An efficient computational system for defect prediction through neural network and bio-inspired algorithms

Abdelwahhab Khatir[1*], Abdelmoumin Oulad Brahim[1], Erica Magagnini[1]

[1]Polytechnic University of Marche, Ancona, Italy
[*]Corresponding author: a.khatir@pm.univpm.it

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ABSTRACT

Detecting and locating damage is essential in maintaining structural integrity. While Artificial Neural Networks (ANNs) are effective for this purpose, their performance can be significantly improved through advanced optimization techniques. This study introduces a novel approach using the Grasshopper Optimization Algorithm (GOA) to enhance ANN capabilities for predicting defective aluminum plates. The methodology begins by deriving input parameters from natural frequencies, with defect locations as the output. A Finite Element Model (FEM) is used to simulate data by varying defect locations, creating a comprehensive dataset. To validate this approach, experimental data from vibration analyses of plates with different defect locations is collected. We then compare the performance of our GOA-optimized ANN against other metaheuristic algorithms, such as the Cuckoo Search Algorithm (CSA), Bat Algorithm (BA), and Firefly Algorithm (FA). Notably, CSA's performance is slightly close to GOA. The results show that our GOA-based method outperforms these traditional algorithms, demonstrating superior accuracy in damage prediction. This advancement holds significant potential for applications in structural integrity monitoring and maintenance.

1. Introduction

The evolution of optimization algorithms spans a vast array of fields, from the mathematical underpinnings to cutting-edge applications in engineering, healthcare, economics, and more. These algorithms play a pivotal role in various engineering disciplines, including civil, mechanical, electrical, and industrial sectors, where they are instrumental in the complex stages of design and optimization (Dr. Benaissa, Kobayashi, Al Ali, Khatir, & Elmeliani, 2024; Kaveh & Eslamlou, 2020; Nadimi-Shahraki, Zamani, Varzaneh, & Mirjalili, 2023). Inspired by principles from physics, swarm intelligence, and biological processes, these advanced methodologies have revolutionized the approach to solving real-world optimization problems (Achouri, Khatir, Smahi, Capozucca, & Brahim, 2023; Gad, 2022). This shift has enabled more efficient and innovative solutions across various industries, driving progress and facilitating advancements in technology and practice.

Optimization techniques have evolved into a rich tapestry of methods, each rooted in unique inspirations and operational principles. At the forefront, Ant Colony Optimization (ACO) draws from the complex foraging behaviors and pheromone trails of ants, creating robust solutions through simulated collective intelligence (Nayar, Gautam, Singh, & Mehta, 2021;

Wang & Han, 2021). The Firefly Algorithm (FA), inspired by the bioluminescence of fireflies, uses light intensity as a metaphor for attractiveness in the search process (Li, Wei, Li, & Zeng, 2022). Meanwhile, the Grey Wolf Optimization (GWO) algorithm captures the predatory and hierarchical dynamics observed in wolf packs during hunting (Makhadmeh et al., 2024).

In the realm of swarm intelligence, Particle Swarm Optimization (PSO) mimics the coordinated movement of bird flocks and fish schools to harness the power of collective behavior (Khatir et al., 2023; Wang, Tan, & Liu, 2018). The Artificial Bee Colony (ABC) algorithm mirrors the sophisticated foraging strategies of honeybees to explore and exploit solution spaces (Kaya, Gorkemli, Akay, & Karaboga, 2022).

Other notable methods include Genetic Algorithms (GAs), which utilize mechanisms of natural selection, crossover, and mutation to evolve solutions (Kucukkoc, Keskin, Karaoglan, & Karadag, 2024; Na, Zhang, Lian, & Zhang, 2022). The BAT Algorithm simulates the echolocation of bats to balance exploration and exploitation (Lu, Wang, & Zhang, 2021; Zenzen, Belaidi, Khatir, & Wahab, 2018). Lastly, the Cuckoo Search Algorithm combines strategies of brood parasitism and stochastic Levy flights to enhance search efficiency (Guerrero-Luis, Valdez, & Castillo, 2021; Le et al., 2021). These diverse approaches enrich the optimization landscape, offering a spectrum of techniques inspired by nature’s ingenuity.

The deployment of Artificial Neural Networks (ANNs) marks a transformative shift in structural damage detection methodologies. Moving beyond traditional model-dependent approaches, ANNs embrace advanced machine-learning techniques, fostering a new era of model-free diagnostic capabilities (Neves, González, Leander, & Karoumi, 2017). The integration of ANNs with metaheuristic algorithms amplifies their effectiveness, creating a powerful hybrid approach for enhanced accuracy and efficiency in detecting structural anomalies across various engineering domains (Gomes, Mendez, da Silva Lopes Alexandrino, da Cunha, & Ancelotti, 2019).

The field of structural health monitoring has advanced significantly with the integration of ANN and various optimization algorithms. Tran, Khatir, De Roeck, Bui, and Abdel Wahab (2019) introduced a method combining ANN with the Cuckoo Search (CS) algorithm to improve accuracy and reduce computational time in damage detection. Oulad Brahim et al. (2024) studied pipeline stress concentration due to corrosion and used ANN with the Jaya algorithm to predict defect sizes, showing real-world applications. (Khatir et al., 2021) used a two-stage approach with an improved Frequency Response Function (FRF) indicator and ANN combined with the Arithmetic Optimization Algorithm (AOA) for damage detection in Functionally Graded Material (FGM) plates, achieving high precision and accuracy. Additionally, Khatir, Capozucca, Khatir, and Magagnini (2022) explored vibration-based damage detection in steel beams using ANN and the Butterfly Optimization Algorithm (BOA), improving crack depth prediction accuracy. Zara et al. (2024) investigated the optimization of multilayer composite structures, focusing on the influence of geometric parameters on mechanical properties. They used a hybrid E-Jaya-ANN technique to predict fracture toughness in bending tests, achieving higher accuracy compared to the Jaya-ANN method. Their study also developed and validated a numerical model using the Hashin damage criterion to optimize laminate layer configurations.

The field of structural integrity faces challenges in accurately detecting and predicting damage, which researchers have addressed through advanced Machine Learning (ML) and optimization techniques (Bao & Li, 2020). Brahim et al. (2024) presented a hybrid approach combining YUKI-RANDOM-FOREST, PSO-YUKI, and BCMO with ANN to optimize composite patch designs for damaged pipes, effectively predicting maximum principal stress using XFEM. Khatir et al. (2024) investigated the Near-Surface Mounted (NSM) strengthening technique using CFRP and GFRP rods. They used PSO and GA to optimize Gradient Boosting models for concrete strain prediction, achieving high accuracy with hybrid models GBPSO and GBGA. Azimi and Pekcan (2020) introduced a CNN-based SHM method using Transfer Learning (TL) techniques to process compressed response data for damage identification and localization in large-scale systems. The method was validated with numerical simulations and experimental data.

This research pioneers the integration of ANN with the GOA algorithm, significantly advancing defect prediction accuracy in plate models. By utilizing experimental vibration data to refine damage localization, the study evaluates GOA's performance against traditional optimization methods like Cuckoo Search Algorithm (CSA), BAT, and Firefly Algorithms (FA). The results highlight GOA's superior effectiveness and suggest its potential to transform structural integrity prediction systems, paving the way for future innovations in predictive modeling within structural engineering.

2. Methodology

To enhance the precision of structural damage prediction, this innovative methodology integrates the Grasshopper Optimization Algorithm (GOA) with Artificial Neural Networks (ANNs) in a novel approach. The goal is to improve ANN performance by optimizing its hyperparameters using GOA.

The process begins with a detailed problem formulation focused on predicting structural damage. Key data, such as natural frequencies, is collected and preprocessed, involving missing value management, feature normalization, and dataset partitioning into training and testing subsets.

A customized ANN is then developed with input nodes for natural frequencies, hidden layers, and output nodes tailored to the prediction task. Optimal activation functions, such as ReLU for hidden layers and linear functions for the output, are selected. After initializing ANN parameters like weights and biases, the network is trained using the dataset with a specified loss function and backpropagation until convergence.

GOA, inspired by the natural foraging strategies of grasshoppers, is employed as a new optimization method. An objective function is created to evaluate the ANN's performance using a validation dataset. GOA optimizes ANN hyperparameters by adjusting parameters such as population size and iteration limits, guided by a fitness criterion based on ANN performance metrics (Meraihi, Gabis, Mirjalili, & Ramdane-Cherif, 2021).

The optimized ANN model is then evaluated on a separate testing dataset to assess its accuracy, using metrics like Mean Square Error (MSE). Depending on the performance results, further adjustments and iterations may be performed. The mathematical formulation governing GOA's solution space exploration involves dynamically adjusting the parameter c according to the iteration count, as expressed by following Equation (1):

$$\mathrm{c} = \mathrm{c}_{\max} - \mathrm{iter}\frac{\mathrm{c}_{\max}-\mathrm{c}_{\min}}{\mathrm{Max}_{\mathrm{iter}}} \tag{1}$$

Where c_{max} and c_{min} are the upper and lower bounds values of c, respectively, *iter* is the actual iteration, and Max_{iter} is the upper bound number of iterations.

The Mean Squared Error is done by Equation (2):

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y}_i)^2 \tag{2}$$

Where y_i represents the actual value, $\bar{y}_i$ signifies the forecasted one, with n denoting the total number of instances.

The following Figure 1 illustrates the GOA-ANN model flowchart:

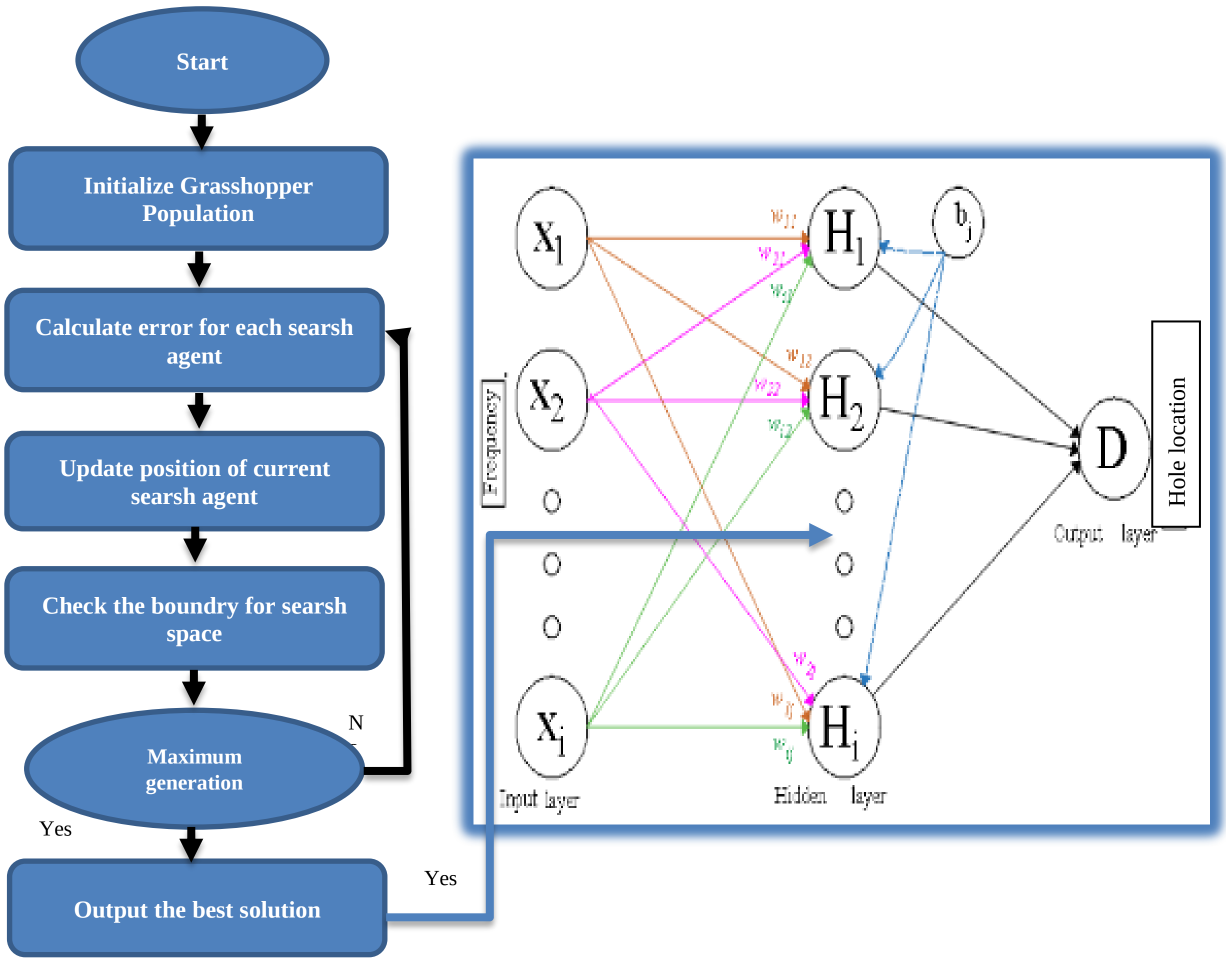


Figure 1. GOA-ANN training model flowchart

3. Numerical simulation and data acquisition

The structural modeling was conducted using ABAQUS 16.4 with free-free boundary conditions. Finite element analysis was performed with eight-node C3D8R brick elements to capture the three-dimensional behavior of the beam, incorporating six degrees of freedom per node (rotational and translational movements).

Two distinct defect scenarios were analyzed to test the accuracy of the GOA-ANN system in detecting defect locations. In the first scenario (D1), a defect was placed at the beam's center and incrementally moved along the central axis towards the edges in 10mm steps. In the second scenario (D2), an off-center defect was similarly introduced and shifted. Figure 2 shows the aluminum plate model with various defect positions. Table 1 details the geometric and mechanical properties of the model. Figure 3 presents the first four mode shapes derived from the simulation, which served as input parameters for natural frequencies.

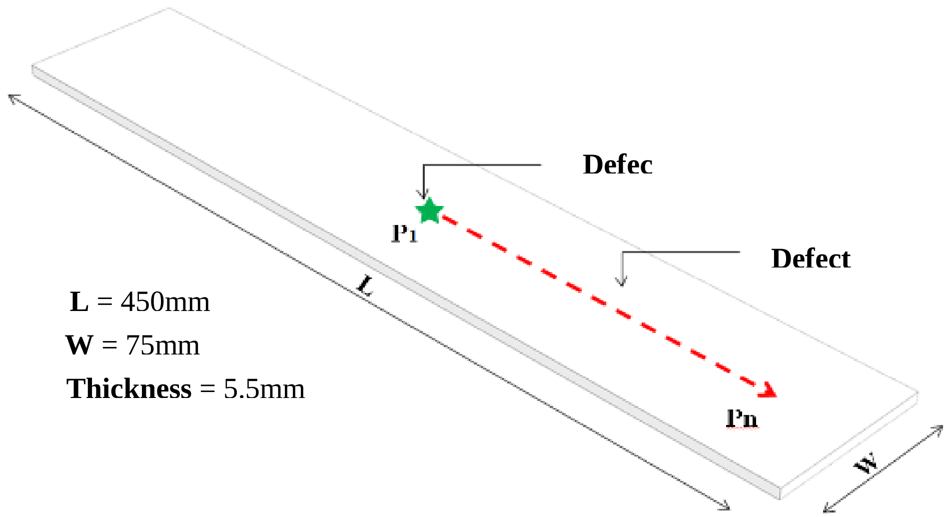


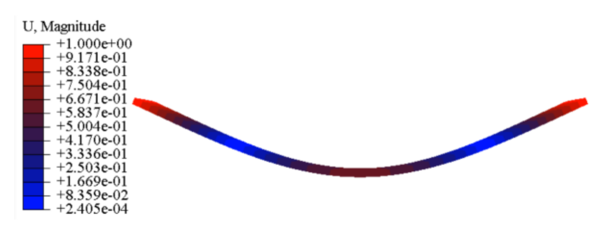
Figure 2. Numerical representation of damaged aluminum plate model

Table 1

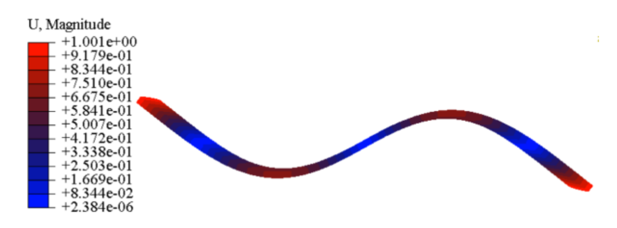
Physical characteristics of undamaged aluminum plate

Length L [m]	Width b [m]	Thickness h [m]	E [MPa]	Density ρ [g/cm^3]
0.4	0.075	0.0055	70000	2.7

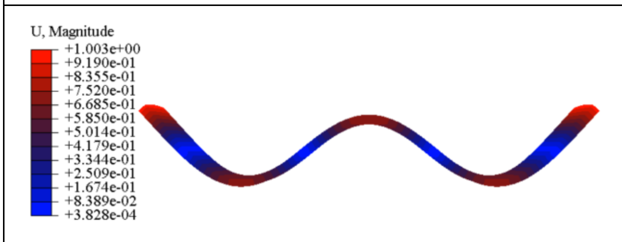
Source: Author



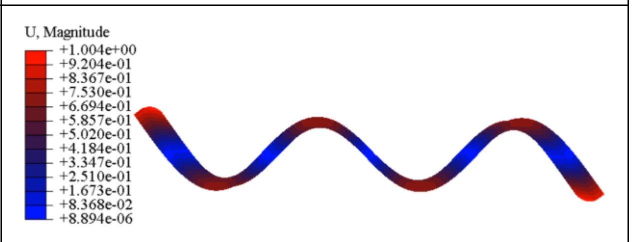
a- f= 184.76 Hz



b- f= 512.10 Hz



c- f= 1004.9 Hz



d- f= 1666.2 Hz

Figure 3. The four vibrations considered modes:
(a) Mode 1, (b) Mode 2, (c) Mode 3, and (d) Mode 4

4. Results and discussion

The dataset was compiled from the results of analytical simulations for defect scenarios D1 and D2, aimed at predicting the precise locations of centralized and off-centerlized defects illustrated in Figure 2 of the plate model. For training the GOA-ANN system, the architecture was set with a static configuration of 04 neurons.

The algorithm's parameters were finely tuned through an iterative process of experimentation and optimization. Initially, a broad range of parameter values was chosen based on insights from previous research and expert knowledge. Extensive experiments were then conducted to test various combinations of these parameters, ensuring optimal algorithm performance. The population size was maintained at a constant 100 throughout these trials.

To assess the GOA's effectiveness in training ANNs, it was compared with other approaches, including ANN trained with CSA, BAT, and FA. This comparative study aimed to determine the superiority of the GOA method in enhancing ANN training efficiency.

4.1. Defect case D1

In this case, the hybrid GOA-ANN model was employed to predict the exact positions of central defects within the plate model at specified X coordinates: 30; 60; 100; and 150mm. This approach aimed to enhance the accuracy and reliability of damage localization. Figures 4 and 5 illustrate a detailed comparative analysis of the regression results, showcasing the performance of the GOA-ANN system in contrast to alternative methodologies, including CSA, BAT, and FA models. All neural network models were uniformly designed with a hidden layer size fixed at 04 neurons to ensure consistency in the evaluation.

To validate the effectiveness of the GOA-ANN model, extensive simulations and performance tests were conducted, highlighting its superior predictive capabilities. The summarized outcomes of these tests are presented in Table 2, providing a clear overview of the model's accuracy and efficiency.

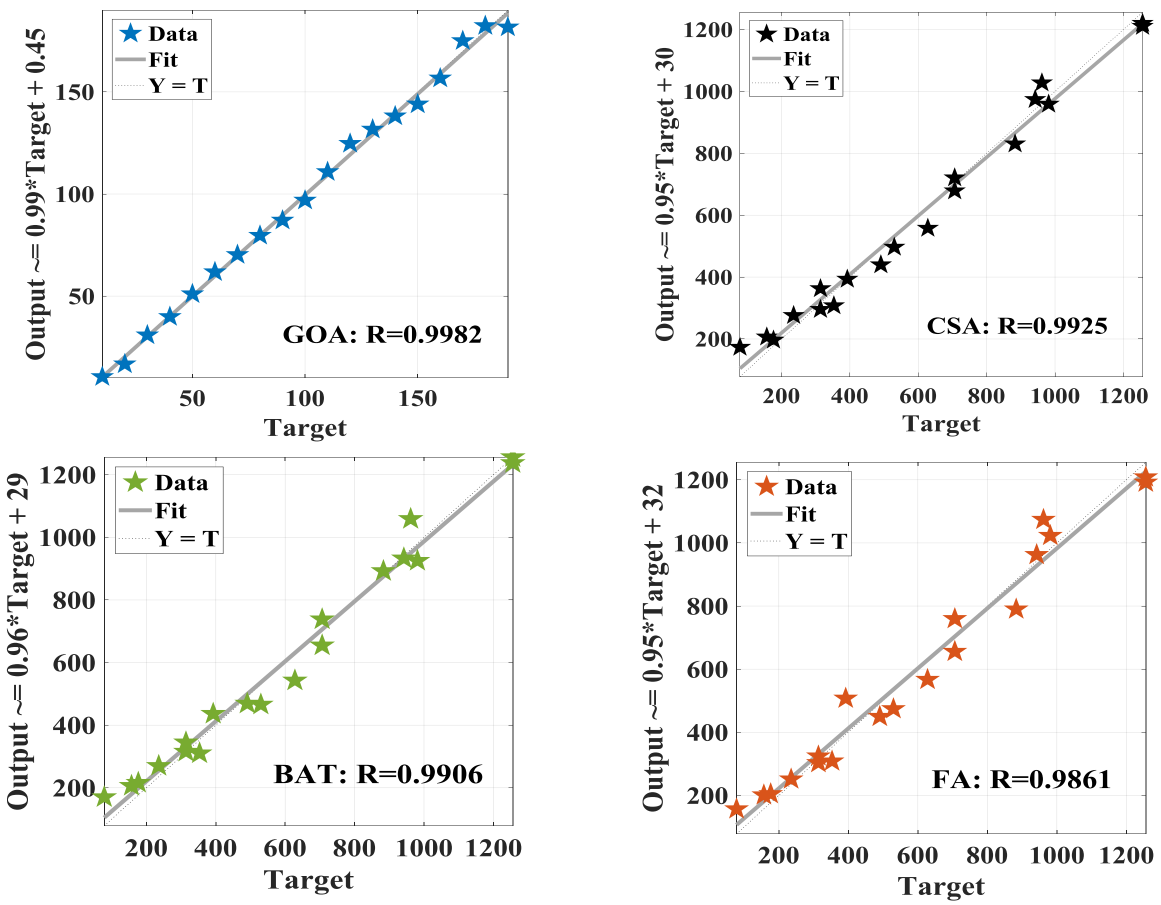


Figure 4. System training analysis for centered defect proposal using GOA, CSA, BAT and FA

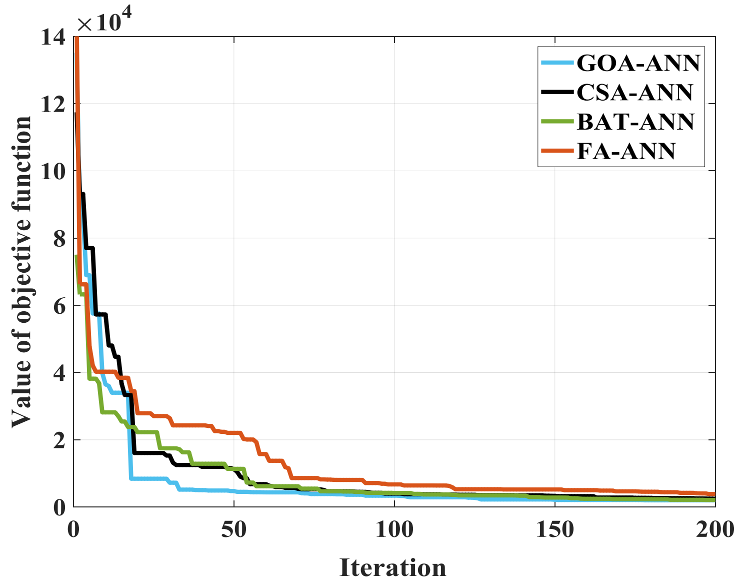


Figure 5. Performance of considered algorithms

The results demonstrate that integrating the GOA with ANN produces significantly better outcomes compared to using ANN alone. This hybrid approach achieves almost perfect alignment between predicted and actual values, with discrepancies being minimal. Even with a straightforward configuration, where the hidden layer size ‘n’ is fixed at 4, the predicted defect positions closely match the target locations, showing an estimated error margin of just 0.67 percent.

While other algorithms like CSA, BAT, and FA also show commendable performance in defect localization prediction, the GOA method stands out for its superior accuracy. This advantage arises from GOA’s ability to tolerate a broader error margin, which offers greater flexibility during the optimization process. Additionally, GOA’s computational efficiency is notable; for instance, the FA algorithm requires more iterations and a larger population size, resulting in longer processing times. Figure 5 provides a graphical representation of these comparative results.

Furthermore, the robustness of GOA in handling complex optimization tasks is evident from its performance. CSA and BAT, while effective, fall short in matching the precision achieved by GOA. This highlights GOA’s adaptability and efficiency, making it a preferred choice for precise defect localization in structural health monitoring. The graphical results in Figure 8 further underline the superiority of GOA, showcasing its ability to consistently deliver accurate predictions with lower computational costs.

4.2. Defect case D2

In this structural damage analysis, we utilized the GOA-ANN approach to predict the locations of off-center defects within the plate model, specifically at coordinates X = 20; 50; 120; and 180mm. This method was chosen to enhance the precision of defect localization. Figures 6 and 7 provide a comprehensive visual analysis of the regression outcomes and demonstrate the effectiveness of the GOA-ANN methodology compared to ANN models trained with CSA, BAT, and FA techniques. All models were standardized with a hidden layer size consistently set at 04 neurons to ensure a fair comparison.

Extensive testing and validation were performed to confirm the robustness of the GOA-ANN approach. The performance metrics illustrated in these figures highlight the superior predictive accuracy of the GOA-ANN model. Table 2 offers a summarized overview of the outcomes, showcasing the efficiency and reliability of our approach.

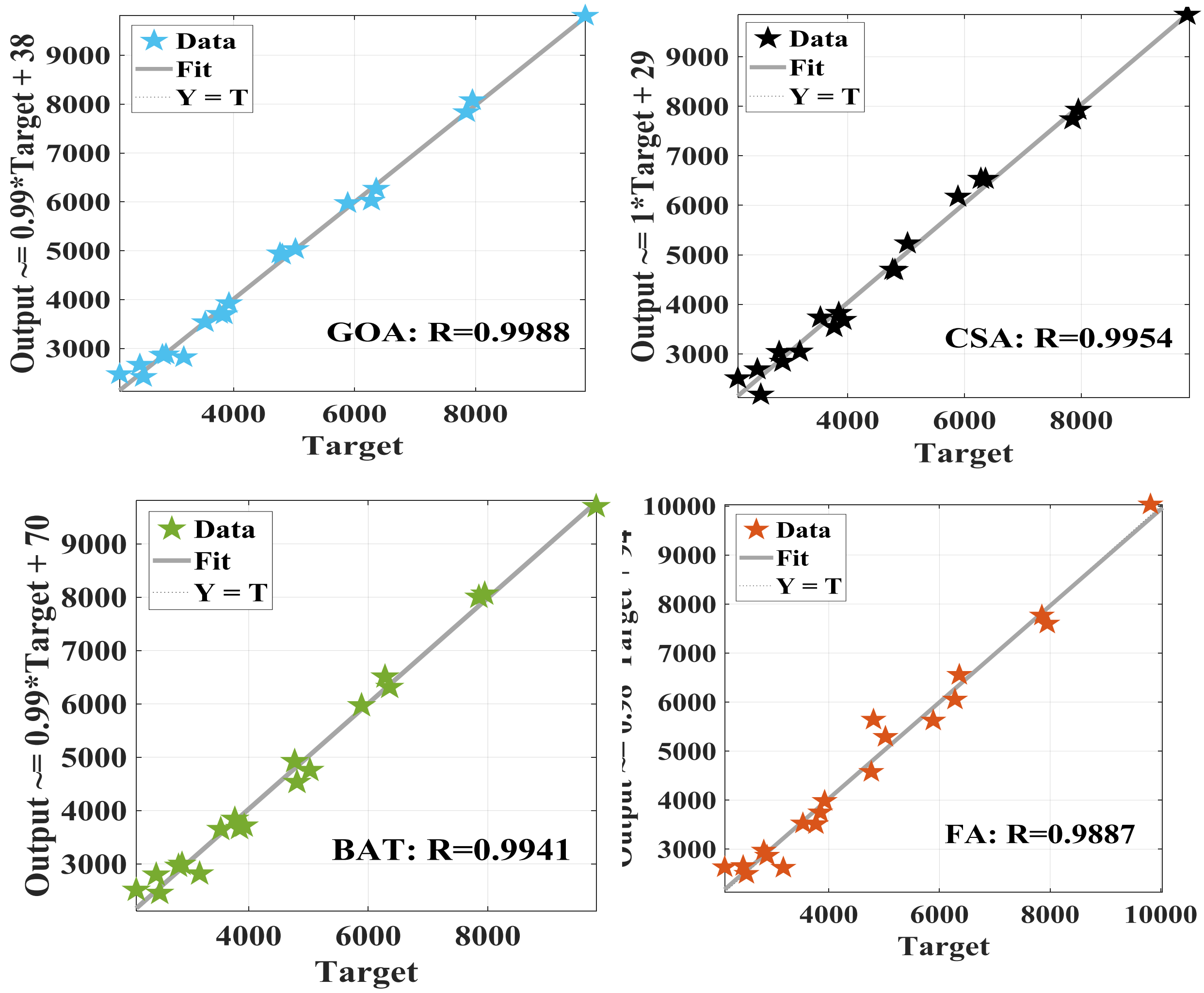


Figure 6. System training analysis analysis for Off-centered *defect* proposal using GOA, CSA, BAT, and FA

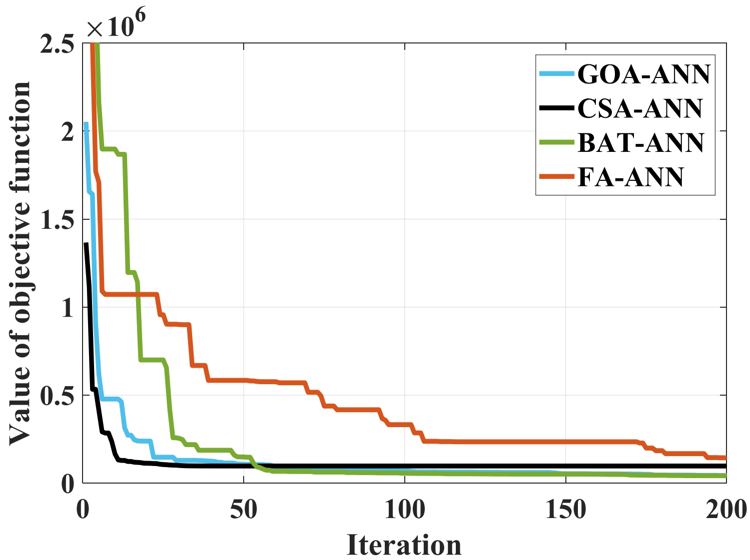


Figure 7. Performance of considered algorithms

Upon comparing the projected outcomes with the desired objectives, it is evident that the GOA achieves a remarkably low maximum error margin of just 1.11 percent. This minimal error is accompanied by a regression value close to unity, underscoring the high accuracy of the GOA approach. Notably, GOA attains these results with fewer iterations, highlighting its efficiency.

Additionally, CSA, BAT, and FA were also evaluated for their predictive performance. Though these algorithms performed commendably, they did not match the precision and efficiency of GOA. The inherent flexibility of GOA, which allows for a broader error margin, contributes to its superior performance. Figure 9 provides a detailed graphical representation of these findings.

Table 2

Different prediction for defect positions for defect proposals D1 and D2 using ANN optimized using GOA, CSA, BAT, and FA

Defect scenario	**Centered defect**			**Off-centred defect**		
ANN trained with	Real defect position (mm)	Predicted defect position (mm)	Error in predicted results (%)	Real defect position (mm)	Predicted defect position (mm)	Error in predicted results (%)
GOA	30	30.0007	0.01	20	20.2222	1.11
CSA		30.1111	0.37		20.5222	2.61
BAT		30.7878	2.63		21.0055	5.03
FA		31.8493	6.16		22.2222	11.11
GOA	60	60.2222	0.37	50	50.1122	0.22
CSA		60.7011	1.17		49.8888	0.22
BAT		61.0000	1.67		48.4534	3.09
FA		61.2222	2.04		52.0000	4.00
GOA	100	100.1414	0.14	120	119.8888	0.09
CSA		100.5849	0.58		120.8585	0.72
BAT		102.2328	2.23		122.1718	1.81
FA		103.0000	3.00		122.9999	2.50
GOA	150	151.0000	0.67	180	181.0000	0.56
CSA		150.8888	0.59		179.0008	0.56
BAT		153.0000	2.00		173.8746	3.40
FA		152.9999	2.00		173.8900	3.39

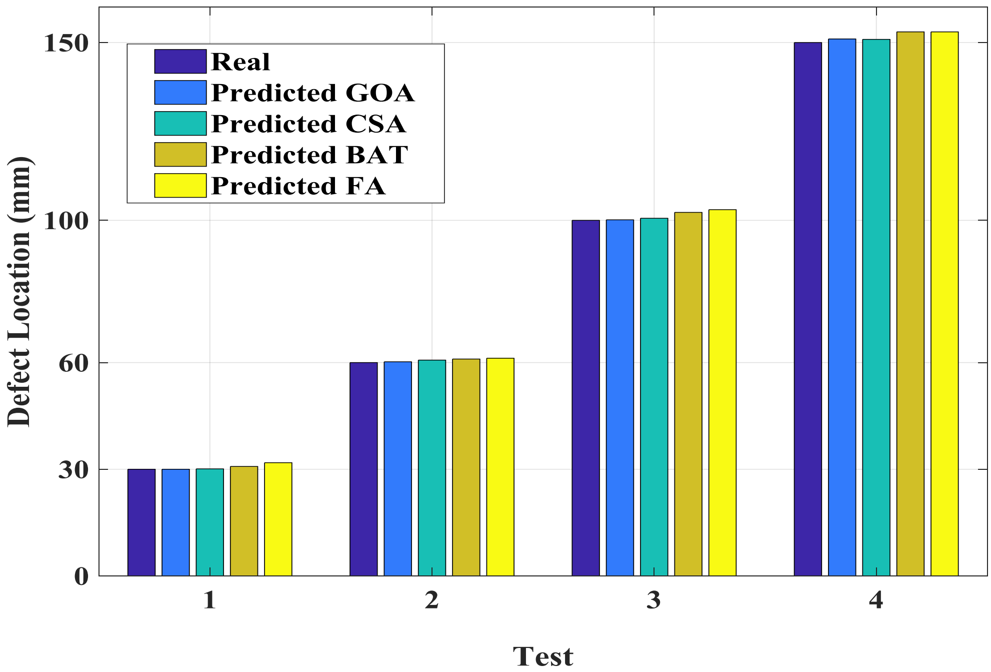


Figure 8. Real and forecasted damage location for defect proposal D1

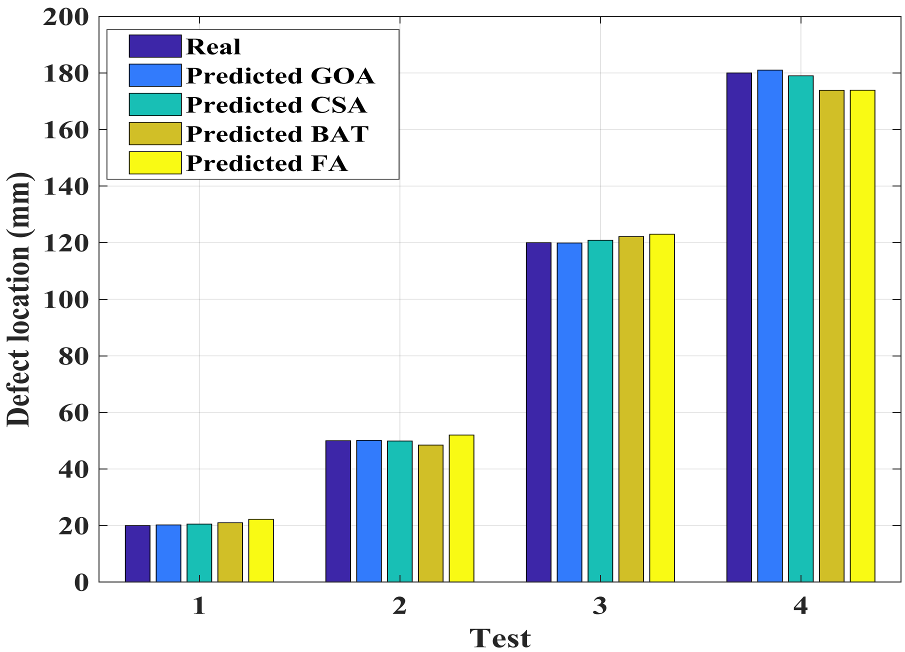


Figure 9. Real and forecasted damage location for defect proposal D2

5. Experimental model

The experimental process involved replicating free-free boundary conditions by suspending the plate models with two flexible strings, as specified in Table 1. Figure 10 visually represents the testing setup, illustrating the arrangement during the experiments. The impact hammer was fixed in place throughout the tests, providing consistent excitation to the structure at various points.

In Figure 10, ‘h’ indicates the position of the impact hammer, while ‘Acc1’, ‘Acc2’, and ‘Acc3’ denote the locations of the accelerometers. These accelerometers were strategically placed to capture the structural responses. The measurement system included signal transformation into the frequency domain using the Fast Fourier Transform (FFT) technique, combined with Pulse software for streamlined data collection. Each accelerometer position was subjected to 10 impacts, and the average values were recorded for further analysis.

After completing the impact tests, frequencies were documented for various damage scenarios at specified defect locations. This extensive data collection was essential for assessing and analyzing the structural integrity of the specimens. The results, including natural frequency values, are summarized in Table 3, providing a comparison with the finite element model results for both intact and damaged cases.

The setup and procedures, which ensured accurate data capture and consistency, involved several critical steps:

1. Suspension of plate models using flexible strings to achieve free-free boundary conditions.
2. Fixed placement of the impact hammer to ensure consistent excitation.
3. Strategic positioning of accelerometers to capture structural responses.
4. Use of FFT and Pulse software for efficient signal transformation and data collection.
5. Repeated impacts at each accelerometer position to obtain reliable average values.
6. Thorough documentation of frequencies under various defect scenarios for comprehensive analysis.

These steps highlight the meticulous approach taken to ensure the reliability and accuracy of the experimental results, which are crucial for evaluating the structural integrity and performance of the tested models.

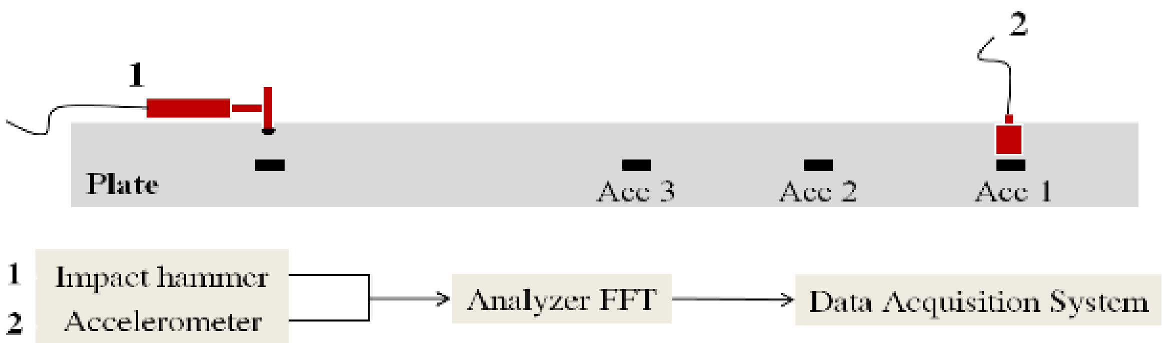


Figure 10. Vibration analysis operating mode

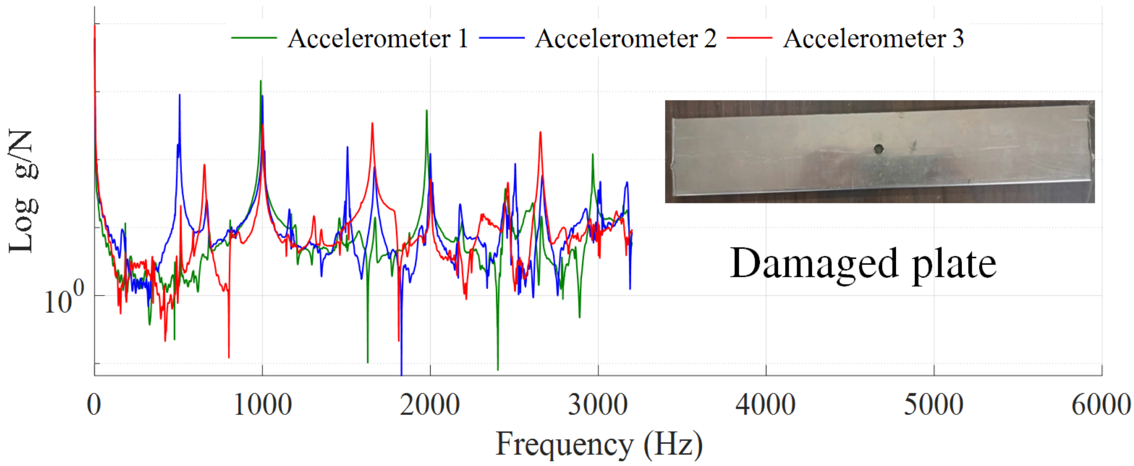
Table 3

Frequency measurements for both intact and damaged plate models

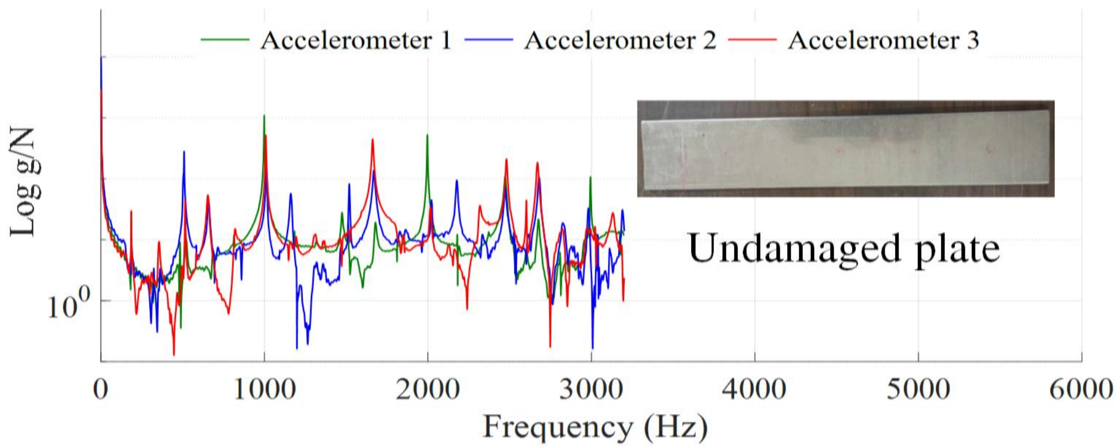
Natural frequencies		***f***$_1$ **(Hz)**	***f***$_2$ **(Hz)**	***f***$_3$ **(Hz)**	***f***$_4$ **(Hz)**
Undamaged plate	Exp	188.10	503.71	1009.21	1660.09
	FEM	184.76	512.10	1004.90	1666.20
	Error (%)	1.776	1.67	0.427	0.368
Damaged plate	Exp	186.11	502.55	1001.34	1620.01
	FEM	182.51	505.70	993.43	1638.22
	Error (%)	1.934	0.627	0.790	1.124

Table 3 presents a comparative analysis of natural frequencies derived from experimental procedures and Finite Element Modeling (FEM) for both intact and damaged plates. The close match between experimental and FEM frequencies highlights the FEM's reliability in predicting structural behavior, as corroborated by the experimental data. Figure 11 provides a visual representation of the experimental frequency response function curves.

The minimal discrepancies between the experimental results and FEM predictions underscore the accuracy of the FEM simulations. This alignment between methods validates the FEM approach, demonstrating its effectiveness in modeling and anticipating the structural dynamics of the plates under various conditions. The experimental frequency response curves shown in Figure 11 further emphasize the consistency and precision of the experimental setup and measurements.



(a)



(b)

Figure 11. Comparison of frequency response function envelopes for intact (a) and defected (b) at accelerometer locations Acc1, Acc2, and Acc3

6. Conclusions

This study introduces an innovative hybrid algorithm that combines Artificial Neural Networks (ANN) with the Grasshopper Optimization Algorithm (GOA) to address complex numerical optimization problems. The primary objective is to enhance the adaptation mechanism within the ANN. The algorithm was rigorously tested across various defect scenarios involving an aluminum plate, and its performance was compared against three other metaheuristic techniques: Cuckoo Search Algorithm (CSA), BAT algorithm, and Firefly Algorithm (FA).

The comparative analysis revealed that while CSA demonstrated commendable performance, GOA surpassed it in terms of both accuracy and computational efficiency. The GOA-ANN hybrid consistently achieved faster convergence and higher precision, outperforming the BAT and FA algorithms as well. Experimental validation confirmed the effectiveness of the proposed model, showing that GOA is superior in handling numerical optimization challenges.

In conclusion, the findings clearly indicate that the integration of GOA with ANN offers significant advantages over other metaheuristic techniques, particularly in convergence speed and computational efficiency. This positions GOA as a leading algorithm for optimizing ANN adaptation mechanisms and solving numerical optimization problems, as evidenced by the experimental results.

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