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October 28, 2023

Available online at www.sciencedirect.com

ScienceDirect

Structural Integrity Procedia 00 (2023) 000–000

Structural Integrity Procedia

www.elsevier.com/locate/procedia

3rd International Workshop on Plasticity, Damage and Fracture of Engineering Materials (IWPDF 2023)

# Optimized Neural Networks for Structural Damage Prediction Based on Modal Analysis

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**Abstract**

Damage detection and localization is a critical task of structural health monitoring. Artificial Neural Network (ANN) has been successfully applied for damage identification in civil and mechanical structures, presenting some limitations. However, it is possible to improve the effectiveness of ANNs by modifying their architecture and training strategies. The present paper proposes an optimization algorithm, particularly the Grasshopper Optimization Algorithm (GOA), to create an optimum ANN for multiple damage prediction in aluminum bars. Natural frequencies are used as input parameters, and crack depths as output. Based on different crack depths, an improved Finite Element Model (FEM) is used to collect data using a simulation tool. In order to test the reliability of the presented technique, experimental data from cracked beam analysis is collected based on different crack depths. The results are compared to similar approaches using metaheuristic algorithms: Ant Colony Optimization (ACO) and Genetic Algorithm (GA). The novel proposed approach presents a good performance for damage prediction.



*Keywords:* Structural health monitoring, Neural Networks, GOA, Finite element analysis, Optimization algorithms

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Peer-review under responsibility of the scientific committee of IWPDF 2023 Chairman

## 1. Introduction

Optimization algorithms have discovered applications across diverse domains, such as applied mathematics, engineering, medicine, economics, etc. These methods, particularly in civil, mechanical, electrical, and industrial engineering initiatives, are prominently employed during the design phase (Ab Wahab et al. (2015), Kaveh et al. (2020) and Jacob et al. (2021)). Optimization algorithms, often called global optimization techniques, have effectively tackled intricate real-world optimization problems. These methods draw inspiration from principles rooted in physics, swarm intelligence, and biology (Zhang et al. (2015) and Khatir et al. (2016)).

The evolution of optimization algorithms in recent years has revolutionized the approach to handling optimization problems across diverse contexts. Among the array of widely adopted optimization techniques are genetic algorithms (GAs) (Ahmed et al. (2019) and Sberna et al. (2023)), which draw inspiration from biological genetic recombination and operate through three key parameters: selection, crossover, and mutation. Another prominent approach is particle swarm optimization (PSO) (Khatir et al. (2023) and Jain et al. (2022)), which finds its roots in the coordinated movement of flocks of birds and schools of fish. The BAT algorithm (Zenzen et al. (2018) Lu et al. (2021)) is specifically based on the echolocation behavior exhibited by microbats when hunting prey. A distinct strategy is embodied by the cuckoo search algorithm (CS) (Mareli et al. (2018) and Cuong-Le et al. (2021)), which incorporates elements of brood parasitism observed in certain cuckoo species, coupled with random walks employing Levy flights. The Firefly algorithm (FA) (Kumar et al. (2021)) takes inspiration from the pulsating luminescence displayed by fireflies. In the realm of ant colony optimization (ACO) (Dorigo et al. (2018)), the guiding principle is the foraging behavior of ants as they communicate food source locations through the use of pheromones. Grey wolf optimization (GWO) (Li et al. (2021)) replicates the hierarchical leadership structure and hunting dynamics prevalent in the natural world among grey wolves. Lastly, the artificial bee colony (ABC) (Zhao et al. (2020)) draws from the intelligent foraging practices of honey bees, resulting in a diversified toolkit of strategies for optimization tasks.

Artificial neural networks (ANNs) are an intelligent computational methodology applied in damage detection across diverse structures. The utilization of ANNs has extended to bridge damage identification, employing both model-independent techniques and machine-learning strategies (Nyirandayisabye et al. (2022)). Moreover, ANNs have been integrated with metaheuristic algorithms in various studies pursuing the same goal (Khatir et al. (2022), Gordan et al. (2020), and Gomes et al. (2019)). (Khatir et al. (2020)) Have elevated the capabilities of ANNs by integrating the Jaya algorithm, a process applied to identify cracks within plates by employing the Extended Isogeometric Analysis (XIGA) in tandem with experimental analysis. Their findings underscore the heightened accuracy achieved in damage prognosis through their enhanced approach, which harnesses Jaya algorithm-derived regression to monitor crack propagation meticulously. A distinct avenue is pursued by (Gomes et al. (2019)), who introduces a sophisticated approach centered on inverse global optimization for pinpointing damage in plate-like structures. This methodology leverages an improved SunFlower Optimization (SFO) algorithm to tackle the intricacies of an inverse problem framework, thereby enabling the identification of damage based on modal parameters of CFRP laminated structures.

Based on the above descriptions, in the present study, an attempt is made to investigate the applicability of ANN combined with a metaheuristic algorithm, particularly the Grasshopper optimization algorithm (GOA), to improve damage prediction in aluminum bars. Experimental modal analysis was carried out to generate natural frequency measurements as the input database for the data process to predict the damage severity. Further comparison with other optimization algorithms, namely, Genetic algorithm (GA) and Ant Colony Optimization (ACO), confirms GOA performance.

## 2. Methodology description

To enhance the accuracy of structural damage prediction, this methodology unites an Artificial Neural Network (ANN) with the Grasshopper Optimization Algorithm (GOA). The core objective revolves around optimizing the hyperparameters of the ANN to bolster its predictive prowess in structural damage assessment. Commencing with a well-defined problem, typically centered on predicting structural damage, the methodology first entails collecting and meticulously preprocessing data. Specifically, the dataset comprises natural frequencies, serving as critical input parameters. Preprocessing involves addressing missing values, feature scaling, and partitioning the data into training and testing subsets. Subsequently, the ANN architecture is established, encompassing input nodes (corresponding to the natural frequencies), hidden layers, and output nodes tailored to the problem. Activation functions, such as ReLU for hidden layers and linear for the output layer, are judiciously assigned, followed by the initialization of weights and biases. The ANN is then trained using the training dataset, employing a pertinent loss function and backpropagation until convergence. Inspired by grasshopper foraging dynamics, GOA is introduced into the methodology as an optimization engine. Here, the objective function is crafted to evaluate the ANN's performance, typically through validation dataset assessment post-training.

GOA's parameters, encompassing population size, maximum iterations, and solution search ranges, are configured. The synergy between GOA and the ANN emerges as GOA is enlisted to optimize the ANN's hyperparameters. A fitness function, contingent upon the ANN's performance evaluation, steers GOA's quest for optimal hyperparameters. The ultimate step entails evaluating the refined ANN model, fortified with optimized hyperparameters, against a distinct testing dataset. Model performance is gauged through Mean Square Error (MSE), tailored to structural damage prediction tasks. Depending on the results, further model refinement or iteration with diverse hyperparameter configurations may be undertaken. The mathematical model used to calculate the position $X_i$ of each solution using GOA can be expressed as the following equation:

$$X_i^d = c\left(\sum_{j=1}^{N} c\,\frac{UB_d - LB_d}{2}\; s\left(\left|x_j^d - x_i^d\right|\right)\frac{|x_j - x_i|}{d_{ij}}\right) + Best\ solution\ , whree\ i \neq j \tag{1}$$

where $d$ indicates dimensions, $UB_d$ and $LB_d$ are the upper and lower bounds in the $d^{th}$ dimension, respectively, and $c$ is decreasing factor according to iterations and can be done by:

$$c = c_{max} - iter\,\frac{c_{max} - c_{min}}{Max_{iter}} \tag{2}$$

where $c_{max}$ and $c_{min}$ are the maximum and minimum values of $c$, respectively, *iter* is the current iteration, and $Max_{iter}$ is the maximum number of iterations.

The Mean Squared Error can be expressed as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y}_i)^2 \tag{3}$$

where $y_i$ denotes the actual value, $\bar{y}_i$ shows the predicted one, and $n$ indicates the total number of instances.

The GOA-ANN trainer algorithm follows a series of distinct steps:

1. ***Initialization***: GOA-ANN initiates by creating a set of grasshoppers, initially randomized.
2. ***Mapping of Grasshoppers*****:** The attributes of these grasshoppers are meticulously assigned to the weights and biases associated with a potential Artificial Neural Network (ANN).
3. ***Fitness Evaluation*****:** The effectiveness of the resultant ANNs is meticulously evaluated using the MSE function, which assesses their performance across all samples within the training dataset.
4. ***Optimal MLP Identification*****:** GOA-ANN endeavors to identify the ANN exhibiting the lowest MSE value. ANNs displaying lower MSEs are given preference over those with higher MSEs.
5. ***Position Updates*****:** The positions of the grasshoppers are updated as part of an iterative process.
6. ***Iterative Loop*****:** Steps 2 through 4 are recurrently performed until the latest cycle is reached.
7. ***Termination and Testing*****:** Ultimately, the process is concluded, and the ANN with the minimal MSE undergoes testing using test/validation instances to validate its performance.

## 3. Numerical model and data collection

The modeling was executed using ABAQUS 16.4 software, considering a free-free boundary condition. The three-dimensional beam modeling was conducted utilizing the eight-node C3D8R brick element, where each node encompasses six degrees of freedom, encompassing rotational (x, y, z) and translational (u, w, v) displacements. Two damage scenarios were investigated to assess the GOA-ANN approach's predictive capability concerning hole location. In the initial scenario (P1), a single hole was introduced at the midpoint of the beam, with its location varying from the center to the edge in 10 mm increments. In the second scenario (P2), an off-center hole was introduced at the beam's midpoint, with its location similarly varying from the center to the edge in 10 mm increments. Fig. 1 illustrates a model of an aluminum plate, including hole positions, and Table 1 details its geometrical and mechanical properties. Fig. 3 showcases the first four mode shapes derived from numerical simulation, which are considered frequency values as input data.

Table 1. Geometrical and mechanical properties of healthy Aluminum plates.

| Length *L* [mm] | Width *b* [mm] | Thickness *h* [mm] | *E* [GPa] | Density *ρ* [$Ns^2/ mm^4$] | Poisson's ratio |
|---|---|---|---|---|---|
| 380 | 70 | 5 | 73 | 2.7 $E^{-9}$ | 0.33 |

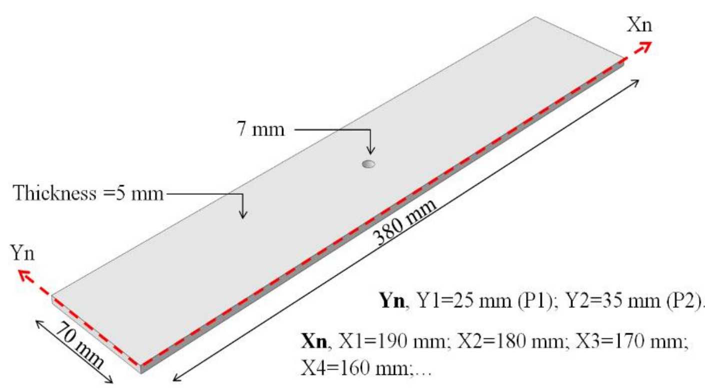


Fig. 1. Numerical model for aluminum plate and damage locations

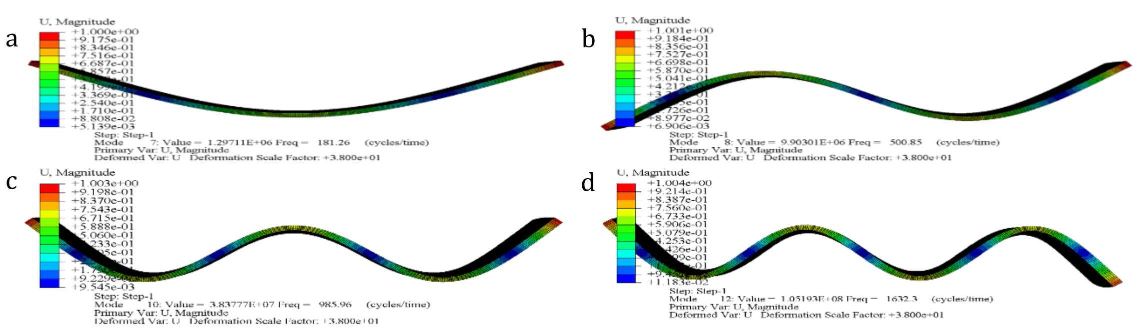


Fig. 2. The first four bending mode shapes of vibration: (a) Mode 1, (b) Mode 2, (c) Mode 3, and (d) Mode 4.

## 4. Results and discussion

The datasets were compiled using the analysis outcomes of damage instances denoted as P1 and P2, aiming to predict the specific centered and eccentric hole positions applied to the plate model illustrated in Figure 1. During the training of the GOA-ANN model, it was configured with a fixed number of neurons set to 4. The configuration of parameters for the considered algorithms was established through an iterative process of experimentation and refinement. Initially, a range of values for each parameter was chosen, drawing from prior research and domain expertise. Subsequently, extensive experimentation ensued, involving various combinations of parameter values to assess each algorithm's performance, and the population number was 100. To assess the efficacy of GOA in the context of ANN training, a comparative analysis was carried out against alternative methods, specifically ACO-ANN and GA-ANN.

### *4.1. Centred hole*

In this damage scenario, the GOA-ANN combination was employed to predict centered hole positions at the plate model, specifically at positions of X= 30, 80, 120, and 150 mm. Fig. 3 illustrates an examination of the regression and performance of the GOA-ANN approach in comparison to ACO-ANN and GA-ANN, all configured with a hidden layer size denoted as *n* and set to 4. A summary of the results is presented in Table 2.

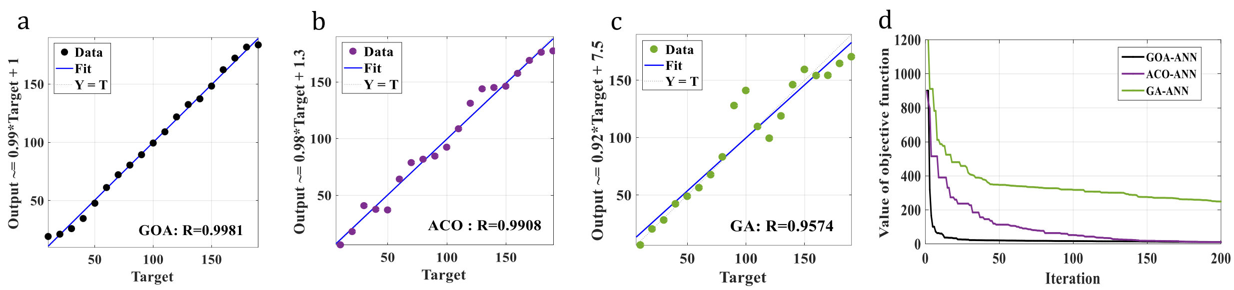


Fig. 2. Regression and convergence for centered hole damage case: (a) GOA, (b) ACO, (c) GA, and (d) Convergences

The results unequivocally highlight the superior performance of the hybrid GOA-ANN methodology when juxtaposed with individual techniques like ACO and GA. The regression value achieved through the hybrid approach closely approaches 1, signifying a remarkably high level of precision. With a hidden layer size of *n* equal to 4, the maximum anticipated disparity between the predicted and desired outcomes is estimated to fall within a mere 0.3 mm range. While ACO and GA all exhibit competence in predicting hole location, it is noteworthy that the GOA approach surpasses them in accuracy. This is primarily attributed to its broader error margin and the fact that GA necessitated more generations and larger populations, resulting in increased computational time. Further insights into these outcomes are depicted in Fig. 4.

### *4.2. Eccentric hole*

In this damage scenario, the GOA-ANN combination was employed to predict eccentric hole positions at the plate model, specifically at positions of X= 20, 60, 140, and 180 mm. Fig. 3 illustrates an examination of the regression and performance of the GOA-ANN approach in comparison to ACO-ANN and GA-ANN, all configured with a hidden layer size denoted as *n* and set to 4. A summary of the results is presented in Table 2.

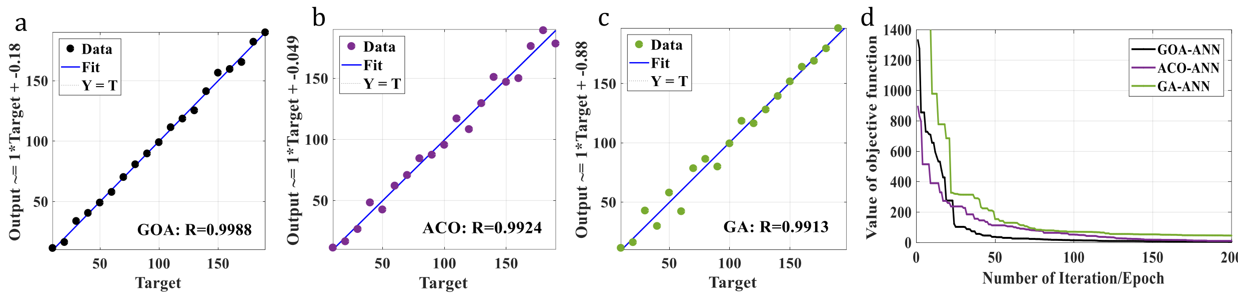


Fig. 3. Regression and convergence for centered hole damage case: (a) GOA, (b) ACO, (c) GA, and (d) Convergences

Upon a comprehensive analysis of the anticipated results against the intended targets, it becomes evident that the GOA technique exhibits a maximum error margin of 0.12 mm. This occurrence coincides with a regression value approaching unity. Intriguingly, the GOA approach accomplishes this with fewer iterations, emphasizing its efficiency. A thorough investigation employing an ANN improved by the GOA reveals that ANN outperforms ACO and GA for predicting hole positions in this specific damage scenario. Conversely, GA exhibits less precision and demands an extended computational time. The comprehensive findings are itemized in Fig. 4.

Table 2. Hole locations prediction for damage cases P1 and P2 using ANN trained by GOA, ACO, and GA.

| Damage case | Centered hole | | | Eccentric hole | | |
|---|---|---|---|---|---|---|
| Approach | Real hole location (mm) | Predicted hole location (mm) | Error in predicted results (%) | Real hole location (mm) | Predicted hole location (mm) | Error in predicted results (%) |
| GOA-ANN | 30 | 30.1013 | 0.3376 | 20 | 19.9898 | 0.0510 |
| ACO-ANN | | 30.2220 | 0.7400 | | 19.1111 | 4.4445 |
| GA-ANN | | 34.0532 | 13.5106 | | 22.0985 | 10.492 |
| GOA-ANN | 80 | 79.9888 | 0.0140 | 60 | 60.1212 | 0.2020 |
| ACO-ANN | | 80.9000 | 1.1250 | | 58.8734 | 1.8776 |
| GA-ANN | | 85.9878 | 7.4847 | | 63.6363 | 6.0605 |
| GOA-ANN | 120 | 120.3434 | 0.2861 | 140 | 141.0000 | 0.7142 |
| ACO-ANN | | 120.8888 | 0.7406 | | 140.8745 | 0.6246 |
| GA-ANN | | 120.9898 | 0.8248 | | 145.9857 | 4.2755 |
| GOA-ANN | 150 | 150.0919 | 0.0612 | 180 | 180.0222 | 0.0123 |
| ACO-ANN | | 148.8888 | 0.7408 | | 180.9999 | 0.5555 |
| GA-ANN | | 153.5409 | 2.3606 | | 181.9875 | 1.1041 |

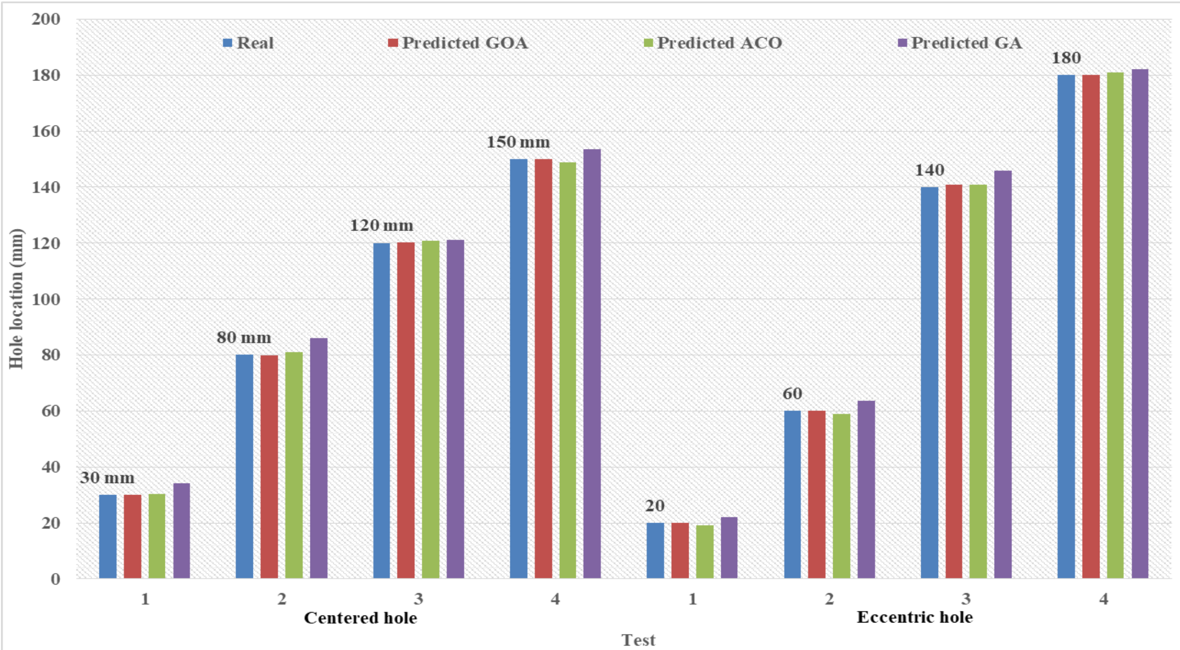


Fig. 4. Real and predicted hole locations for both damage cases P1 and P2

## 5. Experimental model

The test procedure involved simulating free-free boundary conditions by suspending the structure, which possesses the characteristics detailed in Table 1, using two flexible strings. Fig. 5 provides a visual representation of the experimental setup. During this test, the impact hammer was securely positioned at a fixed point, from which the structure was excited at various locations. In Fig. 5, *h* corresponds to the impact hammer's placement, while *a1*, *a2*, and *a3* denote the positions of the accelerometers. A measurement system equipped with the capability to extract frequency values by converting signals into the frequency domain through the Fast Fourier Transform (FFT) technique, in conjunction with Pulse software, was employed. Each accelerometer location underwent a series of 10 impacts, and the resultant average value was recorded. Subsequently, frequency values were measured for the various damage scenarios corresponding to the previously considered crack depths.

a b

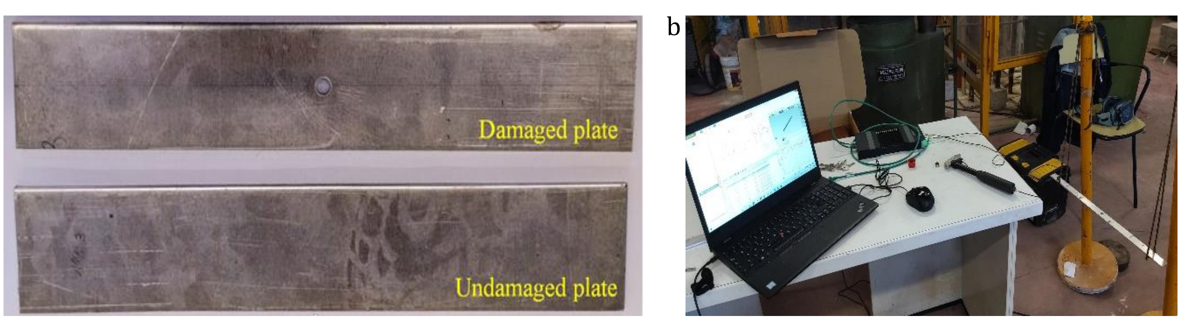


Fig. 5. Operating mode for modal analysis: (a) Beam specimens, (b) Experimental set up

Table 2. Numerical and experimental frequency values for damaged and undamaged plate models.

| EXP and FEM natural frequency values | | $f_1$ (Hz) | $f_2$ (Hz) | $f_3$ (Hz) | $f_4$ (Hz) |
|---|---|---|---|---|---|
| Damaged plate | Exp | 186 | 505.10 | 1000.35 | 1660.00 |
| | FEM | 181.58 | 501.87 | 986.33 | 1633.0 |
| | Error | 2.434 | 0.643 | 1.421 | 1.653 |
| Undamaged plate | Exp | 183.11 | 504.91 | 992.24 | 1654 |
| | FEM | 181.08 | 501.90 | 984.83 | 1633.0 |
| | Error | 1.121 | 0.599 | 0.752 | 1.285 |

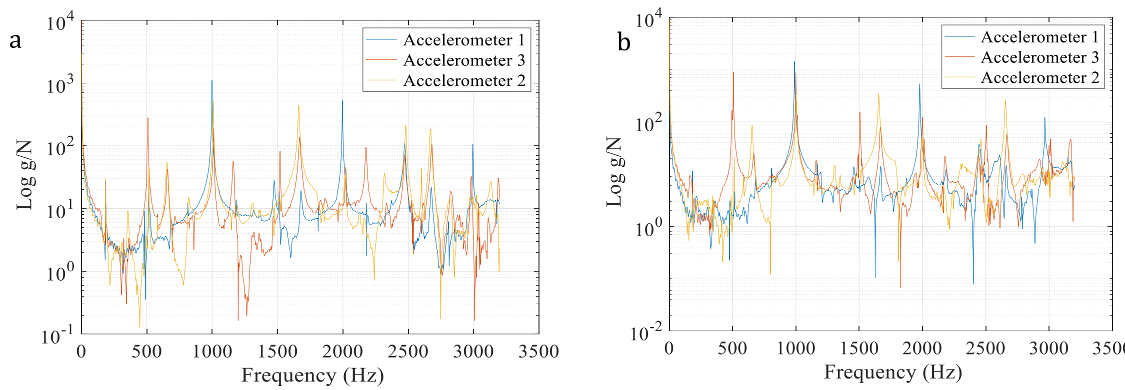


Fig. 6. Comparison of envelopes of FRFs for undamaged (a) and damaged (b) with holes at accelerometer positions a1, a2, and a3

## 6. Conclusion

This article introduces an innovative hybrid algorithm that combines ANN and the Grasshopper Optimization Algorithm (GOA) to address numerical optimization challenges. This approach centers on enhancing the adaptation mechanism within ANN. It was tested through a series of damage scenarios involving an aluminum plate to assess this novel algorithm's efficacy. The performance of this method was benchmarked against two other metaheuristic techniques derived from swarm intelligence and evolutionary computing: ACO and GA. To validate the proposed model, experimental validation was incorporated. The results unequivocally indicate that GOA exhibits superior accuracy in addressing numerical optimization problems compared to the other algorithms considered in terms of convergence and computational time.

## References

Ab Wahab, M. N., Nefti-Meziani, S., & Atyabi, A. (2015). A comprehensive review of swarm optimization algorithms. PloS one, 10(5), e0122827.

Kaveh, A., & Eslamlou, A. D. (2020). Metaheuristic optimization algorithms in civil engineering: new applications. Cham, Switzerland: Springer International Publishing.

Jacob, D. I. J., & Darney, D. P. E. (2021). Artificial bee colony optimization algorithm for enhancing routing in wireless networks. Journal of Artificial Intelligence and Capsule Networks, 3(1), 62-71.

Zhang, Y., Wang, S., & Ji, G. (2015). A comprehensive survey on particle swarm optimization algorithm and its applications. Mathematical problems in engineering, 2015.

Khatir, A., Tehami, M., Khatir, S., & Abdel Wahab, M. (2016). Multiple damage detection and localization in beam-like and complex structures using coordinate modal assurance criterion combined with firefly and genetic algorithms. Journal of Vibroengineering, 18(8), 5063-5073.

Ahmed, B. M., & ALhialy, N. F. F. (2019). Optimum efficiency of PV panel using genetic algorithms to touch proximate zero energy house (NZEH). Civil Engineering Journal, 5(8), 1832-1840.

Sberna, A. P., Di Trapani, F., & Marano, G. C. (2023). A new genetic algorithm framework based on Expected Annual Loss for optimizing seismic retrofitting in reinforced concrete frame structures. Procedia Structural Integrity, 44, 1712-1719.

Khatir, A., Capozucca, R., Khatir, S., Magagnini, E., Benaissa, B., Le Thanh, C., & Wahab, M. A. (2023). A new hybrid PSO-YUKI for double cracks identification in CFRP cantilever beam. Composite Structures, 311, 116803.

Jain, M., Saihjpal, V., Singh, N., & Singh, S. B. (2022). An overview of variants and advancements of PSO algorithm. Applied Sciences, 12(17), 8392.

Zenzen, R., Belaidi, I., Khatir, S., & Wahab, M. A. (2018). A damage identification technique for beam-like and truss structures based on FRF and Bat Algorithm. Comptes Rendus Mécanique, 346(12), 1253-1266.

Lu, S., Wang, S. H., & Zhang, Y. D. (2021). Detection of abnormal brain in MRI via improved AlexNet and ELM optimized by chaotic bat algorithm. Neural Computing and Applications, 33, 10799-10811.

Mareli, M., & Twala, B. (2018). An adaptive Cuckoo search algorithm for optimisation. Applied computing and informatics, 14(2), 107-115.

Cuong-Le, T., Minh, H. L., Khatir, S., Wahab, M. A., Tran, M. T., & Mirjalili, S. (2021). A novel version of Cuckoo search algorithm for solving optimization problems. Expert Systems with Applications, 186, 115669.

Kumar, V., & Kumar, D. (2021). A systematic review on firefly algorithm: past, present, and future. Archives of Computational Methods in Engineering, 28, 3269-3291.

Dorigo, M., & Socha, K. (2018). An introduction to ant colony optimization. In Handbook of approximation algorithms and metaheuristics (pp. 395-408). Chapman and Hall/CRC.

Li, Y., Lin, X., & Liu, J. (2021). An improved gray wolf optimization algorithm to solve engineering problems. Sustainability, 13(6), 3208.

Nyirandayisabye, R., Li, H., Dong, Q., Hakuzweyezu, T., & Nkinahamira, F. (2022). Automatic pavement damage predictions using various machine learning algorithms: Evaluation and comparison. Results in Engineering, 16, 100657.

Khatir, A., Capozucca, R., Khatir, S., & Magagnini, E. (2022). Vibration-based crack prediction on a beam model using hybrid butterfly optimization algorithm with artificial neural network. Frontiers of Structural and Civil Engineering, 16(8), 976-989.

Gordan, M., Razak, H. A., Ismail, Z., Ghaedi, K., Tan, Z. X., & Ghayeb, H. H. (2020). A hybrid ANN-based imperial competitive algorithm methodology for structural damage identification of slab-on-girder bridge using data mining. Applied Soft Computing, 88, 106013.

Gomes, G. F., Mendez, Y. A. D., da Silva Lopes Alexandrino, P., da Cunha, S. S., & Ancelotti, A. C. (2019). A review of vibration based inverse methods for damage detection and identification in mechanical structures using optimization algorithms and ANN. Archives of computational methods in engineering, 26, 883-897.

Khatir, S., Boutchicha, D., Le Thanh, C., Tran-Ngoc, H., Nguyen, T. N., & Abdel-Wahab, M. (2020). Improved ANN technique combined with Jaya algorithm for crack identification in plates using XIGA and experimental analysis. Theoretical and Applied Fracture Mechanics, 107, 102554.

Gomes, G. F., da Cunha, S. S., & Ancelotti, A. C. (2019). A sunflower optimization (SFO) algorithm applied to damage identification on laminated composite plates. Engineering with Computers, 35, 619-626.