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Optimal Sensor Placement using Genetic Algorithm and Hybrid Crossover Operator

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ABSTRACT: In this study, optimal sensor placement (OSP) which plays a key role in the health monitoring of large-scale structures, is investigated using the genetic algorithm (GA). The OSP is among permutation problems that it's challenging to define the crossover operator in this kind of problem. In this study, a new hybrid crossover operator is proposed to find the optimal location for sensors and two different strategies are investigated for selecting members to form the next generation population. Also, the two-structure coding method has been used instead of the typical binary coding method to create the chromosomes of the population members. The objective function and fitness is defined based on the modal assurance criterion (MAC) matrix that is calculated with identified mode shapes and analytical mode shapes. The efficiency of the proposed method was investigated on a high-rise structure. The results show that the mode shapes identified by the optimal placement obtained from the proposed method are identical to the analytical mode shapes of the finite element model. Also, the comparison between the sensor locations obtained by conventional operators and the proposed operator shows that the proposed hybrid crossover operator outperforms other operators in terms of accuracy and convergence speed.

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1- Introduction

Sensor deployment is a fundamental process in constructing a sensor network for structural health monitoring[1]. Various techniques for optimal sensor placement have been developed, including heuristic, exploratory, and systematic optimization methods[2-5]. The GA uses the theory of biological evolution and has shown promising results. However, the problem of optimal sensor placement is complex due to its permutation nature, requiring a suitable crossover operator for GAs. The crossover operator must align with the permutation solution space, avoiding invalid solutions and preserving good parts of parent solutions. This article proposes a new combined crossover operator for GAs to address optimal sensor placement. It describes the problem, and evaluation criteria, presents an optimization algorithm, and applies the method to a representative structure. During sensor placement, an appropriate objective function is required. Based on the reviewed studies on OSP, only a few evaluation criteria exist. Among them is the modal assurance criterion (MAC), which is used in this study, and generally determines the largest off-diagonal values in the MAC matrix as the objective function[6-7].

2- Methodology

Since the primary objective of OSP is to determine the suitable degree of freedom for sensor installation, the optimization of sensor placement can be summarized as follows: Given a set of n candidate positions, find m positions such that $m < n$ and maximize or minimize the objective function for sensor configuration. Therefore, the problem of OSP becomes a permutation optimization problem. The total number of potential sensor configurations containing m sensors is equal to $n!/(m!\times(n-m)!)$. In summary, the evolutionary process of the GA involves the following steps: selection of two parents → crossover → mutation → selection of the best individuals → next generation. Crossover is a process in which new chromosomes are generated by cutting the old chromosomes at a randomly selected crossover point and replacing parts of one string with another string. In this article, three different crossover operators are used. 1) Single-point crossover. 2) OX crossover. 3) Combined crossover: Firstly, with a probability of one-third, one of the single-point crossover operators is randomly selected, and two random points are used. Then, it is examined if there are duplicate elements, and if so, the first occurrence of each duplicate element is replaced with non-existing elements. The process of the proposed crossover operator is shown in Figure 1.

The proposed method was implemented on the reduced-order model of a new television tower in Guangzhou (GNTVT) [9-10], stimulated by white noise. Then, using simulated data

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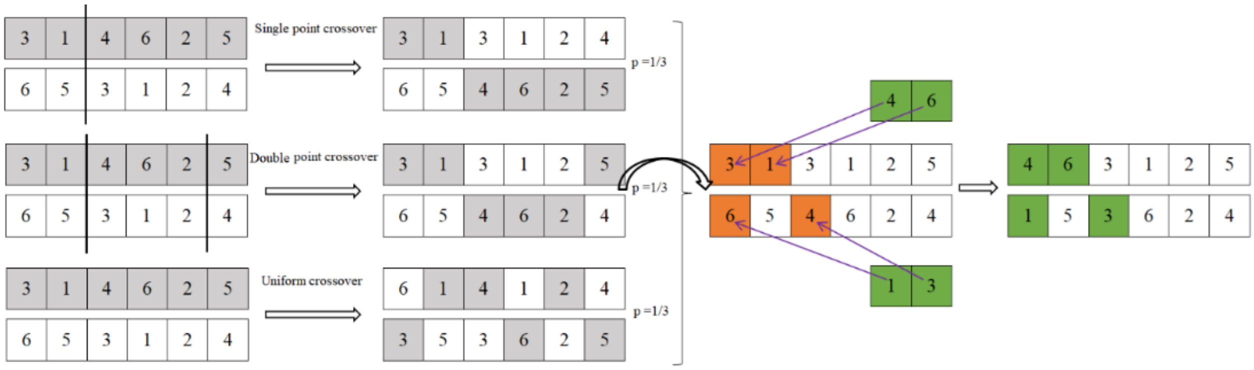

Fig. 1. Proposed combined crossover operator.

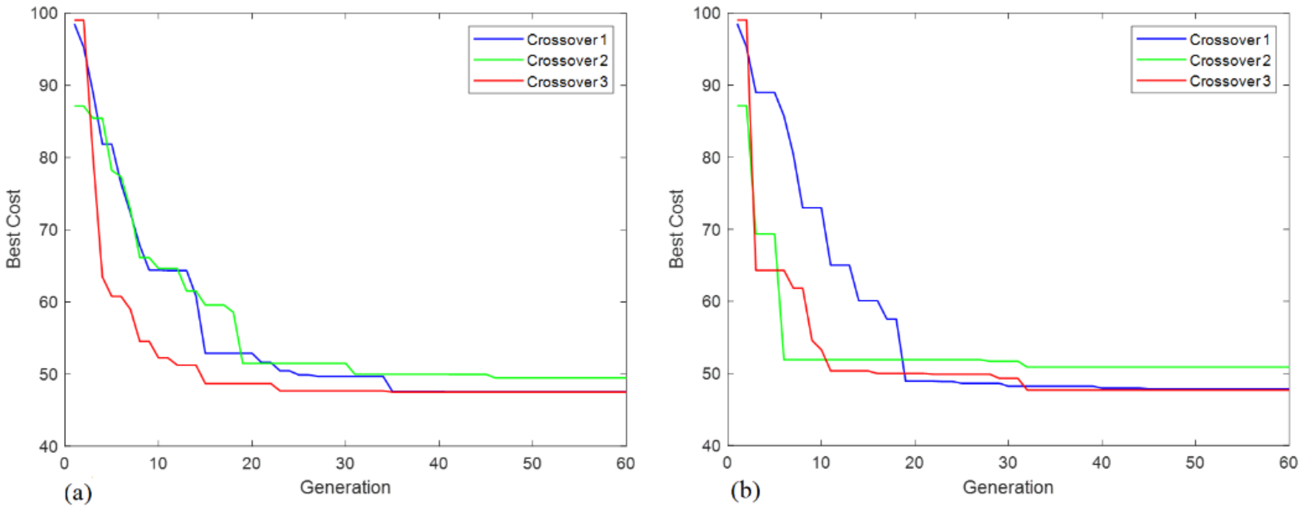

Fig. 2. GA History using crossover methods for the first PSC (a), and second PSC (b).

generated by state-space modeling, modal identification was performed using the frequency domain decomposition method, and the frequencies were also calculated. Next, the MAC matrix between the mode shapes of the identified modal shapes and the mode shapes of the analytical finite element model was computed. This process continued until achieving orthogonal and consistent mode shapes.

3- Results and Discussion

Calculations were performed for 2 population selection cases (PSCs). Figure 2(a) demonstrates that the new operator used in this article (Operator 3) provides significantly better results in terms of convergence speed and cost function value compared to the other two operators for the first PSC. Although the cost function of Operator 1 is slightly higher and approximately equal to Operator 3, it exhibits a greater difference in convergence speed. According to the graph, Operator 2, which is the well-known OX operator, does not yield satisfactory results in the OSP problem. Figure 2(b) illustrates that the difference in convergence speed between Operators 1 and 3 is almost similar for the second PSC. However, the final cost function value is still lower for Operator 3.

It can be observed that the performance of the optimization algorithm in minimizing off-diagonal values of the MAC matrix is highly suitable and remarkable. Finally, for better visualization, out of the 32 identified vibration modes using the obtained optimal arrangement, the first 6 modes are shown alongside the first 6 modes of the finite element model in Figure 3. As observed, the mode shapes are perfectly matched, and the obtained optimal arrangement is capable of accurately capturing the mode shapes of the structure and, consequently, other dynamic characteristics for subsequent health monitoring stages.

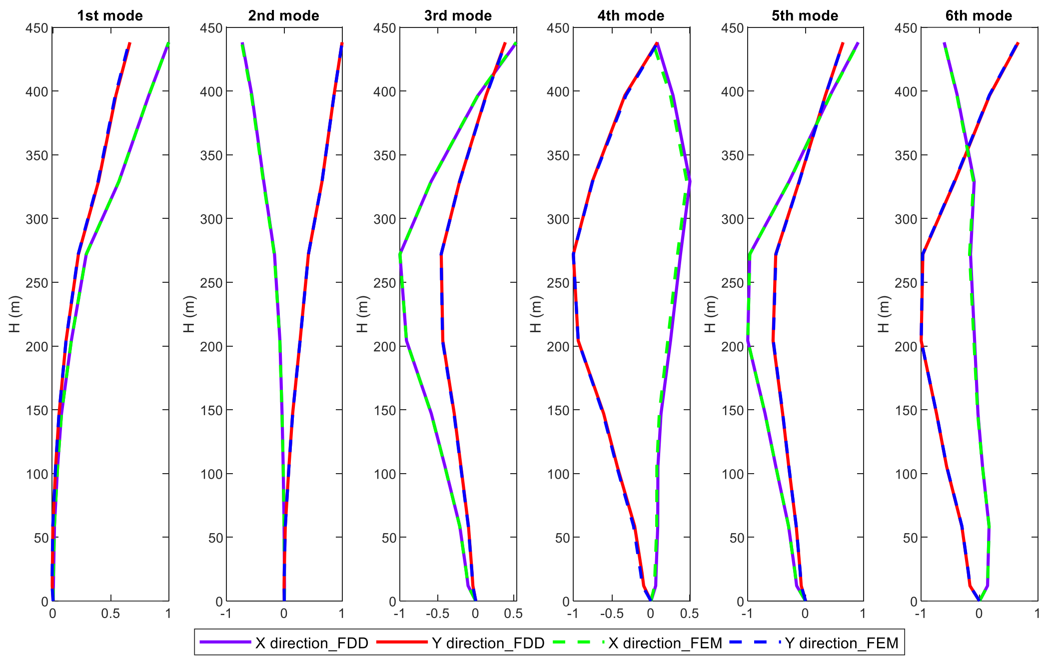

Fig. 3. The first 6 mode shapes were identified using the optimal arrangement with the mode shapes of the FE model.

4- Conclusion

This study implements a GA for the optimal placement of a predefined number of sensors. A combined approach for the crossover operator is proposed and it is compared with commonly used crossover operators. Additionally, two different strategies for creating the next generation are compared. In the first one next generation formation is only based on the merit of candidates, while in the second one, a pre-defined quota for parents, offspring, and mutants is considered. The proposed method is implemented on the television tower in Guangzhou (GNTVT) structure and the results show that the proposed operator achieves higher speed and accuracy in OSP problems compared to the other commonly used operators. Furthermore, it is revealed that selecting candidates based on merit without considering specific quotas for parents, offspring, and mutants has a positive impact on the results. Ultimately, the results obtained using the crossover operator 3 and selecting candidates based on merit (first approach) yield highly desirable outcomes, where the identified mode shapes using the optimized arrangement perfectly match the analytical mode shapes of the finite element model.

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