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Research Article

Prediction of load bearing capacity of carbon-fibre laminates using artificial neural networks

Devendra SAHU[1,*], Renu SAHU[1], Ramit CHUGH[1], Ritesh Kumar DEWANGAN[2], Surendra Pal Singh MATHARU[3], Gaurav K. GUPTA[4]

[1]*Department of University Teaching, Chhattisgarh Swami Vivekanand Technical University (CSVTU), Bhilai Chhattisgarh, 491107, India*

[2]*Rungta College of Engineering and Technology, Raipur Chhattisgarh 490299, India*

[3]*National Institute of Technology, Raipur Chhattisgarh, 492001, India*

[4]*CSIR-Advanced Materials and Processes Research Institute, Bhopal, 462026, India*

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ABSTRACT

Composite materials are extensively utilized across various industries due to their lightweight nature and superior mechanical properties. Enhancing and predicting the mechanical behaviour of these composites is crucial for optimizing their performance in various applications. This research investigates the prediction of load-bearing capacity in carbon-fiber laminates using Artificial Neural Networks (ANNs). The study involved experimental evaluation of the mechanical properties of the carbon metal composite materials, focusing on their behavior under tensile stress. The ANN model was trained on experimental data, including laminate dimensions, volume fraction, and applied load. Results showed the model's robust performance in accurately predicting tensile stress and classifying samples across diverse datasets, indicating high reliability and efficacy.

The study also highlights the potential of ANNs in modeling and predicting the mechanical behavior of composite materials, suggesting their usefulness in the design and analysis of carbon-fiber laminates. It recommends further optimization to improve the model's accuracy and applicability in real-world scenarios. Overall, this research provides significant insights into the mechanical properties of composite materials and emphasizes the practical potential of ANN modeling in engineering applications.

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***Corresponding author.**
*E-mail address: devendrasahu721@gmail.com

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INTRODUCTION

In engineering and material science, the pursuit of advanced materials with precisely tailored mechanical properties has become essential to meet modern application requirements. [1]. Among these materials, laminates stand out for their versatility and adaptability, offering a unique combination of strength, flexibility, and lightweight characteristics. Composed of multiple layers of different materials bonded together, laminates find widespread utilization across diverse industries, ranging from aerospace and automotive to construction and consumer goods [2,3]. The design and engineering of carbon-fibre laminates presents a crucial challenge in accurately predicting and optimizing mechanical properties like tensile strength, modulus of elasticity, and flexural strength. Traditional methods are often time-consuming and lack accuracy as well as efficiency. The prediction of mechanical behaviour of composite material helps to provide a more robust and reliable predictive model that enhance the structural integrity and performance of composite materials [4, 5]. The insights gained have wide-ranging practical implications, including cost and time efficiencies, failure prediction, as well as manufacturing techniques with potential benefits for various industries reliant on composite materials [6].

In recent years, advancements have developed in prediction technologies for the mechanical properties in composite material. Özer et al.[7] compared analytical and numerical solutions for bi-adhesive single-lap joints, emphasising complex stress states at overlap ends and validating against finite element analyses. Gajewski et al.[8] explored neural network analysis of dual adhesive single lap joints in uniaxial tests using Abaqus software, with varied geometric parameters and two adhesive types, supported by research funding. Lee et al.[9] focused on optimizing stacking sequences for multilayered composite structures using parallel evolutionary algorithms. By minimizing weight, maximizing stiffness, and reducing costs, the research demonstrates the effectiveness of this approach in achieving superior structural performance. Sharma et al. [10] used machine learning to revolutionise in material science, particularly in predicting polymer composite behaviour. Recent studies highlight its versatility for prediction, optimization, and uncertainty quantification, though challenges in large-scale implementation persist. Senthil et al.[11] provided a survey on defects particularly delamination, in composite joints/structures. It examines the effects of defects, their initiation, and prediction methods in fiber-reinforced plastics. The review highlights the need for further studies on adhesively bonded joints with closed debonds and discusses the use of the virtual crack closure technique (VCCT) and cohesive zone modelling (CZM) for defect prediction. Yuen and Lam[12] discussed the complexity of artificial neural networks for smart structures monitoring, highlighting the potential applications of neural networks in optimizing the design of composite pressure vessels. Rayhan et al. [13], adopted Ansys Materials Designer to estimate the elastic properties of unidirectional laminate composite (carbon/epoxy and polyethylene/epoxy). Mehdi et al. [14] predicted the elastic propertiesof bidirectional carbon epoxy composites using Mori–Tanaka and self-consistent micro-mechanical techniques. Yang et al. [15] develops an artificial neural network (ANN) model to predict the residual strength of carbon fibre reinforced composites (CFRCs) post low-velocity impact, validated against finite element (FE) simulation results. Mian et al.[16]focused on optimizing composite material systems and lay-up configurations to achieve minimum weight pressure vessels. This study demonstrates the importance of optimization techniques in designing efficient composite pressure vessels.

The literature indicates that calculating the mechanical properties of composite materials is challenging as experimental and mathematical modelling are time-consuming and limited accuracy. To overcome this challenge, the research proposed Artificial Neural Networks (ANNs) to predict the mechanical properties of laminates. The main contribution of this research is to perform experiment on two types of carbon metal laminates whose fiber volume percentage varies from 60 to 70 to understand the mechanical behavior. To develop and train artificial neural networks to predict the tensile stress of carbon-fibre laminates based on experimental results, and to evaluate the performance of the artificial neural network model across training, testing, and validation phases.

EXPERIMENTAL WORK

The experimental process of hybrid composite specimens involved arranging carbon woven fiber sheet of thickness 0.25mm in an alternating lamination pattern with metal plates sized 150*150 mm^{2}and thickness 0.5mm. Before laminate preparation, the treatment of the Al sheet included generating grooves using 180# grit emery paper for improved adhesion, followed by cleaning with NaOH and sulfuric acid solutions. Hand lay-up technique was employed for crafting the hybrid composite plates, followed by an autoclave curing process at 0.5 MPa pressure and 120°C temperature. The measured thickness of laminate after treatment is 4 mm. Araldite LY 556 epoxy resin serves as the matrix material in this work. Its viscosity is between 1000 and 1200 N-s/m2 and its density is between 1.15 and 1.20 MPa at 25 °C. Two types of laminates are prepared, in which the fiber percentage ratio is 60 and 70, they have nomenclature as CML60 and CML70 respectively. Mechanical testing included tensile tests, conducted as per ASTM D3039 standards guidelines. Tensile strength and elastic modulus were determined from stress-strain curves. Figure 1 illustrates the final prepared laminate.

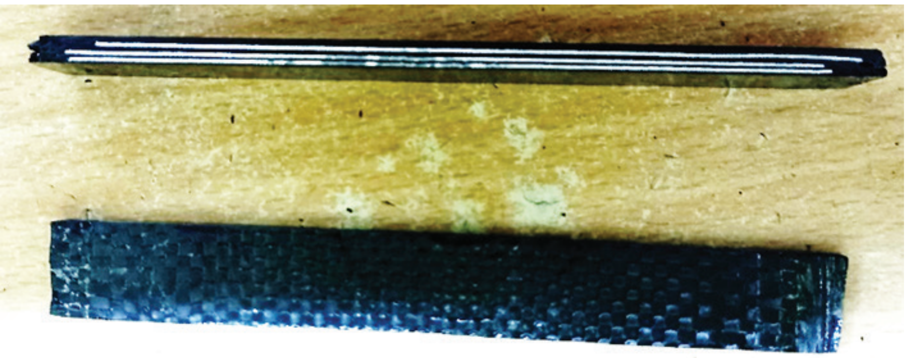

Figure 1. Carbon fibre metal laminate.

ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANNs) model offers an intricate nonlinear function and possesses a remarkable capacity for prediction, mirroring the complexity of organic brain wiring [17]. One commonly employed variant, multilayer perceptron (MLP) networks, excels in approximating nonlinear functions and addressing regression challenges. These networks are structured with interconnected layers, comprising an input layer, hidden layers, and an output layer, each linked by neurons functioning as computational units. These neurons incorporate inputs through weighted connections and biases, transmitting signals only upon reaching a predetermined threshold [18]. The mathematical expression of ANN is shown in equation 1.

$$y_i = f\left(b + \sum_{i=1}^{n} x_i w_{i,j}\right) \tag{1}$$

Where the output is represented by y, with b denoting the bias function, x indicating the input signal, and n representing the number of neurons involved in the process. ANNs undergo a training process involving the analysis of samples with known inputs and outputs, during which connections are adjusted based on the discrepancy between the network's output and the target outcome. This iterative refinement of connections, driven by error minimization, enhances the network's ability to accurately predict outcomes [19–21]. The training process may be supervised, depending on the availability of labelled data. Through strategic modification of weighted connections and biases, ANNs learn to optimize their predictive performance, making them invaluable tools in various domains, from pattern recognition to predictive modelling. The architecture of the ANN model is illustrated in Figure 2.

RESULT AND DISCUSSION

In this research, during the application of tensile forces by the universal testing machine (UTM), the entire structure of the laminate endeavors to withstand the imposed loading. However, as the tensile forces escalate, the matrix within the laminate reaches its limit and subsequently fractures, leading to the separation of the laminate layers into individual laminae. This phenomenon, known as delamination, occurs due to the matrix's inability to endure the applied loads. Prepared laminates, comprising a combination of metal and carbon woven fiber, exhibit distinct mechanical properties due to the higher elastic modulus of the metal sheet compared to the carbon fiber. When bonded with epoxy, these materials act as a single composite. Under

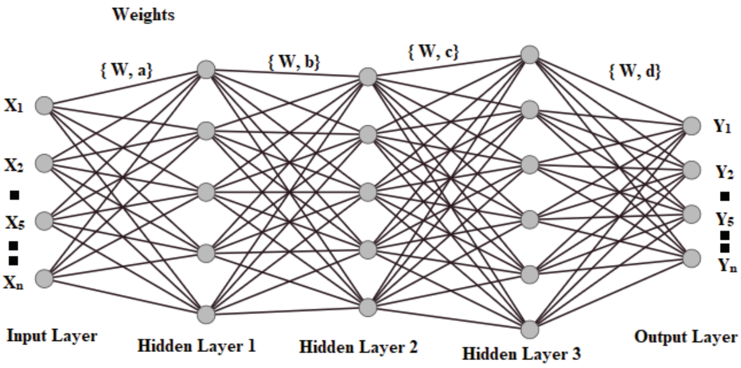

Figure 2. Architecture of ANN model.

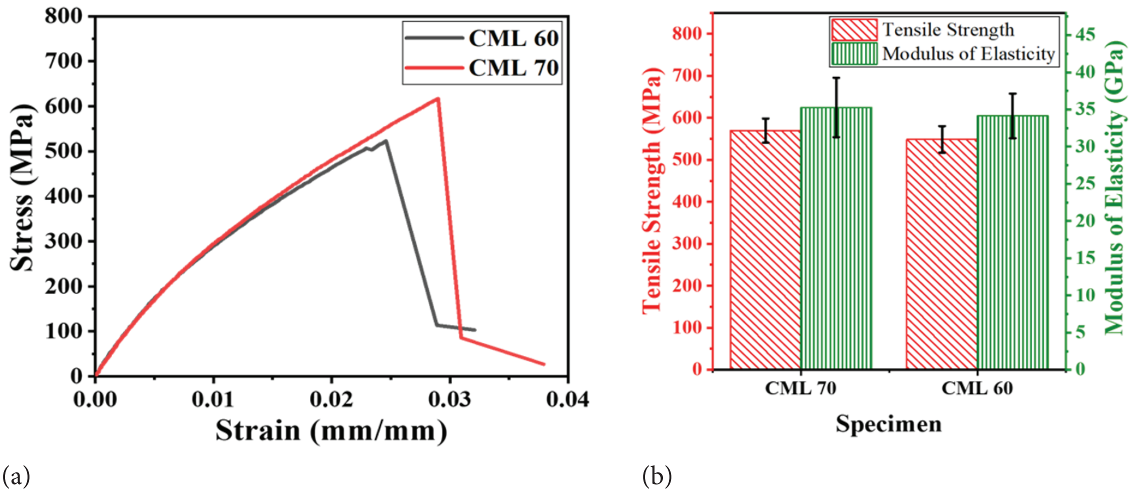

Figure 3. (a) Stress strain curve, (b) Mechanical properties of carbon metal laminate.

tensile loading, both materials attempt to sustain the load together; however, the carbon fiber reaches its tensile limit before the metal. This leads to inadequate elongation and subsequent delamination into separate layers [22, 23]. This delamination highlights the failure of the interlaminar bond between the carbon fiber and metal, formed by the epoxy coating. After breaking the interlaminar bond carbon fiber and metal sheet tries to sustain load separately but carbon fiber unable to elongate and fiber breakage starts and unable to transfer stress to the metal layer in result fails to sustain the load which can be seen by Figure 3 (a), after reaching peak point stress strain curve suddenly comes down.

The stress-strain graph (Figure 3a) demonstrates the linear elastic behavior of the laminate for both samples. The carbon fiber exhibits significant strength and rigiditywhile the metal shows high ductility [24]. As a result, the carbon fiber begins to fail while the metal continues to elongate, causing the interlaminar bond to deteriorate. After reaching the peak tensile strength, the graph indicates a decline.

Figure 3b also shows that the tensile strength of CML70 is 3% higher than that of CML60. Although the same materials were used, the pairing effect and fiber arrangement significantly influence the stress transmission mechanisms. These test results are utilized for training the artificial neural network model.

An artificial neural network is developed to forecast the tensile stress of carbon fiber-based laminate. Experimental measurements of tensile stress are utilized to train the ANN model. Following parameters are used in model such as laminate dimensions (mm), volume fraction (%), extension (mm), load (kN), true strain (N/mm2), and tensile extension (mm). Utilizing 2525 datasets, the ANN is designed and trained using Levenberg-Marquardt and feed-forward back-propagation (FFBP) techniques. Mean square error (MSE) and coefficient of determination (R2) values are

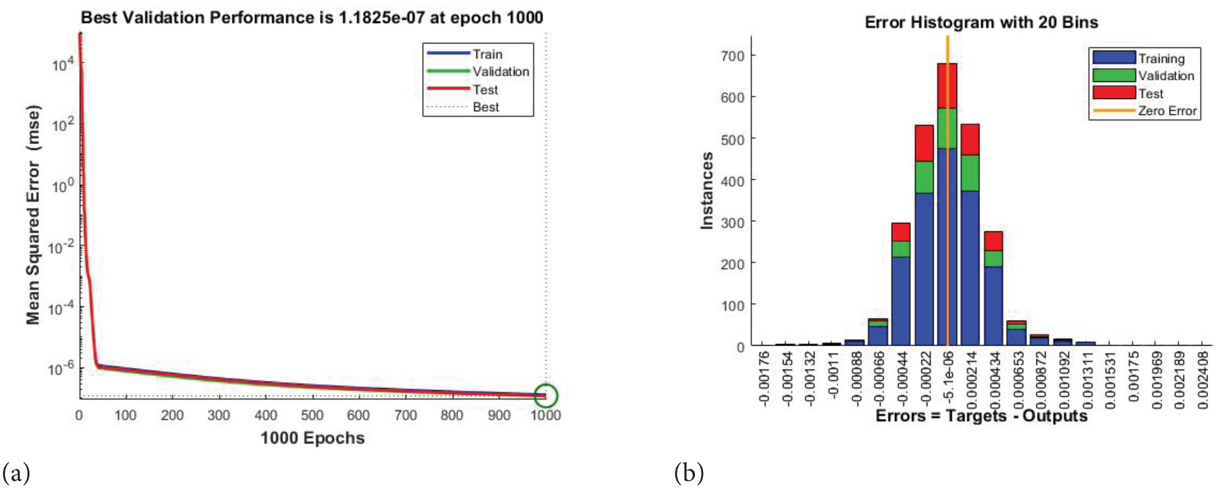

Figure 4. (a)Variations in Mean Square Error with each epoch (b) Error histogram.

employed for the performance evaluation of the developed ANN. An assessment of error rates between tentative data and ANN outputs is conducted using error histogram values.

Experimentation with various networks and comparison of their performance functions lead to the determination of the optimal number of neurons in the hidden layer. Consequently, the network structure yielding the lowest R2 and MSE values was selected as optimal, as depicted in Figure 4. This figure illustrates the fluctuation of MSE values over time. As the training cycles progressed, MSE values gradually decreased, ultimately stabilizing at 1.18258E-07 after 1000 epochs. The ANN training process, which commenced with higher MSE values and concluded with lower ones, was successfully executed. The error histogram indicates that the majority of errors are near the zero line, signifying minimal variation in error. The attainment of the lowest MSE value at the conclusion of the training phase indicates optimal completion of the ANN training process. The results of the training, testing, and validation phases are presented in Table 1.

Table 1. Result obtained in ANN

	Samples	MSE	R-value
Training	1767	1.29330E-7	9.9999E-1
Testing	379	1.18250E-7	9.9999E-1
Validation	379	1.19285E-7	9.9999E-1

MSE: Mean square error.

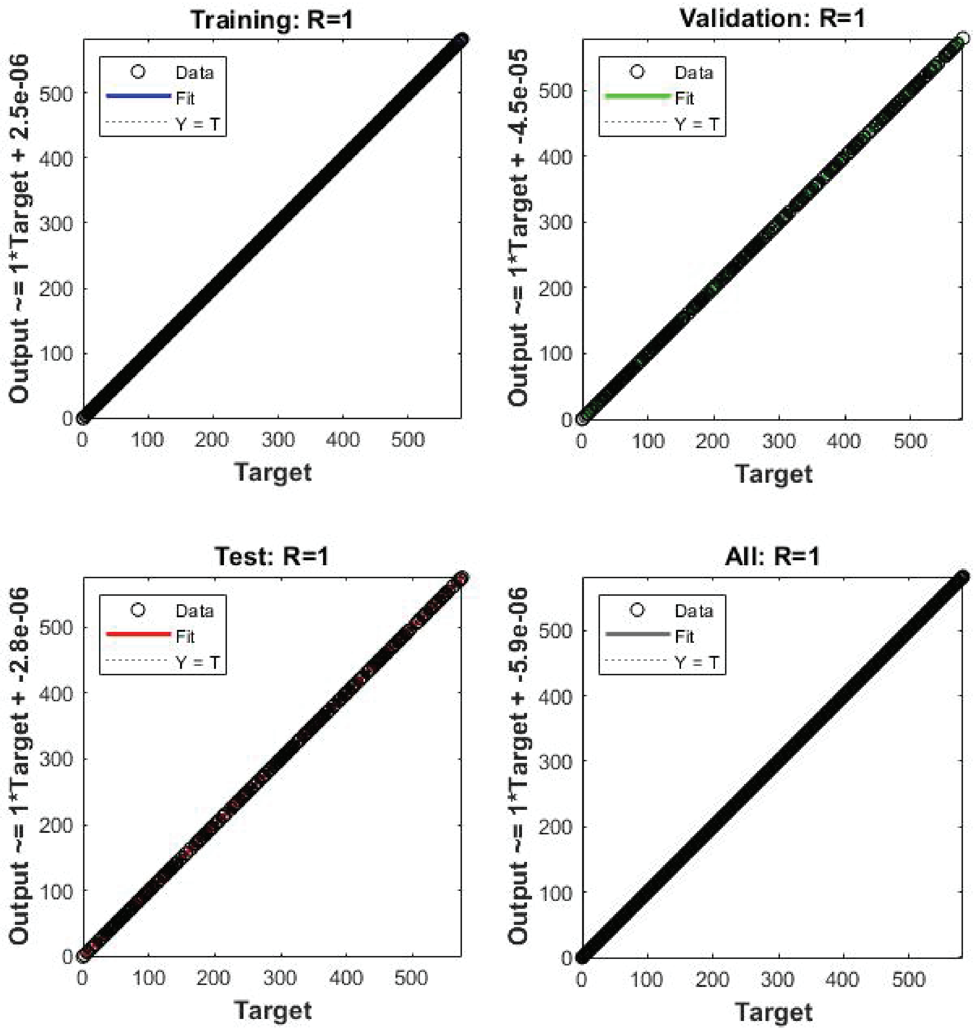

Figure 5. Network result after training, testing, validation and overall performance.

The classification model underwent rigorous evaluation across distinct phases: training, testing, and validation. Trained on a dataset comprising 1767 samples, the model exhibited a mean square error (MSE) of 1.29330E-7 and an R-value of 9.9999E-1 during the training phase. In testing, where 379 samples were assessed independently, the model showcased an MSE of 1.18250E-7 and an R-value close to 1. Subsequently, during validation, also conducted on 379 distinct samples, the mean square error persisted at 1.19285E-7, with an R-value of 9.9999E-1, indicating consistent performance. The R-value during the training, testing and validation are illustrated in Figure 5. These results underscore the model's resilience across varying datasets, highlighting its efficacy in accurately classifying samples. While the model demonstrates commendable performance, ongoing optimization endeavors may further refine its accuracy and applicability in real-world scenarios, ensuring reliable categorization across diverse contexts and datasets.

CONCLUSION

The research article investigates the behavior of carbon fiber-based laminate under tensile stress using experimental measurements and Artificial Neural Network (ANN) modeling. Due to the non-relevant beahaviour of Metal and carbon fiber during the tensile test, their matrix bonding breaks and cause delamination. CML70 have higher tensile strength compare to CML60 by 3%. The ANN model, trained on experimental data, accurately predicts tensile stress using input variables such as laminate dimensions, volume fraction, and load. Through rigorous evaluation across training, testing, and validation phases, the ANN demonstrates robust performance, achieving low Mean Square Error (MSE) values and high R-values consistently. The fluctuations in MSE values over training epochs illustrate the successful execution of the ANN training process, with optimal performance achieved. The results underscore the model's reliability and efficacy in accurately classifying samples across diverse datasets. However, continuous optimization efforts are recommended to further enhance the model's accuracy and applicability in real-world scenarios. But there is a limitation that ANN model will work for arrangement or stacking sequences shown in this study, and for the other type stacking sequences it will not predict the correct data. Overall, the study contributes valuable insights into the behavior of carbon fiber-based laminate under tensile stress and highlights the potential of ANN modeling in predicting mechanical properties with precision.

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AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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