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Optimal sensor placement for health monitoring of high-rise structure using adaptive monkey algorithm

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SUMMARY

Optimal sensor placement is a challenging task in the design of an effective structural health monitoring system. In this paper, a novel optimal sensor placement algorithm, called adaptive monkey algorithm (AMA), to cope with the sensor placement problem for target location under constraints of the computing efficiency and convergence stability is proposed. The dual-structure coding method, instead of the traditional coding method, is adopted to code the solution. The adaptive operator is designed and implemented in the AMA, which provides an automatic technique for adjusting the climb process and watch–jump process of the monkey algorithm according to the observed performance while the search is ongoing. Two new somersault processes, i.e., reflection somersault process and mutation somersault process, are incorporated in the AMA to strengthen its global search ability. Numerical experiments involving two high-rise structures have been carried out to evaluate the performance of the proposed AMA algorithm. The results demonstrated that the innovations in the AMA make it outperform the other algorithms in most cases in terms of less iterations and generating more stable optimal solutions. This algorithm can also be easily applied to other discrete optimization problems. Copyright © 2014 John Wiley & Sons, Ltd.

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KEY WORDS: structural health monitoring; optimal sensor placement; adaptive monkey algorithm; modal assurance criterion; high-rise structure

1. INTRODUCTION

With the extensive utilization of large-scale infrastructures in civil engineering, online monitoring and assessment, as the key feature of a structural health monitoring (SHM) system, has been the major part of research efforts to prolong the service life and enhance the safety of these infrastructures [1–3]. Generally, a typical SHM system includes a paradigm of sensory system, a data acquisition system, a data transmission system, a data storage system, a data processing system, and a condition evaluation system [4]. Among them, the sensory system is the first and most important one, and the design of such a system deals with how many sensors should be placed and what their suitable locations are to yield the desired structural response with minimum cost [5,6]. For the simple and regular structures, the best locations for sensors can be easily determined by engineering judgment or trial-and-error method, because of the better knowledge about these structures by structural engineers. However, for the complicated large-scale structures, special attention for sensor placement should be devoted as the vibratory behaviors of the structures are not perfectly known. In addition, the sensors installed are always sparse compared with the infinite degrees of freedom (DOFs) of the structures. All of these make the sensor placement become a critical issue in the design of an effective SHM system.

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A number of sensor placement approaches for a variety of purposes have been developed and applied to a variety of structures over the last decade. A few methods argued for maximizing the capabilities for measuring and estimating structural deformation and vibration. For instance, Salama *et al.* [7] suggested using modal kinetic energy (MKE) as a kind of sensor placement. By MKE, an optimal sensor set is determined based on the MKE distribution, which gives an index of the dynamic contribution of each finite element (FE) model physical DOF to each of the target mode shapes [8]. Kammer [9–11] simplified this approach and presented the effective independence (EfI) method for sensor placement, which provides a criterion to quantify the independence between two or more reduced mode shapes. Similar to the EfI, a singular value decomposition based method that decomposes the mass-weighted information directly so as to render the selection computation faster is presented by Park and Kim [12]. Li *et al.* [13] discovered EfI method as an iterated version of MKE with re-orthonormalized mode shapes through QR factorization. With this discovery, the EfI can be skillfully computed through row norm of the orthonormal Q matrix [14]. Others focused on minimizing uncertainty in decision-making based on data acquired from the sensory array. The work by Papadimitriou [15] and the previous work by Udwadia [5] and Heredia-Zavoni and Esteva [16] clearly demonstrated the importance of uncertainty in dealing with the optimal sensor placement (OSP). Chang and Markmiller [17] defined the probability of detection as a criterion for quantifying the reliability of a sensor network. Azarbayejani *et al.* [18] proposed a probabilistic method for determining the optimal number and locations of sensors for a SHM system based on the weights of an artificial neural network trained from simulations. In addition, some methods are designed to enhance the probability of damage detection. For example, Cobb and Liebst [19] advanced a method that prioritizes the DOF to sensors by examining the first-order structure sensitivity to changes in the structural stiffness. Shi *et al.* [20] proposed an approach in view of maximizing the Fischer information matrix to find the OSP for the damage identification. Souza and Epureanu [21] provided a sensor deployment method for the damage identification in nonlinear systems using system augmentations. What needs to be mentioned is that the aforementioned methods differ also for the various solution strategies. This is an essential question that needs to be answered properly in the OSP problem, especially if a large number of candidate positions have to be examined [22]. The classical approaches are efficient but suboptimal, which may not ensure the convergence of the errors between the estimated and real structural responses. In the light of this, many attempts have been made to devise sensor placement methods employing combinatorial optimization algorithms based on physical and biological analogies. These include genetic algorithms [23–27], simulated annealing algorithm [28,29], glowworm swarm optimization algorithm [30], artificial bee colony algorithm [31], Particle Swarm Optimization algorithm [32,33], Tabu search [34], ant colony optimization algorithm [35], monkey algorithm (MA) [36,37], and a number of hybrids of these algorithms. The computational performance of the combinatorial optimization algorithms has made them attractive in complex sensor placement problems. However, in most conventional methods, either very limited structural characteristics are considered or several requirements of the application cases are not incorporated into the performance measure of the algorithm.

In this paper, we present a novel method called adaptive monkey algorithm (AMA) to deal with the sensor placement problem for target location under constraints of the computational run-time and the complete coverage. Here, it is assumed that the number of sensors needing to be placed on the building has been determined, and thus optimal locations for the given number of sensors are the target of this paper. The rest of the paper is organized as follows: Section 2 briefly introduces the proposed algorithm. Section 3 describes the main features and detailed implementation procedures of the AMA in sensor placement problem. Section 4 presents the objective function adopted to optimize sensor locations in this paper. Section 5 numerically demonstrates the performance of this novel algorithm for OSP for two high-rise buildings. Finally, Section 6 concludes the paper.

2. OUTLINE OF ADAPTIVE MONKEY ALGORITHM

The MA, originally proposed by Zhao and Tang [38], is a swarm intelligence algorithm that was derived from the simulation of mountain-climbing processes of monkeys. It mainly consists of three processes, i.e., the climb process, the watch–jump process, and the somersault process. The climb process is designed to search the local optima, and the watch–jump process is used to find out other

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positions whose objective function values are better than those of the current solutions in order to enhance the search performance of the algorithm, while the somersault process is employed to make the monkeys transfer to other search domains subtly. Like other swarm intelligence algorithms, the MA can solve a variety of difficult optimization problems, featuring high dimensionality, non-differentiability, and non-linearity. In spite of the MA having these attractive features, it does not mean this algorithm always fulfills as per expectations for sensor placement problem. The problems to be solved are related: coding method, high run-time and poor convergence for large configurations.

Firstly, the original MA is designed to solve global optimization problems with continuous variables, while the sensor placement problem is a single-objective optimization problem involving discrete-valued variables. That means one important consideration for MA is how to best encode the optimization variables into bit strings (i.e., strings with '0's and '1's). Most commonly, the design variables are coded by the binary or the decimal representation. However, these traditional coding methods often generate invalid strings in the iteration process [25]. Here, the dual-structure coding method [37] is adopted to represent design variables in the proposed AMA.

Secondly, in the original MA, the climb process and the watch–jump process are executed sequentially, i.e., the watch–jump process is only implemented when the stop criterion of the climbing process is met. However, it is not clear how to determine the appropriate number of iterations for climb process for a particular problem. As a result, two undesirable cases may emerge. On the one hand, in the climb process, the monkey may encounter other mountains around it higher than its present course; however, it cannot jump from the current position to the mountain encountered. This is because the original climb process and watch–jump process are always fixed, causing the monkey to completely ignore the other mountains around. On the other hand, the monkey may find the local highest mountaintop around its initial point only after several iterations of the climb process; however, the watch–jump process cannot be executed as the predefined number of iterations for the climb process has not been reached. Hence, the original climb process and the watch–jump process are blind and inefficient. The automatic switching of these two processes is therefore appealing. Adaptive operator is an effort in this direction.

Thirdly, the somersault process in the original MA selects only the barycenter of all monkeys' current positions as a pivot, and then the monkeys that somersault along the direction are pointing to the pivot expecting them to find out new searching domains. Obviously, the capability of this single somersault process is limited to find the optimal domain. In view of this, two new somersault processes, i.e., the reflection somersault process and the mutation somersault process, are designed in the proposed AMA to strengthen its global search ability.

Figure 1 shows a schematic drawing of the proposed AMA. It can be summarized intuitively from the previous discussion that the AMA may have the advantages that will be verified from the latter numerical experiments: (i) the dual-structure coding method tackles the coding problem; (ii) the adaptive operator uses a small number of iterations in finding the optimal solution to make it more computationally efficient than the others; and (iii) the three kinds of somersault process will be more reliable than a method used only in finding the optimal solution.

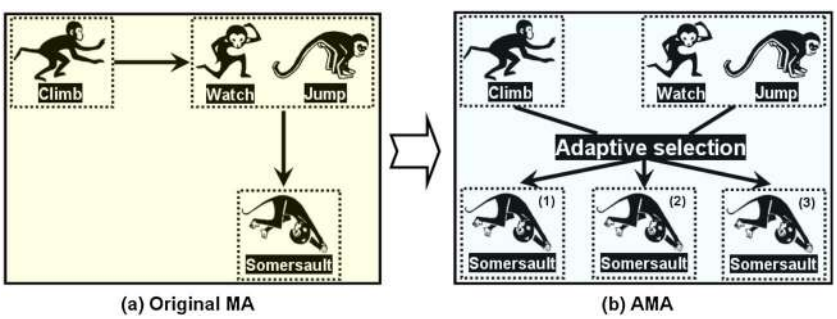

Figure 1. Schematic drawing of the AMA.

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3. IMPLEMENTATION PROCEDURES OF ADAPTIVE MONKEY ALGORITHM FOR SENSOR PLACEMENT

The sensor placement optimization is a kind of combinatorial optimization problem that can be generalized as 'given a set of n candidate locations, find m locations, where $m < n$, which may provide the best possible performance'. The number of all distinct sensor configurations involving m sensors is given by the expression

$$C = \frac{n!}{m!(n-m)!}. \tag{1}$$

Figure 2 presents the flowchart of the computational procedure of the proposed AMA to find the optimal sensor locations. The procedure can be fully implemented easily by using technical computing software, such as the MATLAB [39].

3.1. Coding method and initialization

For the sensor placement problem in this paper, the optimization variables are the sensor's positions. For the sake of completeness, the brief steps of the dual-structure coding method previously proposed by the authors are presented here [37]. Let the ordered pair (x, c) represent the possible solutions, where x is the position vector in the AMA and c denotes the binary vector that stands for the sensor's position (if a sensor is deployed on one of the DOFs, the corresponding bit in the binary vector is set to 1, or else it is set to 0; and the total number of 1 is equal to the sensor number that needs to be located). The basic steps of solution representation using the dual-structure coding method are summarized as follows:

Step (1): Assume that there are f candidate sensor locations (where f is equal to the total DOFs of the developed FE model); thus, the f integers from 1 to f can be obtained.

Step (2): For the monkey i in the monkey population, its solution is expressed as $xc_i = (x_i, c_i) = \{(x_{i,1}, c_{i,1}), (x_{i,2}, c_{i,2}), ..., (x_{i,f}, c_{i,f})\}$, in which the component of the position vector x_i is the real number selected from the interval $[down, up]$ randomly, where $down = -5$ and $up = 5$, and c_i is the binary vector obtained by

$$c_{i,j} = sig\left(x_{i,j}\right) = \frac{1}{1+e^{-x_{i,j}}}. \tag{2}$$

When using Equation (2), a judgment threshold ε needs to be determined first. In other words, if $sig(x_{i,j}) \leqslant \varepsilon$, then $c_{i,j} = 0$; if $sig(x_{i,j}) > \varepsilon$, then $c_{i,j} = 1$, here $j \in \{1, 2, \ldots, f\}$. Here, the ε is defined as 0.5; thus, when

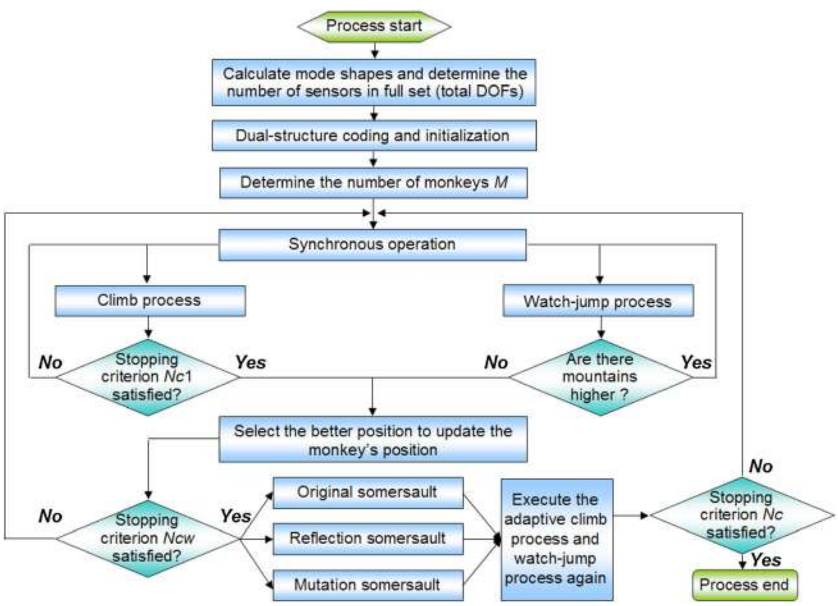

Figure 2. Flowchart of the AMA for OSP.

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selecting each component of the x_i from the interval $[-5, 5]$ randomly, it can be noted that $0.0067 \leqslant sig(x_i) \leqslant 0.9933$ and $sig(0) = 0.5$ which verifies that the judgment threshold given here is suitable.

Step (3): Repeat steps (1) and (2), until M monkeys are generated (M indicates the population size of monkeys).

In the following iterative process of the proposed AMA, the position vector x_i is adopted first, then Equation (2) is adopted to obtain the binary vector c_i that is subsequently adopted to compute the objective function value. As a result, each monkey will arrive at its own optimal position standing for the personal optimal objective value $f(x_i, c_i)$ when the stopping criterion is satisfied.

3.2. Adaptive climb and watch–jump process

The climb process and watch–jump process are the main steps to find the local optima in the original MA, which updates the monkeys' locations sequentially from the initial locations to new ones that can improve the objective function value. However, as aforementioned, the original sequence of the two processes is fixed, which will make the searching efficiency very low. To improve this weakness in the application of MA, a novel adaptive scheme is designed in the AMA, which can automatically control whether the climb process or watch–jump process is implemented in an AMA loop.

(1) Climb process

For the monkey i with location $x_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,f})$, the outline of the climb process can be described as:

Step (1): Generate integers Δx_{ij} in the interval $[-aa, aa]$ randomly, $j \in \{1, 2, \ldots, f\}$, and form an integer vector $\Delta x_i = (\Delta x_{i1}, \Delta x_{i2}, \ldots, \Delta x_{if})^T$, where the parameter aa is the step length of the climb process.

Step (2): Obtain monkey's new positions x_{new1} and x_{new2} by $x_i + \Delta x_i$ and $x_i - \Delta x_i$, respectively, then calculate $f(x_{new1}, c_{new1})$ and $f(x_{new2}, c_{new2})$, and update the monkey's location x_i with a better one between x_{new1} and x_{new2} (update c_i with c_{new1} or c_{new2} accordingly) only if at least one of the $f(x_{new1}, c_{new1})$ and $f(x_{new2}, c_{new2})$ is better than $f(x_i, c_i)$; otherwise keep x_i unchanged.

(2) Watch–jump process

For the monkey i with the location $x_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,f})$, the outline of the proposed watch–jump process is summarized as follows:

Step (1): Generate integer numbers xw_{ij} from $[x_{ij} - ba, x_{ij} + ba]$ randomly, $j \in \{1, 2, \ldots, f\}$, where the ba is a positive integer that stands for the maximum distance that the monkey can see (termed as the eyesight of the monkey); thus, the new location $xw_i = (xw_{i,1}, xw_{i,2}, \ldots, xw_{i,f})^T$ can be obtained.

Step (2): Compute the objective function value $f(xw_i, c_{new_i})$, and update the monkey's location x_i with xw_i in the event that $f(xw_i, c_{new_i})$ is better than $f(x_i, c_i)$; otherwise return to step (1).

For the monkey i with position $x_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,f})$, the proposed adaptive switching scheme of these two processes is given as follows:

Step (1): Carry out the climb process from position x_i until the maximum allowable number of iterations (denoted by $Nc1$) is reached to obtain the monkey's new position xc.

Step (2): Carry out the watch–jump process from position x_i until a better monkey's new location xw is found.

Step (3): The climb process and the watch–jump process in step (1) and step (2) are carried out simultaneously. Evaluate the xc and xw, and then the better one is selected to update the monkey's position x_i.

Step (4): Repeat steps (1)~(3) until it has implemented Ncw generations.

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3.3. Somersault process

After repetitions of the adaptive climb and watch–jump process, each monkey will find a local peak around its initial location. To find a much higher mountaintop, the somersault process is executed hereafter. In the proposed AMA, three types of somersault processes are adopted separately to achieve fast convergence and high accuracy.

(1) Original somersault process ($s1$)

For the monkey i with the location $x_i=(x_{i,1}, x_{i,2}, \dots, x_{i,f})$, the outline of the original somersault process is summarized as follows:

Step (1): Generate an integer number θ from the interval $[ca, da]$ randomly. The interval $[ca, da]$ is designated as the somersault interval, which governs the maximum distance that monkeys can somersault.

Step (2): Obtain the monkeys' pivot $pa=(pa_1, pa_2, \dots, pa_f)^T$ by computing all monkeys' barycenter $pa_j = \sum_i^M x_{ij}/M, j \in \{1, 2, \dots, f\}$.

Step (3): Compute $xs1_{i,j}=x_{i,j}+round(\theta|pa_j - x_{i,j}|)$ ($round$ means rounding), and update the monkeys' position with $xs1_i=(xs_{i,1}, xs_{i,2}, \dots xs_{i,f})$ in the event that the new objective values of $xs1_i$ are better than the former one, and then go back to the adaptive climb process and watch–jump process; otherwise return to step (1).

(2) Reflection somersault process ($s2$)

The reflection somersault process proposed in this paper is inspired by the simplex method [40]. According to the simplex method, the xb monkeys with the worst objective function value are selected firstly; then compute the barycenter (denoted by xp) of the remaining monkeys. Finally, compute the reflection (denoted by xr) of xb,

$$xr = 2\times xp - xb \cdot \tag{3}$$

Thus, the xb monkeys with the worst objective function value can be replaced by the new xr monkeys. Although the aforementioned method is very effective for the xb worst monkeys, it is not applicable to the sensor placement problem because the OSP is a kind of special 0–1 integer programming problem that has distinctive features, i.e., each sensor has an equal importance for data acquisition. Based on this consideration, a modified reflection somersault process is proposed here to assign the same importance to each monkey. For the monkey i with the location $x_i=(x_{i,1}, x_{i,2}, \dots, x_{i,f})$, the outline of the reflection somersault process is as follows:

Step (1): Compute all monkeys' barycenter denoted by $pa=(pa_1, pa_2, \dots, pa_f)^T$.

Step (2): Carry out reflection somersault as

$$xs2_i = round(r\times rand(0, 1)\times pa - x_i) \tag{4}$$

where $rand(0, 1)$ is used to generate a random number from the interval $(0, 1)$. By trial and error, Equation (4) is suitable for sensor placement problem when r is equal to 4.

Step (3) Update the monkeys' location with $xs2_i$ in the event that the new objective values of $xs2_i$ are better than the former one, and then go back to the adaptive climb process and the watch–jump process; otherwise return to step (1).

(3) Mutation somersault process ($s3$)

The mutation somersault process proposed in this paper is derived from the mutation mechanism in genetic algorithms [22]. The mutation is a random process in which some values of elements within a string are selected and then replaced by randomly generated numbers to reduce the chance that the optimization process becomes trapped in local optimal regions. For the monkey i with the position

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$x_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,f})$, set the mutation rate sar $(0 < sar < 1)$, and the outline of the mutation somersault process can be described as follows:

Step (1): For the j component $x_{i,j}$ of the x_i, generate a random number $r1$ from the interval $(0, 1)$, i.e., $r1 = rand(0, 1)$.
Step (2): Update the component $x_{i,j}$ with $-x_{i,j}$ only if $r1 < sar$; otherwise $x_{i,j}$ remains unchanged, $j \in \{1, 2, \ldots, f\}$.
Step (3): Repeat steps (1)~(2), until all components of the monkey i are generated; thus, the new position $xs3_i$ can be obtained.
Step (4): Update the monkeys' position with $xs3_i$ in the event that the new objective values of $xs3_i$ are better than the former one and then go back to the adaptive climb process and the watch–jump process; otherwise return to step (1).

Therefore, the outline of the somersault process in the proposed AMA can be summarized as follows:

Step (1): For the monkey i, carry out the original, reflection, and mutation climb process, respectively, to obtain the three new positions $xs1_i$, $xs2_i$, and $xs3_i$.
Step (2): Execute the adaptive climb process and the watch–jump process from the new positions again until it has implemented Nc generations.
Step (3): Repeat steps (1)~(2) until all of the monkeys complete the somersault process.

4. OBJECTIVE FUNCTION

Before the design of a specific sensor network, the optimum criterion (objective function) should be selected for the goal of the sensor deployment firstly. In the case under investigation, the objective function is derived from the modal assurance criterion (MAC) [41], which is defined as follows:

$$\mathrm{MAC}_{ij} = \frac{\left(\Phi_i^T \Phi_j\right)^2}{\left(\Phi_i^T \Phi_i\right)\left(\Phi_j^T \Phi_j\right)} \tag{5}$$

where Φ_i and Φ_j stand for the ith and jth column vectors in mode shape matrix Φ, respectively, and the superscript T represents the transpose of a vector.

In Equation (5), the element values of the MAC matrix range between 1 and 0. A smaller value of the maximum off-diagonal element in the MAC matrix means that the corresponding mode shapes can be easily distinguished from each other, whereas a larger value denotes that the mode shapes cannot be easily distinguished from each other. That means minimizing the maximum off-diagonal component of the MAC matrix will enable identifying the mode shapes more easily for the purpose of identification, which will be of great benefit to the SHM work. Therefore, the value of the off-diagonal elements can serve as a good indication of the optimal result. For this reason, the objective function adopted here is the largest value of the off-diagonal elements in the MAC matrix.

$$\min \quad f_1(x, c) \tag{6}$$

where $f_1(x, c) = \max\limits_{i \neq j} \left\{\mathrm{MAC}_{ij}\right\}$.

5. CASE STUDY

To demonstrate the effectiveness and superiority of the AMA on allocating the sensors across the structure, two cases to determine the optimal sensor network on two high-rise buildings are considered as follows:

Case 1: The original MA with the dual-structure coding (termed as simple MA, abbreviated as SMA).
Case 2: The proposed AMA.

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5.1. Dalian World Trade Building

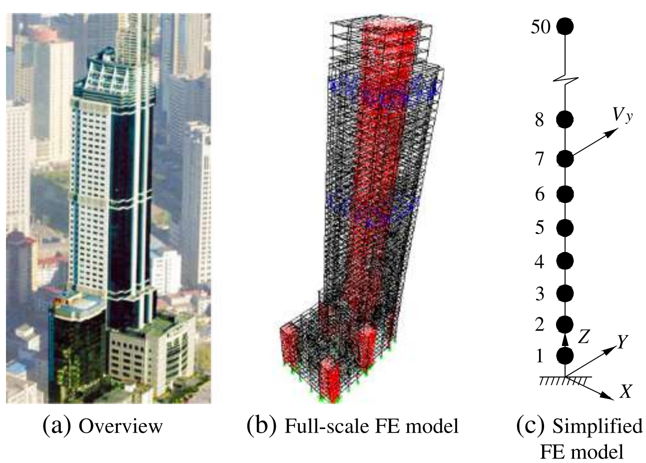
The Dalian World Trade Building (DWTB) located in the city of Dalian, China, is a super-tall structure with a total height of 242.00 m, as depicted in Figure 3(a). It consists of a main tower 201.90 m tall and an antenna mast 40.10 m tall. It has 50 stories above the ground level and four stories under the ground. The structural system utilizes both steel and reinforced concrete, including core wall systems and perimeter steel frame coupled by outrigger trusses at the 30th and 45th floors. So far, the DWTB is still the tallest in northeast China [36].

(1) Computational model for DWTB

The problem considered here is the design of optimal sensor network for modal identification mentioned in Section 4. To provide input data for the proposed method, an FE model of the DWTB is developed using the FE software ETABS (CSI, Berkeley, CA, USA) [42], as depicted in Figure 3(b). In the FE model, all the columns and beams are modeled using 'Frame Elements', and the core wall and slab are simulated using the 'Shell Element' having bending and membrane stiffness terms available in the ETABS library. The FE model has a total of 22,967 shell elements, 13,324 node elements, and 90,062 frame elements. To facilitate the model analysis and other related studies, an equivalent simplified FE model is developed; for more details on the FE model, the reader can refer to Yi *et al.* [43]. The DOFs in the simplified FE model are numbered starting from the bottom of the chain consecutively (Figure 3 (c)). Consequently, a total of 50 DOFs (i.e., $f = 50$) are available for sensor deployment (here assume $sp = 20$), as depicted in Figure 3(c), and the first 10 modes of the DWTB are selected for computation.

(2) Optimization results and discussion

Like other swarm intelligent optimal algorithms, the AMA also has a number of parameters that need to be tuned so that the best performance of the proposed algorithm can be achieved. Thus, in the beginning, a number of experiments were executed to determine the most appropriate parameters. Three critical parameters, the number of iterations in the initial climb process ($Nc1$), the number of iterations in the adaptive climb and watch–jump process (Ncw), and the mutation rate (sar), were tested. The basic parameters of AMA are listed as follows: the number of monkeys $M = 5$, step length $aa = 1$, eyesight $ba = 2$, and the somersault interval is set as $[-3, 3]$. They remain unchanged in the process of parametric analysis. By the orthogonal experimental design, the orthogonal table can be obtained, as listed in Table I, where the numbers in brackets represent levels, i.e., $Nc1$ is set as 10, 20, 40, respectively; Ncw is set as 50, 100, 200, respectively, sar is set as 0.1, 0.4, 0.7, respectively. What needs to be mentioned is that each case is tested five times, and the best results were selected and demonstrated in Table I. The following can be noted from Table I: (i) Larger number of iterations in the initial climb process ($Nc1$) could result in the improvement of results to some extent. However, there are some visible fluctuations in the solutions as the initial climb process is a kind of pure random



(a) Overview (b) Full-scale FE model (c) Simplified FE model

Figure 3. The Dalian World Trade Building and its FE model.

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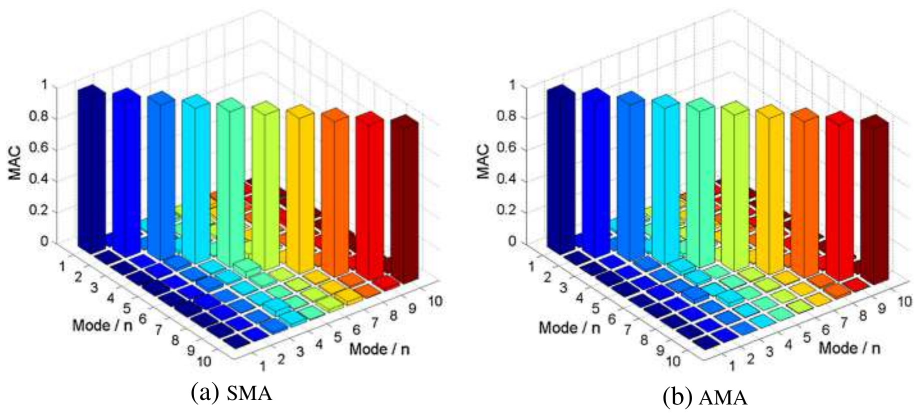
Table I. Empirical study of the impact of different parameters on the solution quality.

Scenario	Different settings of three important parameters			Objective values
	*Nc*1	*Ncw*	*sar*	
1	1 (10)	1 (50)	1 (0.1)	0.0420
2	1 (10)	2 (100)	2 (0.4)	0.0260
3	1 (10)	3 (200)	3 (0.7)	0.0371
4	2 (20)	1 (50)	2 (0.4)	0.0439
5	2 (20)	2 (100)	3 (0.7)	0.0470
6	2 (20)	3 (200)	1 (0.1)	0.0296
7	3 (40)	1 (50)	3 (0.7)	0.0360
8	3 (40)	2 (100)	1 (0.1)	0.0409
9	3 (40)	3 (200)	2 (0.4)	0.0247

search, which will decrease the algorithm's efficiency as aforementioned. For this case, a reasonable value of *Nc*1 is set as 10. (ii) Increasing the number of the *Ncw* slightly, the good performance of the AMA, by adopting adaptive operator, can be achieved. This verified that the proposed adaptive climb process and watch–jump process are rational and effective. The suitable value for *Ncw* can be set as 100 here. (iii) The mutation rate *sar* has some impacts on the improvement of results, which confirms that the parameters need to be explored so that the best performance of the algorithm can be achieved. The results in Table I led to the use of mutation somersault process with probability $sar = 0.4$.

Figure 4(a) and (b) depicts the MAC values obtained by SMA and AMA, respectively. The plots show that the trend and the values of the maximum MAC off-diagonal elements are very close. Compared with the diagonal elements in Figure 4, all values of the MAC off-diagonal elements are very small, which confirms that both SMA and AMA have a good characteristic of convergence, although the performance of AMA is found to be superior to SMA as expected. To further demonstrate the effectiveness of the improvements in the AMA, Figure 5 plots the values of the maximum MAC off-diagonal elements in each of the modes. Three distinct lines are drawn; the first (the blue line with circle) highlights the off-diagonal terms of the 'all DOFs' (i.e., MAC matrix for the full sensor set), while the second (the purple line with asterisk) and the third line (the red line with triangle) represent the maximum MAC off-diagonal value in each of the modes obtained by the SMA and AMA, respectively. The results clearly demonstrate that the AMA outperforms the full sensor set and SMA approaches practically in most of the modes. At the same time, the best objective function values are also compared, and the results are presented in Table II. A close look at the results listed in Table II indicates that the largest off-diagonal MAC term is 0.0399 for the SMA, whereas it is 0.0260 for the AMA, which means that the convergence of the AMA is far better than that of SMA and a 34.84% reduction is gained to reach a satisfactory solution. The reason for the worse result of the full sensor set is that some included sensors may conflict with other ones. In other words, the column vector is nearly a



(a) SMA (b) AMA

Figure 4. MAC values obtained by SMA and AMA.

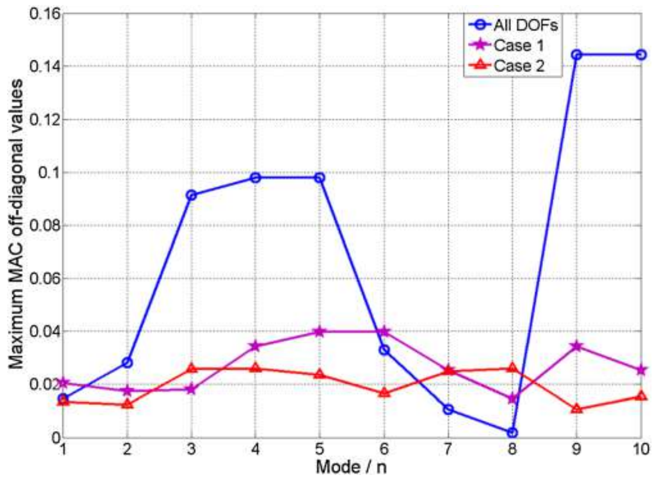


Figure 5. Maximum MAC off-diagonal value in each of the modes.

Table II. Objective function values of each kind of sensor placement scheme.

Scheme selection	All DOFs	Case 1	Case 2
Objective function value	0.1442	0.0399	0.0260

linear combination of other column vectors. Table III shows the optimal locations of sensors obtained using the proposed AMA.

5.2. Dalian International Trade Mansion

The Dalian International Trade Mansion (DITM) (shown in Figure 6(a)) is currently being constructed in the city center of Dalian. When completed in the near future, it will ensure the first place among the super-tall structures in northeastern China with its height of 330.25 m. It has 79 stories above the

Table III. Sensor placements of the DWTB.

Sensor No.	DOFs
1	3
2	4
3	5
4	8
5	10
6	13
7	14
8	16
9	20
10	23
11	26
12	29
13	33
14	35
15	36
16	39
17	41
18	43
19	45
20	47

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(a) Overview (b) Full-scale FE model (c) Simplified FE model

Figure 6. The Dalian International Trade Mansion and its FE model.

ground level and five stories under the ground. The 10th, 23rd, 37th, 50th, 62nd, and 79th floors are the refuge floors, with the height of 5.10 m. The tower is a core tube hybrid structure, consisting of a reinforced concrete inner structure and a steel lattice outer structure [27].

(1) Computational model for DITM

The FE model of the DITM is also established with the commercial software ETABS, and the selected element types are almost identical to those of the DWTB. The simplified model is bending-shear model with 79 DOFs, which was derived from the full model of 29,071 shell elements, 34,791 frame elements, and 34,308 node elements (Figure 6(b)), by using the approach called equivalent rigidity parameter identification method (Figure 6(c)) [27]. According to the modal mass participation ratio obtained by the modal analysis, the first eight modes of the DITM are selected for computation. In addition, assume that there are 25 sensors need to be installed (i.e., $sp = 25$).

(2) Optimization results and discussion

In Table IV, the solution evolution for different parameter settings is shown. According to a comparison on the solution quality, three important parameters of AMA for the sensor placement of DITM are fixed: $Nc1 = 20$, $Nc = 100$, and $sar = 0.5$. The other basic parameters of AMA remain unchanged. Comparative algorithm performance assessment was made on the basis of quality of the solutions; the results obtained by the SMA and AMA for the DITM is depicted in Figure 7. Similar to the

Table IV. Empirical study of the impact of different parameters on the solution quality.

	Different settings of three important parameters			
Scenario	$Nc1$	Ncw	sar	Objective values
1	1 (10)	1 (50)	1 (0.1)	0.0085
2	1 (10)	2 (100)	2 (0.4)	0.0053
3	1 (10)	3 (200)	3 (0.7)	0.0066
4	2 (20)	1 (50)	2 (0.4)	0.0070
5	2 (20)	2 (100)	3 (0.7)	0.0064
6	2 (20)	3 (200)	1 (0.1)	0.0050
7	3 (40)	1 (50)	3 (0.7)	0.0072
8	3 (40)	2 (100)	1 (0.1)	0.0049
9	3 (40)	3 (200)	2 (0.4)	0.0057

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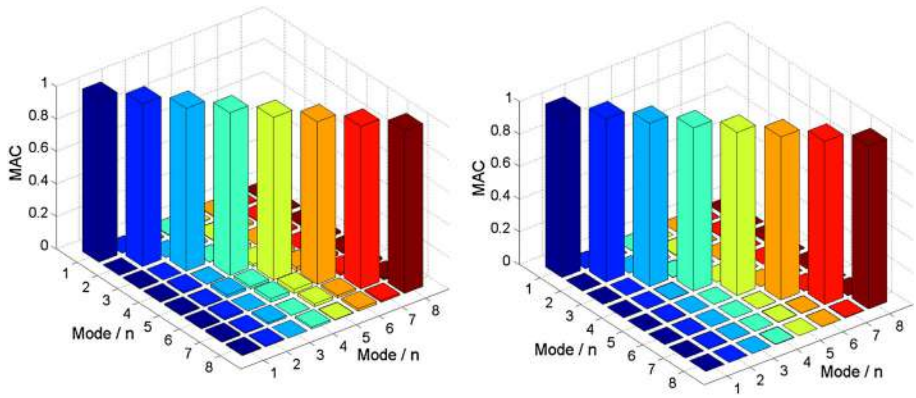

(a) SMA (b) AMA

Figure 7. MAC values obtained by SMA and AMA.

aforementioned numerical case study, it can be noted that the AMA outperforms the SMA very much using less computational resources. Figure 8 shows the maximum MAC off-diagonal value in each of the modes using three methods to further demonstrate the effectiveness of improvements of the AMA. Except mode 7, all of the maximum MAC off-diagonal values obtained by the AMA are much smaller than those of other algorithms, as expected. It is seen from Table V that the AMA can improve the results by 66.67% when compared with the SMA. Comparing the results in Figures 5 and 8 reveals that the AMA demonstrates much more stability and predictability than the other methods. This verifies that the multiple somersault processes are more reliable in finding the optimal solution than using a single method only. Table VI lists the optimal sensor locations for the DITM obtained using the AMA.

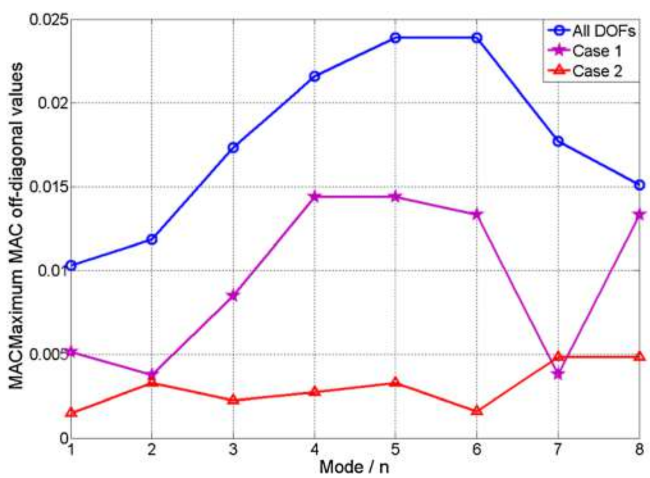

Figure 8. Maximum MAC off-diagonal value in each of the modes.

Table V. Objective function values of each kind of sensor placement scheme.

Scheme selection	All DOFs	Case 1	Case 2
Objective function value	0.0239	0.0144	0.0048

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Table VI. Sensor placement result of the DITM.

Sensor No.	DOFs
1	1
2	2
3	3
4	6
5	7
6	9
7	10
8	16
9	19
10	22
11	26
12	31
13	32
14	34
15	39
16	44
17	45
18	52
19	54
20	60
21	62
22	68
23	70
24	77
25	78

6. CONCLUSIONS

Finding the optimal sensor positions is a complicated nonlinear optimization problem in SHM, and the global optimal solution is often difficult to obtain. This paper presents an AMA that can adjust the climb process and watch–jump process of the MA according to the observed performance. With the numerical case studies, some conclusions are given here:

(1) In the original MA, the climb process and the watch–jump process are carried out sequentially, which makes the searching efficiency very low. To solve this problem, the adaptive operator is designed in the proposed AMA, which provides an automatic technique for adjusting courses while the search process is ongoing. With this feature, the AMA only uses a low number of generations in finding the optimal solution with high computational efficiency.
(2) Two new somersault processes, i.e., the reflection somersault process and the mutation somersault process, are designed in the proposed AMA to strengthen the global search ability of the algorithm. It is confirmed that several somersault processes adopted together are more reliable in finding the optimal solution than the others.
(3) Numerical investigations clearly suggest that the proposed AMA outperforms the other algorithms in most cases in terms of less iterations and generating more stable optimal solutions.

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