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Research paper

Sensor placement optimization of civil engineering structures using GA–SA algorithm

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Abstract: Effectively and accurately obtaining the structure and status information of civil engineering by optimizing the configuration of sensors is the basis for the monitoring of civil engineering structures, and it is also the key content for subsequent monitoring and evaluation. To realize the intelligent development of sensor placement optimization, the simulated annealing algorithm is first used to optimize the genetic algorithm, and the sensor placement optimization method of civil engineering structure using genetic simulated annealing algorithm is obtained. The results showed that in the optimization results under the h_1 and h_2 functions, the function values of the genetic simulation annealing algorithm were 0.000045 and –1.031624 in the 125th iteration, respectively, and the algorithm quickly obtained the global optimal solution. In the practical application of civil engineering structures, the genetic simulation annealing algorithm convergence was the best when measurement points were less than 27, and the optimal solution was obtained after 16 iterations. After measurement points exceeded 28, the genetic simulated annealing algorithm obtained excellent optimization results. The above results show that the proposed method can provide targeted optimization solutions for different types of civil engineering structures to achieve the goal of monitoring.

Keywords: genetic algorithm, simulated annealing algorithm, civil engineering, structural monitoring, sensor placement optimization

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1. Introduction

Civil engineering (CE) closely relates to people's lives, and as the national economy develops, major CE structures like bridges have grown rapidly [1, 2]. However, with the coupling effect of erosion by the external environment, fatigue effect, and material aging, these CE structures will inevitably bring long-term damage and resistance attenuation [3, 4]. Natural disasters such as typhoons, floods, and earthquakes can cause different types of damage to the CE structure, and in severe cases, catastrophic accidents can occur, resulting in huge economic losses and threatening people's lives in severe cases [5]. Therefore, the use of artificial intelligence methods for CE health monitoring is the focus of current research. In the face of the CE structure sensor optimization layout problem, it is necessary to find the best location in line with the system performance under the existing problem constraints. Generally speaking, it is necessary to establish the optimization objective function, determine the optimization criteria and select the optimization algorithm. Among them, genetic algorithm (GA) can better realize the adaptability and optimization ability of the expected system, and can be applied to the CE structure optimization problem in civil engineering [6, 7]. The latter has strong local search ability and general ability, but the convergence speed is slow. To improve these, a GA algorithm using dual-structure coding (DSC) optimization was proposed, and the simulated annealing (SA) algorithm was established, and finally the GA algorithm was optimized by using the SA algorithm to obtain the CE structure sensor layout optimization method using GA–SA. The purpose of this study is to reasonably optimize the sensors under the premise of meeting the monitoring accuracy of CE structure, to reduce the monitoring cost and improve the monitoring efficiency. There are two main innovations in this study, the first is to propose a CE structure sensor layout optimization method using SA algorithm to optimize GA algorithm, and the second is to expand the field of other types of structure monitoring and verify the versatility of the method. The study structure includes four parts, the first part is a review of the relevant research results, the second part is the optimal design of CE structure sensor layout using GA–SA, the third part is the method verification of the effectiveness and feasibility, and the last part is a summary of the research.

2. Related works

As science and technology progress, through real-time detection of CE structure parameters, timely discovery of hidden dangers and abnormalities in the structure, and taking targeted measures, intelligent structural monitoring is possible. Eltouny and Liang proposed a novel unsupervised learning detection framework for the localization of CE structural damage, and the results showed that the framework could successfully diagnose the health state of the structure, with an average accuracy of 93% and 95% for damage detection and localization, respectively [8]. Tannus et al. designed a damage detection method for CE structures based on wavelet recognition and tested the nonlinear structure of a 20-story building, and the results verified the effectiveness of the method [9]. Cherid et al. proposed a CE structural damage detection method based on principal component analysis and GA algorithm, and applied it to structural health management, and the simulation results confirmed the feasibility of the method [10]. Naud et al. found that the results of wood-concrete composites provided a breakthrough solution for multi-storey buildings, so they developed a novel composite connector, and analyzed the results through the Winkler model, which emphasized the importance of intelligent design of connection systems for CE structural failure [11].

GA algorithm and SA algorithm fit in various fields, and in CE construction, it is conducive to improving the safety and reliability of CE structure, promoting the application of intelligent technology, and enhancing the sustainability and durability of CE structure. Shen et al. designed a new fitting method using GA to obtain the main method of polarization curves of proton exchange membrane fuel cell stacks, and the results showed good agreement between the method and the experimental data, and the error range was within 3%, and confirmed the reliability of the method [12]. Chen et al. aimed to construct a CT examination method using GA enhancement, and the results used 140 features to construct a signature that showed robust performance in both internal and external verification cohorts [13]. Liu et al. constructed a task allocation model with complex constraints, and proposed a discrete pigeon optimization SA algorithm to solve the model, and results showed that the average fitness value was higher than that of the discrete pigeon algorithm (13.5%), and the algorithm reached the global optimal 15 times after 30 runs [14]. Umashankar used a hybrid SA algorithm to use efficient and reliable node identification as the cluster head to improve the wireless sensor networks, and results showed that this method improved network throughput and reliability [15].

Based on the above contents, it can be concluded that there are many research results on CE structure health monitoring and intelligent algorithms, but there is a lack of methods to obtain more structure operation information by using the minimum number of sensors in CE structure monitoring. Therefore, the DSC optimization GA algorithm was studied, and the SA algorithm was constructed, and finally the GA algorithm was optimized by using the SA algorithm to obtain the CE structure sensor layout optimization method based on the GA–SA algorithm.

3. Optimal design of CE structure sensor layout based on GA–SA algorithm

In order to solve the problem of frequent collapse accidents caused by complex force and large size of many large CE structures, the study first constructed GA algorithm and SA algorithm, and then proposed the optimal design of CE structure sensor layout based on GA–SA algorithm to realize the health monitoring of CE structure.

3.1. Operation optimization using genetic algorithm

At present, the integration of computers and traditional industrial fields is becoming increasingly close, especially in industrial related structural optimization. Computer simulation optimization plays an increasingly important role in economy, energy conservation, and other aspects. The GA algorithm can provide a solution to practical problems and has strong robustness to the types of problems. However, the random setting of its initial values can easily lead to premature convergence. The GA algorithm process is as follows: the first step requires encoding processing, and the second step is to randomly generate the initial population, followed by calculating the fitness function Fit. For different application problems, different ways need to be used to define them, and Fitthey need to meet the requirements of consistency, versatility, and less computational than continuous, non-negative, single-value, and maximization before construction. There are three main methods of Fit conversion through the objective function $c_{\min}$, one is the direct transformation method, and the expression is shown in Equation (3.1).

$$\text{Fit}\left(f\left(x\right)\right)=\begin{cases} f\left(x\right), & \text{if the objective function is a maximization problem} \\ -f\left(x\right), & \text{if the objective function is a minimization problem} \end{cases} \tag{3.1}$$

The direct transformation method is simple to solve, but it is difficult to ensure the non-negative probability of subsequent roulette selection, and the probability distribution of the function to be solved is scattered, which brings bias to the solution results. The second is the boundary construction method, if $f\left(x\right)$ solves the minimum value problem, Equation (3.2) is obtained.

$$\text{Fit}\left(f\left(x\right)\right)=\begin{cases} c_{\max}-f\left(x\right), & f\left(x\right)<c_{\max} \\ 0, & \text{else} \end{cases} \tag{3.2}$$

In Equation (3.2), $c_{\max}$ is the $f\left(x\right)$ maximum estimate. If $f\left(x\right)$ solves the maximum value problem, Equation (3.3) is obtained.

$$\text{Fit}\left(f\left(x\right)\right)=\begin{cases} c_{\min}+f\left(x\right), & f\left(x\right)>c_{\min} \\ 0, & \text{else} \end{cases} \tag{3.3}$$

In Equation (3.3), $c_{\min}$ is the $f\left(x\right)$ minimum estimate. This method optimizes the direct conversion method, but $c_{\min}$ and $c_{\max}$ need to be estimated in advance, and the accuracy cannot be guaranteed. The third is the transformation method of the boundary construction method, if $f\left(x\right)$ solves the minimum value problem, Equation (3.4) is obtained.

$$\text{Fit}\left(f\left(x\right)\right)=\frac{1}{1+c+f\left(x\right)}, \quad c\geq 0, c+f\left(x\right)\geq 0 \tag{3.4}$$

In Equation (3.4), c indicates a conservative estimate of the $f\left(x\right)$ boundary. If $f\left(x\right)$ solves the maximum value problem, Equation (3.5) is obtained.

$$\text{Fit}\left(f\left(x\right)\right)=\frac{1}{1+c-f\left(x\right)}, \quad c\geq 0, c-f\left(x\right)\geq 0 \tag{3.5}$$

The fourth part is selection and heredity, including selection operation operators, mutation operation operators, and cross operation operators. Among them, roulette wheel selection and optimal preservation strategy are the most classic in GA algorithm. The former, due to limitations such as randomness and population size, may have errors with the expected value of theoretical selection times, and the latter will be affected by the action of random genetic operators, which will destroy the fitness, so this strategy is in conjunction with other genetic operators to obtain better results. In the mutation operation operator, the mutation operation can be combined with the cross-operation to minimize the loss of genetic information of

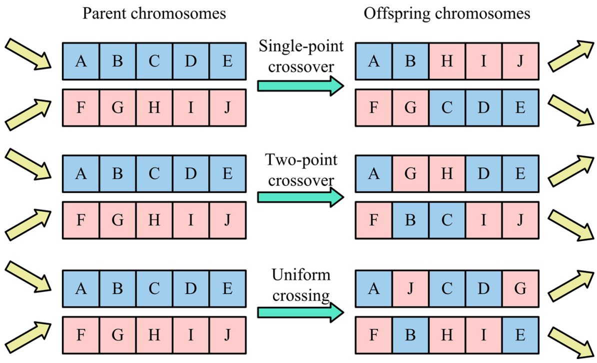

Fig. 1. Principles of different cross operation algorithms

the biological individual caused by the selection operator and the cross-operation, so as to ensure the reliability of the GA algorithm to obtain new individuals. The principle of different cross-operation algorithms is shown in Fig. 1.

In Fig. 1, the selection of intersection positions and the exchange method of some genes need to be comprehensively considered when designing the crossover operation operator, which occupies a key position in GA, and there are three main types: single-point crossing, double-point crossing, and uniform crossing. Among them, single-point crossing is a member of the standard GA algorithm, and double-point crossing is a widely used method, and uniform intersection is suitable for optimization problems in continuous space.

3.2. Parameter optimization based on simulated annealing algorithm

SA derives from solid annealing, which has the advantage that no matter how complex the function form, it can find the global optimal solution as much as possible, and it is not easy to fall into the local optimum, but the initial temperature and the length of the Markov chain will affect the computational time. Fig. 2 shows the flow of the SA algorithm.

In Fig. 2, the initial parameters are determined, such as the initial temperature T, the number of iterations N, and the initial solution s, and then iterate from 1, run the following command, select a random solution s_j, calculate the increment Δ of the evaluation function $g(x)$, if $\Delta < 0$, it will be the new current solution s_j, otherwise, accept s_j as the new current solution through probability $\exp(-\Delta/T)$. If the termination condition is met, that is, the new solution is not accepted for many consecutive times, the current solution can be optimal, and the operation can be terminated. Otherwise, make the iterations $k = k + 1$ and continue the loop operation. Among the key parameters of the SA algorithm, the first is the state generation function, which includes two parts: the way in which the current solution generates the candidate solution and the probability distribution of the candidate solution choosing different states. The second is the state acceptance function, the expression of which is shown in Equation (3.6).

$$\min\left[1, -\Delta E/T\right] \tag{3.6}$$

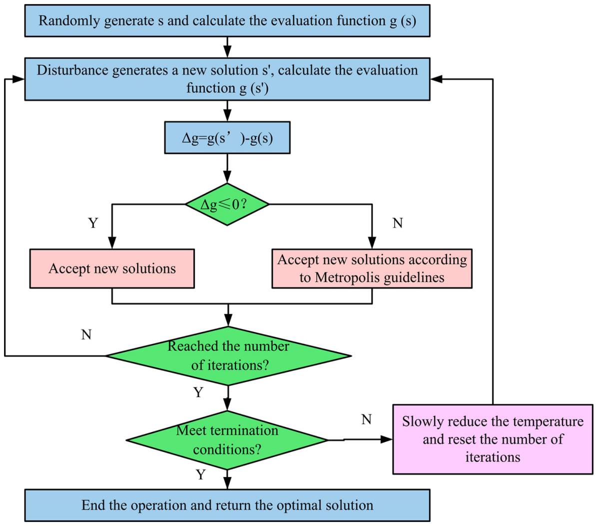

Fig. 2. SA algorithm flowchart

In Equation (3.6), ΔE is the variable of internal energy. The initial temperature also affects the computation time, so the SA algorithm needs to achieve quasi-equilibrium at the beginning, so that the initial acceptance rate χ_0 is approximately 1, which is calculated in Equation (3.7).

$$\chi_0 = \frac{n_a}{n_p} \approx 1 \tag{3.7}$$

In Equation (3.7), n_a and n_p are the number of accepted transformations and the number of proposed transformations, respectively. Considering the efficiency and quality of optimization, the study selects a set of states to be randomly generated, and the initial temperature is determined by calculating the maximum target value difference between the states. At present, the mainstream temperature update function uses exponential dewarming, such as Equation (3.8).

$$t_{k+1} = \zeta t_k, 0 < \zeta < 1 \tag{3.8}$$

In Equation (3.8), ζ is a constant. The Markov chain length is selected based on the known attenuation function, so that the control parameters can restore quasi-equilibrium at each value, usually within 100–1000. According to the above contents, SA is very versatile and simple to operate, but the computational efficiency is low, and it can be combined with the GA algorithm to give full play to its respective advantages.

3.3. Optimization of CE structure sensor layout using GA–SA algorithm

Due to the complexity and huge size of the CE structure, the mechanical relationship and reliability analysis cannot be carried out through mathematical analysis, and many engineering institutions currently use the software ANSYS for analysis. The software can solve hundreds of millions of degree-of-freedom engineering structure models, and can also be used for the analysis and calculation of static and dynamic characteristics and bearing capacity of engineering components. And it has excellent performance in the optimization design and reliability analysis of engineering structures. Therefore, software ANSYS19.0 was used to model the middle and high-rise shear wall structure, steel truss bridge structure and multi-layer frame structure (three-storey) of CE structure, which were used in the subsequent sensor layout optimization. After the construction of the CE structural model is completed, the sensor placement optimization problem can be solved. To improve the GA global optimization performance and convergence speed, DSC is first introduced for encoding. The method represents the chromosomal genes of an individual by means of a variable code $X_{S_{(i)}}$ with an additional code $S_{(i)}$, where $X_{S_{(i)}}$ is 0 or 1. If an individual needs to be genetically encoded, the first line S is generated by a random function, and then the second line X is generated by a random function, and finally, it is guaranteed that the X corresponding "1" value is the same as the number of sensor placements, and needs to be done sequentially. Secondly, the elite preservation strategy removes individuals with low fitness values during heredity and evolution, so as to effectively prevent the superior individuals in the population from being damaged by genetic operators. Then, the Partial Matching Crossover (PMC) and Inverse Variation (IV) operations were used to improve the GA crossover and mutation operations. PMC selects two points of individual genes as intersections through a random function, and the gene codes between the two points are matched segments, and a new generation of individuals can be generated according to the mapping relationship between the two parent individuals corresponding to the matching segments. IV is a process in which two variation points are generated in the parent individual through a random function, and then the $S_{(i)}$ between two points is arranged in reverse order to ensure that the corresponding $X_{S_{(i)}}$ is unchanged. Finally, the fitness function of the GA algorithm is optimized by using the optimization criterion, and the modal assurance criterion (MAC) is selected to improve CE structure configuration optimization. In order to preserve the spatial intersection angle of the measured modal vectors as much as possible, the MAC matrix expression is calculated in Equation (3.9).

$$\mathrm{MAC}_{ij} = \frac{\left(\varphi_i^T \varphi_j\right)^2}{\left(\varphi_i^T \varphi_i\right)\left(\varphi_j^T \varphi_j\right)} \tag{3.9}$$

In Equation (3.9), φ_i and φ_j are the spatial modal vectors corresponding to the i-th and j-th orders of the measured structure, respectively. If $i \neq j$ represents the non-diagonal elements of MAC, calculate the angle formed by the interaction between the two modal vector spaces of the structure. If $\mathrm{MAC}_{ij} = 1$, the two modal vectors will overlap or be parallel, making it impossible to distinguish them; If $\mathrm{MAC}_{ij} = 0$, the two modal vectors exhibit orthogonal states. Therefore, it is necessary to ensure that the non diagonal angle of MAC_{ij} is as small as possible, making it easier to distinguish the spatial vector of the measured structure, which is the objective function corresponding to sensor layout optimization. In the GA algorithm, the calculation of fitness is an important component, but in general, larger fitness value is better. However, this contradicts the requirement of a smaller objective function for sensor layout optimization. Therefore, the expression of the relationship between the two can be obtained, as shown in Equation (3.10).

$$\text{Fit}(x) = 1 - \max\left\{\text{MAC}_{ij}\right\}, \quad i \neq j \tag{3.10}$$

Based on the above contents, the process of solving layout optimization problem of CE structural sensors can be obtained, which is shown in Fig. 3.

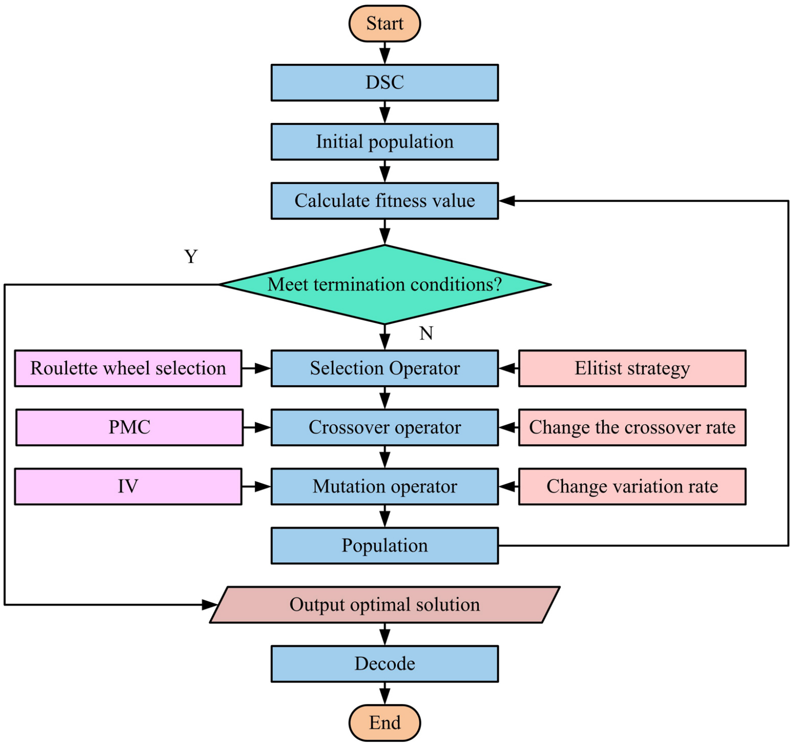

Fig. 3. The process of solving the CE structure sensor layout optimization problem using the GA algorithm based on DSC

In practical application, the GA algorithm will lead to premature phenomena and poor local optimization ability because it emphasizes the evolutionary relationship between two generations and has a strong grasp of the overall search process. The powerful local search ability of the SA algorithm can be fully utilized when large-scale disturbances are introduced, thereby depriving the local ideal value of control over the whole population. Therefore, the study introduces SA algorithm to optimize GA algorithm, integrates the global and parallelism of GA algorithm, the ergodic and local search ability of SA algorithm, and reflects better performance in terms of calculation accuracy and efficiency. The specific process of GA–SA algorithm is as follows: the first step is to generate the initial population and determine the initial temperature; The second step is to cycle the following steps until the convergence condition is met. First, the individual fitness of the current population is calculated, and then the individuals are selected, crossed and mutated. The individuals are then subjected to simulated annealing operations until the sample is stable. Then the optimal preservation strategy is adopted for the population, and finally the descaling operation is completed, and the optimal result can be output when the convergence condition is met.

4. Results of sensor placement optimization using GA–SA

To analyze the performance and application of the proposed CE structure sensor layout optimization based on GA–SA, the performance and the obtained CE structure sensor layout optimization results were first tested by pre-experiments, and then different algorithms' effects in the actual application of CE structure sensor layout optimization were compared.

4.1. Preliminary experiment of sensor placement optimization using GA–SA

To verify the optimization performance, the experiment was conducted using the software MATLAB, and two typical functions were used for experimentation. One is a typical pathological quadratic function that is extremely difficult to minimize, corresponding to a narrow valley between the global optimal and the achievable local optimum, and the probability of finding the global optimal is very small. Another typical function is the Six-Hump Camel-Back function, which has 6 local advantages and 2 global advantages, which makes the algorithm easily fall into the local optimization. The accuracy of the evaluation index selection of feasible solutions and the number of calculations of the adaptation function. To verify the performance of GA–SA more scientifically, GA and SA algorithms were selected for comparative experiments. The crossover probability and variation probability were set to 0.15 and 0.3, respectively, and the population size was set to 50.

Fig. 4a shows the results under two typical functions, and the average convergence times of GA, SA algorithm and GA–SA algorithm under h_1 function are 52, 63 and 37 respectively, and the average convergence times under h_2 function are 58, 59 and 33, respectively. Fig. 4b shows the h_1 optimization results under the function, and the function values of the GA algorithm, SA algorithm and GA–SA algorithm are 0.000148, 0.000341 and 0.000045 respectively at 125 iterations. Fig. 4c shows the h_2 optimization results of different algorithms under h_2 function, and the function values of the GA algorithm, SA algorithm and GA–SA algorithm are –1.031653, –1.031688, and –1.031624 respectively at 125 iterations. The above results showed that the performance of proposed GA–SA is the best, and it overcomes the problem of precocious convergence of the GA algorithm with high accuracy.

The sensor layout optimization schemes for different algorithms under high-rise shear wall structures and steel truss bridge structures are shown in Table 1. In Table 1, a very small number of sensors can be used to achieve monitoring by simply mounting the sensors in the corresponding position and orientation. In the steel truss bridge structure, the sensor arrangement optimization of different algorithms is placed at the upper chord part, and is located in the vertical direction and the vertical direction of the bridge body, which is consistent with the actual engineering experience. The CE structure sensor layout optimization scheme based on GA–SA algorithm comprehensively considers the technical requirements and economic factors, and uses 12 and 8 sensors for high-rise shear wall structure and steel truss bridge structure.

Table 1. Optimization schemes for sensor layout using different algorithms in high-rise shear wall structures and steel truss bridge structures

Algorithm	Structure	Sensor number	Node number	Direction	Sensor number	Node number	Direction
GO	High rise shear walls	1	24	X	7	359	X
		2	80	X	8	383	X
		3	122	X	9	443	And
		4	122	And	10	458	X
		5	224	X	11	461	And
		6	251	X	/	/	/
	Steel truss bridge	1	5	With	5	18	With
		2	9	With	6	22	And
		3	13	And	7	26	With
		4	13	With	/	/	/
HIS	High rise shear walls	1	24	And	5	468	X
		2	128	X	6	703	X
		3	388	X	7	708	And
		4	423	And	/	/	/
	Steel truss bridge	1	4	With	5	19	With
		2	9	With	6	23	X
		3	13	X	7	23	With
		4	13	With	/	/	/
GA–SA	High rise shear walls	1	17	X	7	293	X
		2	92	And	8	329	X
		3	158	X	9	353	X
		4	182	X	10	410	X
		5	191	And	11	416	X
		6	287	X	12	458	And
	Steel truss bridge	1	4	With	5	18	X
		2	8	With	6	18	With
		3	12	With	7	22	X
		4	13	X	8	23	With

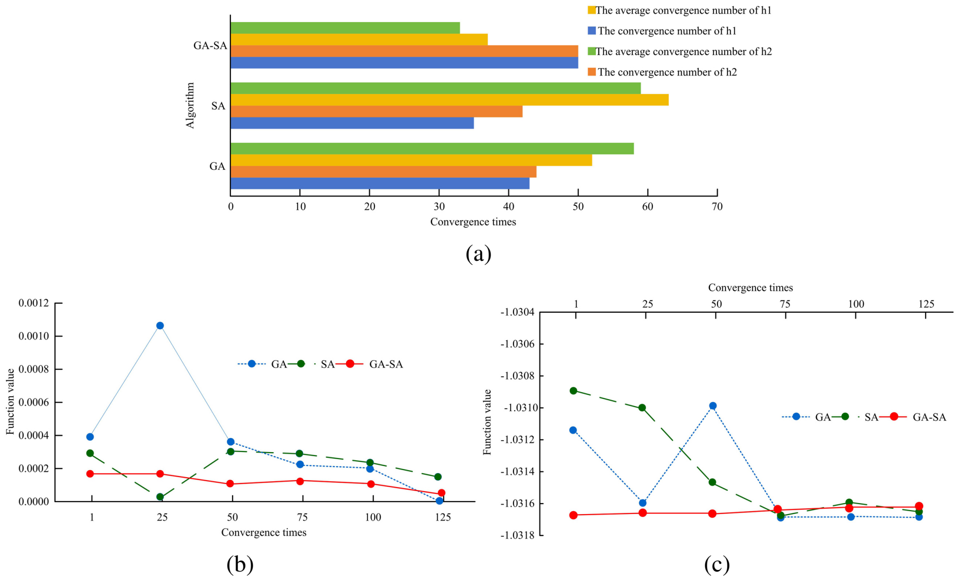

Fig. 4. Performance results of different algorithms under two typical functions

4.2. Application of sensor placement optimization based on GA–SA algorithm

To further compare the effectiveness of different algorithms in practical applications, experiments were conducted using the high-rise shear wall structure of H project, the steel truss bridge of M project, and the three story frame structure of L project.

Fig. 5a and Fig. 5b, Fig. 5c and Fig. 5d, Fig. 5e and Fig. 5f correspond to the comparison of MAC values and number of measurement points for CE high-rise shear wall structure, CE steel truss bridge structure, and CE frame structure, respectively. In Fig. 5, GA is consistent with the SA algorithm and is located above the GA–SA algorithm, which means that despite the number of measurement points, GA–SA convergence is better, and it can obtain the optimal solution after 8 iterations. Most of the variation curves of GA–SA are located at the bottom, and the optimal solution can be obtained after 15 iterations. The GA algorithm and SA algorithm need to be iterated 31 times and 36 times before the optimal solution can be obtained. The above results show that when optimizing the sensor layout of a steel truss bridge structure, if there are few nodes, all three algorithms can be selected, and when considering the high-rise building structure, the running time needs to be considered, so the GA–SA algorithm is more appropriate. It can be observed that when measurement points are less than 27, GA–SA convergence is the best, and when they more than 28, the optimization effect of SA and GA–SA is excellent. In the optimal measurement number of points, GA–SA algorithm is always at the bottom, which means the best optimization performance, and the optimal solution can be obtained after 16 iterations.

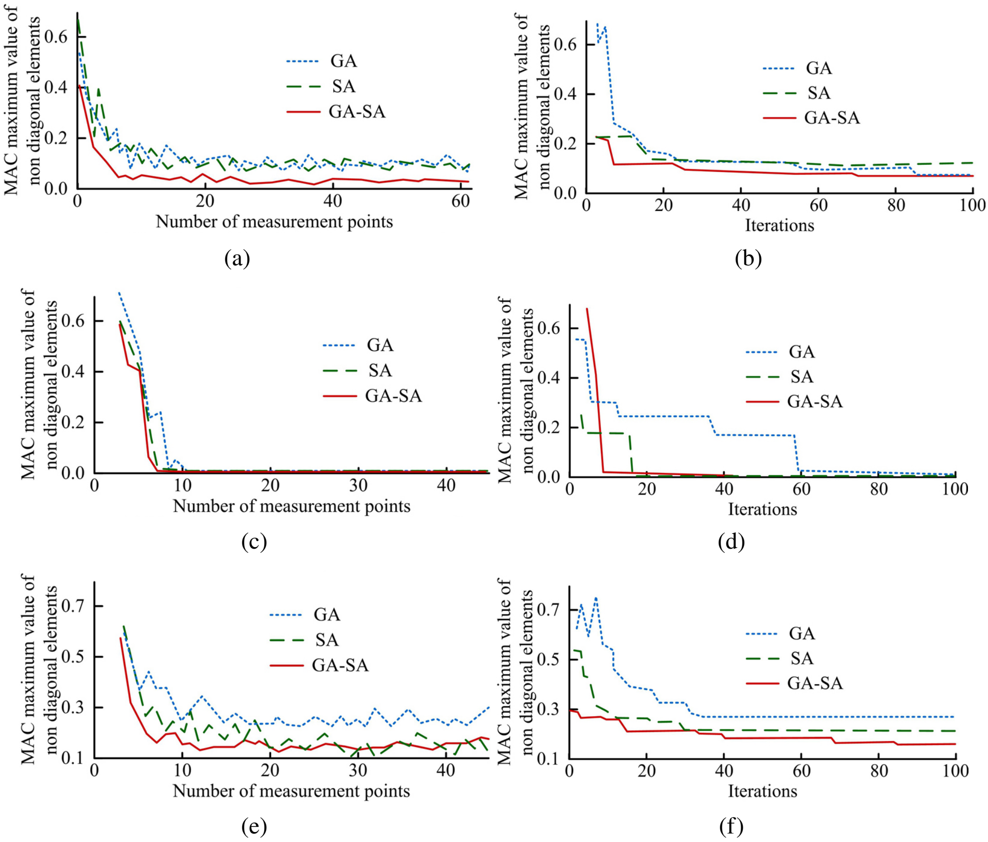

Fig. 5. MAC value and number of measurement points variation curves for various CE structures based on different algorithms

5. Conclusions

Sensor placement is a key part of CE structure monitoring, which aims to effectively and accurately obtain the health status and performance parameters of CE structures, and the development of artificial intelligence provides more options for CE structure monitoring. In order to maximize the monitoring effect and save costs, GA and SA were studied and constructed, and the layout optimization method of CE structure sensor based on GA–SA was designed. Results showed that in the optimization results of different algorithms under functions h_1 and h_2, at 125 iterations, the function values of GA algorithm, SA algorithm, and GA–SA algorithm were 0.000148, 0.000341 and 0.000045, –1.031653, –1.031688, and –1.031624, respectively. This showed that algorithm performance was the best among three algorithms, and it quickly jumped out of the local optimal, with high accuracy. In practical application, when measurement points were less than 27, GA–SA algorithm had the best convergence, and when they were more than 28, the optimization effect of the SA algorithm and GA–SA was excellent. In the optimal measurement number of points, GA–SA was always at the bottom, which meant the best optimization performance, and the optimal solution was obtained after 16 iterations. In summary, GA–SA can well improve the sensor placement optimization of different types of CE structures, and can greatly reduce the operation time and economic cost. However, there are still deficiencies in the research, and there is no standardized criterion for the optimal placement of sensors, so the discrimination of each scheme is not comprehensive, and the unified optimization criterion can be used to further explore the optimal arrangement scheme of sensors in future research.

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