Health Monitoring of Civil Engineering Structures Using Simulated Annealing Genetic Algorithm

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The key to structural health monitoring in civil engineering is to optimize the configuration of sensors in the monitoring system to improve diagnostic accuracy and reduce the consumption of computing resources. In this study, the genetic algorithm and the simulated annealing algorithm are improved, an adaptive simulated annealing genetic algorithm is formed, and the strain mode criterion is integrated to achieve a more accurate sensor optimal configuration. The finite element model of the bridge structure is constructed by ANSYS software and analyzed to obtain the strain mode matrix and displacement mode matrix. The experimental results showed that the simulated annealing genetic algorithm had only 132 iterations in obtaining the minimum MAC index value. This value was significantly lower than the 279 of the object detection algorithms and the 284 of the negative selection algorithms, reducing by 147 times and 152 times, respectively. Meanwhile, the average detection error rate of the simulated annealing genetic algorithm was reduced to 0.52, which was better than 0.66 for the target detection algorithm and 0.61 for the negative selection algorithm, reducing by 0.14 and 0.09, respectively. The proposed algorithm not only shows obvious advantages in convergence speed, but also has higher accuracy than displacement mode in sensor optimization arrangement and has application potential in structural health monitoring of civil engineering. The application of SAGA in civil engineering structural health monitoring helps to detect and deal with structural damages in time and prevent major accidents to guarantee the safety and stability of engineering structures. This is of great significance for improving the overall quality and reliability of civil engineering projects.

Povzetek: Raziskava predstavlja prilagodljiv algoritem simuliranega žarjenja (SAGA) za izboljšanje konfiguracije senzorjev za spremljanje zdravja konstrukcij. Uporaba algoritma je optimizirala postavitev senzorjev v mostni konstrukciji in zmanjšala povprečno napako zaznavanja.

1 Introduction

The safety and reliability of civil engineering structures, as the material foundation of social development and people's livelihood and well-being, are of paramount importance. The stability and long-term effectiveness of engineering structures, environmental stress, material aging, and natural disasters all pose threats to the safety and stability of engineering structures. Therefore, continuous and accurate monitoring methods are widely regarded as an effective way to maintain structural safety [1-2]. New mathematical models and algorithms are emerging in the health monitoring of civil engineering structures. Among them, genetic algorithm (GA), as a commonly used global optimization method, has shown unique advantages in solving optimization problems in structural health monitoring [3]. However, the local search ability and convergence speed of GAs in dealing with complex problems, especially for nonlinear and multi-peak problems, still need to be improved [4]. At the same time, the simulated annealing (SA) algorithm has become another important choice to solve this problem because it can effectively jump out of the local optimal solution [5]. However, SA search strategy is blind, and the convergence speed is slow in the initial stage [6]. In view of the problems existing in the use of these two algorithms alone, the idea of combining SA and GA to complement their advantages came into being. The simulated annealing genetic algorithm (SAGA) is used to improve the structural health monitoring. The research innovation is mainly reflected in the fusion and optimization of algorithms. By introducing the SA concept, the search strategy of GA has been optimized. While balancing the adaptability and robustness of the algorithm under multiple objectives and constraints, it achieves better global optimization capability and faster convergence speed. In addition, the study explores the parameter tuning method and practical strategy of SAGA under different types and different use stages of civil engineering structures. Compared with traditional GA and SA algorithms, SAGA innovatively introduces an adaptive adjustment mechanism. This means that the algorithm can dynamically adjust its parameters during the search process according to the characteristics of the problem and the progress of the search, thus responding more flexibly to complex optimization problems. In summary, this study provides a more efficient and intelligent algorithm tool for health monitoring of civil engineering structures. It can play a decisive role in structural safety assessment in engineering applications, helping engineers to timely identify and address safety hazards, ensuring the reliable operation of civil engineering structures and public safety.

The research content is divided into four parts. The first part reviews the research status of structural health monitoring in civil engineering using SAGA. In the second part, it is proposed to combine the SA algorithm with the GA, introduce the adaptive adjustment mechanism, and utilize the two algorithms to solve the problem of optimal arrangement of bridge structural health monitoring sensors. In the third part, the constructed monitoring model is experimentally verified, and the experimental results are analyzed. The fourth part discusses and summarizes the findings.

2 Related works

As the national economy develops, civil engineering structures are increasing, and the health monitoring of civil engineering structures has become a research hotspot. New mathematical models and algorithms are emerging in this field. In structural health monitoring in civil engineering, new mathematical models and algorithms are constantly emerging. Hedaoo and Pawar used a fuzzy logic approach to evaluate the various risks of residential projects, taking into account fuzzy data and uncertainties, and divided 60 risk factors into 7 categories, and selected the most serious risk factors from them through experiments [7]. Oh et al. proposed a structural response recovery method using convolutional neural networks to detect faults or anomalous data, which proved the applicability of the method after long-term testing in cross-line bridges [8]. Cheng et al. proposed a new data-driven theory to analyze flow-induced vibration system analysis, predicting the evolution of the structural instability range with the change in mass ratio. The system excavated the characteristic information in the structural vibration data through data analysis to realize the monitoring and diagnosis of the structural health status [9]. Zhou et al. monitored the structural health of offshore wind power using GA and analytic hierarchy process (AHP). The simulation results showed that they reliably monitored the health status of offshore wind power structures and accurately evaluated the health status classification to achieve monitoring system improvement [10]. Nasr et al. proposed a robust optimal sensor using optimization algorithm and SA algorithm for damage detection of concrete structures. Results showed that SA optimized the structural monitoring system, improved the global search ability and convergence speed, and increased the accuracy of the results [11].

Modern intelligent algorithms have been widely used in the field of civil engineering monitoring, and intelligent algorithms are used to optimize the arrangement of sensors to make sensor detection more sensitive. The application of SAGA has attracted extensive attention and has become one of the research hotspots in recent years. These studies focus on combining the advantages of SA algorithms and GAs to improve the efficiency and accuracy of civil structure monitoring. Yu et al. proposed an online fitting method to monitor pipeline structural health. This study utilized spatial deformation fitting and modern intelligent algorithms for pipeline health monitoring. The modal confidence criterion was employed to determine the optimal layout of structural sensors in civil engineering, enabling the acquisition of more structural health data with a reduced number of sensors for efficient monitoring [12]. Qin et al. proposed an optimal sensor layout method for initial sensor layout using improved SAGA. The proposed method used segmental exchange, reverse, and insertion operators to avoid the change of the initial sensor position, and the results showed high effectiveness and reliability [13]. Xiong et al. proposed a new SAGA by combining the SA algorithm and GA. Experimental results showed that the genetic simulation annealing algorithm improved the clustering accuracy and accurately classified the faults of rotating machinery bearings, but the local search ability needed to be improved [14]. The main results and methods of the references are summarized in Table 1.

In conclusion, the SAGA shows significant potential in the health monitoring of civil engineering structures. The algorithm has made important progress in optimizing the search strategy and improving the algorithm efficiency, but it also faces the complexity of parameter setting and the challenge of adaptability to different structure types.

Table 1: Summary table of related work

Reference number	Author	Key methods	Result
[7]	Hedaoo and Pawar	Fuzzy logic risk assessment	Divide 60 risk factors into 7 categories and select the most severe risk factor through experiments.
[8]	Oh et al	Convolutional neural network structure	Applied to overpass bridges, its applicability has been proven after

		response recovery	long-term testing, effectively detecting faults or abnormal data.
[9]	Cheng et al	Data driven theory analysis of flow induced vibration system	By analyzing and mining feature information from structural vibration data, monitoring and diagnosing the health status of the structure can be achieved.
[10]	Zhou et al	Combination of GA and AHP with uncertainty	By establishing a hierarchical model through AHP and optimizing with GA to obtain the optimal weights, the health status of offshore wind power structures can be reliably monitored and the classification of health status can be accurately evaluated.
[11]	Nasr et al	SA algorithm for optimizing sensor configuration	Improve the accuracy of concrete structure damage detection, enhance global search capability and convergence speed.
[12]	Yu et al	Fitting method for online pipeline structure health monitoring	Based on spatial deformation fitting and modern intelligent algorithms, optimize sensor layout to achieve obtaining more health data with fewer sensors.
[13]	Qin et al	Improving SAGA to optimize sensor layout	By using segmented exchange, reverse, and insertion operators to avoid initial sensor position changes, the effectiveness and reliability of sensor layout can be improved.
[14]	Xiong et al	SAGA for fault classification of rotating machinery bearings	Improve clustering accuracy and accurately classify bearing faults, but further improvement is needed in local search capabilities.

3 Design of health monitoring of civil engineering structures using SAGA

The study proposes a new SAGA, which combined the SA algorithm with the GA. The coding method of the SAGA adopts the GA and adopts the adaptive adjustment mechanism. At the same time, the annealing strategy is also introduced to achieve a comprehensive optimization of the model.

3.1 Health sensors optimal layout model for civil engineering structures

According to the knowledge of structural dynamics, modal vectors of different orders in a theoretical structure are mutually orthogonal. In the actual structure, it is not possible to spread the sensors all over the bridge, so the measured modal vectors cannot guarantee orthogonality. In the sensor arrangement, the spatial angle between the modal vectors should be large enough to obtain a good degree of discrimination to obtain the overall dynamic information of the bridge [15]. A good tool for evaluating the orthogonality of modal vectors is the modal confidence MAC matrix, the mathematical expression of which is given in equation (1).

$$MAC_{ij} = \frac{\left(\varphi_i^T \varphi_j\right)^2}{\left(\varphi_i^T \varphi_i\right)\left(\varphi_j^T \varphi_j\right)} = \frac{a_{ij}^2}{a_{ii} a_{jj}} \qquad (1)$$

In equation (1), MAC_{ij} represents the element in the i row and j column of MAC. φ_j represents the j-order spatial modal vectors of the measured structural modal matrix. φ_i represents the i-order spatial modal vectors of the measured structural modal matrix. The superscript T represents transpose. $i \neq j$ represents the non-diagonal element. When $MAC_{ij(i\neq j)} = 1$, the i and j modal vectors coincide or are parallel, it is not easy to distinguish them. When $MAC_{ij(i\neq j)} = 0$, the i and j mode vectors are perpendicular to each other, it is easy to distinguish with accurate dynamic information reflection of civil engineering structures. Therefore, the optimal placement objective function of structural health sensors can be understood as the smaller the non-diagonal element of the modal confidence matrix, the better. The objective function is shown in equation (2).

$$\begin{cases} F_{\min}(x) = 1 - \max\left(MAC_{ij}\right) \\ s.t.\begin{cases} m < n \\ i \neq j \end{cases} \end{cases} \quad (2)$$

In equation (2), n represents the degree of freedom of the sensor pre-arrangement point is represented and m represents the sensor placement point. The sensors optimal placement in civil engineering is a typical NP combination optimization problem. Under the premise of low cost, it is necessary to rationally select sensors and arrange them in appropriate locations to ensure that the monitored information can reflect the health status of civil engineering structures [16]. GA is a computational model that emulates the natural selection and genetic mechanisms. This algorithm represents individuals through coding, evaluates their fitness using a fitness function, and simulates the natural evolutionary process by performing operations and mutation to facilitate efficient search [17]. Fig.1 shows the specific process.

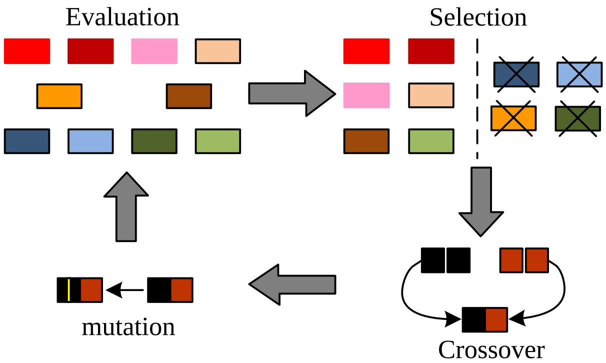


Figure 1: GA schematic diagram

Fig.1 shows the formation of a group of sensor information in the health monitoring. Based on the fitness values of individuals, the study employs a selection operator to choose individuals with higher fitness as parents. These parents then undergo crossover and mutation operations to produce new offspring individuals. Crossover operations facilitate the exchange and combination of gene information, while mutation operations introduce novel gene values. Cross-variation is a critical step in GA to increase population diversity and avoid falling into local optimal solutions [18]. Through selection and genetic manipulation, population composition is updated.

Next, the design gene coding is studied to transform the sensor arrangement problem of the steel truss bridge structure into a 0-1 programming problem. In the coding process, 0 means that the monitoring point does not arrange sensors, and 1 means that the monitoring point arranges sensors. Therefore, the solution vector of the sensor arrangement can be expressed as $\left[u_1, u_2, \cdots, u_n\right]$: In GA, the encoding methods mainly include permutation encoding, real number encoding, decimal encoding, and binary encoding [19]. Considering that the coding needs to meet the constraints of a fixed number of sensors, the decimal coding method is used in the crossover and mutation operations. Table 2 lists the encoding mappings.

Table 2: Encoding mapping table

Encoding location	Sensor placement coding
1	1
2	0
3	0
4	1
5	1
6	0
…	…
n-1	1
n	0

In Table 2, n represents the number of sensors pre-arranged measurement points. A chromosome can represent a random sequence from 1 to n, and the mapping table is fixed in position throughout the algorithm. Due to the decimal encoding, a partial match crossover operation is used here. The partial matching crossover operation first randomly selects two intersections in the parent generation, and then generates two child individuals according to the mapping relationship given between the two intersections, and its flow diagram is shown in Fig.2.

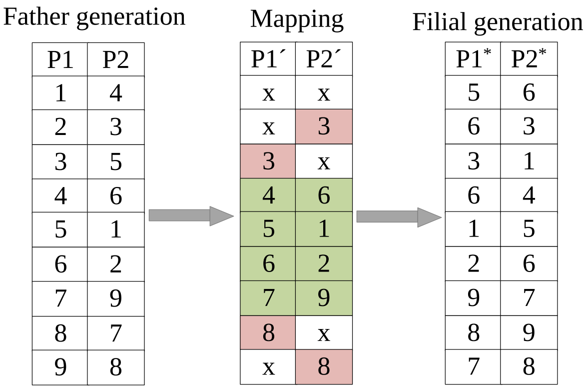


Figure 2: Schematic diagram of partial matching cross-operation

In Fig.2, the middle segments of the chromosomes of the two parents are first exchanged, the selected codes 3 and 8 are retained, and the offspring individuals are generated according to the mapping relationship 7↔9, 6↔2, 5↔1, 4↔6. Then, the inverse mutation genetic operator is used to randomly select two variation points in the parent individual, the upward additional codes between the two points are rearranged in reverse order, and the downward variable codes remain unchanged, as shown in Fig.3.

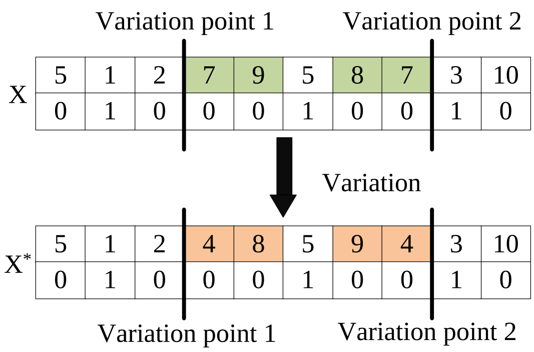


Figure 3: Schematic diagram of the mutation operator inverse variation

To enhance GA global search characteristics and avoid group aggregation, a chaotic operator is introduced. The chaotic operator uses the chaotic sequence to construct a solution with a certain ergodic nature, and the individuals with the worst fitness in the GA are evenly distributed in the solution space through chaotic perturbations and participates in the SA algorithm for search. This can prevent the occurrence of group aggregation problems caused by the randomness of traditional genetic operators. The chaotic operator uses a logistic chaotic sequence to generate a solution with a certain ergodic characteristic, and its expression is shown in equation (3).

$$\begin{cases} x_{n+1}^{i} = 4x_{n}^{1}\left(1-x_{n}^{i}\right) \\ x_{n}^{i} \subset S, i = 1,2,\cdots,N \end{cases} \tag{3}$$

In equation (3), n represents iterations, and x_n^i represents the value obtained by the i individual in the chaotic sequence. The method of adaptive parameter selection improves the convergence performance. The method automatically adjusts the crossover and variation probability by population fitness to avoid premature convergence. In addition, by adaptively adjusting the chaos probability and the increase of genetic generations, a large-scale chaos search is realized at the beginning stage, and the chaos probability is gradually reduced as the optimal solution gradually approaches. The specific crossover probability adaptive expression is shown in equation (4).

$$P_c = \begin{cases} P_{c\max} - \dfrac{\left(P_{c\max} - P_{cmin}\right)\left|f_1 - f_{aug}\right|}{f_{\max} - f_{aug}}, f_1 \geq f_{aug} \\ P_{c\max}, f_1 < f_{aug} \end{cases} \tag{4}$$

In equation (4), $f_{\max}$ and f_{aug} are the maximum and average population fitness and f_1 is the maximum fitness in the two chromosomes to be crossed. $P_{c\min}$ is the minimum crossover probability and $P_{c\max}$ is the maximum crossover probability. Through this method of adaptive parameter selection, convergence performance can be better improved, making the optimization process more efficient and stable [20]. Similarly, the adaptive expression for variation probability is shown in equation (5).

$$P_c = \begin{cases} P_{m\max} - \dfrac{\left(P_{m\max} - P_{mmnin}\right)\left|f_{\max} - f\right|}{f_{\max} - f_{aug}}, f \geq f_{aug} \\ P_{m\max}, f < f_{aug} \end{cases} \quad (5)$$

In equation (5), f represents the individual fitness. P_{mmin} and $P_{m\max}$ are the minimum and maximum variation probability. The chaos probability of generation k is shown in equation (6).

$$P_h\left(k\right) = P\exp\left[\lambda\left(1-k\right)\right] \quad (6)$$

In equation (6), λ represents the attenuation coefficient and $P_h\left(k\right)$ represents the chaos probability of the generation k.

3.2 Optimal design of civil engineering structural sensor based on SAGA

The SA algorithm is a process that simulates the process of heating a solid in nature and then cooling it slowly until the temperature drops to a stable low value. This process is known as the annealing process. During the annealing process, the system gradually reaches equilibrium until it finally reaches the ground state at room temperature [21]. During the annealing process, as the particles within a substance approach the ground state, the internal energy reaches its minimum. This orderly progression follows the principles of the Boltzmann distribution, where the energy of the system is distributed in accordance with statistical thermodynamics, which is expressed in equation (7).

$$P\left(f\right) = \exp\left(-\frac{f}{kT}\right) \quad (7)$$

In equation (7), $P\left(f\right)$ represents the probability of initially accepting the inferior solution. One of the characteristics of the SA algorithm is that it uses the drop in temperature to control the iteration of the algorithm. It is common practice to control the drop in temperature by using an exponential cooling function, as shown in equation (8).

$$T_{k+1} = \alpha \times T_k \quad (8)$$

In equation (8), T_k represents the current temperature, α represents the cooling factor, and the value is generally 0.85-0.99. This method can effectively control the iterative process of the algorithm, gradually converging and finding the optimal solution in the search process. The energy function is expressed as the non-diagonal mean of the modal confidence matrix MAC, and its expression is given in equation (9).

$$f = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} MAC_{ij}}{n\left(n-1\right)} \quad (9)$$

In equation (9), the f energy function is described. For the traditional SA algorithm, it is based on neighborhood search, and usually a perturbation solution is generated randomly. However, for sensor optimization problems with large degrees of freedom, the solution generated by a perturbation has strong randomness. In this paper, the "one perturbation" is converted into "n perturbations" to calculate the objective function values of the solutions corresponding to each perturbation, and the optimal value is the new neighborhood solution. The probability of receiving a new solution can be defined according to equation (10).

$$P = \begin{cases} 1, \Delta < 0 \\ \exp\left(-\Delta / T\right), \Delta > 0 \end{cases} \quad (10)$$

In equation (10), P represents the probability of accepting the new solution. The SAGA combines the advantages of SA algorithm and GA and embeds the SA algorithm into the GA. In this algorithm, some excellent individuals in the population are selected and input into the SA algorithm for annealing optimization to accelerate the population evolution and improve the GA local search ability. SAGA addresses the shortcomings of GAs, including slow convergence rates, susceptibility to local extrema, and large iteration numbers resulting from improper selection, crossover, or mutation techniques. The flow of the SAGA is shown in Fig.4.

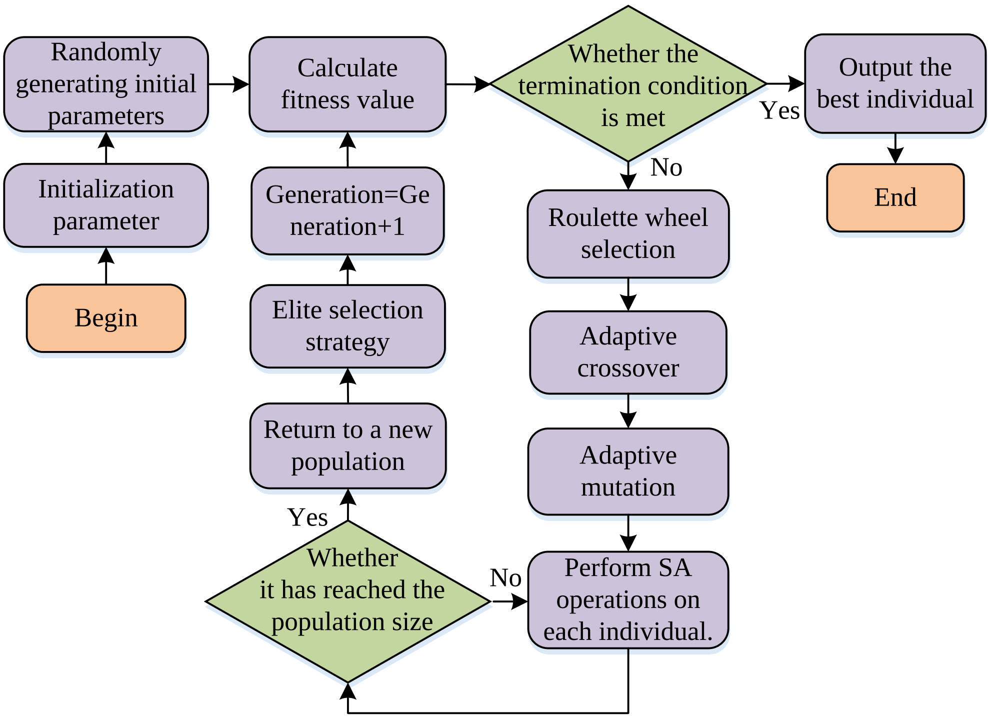
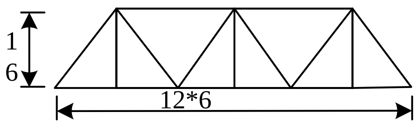


Figure 4: Flow chart of adaptive improved SAGA

In Fig.4, the adaptive improved SAGA introduces chaos operators with ergodic and random properties to maintain population diversity after crossing and mutating operators. It can prevent a few excellent individuals from occupying the entire population, thereby preventing the algorithm from maturing and convergence. Meanwhile, combined with the adaptive mechanism, the crossover probability, mutation probability, and chaos probability are adaptively adjusted according to the population fitness. This allows the population to eventually move closer to the most advantageous position in the later stages of evolution. With a strong optimization ability, SAGA can effectively improve slow solution speed and poor classification accuracy in civil engineering structural health monitoring. Therefore, based on the algorithm, the structural health monitoring system of civil engineering bridges will be designed, and the bridge structure is shown in Fig.5.

(a) Bridge in kind (b) Bridge finite element model



(c) Simplified bridge drawing

Figure 5: Schematic diagram of the physical and structural bridge structure

In Fig.5, the bridge under study consists of 6 segments, each 12m long, 72m long, 10m wide, and 16m high. In addition, the thickness of the concrete slab is 0.3m, and the elastic modulus of concrete and steel is 3.5e10 and 2.1e11, respectively. The density values of concrete and steel are 2500 and 7850, respectively.

Traditional SA algorithms mainly search for global optimal solutions by simulating the solid-state annealing process, but in some cases, they may fall into local optima. SAGA maintains a population by introducing the global search capability of GA, and searches the solution space through selection, crossover, and mutation operations, thereby increasing the possibility of escaping from local optima. Traditional GAs may rapidly lose population diversity and fall into premature convergence due to improper crossover and mutation operations during the search process. SAGA introduces the local search mechanism of SA, allowing for the acceptance of inferior solutions with a certain probability, thereby maintaining population diversity to a certain extent and avoiding premature convergence. Regarding the adaptive adjustment mechanism, SAGA dynamically adjusts the annealing temperature and cross-mutation parameters through adaptive strategies, enabling the algorithm to optimize its performance during the search process based on the characteristics of the problem and the progress of the search.

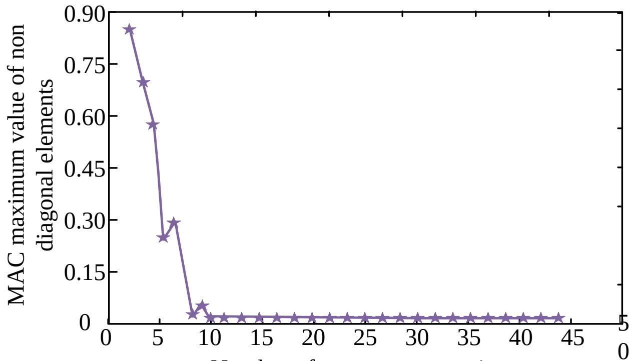
4 Analysis of experimental results

To effectively monitor and evaluate the health status of the structure, it is necessary to reasonably select and adjust the experimental parameters. Due to the large mode participation coefficient of the low-order modes of the steel truss bridge structure, the first six modes are selected for monitoring in the structural health monitoring experiment. Table 3 shows the specific experimental settings of SAGA. The test platform is 8GB of RAM, the system is OSXE | Capitan, and the test software is Python 2.7 with the 2.9GHz Intel i5 processor.

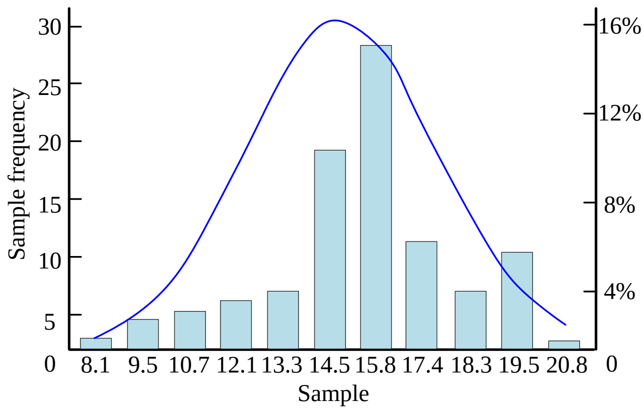
Table 3: Experimental parameter settings

The name of the parameter	numeric value
Population size	100
Maximum number of iterations	300
Markov chain length	30
Number of genes	256
Initial temperature	1000
Probability of variation	0.01-02
Crossover probability	0.3-0.9
Initial chaos probability	0.6
Attenuation factor	0.95

Then, the relationship between the number of measurement points and the maximum value of the non-diagonal element of MAC are obtained by running MATLAB software, and the relationship diagram is shown in Fig.6.



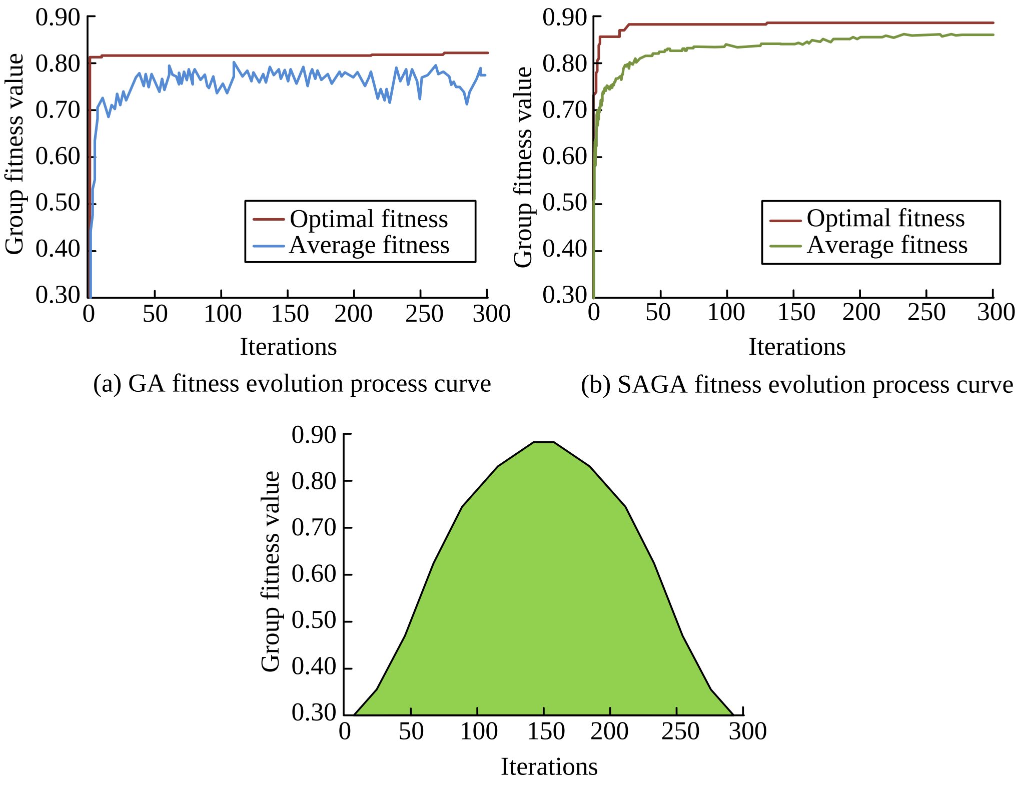
(a) MAC non diagonal element values at different measurement points



(b) Sample confidence interval

Figure 6: Maximum value of MAC non-diagonal element at different measurement points

In Fig.6, the maximum value decreases as the number of measurement points increases. In this process, there is a slight fluctuation in the MAC non-diagonal maximum, but the overall trend decreases. With 5, 8, and 10 measurement points, the maximum non-diagonal values of MAC address are 0.253, 0.0318, and 0.0167, respectively. This indicates that the model obtained by the SAGA has good convergence. For economic reasons, only 8 sensors are required to be installed, which once again highlights the optimal sensor placement's importance. Therefore, the number of installed sensors is set to 8, the SAGA program is run to obtain the optimal solution under the given constraints, and the MAC criterion indicator of the solution is 0.136. The purpose of this setup is to reflect the optimal placement's significance of the sensors when considering economic factors. To evaluate the superiority of the SAGA on the optimal arrangement after the introduction of SA, it is compared with the GA. The relationship between the population fitness values of each generation and the number of iterations of GA and SAGA is shown in Fig.7.



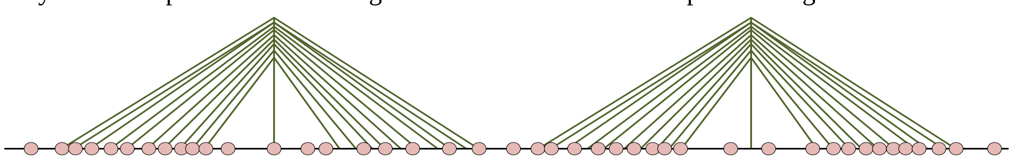
(a) GA fitness evolution process curve (b) SAGA fitness evolution process curve

(c) confidence interval

Figure 7: Evolution process curves of GA and SAGA

In Fig.7(a), GA has the problem of premature convergence to the local optimal solution. In Fig.7(b), the SAGA is rapidly approaching the optimal solution and has a fast convergence speed in the early stage of evolution, indicating that the algorithm has achieved ideal results in the local optimization process. Compared with the GA, the SAGA shows a faster convergence speed, and completely avoids premature convergence and precocious maturity. In general, the optimization effect of the SAGA is significantly better than that of GA, and the convergence efficiency of the optimal solution is greatly improved by adding a SA operation.

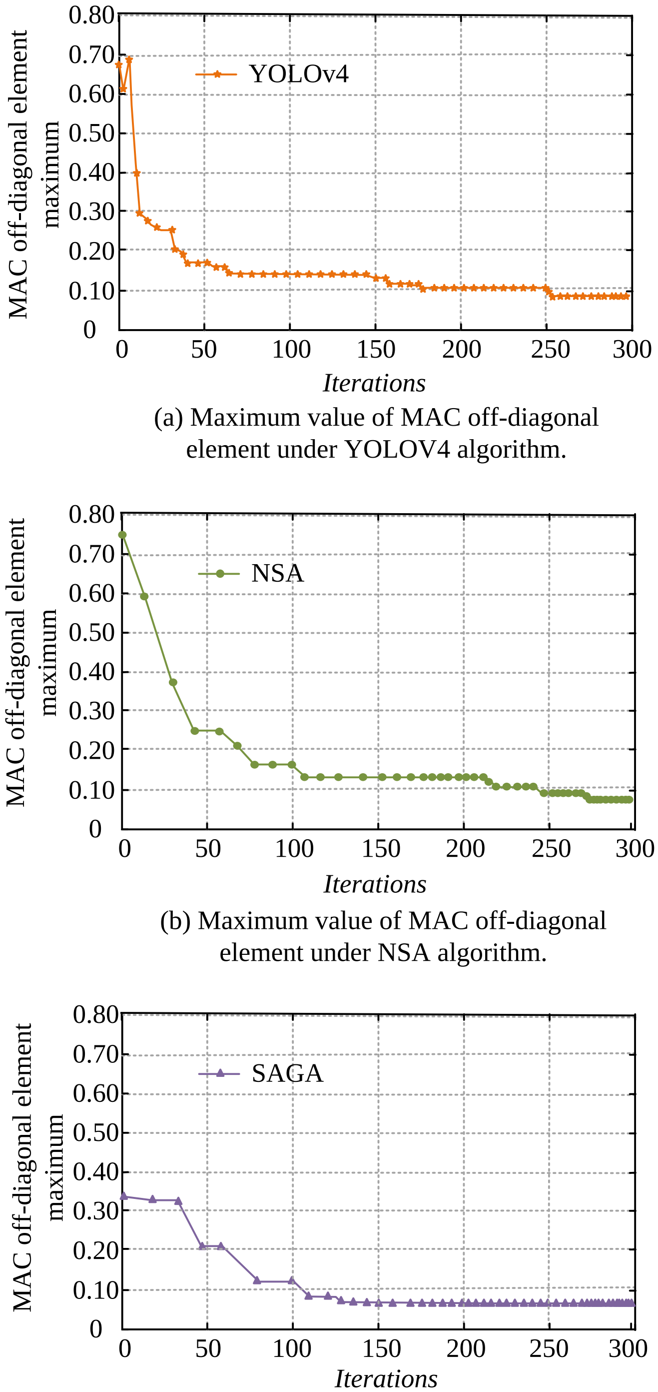
To verify whether the sensor distribution can be more evenly distributed after the SA operation is added, the bridge sensor placement points optimized by GA and SAGA are compared in Fig.8.



(a) GA (b) SAGA

Figure 8: Comparison of the optimal layout points of bridge sensors obtained by GA and SAGA

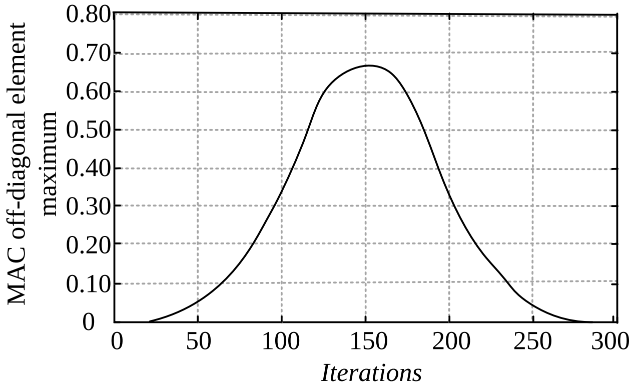
In Fig.8(a), there is an uneven distribution of sensor arrangements without the SA algorithm, and the number of sensors at each task monitoring point varies greatly. In Fig.8(b), the sensor placement points optimized by SAGA are concentrated near the task monitoring points, and the distribution is more uniform. To verify the advantages of SAGA proposed in this study and other advanced civil engineering structural health detection algorithms, the improved YOLOv4 algorithm for crack detection in civil engineering structures in Reference [22] and the global damage detection method based on the negative selection algorithm (NSA) version in Reference [23] are selected for comparative analysis. The relationship between the MAC non-diagonal maxima and iterations is shown in Fig.9.



(a) Maximum value of MAC off-diagonal element under YOLOV4 algorithm.

(b) Maximum value of MAC off-diagonal element under NSA algorithm.

(c) Maximum value of MAC off-diagonal element under SAGA algorithm.



(d) confidence interval

Figure 9: The relationship between the maximum value of MAC non-diagonal element and the number of iterations under different algorithms

In Fig.9, YOLOv4 obtains the minimum MAC indicator value after 279 iterations, the NSA needs 284 iterations to reach the minimum MAC indicator value, and the SA algorithm only needs 132 iterations to reach the minimum MAC indicator value. In practice, the smaller the maximum value of the element, the better. Therefore, when the truss structure sensors are optimally arranged for a steel truss bridge, the advantages of simulating the annealing algorithm are more significant from the overall parameter setting, with fewer iterations required. As shown in Fig.9 (c), the sample confidence level is 95% and the confidence interval is 96%. According to the algorithm proposed in this study, 8 sensors are scattered in the area to be monitored, and the average error of the three algorithms for structural health monitoring is shown in Fig.10.

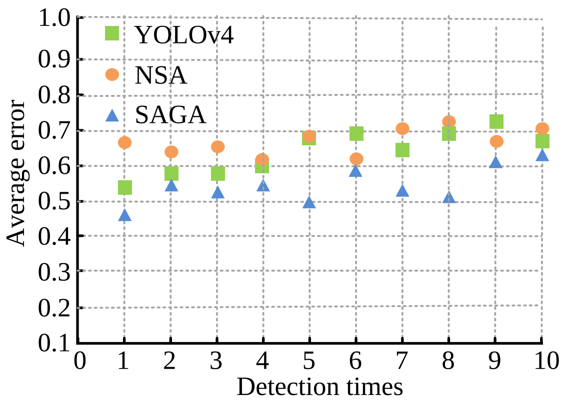


Figure 10: Comparison of the average errors of the three algorithms for structural health monitoring

In Fig.10, the YOLOv4's average detection error rate is 0.66, the NSA's average detection error rate is 0.61, and the SAGA's average detection error rate is 0.52. This shows that compared with the NSA and the YOLOv4, SAGA has a lower average detection error rate and better performance. In this study, the monitoring application effect of the monitoring algorithm needs to be statistically analyzed, and the sensors optimized by the three algorithms are applied to the bridge structure. The sensitivity is compared and analyzed, and the results are shown in Fig.11.

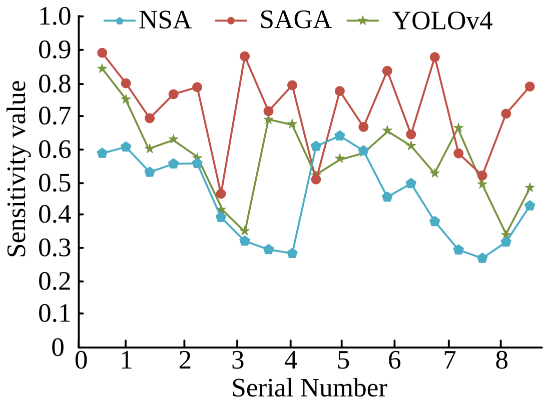
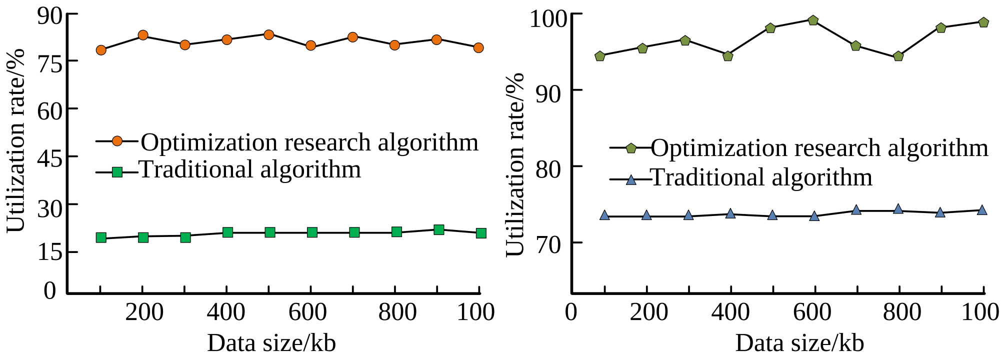


Figure 11: Comparison of the sensitivities of the three algorithms

In Fig.11, the sensitivity indicator quantifies the system's responsiveness to variations in input parameters. A value closer to 1 signifies a higher level of sensitivity to changes in the input parameters. Compared with YOLOv4 and NSA, the detection system using SAGA is higher than that of different system monitoring.

Fig.12 shows the memory and CPU usage of the research algorithm before and after improvement. Fig.12 (a) shows the memory usage results. The computer memory usage increases from 16% to 76% before and after optimization. Fig.12 (b) shows the CPU utilization results. The average CPU utilization of the computer is 74% and 97% before and after optimization.

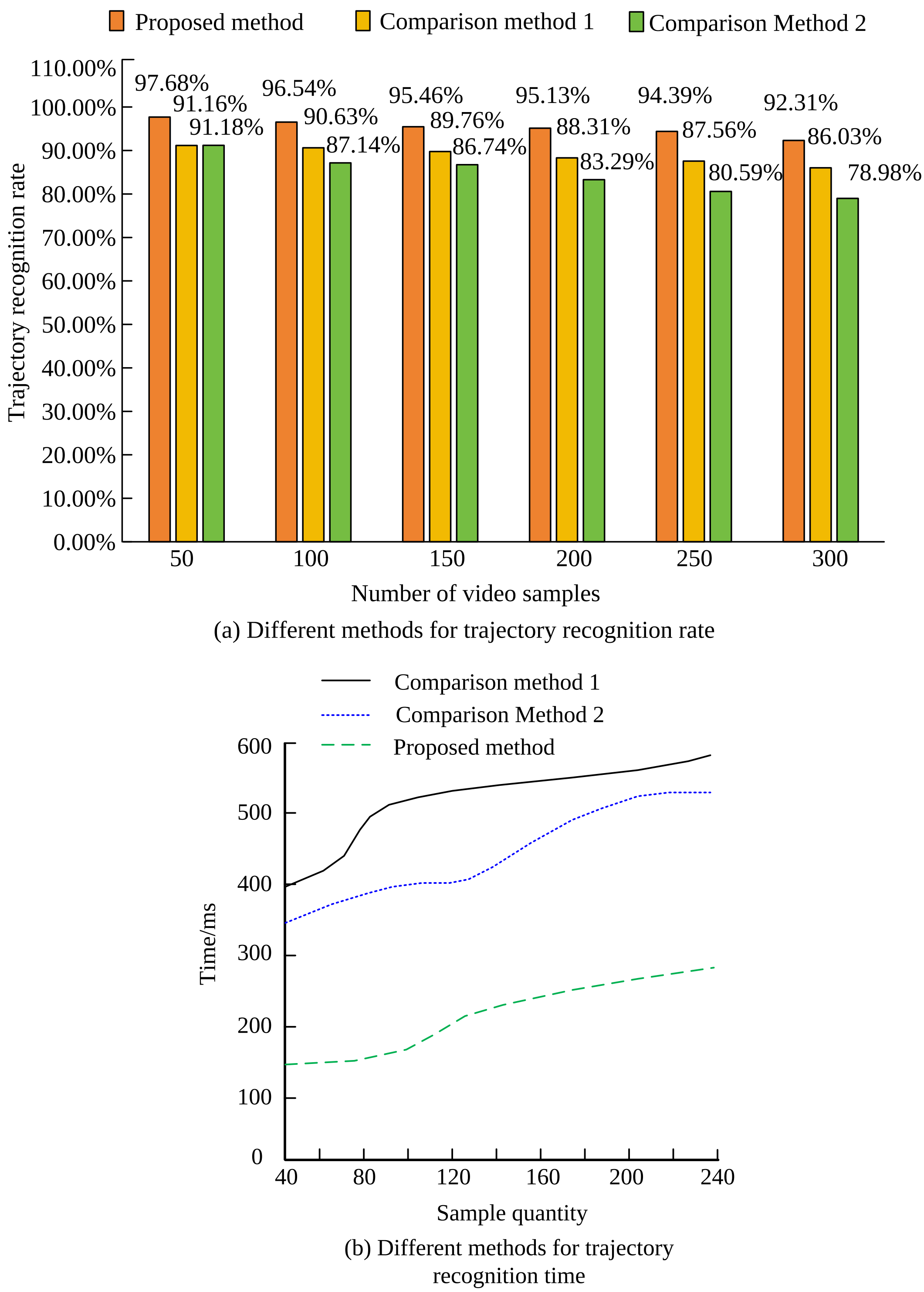


(a) Memory usage result

(b) CPU usage results

Figure 12: Memory and CPU usage before and after optimization

Fig.13 shows the comparison of trajectory recognition rates and recognition times between different methods. Method 1 is a new genetic SA algorithm proposed by Xiong J et al., which combines SA algorithm and GA. Method 2 is a fitting method proposed by Yu H et al. for online pipeline structural health monitoring. From Fig.13 (a), as the number of video samples increases from 50 to 300, the trajectory recognition rates of each method slightly decreases. The proposed method decreases from 97.68% to 92.31%, a decrease of 5.37%. The other two methods decrease by 5.13% and 12.2%, respectively, to 83.03% and 78.98%, indicating that the research method has a better trajectory recognition rate. In Fig.13 (b), with the same sample training, the proposed method has a better running time, ranging from 150-280ms, while the other two compared methods are above 350ms and 400ms, respectively.



(a) Different methods for trajectory recognition rate

(b) Different methods for trajectory recognition time

Figure 13: Comparison of trajectory recognition rates and recognition times using different methods

4 Discussion

The SAGA combines the global search capability of GA with the local search capability of SA. By adaptively adjusting parameters, it can quickly converge to the optimal solution while maintaining diversity. This hybrid algorithm performs well in solving complex optimization problems, especially in scenarios that require balancing global and local search capabilities. In references [7]-[8], research on risk factors in fuzzy logic assessment, data-driven theory analysis of vibration systems, and the combination of GA and AHP for monitoring wind power structures were conducted. SAGA was used to optimize parameter selection or weight allocation in fuzzy logic, improving the accuracy of risk assessment. In reference [9], SAGA was used to optimize the architecture or hyperparameters of convolutional neural network, accelerate the training process, and improve the accuracy of fault detection. SAGA introduced a probability acceptance mechanism into the SA algorithm, which to some extent maintains the diversity of the population and increases the possibility of finding the global optimal solution. In references [10-11], SAGA directly replaced or optimized the GA part to improve the accuracy and convergence speed of weight allocation. Due to its ability to more accurately locate potential optimal solution regions and quickly converge to them during the search process, SAGA typically had a faster convergence speed than single GA or SA algorithm. The parameters in SAGA, such as temperature, crossover rate, mutation rate, etc., can be adaptively adjusted according to the search process, making it more flexible in handling different problems and datasets.

5 Conclusion

In response to the civil engineering issue of structural health monitoring, this study designed a SAGA experiment to improve the monitoring. The algorithm was validated by simulating steel beam bridge structures. The experimental results showed that SAGA could reduce the required number of iterations in the modal analysis and identification process, overcome the dilemma of GA premature convergence, and achieve faster convergence speed. Compared with GA, the SAGA improved computational efficiency and optimization quality. The required number of iterations for YOLOv4, NSA, and SAGA to obtain the minimum MAC metric value was 279, 284, and 132, respectively. The SA algorithm required fewer iterations and had a more significant advantage. In addition, the average detection error rates of YOLOv4, NSA, and SAGA were 0.66, 0.61, and 0.52, respectively. Compared to the NSA and YOLOv4 algorithms, SAGA had a lower average detection error rate, higher sensitivity, and better performance. The model designed in this study is relatively reliable, and the SAGA provides a strong theoretical basis to design bridge structural health monitoring systems. However, the shortcomings of this study lie in the need for further validation of the generalization ability of SAGA for different types and scales of civil engineering structures. Further in-depth research can be conducted in expanding the application scope of the algorithm, further refining parameter adjustments, and enhancing algorithm adaptability, to achieve more comprehensive and accurate structural health monitoring.

References

[1] S. L. Feudo, S. Job, M. Cavallo, A. Fraddosio, M. D. Piccioni, and A. Tafuni, "Finite contact duration modeling of a Vibro-Impact Nonlinear Energy Sink to protect a civil engineering frame structure against seismic events," Engineering Structures, vol. 259, no. 5, pp. 1-14, 2022. https://doi.org/10.1016/j.engstruct.2022.114137

[2] M. F. Bado and J. R. Casas, "A review of recent distributed optical fiber sensors applications for civil engineering structural health monitoring," Sensors, vol. 21, no. 5, pp. 1-83, 2021. https://doi.org/10.3390/s21051818

[3] N. Sepehry, M. Ehsani, W. Zhu, and F. Bakhtiari-Nejad, "Application of scaled boundary finite element method for vibration-based structural health monitoring of breathing cracks," Journal of Vibration and Control, vol. 27, no. 23-24, pp. 2870-2886, 2021. https://doi.org/10.1177/107754632096864

[4] E. Hasanlou, A. Shams-Nateri, and H. Izadan, "Instrumental shade sorting of coloured fabrics using genetic algorithm and particle swarm optimization," Coloration Technology, vol. 139, no. 4, pp. 454-463, 2023. https://doi.org/10.1111/cote.12663

[5] Z. X. Li and S. W. Rao, "The inversion of one-dimensional soil parameters in the frequency domain with considering multilayered earth based on simulated annealing algorithm," IEEE Transactions on Electromagnetic Compatibility, vol. 62, no. 2, pp. 425-432, 2020. https://doi.org/10.1109/TEMC.2019.2906486

[6] M. S. Dizaji, M. Alipour, and D. K. Harris, "Subsurface damage detection and structural health monitoring using digital image correlation and topology optimization," Engineering Structures, vol. 230, no. 3, pp. 1-18, 2021. https://doi.org/10.1016/j.engstruct.2020.111712

[7] N. Hedaoo and A. Pawar, "Risk assessment model based on fuzzy logic for residential buildings," Slovak Journal of Civil Engineering, vol. 29, no. 4, pp. 37-48, 2021. https://doi.org/10.2478/sjce-2021-0026

[8] B. K. Oh, B. Glisic, Y. Kim, and H. S. Park, "Convolutional neural network-based data recovery method for structural health monitoring," Structural Health Monitoring, vol. 19, no. 6, pp. 1821-1838, 2020. https://doi.org/10.1177/1475921719897571

[9] Z. Cheng, F. S. Lien, E. H. Dowell, R. Wang, and J. H. Zhang, "Data-driven stability analysis via the superposition of reduced-order models for the flutter of circular cylinder submerged in three-dimensional spanwise shear inflow at subcritical Reynolds number," Physics of Fluids, vol. 34, no. 12, pp. 123606-123629, 2022. https://doi.org/10.1063/5.0131214

[10] L. Zhou, P. Huang, S. Chi, M. Li, H. Zhou, H. Yu, H. Ca, and K. Chen, "Structural health monitoring of offshore wind power structures based on genetic algorithm optimization and uncertain analytic hierarchy process," Ocean Engineering, vol. 218, no. 12, pp. 1-5, 2020. https://doi.org/10.1016/j.oceaneng.2020.108201

[11] D. Nasr, R. E. Dahr, J. Assaad, and J. Khatib,

"Comparative analysis between genetic algorithm and simulated annealing-based frameworks for optimal sensor placement and structural health monitoring purposes," Buildings, vol. 12, no. 9, pp. 1383-1394, 2022. https://doi.org/10.3390/buildings12091383
[12] H. Yu, X. Chen, M. Ren, Q. Liu, K. Yang, K. Chang, Q. Wu, and J. Zhan, "An online pipeline structural health monitoring method based on the spatial deformation fitting," IEEE Transactions on Industrial Electronics, vol. 69, no. 7, pp. 7383-7393, 2021. https://doi.org/10.1109/TIE.2021.3101003
[13] X. Qin, P. Zhan, C. Yu, Q. Zhang, and Y. Sun, "Health monitoring sensor placement optimization based on initial sensor layout using improved partheno-genetic algorithm," Advances in Structural Engineering, vol. 24, no. 2, pp. 252-265, 2021. https://doi.org/10.1109/10.1177/1369433220947198
[14] J. Xiong, X. Liu, X. Zhu, H. Zhu, H. Li, and Q. Zhang, "Semi-supervised fuzzy c-means clustering optimized by simulated annealing and genetic algorithm for fault diagnosis of bearings," IEEE Access, vol. 8, no. 12, pp. 181976-181987, 2020. https://doi.org/10.1109/ACCESS.2020.3021720
[15] Y. Zhang, J. Guo, N. Hao, J. Yang, and S. Li, "Damage detection on hull girder of ship subjected to explosion loading," Ocean Engineering, vol. 198, no. 2, pp. 107006.1-107006.17, 2020. https://doi.org/10.1016/j.oceaneng.2020.107006
[16] E. M. Coraça, J. V. Ferreira, and E. G. O. Nóbrega, "An unsupervised structural health monitoring framework based on variational autoencoders and hidden markov models," Reliability Engineering & System Safety, vol. 231, no. 3, pp. 1-15, 2023. https://doi.org/10.1016/j.ress.2022.109025.
[17] D. Pham-Toan and T. Vo-Van, "Building the classification model based on the genetic algorithm and the improved Bayesian method," International Journal of Data Science and Analytics, vol. 7, no. 8, pp. 1-17, 2023. https://doi.org/10.1007/s41060-023-00436-2.
[18] S. Shamshirband, J. H. Joloudari, S. K. Shirkharkolaie, S. Mojrian, F. Rahmani, S. Mostafavi, and Z. Mansor, "Game theory and evolutionary optimization approaches applied to resource allocation problems in computing environments: A survey," Mathematical Biosciences and Engineering, vol. 18, no. 6, pp. 9190-9232, 2021. https://doi.org/10.3934/mbe.2021453
[19] M. S. Amri Sakhri, "Comparative analysis of different crossover structures for solving a periodic inventory routing problem," International Journal of Data Science and Analytics, vol. 14, no. 2, pp. 141-153, 2022. https://doi.org/10.1007/s41060-021-00280-2
[20] S. Choudhuri, S. Adeniye, and A. Sen, "Distribution alignment using complement entropy objective and adaptive consensus-based label refinement for partial domain adaptation," Artificial Intelligence and Applications, vol. 1, no. 1, pp. 43-51, 2023. https://doi.org/10.47852/bonviewAIA2202524
[21] H. Luo, Y. Li, H. Li, X. Cui, and Z. Chen, "Simulated annealing algorithm-based inversion model to interpret flow rate profiles and fracture parameters for horizontal wells in unconventional gas reservoirs", SPE Journal, vol. 26, no. 4, pp. 1679-1699, 2021. https://doi.org/10.2118/205010-PA
[22] G. Yao, Y. Sun, M. Wong, and X. Lv, "A real-time detection method for concrete surface cracks based on improved YOLOv4", Symmetry, vol. 13, no. 9, pp. 1716-1726, 2021. https://doi.org/10.3390/sym13091716
[23] A. Barontini, M. G. Masciotta, P. Amado-Mendes, L. F. Ramos, and P. B. Lourenço. "Negative selection algorithm-based methodology for online structural health monitoring", Engineering Structures, vol. 229, no. 15, pp. 1-16, 2021. https://doi.org/10.1016/j.engstruct.2020.111662.