Structural Damage Identification of Large-Span Spatial Grid Structures Based on Genetic Algorithm

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Large-span spatial grid structures often face structural damage and defects during long-term service. To extend the lifespan of these structures and promptly detect damage and defects, this study proposes a model for structural damage identification in large-span spatial grid structures based on an improved genetic algorithm using simulated annealing optimization. Firstly, the Monte-Carlo sampling method is used to complete the sensitivity analysis of the finite element structural model. Then, a search heuristic algorithm, genetic algorithm, which simulates the process of biological evolution, is used for the identification of structural damages. Finally, a probability-based general optimization algorithm, simulated annealing algorithm, is used to optimize and improve the initial population generation and genetic operation of the genetic algorithm. Experimental results demonstrate that the hybrid intelligent algorithm's damage identification model achieves a balanced advantage between precision and recall, and the model's recall is 0.93 at a precision rate of 0.9. The area under the receiver operating characteristic curve reaches the highest level at 0.927. The optimization error evaluation indicators for different test functions consistently fall below 0.4, indicating superior optimization accuracy compared to other models. The genetic improvement strategy significantly enhances convergence performance for three convergence indicators, achieving a 100% convergence rate and the fastest iteration speed among the models. The algorithm accomplishes the convergence of the optimal value of the objective function at 140 generations of the population, with an optimal convergence value of 0.17. The damage identification model yields recognition results of 0.94 for single-member damage and 0.95 for multi-member damage, with recognition errors for other members within a reasonable range. The recognition model achieves more than 90.0% accuracy in recognizing both random defects and actual damage. The model can also effectively identify damage under random defects. This research enriches theoretical knowledge in the field of structural damage identification, playing a crucial role in ensuring the safety and reliability of large-span spatial grid structures.

Povzetek: Študija uvaja izboljšan model za prepoznavanje poškodb v velikorazponskih prostorskih mrežnih strukturah. Z uporabo genetskega algoritma in optimizacije s simuliranim ohlajanjem izboljša zanesljivost konstrukcij.

1 Introduction

Large-span spatial grid structures, characterized by large spans and no internal beam and column support, enable open and flexible layouts over a considerable spatial range. In recent years, these structures have seen widespread use and development in venues such as sports stadiums, exhibition halls, airport terminals, large equipment maintenance workshops, and large commercial complexes, thanks to their use of high-strength, lightweight materials allowing the design of large enclosed structures with high clearance requirements [1-2]. However, defects such as material defects, cross-sectional area deviations, and poor seam quality often occur during the fabrication of grid structures. Long-term exposure to damp and corrosive environments can also lead to fatigue and corrosion damage in these structures, while large loads can cause damage such as loose connections and detachment at component connection points [3]. These defects and damages can compromise the structural integrity of spatial grid structures, resulting in equipment damage, structural instability, deformation, or collapse, posing significant economic losses [4]. Therefore, timely detection and repair of damage and defects in large-span spatial grid structures are essential. Common techniques for structural damage detection include monitoring sensors, acoustic wave detection, thermal imaging, and vibration analysis. With the advancement of computer technology, the use of image processing techniques for identifying potential structural damage and the application of computer algorithms or machine learning in conjunction with structural monitoring data have gradually gained traction. However, damage identification methods based on computational intelligence still have some shortcomings and exhibit low accuracy in the face of complex structural damage [5]. To address this, this study designs a damage identification model for large-span spatial grid structures based on genetic algorithm (GA) and simulated annealing (SA), and conducts experiments on the structural damage identification model. The study comprises four main parts: firstly, a review of the current state of computational intelligence in structural damage identification technology both domestically and internationally; secondly, an explanation of the design process of the structural damage identification model for large-span spatial grid structures based on SA-GA; thirdly, performance evaluation and simulation experiments of the designed identification model; and finally, a summary and conclusion of the research experiment results. The realization of this study is expected to enrich the theoretical aspects of structural damage identification technology for large-span spatial grid structures and extend their lifespan.

2 Background

The research related to the automatic identification and localization of structural damage through the learning and training of structural feature data using machine learning and artificial intelligence algorithms has gained widespread attention in the field of structural engineering. In order to further enhance structural damage identification technology, scholars both domestically and internationally have conducted a series of studies on computational intelligence for structural damage identification. Existing strategies for assessing structural damage states primarily rely on traditional visual inspection, which is limited by the subjectivity or professional expertise of the inspection personnel, leading to lower reliability in detecting structural damage features. Barkhordari et al. designed a structural damage identification model using deep convolutional networks and ensemble learning algorithms. Experimental results indicated that the proposed method achieved a 94% accuracy and 92% recall rate in distinguishing various damage types such as bending, shearing, combination, or undamaged conditions [6]. Structural damage identification is crucial for ensuring the safety and functionality of structures. Mohebian et al. proposed a metaheuristic optimization algorithm based on visible particle sequence search for structural damage identification. Inspired by the visibility graph technique, this method treated candidate solutions as particle sequences and mapped them to a visible graph network to obtain visible particles for optimizing solutions. Experimental results demonstrated that this method exhibited high accuracy, reliability, and computational efficiency in damage identification [7]. The task of monitoring the structural safety and integrity of aging bridges was urgent. An indirect data-driven identification method, using instrumented vehicles to measure and receive indirect data of bridge structural damage features, has attracted considerable attention. To mitigate environmental and operational interferences, Hajializadeh designed a bridge damage identification model based on deep learning algorithms. This model achieved automatic extraction of damage features from measurement data. Under four positive damage scenarios and three different driving speeds, this method could detect and classify bridge damage through instrument measurements [8]. Lei et al. developed a steel frame structural damage detection method based on support vector machines. By setting up ten structural scenarios, different damage indicators were extracted as features. Experimental results demonstrated that this method exhibited good recognition capability for different indicators of damage features, with good detection accuracy and robustness [9].

The sensitivity method based on modal data exhibits lower damage detectability and encounters prominent issues related to the ill-conditioning of modal data noise in structural damage localization and quantification. To address this, Daneshvar et al. developed a damage localization and quantification method using an optimized iterative regularization approach employing iterative reweighted norm-based tracking for denoising. This method enhanced damage detectability, accuracy, and effectiveness, enabling adaptation to incomplete noisy modal data for structural damage localization [10]. Composite structures, particularly laminated composite structures, suffer significantly from the impact of imperceptible material losses at their surfaces, necessitating the development of methodologies and technologies to monitor structural health. Gomes and Giovani devised a two-step composite laminate damage identification method using a metaheuristic sunflower optimization algorithm and finite element analysis simulation. Experimental results demonstrated the method's capability to identify locations and severity of multiple damages within material structures, exhibiting high identification efficiency [11]. In order to enhance the accuracy of Bayesian damage identification methods, Luo et al. improved the objective function and sampling methods for Bayesian damage identification based on autoregressive coefficients and particle swarm optimization algorithms. Experimental results validated the method's strong identification ability and high sampling statistical efficiency in scenarios involving multiple damages, affirming its feasibility and accuracy [12].

Conventional damage identification methods exhibit poor accuracy in identifying fatigue cracks and loosening of bolts in transmission tower structures. Zuo and Guo proposed a time-domain damage identification method based on linear and nonlinear autoregressive model expressions and Itakura distance, employing a greedy strategy with a random pruning algorithm to optimize and enhance both linear and nonlinear autoregressive models. Experimental results demonstrated the method's effectiveness in identifying nonlinear damage in frame models and transmission tower models [13].

The results of the related work are summarized in Table 1. In summary, numerous studies have addressed structural or material damage identification, affirming the practicality of computer technology and data-driven approaches in damage detection. However, research specifically targeting structural damage identification in large-span spatial structures remains relatively scarce, with room for improvement in accuracy and practicality. To address this gap, research integrating GA and SA for structural damage identification in large-span spatial structures has been initiated.

Table 1: Summary of relevant research work

Literature coding	Literature Information	Methodology	Result	Limitations
[6]	Barkhordari et al.	Deep convolutional networks and ensemble learning algorithms	94% accuracy and 92% recall	High model complexity and low computational efficiency
[7]	Mohebian et al.	Visible particle sequence search algorithm	This algorithm outperforms other metaheuristic algorithms in terms of accuracy, robustness, and convergence speed	High model complexity
[8]	Hajializadeh	Deep learning and Bayesian optimization techniques	Under conditions of variable speed, uneven track, and operating noise, bridge damage can be accurately and automatically detected and classified solely through train measurements	The accuracy of damage identification can be further improved
[9]	Lei et al.	Support vector machine	Obtain acceptable detection accuracy, with good detection accuracy and robustness	The model is too simple and has poor performance
[10]	Daneshvar et al.	Optimized iterative regularization method	Improved the detectability of damage, determined the optimal regularization value, and obtained accurate solutions.	High model complexity
[11]	Gomes and Giovani	Meta heuristic sunflower optimization method and finite element analysis simulation	Effectively identifying the location and severity of multiple damage situations in composite structures has high efficiency in saving time and computational costs	Only applicable to composite material structures
[12]	Luo et al.	Autoregressive coefficient objective function and particle swarm optimization	Strong recognition ability and high sampling and statistical efficiency	High model complexity

		algorithm for Bayesian optimization		
[13]	Zuo and Guo	Linear and nonlinear autoregressive models, linear and nonlinear autoregressive models	Nonlinear damage identification methods can effectively identify nonlinear damage in framework models and transmission tower models	Only for the transmission tower model, the model complexity is relatively high

3 Design of a structural damage identification model for large-span spatial grid structures based on SA-Optimized GA

During long-term service, defects and damage inevitably occur in large-span spatial grid structures. To enhance the damage identification technology for such structures, a research initiative was undertaken to design a damage identification model suitable for large-span spatial grid structures, utilizing GA and SA.

3.1 Design of damage identification model based on numerical simulation and GA

Material fatigue, corrosion, dynamic loading, and design/construction defects can all lead to damage and defects in structures. In order to address the issue of damage identification in large-span space grid structures, ensuring structural integrity, maintenance of equipment operation, and reducing property damage and casualties, research is conducted using finite element numerical simulation and GA for damage identification [14]. GA is an optimization algorithm that mimics the evolution of nature and has the ability of parallel search for large-scale problems. The loss identification problem of large-span spatial grid structure involves the selection and optimization of multiple variables, and GA can deal with multivariate optimization problems with strong interpretability. The probabilistic design method in finite element software can complete the reliability analysis of the structure, and the correlation coefficients of the variables to the vibration frequency of the structure can be obtained by using the finite element method to determine the damage influencing factors. Based on this, GA can realize the identification of damage location.

Using ANSYS software, a model of a large-span spatial grid structure is established. Material and geometric uncertain characteristics, such as the elastic modulus of the structure, the cross-sectional area of the truss members, and density, are selected for structural stability sensitivity variable analysis. Structural vibration frequency is chosen as the output variable for damage identification. The study utilizes the Monte-Carlo method combined with Latin hypercube techniques to improve variable sampling methods. The Monte-Carlo method is a statistical inference method based on random samples, which approximates problems that cannot be directly solved analytically by generating a large number of random samples using statistical principles [15]. Monte-Carlo computations leverage multi-core or distributed computing, ensuring high computational efficiency. Due to the strong randomness of installation errors and defect losses in space grid structures, the parallel processing mode of Monte-Carlo is suitable for cyclic experiments under different working conditions of space grid structures.

The probability distribution function of Monte-Carlo failure probability is calculated as shown in Equation (1), where $G(X)$ represents the functional function, and $g(X)$ represents the joint probability density function of random variables.

$$P\{G(X)<0\}=\int\ldots\int_{G(X)<0} g(X)\,dX_1\ldots dX_n \quad (1)$$

The structural reliability index and failure probability calculation are shown in Equation (2), where Φ represents the probability function of the standard normal distribution; p_f represents the failure probability; p_f is the Monte-Carlo representation; I represents the indicator function; N represents the number of experimental analyses.

$$\begin{cases} \beta=\Phi^{-1}\left(1-p_f\right) \\ p_f=\dfrac{1}{N}\sum_{i=1}^{n} I\left[G\left(X_i\right)\right] \end{cases} \quad (2)$$

The generation of random samples in the Monte-Carlo method is crucial, and the uncertainty of Monte-Carlo will affect the distribution and quantity of random samples. The study introduces Latin Hypercube Sampling (LHS) for sample generation. LHS technology ensures an even distribution of samples, avoiding the repetition and overlap sampling of traditional Monte-Carlo methods, which can be used for sensitivity analysis and reliability analysis of variables, as shown in the sampling process comparison in Figure 1.

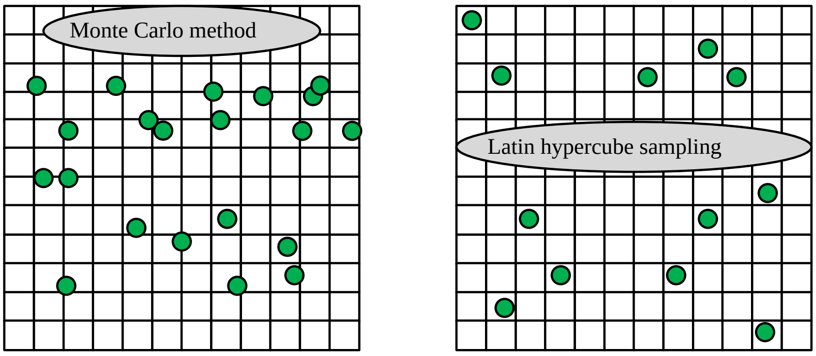


Figure 1: Schematic diagram of the LHS process

The LHS random sampling process is shown in Equation (3), where X represents the random variable; i represents a certain stratified interval, and there are N stratified intervals.

$$\begin{aligned} X_i &= X / N + (i-1) / N \\ (i-1)/N &< X_i < i/N \end{aligned} \tag{3}$$

After Monte-Carlo-LHS sampling, the probability design system of ANSYS software is used to analyze the material and geometric uncertain characteristics and their effects on structural modes. This determined the defect-sensitive parameters of the large-span grid structure, facilitating damage identification when the grid structure has random defects. Based on GA, a structural damage identification model is designed. GA is a search heuristic algorithm that simulates the process of biological evolution, by simulating the phenomena of reproduction, crossover and gene mutation in natural selection and genetic mechanism, a set of candidate solutions is kept in each iteration. The better individuals are selected from the solution group according to some index, and these individuals are combined using genetic operators (such as selection, crossover, mutation, migration and local and neighborhood search) to produce a new generation. The process is repeated until some convergence index is satisfied.

The GA can simultaneously process multiple individuals and automatically adjust search behavior. It has advantages of strong adaptability, high robustness, and parallelism and is widely used in solving optimization problems in computer science. The workflow of GA is shown in Figure 2 [16]. GA first uses parameter encoding to transform feasible solutions to the structural damage identification problem in space into floating-point number encodings, which represent a series of genes or chromosomes. Floating-point number encoding can significantly reduce computational complexity and ensure operational efficiency.

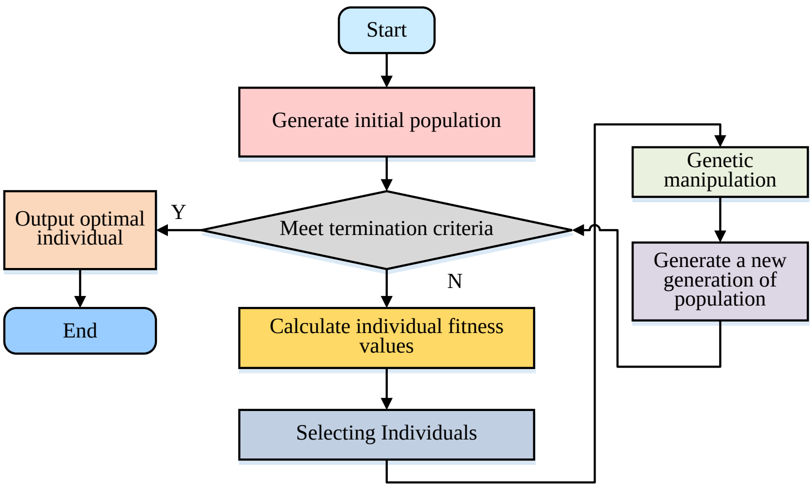


Figure 2: GA workflow diagram

The selection process of the GA is designed to mimic the natural selection mechanism. The fitness function is constructed based on the modal information of the grid structure. The fitness function measures the quality of individuals, with higher fitness values leading to retention and participation in the next iteration, while lower fitness values result in elimination [17]. After multiple iterations, the individual with the highest fitness value in the population, representing the global optimal solution for the optimization problem, is obtained. The research employs the roulette wheel selection method for individual selection, with the selection probability calculated as shown in Equation (4). In this equation, f represents the individual's fitness value, and f_i represents the fitness values of individuals in the population. The principle of setting the population size of GA needs to consider the complexity of the problem, computational resources, and convergence speed. Complex problems require a larger population size to increase the diversity of the search and the possibility of finding a globally optimal solution. The study considers setting the population size from 20 to 160.

$$p_i = \frac{f}{\sum_{i=1}^{n} f_i} \tag{4}$$

The selected superior individuals act as parents for crossover operations, where genetic segments are combined to form new individuals. The study utilizes uniform crossover for the crossover operation. After performing mutation operations, certain genes in the next-generation population undergo mutation with a certain probability, enhancing the exploration ability of the search space. The iterative process of selection, crossover, and mutation continues until the stop condition is met. The principle of setting the crossover rate needs to consider the size of the search space, early convergence and the search range. It not only needs to increase the diversity of the population but also need to avoid the problem of early convergence, the crossover rate of the value of the range of 0.6-0.9. At the same time, according to the diversity of the population, do not destroy the good solution and to avoid the early convergence of the principle of setting the rate of variation, the research set the rate of variation of the consideration of the range of 0.5 percent to 1.0 percent.

The damage identification process based on GA is illustrated in Figure 3. The selection of parameters such as population size, crossover rate, and mutation rate is crucial in GA. Improper parameter selection can slow down the evolution of GA. For the problem of damage identification in large-span network spatial structures, GAs need further improvement [18].

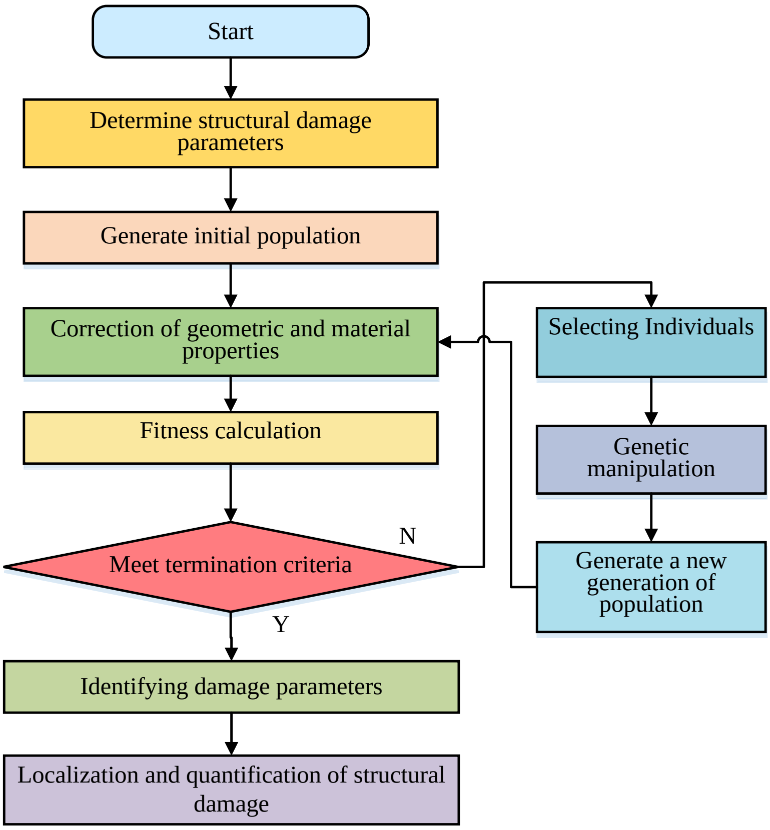


Figure 3: GA-based damage identification process

3.2 Design of a damage identification model for large-span grid spatial structures based on SA-Optimized GA

In the structural identification process using GA, structural damage locations and extents are identified through modal corrections of intact structures. To enhance the accuracy of GA in the damage identification process, optimizations and improvements are made regarding the initial population generation and genetic operations.

The traditional GA search process is conducted based on the population form, and the distribution of individuals in the initial population has a crucial impact on the effectiveness of GA. Diversification in the initial population improves the exploration ability of the solution space, while a concentrated or singular distribution may lead GA to a local optimum without finding the global optimum. Additionally, the distribution of individuals in the initial population is related to the convergence speed. Therefore, considering the concept of Hamming distance, which measures the number of differing characters at corresponding positions in two equally long strings, the study sets a distance limit for the population individuals to ensure diversity.

Crossover and mutation operations determine the diversity and evolutionary potential of offspring individuals. Reasonable crossover and mutation parameters contribute to maintaining algorithm diversity and improving exploration ability and convergence speed. The study proposes an improved adaptive crossover probability, as shown in Equation (5). The crossover operation is performed based on the individual's fitness value. In Equation (5), f', $f_{\max}$, $f_{\min}$, and f_{avg} represent the individual's fitness value, maximum fitness value, minimum fitness value, and average value, respectively; k_1 and p_{c1} are random constants.

$$\begin{cases} p_c = p_{c1} - k_1 \dfrac{f' - f_{avg}}{f_{\max} - f_{\min}} & f' \ge f_{avg} \\ p_c = p_{c1} & f' < f_{avg} \end{cases} \tag{5}$$

The calculation process of the arithmetic crossover operator is shown in Equation (6), where x_A and x_B represent the parents, and x_B and x_B' represent the offsprings. β and β are random constants.

$$\begin{cases} x_A' = \alpha x_A + (1-\alpha) x_B \\ x_B' = \beta x_B + (1-\beta) x_A \end{cases} \tag{6}$$

From Equations (5) and (6), when the average fitness of parents and offspring stabilizes, the optimization process gradually stops. To address this, the study employs a heuristic crossover operator for mutation operations, as shown in Equation (7).

$$\begin{cases} x_A' = \gamma x_A + (1-\gamma) x_B \\ x_B' = \gamma x_B + (1-\gamma) x_A \end{cases} \tag{7}$$

In Equation (7), γ represents the heuristic crossover coefficient, and the calculation process is described in Equation (8). χ represents a random number, and n represents the number of times the calculation in Equation (7) is performed during the crossover process.

$$\gamma = \left[\frac{f(x_A)}{f(x_A) + f(x_B)} \right]^{\chi^{(n-1)}} \tag{8}$$

Similarly, the improved calculation of the mutation probability p_m is described in Equation (9), where p_{m1} and k_2 are constants.

$$\begin{cases} p_m = p_{m1} - k_2 \dfrac{f' - f_{avg}}{f_{\max} - f_{\min}} & f' \ge f_{avg} \\ p_m = p_{m1} & f' < f_{avg} \end{cases} \tag{9}$$

Building upon the improved GA, a fusion with an enhanced SA is introduced to further enhance the accuracy of damage detection. SA is a global optimization algorithm based on the principles of physical annealing. It employs a strategy of random search to simulate the temperature variations and structural adjustments in the annealing process of materials. By adjusting the probability of accepting inferior solutions, it escapes local optima and facilitates the search for global optima, as illustrated in Figure 4 [19]. The SA heats the solid to a sufficiently high temperature and then allows it to cool slowly. When the solid is heated, the particles become disordered as the temperature rises, and the internal energy increases. When it is cooled, the particles become orderly and reach equilibrium at each temperature, and finally reach the ground state at room temperature, and the internal energy is minimized. The SA algorithm gives the search process a time-varying and zero probability of jumping, which can effectively avoid falling into local minima and eventually converge to the global optimum.

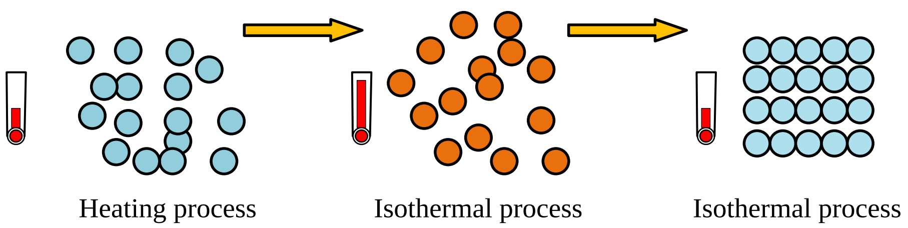


Figure 4: Simulation of physical annealing process

SA possesses strong global search capabilities. As the temperature decreases, the probability of accepting inferior solutions gradually diminishes, leading the search process towards stability and eventually reaching a global optimum. Compared to other optimization algorithms, SA requires relatively small parameter adjustments. Therefore, a combined optimization with SA and the improved GA is chosen. The workflow of traditional SA is depicted in Figure 5 [20]. SA starts from the set initial temperature T_0 and goes through three iterative processes of heating, isothermal, and cooling. By calculating the energy state generated during the iteration process, the energy difference, i.e. the change in the objective function, is solved. Based on the Metropolis criterion, it is determined whether to accept the new state. As the temperature decreases, the probability of accepting a poor solution gradually decreases, and the search process gradually tends to stabilize, ultimately reaching the global optimal solution.

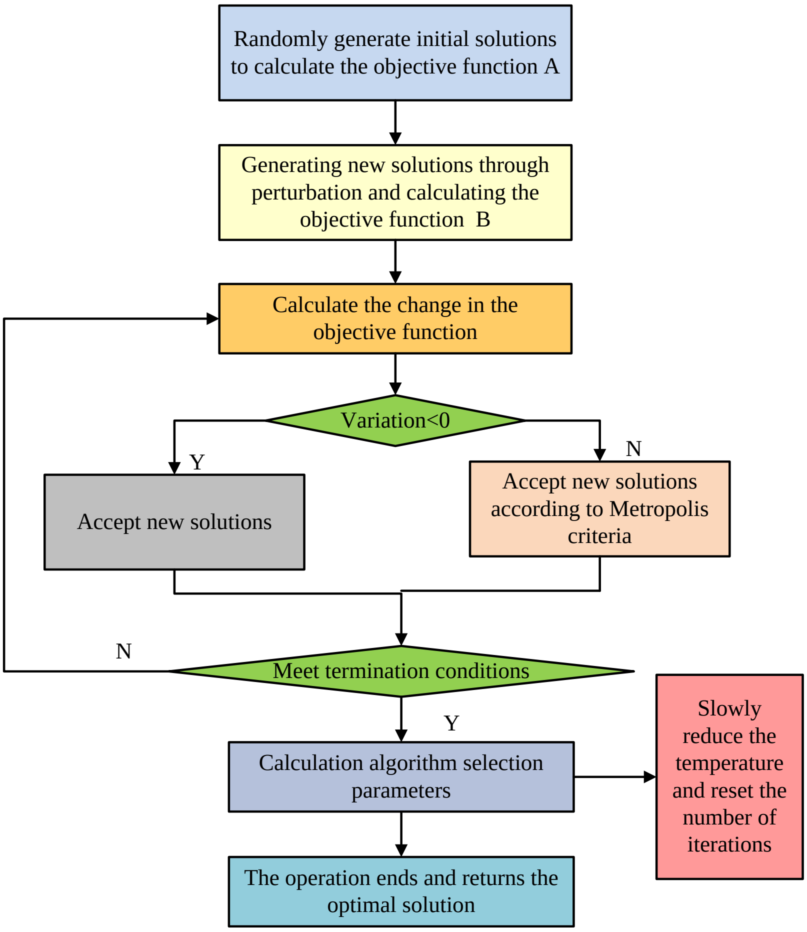


Figure 5: The workflow of traditional SA

The calculation of the objective function's variation is shown in Equation (10), where S_1 and S_2 represent the solution after perturbation, and $f(S_1)$ and $f(S_2)$ represent the objective function values of the solution.

$$df = f(S_1) - f(S_2) \tag{10}$$

The computation process of the Metropolis criterion is given in Equation (11), where p represents the probability of accepting a solution.

$$p = \begin{cases} 1 & df > 0 \\ \exp\left(-\dfrac{df}{T}\right) & df \le 0 \end{cases} \tag{11}$$

Although SA is effective in searching for global optima, it lacks control over the search space and tends to have slower convergence compared to other optimization algorithms. The initial temperature setting and the strategy for temperature reduction are critical. The initial temperature setting needs to consider the complexity of the problem and the limitation of computational resources, and the initial temperature can be estimated according to the characteristics of the objective function. The temperature descent strategy includes linear decay, exponential decay and adaptive decay, etc. It is necessary to balance the global search and local search ability, and the temperature descent strategy needs to be adjusted through experiments.

Optimization improvements are made to SA, including the design of a temperature parameter decay function shown in Equation (12), where α represents the decay coefficient, adjusted as needed.

$$t_{k+1} = \alpha * t_k \tag{12}$$

The rate of temperature parameter reduction determines the length of the Markov chain L_k in SA. The length of the Markov chain affects the search range of the solution space. The relationship between the established functions of L_k and n, representing the number of damaged elements n in the spatial framework structure, is shown in Equation (13), where γ is a tuning coefficient, a constant.

$$L_k = \gamma * N \tag{13}$$

The calculation of the variation in the objective function ΔE_k for the initial population individuals in SA is given in Equation (14), where $fitness\left(x^{'}\right), avgfitness$ represent the current fitness and the average fitness.

$$\Delta E_k = fitness\left(x^{'}\right) - avgfitness \tag{14}$$

According to Equation (11), the calculation of the probability p of accepting new individuals in the offspring population is given in Equation (15), where k represents the probability calculation parameter.

$$p = \exp\left(-\frac{k\Delta E_k}{t_k}\right) \tag{15}$$

To address the issue of preserving excellent individuals in GA, a hybrid approach is introduced, where both improved SA and improved GA are combined. SA operations are applied to individuals after genetic crossover and mutation, as illustrated in Figure 6.

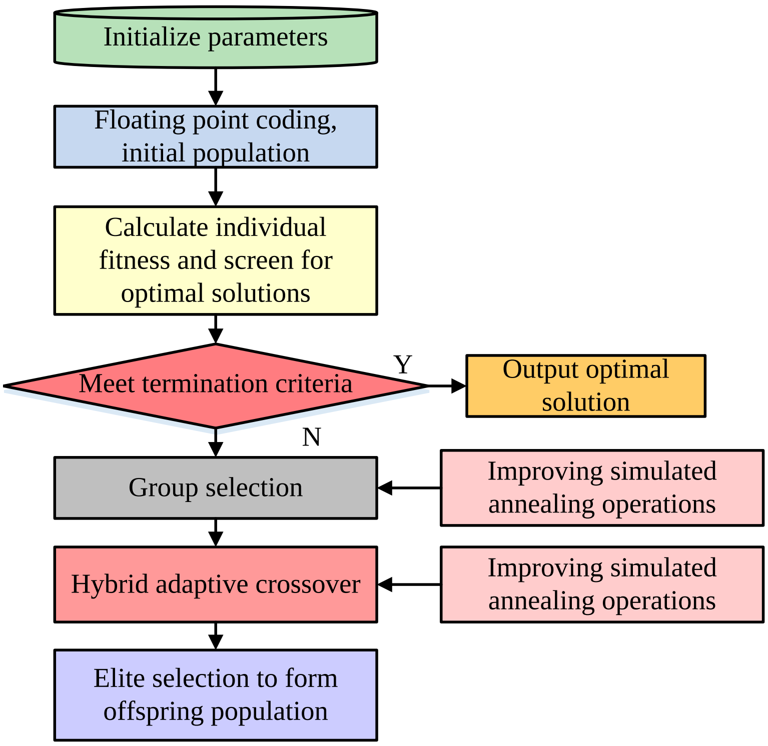


Figure 6: Improved hybrid SA-GA workflow

4 Performance testing and structural damage identification analysis of SA-GA in large-span spatial grid structures

To validate the effectiveness of the proposed structural damage model for large-span spatial grid structures, performance testing experiments and application effectiveness analyses were conducted, followed by a detailed discussion of the results.

4.1 Performance testing of SA-GA damage identification model

The experiment was conducted based on a 64-bit WIN10 operating system with an NVIDIA GeForce MX150 2GB graphics card and 125GB of RAM. The central processor was a 2.7 GHz Intel Core i5-6500. To conduct the algorithm's performance testing, a program was implemented in the C++ language to execute the required testing algorithms. Initially, the study focused on evaluating the optimization performance of the hybrid improved SA-GA through five test functions, including single-modal benchmark functions like Sphere Function and Schwefel Function, and multi-modal benchmark functions like Rastrigin Function, Griewank Function, and Ackley Function. Sphere Function is a convex function whose goal is to minimize the sum of squares of all variables; Schwefel Function has multiple local minima; Rastrigin Function and Griewank Functio are commonly used test functions for multi-modal optimization problems, which are non-convex functions with multiple local minima. The Ackley function is a multi-dimensional function with a large number of local minima.

The study compared the performance of the algorithm with Firefly Algorithm (FA), Whale Optimization Algorithm (WOA), and traditional GA. Precision, recall, and Receiver Operating Characteristic Curve (ROC) were chosen as the evaluation metrics for algorithmic optimization capabilities. Precision and recall jointly assessed the model's classification ability, maintaining a balance between accuracy and comprehensiveness. The study utilized the Precision-Recall curve (PR) to depict the relationship between precision and recall. The Area Under the Curve (AUC) of the ROC curve comprehensively evaluated the algorithm's performance, with experimental statistical results illustrated in Figure 7.

Figure 7 indicates that the hybrid SA-GA designed in the study exhibited superior performance in both PR and ROC curves, positioned at the far right and left extremes of the coordinate axes, respectively. At a precision of 0.9, the hybrid SA-GA achieved a recall of 0.93, outperforming FA, GA, and WOA with recalls of 0.61, 0.68, and 0.79, respectively. In the same experimental environment, the hybrid SA-GA demonstrated a relative advantage in balancing precision and recall. The AUC values for the hybrid SA-GA, FA, GA, and WOA were 0.927, 0.804, 0.673, and 0.758, with SA-GA having the highest AUC value, indicating the best overall model performance.

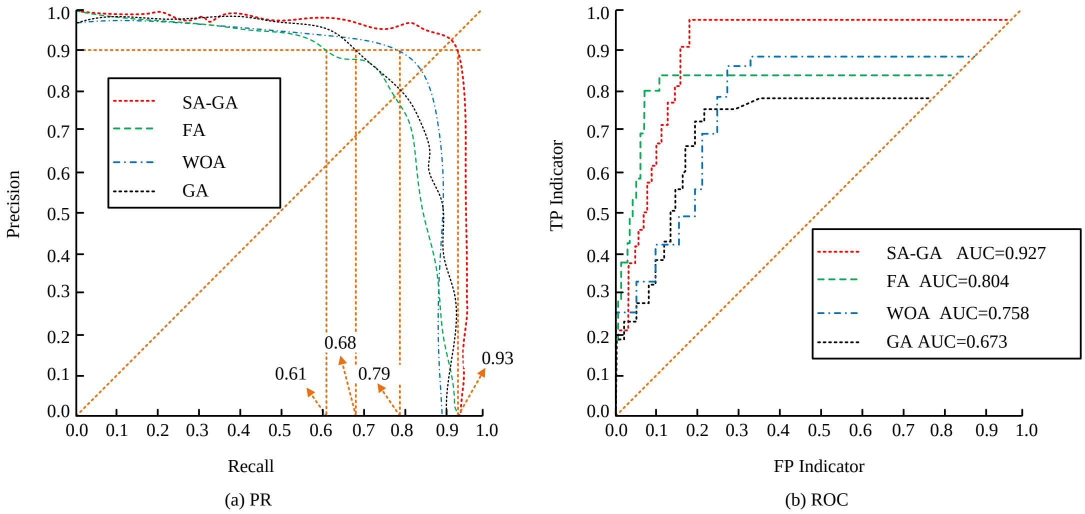


Figure 7: Comparison of PR and ROC curves for different intelligent optimization algorithms

The study employed Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to evaluate optimization errors for different intelligent optimization algorithms. MAE and RMSE exhibited varying sensitivities to outliers, providing a comprehensive assessment of errors between optimized values and true values. Results in Figure 8 showed that the SA-GA designed in the study consistently achieved low error values across different test functions, distinguishing itself from the other three algorithms. The median levels of MAE and RMSE remained below 0.4, indicating high optimization accuracy.

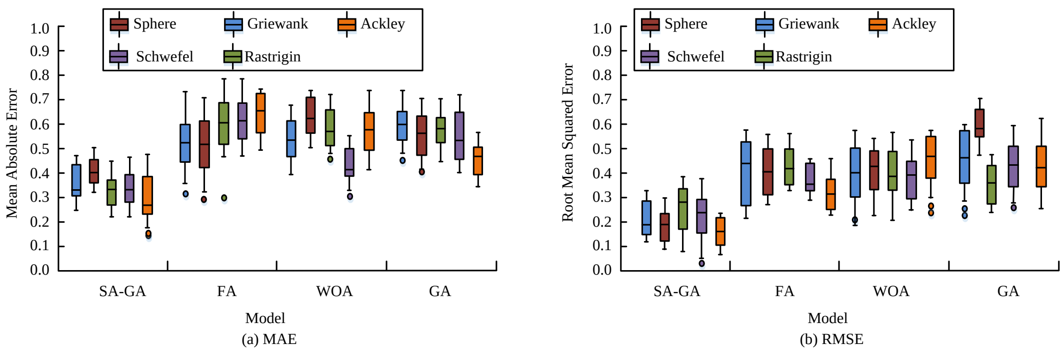


Figure 8: Comparison of MAE and RMSE of different intelligent optimization algorithms

Table 2 presents the convergence results of the proposed GA improvement method. It was evaluated based on the mean of the best solution in 30 independent experiments. The number of times the optimal solution was reached, and the minimum iteration counted. The hybrid improved SA-GA outperformed the other two algorithms from all three evaluation perspectives. In 30 independent experiments, the traditional GA reached the optimal solution only 19 times, indicating lower optimization accuracy. The improved GA achieved the optimal solution 27 times but demonstrated less stable optimization accuracy across different test functions. SA-GA achieved a 100% convergence rate, consistently obtaining the target optimal solution. Additionally, this method exhibited the fastest convergence speed.

Table 2: Comparison of convergence of improved algorithms

Test function	Algorithm	Average convergence value	Convergence times	Minimum number of iterations
Sphere	GA	6.246E-6	13	627
	Improve GA	5.246E-10	23	432
	SA-GA	4.236E-15	30	246
Schwefel	GA	9.165E-6	19	416
	Improve GA	5.161E-8	27	364
	SA-GA	4.357E-12	30	221
Rastrigin	GA	8.554E-6	16	475
	Improve GA	6.458E-8	21	349
	SA-GA	2.497E-12	30	221
Griewank	GA	7.165E-6	14	513
	Improve GA	2.674E-10	24	416
	SA-GA	2.348E-15	30	260
Ackley	GA	8.512E-6	16	468
	Improve GA	3.254E-9	24	314
	SA-GA	2.177E-11	30	224

Continuing to compare and analyze the solution space search ability of different algorithms, the Hypervolume Indicator (HV) and Inverted Generational Distance (IGD) were used as evaluation indexes, and the experimental results are shown in Fig. 9. From Fig. 9(a), the research improved SA-GA had obvious advantages over the traditional GA, FA, and WOA algorithms in terms of the HV value.The HV value of the SA-GA algorithm could be up to 0.92, and the volume between the algorithm's Pareto front and the reference point was large. In Fig. 9(b), the IGD value of the improved SA-GA was the smallest in the same experimental environment, and was less than 0.1 at the early stage of the iteration. In contrast, the IGD values of the GA, FA, and WOA algorithms were all greater than 0.20. The GA, FA, and WOA algorithms generated the solutions that were closest to the real Pareto front.

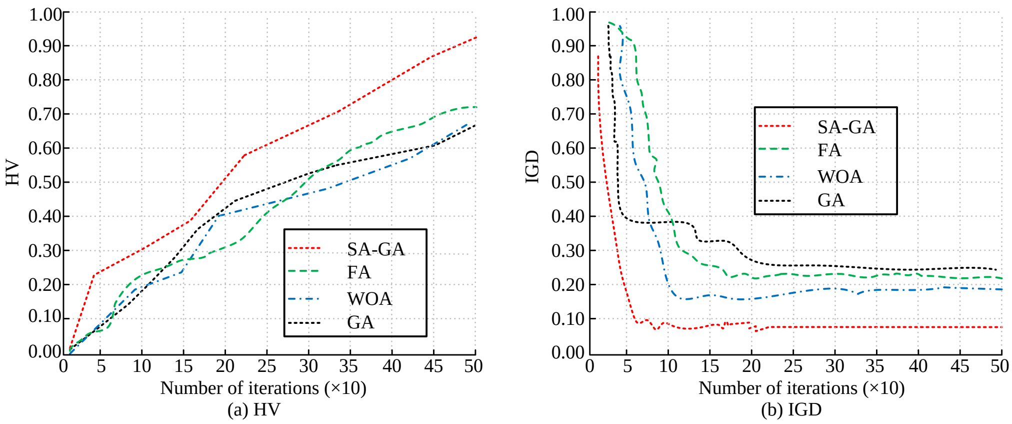


Figure 9: Comparison of HV and IGD for different algorithms

The F1 values of different algorithms are shown in Fig. 10 in comparison with the execution efficiency. In Fig. 10(a), the F1 value curve of the improved SA-GA was at the highest level, and the maximum F1 value was close to 1. The classification F1 values of GA and FA did not differ much, and they were all in the range of 0.8-0.9, and the F1 value of the WOA was the lowest, and the highest value only reaches 0.68. In Fig. 10(b), the computation time of the different algorithms were in an increasing trend with the increase of the number of training samples, and the improved SA-GA took the least time, and the model classification took 4.21s when the data samples reached 8000. In terms of the combined F1 value reception and computation time consuming, the improved SA-GA had a better performance, and the improved strategy played an improved role.

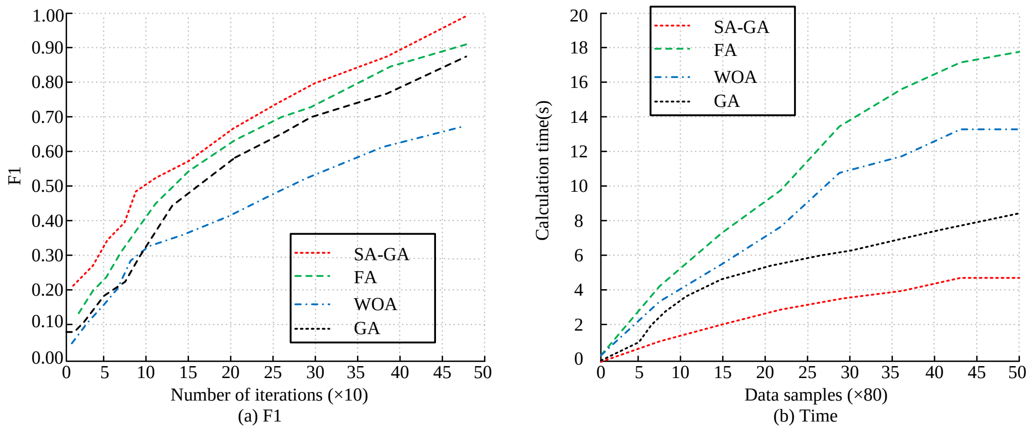


Figure 10: Comparison of F1 value and execution efficiency of different algorithms

4.2 Analysis of damage identification effect in large-span spatial grid structure based on SA-GA

The study developed an analysis of the damage identification effect in a large-span space grid structure based on the SA-GA. The designed grid structure comprised 70 nodes and 186 members, with fixed supports at the truss base and hinged connections between members. The structural model was constructed using ANSYS, and damage identification was performed based on the optimization of a target function constructed using frequency and mode shapes. The structural composition and node numbering are shown in Figure 11.

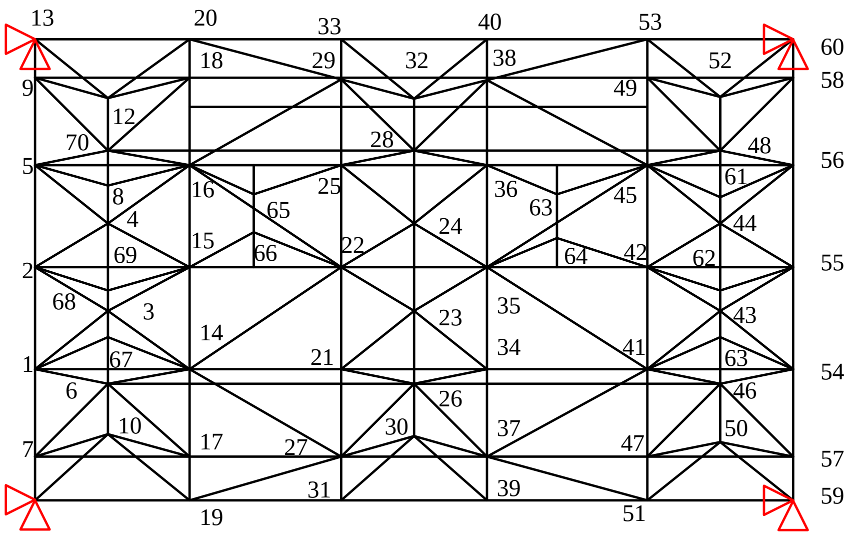


Figure 11: Schematic diagram of the structural composition form and node numbering of the experimental setup

Firstly, various damage scenarios were considered, including undamaged conditions and 100% damage to single members (members 27, 47, and 48). The results of identifying 100% damage to member 27 are shown in Figure 12. The algorithm converged to the optimal value of the target function in 140 generations, with a minimum value of 0.17. In Figure 12(b), it is observed that, under the SA-GA model, the damage level of member 27 was 0.94, significantly distinguishing it from other members. While several other members exhibited damage levels above 0.2, the considerable gap from member 27 suggested the need to consider a certain level of damage identification error in the experiment.

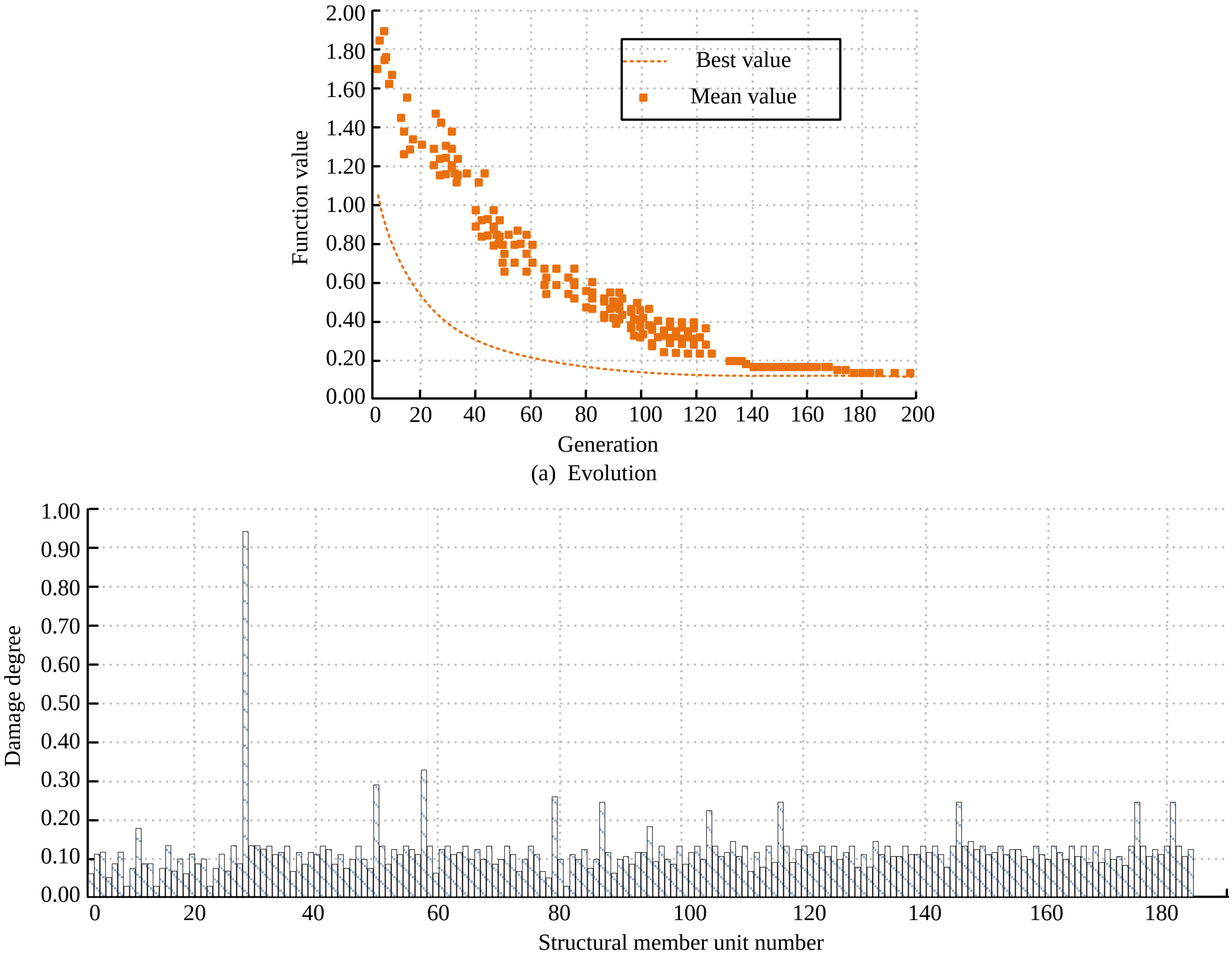
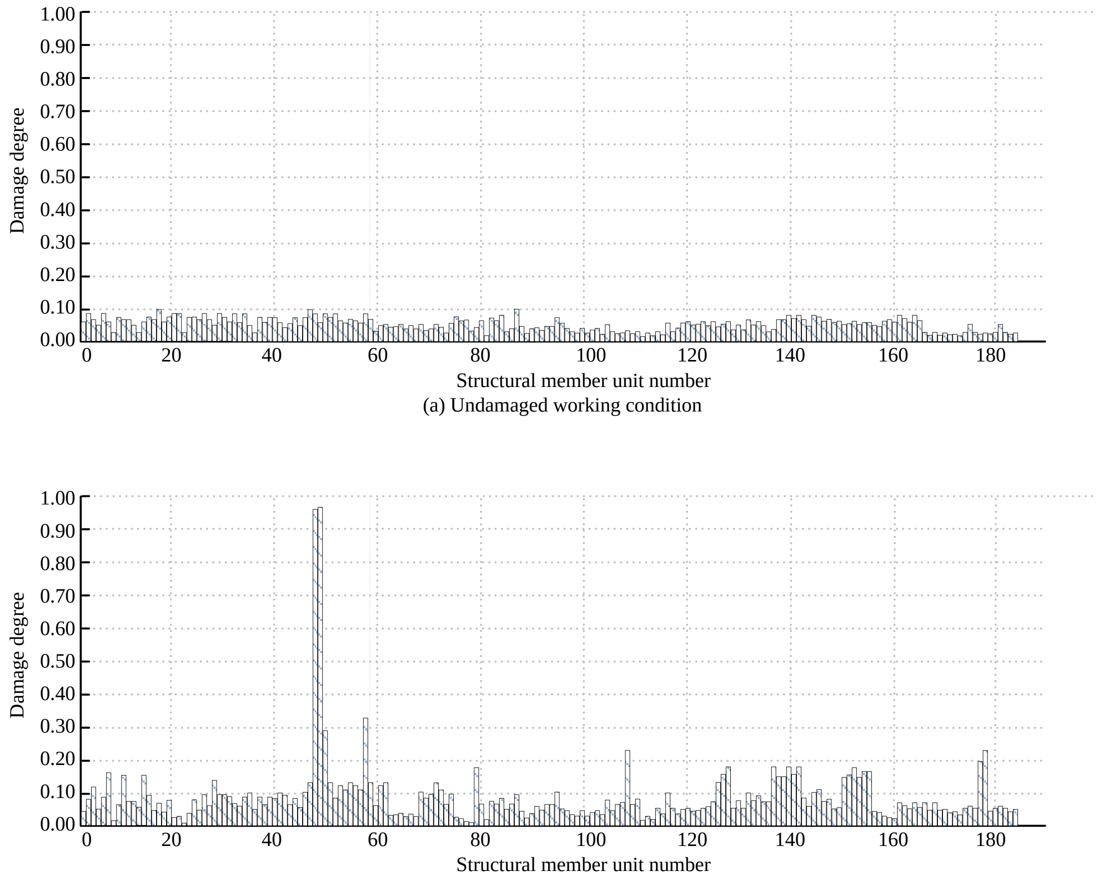


Figure 12: 100% damage identification result of single member 27

The identification results for undamaged conditions and 100% damage to members 47 and 48 are presented in Figure 13. For undamaged conditions in Figure 13(a), the SA-GA model demonstrated high accuracy, with all members' damage identification values below 0.10, indicating an undamaged state. In the case of multiple damages in Figure 13(b), the SA-GA model performed well, with damage identification values for members 47 and 48 exceeding 0.95, indicating significant damage. However, some members showed damage levels above 0.20, considered reasonable identification errors.

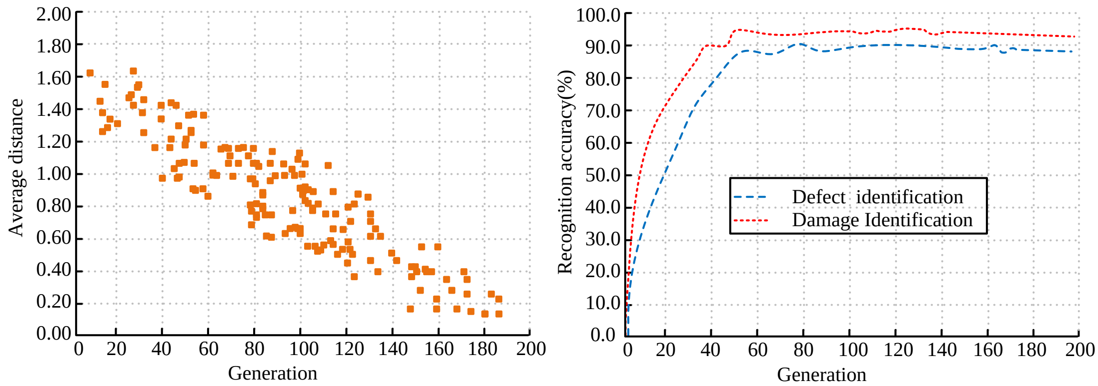


(a) Undamaged working condition

(b) Multiple damage conditions

Figure 13: Identification of multiple damage and non damage conditions

Finally, random defects in the elastic modulus of the grid structure were introduced in multiple damage scenarios, and the distribution of the population and the accuracy of damage identification are shown in Figure 14. The average distance gradually decreased with random defects. evolutionary iterations, maintaining a certain diversity in the population. The identification model achieved accuracy rates of over 90.0% for recognizing random defects and actual damage, demonstrating the capability to identify damage in the grid structure with



(a) Individual population distribution

(b) Recognition accuracy

Figure 14: Structural damage identification under random defects

5 Discussion

As an important form of building structure, the safety and stability of the net frame structure is crucial for the safe use of the overall building. Defects in the rod material, negative deviation of the cross-sectional area, and initial deflection caused by collision during transportation or installation can easily lead to random defects in the rod material. Therefore, periodic damage detection of in-service grid structures is an effective means to detect structural damage and provide early warning in a timely manner. Existing common techniques for structural damage detection include monitoring sensors, acoustic wave detection, thermal imaging technology and vibration analysis. With the rapid development of computer technology, the use of image processing technology to identify potential structural damage, as well as structural monitoring data combined with computer algorithms or machine learning to identify structural damage has gradually been widely used. However, while the damage identification approach based on computational intelligence brings many advantages, it also has some shortcomings. For example, in the studies of literature [6], literature [7], literature [10], and literature [12], although the detection accuracy, robustness, convergence speed, and damage recognition ability have been enhanced, the high model complexity and low computational efficiency increase the training difficulty and time cost of the model, and may also lead to a decrease in the model's generalization ability in practical applications. Moreover, there is a strong dependence on the quality and quantity of input data, which limits the performance of the recognition results. The studies in literature [11] and literature [13] only focus on composite structures and transmission tower models, and the scalability and applicability of the models are low.

Combining the shortcomings of the existing studies, the study firstly used Monte-Carlo sampling method to complete the sensitivity analysis of the finite element structural model. Then, GA was utilized for structural damage identification. Finally, SA was used to optimize and improve the initial population generation and genetic operation of GA. It was found that the recall of the hybrid SA-GA was 0.93 at a precision of 0.9, while the recall of the other algorithms was below the 0.80 level. The single-rod damage degree recognition result was 0.94, and the multi-rod damage recognition degree values were all above 0.95, and the damage recognition error was in the reasonable error range. Comparing the study of literature [6] and others, Barkhordari M S et al. achieved only 94% precision and 92% recall. The studied design achieved better performance. Also comparing the study of literature [8], the combined visible advantages of intelligent optimization algorithms in solving the decision-making problems made the model to have a superior performance compared to deep learning techniques. The study's optimization strategies for GA population, GA and SA parameters played a role in simplifying the model and improving the performance.

6 Conclusion

The development and application of computer technology and intelligent algorithms in structural damage identification have made significant progress. To further improve the precision of structural damage identification in large-span space grid structures, a damage identification model based on SA-GA was designed. Experimental results showed that the PR curve and ROC curve of the hybrid SA-GA performed well. When the precision was 0.9, the recall rate of the hybrid SA-GA was 0.93, while the recall rates of other algorithms were below 0.80. The maximum AUC value of the hybrid SA-GA was 0.927, indicating the best overall performance of the model. The MAE and RMSE errors of SA-GA were at a low level, significantly better than the values of the other three algorithms, demonstrating high optimization accuracy. For different test functions, SA-GA found the optimal solution up to 30 times, surpassing the two algorithms before improvement. Additionally, SA-GA required fewer optimization iterations and converged faster. The SA-GA algorithm had obvious advantages over the traditional GA, FA, and WOA algorithms in terms of HV value, which could reach up to 0.92. The IGD value was the smallest among the same experimental environments, which was less than 0.1 at the early stage of the iteration. At the same time, the F1 value of the algorithm was close to 1 and the algorithm execution time was shorter, which was only 4.21 s. The algorithm could be executed in a short period of time, which was only 4.21 s. The algorithm was also very simple. The SA-GA model performed well in the conditions of no-damage, single-damage, and multi-damages. The recognition accuracy was excellent, with a degree of 0.94 for single-damage and degree above 0.95 for multi-damages. The damage identification errors were within a reasonable range. Furthermore, the improved genetic operations of the SA-GA model achieved good results, maintaining good population diversity and enabling damage identification under random defects. The designed SA-GA damage identification model achieved good application effects in large-span spatial grid structures, enabling timely identification of structural damage and monitoring. This contributes to the development of industries related to structural damage and monitoring. However, further research can focus on the identification of the extent of damage in grid structures. Meanwhile, GA may encounter certain challenges when optimizing larger grid structures, and the number of evolutionary generations of GA increases significantly with the complexity of the structure and the number of rods and nodes, making the algorithm's running time and computational cost increase significantly. Therefore, future research efforts may consider the improvement of GA coding methods by using more efficient coding methods to reduce the coding length and increase the efficiency of genetic operations or using parallel computing techniques to accelerate the operation process of GAs.

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