare with the proposed method. Some conclusions can be made as follows:

- For the given multiple structural damage conditions under environmental noises, the WOA-based SDI method can effectively locate structural damages and accurately estimate severities of damages.
- Compared with both other optimization methods, such as PSO and DA, the proposed WOA-based method outperforms better in accuracy and efficiency, it can provide a more effective and potential tool for the SDI problem.
- The proposed WOA-based SDI method has fewer parameters, fast convergent rate, and strong global searching ability.
- Although the proposed WOA-based SDI method performs well in the numerical examples in this study, there is still much work to be done in the future. Smaller damage conditions and higher noise levels need to be considered, and more complicated structures are necessary for consideration. And it is necessary to carry out experimental verifications in laboratory, further field tests to verify the possibility of applying the proposed method to practical engineering.

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References

Alireza, G., Adel, A. and Armin, J. (2018), "Accelerated cuckoo optimization algorithm for capacitated vehicle routing problem in competitive conditions", *J. Artifical Int.*, **16**(1), 88-112.

Arturo, G. and Omar, M. (2019), "Damage detection in bridges based on patterns of dynamic amplification", *Struct. Control Health Monitor.*, **26**(7), e2361. https://doi.org/10.1002/stc.2361.

Cha, Y.J. (2015), "Structural damage detection using modal strain energy and hybrid multi-objective Optimization", *J. Comput. Aid. Civil Infrastruct. Eng.*, **30**, 347-358. https://doi.org/10.1111/mice.12122.

Chang, C.C. and Chen, L.W. (2003), "Vibration damage detection of a Timoshenko beam by spatial wavelet based approach", *Appl. Acousitcs*, **64**(12), 1217-1240. https://doi.org/10.1016/S0003-682X(03)00070-7.

Chen, C.B. and Yu, L. (2020), "A hybrid ant lion optimizer with improved Nelder–Mead algorithm for structural damage detection by improving weighted trace lasso regularization", *Adv. Struct. Eng.*, **23**(3), 468-484. https://doi.org/10.1177/1369433219872434.

Chen, Z.P. and Yu, L. (2017), "A novel PSO-based algorithm for structural damage detection using Bayesian multi-sample objective function", *Struct. Eng. Mech.*, **63**(6), 825-835. https://doi.org/10.12989/sem.2017.63.6.825.

Chen, Z.P. and Yu, L. (2018), "A new structural damage detection strategy of hybrid PSO with Monte Carlo simulations and experimental verifications", *Measurement*, **122**, 658-669. https://doi.org/10.1016/j.measurement.2018.01.068.

Ding, Z.H., Huang, M. and Lu, Z.R. (2016), "Structural damage detection using artificial bee colony algorithm with hybrid search strategy", *Swarm Evolution. Comput.*, **28**, 1-13. https://doi.org/10.1016/j.swevo.2015.10.010.

Ding, Z.H., Li, J. and Hao, H. (2019), "Structural damage identification using improved Jaya algorithm based on sparse regularization and Bayesian inference", *Mech. Syst. Signal Process.*, **132**, 211-231. https://doi.org/10.1016/j.ymssp.2019.06.029.

Gao, Y.Q. and Khalid, M.M. (2018), "Deep transfer learning for image-based structural damage recognition", *J. Comput. Aid. Civil Infrastruct. Eng.*, **33**, 748-768. https://doi.org/10.1111/mice.12363.

Ghannadi, P. and Kourehli, S.S. (2019), "Structural damage detection based on MAC flexibility and frequency using moth-flame algorithm", *Struct. Eng. Mech.*, **70**(6), 649-659. https://doi.org/10.12989/sem.2019.70.6.649.

Guo, H.Y. (2017), "Structural multi-damage identification based on strain energy and micro-search artificial fish swarm algorithm", *J. Vibroeng.*, **19**(5), 3255-3270. https://doi.org/10.21595/jve.2017.17503.

Hou, R.R., Xia, Y., Zhou, X.Q. and Huang, Y. (2019), "Sparse Bayesian learning for structural damage detection using expectation-maximization technique", *Struct. Control Health Monitor.*, **26**(5), e2343. https://doi.org/10.1002/stc.2343.

Huang, J.L. and Lu, Z.R. (2017), "BB-BC optimization algorithm for structural damage detection using measured acceleration responses", *Struct. Eng. Mech.*, **64**(3), 353-360. https://doi.org/10.12989/sem.2017.64.3.353.

Huang, M.S., Cheng, S.X., Zhang, H.Y., Gul, M. and Lu, H. (2019), "Structural Damage Identification under Temperature Variations Based on PSO–CS Hybrid Algorithm", *J. Struct. Stability Dynam.*, **19**(11), 1950139. https://doi.org/10.1142/S0219455419501396.

Huang, M.S., Gul, M. and Zhu, H.P. (2018), "Vibration-Based Structural Damage Identification under Varying Temperature Effects", *J. Aerosp. Eng.*, **31**(3), 04018014. https://doi.org/10.1061/(ASCE)AS.1943-5525.0000829.

Huang, M.S., Lei, Y.Z. and Li, X.F. (2019), "Structural Damage Identification based on L-1 Regularization and Bare Bones Particle Swarm Optimization with Double Jump Strategy", *Math. Problems Eng.*, 5954104. https://doi.org/10.1155/2019/5954104.

Kang, F., Li, J.J. and Xu, Q. (2012), "Damage detection based on improved particle swarm optimization using vibration data", *Apply. Soft Comput.*, **12**(8), 2329-2335. https://doi.org/10.1016/j.asoc.2012.03.050.

Kao, C.Y. (2003), "Detection of structural damage via free vibration responses generated by approximating artificial neural networks", *Comput. Struct.*, **81**(28-29), 2631-2644. https://doi.org/10.1016/S0045-7949(03)00323-7.

Yu, L. and Li, C. (2014), "A Global Artificial Fish Swarm Algorithm for Structural Damage Detection", *Adv. Struct. Eng.,* **17**(3), 331-346. https://doi.org/10.1260/1369-4332.17.3.331.

Mafarja, M. and Mirjalili, S. (2018), "Whale optimization approaches for wrapper feature selection", *Appl. Soft Comput.*, **62**, 441-453. https://doi.org/10.1016/j.asoc.2017.11.006.

Mirjalili, S. (2015), "Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm", *Knowledge Based Syst.*, **89**, 228-249. https://doi.org/10.1016/j.knosys.2015.07.006.

Mirjalili, S. (2016), "Dragonfly algorithm: a new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems", *Neural Comput. Appl.*, **27**(4), 1053-1073. https://doi.org/10.1007/s00521-015-1920-1.

Mirjalili, S. and Lewis, A. (2016), "The whale optimization algorithm", *Adv. Eng. Software*, **95**, 51-67. https://doi.org/10.1016/j.advengsoft.2016.01.008.

Mirjalili, S., Mirjalili, S.M. and Lewis, A. (2014), "Grey Wolf Optimizer", *Adv. Eng. Software*, **69**, 46-61. https://doi.org/10.1016/j.advengsoft.2013.12.007.

Oliv, D., El Aziz, M.A. and Hassanien, A.E. (2017), "Parameter estimation of photovoltaic cells using an improved chaotic whale optimization algorithm", *Appl. Energy*, **200**, 141-154. https://doi.org/10.1016/j.apenergy.2017.05.029.

Pan, C.D., Yu, L., Chen, Z.P., *et al*. (2016), "A hybrid self-adaptive Firefly-Nelder-Mead algorithm for structural damage detection", *Smart Struct. Syst.*, **17**(6), 957-980. https://doi.org/10.12989/sss.2016.17.6.957.

Perera, R. and Torres, R. (2006), "Structural damage detection via modal data with genetic algorithms", *J. Struct. Eng. ASCE*, **132**(9), 1491-1501. https://doi.org/10.1061/(ASCE)0733-9445(2006)132:9(1491).

Precup, R.E., David, R.C. and Petriu, E.M. (2016), "Grey wolf optimizer-based approach to the tuning of PI-fuzzy controllers with a reduced process parametric sensitivity", *IFAC-PapersOnLine*, **49**(5), 55-60. https://doi.org/10.1016/j.ifacol.2016.07.089.

Seo, J., Hu, J.W. and Lee J. (2016), "Summary review of structural health monitoring applications for highway bridges", *J. Performance Construct. Facilities*, **30**(4), 04015072. https://doi.org/10.1061/(ASCE)CF.1943-5509.0000824.

Su, C., Liao, W., Tan, L. and Chen, R. (2016), "Reliability-based damage identification using dynamic signatures", *J. Bridge Eng.*, **21**(3), 04015058. https://doi.org/10.1061/(ASCE)BE.1943-5592.0000819.

Xu, H.J., Liu, J.K. and Lv, Z.R. (2016), "Structural damage identification based on modified Cuckoo Search algorithm", *Struct. Eng. Mech.*, **58**(1), 163-179. https://doi.org/10.12989/sem.2016.58.1.163.

Yu, L., Xu, P. (2011), "Structural health monitoring based on continuous ACO method", *Microelectronics Reliability*, **51**(2), 270-278. https://doi.org/10.1016/j.microrel.2010.09.011.

Yuen, K.V. (2010), "Efficient model correction method with modal measurement", *J. Struct. Eng. ASCE*, **136**(1), 91-99. https://doi.org/10.1061/(ASCE)EM.1943-7889.0000068.

Zheng, T.Y., Liu, J.K. and Luo, W.L. (2018), "Structural damage identification using cloud model based fruit fly optimization algorithm", *Struct. Eng. Mech.*, **67**(3), 245-254. https://doi.org/10.12989/sem.2018.67.3.245.

Zhu, F.T. and Wu, Y.J. (2014), "A rapid structural damage detection method using integrated ANFIS and interval modeling technique", *Appl. Soft Comput.*, **25**, 473-484. https://doi.org/10.1016/j.asoc.2014.08.043.

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