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Exploration of Sensor Layout Optimal Methods for Bridge Health Monitoring

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Abstract: The arrangement of sensors is a key step in health monitoring of bridges. A reasonable layout can reduce information redundancy and costs while improving data accuracy. This paper compares the advantages and disadvantages of traditional sensor optimization methods with those based on machine learning algorithms and intelligent optimization algorithms, and analyzes the future prospects of applying these three methods.

Keywords: Bridge health monitoring, sensor layout optimization, intelligent optimization algorithms, machine learning

1. Introduction

Sensor monitoring systems are used to collect large amounts of data related to the health of bridges in order to assess their condition. Therefore, the selection and arrangement of sensors are crucial steps in bridge health monitoring. The types of commonly used sensors and their monitoring projects are shown in the table below:

Table 1: Types of Sensors

Monitoring classification	Content	sensor	Monitoring results and identification parameters
Environmental load	Load made by temperature	Temperature sensor	Temperature of key parts of the bridge
	Load made by wind	Anemometer	Wind turbulence intensity
	Load made by earthquake	Acceleration sensor	Acceleration of key measuring points
Operating load	Load made by cars	Vehicle speed axle meter	Velocity of motor vehicle
Bridge characteristics	Vibration performance	Acceleration sensor	Mode shape, damping and modal frequency
	Displacement deformation	Inclinometer displacement meter	Displacement influence line

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Table 1: (continued).

Bridge response	Section stress	Static and dynamic strain gauge	Static and dynamic stresses of key sections
	Cable force	Acceleration sensor	Force and natural frequency of stay cable

Theoretically, sensors can be arranged throughout the bridge to monitor its response comprehensively. However, experimental analysis shows that placing an excessive number of sensors not only significantly increases economic costs but also results in information redundancy. A rational arrangement of sensors can improve the accuracy of monitoring data, reduce data anomalies, provide comprehensive monitoring of the bridge's condition, lower monitoring costs, and enhance monitoring efficiency. Carne et al. [1] emphasize that the sensor configuration should ensure that the modal test results have good robustness and visibility. However, the current sensor layout does not adequately meet these requirements, with many issues existing in information acquisition, optimal solution finding, and evaluation of optimization results. Based on the previous discussion on sensor types, different sensor types may be affected by various factors. For example, strain sensors are susceptible to temperature effects and long-term usage, which can lead to sensor damage and data drift, resulting in errors. On the other hand, a scientific sensor layout scheme should fully consider the structural behavior characteristics of the bridge under various environmental conditions, using as few sensors as possible to obtain sufficiently comprehensive and accurate data. However, existing methods are still far from perfect, facing issues such as finite element model errors, inconsistent evaluation criteria, difficulty in determining the number of sensors, low computational efficiency, and challenges in finding optimal solutions [2]. Currently, a research hotspot in bridge sensor layout optimization is achieving the optimal combination of economic and technical factors by arranging n sensors on m degrees of freedom (where $n < m$). Previous research on traditional bridge sensor optimization mainly focused on geometric shapes and material mechanical properties. Some relatively mature methods include: the Effective Independence Method (EI method), modal strain energy criteria, sequential methods, and nonlinear optimization programming methods. Research on sensor optimization based on computer technology mainly focuses on machine learning algorithms such as support vector machines, random forests, neural networks, etc.; intelligent optimization algorithms such as genetic algorithms, simulated annealing, particle swarm optimization, and ant colony algorithms; as well as improvements to these intelligent algorithms. These optimization methods currently have certain limitations, and inherent problems remain to be addressed. This paper provides a comprehensive analysis of the performance of these methods in terms of convergence speed, global optimization performance, and computational accuracy, and summarizes and looks forward to solutions for their inherent issues.

2. Traditional Methods for Optimizing Sensor Layout in Bridge Monitoring

2.1. Effective Independence Method

Kammer et al. [3] proposed the Effective Independence (EI) method based on the modal matrix theory. This method improves the resolution of the target by progressively eliminating the degrees of freedom with the smallest contribution to the independence of the target parameters, achieving optimal resolution. It is applicable to structural parameter identification under static loading and modal identification under dynamic loading. The advantages of the EI method are its efficiency and accuracy, which enhance the efficiency of modal parameter information acquisition through sensors.

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Furthermore, the method focuses on the linear independence of the target modal vectors during optimization, which helps improve the accuracy of the monitoring results after optimization. However, it has limitations, such as its inability to fully capture high modal strain energy regions of the structure in some cases, which leads to low modal strain energy measurements, potentially resulting in information loss and affecting subsequent data analysis. Additionally, it is sensitive to measurement noise and prone to getting trapped in local optima. For structures with high degrees of freedom and complex configurations, the selection of modes is often neither reasonable nor theoretically justified. To address this issue, Yang Zhi-kui et al. [4] proposed a modification to the EI method based on sensitivity coefficients reflecting structural damage, resulting in the Sensitivity-Effective Independence method. This method combines vector operations to account for both the observability of modes and the recognizability of damage. They introduced a method based on modal progressiveness to select the number of modes, solving the problem of selecting the number of modes for bridge dynamic systems based on experience and poor observability. This method made the selection of the number of modes more objective and reasonable, and verified its accuracy under various evaluation criteria.

Jiezi Zhan et al. [5] addressed the EI method's poor noise resistance by proposing a new modal strain energy analysis method, which significantly improves the noise resistance of the traditional EI method.

2.2. Modal Kinetic Energy Method and Residual Method

The Modal Kinetic Energy (MKE) method and the Drive Point Residue (DPR) method, proposed by Chung et al. [6], are applicable to optimizing sensor layouts for large spatial structures such as rail structures. MKE is based on modal theory, using modal shapes to describe actual vibration patterns. If the modal kinetic energy at a point is maximized, it indicates that this point is the most sensitive to vibration, thus being the optimal measurement point. However, MKE is heavily dependent on finite element mesh refinement. If the mesh is too coarse, sensors will be placed too far apart, making it difficult to capture vibration characteristics accurately. Conversely, if the mesh is too fine, sensors will be placed too closely together, increasing costs and introducing additional errors. DPR, based on the excitation degree of freedom, selects sensor locations where sensor placement is most beneficial. It is particularly useful when precise sensor placement is required. However, the DPR method involves complex calculations and may be affected by nonlinear factors, leading to errors.

2.3. Sequential Method

Xian-rong Qin et al. proposed the Sequential Method (which includes the step-by-step accumulation method and the step-by-step elimination method) [7]. The step-by-step accumulation method continuously selects the optimal sensor from available positions based on QR decomposition and adds it to the optimization configuration until the off-diagonal elements reach a preset value. The step-by-step elimination method selects the sensor with the least contribution to the objective function from the remaining sensors and eliminates it until the preset value is reached, progressively approaching the optimal solution. This method is suitable for large spatial structures but has limitations, such as weak ability to find the optimal solution, dependency on the number of initial measurement points, and lack of flexibility. Huang Min-shui et al. [5] studied the engineering application of the sequential method through finite element analysis. They analyzed a 5×50m prestressed concrete T-shaped continuous beam on the Wanping Highway bridge across the Chongsong Reservoir in Nanyang, Henan Province. They concluded that the sequential method, based on finite element models, is inevitably affected by modeling errors in the finite element method, which adversely impacts the optimization results. Therefore, a key challenge is evaluating the model

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errors. To assess the quality of optimization results, evaluation criteria such as modal confidence criteria [8], singular value ratio (matrix condition number) criteria [9], and modal kinetic energy criteria [10] can be used to verify which algorithm better preserves the modal information of the dynamic structure.

3. Sensor Optimization Layout Based on Intelligent Optimization Algorithms

3.1. Principles and Applications of Classical Intelligent Optimization Algorithms

Intelligent optimization algorithms, also known as modern heuristic algorithms, are global optimization algorithms with strong generality and parallel processing capabilities. These algorithms can find the optimal or near-optimal solutions within a given time frame. Common intelligent optimization algorithms include genetic algorithms, simulated annealing algorithms, particle swarm optimization algorithms, and ant colony optimization algorithms. Below is a brief introduction to some applications of these algorithms in optimizing sensor layouts.Holland [11] proposed the genetic algorithm (GA), which simulates the genetic evolution process of organisms in nature. It searches for global optimal solutions by encoding individuals, selecting, crossing, and mutating them. In sensor layout optimization, the sensor positions and quantities can be treated as the search space of the genetic algorithm. The best layout solution can be found by evaluating the fitness function. Dorigo et al. proposed the ant colony optimization (ACO) algorithm, which simulates the pheromone transfer and path selection behavior of ants during their foraging process to guide them toward the optimal path. In sensor layout optimization, the monitoring area can be divided into multiple grids, and the ant colony algorithm can be used to find the optimal sensor layout to cover the monitoring area. Metropolis et al. [12] proposed the simulated annealing algorithm (SA), which is based on the similarity between the annealing process of solid materials in physics and combinatorial optimization problems. It is a general global optimization algorithm that is simple to compute, robust, and capable of solving the nonlinear relationships between sensors. However, its convergence speed is slow, the algorithm is complex, and its performance depends on the initial state and parameter values. Other types of intelligent optimization algorithms include neural network algorithms and flower pollination algorithms [13]. Classical intelligent optimization algorithms can be used for bridge sensor layout optimization, as demonstrated by Gao Wei et al. [14], who used genetic algorithms to optimize sensor placement. Gao Rongxiong et al. [12] studied the application of simulated annealing based on the MAC criterion to optimize the placement of accelerometers on cable-stayed bridges. The experimental results show that intelligent optimization algorithms possess high intelligence and global optimization capabilities.

3.2. Improvements and Applications of Intelligent Optimization Algorithms

Currently, effectively combining traditional sensor layout optimization theories with intelligent optimization algorithms for specific bridge structures is a key research direction in the field of bridge health monitoring sensor optimization. For instance, Jianqiang Chen et al. [15] used a genetic annealing algorithm, which combines genetic algorithms and simulated annealing algorithms, to optimize sensor placement on cable-stayed bridges. They improved the genetic annealing algorithm, which enhanced its global search capability and accelerated convergence toward the optimal solution. The genetic algorithm required 60 iterations, but the optimization result was not ideal. The simulated annealing algorithm was more accurate, but required 900 iterations. The improved algorithm required only 40 iterations and produced better optimization results. Peiyuan Xiao et al. [16] optimized sensor placement on cable-stayed bridges using an improved genetic algorithm. Compared with traditional genetic algorithms, the improved genetic algorithm demonstrated higher confidence and stability in solving the objective function, significantly reducing the large differences in sensor values during

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each iteration. It also reduced the manual optimization workload for algorithm parameters under different working conditions, allowing for better searching in the sample space. Based on the two examples and analyses above, intelligent optimization algorithms have significant advantages over traditional optimization methods, such as stronger intelligence, better global optimization capability, and faster convergence. However, each algorithm has certain shortcomings. To improve the performance of the algorithms, various strategies can be employed, such as hybridizing multiple algorithms, developing ensemble learning frameworks, designing new mutation and crossover operators, introducing intelligent walking strategies, controlling adaptive parameters, and using deep neural networks to predict optimal solutions during the optimization process. For example, the optimization of inertia weights in the dragonfly algorithm leads to more precise results, while combining genetic and annealing algorithms results in faster convergence and better optimization outcomes.

4. Sensor Optimization Layout Based on Machine Learning

Machine learning-based sensor optimization methods include data-driven optimization and multi-source data fusion. Data-driven optimization utilizes historical monitoring data and machine learning algorithms to train models, which in turn optimize the sensor layout. Machine learning algorithms used for this purpose include support vector machines, random forests, and neural networks. Machine learning techniques not only consider the structural characteristics and monitoring requirements of the bridge but can also continuously adjust and optimize the number and placement of sensors based on real-time monitoring data feedback, selecting the best solution. Additionally, machine learning allows for deep analysis and extraction of effective features from the large volumes of response data collected, thereby improving the performance of the sensors. Currently, there is relatively little research in China on machine learning-based bridge sensor layout optimization, though there has been some research on sensor layout optimization in other fields using machine learning. For example, Zhang Yu et al. [17] conducted a study on optimizing the layout of gas sensors using machine learning, analyzing four common pattern recognition algorithms: support vector machines, k-nearest neighbors, random forests, and self-organizing map networks. They found that support vector machines, due to their strong nonlinear expression capabilities, performed best in recognition among the four models. Comparing the four algorithms showed that machine learning methods are highly efficient and accurate in data processing and analysis, enabling real-time monitoring and response, and offering more intelligent solutions. Ziyou Yang et al. [18] conducted research on the optimization design of temperature sensor layouts based on machine learning. Their findings showed that combining simulation models with machine learning can improve simulation accuracy and significantly increase optimization efficiency. While machine learning algorithms have advantages in balancing global and local optimization, dealing with parameter uncertainty, and processing data quality and speed, they still face issues. These can be addressed by improving feature selection, model selection and integration, adjusting optimizers and learning rates, and applying regularization to enhance optimization performance and convergence speed.

5. Comparison of Traditional Methods and Computational Methods

Traditional methods are generally based on statistics and the structural characteristics of the bridge, using the mathematical properties of the monitoring matrix to achieve sensor layout optimization. The advantages of these methods include simplicity in implementation and the ability to obtain good optimization results in specific situations. However, they rely heavily on manual intervention and experience, and for complex bridge structures, the optimization results may not be ideal. In contrast, sensor layout optimization based on machine learning and intelligent optimization algorithms has

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significant advantages in handling and analyzing large volumes of data and complex data relationships. These methods can better uncover hidden information, possess strong adaptability, and can adjust optimization strategies as the structure of the bridge changes. However, the drawbacks include the need for large amounts of training data, and the quality of the training data directly affects the optimization results. For intelligent optimization algorithms, they offer strong versatility and can handle large, complex bridges with high degrees of freedom. These algorithms are also characterized by fast convergence and high accuracy, making it possible to find optimal sensor layouts in a short amount of time. However, the tuning of algorithm parameters can have a significant impact on the results, and in certain situations, they may get stuck in local optima, unable to find the global optimum solution. The theoretical basis, complexity, computational efficiency, and applicability of the three methods are summarized in the table below.

Table 2: Comparison of Various Algorithms

	Theoretical Basis	Implementation Difficulty	Computational Efficiency	Optimization Effectiveness	Applicable Scope
Traditional Methods	Statistics	Low	Low	Poor for Complex Structures	Simple Structures
Machine Learning	Artificial Intelligence	High	High	Strong (For complex data relationships)	Complex Data Processing
Intelligent Optimization Algorithms	Biological Phenomena in Nature	Moderate	High	Hogh (For complex optimization problems)	Widely Applicable

6. Conclusion

Compared with traditional bridge sensor optimization methods, computer-based methods lack intelligence and exhibit limited global optimization performance. Sensor layout optimization based on intelligent optimization algorithms and machine learning demonstrates excellent global optimization capabilities; however, specific algorithms have inherent limitations. Combining or improving different algorithms can enhance their performance. In the future, improvements in machine learning and intelligent optimization algorithms may help enhance their performance and overcome the limitations inherent in individual algorithms.

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