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Predictions of ANN Model for Axial Strength of FRP-Confined CFST Columns

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ABSTRACT

The present investigation aims to predict theoretically the axial compression capacity of carbon fibre-reinforced polymer (CFRP)-wrapped concrete-filled steel tube compressive members (CCFST) by suggesting an artificial neural network (ANN) model. For achieving the aim of this study, a database of 216 CCFST compression members was engaged from a preceding investigation, and the training, validation, and testing of the ANN model were carried out. The training and validation of the suggested ANN model were performed for a different number of layers and neurons. The suggested model considers the interaction mechanism and interrelations of the various variables of CCFST compression members. Lastly, the improved ANN model depicted a good correlation with the database results of CCFST compression members.

KEYWORDS: steel-tube; confinement mechanics; compression capacity model, neural networks, database

1 INTRODUCTION

Due to the better efficiency of stainless-steel tubes in terms of durability, strength, cost, maintenance, resistance to heat, aesthetics, and corrosion resistance, these are being widely used in the construction industry. The prominent benefits of using stainless steel tubes in structural columns include high compressive strength and improved ductility. However, when the buckling of columns occurs, the efficiency of steel tubes is significantly reduced to bear the axial loads [1-3]. Consequently, it is essential to provide lateral support to the columns to enhance the compression capacity d stiffness of the columns to resist the buckling effects that can be provided by the application of external carbon fibre reinforced polymer (CFRP) sheets [4-6]. After wrapping the steel tube-wrapped concrete columns with externally bonded CFRP sheets, the compression capacity and stiffness of the compressive members are significantly improved against static as well as seismic loads [7-13]. Therefore, it is most effective to apply the external CFRP sheets on steel tube-wrapped concrete-filled columns to avoid the lateral buckling and to enhance the compression capacity and stiffness of the columns.

Previous investigations lack the theoretical predictions of CFRP wrapped concrete-filled steel tube (CCFST) columns. However, some investigations aimed to predict the compression capacity of such structural components based on an insignificant dataset, simple regression analysis, and

simple curve fitting techniques employing the noisy data without validation considering a limited number of test parameters. Most of the parameters of CCFST compressive members were neglected in the previous investigations which resulted in the higher discrepancies in the estimations from the experiments. The interaction behaviour between the various parameters of CCFST compressive members was also neglected to explicitly predict the compression capacity. Artificial neural networks (ANNs) tools are advanced machine learning models that work like the human brain to explicitly predict the structural efficiency of CCFST compressive members. These networks use neurons to find the interaction between various variables without knowing their nature [1, 5, 14-16]. Such type of machine learning models has become the effective tools to predict the behaviour of composite structures that attract modern research [16].
Literature review showed that no significant ANN modelling was done on CFST columns based on a large experimental database. Some studies are available in the literature that were based on small database due to which their accuracy cannot reliable. Therefore, it is essential to propose ANN model for capturing the axial strength of CFST columns using a large database like the authors have done in the present work. The main objective of the present study is to suggest novel ANN models for capturing the behaviour of CCFST compressive members precisely based on the experimental database. The confining process of external tubes and CFRP sheets was considered in the presently proposed ANN model by considering various parameters of CCFST columns.

2 ARTIFICIAL NEURAL NETWORK MODEL

2.1 General

ANN models consider the neurons and hidden layers for the predictions of the structural efficiency precisely. Nowadays, these networks are being preferred over the conventional approaches for capturing the axial efficiency of composite structures [17]. The nature of these networks is nonlinear that can consider the complicated interactions and interrelationships occurring between the variables of CCFST compressive members. During the ANN process, various parameters of CCFST compressive members are automatically arranged for training and validation of the models. The weights defined by the neurons for each of the parameters of CCFST columns are then summed up with the bias values. These values are then employed by the predefined functions that simulate the interaction between the hidden layers consisting of neurons.

The compression capacity of CCFST columns has been captured employing ANN in this study. The MLFNNs depicted the optimized estimations for the FFRP constrained concrete members in the preceding studies [18, 19] as presented in Figure 1. Consequently, the feed forward and backward networks were taken in the current study for estimating the compression capacity of CCFST compressive members. The input layer for the ANN models contained ten (10) diverse variables of CCFST compressive members consisting of the diameter of CCFST compressive members (D), the strength of concrete (f'_{co}), the thickness of tube (t_{st}), total area of tube (A_{st}), the number of CFRP sheets (n), the strength of tube (f_{ys}), and gross area of CCFST compressive members (A_c). The output parameter was axial compression capacity of CCFST columns (P_n).

Concerning the structure of the ANN model anticipated in the current investigation, it contained activation functions, neurons, and the hidden layers containing neurons. These three parameters affect the output efficacy of the proposed ANN models. The structure can be selected based on the trial-and-error method based on the problem being considered. The inputs, outputs, and sample points also affect the selection of the total number of hidden layers and the number of neurons. Table 1 presents the structure of the suggested ANN models in the current investigation for capturing the axial compressive capacity of CCFST compressive members. Ten (10) ANN models with a different number of neurons the 1st and/or 2nd hidden layer having the activation functions are assessed for the output (compression capacity of CCFST compressive members). A sigmoid function was employed for the definition of activation function between the inputs and the 1st hidden layer while the $NTanH$ function was used for the definitions of activation functions between the second hidden layer and the output layers of the proposed ANN models to capture the compression capacity of CCFST compressive members. The selection of $NTanH$ function between the output layer and the second layer was performed due to its effective efficiency for CCFST compressive members. Two hidden layers having seven (7) neurons in the 1st and 2nd hidden layer were used obtained after the calibration method.

Table 1: Structure of different proposed ANN models

Model	Input variables	Function b/w input and hidden layer	Function b/w hidden and output layer	Neurons in the hidden layer	Output
ANN_1	D, f'_{co}, t_{st}, A_{st}, n, f_{ys}, A_c	Sigmoid	$NTanH$	3	P_n
ANN_2				4	
ANN_3				5	
ANN_4				6	
ANN_5				7	
ANN_6				7-3	
ANN_7				7-4	
ANN_8				7-5	
ANN_9				7-6	
ANN_{10}				7-7	

2.2 Normalization and Calibration of Data

The normalization of the developed test data significantly affects the accuracy of the proposed ANN models for the axial compression capacity of CCFST columns. Due to the diverse units, the different input variables are transformed into unit-less variables during the normalization method to create the ANN technique capable of producing accurate estimates. The reduced learning process of the ANN models generates problems for the accurate estimates, hence, the normalization process of the input parameters should be carried out within a specific range [20].

In the present study, the normalization process of all inputs is carried out within the range of 0.8-0.2 to precisely predict the axial capacity of CCFST compressive members using Equation (1).

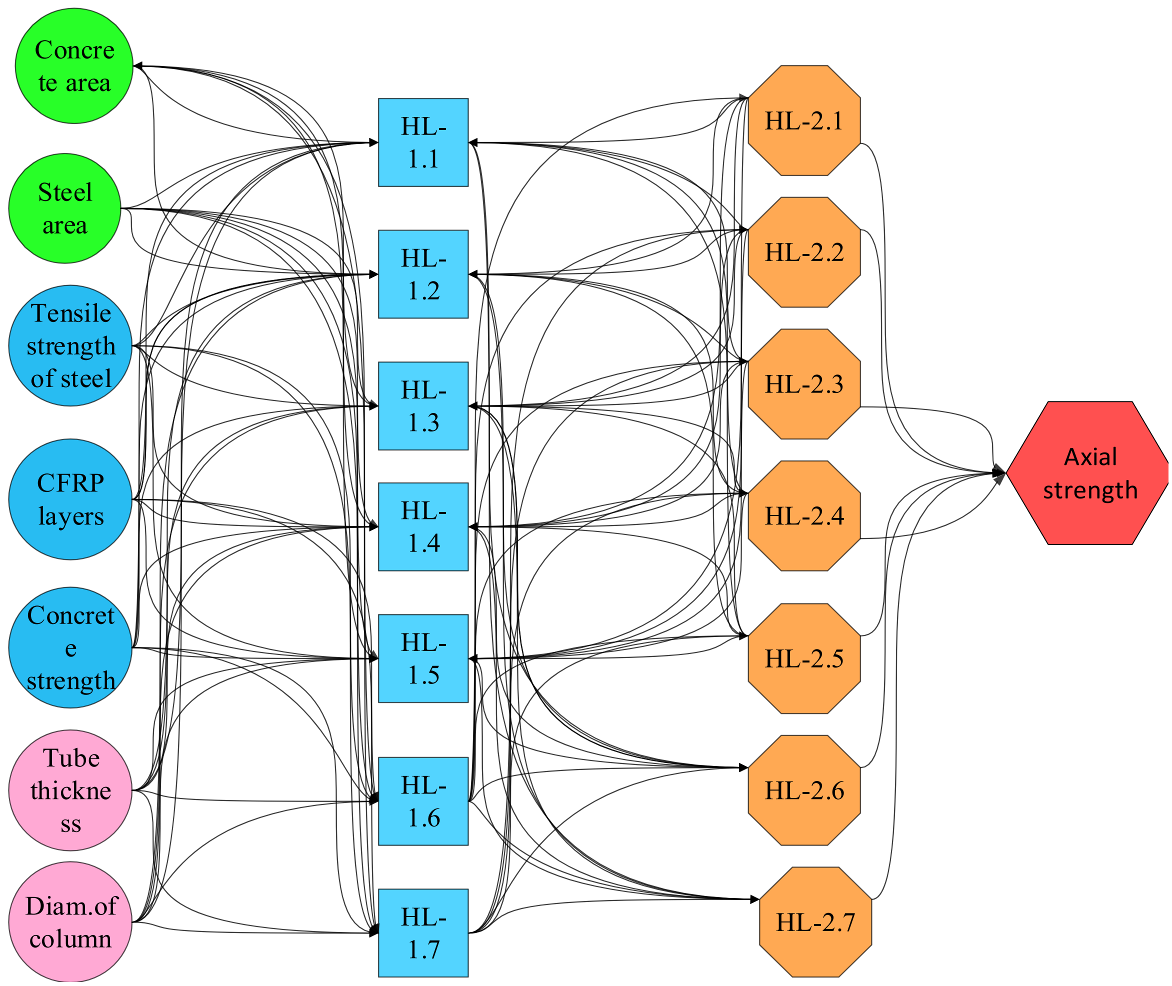

Figure 1. Structure of proposed ANN model for compression capacity of CCFST members

$$X = (0.6/\Delta)x + [0.9 - (0.6/\Delta)x_{max}] \quad (1)$$

The multilayer feed-forward process is an effective technique in ANN modelling to accurately capture the outputs due to its repetitions process [20]. Thus, this technique is being in the present study for precise predictions of the compression capacity of CCFST compressive members. The training of the ANN models was done using 60% of the database while the validation was performed using 20% data points keeping 20% for testing. The remaining data points were used for testing purposes. The statistical indices used for the assessment of the proposed ANN models consisted of mean absolute error (MAE), coefficient of determination (R^2), and root means squared error ($RMSE$). These indices are shown by Equations (2-4), individually.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|N_i - N_i'| \tag{2}$$

$$R^2 = \left(\frac{n(\sum_{i=1}^{n} N_i N_i') - (\sum_{i=1}^{n} N_i)(\sum_{i=1}^{n} N_i')}{\sqrt{\left[n\sum_{i=1}^{n} N_i{}^2 - (\sum_{i=1}^{n} N_i)^2\right]\left[n\sum_{i=1}^{n} N_i'^2 - (\sum_{i=1}^{n} N_i')^2\right]}}\right)^2 \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(N_i - N_i')^2} \tag{4}$$

In these relationships, N_i and N_i' are the test and estimated axial compression capacity of CFST compressive members, correspondingly. Figure 2 shows the statistical parameters for the estimations of the proposed ANN model for different numbers of neurons in the 1st and 2nd layer for the training, validations, and testing processes. It can be observed that the accuracy of the ANN model is improved by enhancing the neurons and the number of hidden layers. When three neurons were selected for only one layer, the values for the indices were $R^2 = 0.872$, $RMSE$ = 6.54, and MAE = 6.55. When the seven neurons were selected for the first layer by adding a second layer having seven neurons also, the values for the indices were $R^2 = 0.998$, $RMSE$ = 1.58, and MAE = 2.68. Thus, by enhancing the number of hidden layers and the number of neurons, the accuracy of the proposed ANN model improved forming a complex structure. Thus, it is essential for the ANN models to keep their structure simple and avoid computational time. Thus, the final proposed model contained seven neurons in the 1st and 2nd layer.

Table 2 presents statistical parameters related to the compression capacity of CCFST compressive members obtained from different proposed ANN models. The table compares the predicted values from these models with the actual test results. In terms of the minimum estimate, the anticipated value was 245 kN, though the test minimum compression capacity was 301 kN. This indicates that ANN model ANN10 captured the minimum test value with an 18% deviation. Similarly, for the peak estimate, the calculated value was 7562 kN, whereas the test peak compression capacity was 8127 kN. Here, ANN model ANN_{10} apprehended the peak test value with a 6.94% error. Regarding the difference between the minimum and peak values, the estimated difference was 7317 kN, while the test deviation of compression capacity was 7799 kN. This means that ANN model ANN_{10} anticipated the deviation between the minimum and peak values of compression capacity with only a 6.18% inconsistency.

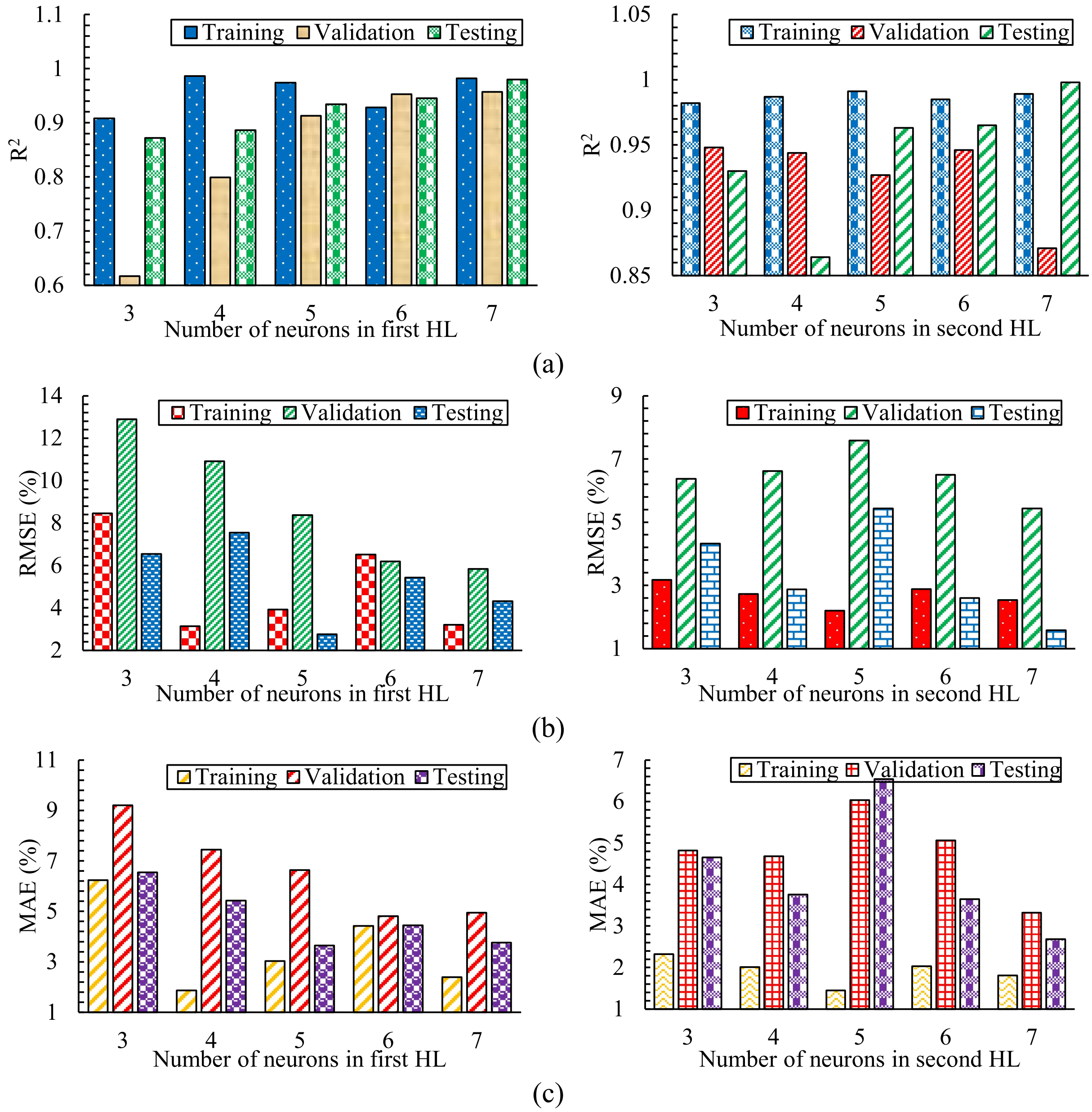

Figure 2: Statistical indices for the ANN models for R^2, RMSE, and MAE, respectively

2.3 Predictions of ANN Models

Figure 3 presents the efficiency of numerous proposed ANN models against the axial compression capacity of CCFST columns taken from the database. ANN_{10} model having $R^2 = 0.998$, $RMSE = 1.58$, and $MAE = 2.68$, and mean square error (MSE) = 1.47 presented the peak accuracy for the axial compression strength of CCFST columns. The values for the statistical indices (R^2, $RMSE$, MAE, MSE) are presented in Figure 4 for various proposed ANN models for capturing the compression strength of CCFST columns. The model representing the peak values of R^2 and the minimum values for the errors ($RMSE$, MAE, MSE) will be the optimized model. Therefore, the model ANN_{10} is the most accurate model with 7 neurons in the 1st and 2nd layer reporting the reduced statistical errors ($RMSE$ = 1.58, MAE = 2.68, and MSE = 1.47) and improved R^2 = 0.998. Thus, this model has been chosen as the final for capturing the compression capacity of CCFST compressive members. The ANN model, featuring a configuration with 7 neurons in its layers, stands out as the optimal choice. This selection is predicated on its ability to minimize both time consumption and computational effort, rendering it scientifically advantageous for the research community. The strategic use of a compact neural network architecture, characterized by a modest number of neurons, not only expedites the model training process but also ensures efficient use of computational resources. This streamlined approach aligns with the requirements of scientific research, where the expeditious execution of experiments and analyses is important. By striking a balance between model complexity and computational efficiency, the ANN with 7 neurons emerges as a judicious and effective solution, poised to enhance the productivity and feasibility of research endeavours in different multidisciplinary domains.

Table 2: Statistical information of different ANN models for compression capacity of CCFST compressive members

Parameters	Maximum	Minimum	Difference	Average	COV	St. Dev
Test results	3043	1090	1952	1829	0.28	500
ANN_1	3096	1126	1969	1816	0.28	508
ANN_2	3146	987	2158	1813	0.29	510
ANN_3	3132	1031	2101	1820	0.29	510
ANN_4	3103	1046	2057	1808	0.29	507
ANN_5	3140	1011	2128	1813	0.28	507
ANN_6	3009	1144	1865	1812	0.28	502
ANN_7	3050	1104	1946	1809	0.29	508
ANN_8	2950	1069	1881	1813	0.29	515
ANN_9	3104	1063	2041	1816	0.28	501
ANN_{10}	3118	1176	1941	1819	0.28	493

3 PRACTICAL IMPLEMENTATION

ANN modeling is pivotal for optimizing CFST column design, known for its strength and resistance to lateral loads. ANNs play an important role significantly in design optimization, performance prediction, nonlinear analysis, and material property estimation for these columns. By discerning complex relationships among design parameters, ANNs streamline the design process, providing configurations that meet performance criteria and improve efficiency. These models predict CFST column performance under various conditions, helping in pre-construction assessments, compliance with safety standards, and design refinement. ANNs also model nonlinear behavior, precisely forecasting post-yield outcomes, ultimate capacity, and failure mechanisms, leading to more resilient designs. Furthermore, they help in estimating material properties vital for precise structural analysis, ensuring CFST columns meet desired performance criteria.

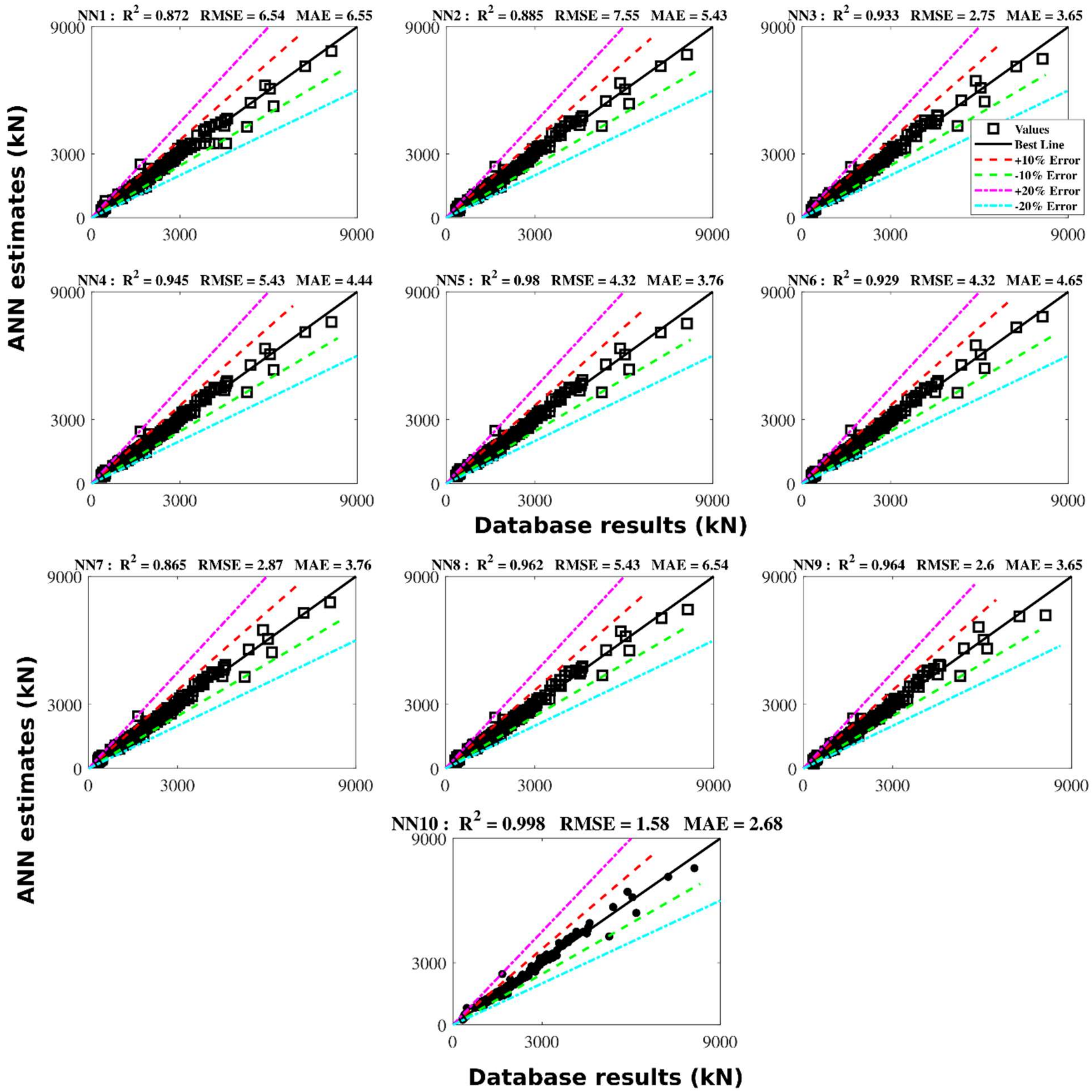

Figure 3: Efficiency of various ANN models for the database

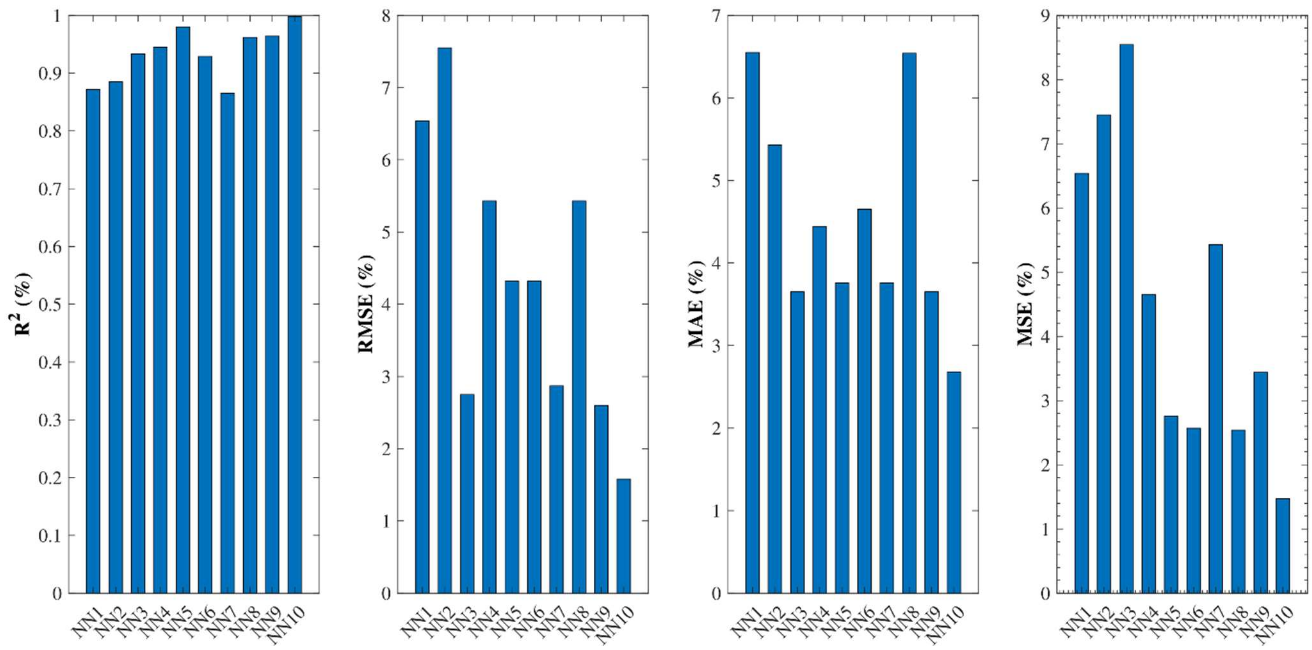

Figure 4: Statistical indices for various ANN models

4 CONCLUSION

This study aims to predict the axial compression capacity of carbon fiber-reinforced polymer-wrapped concrete-filled steel tube compressive members using an artificial neural network model. The present study concludes with the following main findings:

1. The currently proposed ANN model explicitly considers the confining action of steel tubes and CFRP wraps to predict accurately the axial compression capacity of CCFST columns. The assessment of the estimations of the ANN model with the test results of CCFST compressive members sturdily authenticated their precision.

2. Ten discrete ANN models are recommended in the present research by varying the number of layers and neurons. The optimized ANN model (ANN_{10}) with seven neurons in the 1st and 7 neurons in the 2nd layer portrayed the peak precision with $R^2 = 0.872$, $RMSE = 6.54$, and $MAE = 6.55$.
3. The comparison between the estimations of the ANN model and database results determined that the suggested ANN model described higher correctness. The estimates of ANN models showed their relationship with the database results portraying $R^2 = 0.998$. Therefore, the suggested ANN model is competent for forecasting the axial compression capacity of CCFST columns.

The proposed ANN model will be helpful for the practitioners while analyzing and designing the CFST columns under different complex loading mechanisms. Furthermore, the current study will pave way to further research on the effect of path dependance of stress-strain behavior of CFST columns for the better and accurate simulations of CFST columns.

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