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Research Article

Optimal Sensor Placement for Health Monitoring of High-Rise Structure Based on Genetic Algorithm

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Optimal sensor placement (OSP) technique plays a key role in the structural health monitoring (SHM) of large-scale structures. Based on the criterion of the OSP for the modal test, an improved genetic algorithm, called "generalized genetic algorithm (GGA)", is adopted to find the optimal placement of sensors. The dual-structure coding method instead of binary coding method is proposed to code the solution. Accordingly, the dual-structure coding-based selection scheme, crossover strategy and mutation mechanism are given in detail. The tallest building in the north of China is implemented to demonstrate the feasibility and effectiveness of the GGA. The sensor placements obtained by the GGA are compared with those by exiting genetic algorithm, which shows that the GGA can improve the convergence of the algorithm and get the better placement scheme.

1. Introduction

Civil engineering structures, particularly high-rise structures, are especially susceptible to random vibrations, whether they are due to large ground accelerations, strong wind forces, or abnormal loads such as explosions [1]. Research activities in the last few years have been focused on making use of the significant technological advances in sensing and communication technology to enhance safe measures in these important structures. Structural health monitoring (SHM) research represents the integration domain of these efforts striving to enhance the safety and prolong the service life of infrastructures [2]. In general, a typical SHM system includes three major components: a sensor system, a data processing system (including data acquisition, transmission, and storage), and a health

evaluation system (including diagnostic algorithms and information management) [3]. The sensors utilized in the SHM are required to monitor not only the structural status including stress, displacement, and acceleration but also those influential environmental parameters, such as wind speed, temperature, and the quality of its foundation. Since a large number of sensors are involved in a health monitoring system, how to optimally deploy them in a large and spatially extended structure so that the data acquired from those locations will result in the best identification of structural characteristics is a challenging task. On the other hand, high cost of data acquisition systems (sensors and their supporting instruments) and accessibility limitation constrain in many cases the wide distribution of a large number of sensors on a structure.

As known, finding the rational sensor locations is a complicated nonlinear optimization problem, and the global optimal solution is often difficult to obtain [4, 5]. For a structure that has simple geometry or smaller number of degrees of freedom (DOF), the experience and a trial-and-error approach may suffice to solve the problem. For a large-scale complicated structure, whose finite element (FE) model may have tens of thousands of DOFs, a systematic and efficient approach is needed to solve such a computationally demanding problem. Numerous techniques have been advanced for the optimal sensor placement (OSP) problem and are widely reported in the literature [6]. These have been developed using a number of approaches and criteria, some based on intuitive placement or heuristic approaches, others employing systematic optimization methods. Among them, one of the most significant and commonly cited OSP approaches called the effective independence method (EfI) used for the structural monitoring was developed by Kammer in 1991 [7]. In the recent years, computational intelligence approaches have been applied to optimal sensor placements. Genetic algorithm (GA) based on the theory of biological evolution is one example. Yao et al. [8] took GA as an alternative to the EFI method, and the determinant of the FIM is chosen as the objective function. Worden and Burrows [9] reviewed the recent work on sensor placement and applied the GA and the simulated annealing to determine the optimal sensor placement in structural dynamic test. GA has been proved to be a powerful tool for OSP, but it still has some faults that need to be improved [10, 11]. When GA is used to solve OSP, the general crossover and mutation operators may generate chromosomes which do not satisfy the constraints. Another drawback of the GA is that it may spend much time on complex optimization problems as a result of the repeated evolution of the objective function and the population. Some attempts have been made to overcome the faults of the GA. For example, Liu et al. [12] proposed to code the solution by the decimal two-dimension array coding method instead of binary coding method. The results of a computational simulation of a 12-bay plain truss model showed that proposed GA can enlarge the genes storage and improve the convergence of the algorithm. Javadi et al. [13] presented a hybrid intelligent GA which is based on a combination of neural network and GA. Hwang and He [14] use simulated annealing and adaptive mechanism to insure the solution quality and to improve the convergence speed. In order to improve the convergence speed and avoid premature convergence, virus evolutionary theory [15, 16] was introduced into parthenogenetic algorithm. A kind of virus coevolutionary parthenogenetic algorithm, which combined a parthenogenetic algorithm with virus evolutionary theory, was proposed by Kang et al. [17] to place sensors optimally on a large space structure for the purpose of modal identification.

This paper is aimed at adopting a kind of the improved GA called the generalized genetic algorithm (GGA) that could be used practically by engineers to solve the OSP problem. The remaining part of the paper is organized as follows. Section 2 gives the basic

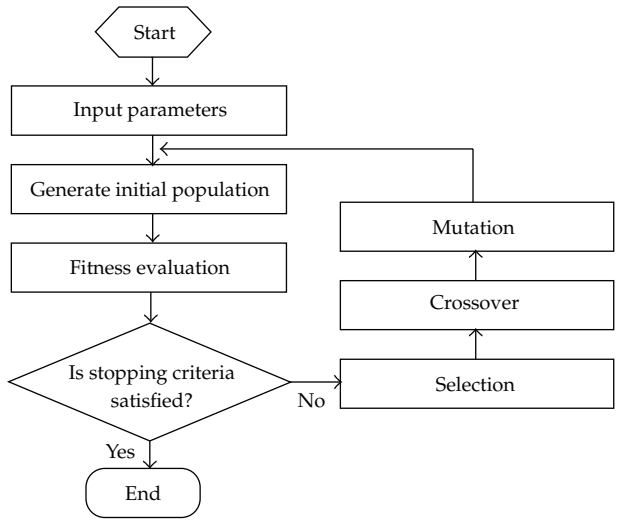


Figure 1: Flowchart of the GA.

theory of the improved GA including the selection of the fitness function, the presented coding system, and genetic operators. In the following section, the effectiveness of the proposed scheme is demonstrated via a numerical simulation study and also compared to the simple GA. Finally, a few concluding remarks are given.

2. GA Methods for the Sensor Placement Problem

The sensor placement optimization can be generalized as follows: "given a set of n candidate locations, find the subset of m locations, where $m \leq n$, which may provide the best possible performance" [18]. The problem is a kind of combinatorial optimization problem. Civil engineers have developed lots of methods for determining an arrangement of sensors suitable for characterizing the dynamic behavior of the structure. Among the methods, the GA is an effective one due to its many advantages over classical optimization techniques as it is blind search method and highly parallel.

Inspired by Darwin's theory of evolution, the GAs try to imitate natural evolution by assigning a fitness value to each candidate solution of the problem and by applying the principle of survival of the fittest [19]. Their basic components are the representation of candidate solutions to the problem in a "genetic" form, the creation of an initial, usually random population of solutions, the establishment of a fitness function that rates each solution in the population, the application of genetic operators of selection, crossover, and mutation to produce new individuals from existing ones, and finally the tuning of the algorithm parameters like population size and probabilities of performing the prementioned genetic operators. Figure 1 briefly illustrates the procedures of the GA.

GA has been proved to be a powerful tool for OSP, but it also has some faults that need to be improved. For example, two or more sensors may be placed in one sensor location or sensor number is not equal to a certain number [10]. In order to improve the convergence speed and avoid premature convergence, a kind of generalized genetic algorithm (GGA) [19] is adopted here. The GGA is based on some modern biologic theories such as the

genetic theory by Morgan, the punctuated equilibrium theory by Eldridge and Gould, and the general system theory by Bertalanffy. So it is superior in biologics to the classical GA. The GGA could be described by applying the crossover on the two parents selected from the initial population, yielding two individuals with best fitness values from the four individuals, of which two were present before crossover and two were created after crossover (i.e., two-quarter selection), eliminating the two individuals with worst fitness values, applying the mutation on the two remains and using two-quarter selection on the four individuals according to the fitness values, and finally the next generation is produced by N/2 times repeating the above steps.

The difference between the GGA and simple genetic algorithm (SGA) mainly exists in the evolutionary process. In short, the evolutionary process of the SGA is as follows.

Two-parent selection · crossover · mutation · survival selection · next generation

While the process of the GGA is as follows.

Two-parent selection · crossover · a family of four · two-quarter selection · mutation · a family of four · two-quarter selection · next generation

It can be found that the two-quarter selection is introduced in the GGA. The parents are allowed to compete with the children during the process of crossover and mutation, and only the best one could enter next competition, which can ensure the stability of iterative procedure and complete the function of realizing global optimum. In addition, the crossover and mutation of GGA have little difference with the SGA. In the SGA, the crossover may operate according to a certain probability, while, for the GGA, since the parents are certain to join in the competition, the crossover probability remains 1. The evolutionary process of the GGA has two stages: the gradual change and sudden change. During the gradual change, the local optimum could be achieved mainly by crossover and selection in which the single-point crossover and swap mutation are generally used and the sequence of operations is first crossover and then mutation. In the sudden change, the global optimum may be reached mainly by the mutation and selection which realize the escape from one local optimum to better local optimum, in which the uniform crossover and inversion mutation are mainly used and the sequence of operations is first mutation and then crossover.

2.1. Dual-Structure Coding Method

From the view of mathematics, the OSP is a kind of particular knapsack problem, which places specified sensors at optimal locations to acquire more structural information. Its mathematic model is a 0-1 programming problem, if the value of the jth gene code is 1; it denotes that a sensor is located on the jth DOF. In contrast, if the value of the jth gene code is 0, then it denotes that no sensor is placed on the jth DOF. The total number of 1 in a chromosome is equal to the sensor number [20]. As known, most commonly the design variables are coded by the simple one-dimensional binary coding method that is very simple and intuitionistic. However, the number of 1 will be changed in the crossover and mutation (i.e., the number of sensors will be changed), which cannot meet the demand of the OSP. Here, a dual-structure coding GA is adopted to overcome this problem.

The dual-structure coding method is shown in Table 1. The chromosome of individual is composed of two rows, where the upper row $s(i)$ denotes the append code of x_j, and $s(i) = j$, and the lower row represents the variable code $x_{s(i)}$ corresponding to append $s(i)$. When coding certain individuals, the shuffle method is firstly used to produce stochastic $\{s(i), (i = 1, 2 \ldots n)\}$ and list on the upper row, then the variable code (0 or 1) is generated randomly. From Table 1, one can easily find that, in dual-structure coding, the genetic operators may

Table 1: Dual-structure coding method.

Append code	$s(1)$	$s(2)$	$s(3)$	$\cdots$	$s(i)$	$\cdots$	$s(n)$
Variable code	$x_{s(1)}$	$x_{s(2)}$	$x_{s(3)}$	$\cdots$	$x_{s(i)}$	$\cdots$	$x_{s(n)}$

Table 2: Example of a dual-structure coding method.

4	3	5	8	6	10	2	7	9	1
0	1	1	0	1	0	0	1	0	1

only operate on upper append code and the lower variable value of offspring is fixed. This means that the number of sensors can be unchanged.

For example, an OSP problem with 10 sensors and the randomly generated order of append code is (4, 3, 5, 8, 6, 10, 2, 7, 9, 1); therefore, the dual-structure code is presented as shown in Table 2. It corresponds to a feasible solution, namely, the sensors are located on the third, fifth, sixth, seventh, and first DOFs.

2.2. Fitness Function

In the case under investigation, the fitness function is a weighting function that measures the quality and the performance of a specific sensor location design. This function is maximized by the GA system in the process of evolutionary optimization. As known, the measured mode shape vectors in the SHM have to be as much as possible linearly independent, which is a basic requirement to distinguish measured or identified modes. Moreover, the linear independency is particularly important when the test results are to validate or to update the FE model. The simple way to check this linear dependence of mode shapes is to calculate the modal assurance criterion (MAC) [21]. The MAC without mass weighting is just to compare the direction of two vectors. When two vectors lie in the same direction or near, the MAC value or the correlation coefficient is one or approximately one. To check the off-diagonal terms of the MAC matrix formed by the mode shapes identified or computed from finite element model provides an indication to which degree the truncated mode shape vectors are linearly independent. Therefore, the fitness functions presented in this paper are constructed by the MAC, that is, the biggest value in all the off-diagonal elements in the MAC matrix. The reason for the selection of this kind of fitness function is that the MAC matrix will be diagonal for an optimal sensor placement strategy so the size of the off-diagonal elements can be taken as an indication of the fitness.

The MAC can be defined as in (2.1), which measures the correlation between mode shapes:

$$\mathrm{MAC}_{ij} = \frac{\left(\Phi_i^T \Phi_j\right)^2}{\left(\Phi_i^T \Phi_i\right)\left(\Phi_j^T \Phi_j\right)} = \frac{a_{ij}^2}{a_{ii} a_{jj}}, \tag{2.1}$$

where Φ_i and Φ_j represent the ith and jth column vectors in matrix Φ, respectively, and the superscript T denotes the transpose of the vector. In this formulation, the values of the MAC range between 0 and 1, where zero indicates that there is little or no correlation between the off-diagonal elements MAC_{ij} $(i \neq j)$ and one means that there is a high degree of similarity between the modal vectors.

Then the MAC fitness function is given as

$$f = 1 - \max\left(\operatorname{abs}\left(\mathrm{MAC}_{ij}\right)\right), \quad i \neq j, \tag{2.2}$$

where abs(·) represents the absolute value and max(·) denotes the maximal value.

2.3. Genetic Operators

2.3.1. Selection Scheme

The first step in the GGA is to create an initial population of randomly generated individuals. The "group in group" scheme is used here; that is, for the initially generated population of N individuals, a small size population of k individuals (called leading population) which are the best ones in current population is simultaneously defined; to ensure the diversity of the leading population, the individuals of the leading population are different from each other and the residual n-k individuals are called supporting population. Selection is the process of choosing the fittest string from the current population for use in further reproductive operations to yield fitter generations. In different population, the different selection mechanism is used. In leading population, the roulette wheel selection (RWS) scheme is used. As in supporting population, the stochastic universal sampling (SUS) method is adopted.

2.3.2. Crossover Strategy

The crossover is the process whereby new chromosomes are generated from existing individuals by cutting each old chromosome at a random location (crossover point) and replacing the tail of one string with that of the other. In this paper, the order crossover (OX) method is applied. The OX involves two parents creating two children at the same time. This operator allows the order in which the parts are placed into the creation vat to be changed.

2.3.3. Mutation Mechanism

The crossover enables the method to extract the best genes from different individuals and recombine them into potentially superior children. The mutation is a random process whereby values of element within a genetic string is changed. Considering that there are gradual change and sudden change in the GGA, the swap mutation and inversion mutation are used herein. The mutation process adds to the diversity of a population and thus reduces the chance that the optimization process will become trapped in local optimal regions.

To sum up, the whole flowchart of the genetic search to find the optimal sensor locations presented in this paper is shown in Figure 2.

3. Demonstration Case

To demonstrate the possible enhancement of the GGA compared to the SGA by optimally allocating the sensors across the structure, a case study to determine the optimal sensor locations on a high-rise building is given here.

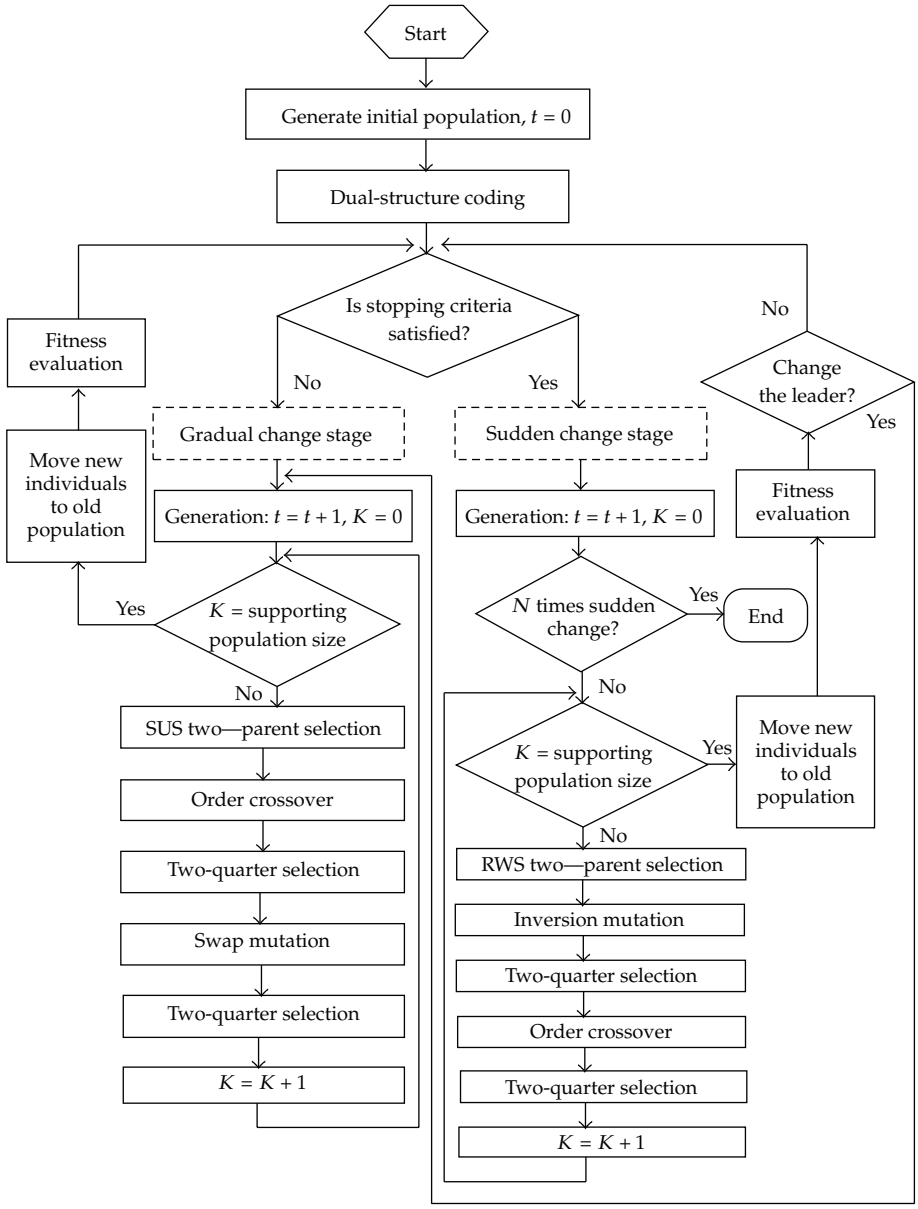
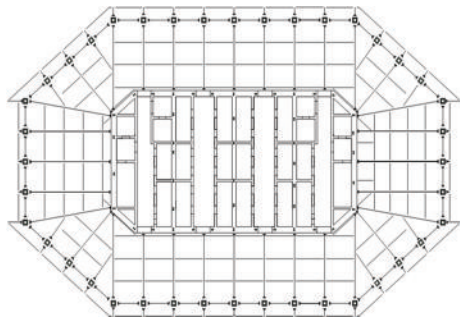


Figure 2: Flowchart of the dual-structure coding based GGA.

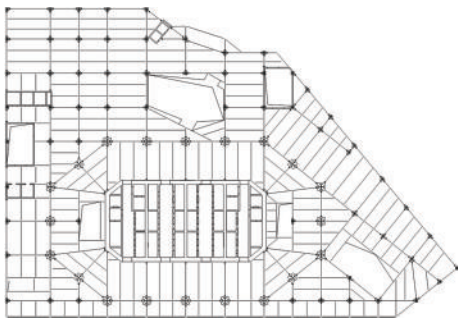
3.1. Dalian International Trade Mansion

The Dalian International Trade Mansion (DITM), currently being constructed in the centre of Dalian city, when completed in the near future, will be the tallest building in the north of China [22]. It has 5 stories under the ground level and 79 stories above. The main structure is about 330.25 m high from ground level. The plan of a standard floor is 77.70 m long in the east-west direction and 44.00 m wide in south-north direction, and the floor-to-floor height is

(a) Bird view of the Mansion



(b) Standard floor plan



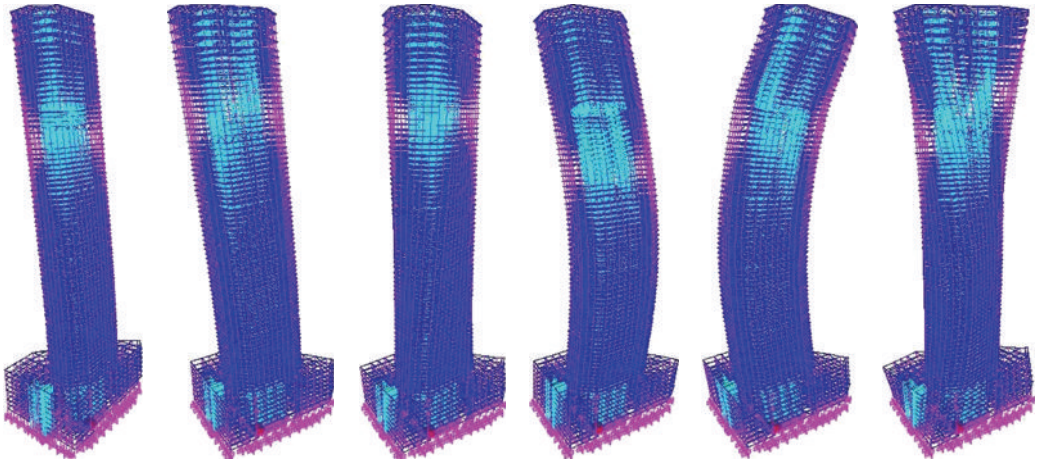
(c) First floor plan

Figure 3: Dalian International Trade Mansion.

3.8 m. The 10th, 23rd, 37th, 50th, 62nd and 79th floors are the refuge floors, with the height of 5.10 m. Figure 3 shows the bird view and standard and first floor plans of the DITM.

3.2. Numerical Model for DITM

In order to provide input data for the OSP method, a three-dimensional FE model of the mansion is built using the ETABS software. The FE model is built considering the bending and shearing deformation of the beam and column and also the axial deformation of the column. The rigid-floor assumption is used. To the strengthened story, for the axial deformation of the column needs to be considered, the corresponding floors are computed as flexible floors. The overall model has 34,308 node elements, 34,791 frame elements and 29,071 shell elements, considering 36 section types and 11 materials' properties. The mesh representing the model



(a) Mode 1 (b) Mode 2 (c) Mode 3 (d) Mode 4 (e) Mode 5 (f) Mode 6

Figure 4: First six mode shapes of the DITM.

Table 3: Calculated periods of DITM using FE model.

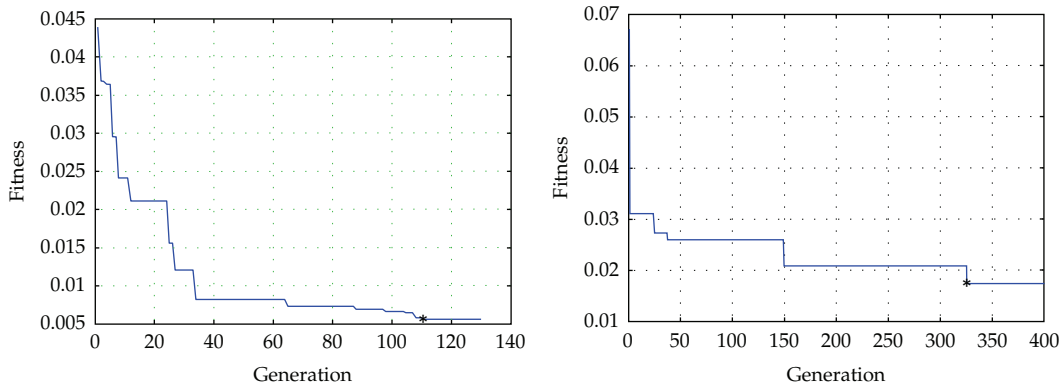
Mode	1	2	3	4	5	6
Period(s)	6.80561	4.94373	2.3094	1.53486	1.34306	0.88573

has been studied and is sufficiently fine in the areas of interest to ensure that the developed forces can be accurately determined. Then, the modal analysis is carried out, the periods of the first 6 modes are listed in Table 3, and the mode shapes are shown in Figure 4.

3.3. Calculation Process and Result Analysis

For the problem at hand, the size of the searching space is the number of nodes on the FE model excluding the constrained nodes and the vibration nodes of the selected modes. Since the structural stiffness of the DITM in two translational directions is obviously different, it should mainly take into account the structural vibration monitoring in the direction of weaker stiffness. On the other hand, although the structure has a large number of DOFs, only translational DOFs are considered for possible sensor installation in the on-site test, as rotational DOFs are usually difficult to measure. Consequently, a total of 79 DOFs are available for sensor installation. In order to improve the results of optimal sensor layout, the first 10 modes of the DITM are selected for calculation.

As known, the GGA has a number of parameters that are problem specific and needs to be explored and tuned so that the best algorithm performance is achieved. These parameters are the population size, leading population size, and number of sudden changes. To find out the most appropriate population size for minimal computation cost, various simulations with different population size have been first done, and population size of 200 has been found to be adequate. In the simulation of the GGA process, the leading population size is defined as one quarter of the population size, and a relative large number of 10 sudden changes are selected to avoid redundant iteration. In order to demonstrate the possible enhancement of the GGA compared to the SGA, the SGA is also used to determine the optimal sensor locations. In the



(a) GGA (b) SGA

Figure 5: Evolution progress of the best fitness value of the GGA and SGA.

Table 4: Comparison of the optimal sensor locations of the GGA and SGA.

Sensor no.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
GGA	4	6	7	9	10	12	13	15	16	29	34	43	45	49	51	60	65	66	75	77
SGA	2	3	6	8	10	11	18	21	23	25	26	32	36	55	57	61	67	68	69	71

calculation of the SGA process, the population size of 200, the crossover rate of 95% (i.e., 95% parents produce their child), and the mutation rate of 5% (i.e., a selected chromosome bit flips in the mutation with a probability 10%) are used.

Suppose that there are 20 one-dimensional accelerators needed to be installed. It should be noticed that due to the nature of the GA method, the results are usually dependent on the randomly generated initial conditions, which means the algorithm may converge to a different result in the parameter space. For the problem considered in this paper, the GGA and SGA processes have been run for 10 times with a different stochastic initial population, and the best result is shown in Figure 5. The optimal locations for the DITM are illustrated in Table 4.

From Figure 5(a), it is obviously show that the best fitness values tend to a constant quickly along with increasing number of generations, despite the lots of fluctuations caused by the search process through the genetic operators of crossover and mutation. It gives a good characteristic of convergence, which needs only 111 generations to reach the optimal value 0.005646. For the SGA method (Figure 5(b)), the number of convergence generations is 326, which means that the convergence speed of the GGA is far higher than that of SGA method and about 3 times reduction in computational iterations is gained to reach a satisfactory solution. At the same time, the fitness function value of the GGA is better than those of SGA, of which the optimal value is 0.017342. The results imply that the measured mode shape vectors using the sensor locations of the GGA may be more linearly independent than using the sensor locations of the SGA, which meet the demand of SHM to distinguish measured or identified modes. On the other hand, if the test mode shapes are not spatially independent, test-analysis mode shape correlation using orthogonality and cross-orthogonality computations cannot be performed. This is the reason why we pursue to minimize the off-diagonal elements of the MAC matrix.

4. Conclusions

This paper describes the implementation of GGA as a strategy for the optimal placement of a predefined number of sensors. The dual-structure coding method instead of binary coding method is adopted to code the solution. Accordingly, the selection scheme, crossover strategy, and mutation mechanism used in this paper are given in detail. These methods operate only on upper append code, and the lower variable value of offspring is kept fixed to guarantee the number of sensors can be unchanged. Then, the GGA and SGA are used for selecting optimal sensor locations of the tallest building, DITM, in the north of China. The optimal results obtained by the GGA are compared with those by the SGA, which demonstrated that the GGA was particularly effective in solving the OSP problem, and it can get the better results with lower computational iterations.

Acknowledgments

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