

An Investigation into Strength Prediction of Columns Strengthened with CFRP Using Artificial Neural Networks

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Abstract

This study presents an investigation into the strength prediction of columns strengthened with Carbon Fiber Reinforced Polymer (CFRP) using Artificial Neural Networks (ANNs). The research aims to develop a reliable predictive model for estimating the ultimate load-carrying capacity of CFRP-strengthened columns by considering key influencing parameters. A dataset comprising numerical results was used to train and validate the ANN model. The selected input parameters included column length, column diameter, steel tube thickness, concrete compressive strength, steel yield strength, CFRP ultimate tensile strength, CFRP thickness, and the number of CFRP layers. The ultimate axial strength served as the output parameter. The developed ANN model demonstrated high accuracy in predicting the column strength, capturing the nonlinear relationships among the variables effectively. The results confirm that artificial neural networks can serve as a powerful tool for structural strength prediction, reducing the need for extensive experimental testing and offering valuable insights for engineering design and assessment.

1. Introduction

Columns are fundamental structural elements that serve as the main vertical support system in structures and transferring the weight of the superstructure safely to the foundations. The performance of columns directly affects the stability, safety, and durability of the entire structure. Any failure in these elements can lead to partial or total collapse, especially during extreme events such as earthquakes or overloads [1-3]. Therefore, ensuring the strength and reliability of RC columns is a critical aspect of structural design, maintenance, and retrofitting practices. In recent years, the demand for strengthening and retrofitting existing structural elements has significantly increased due to aging infrastructure, changes in design requirements, and the need for enhanced load-carrying capacity [4-6]. Among various strengthening techniques, the use of Carbon Fiber Reinforced Polymer (CFRP) has emerged as a popular and effective method due to its high strength-to-weight ratio, corrosion resistance, and ease of application [7-10]. CFRP wrapping is widely employed to enhance the axial and flexural strength of structural components, particularly columns, which are critical load-bearing elements in buildings and bridges. Accurately predicting the strength of columns strengthened with CFRP is essential for safe and cost-effective structural design. Traditional analytical and empirical methods, while useful, often fall short in capturing the complex nonlinear behavior of CFRP-confined columns, especially when multiple design parameters are involved.

The integration of artificial intelligence (AI) into structural engineering has significantly transformed the discipline by improving design efficiency, analytical accuracy, and informed decision-making processes [11-14]. AI methods excel at processing massive datasets to detect trends, optimize material consumption, and enhance structural performance. Furthermore, they contribute to structural health monitoring by identifying irregularities and enabling early detection of potential failures [15-17]. Among these methods, artificial neural networks (ANNs) have recently emerged as effective tools for predicting strength in columns [18-20]. ANNs, which are inspired by the architecture and function of the human brain, offer a data-driven method capable of modeling intricate variable interactions without the need for explicit mathematical equations. These computational models can learn from data, recognize intricate patterns, and generate predictive insights based on acquired knowledge [21-22]. Their ability to model nonlinear behaviors and adapt to varying input parameters has made them increasingly valuable in structural engineering applications.

Utilizing ANNs to predict the compressive strength of columns presents several benefits compared to conventional analytical approaches [23-25]. ANNs are capable of processing extensive and varied datasets, facilitating a more in-depth analysis of how different input parameters influence strength behavior. They excel at capturing and modeling complex interactions among variables, enabling precise predictions in both linear and nonlinear systems. Additionally, ANNs prove strong generalization capabilities, allowing them to perform reliably on previously unseen data, which enhances their practicality in real-world engineering scenarios. Their widespread adoption is largely attributed to their robustness in delivering accurate results, even when trained on incomplete or imperfect datasets [26-27].

In the field of structural engineering, numerous studies have explored the use of ANNs to predict the strength behavior of civil structures. For instance, Mojtabaei et al. [28] investigated the potential of ANNs for estimating buckling parameters of slender channel sections subjected to combined compression and bending. The neural networks were trained using various input variables, such as element dimensions, thickness, stiffener positions, and lengths, while the corresponding buckling loads served as output data. A hybrid method, combining the finite strip method with the equivalent nodal force approach, was used to generate the training dataset. The results indicated that the trained ANNs achieved high accuracy, with a correlation coefficient of 98% in predicting buckling loads. Additionally, the study highlighted opportunities for further enhancement of ANN-based models in buckling prediction applications.

Subsequently, Wu et al. [29] carried out an analytical study on the behavior of prestressed stayed beam-columns, introducing an intelligent method based on ANNs to evaluate nonlinear failure modes and predict ultimate loads. Their results demonstrated that the ANN model delivered precise predictions of both failure modes and ultimate load capacities. In a separate study, Tahir et al. [30] applied ANNs to predict the compressive strength of slender shell structures subjected to axial compression. They assembled a dataset of 516 specimens on the strength behavior of thin-walled shells under axial loading. The neural networks were trained using the backpropagation algorithm and included nine input parameters, comprising two mechanical properties, six geometrical variables, the fabrication tolerance class, and one output representing the buckling load.

In recent years, numerous studies have investigated the strengths and limitations of using ANNs to predict the load-carrying capacity of columns strengthened with CFRP [31-36]. Comparative analyses have shown that ANNs can offer improved prediction accuracy over experimental and theoretical methods in columns. However, further research is still needed to fully evaluate their efficiency. This study developed an ANN model to predict the ultimate load of CFRP-strengthened columns, using key input parameters such as column dimensions, material properties, and CFRP characteristics. Trained on a comprehensive dataset, the model demonstrated high accuracy and reliability, confirming the effectiveness of ANN as a predictive tool and supporting the practical application of CFRP in structural strengthening.

2. Methodology

2.1 Artificial Neural Networks

Artificial Neural Networks (ANNs) are sophisticated computational models inspired by the structure and functioning of biological nervous systems. They are capable of performing tasks such as pattern recognition, classification, and modeling complex nonlinear relationships [37]. An ANN functions as a mathematical representation of a biological neuron, designed to handle nonlinear interactions between input (independent) and output (dependent) variables simultaneously. By learning from provided input-output data, ANNs are able to formulate their own internal algorithms and generate meaningful predictions [38]. A typical ANN architecture includes an input layer, one or more hidden layers, and an output layer. Figure 1 illustrates a standard three-layer neural network structure.

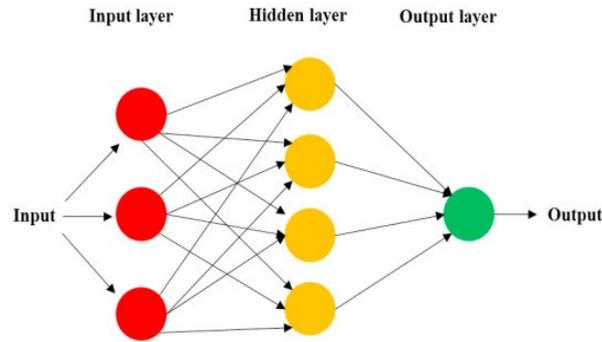


Fig. 1 The architecture of three-layer ANN model

As illustrated in Figure 2, each neuron is associated with a synaptic weight that is adjusted during the training process. The neuron calculates the weighted sum of its inputs and processes it through an activation function [D-E]. Among various architectures, the multi-layer feedforward neural network utilizing the backpropagation algorithm is the most widely adopted, owing to its high accuracy and flexibility in handling complex tasks. This architecture is commonly applied in civil engineering problems [39-41]. The performance of the backpropagation algorithm is typically evaluated using the mean square error (MSE) as a statistical metric. During training, the network compares its output with the target values and continuously updates the weights to reduce the error. This iterative process continues until the MSE reaches a minimum value, at which point training is completed. The trained network is then validated by testing it with a separate dataset.

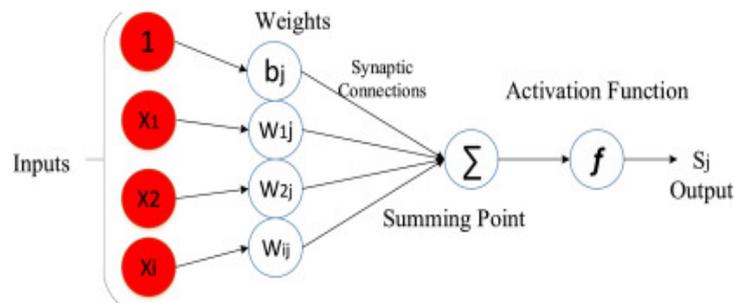


Fig. 2 The diagram of an artificial neuron [42]

2.2 Strength Prediction of Columns Strengthened with CFRP

Carbon Fiber Reinforced Polymer (CFRP) has emerged as a highly effective material for strengthening structural columns, particularly in aging or damaged buildings. Its exceptional tensile strength, lightweight nature, and resistance to corrosion make it an ideal choice for retrofitting applications. Predicting the enhanced strength of columns after CFRP strengthening is critical for ensuring structural safety and optimizing design strategies. By using experimental data, numerical simulations, or machine learning models, engineers can estimate the load-carrying capacity of CFRP-confined columns under various conditions. Accurate strength prediction not only improves the reliability of rehabilitated structures but also helps reduce construction costs and enhance sustainability in infrastructure development. In this research, MATLAB was used to implement the artificial neural network (ANN) due to its powerful built-in tools and user-friendly interface for modeling and training neural networks. The Neural Network Toolbox in MATLAB allows users to easily define the network architecture, assign input and target data, choose training algorithms, and monitor performance metrics such as error rates and regression plots. This makes MATLAB an effective and widely adopted platform for applying ANN in engineering problems, including the prediction of structural strength in CFRP-strengthened columns. In this study, a total of 500 datasets were collected numerically on columns strengthened with Carbon Fiber Reinforced Polymer (CFRP). The dataset included key input parameters such as column length, diameter, steel tube thickness, concrete compressive strength, steel yield strength, CFRP ultimate tensile strength, CFRP thickness, and the number of CFRP layers. An ANN model was developed and trained using this dataset to predict the ultimate load-capacity of the columns. The model was validated using a subset of data not involved in training. The predicted results were then compared with actual experimental values to assess the accuracy and effectiveness of the ANN model.

3. Results and Discussions

This section addresses the essential steps for developing ANNs that predict column strength utilizing CFRP. A comprehensive dataset is initially compiled, including input variables such as column dimensions, concrete and reinforcing qualities, loading conditions, and shear strength values. Subsequently, the dataset undergoes preprocessing, which involves partitioning the data into training and testing sets and normalizing them. The subsequent stage involves selecting suitable artificial neural network architecture, often comprising multiple layers of interconnected artificial neurons. Prediction errors are minimized by iteratively adjusting connection weights and biases across the training dataset and employing techniques such as backpropagation. The efficacy of the trained ANN is subsequently evaluated using the testing dataset and metrics such as correlation coefficients and mean squared error. The numerical database's descriptive statistics are shown in Table 1. Column length (L), column diameter (D), steel tube thickness (ts), compressive strength (fc), yield strength (fy), CFRP ultimate tensile strength (fFRP), thickness of CFRP (tFRP), number of CFRP layers (nFRP), and strength of column strengthened with CFRP (Pu) are the parameters selected to create an appropriate network based on previous studies.

Table 1 Descriptive statistics of datasets in this research

| Parameter | Range | | | |
|-------------------------------|--|------|--------|---------|
| | Min | Max | Mean | |
| Column length, (L) mm | 400 | 900 | 628.97 | |
| Column diameter, (D) mm | 110 | 350 | 209.47 | |
| Steel tube thickness, (ts) mm | 1.83 | 4 | 2.76 | |
| Compressive strength, (fc) mm | 32 | 140 | 45.56 | |
| Input Parameters | Yield strength, (fy) MPa | 226 | 340 | 284.9 |
| | CFRP ultimate tensile strength, (fFRP) | 1826 | 4105 | 3209.64 |
| | Thickness of CFRP, (tFRP) | 1 | 4 | 2.14 |
| | Number of CFRP layers, (nFRP) mm | 0.2 | 0.8 | 0.42 |
| Output Parameter | Strength of column strengthened with CFRP, (Pu) kN | 2045 | 4855 | 3757.36 |

In this study, the datasets were partitioned into 70% for training, 15% for validation, and 15% for testing the network. Training set adjustments modified connection weights and biases. Validation data used for checking overtraining. Overtraining increases validation data errors. Overtraining a neural network model impairs prediction. The larger training set gives the network enough data to analyze complex data set patterns and correlations and modify parameters and fit models. This study employed two-layer feed-forward for architecture of ANN. The predictive capacity of a model is compromised when it is excessively trained. Upon concluding the training process, the network's efficacy was assessed by an analysis of the testing data. Figure 3 shows the ANN architecture of Two-Layer Feed-Forward.

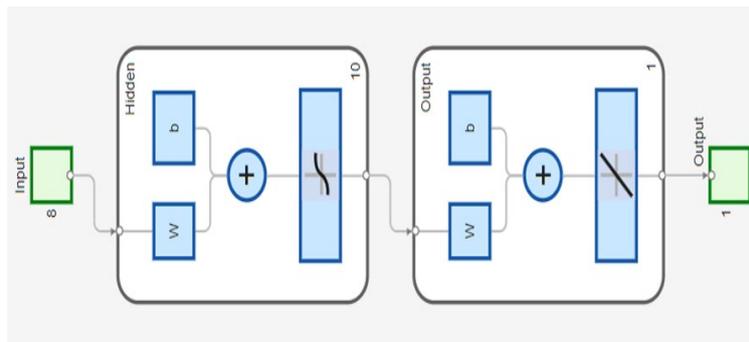


Fig. 3 ANN architecture two-layer feed-forward

The number of neurons is a crucial aspect in the training of ANNs. Predictions generated by a network without an adequate number of neurons will consequently be insufficient. An excessive number of neurons in a network can lead to overtraining, resulting in suboptimal performance. This experiment employs a minimum of ten neurons. The Mean Square Error (MSE) and the Correlation (R-value) were the principal metrics assessed to ascertain the proper cessation of network training. The mean squared error (MSE) quantifies the disparity between actual results and anticipated outcomes. Decreased values signify enhanced network performance. An elevated R-value of 1 signifies a robust correlation between network outputs and targets. A 0 R-value indicates no correlation.

The artificial neural network models that were utilized in this research were utilized in order to make a prediction regarding the strength of 214 columns that were strengthened with CFRP datasets. With the help of the training data, the model structure of ANN was developed. Both the determination coefficient (R^2) and the mean square error (MSE) were utilized in order to evaluate the performance of the artificial neural networks. This study trained the artificial neural network using the Levenberg-Marquardt method. This approach uses Gauss-Newton and gradient descent. Effectiveness greatly reduces regression difficulties. The hidden neurons activation function was sigmoid, while the output neurons were linear. This section focuses on two-layer neural network architectures. The chosen network architecture is 8-10-5-1 and comprises three levels. This architecture consists of four layers: an input layer with 8 neurons corresponding to the input features, two hidden layers with 10 and 5 neurons respectively, and a single output neuron. The input layer receives data, which is processed through the hidden layers using activation functions to learn patterns and relationships within the data. The final output layer generates one prediction value, which in the context of this study represents the estimated strength of a CFRP-strengthened column.

The training set has R^2 values of 0.9828 for the training set, 0.9687 for the validation set, and 0.8601 for the test set show that the expected and actual values are substantially correlated. Despite its absolute value mistake, the model's ability to apply to a variety of datasets shows that it can capture the data's overall pattern and direction. To reduce the increasing Mean Squared Error (MSE) and improve model accuracy, extra model analysis and improvements may be needed. Figure 4 shows the Mean Squared Error of the ANN for training, validation, and test sets. This performance is calculated for all three sets.

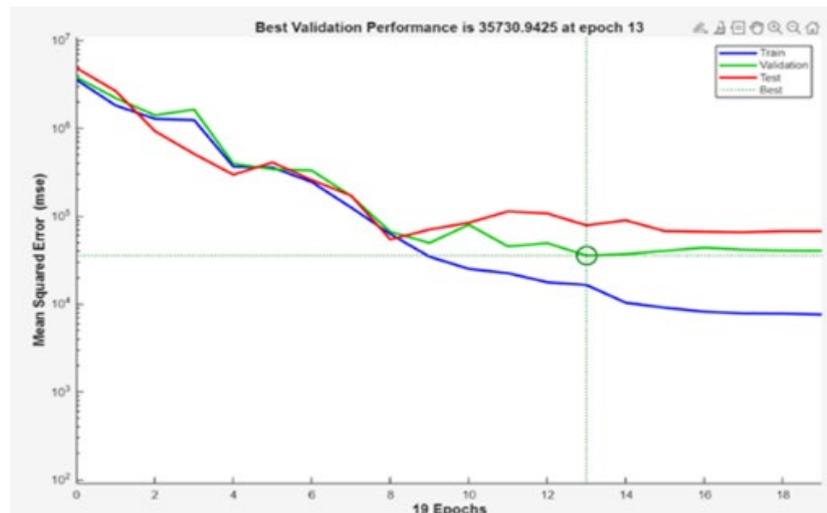


Fig. 4 Performance of the ANN with respect to MSE

Table 2 shows performance measurements that show how well the Two-Layer Feed-Forward Architecture calculates CFRP-reinforced column strength. Training (1652), validation (3573), and test (7875) mean squared errors were recorded by the Two-Layer model. Two-Layer consistently shows value based on R-values, which measures the correlation between predicted and observed values. The training dataset has an R-value of 0.9828 and the validation dataset 0.9687. The test dataset R-value is 0.8601.

Table 2 Model performance results for different datasets

| Architecture | MSE | | | R ² | | |
|-------------------------------|----------|------------|--------|----------------|------------|--------|
| | Training | Validation | Test | Training | Validation | Test |
| Two-layer Feed-Forward | 0.0074 | 0.0058 | 0.0063 | 0.9828 | 0.9687 | 0.8601 |

The analysis shows that the two-layer feed-forward ANN architecture delivers the best performance among all tested models, achieving the highest correlation coefficients and lowest mean squared error. This architecture proves to be the most effective for predicting the strength of CFRP-reinforced columns due to its strong generalization ability and capacity to model complex relationships within the data. However, excessive training can lead to overfitting, reducing the model's accuracy on test data. Evaluating the ANN's performance across training, validation, and testing phases provides important insights into its predictive reliability. The results, illustrated in Figure 5, highlight the model's effectiveness and limitations.

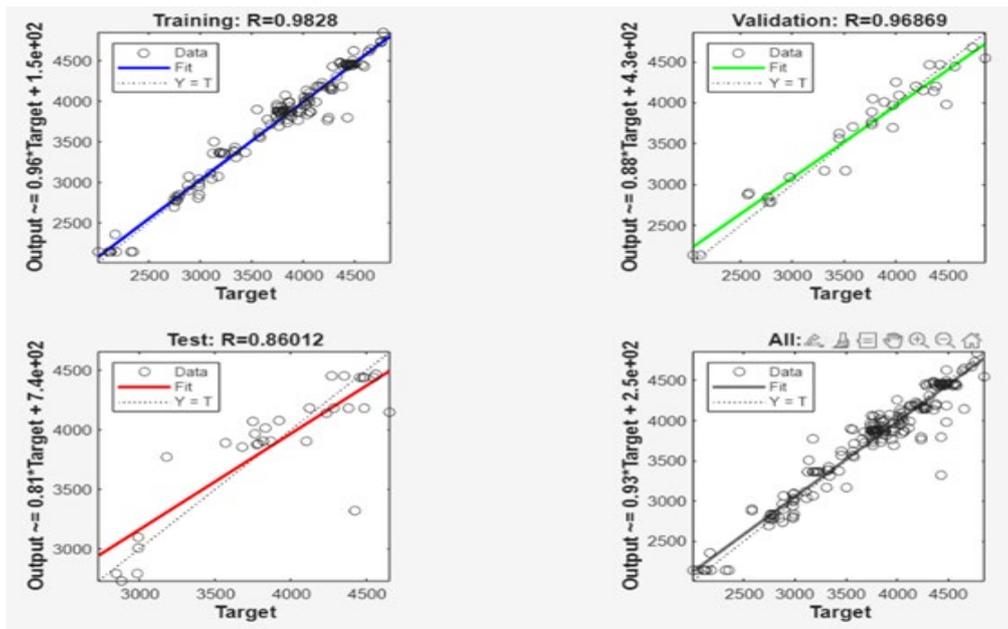


Fig. 5 Regression values of two-layer feed-forward

Throughout the training process, the model achieved an R² value of 0.9828, and a mean square error (MSE) of 0.0074. Subsequently, it demonstrates that the network utilized the samples for training, enabling it to successfully estimate the strength of a CFRP-reinforced column when presented with new data, within an acceptable margin of error. To predict the performance of CFRP-reinforced columns utilizing datasets external to the training sets, the ANN model is initially trained. Subsequently, the precision of the chosen architecture was evaluated utilizing the testing set after network training. The results illustrate that the neural network regularly exhibits exceptional predictive performance during the testing phase. The assessment metrics indicate that the neural network, configured with 10 neurons in the first hidden layer and 5 neurons in the second layer, can accurately predict the new test datasets.

Moreover, validation is essential for ANNs to prevent overfitting and to verify generalization efficacy. A neural network may adjust to its training data, but it risks becoming overly specialized and may underperform with unfamiliar input. Validation aims to assess the model's efficacy on a dataset that was excluded from the training process. It optimizes learning rates and hidden layers, two hyperparameters, without retaining training data in memory. Neural networks validated with independent data, rather than only memorizing patterns from the training set, demonstrate superior capability in predicting novel inputs, resulting in more resilient and efficient models. Reduced mean squared error (MSE) shows improved accuracy because it measures average prediction errors. The model's high R² value of 0.9687, which shows a strong positive correlation between predicted and actual results, supports its ability to recognize patterns and correlations in datasets. Overall, these results suggest that the ANN can accurately predict output from input data during validation.

The results indicate that the ANN model demonstrates strong predictive performance across all three datasets: Training, Testing, and Validation. The model demonstrates an effective equilibrium between training

and generalization performance, as the MSE percentage value was closely aligned across datasets. It is essential to ensure that the testing dataset is sufficiently represented during model training, given its lesser connection with the validation dataset. In conclusion, ANN's elevated correlations and minimal error metrics demonstrate its dependability and resilience. The results indicate potential; nevertheless, the model could significantly improve with further fine-tuning, such as hyperparameter optimization or the application of regularization techniques, to enhance predictive accuracy and reduce RMSE. The results indicate that the ANN is prepared for application in practical settings and exhibits strong generalization capabilities.

4. Conclusion

This study highlights the substantial potential of ANNs in precisely predicting the compressive strength of columns strengthened with Carbon Fiber Reinforced Polymer (CFRP). The developed ANN model, implemented using MATLAB's Neural Network Toolbox, efficiently captured the complex nonlinear interactions between multiple input parameters and the resulting column strength. The model demonstrated a high level of precision, as evidenced by the robust correlation between actual data and predicted outputs. A dataset comprising 214 samples was applied to train, validate, and test the network, and the use of regression analysis further enhanced the model's precision and reliability. The findings recommend that even with a moderately sized dataset, ANNs can establish meaningful and accurate relationships between input and output variables. The two-layer feedforward neural network used in this study proved to be an efficient and robust structure for problems of moderate complexity. However, for problems involving higher degrees of nonlinearity or larger data variability, deeper or more advanced network architectures may be explored in future research. One of the most important outcomes of this study is the confirmation that ANNs offer a significant computational advantage over traditional predictive methods, both in terms of adaptability and accuracy. The versatility of the ANN method allows for its application across various structural engineering challenges, particularly in situations where empirical or analytical methods fall short due to complex parameter interactions. In conclusion, the successful application of ANNs in this study underscores their growing importance as a powerful tool in civil engineering, especially for modeling and predicting the structural performance of strengthened components.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

*The authors confirm the contribution to the paper as follows: F.E.A. Rudi: **study conception, Data collection and analysis**; S.J.S. Hakim: **study conception and design, analysis and interpretation of results, supervision**; S.B.H.S. Mohamad: **analysis and interpretation of results**; M. Paknahad: **Methodology, draft manuscript preparation**; M. Mohammadhasani: **data collection, methodology**; Z. Jamellodin: **data collection and analysis**; H. Tami: **conceptualization and final version of the manuscript**. All authors reviewed the results and approved the final version of the manuscript.*

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