A Two-Step Approach for Damage Detection in a Real 3D Tower Using the Reduced-Order Finite Element Model Updating and Atom Search Algorithm (ASO)

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Abstract In this paper, an effective approach is presented for solving damage identification problems. The key factor of this approach is based on the model updating and inverse method. First, Root-Mean-Square-Error (RMSE), which registers the differences between frequencies at two states; damaged stage and undamaged stage, is used to establish the objective function. Then, an effective optimization algorithm named the Atom search algorithm (ASO) is employed to minimize the objective function, which accounts for variables related to stiffness reduction in the structures. The process of calculating the objective function during the course of iterations is based on the reduced-order finite element model of a real 3D tower named Guangzhou New TV Tower (GNTT) to extract the frequencies at each iteration. This process will implement continuously until finding the damaged values that agree with the objective function with the minimum error. The results obtained in this paper prove that the proposed approach can predict damaged stories with high reliability and acceptance error.

Keywords Structural damage detection · Natural frequency · Finite element method · Atom search algorithm · Model updating

1 Introduction

Structural Health Monitoring (SHM) is a significant factor in research over the past two decades because assessing the location and extent of damaged elements in the structure will ensure effective working of the structure and timely repair. The inverse method combined with model updating is a reliable method to predict damaged

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elements in SHM. This approach has been used widely and successfully in recent studies [1–3]. Friswell [4] introduced a brief overview of applying the model updating technique and inverse methods for SHM from vibration data obtained from measurements. The main features of this method include three steps: (i) establish the objective function, (ii) the model updating technique is used to calculate the objective function, and (iii) finding a reliable algorithm to minimize the objective function. Thus, the selection of a suitable optimization algorithm takes a crucial role in the successful method. The robust development of metaheuristic algorithms with different inspirations has brought many choices to solve optimization problems. There are many algorithms such as Atom search algorithm (ASO) [5], Cuckoo search (CS) [6], Gravitational Search Algorithm (GSA) [7], Black Hole [8], Grey Wolf optimizer (GWO) [9], The Whale Optimization Algorithm (WOA) [10], and so on. These algorithms have proven effective in their application to SHM. Minh et al. [11] presented a new model updating technique combined with an improved PSO named (EHVPSO) for damage detection in a real 3D structure. In this study, a real 3D transmission tower was used to prove the effectiveness of the method. The results obtained in this study prove the reliability and high level. Cuong-Le et al. [12] utilize PSO to enhance the ability of support vector machine in damage detection. Alkayem [13] used a finite element (FE) model built in MATLAB and some algorithms, including Particle Swarm Optimization (PSO), and Differential Evolution (DE) and Genetic Algorithm (GA), to detect damaged elements in 3D frame structures. Chen [14] proposed a new method for calculating the objective function, then the new objective function collaborated with Whale optimization algorithm (WOA) to predict the damaged elements in a simply-supported beam and 31-bar truss structures. Nozari et al. [15] used a FE model updating for damage detection of 10-story building using ambient vibration measurements, etc. Almost all previous public studies in this field concerned with simple structures including 2D or 3D frames.

In this paper, to assess generally this method, a real structure named Guangzhou New TV Tower located China is used to detect the damaged elements. First, For simplicity and to reduce the number of degrees of freedom of the structure, a reduced-order FE model generated from the full-order model is conducted by MATLAB. Then, a recent optimization algorithm named Atom search optimization (ASO) is employed as a reliable algorithm to detect damaged elements in this structure. The damaged detection process will be secured by the exchange data between the FE model and the ASO algorithm. This process will stop if the objective function achieves a suitable convergence rate and at the same time, these variants in the objective function will determine the extent of damage in the structure.

2 Structural Modeling of the Guangzhou New TV Tower

In this section, a real 3D tower named the Guangzhou New TV Tower is selected to validate the proposed method. The system of this structure is tube-in-tube with 600 height. The tower includes two main parts; the first part is the main tower with 454 m

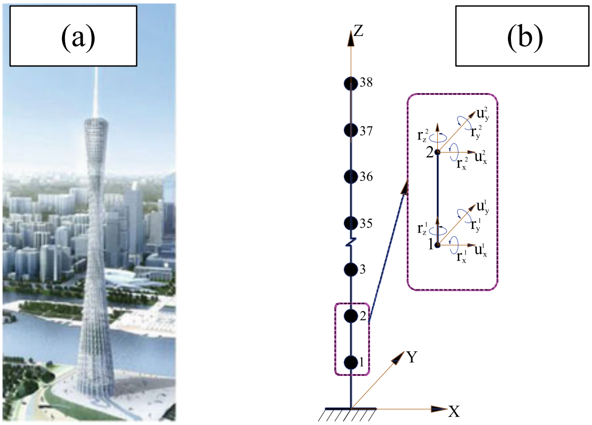


Fig. 1 **a** The Guangzhou New TV Tower according to Chen et al., **b** a reduced-order FE model

height, and the second part is the antenna mast with 146 m height, according to Chen et al. [16] as shown in Fig. 1a. Because of the complicated geometry of the structure, using the full-scale FE model will have difficulties in this study. To simplify the model, a reduced-order FE model is simulated in a simple way. Thus, the simple FE model includes 37 elements; each element is simulated as a linear elastic beam element. Consequently, the FE model is modelled as a cantilever beam including 37 elements. Each element registers two nodes at start and end, respectively. The total number of nodes is 38, the label of nodes will in a gradual increase from 1 to 38, the vertical coordinates of each node are given in Table 1. In the reduced model, the mass of each story is lumped at a node that is located at the same high level of the story mentioned, then these masses are lumped to the adjacent reducing center, as shown in Fig. 1b. The vertical displacement following the Z direction is ignored in the FE reduced model. Thus, each node registers 5 DOFs, including two horizontal translational DOFs and three rotational DOFs, as shown in Fig. 1b. Thus, each element has 10 DOFs and will register stiffness matrix with dimensions 10 × 10. The FE model in this study is referred to the model presented by Ni, Xia [21] and Chen, Lu [20]. Thus, each element stiffness matrix is given in Eq. (1).

$$K_i^e = \begin{bmatrix} K_{11}^e & K_{12}^e & K_{13}^e & K_{14}^e & K_{15}^e & K_{16}^e & K_{17}^e & K_{18}^e & K_{19}^e & K_{110}^e \\ & K_{22}^e & K_{23}^e & K_{24}^e & K_{25}^e & K_{26}^e & K_{27}^e & K_{28}^e & K_{29}^e & K_{210}^e \\ & & K_{33}^e & K_{34}^e & K_{35}^e & K_{36}^e & K_{37}^e & K_{38}^e & K_{39}^e & K_{310}^e \\ & & & K_{44}^e & K_{54}^e & K_{46}^e & K_{47}^e & K_{48}^e & K_{49}^e & K_{410}^e \\ & & & & K_{55}^e & K_{56}^e & K_{57}^e & K_{58}^e & K_{59}^e & K_{510}^e \\ & & & & & K_{66}^e & K_{67}^e & K_{68}^e & K_{69}^e & K_{610}^e \\ & & & & & & K_{77}^e & K_{78}^e & K_{79}^e & K_{710}^e \\ & & & Sym & & & & K_{88}^e & K_{89}^e & K_{810}^e \\ & & & & & & & & K_{99}^e & K_{910}^e \\ & & & & & & & & & K_{1010}^e \end{bmatrix} \tag{1}$$

Table 1 The nodal coordinate (z) of the reduced model

Floor	Label of node	Z (m)	Floor	Label of node	Z (m)
F1	1	−10	F21	21	375.85
F2	2	0	F22	22	381.2
F3	3	12	F23	23	396.65
F4	4	22.25	F24	24	407.05
F5	5	27.6	F25	25	417.45
F6	6	58.65	F26	26	427.85
F7	7	84.65	F27	27	438.25
F8	8	95.05	F28	28	443.6
F9	9	105.45	F29	29	480
F10	10	116.2	F30	30	497
F11	11	147.05	F31	31	505.2
F12	12	157.45	F32	32	520.7
F13	13	168	F33	33	531.2
F14	14	204.25	F34	34	545.2
F15	15	225.2	F35	35	565.2
F16	16	272	F36	36	580.7
F17	17	308.25	F37	37	598
F18	18	329.2	F38	38	610
F19	19	344.64			
F20	20	355.05			

3 The Objective Functions

The objective function is selected from the correlation of natural frequencies obtained from the FE model with cases of damage and data measured from testing of healthy structure. By solving Eq. (2) using the FE model, we can get the natural frequencies.

$$\left[K - \omega_i^2 M\right]\{\phi_i\} = \{0\} \tag{2}$$

where $\boldsymbol{K}$ and $\boldsymbol{M}$ are the structural stiffness matrix and mass matrix, respectively. ω_i is natural period and ϕ_i is mode shape vector.

From ω_i, we can calculate the frequencies as follows Eq. (3):

$$T_i = \frac{2\pi}{\omega_i}, \ f_i^{FE} = \frac{1}{T_i} \tag{3}$$

The objective function is selected by using Root-Mean-Square-Error (RMSE) as shown in Eq. (4).

$$f_{ofun} = \frac{\sqrt{\sum_{i=1}^{n}\left(f_i^{Measured} - f_i^{FEM}\right)^2}}{n} \tag{4}$$

where n is the number of frequencies obtained using the FE model.

4 Atom Search Algorithm (ASO)

ASO [5] is inspired by basic molecular dynamics. From this perspective, each position X_i $(i = 1, 2, ..., N)$ is considered as a candidate solution in an unknown search space dimension.

4.1 Interaction Force in ASO

The interaction force obtained from the Lennard–Jones (L-J) potential is a simple mathematical revised to obtain more positive attraction and less negative repulsion as iterations increase. The interaction force impact on the ith Atom from jth Atom at tth iteration is shown in Eq. (5)

$$\begin{aligned} F_{ij}^{d} &= -\eta(t)\left[2\left(h_{ij}(t)\right)^{13} - \left(h_{ij}(t)\right)^{7}\right] \\ \eta(t) &= \alpha\left(1 - \frac{t-1}{T_{\max}}\right)^{3} e^{-\frac{20t}{T_{\max}}}, \quad \alpha = [10,\ 20,\ 30, ..., 100] \end{aligned} \tag{5}$$

where α is the depth weight, t is the current of iteration, and $T_{\max}$ is the maximum of iterations.

$h_{ij}(t)$ is the ratio of the distance between two ith and jth atoms to the length scale $\sigma(t)$ as given in Eq. (6).

$$h_{ij}(t) = \begin{cases} h_{\min} & \frac{\left\|r_{ij}(t)\right\|_2}{\sigma(t)} < h_{\min} \\ \frac{\left|r_{ij}(t)\right|}{\sigma(t)} & h_{\min} \le \frac{\left\|r_{ij}(t)\right\|_2}{\sigma(t)} \le h_{\max} \\ h_{\max} & \frac{\left\|r_{ij}(t)\right\|_2}{\sigma(t)} > h_{\max} \end{cases} \tag{6}$$

where $h_{\max}$ and $h_{\min}$ are lower and upper boundaries, respectively and defined as Eq. (7).

$$\begin{cases} h_{\min} = g_0 + g(t) \\ h_{\max} = u \end{cases} = \begin{cases} h_{\min} = g_0 + 0.1 \sin\left(\dfrac{\pi t}{2T_{\max}}\right) \\ h_{\max} = u \end{cases} \tag{7}$$

$\sigma(t)$ is denoted the length scale, and it can be expressed by Eq. (8)

$$\begin{aligned} \sigma(t) &= \left\| X_{ij}(t), X_{Kbest}(t) \right\|_2 \\ X_{Kbest}(t) &= \frac{\sum\limits_{j \in K_{best}} X_{ij}(t)}{K(t)} \end{aligned} \tag{8}$$

where K_{best} can be defined as a high-reliability search space for next iterations, and it is described by Eq. (9).

$$K_{best}(t) = N - (N-2)\sqrt{\frac{t}{T_{\max}}} \tag{9}$$

4.2 Mathematical Representation of Geometric Constraint and the Mass of Atom

To increase the convergence rate, each Atom is linked with the best Atom. In other words, each Atom is affected by the best Atom through the force called geometric constraint force shown in Eq. (10).

$$\begin{aligned} G_i^d(t) &= \lambda(t)\left[X_{best}^d(t) - X_i^d(t)\right] \\ \lambda(t) &= \beta e^{-\frac{20t}{T_{\max}}} \\ \beta &= [0.1;\ 0.2;\ 0.3;\ 0.4;\ 0.5;\ 0.6;\ 0.7;\ 0.8;\ 0.9;\ 1] \end{aligned} \tag{10}$$

where $X_{best}^d(t)$ is the best solution at tth iteration, $\lambda(t)$ is the Lagrangian multiplier.

In ASO, each Atom $X_i^d(t)$ registers a changeable mass and can be expressed in Eq. (11).

$$\begin{aligned} M_i(t) &= e^{-\frac{\left(Fit_i(t) - Fit_{best}\right)}{Fit_{worst} - Fit_{best}}} \\ m_i(t) &= \frac{M_i(t)}{\sum\limits_{j=1}^{N} M_j(t)} \end{aligned} \tag{11}$$

where $Fit_{best}(t)$ and $Fit_{worst}(t)$ are the maximum and minimum values of the objective function at the tth iteration, respectively. N is the number of Atom, $Fit_i(t)$ is the value of the objective function of Atom ith at tth iteration. $Fit_{best}(t)$ and $Fit_{worst}(t)$ are expressed as Eq. (12).

$$\begin{aligned} Fit_{best}(t) &= \min_{(i=1,2,\ldots,N)} [Fit_i(t)] \\ Fit_{worst}(t) &= \max_{(i=1,2,\ldots,N)} [Fit_i(t)] \end{aligned} \tag{12}$$

4.3 Atomic Motion

The process of acceleration updating is calculated by Eq. (13).

$$\begin{aligned} a_i^d(t) &= \frac{F_i^d(t)}{m_i^d(t)} + \frac{G_i^d(t)}{m_i^d(t)} \\ &= \alpha\left(1 - \frac{t-1}{T_{\max}}\right)^3 e^{-\frac{20t}{T_{\max}}} \sum_{j \in K_{best}} \frac{rand_j\left[2\left(h_{ij}(t)\right)^{13} - \left(h_{ij}(t)\right)^7\right]}{m_i(t)} \frac{\overrightarrow{r_{ij}}}{\left\|r_{ij}\right\|_2} \\ &\quad + \beta e^{-\frac{20t}{T_{\max}}} \frac{\left(X_{best}^d(t) - X_i^d(t)\right)}{m_i(t)} \end{aligned} \tag{13}$$

where $\overrightarrow{r_{ij}}(t)$ and $\left\|r_{ij}(t)\right\|_2$ are the position difference vector and Euclidean distance between the ith and the jth Atoms, respectively and can be expressed by Eq. (14).

$$\overrightarrow{r_{ij}}(t) = \left(X_j^d(t) - X_i^d(t)\right), \quad \left\|r_{ij}(t)\right\|_2 = \sqrt{\sum_{k=1}^{D} (x_{jk} - x_{ik})^2} \tag{14}$$

The position updating of each Atom is updated through the velocity updating process and can be written as Eqs. (15 and 16).

$$V_i^d(t+1) = rand_i^d V_i^d(t) + a_i^d(t) \tag{15}$$

$$X_i^d(t+1) = X_i^d(t) + V_i^d(t+1) \tag{16}$$

5 Application to Structural Health Monitoring

5.1 Structural Damage Identification Approach

The damaged identification can be illustrated by a scalar vector $X_i = \left(x_{1,}x_2, \ldots, x_n\right)$ with each individual x_i $(i = 1, 2, ..n)$ bounded in the ranged $[0,\ 1]$. Thus, the global stiffness matrix will reduce at damaged stage and given in Eq. (17).

$$[K] = \sum_{i=1}^{n} (1 - x_i)k_i; \quad 0 \le x_i \le 1 \tag{17}$$

where k_i is the stiffness matrix of element ith at the healthy stage.

The goal of structural damage identification is to determine the scalar vector $X_i = \left(x_{1,}x_2, \ldots, x_n\right)$, which agrees with the objective function with acceptable error. The process of detecting $X_i = \left(x_{1,}x_2, \ldots, x_n\right)$ is secured by an optimization algorithm. In this paper, ASO is employed to do this. And the process of damage identification using FE model updating and ASO is illustrated in Fig. 2.

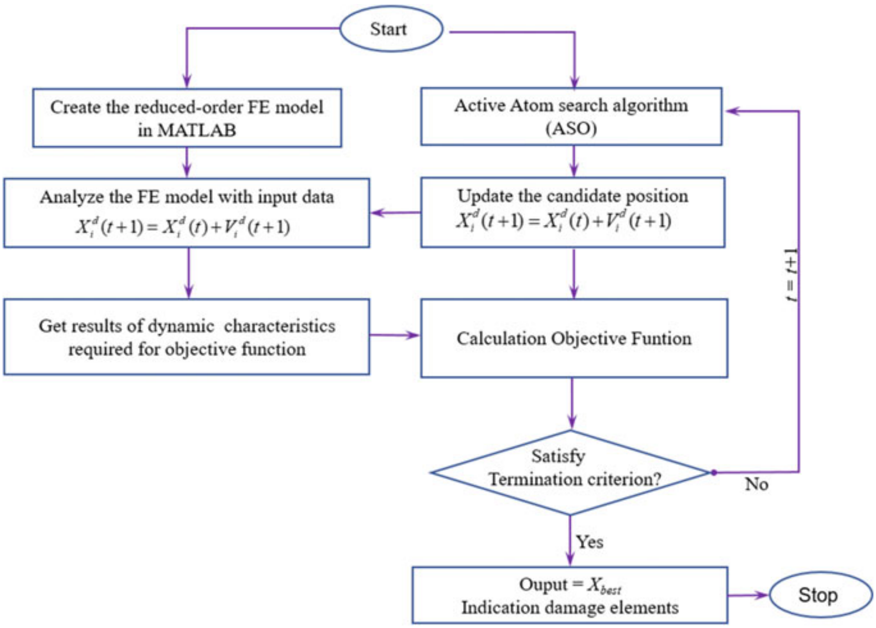


Fig. 2 The process of detecting damaged structures using a reduced-order FE model and Atom search algorithm

Table 2 Reduction in stiffness in stories of Guangzhou New TV Tower for different damage cases

Case study	Damaged story	Damaged severity (%)
Case 1	Story 01 Story 10	$x_{65} = 35$ $x_{10} = 50$
Case 2	Story 02 Story 12 Story 17	$x_{02} = 20$ $x_{05} = 10$ $x_{10} = 25$

5.2 *Application to Guangzhou New TV Tower*

To demonstrate the reliability of the proposed method, two damaged cases with different reductions of stiffness of each story are considered as given in Table 2. The value of frequencies at two stages damaged and undamaged are shown in Table 3.

Table 3 The values of the 40 first frequencies using the reduced-FE model at undamaged stage and two cases of damaged stage

Mode	Frequency			Mode	Frequency		
	undamaged structure	damaged Case 1	damaged Case 2		undamaged structure	damaged Case 1	damaged Case 2
1	0.1104	0.107	0.1234	21	2.6741	2.6386	2.2999
2	0.1587	0.1633	0.1319	22	2.8391	2.7123	2.4595
3	0.3463	0.3391	0.1885	23	2.9926	2.8829	2.5209
4	0.3688	0.3704	0.4027	24	3.1085	3.0383	2.5653
5	0.3994	0.3865	0.4138	25	3.1542	3.1076	2.6515
6	0.4605	0.4541	0.4273	26	3.2686	3.1817	2.8079
7	0.485	0.4763	0.4373	27	3.3336	3.2465	2.8952
8	0.7381	0.5977	0.5187	28	3.4356	3.3398	2.9331
9	0.9026	0.7702	0.6611	29	3.4725	3.4125	2.968
10	0.9972	0.9848	0.9138	30	3.8553	3.5174	3.1053
11	1.0373	1.016	0.9433	31	3.967	3.5822	3.2253
12	1.1218	1.0838	0.9959	32	4.1373	3.9573	3.5532
13	1.2436	1.1958	1.0593	33	4.191	4.1902	3.6583
14	1.5031	1.4395	1.2325	34	4.2603	4.2592	3.7393
15	1.7261	1.6523	1.431	35	4.3642	4.2804	3.8077
16	1.8051	1.7219	1.4944	36	4.713	4.363	4.2691
17	1.9809	1.9669	1.5112	37	4.7321	4.713	4.4802
18	1.995	1.9897	1.5436	38	5.2113	4.9201	4.5175
19	2.1916	2.0908	1.8409	39	5.3721	5.2079	4.6543
20	2.3632	2.2616	1.9492	40	5.6646	5.3282	4.7345

The results of the damaged indicator process will be presented according to the following:

- *The convergence trend of objective function*: These curves show the trend of the value of the objective function over the course of iterations.
- *The historical trend of damaged elements*: These curves show the changes in the values of the damaged variables, which are defined as a reduction of stiffness. They also illustrate the fast or slow convergence rate of ASO algorithm.
- *The damage identification bar chart*: The final values are shown in the bar chart. The chart shows the correlation between the values of two damaged cases and damaged indicators using FE model updating combined with ASO.

The results are shown from Figs. 3, 4, 5, 6, 7, and 8 and the statistical table in true value and indicator value is given in Table 4.

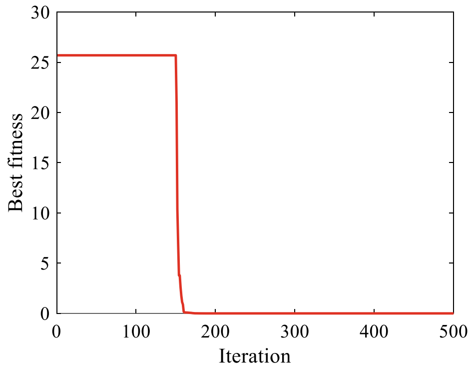


Fig. 3 The convergence trend of objective function in Case 1

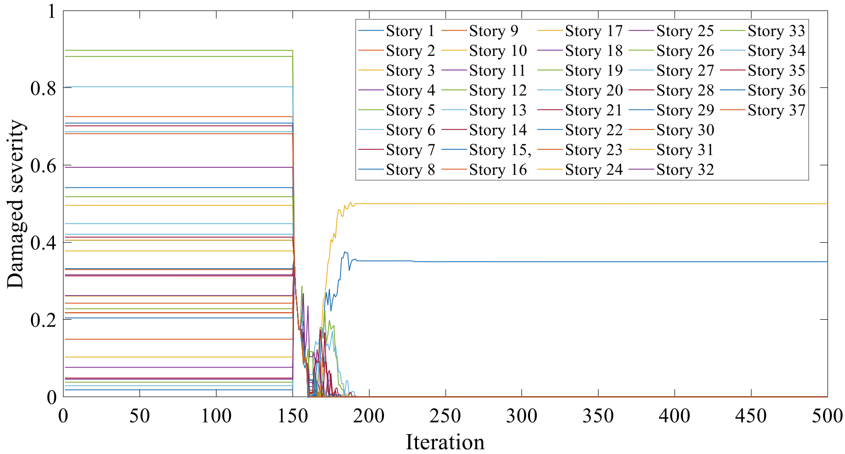


Fig. 4 The historical trend of damaged elements in Case 1

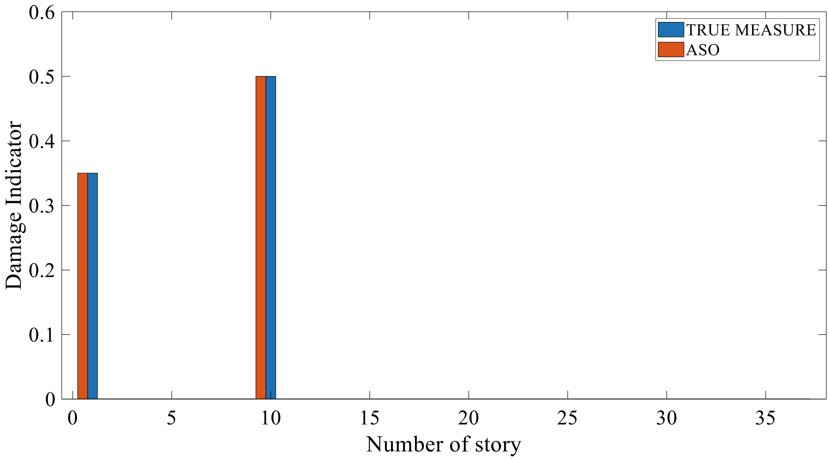
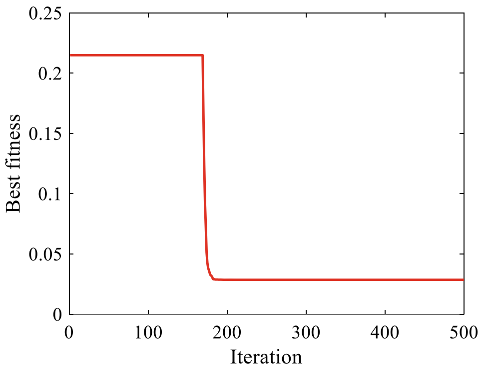


Fig. 5 The damage identification bar chart in Case 1

Fig. 6 The convergence trend of objective function in Case 2



The results in Table 4 show that ASO can predict accurately the damaged stories in Case 1 and acceptable errors in Case 2. There is a general acceptance that the ability to explore ASO during the first few iterations does not appreciate. However, this ability is improved more clearly during the last iterations, and ASO achieves stability in convergence rate and accuracy level because of reducing the Lennard-Jones (L-J) potential force during the last iterations.

6 Conclusion

The paper introduced an effective method to predict damaged structures for a real complex structure named Guangzhou New TV Tower. In the paper, a complex model structure can be simplified by a simple model structure in which each floor is lumped

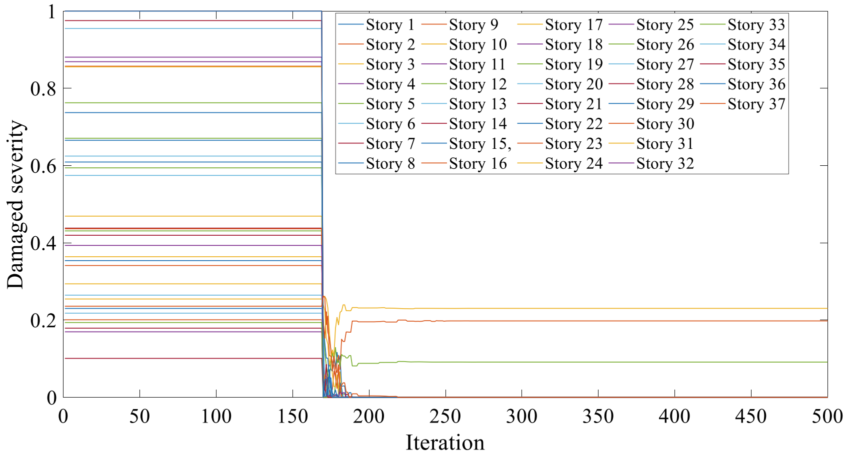


Fig. 7 The historical trend of damaged elements in Case 2

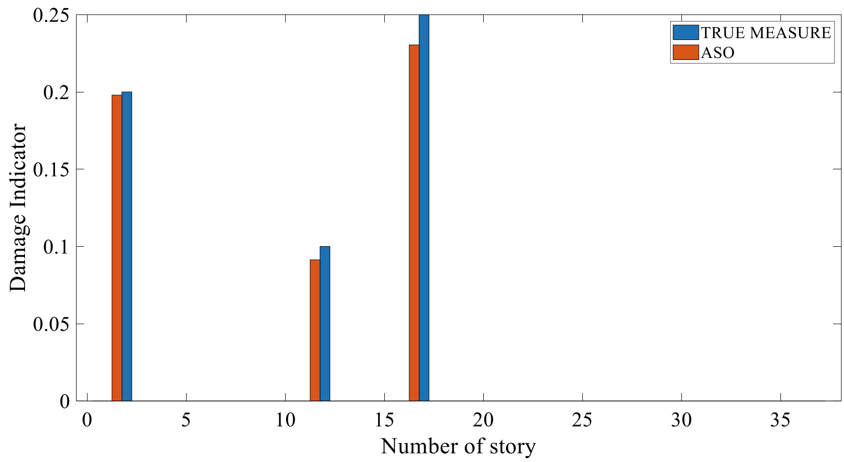


Fig. 8 The damage identification bar chart in Case 2

Table 4 The results of ASO algorithms for predicting damage elements

Case study	Story	True measure	ASO algorithm
			Damaged indicator
Case 1	Story 01	0.35	0.35
	Story 10	0.5	0.5
Case 2	Story 02	0.2	0.198
	Story 12	0.1	0.0914
	Story 17	0.25	0.2304

at the same level as the real floor. The stiffness of each story is converted to the stiffness of the frame whose registers ten degrees of freedom. The process of damaged identification is performed using the FE model updating and inverse method. The results obtained in this paper prove the effectiveness of the method and the reliability of the ASO algorithm. However, this method still has limitations because it cannot predict the level of damage severity of the individual elements on each floor. This method can be used as a reference method to assess the level of damage story quickly. For a more detailed assessment, we need to apply a new model updating technique with a full-scale model, which can be simulated by finite element software.

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