International Journal of Structural Stability and Dynamics
Vol. 14, No. 5 (2014) 1440012 (18 pages)

DOI: 10.1142/S0219455414400124

Sensor Placement Optimization in Structural Health Monitoring Using Niching Monkey Algorithm

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Received 12 December 2013
Accepted 18 March 2014
Published 12 May 2014

Optimal sensor placement (OSP) method plays a key role in setting up a health monitoring system for large-scale structures. This paper describes the implementation of monkey algorithm (MA) as a strategy for the optimal placement of a predefined number of sensors. To effectively maintain the population diversity while enhancing the exploitation capacities during the optimization process, a novel niching monkey algorithm (NMA) by combining the MA with the niching techniques is developed in this paper. In the NMA, the dual-structure coding method is adopted to code the design variables and a chaos-based approach instead of a pure random initialization is employed to initialize the monkey population. Meanwhile, the niche generation operation and fitness sharing mechanism are modified and incorporated to alleviate the premature convergence problem while enhancing the exploration of new search domain. In addition, to promote interactions and share the available resources, the replacement scheme is proposed and adopted among the niches. Finally, numerical experiments are conducted on a high-rise structure to evaluate the performance of the proposed NMA. It is found that the innovations in the proposed NMA can effectively improve the convergence of algorithm and generate superior sensor configurations when compared to the original MA.

Keywords: Structural health monitoring; optimal sensor placement; monkey algorithm; niching techniques; modal assurance criterion.

1. Introduction

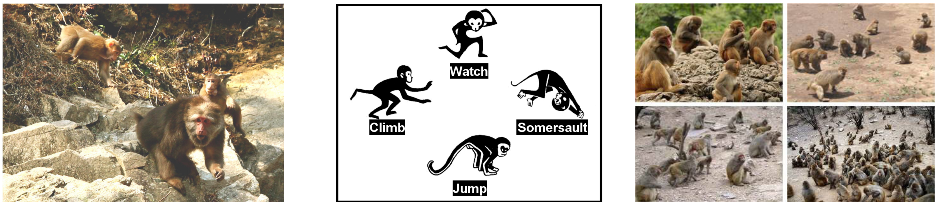
The effects of environmental and service loads (corrosion, fatigue, etc.) or unpredictable external events (earthquakes, impact, etc.) on civil infrastructures have profound engineering and safety implications.[1] In the recent years, great efforts have been made to make use of the significant technological advances in sensing, data acquisition and evaluation technology to enhance the safe operation of critical infrastructure and enable operational cost reduction by performing prognostic and preventative maintenance.[2–4] However, the performance of these structural health assessment activities utilizing measured dynamic characteristics depends very much on the quantity and quality of the measured data, which in turn relies on the number of sensors used and their corresponding locations. Thus, deciding on an optimal sensor placement (OSP) is a crucial issue in the construction and implementation of an effective structural health monitoring (SHM) system. An optimal configuration can minimize the number of sensors required, increase accuracy and provide a robust system. Otherwise, incomplete dynamic properties will be measured and an accurate condition assessment will be impossible.

The OSP problem can be generalized as "given a set of n candidate locations, find m locations, where $m \ll n$, which provide the best possible performance".[5] The placement methodology for sensor arrays for the SHM has been a well-studied subject, as demonstrated by Yi and Li,[6] who have produced thorough reviews of the existing literature in this area. Generally, emerged research work can be classified mainly as three categories: (i) Observability-based methods. The observability is the capacity of the sensor network to provide information about the important parameters for the structures under monitor. The Effective Independence (EfI) method,[7,8] which quantifies the independence between two or more reduced mode shapes, is one of the most commonly used, as shown in its highly cited record. Another influential method that to some extent has been derived from the EfI method is the modal kinetic energy (MKE) method,[9,10] which maximizes the kinetic energy content of the signals acquired. There are several variants on this theme, such as the average kinetic energy and weighted average kinetic energy (WAKE) proposed by Chung and Moore.[11] And the EfI-DPR[12] method is a compromise between the EfI and the energetic approach, the driving-point residue (DPR).[13] Li *et al.*[14] analyzed the relation between the EfI method and the MKE method. The method presented by Stubbs[15] is an extension of Shannon's sampling theorem in the space domain, which picks sensor locations at equidistant points for the half wavelength of the highest modes of interest. The modal assurance criterion (MAC) method, proposed by Carne and Dohrmann,[16] uses the minimization of the off-diagonal terms in the MAC matrix as a measure of the utility of a sensor configuration. (ii) Detectability-based methods. This category specifically addresses whether the sensor network can detect structure damages. Cobb and Liebst[17] proposed one of the first such approaches. They made no assumption about damage location and, instead, focused on a sensitivity analysis to find the degrees of freedom (DOF) which maximized the changes due to damage in the observable partial eigenstructure. Shi *et al.*[18] proposed a method that based on maximizing the Fisher information matrix (FIM) to find the optimum sensor placement for the damage detection. Souza and Epurean[19] provided a sensor placement method for the damage detection in nonlinear systems using system augmentations. Guratzsch and Mahadevan[20] defined the optimum sensor network under uncertainty as the sensor configuration that could maximize the probability of damage detection. Ntotsios *et al.*[21] presented a Bayesian method that quantified damage in the structure based on the change in the modal information. (iii) Reliability-based methods. This category specifically addresses sensor reliabilities and how sensor availability impacts the overall sensor network performance. Ali and Narasimhan[22] defined the concept of sensor reliability and the minimum product of input sensor reliabilities for each estimated parameter as the network objective function. Others focused on enhancing the detection efficiency and minimizing uncertainty in the decision-making based on the data acquired from the sensor networks.[23] In addition, Chang and Markmiller[24] introduced the probability of detection (POD) as the measurement for quantifying the reliability of a sensor network. What need to be mentioned is that the efficiency of these approaches is based on the effective solution strategies. This is not a marginal question in the OSP problem, especially if large numbers of sensors are adopted for a SHM system.[25] In this sense, from a mathematical standpoint, the OSP is a constrained topologic combinatorial optimization problem. The meta-heuristic algorithm based on the swarm intelligence is especially appropriate and effective to use in such cases. For example, the genetic algorithms, the glowworm swarm optimization algorithm, the particle swarm optimization algorithm, the artificial bee colony algorithm, the ant colony optimization algorithm and the monkey algorithm (MA),[26] have acquired successful application in the OSP problem.

In this paper, a novel algorithm called niching monkey algorithm (NMA), which combines the MA with the niching technique to cope with the sensor placement problem, is proposed for the purpose of health monitoring. The outline of the paper is as follows: Section 2 gives a brief survey of the concepts and existing problems of the MA. Section 3 presents the main features of the NMA under study and gives the detailed implementation steps of the NMA to sensor placement. This is followed in Section 4 by an introduction of the objective function to sensor placement optimization. Section 5 shows the performance of this novel algorithm for the OSP in a high-rise structure. Finally, a few concluding remarks are given.

2. Brief Description of Monkey Algorithm

The MA, developed by Zhao and Tang,[27] is inspired by the behavior of mountain-climbing process of monkeys. It consists of three main process namely the climb process, watch-jump process and somersault process (Fig. 1), in which, the climb process is designed to search for the local optimum, the watch-jump process looks around to find out whether there are higher mountains around it and jump toward the mountain from the current position and the somersault process enables the monkeys to find new searching domains. Similar to other evolutionary algorithms, the MA can solve a variety of difficult optimization problems featuring the nonlinearity, non-differentiability and high dimensionality. Yi *et al.*[30,32] first adopted the MA in the field of sensor placement. In the Ref. 32, the integer coding method is adopted in the modified MA, which is proved more efficient than binary coding



(a) Monkey climbing the mountain (b) Monkey's characteristics (c) Niching mechanism

Fig. 1. Schematic drawing of the NMA.

method because it does not need coding/decoding of real/binary variables. In addition, the hamming distance operator and the stochastic perturbation mechanism of harmony search algorithm are employed to improve the local and global search capability. In the Ref. 33, Yi *et al.* designed another kind of coding method called dual-structure coding method for the representation of the design variables. The asynchronous-climb process is proposed and incorporated in the original MA to build a much stronger intensification mechanism into the algorithm. Despite of the original and improved MA having attractive features; it does not imply these algorithms are suitable for any OSP problems. For example, the random initialization process in the MA is prone to generate similar positions for different monkeys, i.e. similar scheme of sensor placement. In addition, the MA suffers from two main drawbacks in the climb process: the premature convergence and weak exploitation capabilities. The main reason of premature convergence is loss of diversity in the monkey population, where all monkeys in a population become nearly identical before the optima has been located since the climb process is done randomly; on the other hand, weak exploitation capabilities often cause slow convergence of MA since the monkeys do not learn from each other and the information obtained by each monkey does not transfer to other monkeys. So some improvements to maintain the population diversity are necessary to enhance the exploration of new search domain during the climb process.

3. Niching Monkey Algorithm for Sensor Placement

The use of distributed multi-population approach, which is a simple and intuitive way, increases diversity by maintaining isolated subpopulations, but this approach cannot make the monkeys exploiting information from their respective neighbors that hold valuable knowledge. In order to tackle this problem, the niching techniques are modified and adopted here. The basic idea of the niching methods is based upon the natural ecosystems.[28,29] In ecology, an ecosystem is typically composed of different physical niches that exhibit different features and allow both the formation and the maintenance of different types of species. Within a niche, individuals are forced to share the available resources, whereas among different niches, there will be no conflict for the resources. Using this analogy, each search space can be seen as a niche that supports a number of individuals directly proportional to its "fertility", which is measured by the fitness of this peak relatively to the fitness of other peaks of the domain. Compared with the distributed multi-population approach, the uniqueness of niching techniques lies in the fact that it preserves not only the highly-fit monkeys, but also weaker monkeys so long as they are not similar ones. This gives the population an opportunity to pass the information of such monkeys to their offspring, and it ensures that the diversity in the monkey population is kept well. So the proposed NMA by combining the MA with the niching techniques can effectively alleviate premature convergence and improve exploitation capacities of the MA. The balance between exploration and exploitation can be maintained effectively during the climb process. Figure 1 depicts a schematic diagram of the proposed NMA.

3.1. *Coding method*

The MA differs from more conventional optimization techniques in that they work on encoded forms of the possible solutions. In the sensor placement, the minimization variables are the discrete sensor locations and the size of the parameter space varies from different structures and different number of available sensors while the original MA was designed to solve problems with continuous variables. Thus, the first hurdle in setting up a problem for solution by the MA is working out how best to encode the possible solutions. Since real-value and binary coding methods have various kind of drawbacks, the dual-structure coding method[30] is adopted here for the representation of design variables in the NMA.

Let the ordered pair (x, c) stand for the possible solutions of each monkey, where x denotes the position vector in the NMA and c means the binary vector which represents the sensor's location. If the value of the jth bit position of the vector c_i is 1, it implies that a sensor is located on the jth positions. In contrast, if the value of the jth bit position is 0, it represents that no sensor is located on the jth positions. The outline of solution representation using dual-structure coding method is given as follows:

Step 1: Suppose there be f candidate sensor positions (i.e. the total DOFs of the developed finite element (FE) model), thus the f integers from $1 \sim f$ can be obtained.

Step 2: For the monkey i in the monkey population, its solution of sensor placement problem can be denoted as $xc_i = (x_i, c_i) = \{(x_{i,1}, c_{i,1}), (x_{i,2}, c_{i,2}), \dots, (x_{i,f}, c_{i,f})\}$, in which the component of the position vector x_i is the real number selected randomly from the interval [down, up], where down $= -5$ and up $= 5$, and c_i is the binary vector which can be obtained by the following equation[30]:

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

When using Eq. (1), a judgment threshold ε should be defined first. That is, if $\mathrm{sig}(x_{i,j}) \leq \varepsilon$, then $c_{i,j} = 0$; if $\mathrm{sig}(x_{i,j}) > \varepsilon$, then $c_{i,j} = 1$, here $j \in \{1, 2, \ldots, f\}$. In this paper, the ε is defined as 0.5, thus when selecting each component of x_i randomly from the interval $[-5, 5]$, it can be seen that $0.0067 \leq \mathrm{sig}(x_i) \leq 0.9933$ and $\mathrm{sig}(0) = 0.5$ which proves that the judgment threshold given here is practical.

3.2. *Population initialization*

Population initialization is a crucial task in the MA because it will affect the convergence speed and the quality of the final solution. However, the original random initialization process in the MA may generate similar positions for different monkeys (i.e. similar scheme of sensor placement). Considering that the chaotic map having the characteristics of certainty, ergodicity and randomicity,[31] it is suitable to initialize the monkey population for the purpose of increasing the population diversity and achieving high-quality solutions. Thus, a chaos-based approach is suggested to initialize the population of the NMA (i.e. generate chaos variables from the interval [down, up] as the initial population).

The chaos is a universal natural phenomenon and can be generated by the following logistic equation[31]:

$$h_j = \mu \times h_{j-1} \times (1 - h_{j-1}), \tag{2}$$

where μ is a control parameter, h_i is a chaos variable, and $i = 1, 2, \ldots$, especially, it behaves as a chaotic dynamics when $\mu = 4$ and $h_0 \notin \{0, 0.25, 0.5, 0.75, 1\}$.

Thus, for the monkey i with the position x_i, the outline of population initialization using the principle of chaos is listed as follows:

Step 1: Set the initial chaos variable h_0;
Step 2: Generate the chaos variable j of the monkey i using Eq. (2);
Step 3: Calculate the variable j in the position vector of the monkey i using the following equation:

$$x_{i,j} = \mathrm{down} + h_j \times (\mathrm{up} - \mathrm{down}), \tag{3}$$

where $j \in \{1, 2, \ldots, f\}$.

Step 4: Repeat Steps 1–3, until $F = M \times N$ monkeys are generated (F is defined as the population size of monkeys, N and M represent numbers of niches and monkeys in each niche, respectively).

In the following iterative process of the proposed NMA, the position vector x_i is used first; then Eq. (1) is adopted to obtain the binary vector c_i which is subsequently used to calculate the optimal objective value (fitness value); as a consequence, each monkey will arrive at its own best position representing the personal optimal objective value $f(x_i, c_i)$ when the iteration accuracy has been achieved or a relative large number of iterations has been reached.

Remark 1. It has to be noted that the total number of sensors in c_i may not be equal to the sensor number sp after the initialization process. It is impractical and must be avoided. In this paper, the initial monkey population is generated by the regeneration method when encountering this issue, i.e. go back to Step 2.

3.3. *Niche generation operation*

The analogy with nature is straightforward, as in an ecosystem there are different niches that contain many diverse species. Thus, after the monkey population initialization, the whole population is classified to form the niches according to the similarity between monkeys. Similarity can be estimated using the Hamming distance for binary coded variables, the Euclidian distance for real coded variables or any other defined measure. The number of monkeys in a niche is determined by its resources and by the efficiency of each individual in taking the profit of these resources.

For a monkey i ($i \leq N$) with the position x_i, which was randomly selected from the whole population, a niche can be created as follows:

Step 1: Calculate the Hamming distance $d_{i,j}$ $(j \neq i)$ between the monkey i and other monkeys. Taking the jth monkey x_j as an example, $d_{i,j}$ can be obtained using the following equation[32]:

$$d_{i,j} = ||c_i - c_j|| = \sum_{k=1}^{f} ||c_{i,k} - c_{j,k}||, \tag{4}$$

where c_i and c_j represent the binary vector of monkeys i and j, respectively. If the k bit position of the vectors c_i and c_j is the same, $||c_{i,k} - c_{j,k}|| = 0$; otherwise $||c_{i,k} - c_{j,k}|| = 1$.

Step 2: Select $M - 1$ monkeys whose Hamming distances are the smallest to create a niche with the monkey i.

Step 3: Repeat Steps 1 and 2, until N niches are generated.

3.4. *Modified climb process*

The climb process is the main process to search the local optimal solution in the MA, which step-by-step changes the monkeys' positions from the initial positions to new ones that can make an improvement in the objective function. After the niche generation operation, each niche is used to search the space in different directions in parallel. Keeping the existing problems in view, the climb process in the original MA is significantly modified using the niching techniques. The modified climb process includes three parts, which is summarized as follows:

(1) Initial climb process

For the monkey i with the position $x_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,f})$ in a niche, an outline of initial climb process is given as follows:

Step 1: Randomly generate integers Δx_{ij} in the interval $[-a, a]$, $j \in \{1, 2, \ldots, f\}$, and form an integer vector $\Delta x_i = (\Delta x_{i1}, \Delta x_{i2}, \ldots, \Delta x_{if})^T$, where the parameter $a(a > 0)$ is called the step length of the initial climb process.

Remark 2. The parameter a plays a key role in the precision of approximation of local solution in the iteration process. Usually, the smaller the a is, the more precise the solutions are. Considering the characteristics of sensor placement problem, a should be defined as 1, 2, or another positive integer.

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 $f(x_{\text{new1}}, c_{\text{new1}})$ and $f(x_{\text{new2}}, c_{\text{new2}})$, 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 $f(x_{\text{new1}}, c_{\text{new1}})$ and $f(x_{\text{new2}}, c_{\text{new2}})$ is better than $f(x_i, c_i)$, otherwise keep x_i unchanged.

Remark 3. It should be noted that the "spillover" phenomenon may occur in Step 2 and the following other steps sometimes (i.e. the new components in $x_i + \Delta x_i$ or $x_i - \Delta x_i$ may exceed the interval [down, up]). Thus, here if a new component exceeds the upper limit up, then take the component to up; if a new component below the lower limit down, then take the component to down.

Step 3: Repeat Steps 1 and 2 until the maximum allowable number of iterations (called the initial climb number, denoted by $Nc1$) has been reached.

(2) Fitness sharing mechanism

At present, various niche techniques, such as the clustering-based methods, fitness sharing methods, clearing method and crowding methods, have been proposed and applied successfully to global optimization problems. Among them, the fitness sharing[33] is the best known and the most widely used method, which modifies the search space by reducing the fitness of an individual in densely populated regions. Thus, using this scheme, it is ideal for the NMA to maintain the population diversity of its monkeys in a searching domain.

The fitness sharing consists in the reduction of the fitness of a monkey proportionally to the number of nearby monkeys. The shared fitness value F_i of the ith individual is given by[33]

$$F_i = f_i / \sum_{j=1}^{M} \text{sh}(d_{i,j}), \tag{5}$$

where f_i is the original fitness of the ith monkey; M and d_{ij} are the population size and the Hamming distance between monkeys i and j, respectively; and the share function that quantifies this proximity is the following:

$$\mathrm{sh}(d_{i,j}) = \begin{cases} 1 - (d_{i,j}/R)^{\alpha} & \text{if } d_{i,j} < R, \\ 0 & \text{otherwise,} \end{cases} \tag{6}$$

where R and α are the pre-defined constants. The first constant R is called the niche radius requiring knowledge of the search space to be properly chosen. Generally it is estimated on a trial and error basis. The second constant, α, is generally set to 1.0, so that the function is linear.

The fitness sharing mechanism in a niche is described as follows:

Step 1: Calculate the sharing function value F_i for each monkey in a niche after the initial climb process.
Step 2: Sort F_i in descending order according to their sharing function values and remove the first one.
Step 3: Generate a new monkey randomly and add it to the niche.

(3) Interactions between the niches

Although the aforementioned fitness sharing mechanism can effectively maintain the population diversity of the monkeys in niche, there is no communication between the niches. In order to promote interactions among the niches, a new scheme called "replacement" is adopted here. As the replacement occurs, the information about different regions of the search space is exchanged between the best and worst niches, providing the worst monkey valuable information from the best monkey that holds valuable knowledge, which can enhance the exploitation capability significantly. The corresponding "replacement" procedure is shown below:

Step 1: Evaluate the fitness value for each monkey in every niche and the average fitness value for each niche.
Step 2: Rearrange the niches in order according to their average fitness values.
Step 3: Replace the worst monkey of the niche which has the worst average fitness value with the best monkey of the niche which has the best average fitness value.

Thus, an outline of the modified climb process in the proposed NMA can be summarized as follows:

Step 1: Initialize the parameters in climb process and define a suitable niche radius R.
Step 2: Carry out the initial climb process.
Step 3: Apply the sharing function mechanism to every niche.
Step 4: Execute the replacement scheme between the niches.
Step 5: Repeat Steps 2–4 until it has implemented Nc generations.

3.5. *Watch-jump process*

After the climb process, each monkey arrives at its own mountain top. And then it is natural to have a look and to find out whether there are other mountains around it higher than its present position. If yes, it will jump there from the current position (called "watch-jump process") and then repeat the climb process until it reaches the top of the mountain.

For the monkey i with the position $x_i = (x_{i,1}, x_{i,2}, ..., x_{i,f})$ in a niche, the outline of the proposed watch-jump process is as follows:

Step 1: Randomly generate integer numbers xw_{ij} from $[x_{ij} - b, x_{ij} + b]$, $j \in \{1, 2, \ldots, f\}$, where the parameter b is a positive integer which represents the eyesight of the monkey (i.e. the maximal distance that the monkey can see), thus the new position $xw_i = (xw_{i,1}, xw_{i,2}, \ldots, xw_{i,f})^T$ can be obtained.

Remark 4. Usually, the bigger the feasible space of optimal problem is, the bigger the value of the parameter b should be taken. The eyesight b can be determined by specific situations, like the step length a, the eyesight b should also be defined as 1, 2, or other positive integer in the sensor placement problem.

Step 2: Calculate the objective function $f(xw_i, c_{new_i})$, update the monkey's position x_i with xw_i provided that $f(xw_i, c_{new_i})$ is better than $f(x_i, c_i)$, otherwise go back to Step 1.

3.6. *Somersault process*

The main purpose of somersault process is to enable monkeys to find out new searching domains. In the MA, the barycenter of all monkeys' current positions is selected as a pivot. And then the monkeys will somersault along the direction pointing to the pivot.

For the monkey i with the position $x_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,f})$, the outline of the proposed somersault process is as follows:

Step 1: Generate integer numbers θ randomly from the interval $[c, d]$ (called the somersault interval which governs the maximum distance that monkeys can somersault).

Step 2: Obtain the monkeys' pivot $p = (p_1, p_2, \ldots, p_f)^T$ by calculating all the monkeys' barycenter $p_j = \sum_i^M x_{ij}/M$, $j \in \{1, 2, \ldots, f\}$.

Step 3: Calculate $xs_{i,j} = x_{i,j} + \text{round}(\theta|p_j - x_{i,j}|)$, where the round denotes rounding function, update the monkeys' position with $xs_i = (xs_{i,1}, xs_{i,2}, \ldots, xs_{i,f})$ provided that the new objective values of xs_i are better than former one, and then return to the climb process; otherwise go back to Step 1.

If the predefined stopping condition (generally the maximum number of generations specified in which there is no improvement in the objective function) is met,

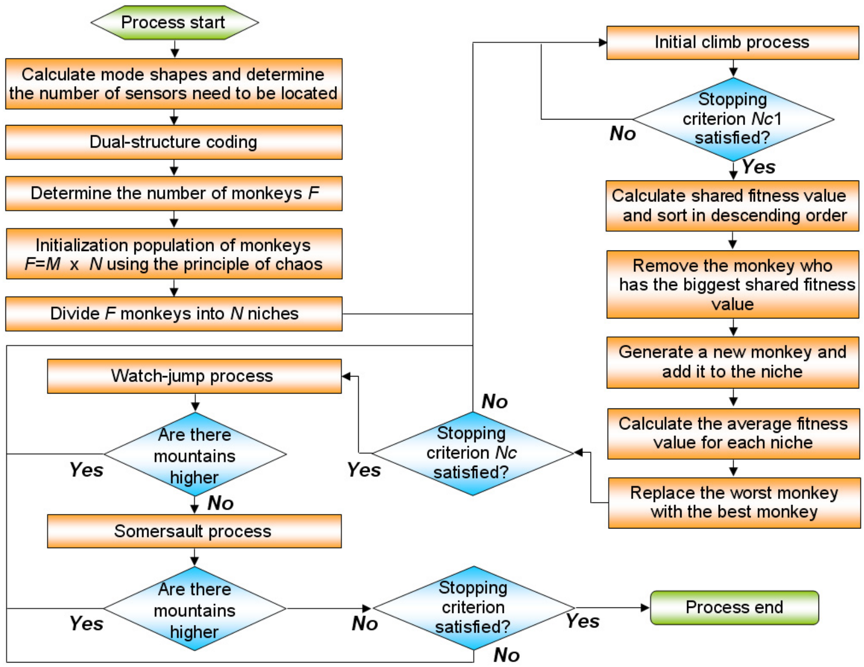


Fig. 2. Flowchart of proposed NMA for sensor placement.

the NMA iteration is stopped, and return the best solution in a niche. Figure 2 demonstrates the whole procedure of the proposed NMA to find the optimal sensor locations presented herein. The procedure can be fully implemented easily with the high-level technical computing language MATLAB.[34]

4. Objective Function

The quality of sensor network designs is evaluated according to an objective function, i.e. the fitness function, which must be formulated in relation to the specific optimization problem. In the case under investigation the objective function is the MAC.[16] The MAC is defined as Eq. (7), which measures the correlation between mode shapes, small maximum off-diagonal element of the MAC matrix indicates the less correlation between corresponding mode shape vectors, and renders them discriminable from each other[16]:

$$\mathrm{MAC}_{ij} = \frac{(\Phi_i^T \Phi_j)^2}{(\Phi_i^T \Phi_i)(\Phi_j^T \Phi_j)}, \tag{7}$$

where Φ_i and Φ_j represent the ith and jth column vectors in the matrix Φ, respectively, and the superscript T denotes the transpose of the vector.

The reason for the selection of this criterion is that the MAC matrix will be diagonal for an OSP strategy, so the size of the off-diagonal elements can be defined as an indication of fitness. Thus, the objective function can be constructed as follows:

$$f(x, c) = \max_{i \neq j} \{\mathrm{MAC}_{ij}\}. \tag{8}$$

5. Demonstration Cases

In order to demonstrate the superiority and also the computational performance of the proposed NMA, two cases to determine the optimal sensor network on a high-rise structure are taken into account.

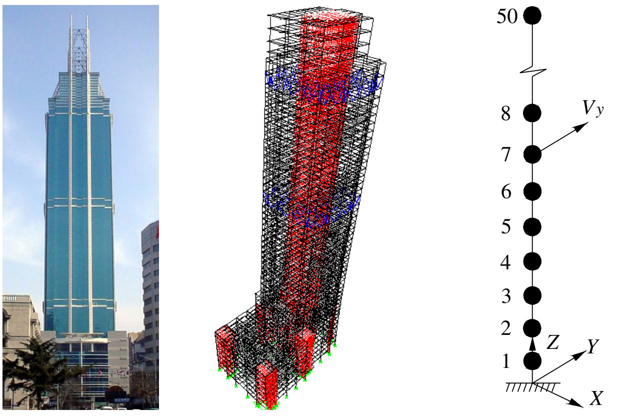
Case 1: The original MA with the dual-structure coding (called the SMA);
Case 2: The proposed NMA.

5.1. *Dalian world trade building*

The Dalian World Trade Building (DWTB), located in Dalian, China, is a super-high-rise structure with a height of 242 m, consisting of a 201.9 m high main structure and a 40.1 m antenna mast, as shown in Fig. 3(a). It has four stories under the ground level and 50 stories above. The structural system utilizes both steel and reinforced concrete, including core wall systems and perimeter steel frame coupled by outrigger trusses at two levels (the 30th and 45th floors). Up to now, the building has still been the tallest in the northeast of China.

(1) Calculation model for DWTB

In order to provide input data for the proposed NMA, a precise 3D full FE model of the building is developed using the ETABS software,[35] as shown in Fig. 3(b).[36] The model contains 13,324 node elements, 90,062 frame elements and 22,967 shell elements in total. In the model, the "Frame Element" is employed to simulate the beams and columns, the "Shell Element" is used to model the slab and core wall, and the "Link Element" is adopted to simulate the supporting of building. In this paper, only translational DOFs are considered for possible sensor installation, as rotational DOFs are usually difficult to measure in the on-site test. In addition, the structural modes only in the weak axis are taken into account for the sensor placement since the structural stiffness of the DWTB in two translational directions is different. Consequently, a total of 50 DOFs are available for the sensor installation (Fig. 3(c)). The nodal number increases from 1 at the fixed base to 50 at the free top end. With this model, the modal analysis is carried out, and the first 10 mode shapes of the DWTB are selected for calculation. Here, it is assumed that the number of sensors (accelerometer) need to be placed on the building is 20 which have been made and thus optimal locations for the given number of sensors is the target of this paper.



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

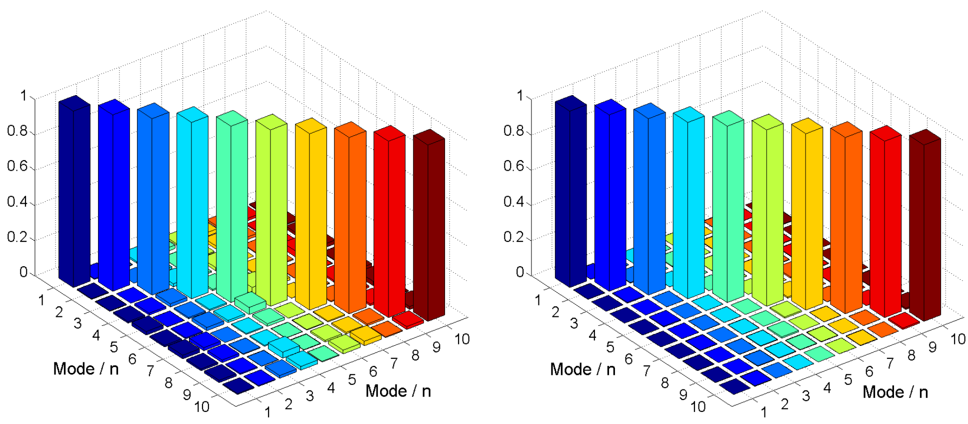
Fig. 3. The DWTB and its FE model.

(2) Optimization results and comparison

Like other swarm intelligent algorithms, the proposed NMA requires adjustable tuning parameters. The important tuning parameters are the overall modified climb process number (Nc), the initial climb number ($Nc1$) and the niche radius (R). In the process of parametric analysis, the basic parameters of NMA remain unchanged and listed as follows: $h_0 = 0.2$, $a = 1$ and $b = 2$, the somersault interval is defined as $[-3, 3]$, $M = 3$ and $N = 3$. By the orthogonal experimental design, the orthogonal table can be obtained as shown in Table 1, where the numbers in brackets are level. It can be noted that: (1) the larger Nc, the higher quality is achieved, but usually more iterations are needed for the algorithm to find the optimal solution. (2) Large number of iterations in the initial climb process ($Nc1$) could cause the improvement of results to some extent. However, this trend is not always very obvious since the

Table 1. Empirical study of the impact of different parameters on the solution quality.

	Different settings of three important parameters			
Scenario	Nc	$Nc1$	R	Objective values
1	1 (50)	1 (10)	1 (20)	0.0125
2	1 (50)	2 (20)	2 (25)	0.0136
3	1 (50)	3 (40)	3 (30)	0.0140
4	2 (100)	1 (10)	2 (25)	0.0088
5	2 (100)	2 (20)	3 (30)	0.0078
6	2 (100)	3 (40)	1 (20)	0.0083
7	3 (200)	1 (10)	3 (30)	0.0092
8	3 (200)	2 (20)	1 (20)	0.0099
9	3 (200)	3 (40)	2 (25)	0.0070



(a) SMA

(b) NMA

Fig. 4. MAC values obtained by SMA and NMA.

original climb process has two main drawbacks including the premature convergence and weak exploitation capabilities. (3) The niche radius has a significant impact on the improvement of results, which confirms that adopting the niching techniques can effectively lead to the increase in the solution quality. Based on this empirical study, it can be found that the parameters Nc, $Nc1$ and R for the NMA here can be set as 100, 20 and 30, respectively. The parameters settings for the SMA are the same as those of NMA.

Figure 4 demonstrates the MAC values obtained by the SMA and NMA, respectively. The corresponding objective function values of each kind of sensor placement scheme are shown in Table 2. A close look at the results given in Fig. 4 indicates that the proposed NMA can yield optimal sensor locations compared to the SMA. Examining Fig. 4(a), one can see that a number of off-diagonal elements are fairly large. The largest off-diagonal MAC term is 0.0399 for the SMA, whereas 0.0078 for the NMA, which denotes the computational performance of the NMA that has been effectively improved by adopting the niching techniques and 80.45% reduction is gained to reach a satisfactory solution. In order to clearly demonstrate the superiority of the proposed NMA, comparisons with maximum MAC off-diagonal value in each of the modes have been made with the SMA and NMA, which are illustrated in Fig. 5. From Fig. 5, it can be easily found that the NMA is far superior to the SMA implementations in finding the optimal sensor locations. All of the

Table 2. 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	0.0078

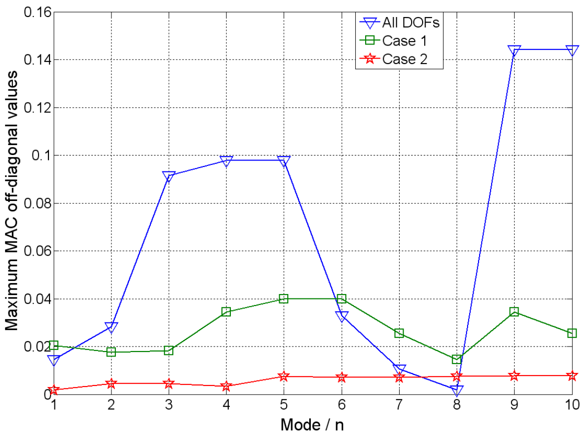


Fig. 5. Maximum MAC off-diagonal value in each of the modes.

Table 3. Sensor placements of the DWTB determined by NMA.

Sensor no.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Nodes	1	3	4	5	6	8	10	13	16	20	23	27	28	31	35	36	40	43	45	48

maximum MAC off-diagonal values obtained by the NMA are much smaller than the SMA. In addition, Fig. 5 shows that some off-diagonal terms of the "All DOFs" (i.e. MAC matrix for the full sensor set) are quite large compared to other two algorithms. This phenomenon means that some row vectors may be nearly a linear combination of other row vectors of the mode shape matrix specified by redundant sensors. A conclusion can be drawn from this phenomenon is that the full sensor set for the sensor placement may be not as good as expected for the MAC criteria. Table 3 shows the optimal sensor locations obtained using the proposed NMA.

6. Conclusions

This paper presents a new hybrid algorithm called the NMA for the optimal selection of sensor location on large-scale structures. Considering the characteristics of the OSP, some innovations in the MA such as the population initialization, niche generation operation, fitness sharing mechanism and replacement scheme were proposed to maintain the population diversity and alleviate premature convergence of the algorithm. Some conclusions are summarized as follows:

(1) Owing to the randomness and sensitivity dependence on the initial conditions of chaotic maps, a chaos-based approach instead of a pure random initialization is proposed to initialize the monkey population so that the search space information can be extracted to increase the population diversity in the proposed NMA.

(2) The limitation in the performance of the MA is overcome by the niching techniques that creates and maintains several niches within the search space. Compared with the distributed multi-population approach, the uniqueness of NMA lies in the fact that they preserve not only the highly-fit monkeys, but also weaker monkeys so long as they are not similar ones. This gives the population an opportunity to pass the information of such monkeys to their offspring, and it ensures that the diversity in the monkey population is kept well.
(3) In order to promote interactions among the niches, a new scheme called "replacement" is presented in the NMA, which makes information about different regions of the search space exchanged between the best and worst niches, providing the worst monkey valuable information from the best monkey that hold valuable knowledge, which can enhance the exploitation capability effectively.
(4) Numerical studies have been carried out to validate and also demonstrate the efficacy of the proposed NMA by considering a high-rise structure. Comparison has been made between the original MA and NMA in detail. It is found that the sensor locations obtained using the NMA are far superior to the MA although both methods have been capable of providing satisfactory results.

Acknowledgments

This research work was jointly supported by the National Natural Science Foundation of China (Grant No. 51222806, 51121005, 51327003), and the Fundamental Research Funds for Central Universities (Grant No. DUT13YQ105).

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