Numerical investigation the influence of layers number and their orientation in a CFRP using improved ANN

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ABSTRACT

Technological advancements in the field of artificial intelligence have enabled significant progress in various areas, particularly in optimizing the structural configuration of multi-layer composites. The main objective of this study is to investigate how geometric parameters, such as fiber orientation and number of layers, influence the mechanical properties of these materials. To predict the mechanical properties based on the number and orientation of layers during bending tests, we used a hybrid E-Jaya-ANN optimization technique and compared it with the hybrid Jaya-ANN to evaluate the accuracy of the approach. Additionally, using ABAQUS software, a numerical model has been created based on Hashin's damage criterion to predict the behavior of composite specimens (CFRP) under bending loads and to collect a number of databases starting with the validation model. Subsequently, we generated a series of numerical results representing various practical scenarios to serve as a basis for training an Improved Artificial Neural Network (IANN). Our ability to obtain a better architecture for the laminated layers was made possible by the influence and variation of these materials' mechanical properties.

1. Introduction

Recently, Fiber Reinforced Polymer (FRP) composites have gained widespread use across numerous industries, notably in aerospace, automotive, and civil engineering, owing to their exceptional properties, ease of processing, and lightweight nature in comparison to other materials.

To establish a foundational understanding of the field of materials science, a plethora of fundamental research endeavors have been undertaken to investigate their mechanical behavior. These investigations encompass both static (Ahmed & Wei, 2014; Humeau, Davies, & Jacquemin, 2018; Li, Mines, & Birch, 2001) and dynamic (Can & Meram, 2022; Capozucca & Bonci, 2015; Hong et al., 2013) analyses aimed at extracting the mechanical properties essential for material evaluation. The majority of this research is dedicated to studying the mechanical behavior of unidirectional (UD), bidirectional, or even short fiber laminates under various stress conditions. Mechakra, Nour, Lecheb, and Chellil (2015) experimentally studied the mechanical properties of a composite material reinforced with Alfa. Capozucca and Bossoletti (2014) carried out static and dynamic (free vibration) experimental studies on the behavior of reinforced concrete beams strengthened with NSM CFRP and GFRP. Mansouri, Djebbar, Khatir, and Abdel Wahab (2019) studied the impact of hygrothermal aging time and temperature on the mechanical properties such as yield strength, maximum stress, and flexural modulus, of a mixed short fiber/fabric composite. Also, some studies delved into the structure of the layers, to scrutinize the impact of fiber orientation (Berton, Coussa, Berthe, Brieu, & Deletombe, 2022; Cepero-Mejías, Phadnis, Kerrigan, & Curiel-Sosa, 2021; Samyal, Singh, & Bagha, 2019) and stacking sequence (Lopes et al., 2009; Malik & Arif, 2013; Park, 2001) on the performance and mechanical properties of laminated composites.

Optimization methods grounded in Artificial Neural Networks (ANN) offer efficient and rapid solutions for addressing complex and non-linear problems. These approaches leverage innovative mathematical tools and behavioral principles, finding widespread applications in construction and structural engineering, including damage identification. Migallón, Jimeno-Morenilla, Sánchez-Romero, Rico, and Rao (2019) established the Jaya Parallel Algorithm (JPA) based on static multipopulation, in order to improve the efficiency of cluster computing. Khatir et al. (2020) introduced an efficient approach that combines ANN with the Jaya algorithm to optimize parameters using data collected from measurements and both experimental and numerical models. (Zenzen, Khatir, Belaidi, Le, and Wahab (2020) proposed a new modified damage indicator to predict the position and level of damage in a composite structure based on transmissibility techniques combined with ANN. Ghandourah et al. (2022) introduce an improved Artificial Neural Network (ANN) designed for predicting the displacement of composite material pipelines subjected to varying falling hammer impact velocities. Ouladbrahim et al. (2022) employed various optimization techniques (WOA-ANN, GA-ANN, AOA-ANN, WOABAT-ANN) for crack length identification, while Gholami, Kamankesh, Mohammadi, Hosseinkhani, and Abdi (2022) enhanced the Jaya algorithm's performance, resulting in the Powerful Enhanced Jaya (PEJAYA), which outperformed other algorithms in various applications. Khatir, Capozucca, Khatir, and Magagnini (2022) integrated ANN with the Butterfly Optimization Algorithm (BOA) to predict cracks in steel and aluminum beams. Additionally, they employed Particle Swarm Optimization (PSO) in conjunction with the Yuki Algorithm to forecast cracks in CFRP composite beams (Achouri, Khatir, Smahi, Capozucca, & Brahim, 2023; Khatir et al., 2023).

In our study, we introduce a novel approach to optimize FRP composite structures using hybrid neural network techniques. We develop a validated numerical model based on the Hashin damage criterion, assessing the impact of fiber orientation and layer count on peak load and displacement. The novelty lies in applying Jaya-ANN and E-Jaya-ANN optimization algorithms to enhance multilayer structure performance, showcasing the effectiveness of our approach in tailoring FRP composites for improved functionality. This comprehensive methodology offers a practical and innovative means of optimizing FRP composite structures for real-world applications. By bridging advanced numerical modeling, experimental validation, and state-of-the-art optimization, our study contributes a holistic understanding and practical solutions for enhancing the performance of these structures.

2. FE Analysis

A numerical simulation employing the Finite Element Method (FEM) was conducted using the commercial software ABAQUS to assess the material's capacity to withstand a three-point bending load. This evaluation was based on experimental data derived from the writer's previous work (Ahmed & Wei, 2014), which examined the impact of fiber orientation on a laminated composite with a quasi-isotropic stacking sequence. The composite was reinforced with 16 plies of unidirectional carbon fibers embedded in an epoxy resin. Mechanical characterization was carried out through three-point bending tests using a computer-controlled universal electronic machine (type: WDW-20). The model's geometry was defined with dimensions of 40mm in length between supports, 15mm in width, and 1.76mm in thickness (see Figure 1). Boundary conditions were selected to mirror the experimental setup. In this study, the Hashin damage criterion was employed, utilizing the parameters outlined in Table 1. Subsequently, a fine mesh of type (S4R: A 4-node doubly curved thin or thick shell, reduced integration, hourglass control, finite membrane strains) was created and refined to encompass 1,425 elements and 1,520 nodes, ensuring precise numerical results (see Figure 2, (a-b)).

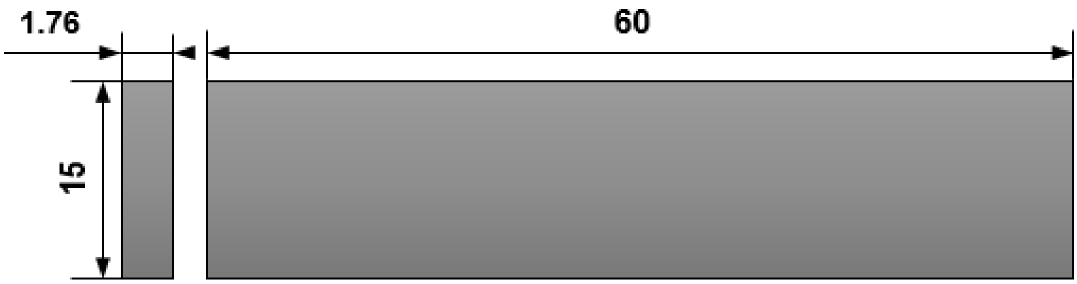


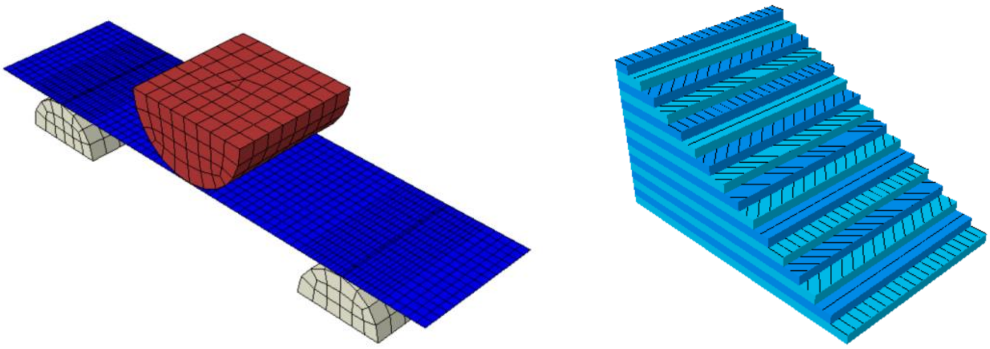
Figure 1. Dimensions presentation of the numerical model

Table 1

Parameters of Hashin damage model

Parameters	Notation	Value
Elastic modulus in longitudinal direction	E_{11}	135 $[GPa]$
Elastic modulus in transverse direction	$E_{22} = E_{33}$	5.331 $[GPa]$
Shear modulus in plane containing fiber	G_{12}	5.411 $[GPa]$
Shear modulus in plane containing fiber	$G_{13} = G_{23}$	2.221 $[GPa]$
Poisson’s ratio	ν_{12}	0.25 $[-]$
Poisson’s ratio	$\nu_{13} = \nu_{23}$	0.2 $[-]$
Density	ρ	$1.52*10^{-9}$ $[Ns^2 / mm^4]$
Fiber volume fraction	V_f	0.85 $[\%]$
Tensile strength in longitudinal direction	X_t	2051.73 $[MPa]$
Compressive strength in longitudinal direction	X_c	1025.86 $[MPa]$
Tensile strength in transverse direction	Y_t	23.1 $[MPa]$
Compressive strength in transverse direction	Y_c	54.6 $[MPa]$
Longitudinal shear strength	S_{12}	60.2 $[MPa]$
Transverse shear strength	S_{13}	22 $[MPa]$
Fracture toughness in longitudinal tensile direction	G_f^t	160 $[KJ / m^2]$
Fracture toughness in longitudinal compressive direction	G_f^c	25 $[KJ / m^2]$

Parameters	Notation	Value
Fracture toughness in transverse tensile fracture mode	G_m^t	10 $[KJ/m^2]$
Fracture toughness in transverse compressive fracture mode	G_m^c	2.25 $[KJ/m^2]$



(a) (b)

Figure 2. (a) Boundary condition and mesh model;

(b) The Stacking sequence of CFRP composite

The objective of the ABAQUS simulation of the laminate composite (carbon/epoxy) is to predict the three-point bending response and then to compare and verify them with the experimental results.

The experimental and numerical load-displacement evolution curves are illustrated in the following Figure 3.

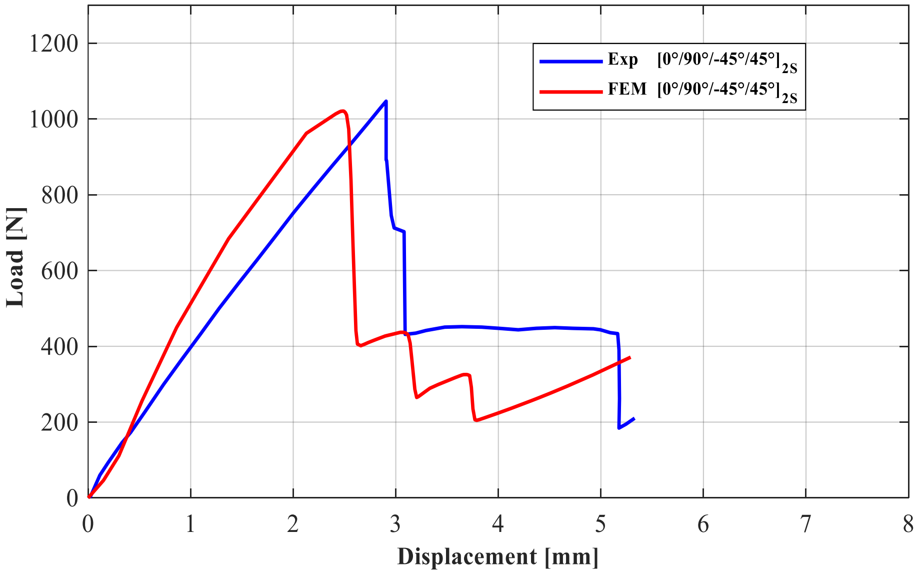


Figure 3. Comparison between experimental and FEM load-displacement curves

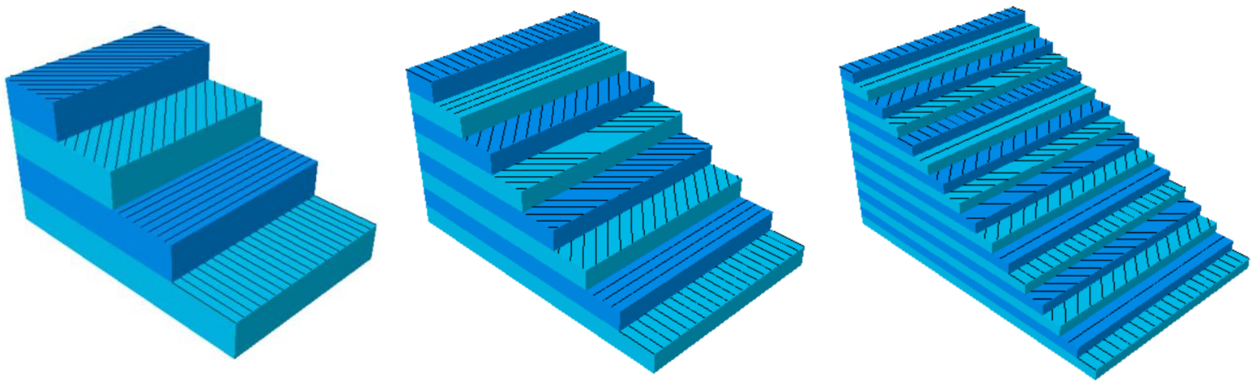
Source: Ahmed and Wei (2014)

Based on this comparison, it is observed that the curves have almost the same slope, which implies that the values obtained from the experimental and numerical tests are very similar.

From this validation, we proposed a numerical study on the parameters that directly influence the structural and mechanical properties of multilayer composites, in particular, the number of layers and fiber orientations.

2.1. The influence of the number of layers

This experiment was conducted to study the influence of the layer numbers on the mechanical behavior of CFRP composite specimens, in the same type of fiber and the same thickness of the layers, varying the layer numbers (see Figure 4).



[0° / 90° / –45° / 45°] Total thickness = 0.44 mm

[0° / 90° / –45° / 45°]$_s$ Total thickness = 0.88 mm

[0° / 90° / –45° / 45°]$_{2s}$ Total thickness = 1.76 mm

Figure 4. Sequences of different layers number used

The following Figure 5 shows the load-displacement comparison curves between three cases with different numbers of layers.

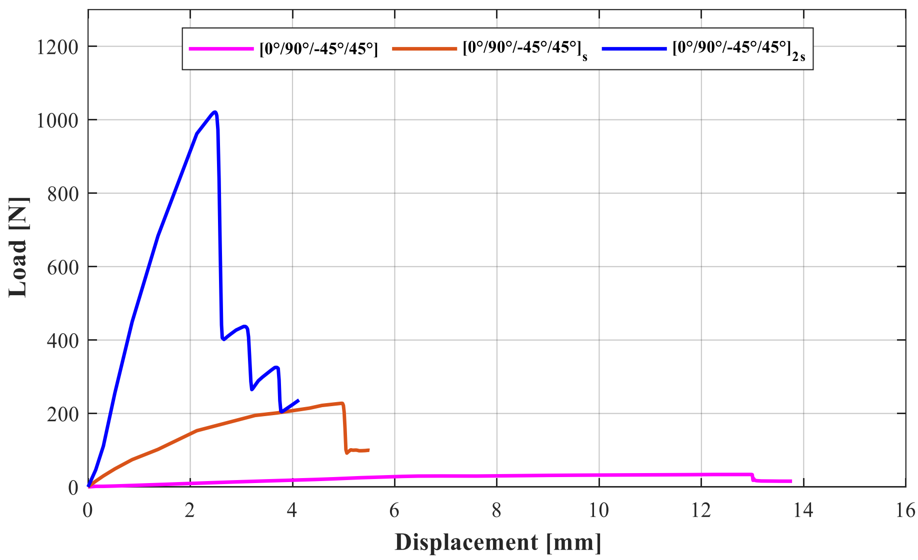
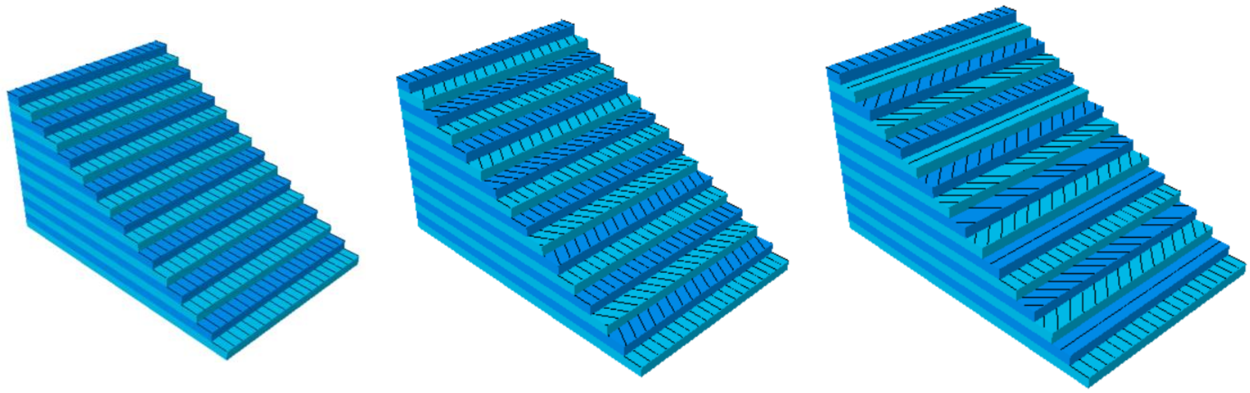


Figure 5. Evolution load-displacement curves obtained for different layer numbers

The results of this analysis show that the peak load of the structure changes proportionally to the number of layers (see Figure 5).

2.2. Influence of fiber orientation

In this part, different orientations of the layers were considered (see Figure 6), in order to determine their influences on the peak load in bending. All specimens are characterized by the same type of fibers and the same total number of plies; furthermore, the thickness of each layer is equal.



$[0°]_{8s}$ **$[0° / -30° / 30° / 0°]_{2s}$** **$[0° / 90° / -45° / 45°]_{2s}$**

Total thickness = 1.76 mm

Figure 6. The sequences of layer orientation used

The obtained results are plotted in the following Figure 7.

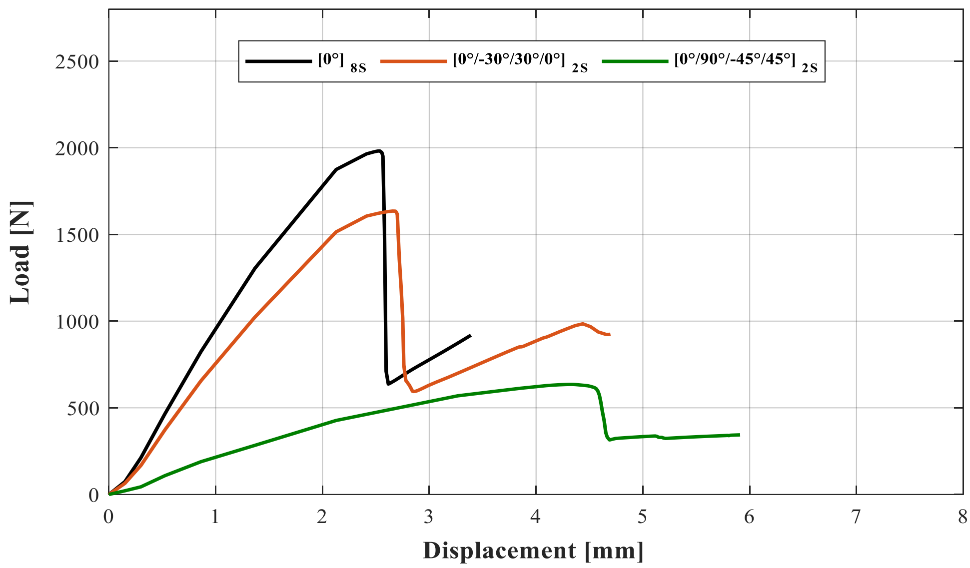


Figure 7. Evolution load-displacement curves of different layer orientations

Upon analyzing these results, it was evident that the resistance to bending fracture gradually diminishes as the orientation angle deviates from 0°, in relation to the primary axis of reinforcement, ultimately reaching its minimum as it approaches a 90° angle.

With these findings in mind, a numerical study was conducted utilizing finite element analysis on CFRP laminate composites, with a primary focus on varying layer orientations and their impact on mechanical properties. Consequently, these outcomes provide valuable data that can be harnessed for training a neural network to predict the peak load and maximum displacement under the influence of a bending load.

3. Improved ANN using Jaya and E-Jaya

Artificial intelligence is moving towards new techniques for processing and representing knowledge that is closer to human reasoning. The Artificial Neural Network (ANN) model is a powerful training tool for simulating a variety of dynamic and static systems. This model has a multi-layered structure based on biological nervous systems, which are connected by nodes to three main layers, namely the input layer, hidden layers, and output layer. ANN is formed by the combination of neurons and processing nodes, the sum of the weighted inputs created by the neurons is illustrated in the following formulation:

$$X = \sum_{i=1}^{n} \left(w_{ij} a_i + b_j \right) \tag{1}$$

Where, w_{ij} are the interconnect weights of the input data, a_i is the number of data collected, and b_j are the bias for the neuron (Figure 8).

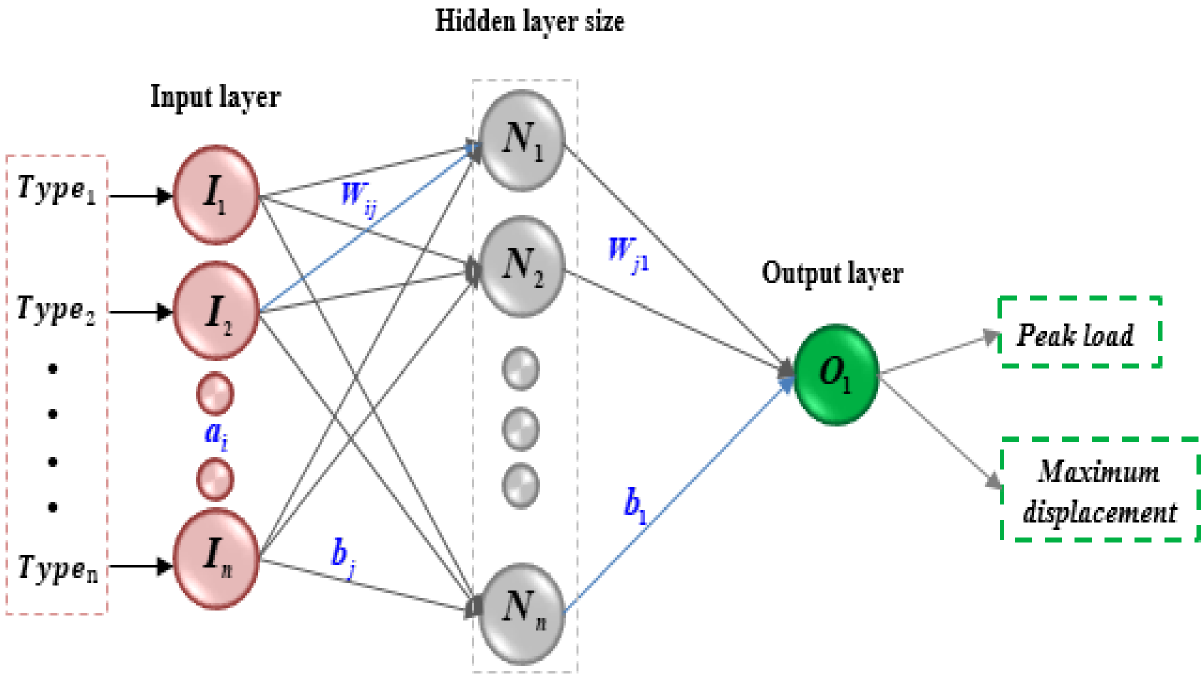


Figure 8. ANN structure to determine peak load and maximum displacement

After creating the ANN structure, training with the input and output dataset is performed, to obtain the optimal weights and biases of the neurons. Various learning techniques are designed and used to adjust the optimal weights and biases for the ANN to reduce the difference between the actual and desired products. In this work, MATLAB software is used to make a connection between inputs and outputs using the Jaya and E-Jaya algorithm, to determine the peak load to starting failure and maximum displacement under the effect of a bending load (see Figure 8). Many studies have previously used this technique, where more details can be found, such as Zara et al. (2023), who studied the detection of different crack lengths using several improved optimization techniques, such as enhanced Jaya ANN based on experimental natural frequency results. Also, Fahem et al. (2023) predicted the strength and tensile load reduction in a GFRP composite using Jaya's improved algorithm.

The peak load is taken as the output parameter, while the different types of orientation are selected as input. The parameters required for data training are shown in the following Table 2.

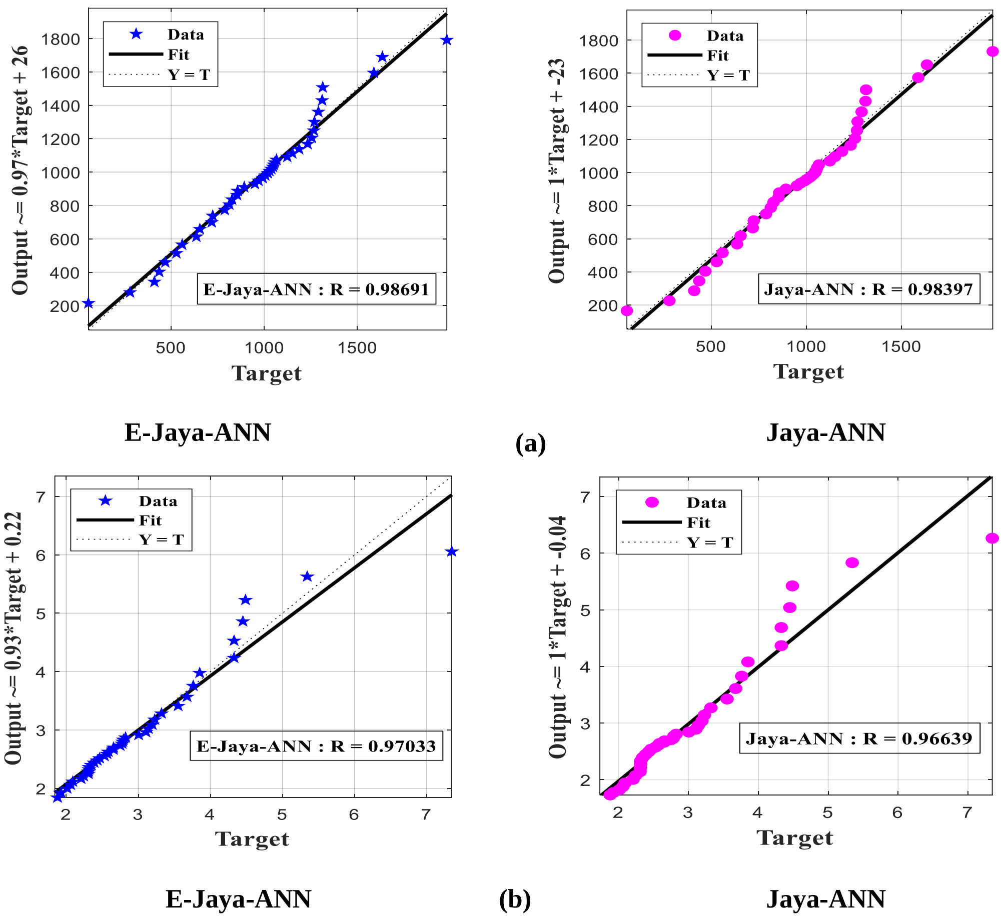
Table 2

Inputs and target parameters used in this work

Parameter	Minimum	Maximum	Number of collected data
Input			
Layers orientation	41 types		41
Target			
Peak load (N)	54.3928	1981.360	41
Maximum displacement [mm]	1.8790	7.3478	41

As mentioned earlier, Jaya-ANN and E-Jaya-ANN were used. The optimal configuration of these networks, which presents an accurate prediction of the peak load and maximum displacement, consists of a hidden layer that includes 8 neurons.

The regression curves of the current values of the peak load and the maximum displacement with respect to the predicted values are presented respectively in Figures 9 (a) and (b).



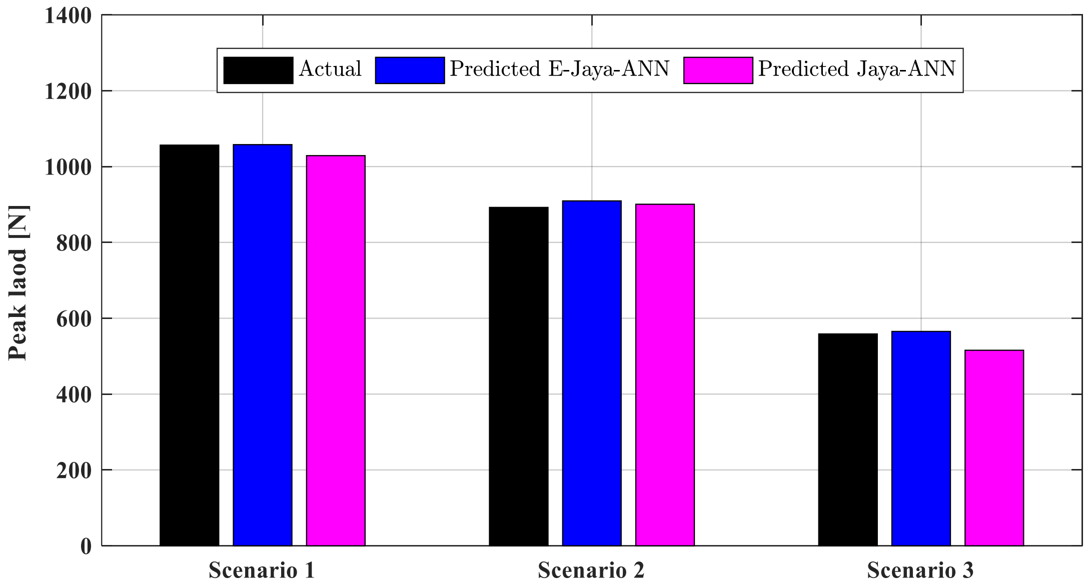
Notation: Used in this study: 1,000 populations-500 iterations.

Figure 9. Regression analysis: (a) Peak load, (b) Maximum displacement

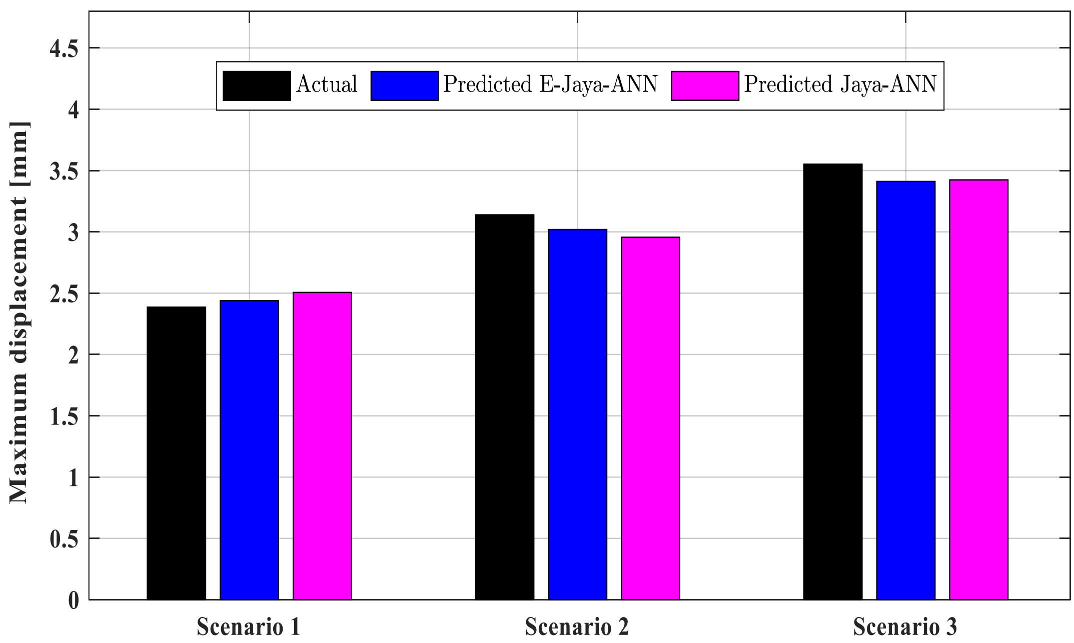
The data points scattered around the dotted line inclined at 45° are very close to the line and show a strong correlation between the calculated values and the numerical values (FEM).

This indicates an appropriate prediction and confirms that the number of neurons selected for these techniques is appropriate.

After training, the model is ready to predict the three studied scenarios. The obtained results are presented in the following Figures 10 (a)-(b) and 11.



(a)



(b)

Figure 10. Predicted using 41 collected databases: (a) Peak load, (b) Maximum displacement

From this result, it was observed that the most efficient and accurate predicted values can be found by E-Jaya-ANN with respect to the peak load and maximum displacement. For further evaluation, Figure 11 shows the errors between the actual and predicted peak load and maximum displacement for all scenarios using two optimization techniques.

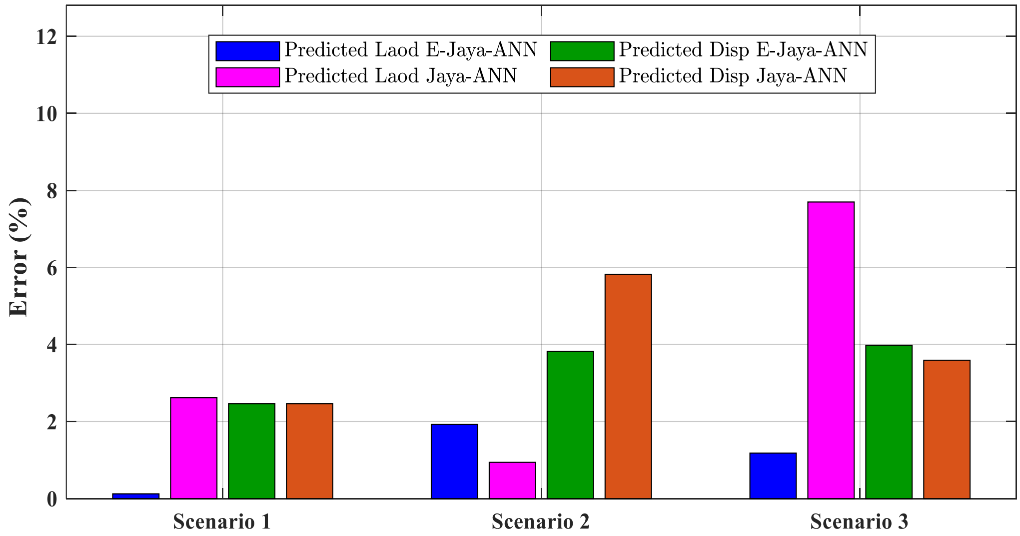


Figure 11. Percentage error of predicted using 41 collected databases

Tables 3 and 4 present the results of several scenarios of the predicted peak load and maximum displacement compared to the actual results, respectively, with the percentage of error between them. The parameters used for the analysis are the same for each optimization technique: 1,000 populations and 500 iterations. The obtained results are carried out using a computer with characteristics of 16 GB RAM memory and Intel(R.) Core(TM) i7-6700 HQ CPU @ 2.60 G. Hz 2.59 G. Hz.

Table 3

Percentage error of predicted JAYA-ANN and E-JAYA-ANN for Peak load scenarios

	Type of orientation	Optimization	Peak load [N]		
			Actual	predicted	Error (%)
Sce 1	15	Jaya-ANN	1056.48	1028.8	2.62
		E-Jaya-ANN		1057.8	0.125
Sce 2	25	Jaya-ANN	892.20	900.6	0.942
		E-Jaya-ANN		909.38	1.925
Sce 3	35	Jaya-ANN	558.584	515.577	7.699
		E-Jaya-ANN		565.196	1.183

Table 4

Percentage error of predicted JAYA-ANN and E-JAYA-ANN for Maximum displacement scenarios

	Type of orientation	Optimization	Maximum displacement [mm]		
			Actual	predicted	Error (%)
Sce 1	15	Jaya-ANN	2.46253	2.3561	4.32198
		E-Jaya-ANN		2.41532	1.91713

	Type of orientation	**Optimization**	**Maximum displacement [mm]**		
			Actual	**predicted**	**Error (%)**
Sce 2	25	Jaya-ANN	2.82217	2.7117	3.91436
		E-Jaya-ANN		2.7917	1.079666
Sce 3	35	Jaya-ANN	3.85076	3.7422	2.81918
		E-Jaya-ANN		3.796	1.42206

Based on the obtained results, we compared the two proposed optimization techniques; it was found that the E-Jaya-ANN technique is the most precise and efficient than the Jaya-ANN technique, with a reduced computation time.

Table 5 summarizes the results of the CPU time for the two proposed optimization techniques.

Table 5

CPU time of Jaya-ANN, E-Jaya-ANN for eight hidden layer sizes

Hidden layer	**Optimization**	**CPU Time (Sec)**	
		Peak force [N]	**Maximum displacement [mm]**
H = 8	Jaya-ANN	4153.1709	3844.200724
	E-Jaya-ANN	3708.0249	3679.267123

The best calculation time is found in the E-Jaya-ANN technique improved over the Jaya-ANN technique, with a time gap between them of 445 seconds for Peak load and 165 seconds for maximum displacement.

4. Conclusions & recommendations

Multi-layered composite structures experience various stress factors during their operational lifespan, potentially leading to performance degradation or deformation. In our research, we conducted a numerical investigation to assess the impact of geometric parameters on the maximum resistance of CFRP composites when subjected to a bending load.

Prior to this analysis, we developed a Finite Element Model (FEM) using the ABAQUS commercial software to replicate experimental tests, thereby validating the accuracy of the numerical model. Subsequently, we introduced an enhanced approach, denoted as "E-Jaya-ANN" which leverages improved artificial neural networks to predict the peak load and maximum displacement of these composites under bending loads.

Finally, we conducted a comparative evaluation against the optimization method "Jaya-ANN" to demonstrate the effectiveness of the proposed approach. In this work, the main conclusions are presented as follows:

- The obtained results from the numerical and experimental tests are very similar, with a low percentage of error, which the precision of the numerical model implies.

- Geometric modification (thickness, layer number, and fiber orientations) plays a very important role in laminated composite structures in determining the levels of peak load under static stress. This allows us to choose a structure resistant to the force applied in a specific field.

- Comparing the results of the optimization techniques, E-Jaya-ANN provided slightly better prediction accuracy than Jaya-ANN, indicating a small advantage of E-Jaya-ANN over Jaya-ANN.

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