Comparative study of metaheuristic algorithms in the identification of structural damage in composite beams

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ABSTRACT

Structural damage, whether visible or hidden, is an inevitable occurrence in all structures, machines, and tools, arising from factors such as machining processes, wear, and impact. Over the years, significant efforts in structural dynamics have been devoted to evaluating and reconciling numerical models with experimental data to accurately detect and quantify such damage. This study presents a comprehensive approach to identifying and quantifying structural damage in multilayer composite beams by first assessing the global modal and frequency differences between undamaged and damaged structures using the Frequency Response Function (FRF) method. These results are then utilized in various metaheuristic optimization algorithms to precisely detect and quantify the extent of the damage. The focus of this work is to evaluate the effectiveness of three optimization algorithms: the African Vulture Optimization Algorithm (AVOA), the Salp Swarm Algorithm (SSA), and the Whale Optimization Algorithm (WOA). These algorithms are tested on a composite structure to determine their accuracy and computational efficiency in identifying structural damage.

1. Introduction

Early methods for detecting structural damage were basic and often inaccurate, mainly relying on visual inspections or acoustic signals to spot potential issues. Over time, more advanced non-destructive testing methods have been developed, incorporating various aspects of materials and structures to improve precision (Kahouadji et al., 2022).

As various industries have grown, the condition of structures has become a key focus for researchers and professionals. The advancement of this field has been greatly boosted by the rise of computers and improved data processing methods. Ongoing technological development has led to the creation, testing, and improvement of various methods for detecting and measuring damage in structures.

These approaches, which extend over the last two centuries, can be classified into three groups: techniques based on experimental data, techniques based on modal data and finite element data, and hybrid techniques that combine elements of both approaches (Hwang & Kim, 2004). This classification reflects the dynamic nature of structural damage detection, showing interdisciplinary efforts to improve the reliability and accuracy of assessment methods.

Cawley and Adams (1979) suggested that if a set of natural frequencies is measured before a structure becomes operational, these frequency measurements can be used to identify damage by comparing them with the original natural frequencies. However, the statistical methods proposed by Friswell et al. (1994) for damage detection, though pioneering, were found to be somewhat impractical due to limitations in the chosen modeling approaches and the neglect of several influential parameters, some of which have since been addressed.

The advent of optimization methods and algorithms has significantly advanced the field. Many of these algorithms are inspired by the collective behavior of organisms or evolutionary processes in nature. Metaheuristic optimization algorithms, in particular, have become essential for solving complex optimization problems. They offer versatility, adapting to a wide range of challenges, especially when conventional optimization techniques fall short due to problem complexity, non-linearity, or expansive search spaces (Wong & Ming, 2019). These algorithms systematically explore the solution space through iterative processes, progressively refining the initial solution or a population of solutions across multiple iterations (Agrawal et al., 2021).

This characteristic makes them applicable to problems presenting objective functions that are non-differentiable, discontinuous or noisy. They can be divided into four main categories that can hybridize with each other, and which are algorithms: evolutionary, individual or swarm animal intelligence, the laws of physics and human behavior.

Tiachacht et al. (2018) introduced a combination of Modified Cornwell Indicator (MCI) and Genetic Algorithm. The objective function, based on the modal parameters of damaged structures, was designed to quantify accurately the damage. The numerical results indicated the strength of the suggested approach.

The second group of metaheuristic methods includes the methods of individual animal intelligence or swarm based on the social behavior of animals. The most popular are the Ant Colony Optimization algorithm (ACO), the Artificial Bee Algorithm (ABC), the Gray Wolf Optimization algorithm (GWO) and the Dung Beetle Optimizer (DBO) The optimization of ant colonies (ACO) for example derives its fundamental principles from the complex foraging behaviors presented by real ants (Dorigo & Stützle, 2003). This algorithm uses artificial ants as agents that cross a given solution space in search of optimal solutions (Dorigo et al., 2006). The navigation strategy closely mimics the foraging patterns observed in nature, where real ants communicate through chemical signals called pheromones to guide each other artificial ants leave virtual traces of to guide the decisions of subsequent ant agents. allowing the discovery of optimal or high-quality solutions in complex optimization scenarios (Dorigo & Stützle, 2019).

Benaissa et al. (2024) present an insightful comparison of the strengths and limitations of metaheuristic algorithms versus gradient-based optimization methods. Their paper offers a comprehensive overview of the applicability of these techniques across various problem domains and under different resource constraints.

Physics-based algorithms are inspired by the laws of physics and nature, we can mention the most popular of them Harmony Search (HS) the Gravitational Search Algorithm (GSA), the Atom Search Optimization algorithm (ASO), the Big Bang-Big Crunch algorithm (BBBC), the Small World Optimization Algorithm (SWOA), the Black Hole algorithm (BH). Harmony Search (HS), for its part, is inspired by the collaborative and iterative nature of musical composition (Yang, 2009). In HS, a population of candidate solutions is analogous to the musical elements, and they undergo iterative adjustments, reflecting the process of fine-tuning the musical composition (Geem et al., 2001). This iterative approach allows HS to constantly explore the solution space, in order to optimize the solutions encountered. The main objective of the algorithm is to identify and converge on improved solutions, following the example of musicians who create harmonious compositions through creative improvisations. The effectiveness of HS in the optimization of complex problems lies in its ability to capture the essence of the harmonization and refinement of the musical world, resulting in solutions that demonstrate precision and art, similar to a well-composed musical piece (Geem, 2010).

For the fourth category which are the algorithms based on human behaviors, they are characterized by two processes: exploration and exploitation, these methods include Tabu Search

(TS) Teaching-Learning-Based Optimization (TLBO), Group Search Optimizer (GSO), Fireworks Algorithm (FA), researcher optimization algorithm (SOA), Mountaineering Team-Based Optimization (MTBO). Tabu Search (TS) is based on its short-term memory, which fulfills a double objective in the algorithm (Gendreau & Potvin, 2005). This distinctive feature of Tabu Search (TS) enhances the algorithm in several ways. It increases computational efficiency by preventing the re-examination of already evaluated solutions and enhances the overall robustness and versatility of TS. By avoiding redundant visits and promoting diversification, TS explores the solution space more thoroughly, thereby increasing the likelihood of discovering superior solutions (Hertz et al., 1995).

We can also mention recently published algorithms such as

- The algorithm of the solar system (Zitouni et al., 2020),
- The YUKI algorithm which introduces a dynamic methodology for reducing the search space (Benaissa et al., 2021),
- Hunter-Prey optimization (Naruei et al., 2022),
- The Algorithm for optimizing planets (Wahab et al., 2022),
- The Sinh cosh optimizer (Bai et al., 2023),
- The Coati Optimization Algorithm (Dehghani et al., 2023).

This research presents an efficient approach for detecting, locating, and quantifying damage in laminated beam structures. The technique integrates the Frequency Response Function (FRF) indicator with advanced optimization algorithms, including the African Vulture Optimization Algorithm (AVOA), Salp Swarm Algorithm (SSA), and Whale Optimization Algorithm (WOA). The proposed method demonstrates high accuracy and effectiveness in identifying both single and multiple damages. Additionally, it enables real-time monitoring of the structural health of laminated beam structures, which is critical for ensuring their safety and reliability.

2. Problem formulation

Damage localization and quantification in multilayer composite beams can be achieved using the Frequency Response Function (FRF) indicator combined with optimization techniques.

2.1. Frequency Response Function (FRF)

FRF is a damage indicator that is computed from the mass and stiffness matrices of a structure and is based on the vibrational response of the structure.

The FRF for the damaged and healthy structures is presented in the following formulation.

$$\begin{cases} \left[H(\omega)\right]^A = \left(-\omega^2\left[M\right]^A + \left[K\right]^A\right)^{-1} \\ \left[H(\omega)\right]^T = \left(-\omega^2\left[M\right]^T + \left[K\right]^T\right)^{-1} \end{cases} \tag{1}$$

Where $[M]$ and $[K]$are mass and stiffness matrices, the symbol $[\ ]^A$, $[\ ]^T$ are undamaged and damaged, the stiffness changes as follows:

$$[\Delta K] = [K]^A - [K]^T \tag{2}$$

Where $[K]^A$, $[K]^T$ denotes the stiffness healthy and damaged structure, respectively.

2.2. African Vultures Optimization Algorithm (AVOA)

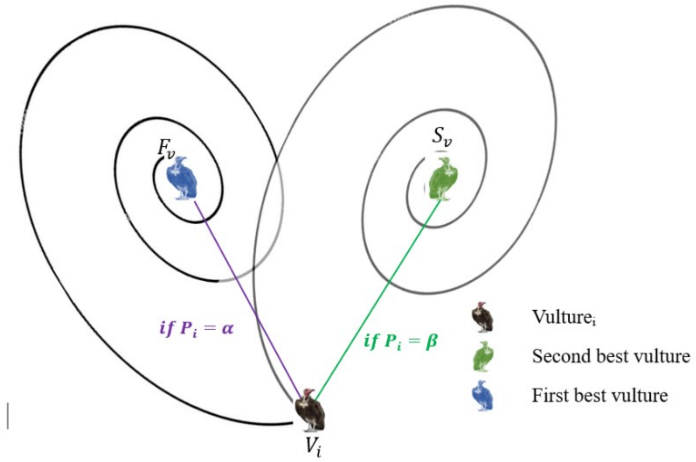
Vultures are a group of predatory birds known for inhabiting harsh, often desert climates.

While they generally avoid attacking healthy animals, they may prey on the injured or sick. Their diet primarily consists of carcasses and other remains. In Africa, various vulture species exist, each with distinct physical features, though they share similar lifestyles. In times of food scarcity, vultures engage in fierce battles and confrontations to secure even the smallest scraps for survival.

Vultures' intelligence is evident in their movement patterns, strategic approaches, dominance tactics, food acquisition strategies, and defensive behaviors. This remarkable intelligence is depicted in Figure 1. Inspired by these characteristics, a group of researchers, led by Benyamin et al., developed an optimization algorithm. This algorithm is based on fundamental vulture behaviors and incorporates four key hypotheses to simulate the optimization process, which is then structured into four distinct stages (Gürses et al., 2022).

Figure 1

Vulture Manner Approaches



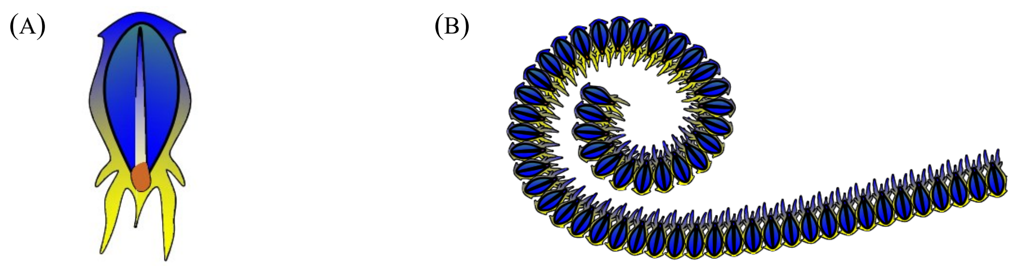
2.3. Salp Swarm Algorithm (SSA)

Salps are marine organisms with a structure and movement style akin to jellyfish. The inspiration for this optimization algorithm comes from observing the navigation and foraging behaviors of salps in the marine environment. During their quest for food, salps form chains, providing each member with the opportunity for a coordinated change in troop movement, progressing toward their objective. The mathematical model for these salp chains involves initially dividing the population into two groups: a leader and followers or a leader and a salp forming the chain and directing movement, followed by other salps, as illustrated in Figure 2.

The article titled "Salp Swarm Algorithm," authored by a group of researchers including Mirjalili and Gandomi, and others, highlights the practicality of this approach, demonstrated through testing in various fields (Mirjalili et al., 2017).

Figure 2

(a) Individual Salp, and (b) Salps Chain

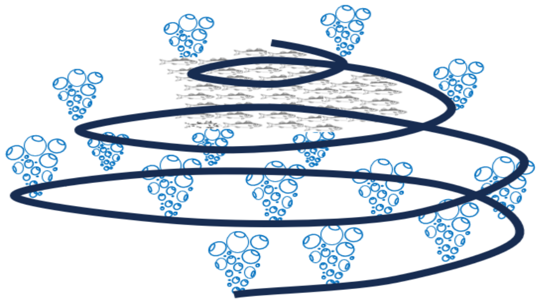


2.4. Whale Optimization Algorithm (WOA)

Whales hold the title of being the largest mammals on Earth and are considered formidable predators. One fascinating aspect of whales lies in their intelligence. Among the various whale species, humpback whales stand out due to their unique hunting method. This distinctive foraging behavior is known as the bubble net feeding method. Humpback whales exhibit a preference for hunting small fish near the water's surface. Researchers have identified two maneuvers associated with the use of bubbles, naming them "upward spirals" and "double loops." By circling their prey, these whales can pinpoint the location and engulf it efficiently, as illustrated in Figure 3. In their article, (Mirjalili & Lewis, 2016) propose a mathematical optimization model, demonstrating that the whale's target and the best solution of the model closely approximate the optimum.

Figure 3

Whales Upward Spirals



3. Numerical analysis

3.1. Composite materials

Due to their associated advantages of weight reduction and durability and toughness, composite materials are used in different fields. They are generally composed of solid and rigid fibers in a resistant resin matrix. Usually these are Carbon Fiber Reinforced Plastic (CFRP), Glass Fiber Reinforced Plastic (GRFP), honeycomb cores and carbon laminates. Composite defects can form during the manufacturing process and include and they can be in Bonding defects, Delamination, Misalignment of Fibers Presence of foreign body, Cracking of the folds, in addition to manufacturing defects, etc.

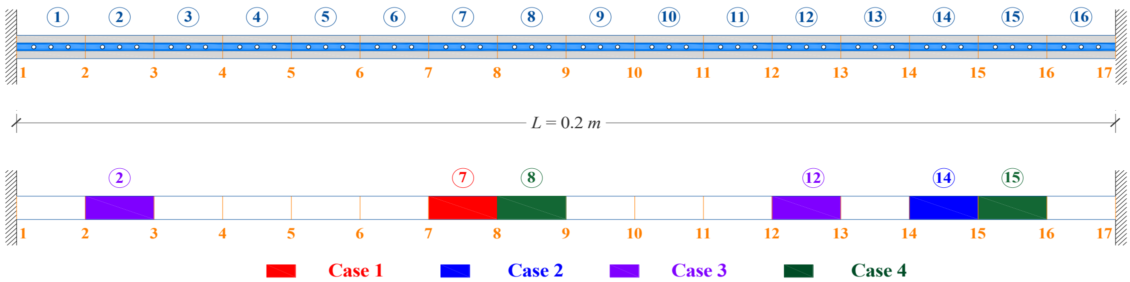
3.2. System's characteristics

The study focuses on a multi-layer composite beam recessed on both ends, with four different cases of damage tested, as depicted in Figure 4.

Other characteristics are mentioned in Table 1.

Figure 4

Doubly Embedded Composite Beam Discretized on 16 Elements whith the Fourth Damage Cases



Source. The data are from "An efficient approach for optimal sensor placement and damage identification in laminated composite structures" by D. C. Dinh, H. T. Dang and T. T. Nguyen, 2018, *Advances in Engineering Software, 119*, pp. 48-59

Table 1

Characteristic of the Structure

Characteristic	Value
Length l (m)	0.2
Width b (m)	0.02
Thickness h (m)	0.02
Number of elements	16
Number of ply	3

Source. The data are from "An efficient approach for optimal sensor placement and damage identification in laminated composite structures" by D. C. Dinh, H. T. Dang and T. T. Nguyen, 2018, *Advances in Engineering Software, 119*, pp. 48-59

3.3. Model validation

With the implementation of the physical model, the use of the modal frequency analysis method gives the different eigenmodes of the structure. the five initial modes are compared with other previous work mentioned in Table 2.

Table 2

The Natural Frequencies of the Composite Beam

	Modal frequency (Hz)				
Frequency mode	1st	2nd	3rd	4th	5th
Present structure	19.125	38.983	61.861	85.374	109.741
IIRS method (k = 2), using 6 optimal (Dinh et al., 2018)	19.125	38.985	62.472	86.191	127.987
Frequencies calculated by various models (Dinh et al., 2018)	19.125	38.983	61.861	85 .374	109.741

Source. The data are from "An efficient approach for optimal sensor placement and damage identification in laminated composite structures" by D. C. Dinh, H. T. Dang and T. T. Nguyen, 2018, *Advances in Engineering Software, 119*, pp. 48-59

The comparisons highlight the accuracy of the results and validate the chosen model. Various damage scenarios are considered (see Table 3), and a damage indicator is obtained for each scenario. These damage indicators serve as initial data for the subsequent optimization and quantification processes.

Table 3

Damage Scenarios

Cases	Elements Damaged	Damage%	Iteration	Population
Case 1	7	20	1500	100
Case 2	14	35	1500	100
Case 3	2	15	2000	200
	12	30	2000	200
Case 4	8	10	2000	200

Cases	Elements Damaged	Damage%	Iteration	Population
	15	25	2000	200

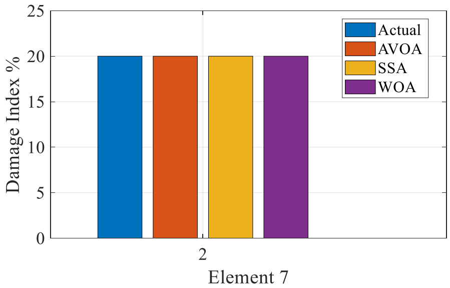
Source. The researcher's data analysis

4. Optimization results

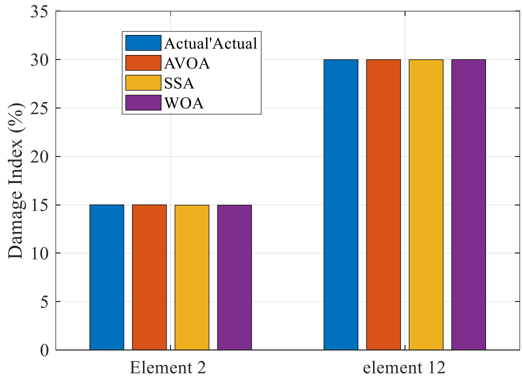
The damage indicators for each case are used as initial data for optimizing and quantifying the assumed damage using the three methods. After executing the optimization, the results of the iterations are displayed in Figure 5, which shows the damage index for the three methods compared to the reference bar. These figures demonstrate that all three methods effectively detect and quantify both single and multiple damage scenarios.

Figure 5

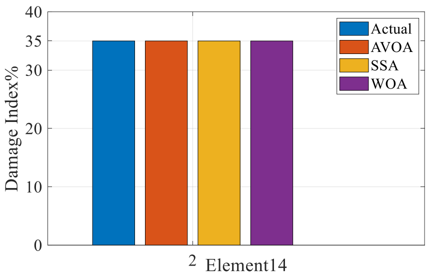
Damage Index in different Damage Cases



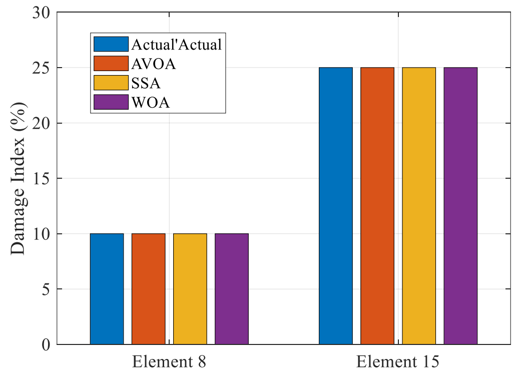
(a) Case 1



(c) Case 3



(b) Case 2



(d) Case 4

Figure 6 shows us the execution time of the three programs of 1,500 iterations and single damage for cases 1 and 2 and 2,000 iterations and two damage for cases 3 and 4.

The figures give us an almost identical time for the AVOA and WOA programs, a shift of around 1% to 3%.

Figure 6

Execution CPU Time's

	AVOA	SSA	WOA
Case 1	516.6	542	501.8
Case 2	553.6	575.2	496.7
Case 3	674.2	732.4	657.2
Case 4	569.6	633.4	576.8

As for the SSA algorithm, it is longer by around 5 to 11 compared to the other two.

Figures 7(a) illustrate the algorithms' approach to the exact solution.

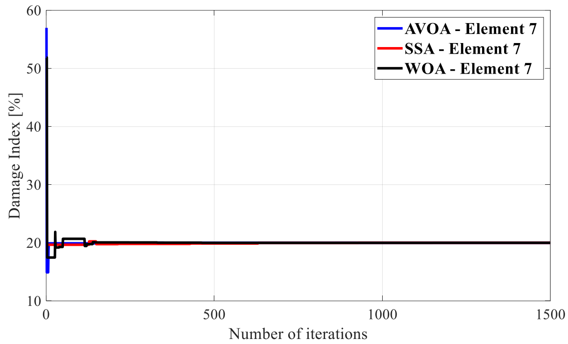
In the case of a single damage, depicted in Figures 7-a Case 1 and 7-a Case 2, all three methods exhibit faster convergence.

However, for scenarios involving two damages, as shown in Figures7-a Case 3 and 7-a Case 4, the approximation process takes a longer duration.

Figure 7

(a) Convergence Damage Level using different Optimization Techniques

(b) Number of Iterations necessary to obtain the Result

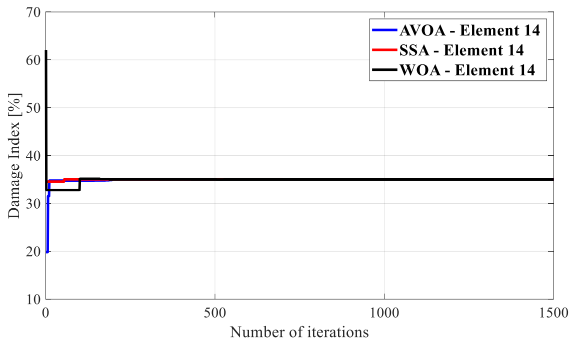


Element 7

Iteration	AVOA	SSA	WOA
564	20	19.88	19.99
929	20	20	19.99
1150	20	20	20

Optimization Method

(a) Case 1 (b) Case 1

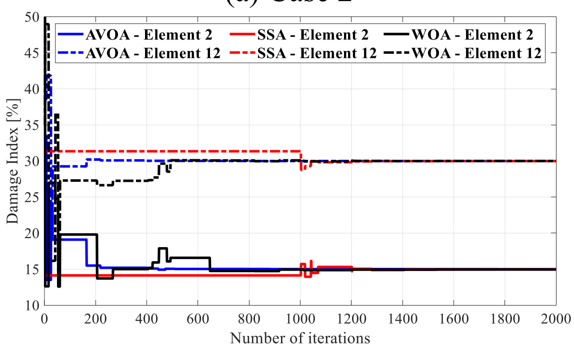


Element 14

Iteration	AVOA	SSA	WOA
815	35	35.03	34.99
1228	35	35	35.01
1612	35	35	35

Optimization Method

(a) Case 2 (b) Case 2



Element 2

Iteration	AVOA	SSA	WOA
510	15	14.1	16.6
1408	15	15	14.9
1533	15	15	15

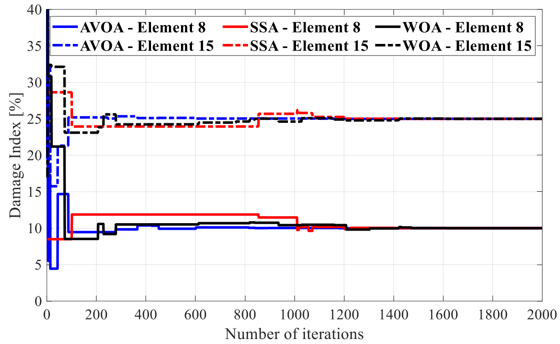
Optimization Method

Element 12

Iteration	AVOA	SSA	WOA
510	30	31.4	30.1
1408	30	30	30
1533	30	30	30

Optimization Method

(a) Case 3 (b) Case 3



(a) Case 4

(b) Case 4

Figure 7 provides insights into the number of iterations required to achieve the desired values. Specifically, Figure 7-a illustrates Case 1 and Case 2 for one iteration, while Figure 7-b depicts Case 3 and Case 4 for two iterations. It is evident that the AVOA requires fewer iterations compared to the other methods.

SSA needs more iterations, with increases ranging from 37 to 64 for single damage scenarios and from 47 to 174 for multiple damage scenarios. Conversely, WOA converges more slowly, requiring between 63 and 103 more iterations for single damage and between 97 and 200 more iterations for multiple damages.

5. Conclusions

This study examined a multilayer composite beam using the Frequency Response Function (FRF) method to identify various modal and frequency characteristics of the structure. The results were applied to damage optimization. The effectiveness of three optimization algorithms - the African Vulture Optimization Algorithm (AVOA), Salp Swarm Algorithm (SSA), and Whale Optimization Algorithm (WOA) - was evaluated in terms of detecting and quantifying damage. The findings revealed that AVOA achieved results with a slight delay ranging from 5 to 11 compared to the other methods. Significantly, AVOA demonstrated superior performance by requiring 37 to 200 fewer iterations than SSA and WOA to reach the desired outcomes. Therefore, AVOA is identified as the most effective algorithm for optimizing damaged structures.

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