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Optimal allocation of structural sensor in civil engineering based on simulated annealing genetic algorithm

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Abstract. Aiming at the problem of combinatorial optimization of sensor optimal configuration, this paper presents an improved adaptive simulated annealing genetic algorithms based on Modal Assurance Criterion (MAC). Taking the maximum off-diagonal element of the MAC matrix as a target function and the sensor number is not change as a constraint condition, a dualistic coding genetic algorithm is proposed, and after improve the traditional simulation annealing algorithms, use it as an independent operator of GA. Therefore, adaptive crossover and mutation probabilities are adopted to prevent premature convergence. The results of research show that the hybrid algorithm optimizes the number and position of the sensor at the same time, and obtains the optimal configuration of the sensor to meet different accuracy requirements.

Key words. Optimal sensor placement, modal assurance criterion (MAC), dualistic coding, simulated annealing genetic algorithm.

1. Introduction

Structural health monitoring technology [1], using the integrated sensor network structure in real-time monitoring structure of the environmental excitation (human or natural) response signal, and from the structural health status-related information, combined with advanced signal processing methods, extract structural damage parameters, determine whether the structure is damaged and the location and extent of damage. The most important thing of optimal sensor placement is to select the appropriate optimization method [2]. Traditional optimization algorithms mainly include: effective independent method, kinetic energy method, Guyan model reduction method, these methods have their own limitations. In recent years, some new intelligent optimization methods have been developed, mainly simulated annealing algorithm, genetic algorithm and neural network algorithm, these new algorithms to solve complex problems provides a new way of thinking and means. Genetic algorithm (GA) has a good global search capabilities, it is currently the most widely

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used method [3]. However, the practice result shows that genetic algorithm has some shortcomings, the most important problem is that it can bring easily premature convergence and local search capability is bad. Another widely used algorithm is the simulated annealing algorithm (SA) [4]. SA algorithm is a heuristic random optimization algorithm, because the algorithm uses Metropolis probability acceptance criteria, it has a strong local search capabilities to avoid falling into the local optimal solution. But the algorithm has the problem of bad global search ability, slow convergence rate and low efficiency. In addition, the existing sensor optimal configuration method, most of them are directly given the number of sensors, how to determine the optimal design to meet the number of sensors is still a stubborn problem.

In this paper, an adaptive genetic algorithm based on simulated annealing is proposed to optimize the number and position of the sensor, in order to optimize the configuration of the sensors with different precision requirements. The basic idea is to combine the simulated annealing algorithm (SA) with strong local search ability and genetic algorithm (GA) to learn from each other and enhance the local search capability of GA [5]. At the same time, in order to avoid premature convergence, adaptive crossover and mutation probabilities are introduced. And the feasibility of the algorithm is verified by a numerical

2. Literature review

Civil engineering is closely related to the life of the country and the people. Along with the rapid development of economy, the civil engineering structures such as bridges, dams, high-rise buildings and ocean platforms have increased dramatically. Their service period is generally several decades or even hundreds of years. At the same time they are affected by long-term environmental erosion, material aging, the long-term effects of load, fatigue and other adverse factors coupling effect, this will result in structural damage and structural damage accumulation and resistance, coupled with earthquakes, storms, floods and other natural disasters, many factors lead to different degrees of structural damage, serious may lead to catastrophic accidents, endangering the state and the people's lives and property, resulting in adverse social impact [6].

In recent years, civil engineering construction in our country is rapidly rising, the changing high-rise buildings, exhibition centers, railways, highways, bridges, ports and other major livelihood projects across the country have sprung up. However, many large civil engineering structures due to large size, complex forces, lack of monitoring and other reasons causes frequent problems [7]. Civil engineering accident not only caused huge economic losses, but also seriously threatened the people's life safety and affected the economic and social development and stability.

If civil engineering structures can be predicted and evaluated before an accident or disaster occurs, it is important to take early measures to prevent and mitigate the losses caused by the accident. With the rapid development of modern science and technology, in order to ensure the safety, applicability and durability of various engineering structures, people should know the running state of the structure in real time and carry out structural health monitoring. Health monitoring of civil engineering structures is inseparable from the sensor layout, the use of different types of sensors to collect engineering structure of the various data through software analysis and processing to get the relevant health information to identify the location of the injury, so that people take measures to do the appropriate preparation [8]. However, civil engineering structures tend to be large in size, numerous in number of nodes, taking into account the economic and structural operation of the state, the layout of the sensor is not the more the better, people should use a limited number of sensors to obtain information about the structure of the information, which can reflect the whole and local state change of the structure. That is to say, the optimal placement of sensors has become one of the key problems in the structural health monitoring system. This problem determines whether the system can truly and accurately obtain information on the whole structure and the partial operation state.

It is the key problem of the optimal layout of the sensors to arrange as few sensors as possible to obtain as much of the civil engineering structure of health information, and also the important issue of structural health monitoring to be resolved first. To sum up, in the civil engineering structure to carry on the optimal placement of the sensor has great application value, and also has profound social significance.

3. Research contents and methods

Sensor optimization problem is a special kind of knapsack problem—the given sensor configuration in the optimal location, amd the mathematical model is actually a 0–1 planning problem. If the ith gene code is 1, the sensor is arranged on the ith degree of freedom, if the th gene code is 0, the sensor is not arranged at this degree of freedom. Assuming that the number of sensors is m, and the number of candidate points is n, the mathematical model can be represented by the following equation, the key problem is how to express x_i such that the objective function X is maximized. The function is subject to

$$\sum_{i=1}^{n}(x_i - m), \quad x_i = 0 \text{ or } 1, \ i = 1, 2, \cdots, n\,. \tag{1}$$

Simulated annealing algorithm, as one of many stochastic optimization algorithms, simulates the high temperature objects with large internal energy. The simulated process is the gradual annealing process of the particles inside the material, including the annealing at different temperatures point to equilibrium state until the normal temperature of the ground state of the process, when the particles inside the material reaches the ground state, the internal energy is in the minimum value. During the annealing process, the energy of the system is subject to Boltzmann distribution, that is

$$P(f) = \exp\left(-\frac{f}{kT}\right)\,. \tag{2}$$

First of all, according to the above formula to build energy function f, the optimal solution is found by using Metropolis sampling and an annealing process that tends to be orderly. Here, the energy function f refers to the non-diagonal element mean value of the MAC of the mode confidence matrix, that is

$$f = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} MAC_{ij}}{n(n-1)} . \tag{3}$$

In the formula, $\mathrm{MAC}_{ij},\ i \neq j$ is called the non-diagonal element of the modal confidence matrix MAC, n is the selected modal number, and the important goal of the sensor optimization arrangement is to ensure that the value of f is minimized. Considering that the asymptotic convergence of the simulated annealing algorithm needs to be realized with certain conditions, a set of cooling schedule parameters should be set as the termination condition for the iterative calculation using MATLAB programming. The specific parameters are as follows:

Initial temperature t_0: in order to prevent the simulated annealing process from evolving into a local stochastic search process, it is necessary to ensure that the quasi-equilibrium is achieved in the initial stage of operation, a sufficiently large initial temperature t_0 is selected according to the Metropolis criterion. The attenuation function of the control parameter: in general, select $t_k + 1 = \alpha t_k$, where α is called the attenuation coefficient, often take 0.5∼0.99.

Iteration termination criterion: according to the solution obtained by the algorithm in each operation stage, we can see whether the convergence quality of the existing solution has a big improvement, that is to say, the algorithm stops when the solutions of some adjacent Mopkob chains are not significantly improved. It is clear that this criterion is determined by the degree of convergence of the solution at each stage, which ensures that the optimal result of the solution converges to an approximate solution with sufficient accuracy.

The length of the Mopkob chain L_k: L_k selection first needs to determine the attenuation function, and then L_k should ensure that the control parameters corresponding to the various values can be restored to quasi-balanced state.

4. Results and analysis

4.1. Optimum layout of high-rise shear wall structure sensor based on simulated annealing genetic algorithm

In MATLAB software, the maximum value of non-diagonal element of MAC matrix is obtained by changing the number of measuring points, as shown in Fig. 1.

As can be seen from this figure, the MAC non-diagonal element maximum value decreases with the increase of the number of measuring points, at the same time as the number of measuring points increases, MAC non-diagonal element maximum slightly ups and downs, the overall trend is gradually decreasing. It can be seen from the coordinate data in the figure that when the number of measuring points reaches 12, the maximum value of MAC non-diagonal elements has reached

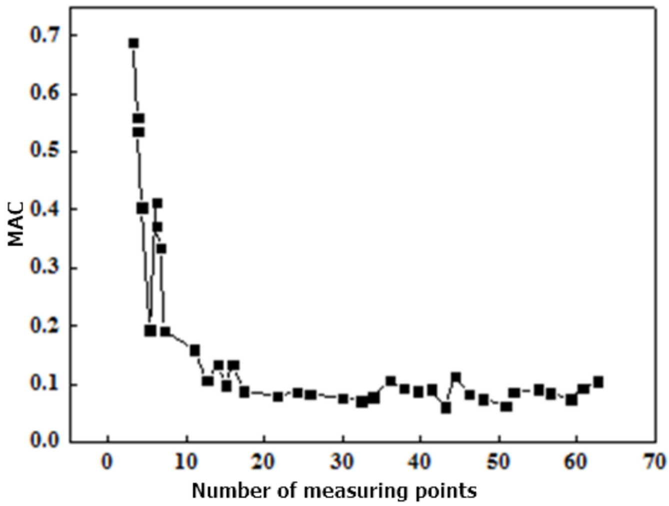

Fig. 1. The relationship between the maximal value of non-diagonal element of MAC matrix and the number of measuring points

0.0943. When the number of measuring points is 17, the MAC non-diagonal element maximum value is 0.08404; when the number of measuring points is 21, the MAC non-diagonal element maximum value is 0.07231, which indicates that the model has good convergence under the simulated annealing genetic algorithm. Taking into account the economic factors, only 12 sensors can be installed to meet the technical requirements, which also once again embodies the significance of the optimal sensor placement. Therefore, the number of sensors to be installed here is set to 12, run the simulated annealing genetic algorithm program to get the optimal scheme of the MAC criterion index 0.1251, the mac index value and the annealing temperature with the iteration number of the relationship shown in Figure 2. The optimization scheme is shown in Table 1.

When the number of measuring points is 8, the MAC non-diagonal element maximum is 0.02033; when the number of measuring points is 10, the MAC non-diagonal element maximum is 0.01469. From Fig. 3, it can be seen that when the number of measuring points is equal to 8, the maximum value of MAC non-diagonal elements tends to be minimum. When the number of measuring points is greater than or equal to 10, with the increase in the number of measuring points MAC non-diagonal maximum value no longer changes. Therefore, considering the economic factors, the number of sensors to be installed in the steel truss bridge model is 8, and the simulated annealing algorithm program can be used to get the iterative curve of the mac criterion index value in each generation. The relationship between the fitness value and iteration number as shown in Fig. 2.

4.2. Optimum layout of steel truss bridge sensors based on simulated annealing genetic algorithm

The optimal layout of simulated annealing genetic algorithm in steel truss bridge is studied here. First obtained MAC non-diagonal element maximum and the number of measuring points of the curve, as shown in Table 2.

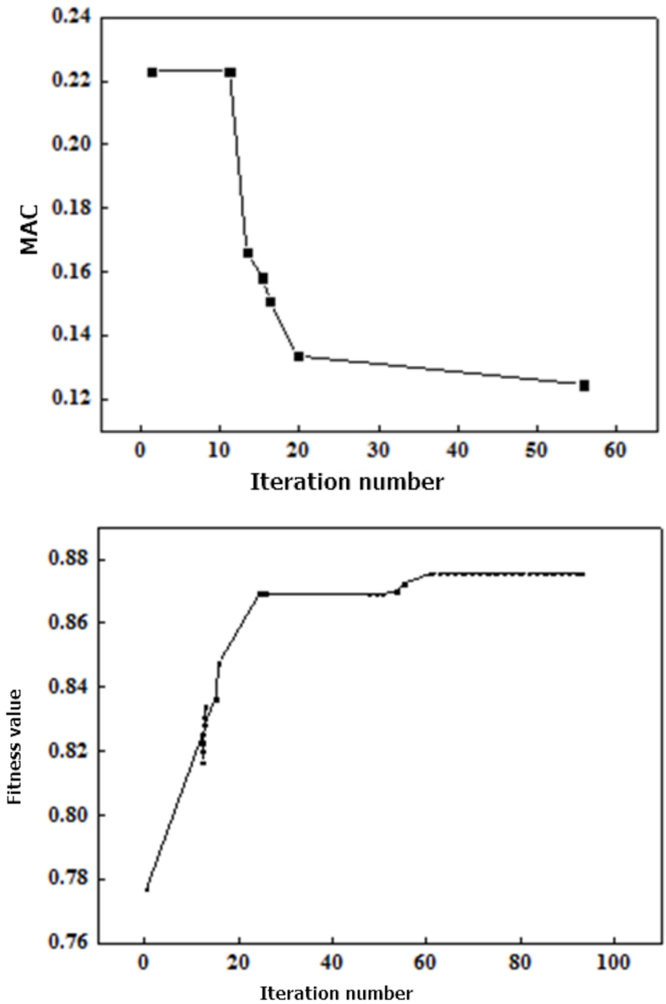

Fig. 2. Configure GA-SA plots for 12 sensors: up–relationship between the maximum value of the MAC non diagonal element and the iteration number, bottom–relationship between fitness value and number of iterations in each generation

Table 1. Optimal placement of 12 sensors

Sensor number	Node number	Direction	Sensor number	Node number	Direction
1	16	X	7	292	X
2	91	Y	8	328	X
3	157	X	9	352	X
4	181	X	10	409	X
5	190	Y	11	415	X
6	286	X	12	457	Y

Table 2. Optimum layout scheme of steel truss bridge with 8 sensors

Sensor number	Node number	Direction	Sensor number	Node number	Direction
1	3	Z	5	17	X
2	7	Z	6	17	Z
3	11	Z	7	21	X
4	12	X	8	22	Z

Optimum layout of multi-story frame sensor based on simulated annealing genetic algorithm: The content of the research process is the same as (2), the maximum value of the non diagonal element of MAC decreases with the increase of the number of points, at the same time, with the increase of the number of measuring points, the maximum value of the MAC non diagonal elements is slightly ups and downs, and the overall trend is gradually decreasing. It can be seen from the coordinate data in the figure that when the number of measuring points reaches 12, the MAC non-diagonal element maximum has reached 0.1769, when the number of measuring points is 17, the MAC non-diagonal element maximum is 0.1692, when the number of measuring points is 21, the maximum value of MAC non-diagonal element is 0.1386, which indicates that the model has good convergence under simulated annealing genetic algorithm. Taking into account the economic factors, only 12 sensors can be installed to meet the technical requirements, which also once again embodies the significance of the optimal sensor placement. Here, the number of sensors to be installed is set to 12, running the simulated annealing genetic algorithm program, get the best scheme of the MAC criterion index of 0.2123.

5. Conclusion

This paper combines the genetic algorithm and simulated annealing algorithm, proposed an efficient global optimization of hybrid genetic algorithm, and applied to the optimal layout of bridge health monitoring sensors. The main conclusions are as follows:

The position of the optimal measuring point increases with the increase of the number of sensors and presents the inheritance, that is, when only 5 sensors are installed, the sensor will also appear when the 12 sensors are installed. It can be seen that the search of hybrid genetic algorithm is based on the contribution of each measuring point to the amount of test information. The important measuring points are selected first, and the required number of measuring points are selected according to the importance order of each measuring point.

The algorithm is based on two-dimensional coding genetic algorithm as the main algorithm, and the simulated annealing algorithm is introduced into it as a separate operator. On this basis, MATLAB optimization interface was designed, and the optimal placement of the sensor is carried out for the high-rise shear wall, the steel truss bridge and the multi-story frame structure, the position of the sensor in the measurement of the first 5 order modes is given. The results show that the method is ideal and the expected results are achieved.

References

[1] T. H. Yi, H. N. Li: *Methodology developments in sensor placement for health monitoring of civil infrastructures.* International Journal of Distributed Sensor Networks *8* (2012), No. 8, paper 612726.

[2] I. Fister, X. S. Yang, J. A. Brest: *A comprehensive review of firefly algorithms.* Swarm and Evolutionary Computation *13* (2013), 34–46.

[3] T. H. Yi, H. N. Li, G. Song, X. D. Zhang: *Optimal sensor placement for health monitoring of high-rise structure using adaptive monkey algorithm.* Structural Control and Health Monitoring *22* (2015), No. 4, 667–681.

[4] K. V. Yuen, S. C. Kuok: *Efficient Bayesian sensor placement algorithm for structural identification: a general approach for multi-type sensory systems.* Earthquake Engineering & Structural Dynamics *44* (2015), 757–774.

[5] A. Khare, S. Rangnekar: *A review of particle swarm optimization and its applications in solar photovoltaic system.* Applied Soft Computing *13* (2013), No. 5, 2997–3006.

[6] M. Mohammadi, M. Nastaran, A. Sahebgharani: *Development, application, and comparison of hybrid meta-heuristics for urban land-use allocation optimization: Tabu search, genetic, GRASP, and simulated annealing algorithms.* Computers, Environment and Urban Systems *60* (2016) 23–36.

[7] U. Can, B. Alatas: *Physics based metaheuristic algorithms for global optimization.* American Journal of Information Science and Computer Engineering *1* (2015), No. 3, 94–106.

[8] M. G. Soto, H. Adeli: *Placement of control devices for passive, semi-active, and active vibration control of structures.* Scientia Iranica *20* (2013), No. 6, 1567–1578.

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