Application of Artificial Neural Networks for Predicting Axial Strain of FRP-Confined Concrete

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Abstract: Multiple research studies have developed frameworks to forecast the ability of concrete structural elements to withstand compression along their length. However, further exploration is required to refine predictions for the axial compressive strain, as existing strain models lack precision. The earlier models were created with restricted and noisy data sets and basic modelling methods, underscoring the necessity for a more meticulous approach to introduce a more accurate strain model and to evaluate its forecasts against those of current models.This study wants to fill in the gap by creating models for how much concrete reinforced with fiber-reinforced polymer (FRP) can stretch using computer simulations called artificial neural networks (ANN). This approach is based on a substantial database comprising 570 sample points. The comprehensive investigation of these estimates robustly validates the accuracy and practicality of the suggested ANN models for predicting the axial strain of FRP -confined concrete compression members.

Keywords: fiber reinforced polymer (FRP); confined concrete; artificial neural networks; strain model

1. INTRODUCTION

The crucial cause for the attraction of fiber reinforced polymers (FRPs) usage is to enhance the axial strength and axial strain of concrete column. In addition, FRP is frequently used to improve the flexural strength of structural components [1]. Other usages of FRPs is the strengthening, repairing and enhancement of the ductility of reinforced concrete columns in the corrosive and aggressive environments [2]. The FRP composites are durable,

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lightweight, corrosion-resistant, electromagnetic resistant, chemical resistant, and have high tensile strengths [3-8]. The FRPs are the most suitable materials to be used in the marine structures and the coastal environments due to their high corrosion resistance property [9]. These composites are very efficient in providing the confinement mechanism. The confinement mechanism depends upon their thickness, elastic modulus, the number of wraps, strength of confined material and the angle of orientation wrap to the structural element [10]. The lateral confining impact of structural concrete with the FRPs has become an advanced and the most popular technology to enhance the efficiency and strength [11]. The FRPs are being favored over steel jackets due to the advantages of easy installation, easy handling, slight disturbance of the structural elements, and reduced construction time [12].

In various structural engineering problems, the applications of artificial neural networks (ANNs) are increasing [13]. Using ANNs, the complex interaction mechanisms between various variables and their behaviors can be determined without knowing the nature of the interactions. The compressive strength of confined plastic concrete can be accurately predicted by the ANNs [14]. Reddy [15] and Khademi et al. [16] predicted the axial compression strength of FRP -confined concrete members using ANNs technique. The influence of carbon fiber reinforced polymer (CFRP) wraps was examined on the compressive, flexure and tensile strength of concrete members and a close approximation was noted between the experimental and theoretical results [17, 18].

The present work endeavors to explore the FRP confinement mechanism of concrete and proposes new models to estimate the axial compressive strains of such members using a large database of 570 experimental sample points. A novel technique, i.e., ANN was used to propose the strain models. The previous models for the axial strains of fiber-reinforced polymer confined concrete were examined using constructed database. Finally, a comprehensive comparative analysis was carried out between the estimates of ANN models. The newly developed models based on the large database precisely simulate the axial compression strains of FRP confined concrete compression elements that will assist the construction industry to analyze and design similar elements.

2. ARTIFICIAL NEURAL NETWORKS

Inspired by biological neural networks, artificial neural networks (ANNs) mimic the structure and function of the human nervous system and brain [19]. ANNs are capable of effectively analyzing complex relationships among different parameters, even when these relationships are not clearly understood. The processes of learning, classification, and generalization employed by ANNs enable them to estimate final outcomes [20].

ANNs achieve this by leveraging their ability to minimize computational costs. During the training procedure, ANNs save computed results in associated memory, which helps streamline tasks. Comprising multiple hidden layers, ANNs define the complexity of linkages among these hidden "neurons." Each link between two neurons is assigned a specific weight, which is multiplied by the neurons' estimates. These products undergo a conversion process via the connections and added to a bias, illustrated in Fig. 1. The resulting summation is passed through an activation function that represents the interrelationship of various hidden layers, as shown in Equation (1).

$$O = f(\sum x_i w_i + b) \quad (1)$$

In this equation, 'O' designates the output given by the ANNs, x_i is the input value, w_i is the coefficient of weight, and b depicts the added bias value.

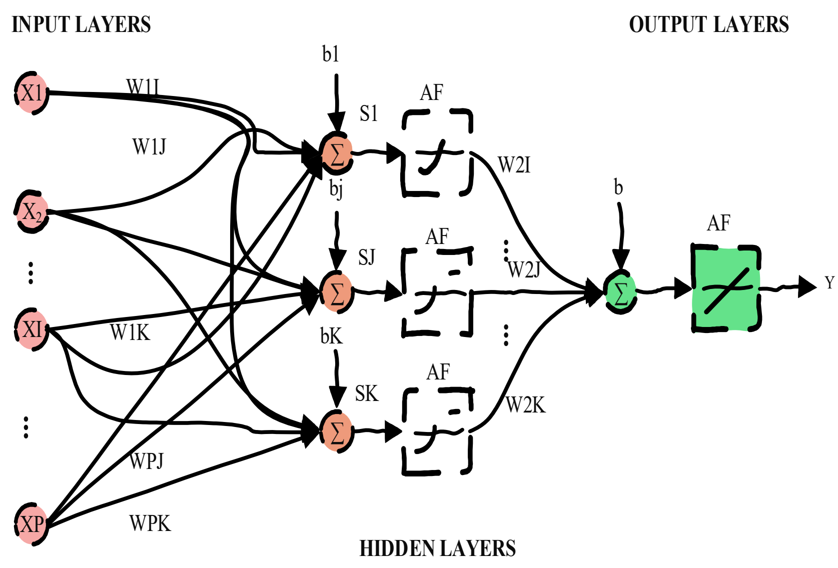

Fig. 1. Typical structure of ANNs (X1,X2,XP:Input parameter, W1I,W1J,W1k,WPJ,WPK:Weights, b1,bj,bK:Biase, S1,SJ,SK:Weights in second layer, AF:Activation Function, W2I,W2J,W2J:Weights between output layers, b:Biase, Y:Output)

As presented in Figure 1, the input values for the neurons of subsequent layers are sourced from the outcomes. At the start, some random weights are assigned and then, the actual weights are attained from the process of validation. In the current work, the axial compression strain of FRP confined concrete was predicted using the ANNs for which the multilayer feed-forward neural networks (MLFNNs) are considered to be the utmost relevant [21, 22]. These networks consist of input, output, and various hidden layers. The hidden layers are defined by the structure of ANNs during the training process. The ANNs consist of a predefined activation function affecting the performance of outputs. The indications produced by the neurons proceed to the right-hand side via the path as defined in Figure 2. Two different types of functions, i.e., logistic as well as hyperbolic were used between the input and hidden layers and hyperbolic functions were used between the hidden layers and output layers. The discrepancies produced during this process were measured using Eq. (2).

$$E(w) = \frac{1}{2} \sum_i [T - O]^2 \tag{2}$$

In this equation, *T* is the value of the defined target and *O* is the value of the required output given by the ANNs. The discrepancies attained from Eq. (2) were minimized using the DETA RULE [23]. Such an iterated search procedure is performed in reverse, specifically from right to left of the NN as presented in Fig. 2. The procedure primarily aimed to modify different randomly chosen initial weights to conform the outcomes with desired targeted outputs of the database. This iteration continued until no further enhancement in mean squared error (MSE) value was observed. For more reliable results, the ANN approach utilized the adjusted weights with negligible errors.

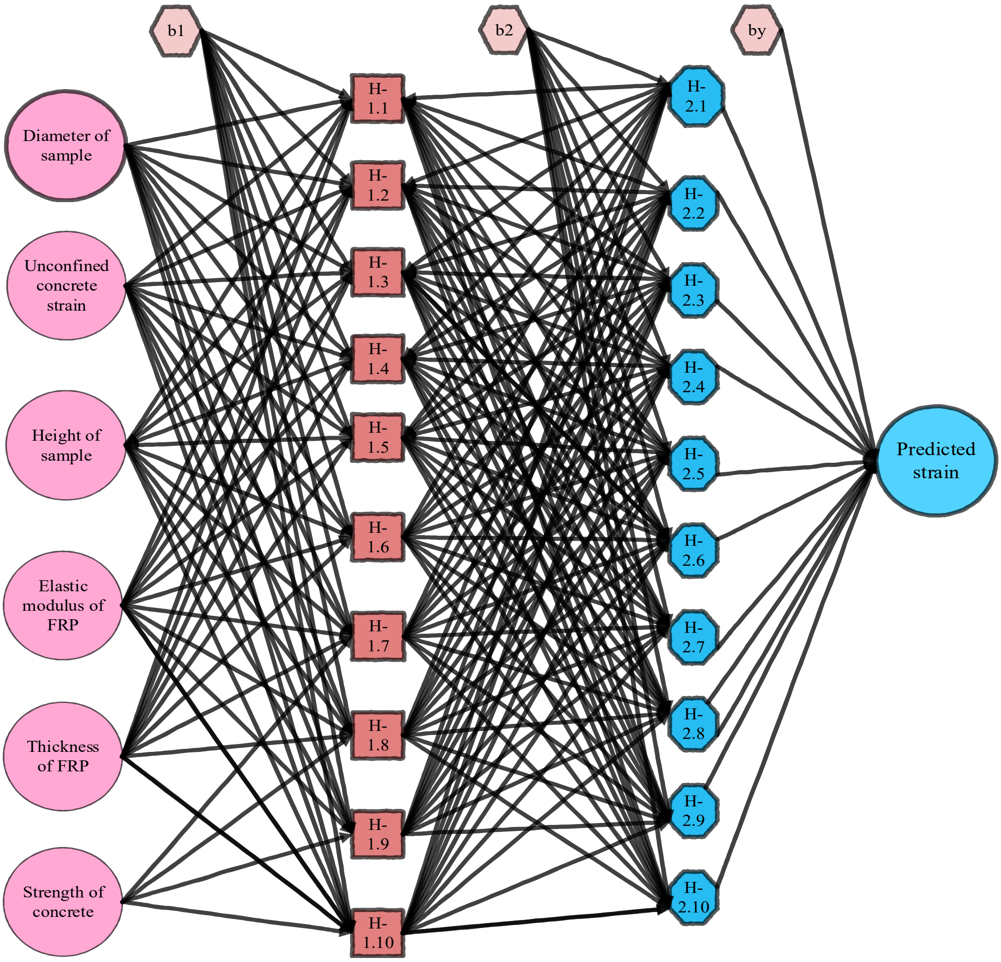

Fig. 2. ANN model used in the present work (H-1.1: First neuron in 1st hidden layer, H-1.10: First neuron in 10th hidden layer, H-2.1: 1st neuron in 2nd layer, H-2.10 10th neuron in 2nd layer, b1, b2, by: Biase)

2.1 Development of Database

A large database of 570 sample points was constructed from previously published studies. All the parameters that can affect the axial compressive strain of FRP confined concrete compression elements were added to the database. A few sample points presented poor predictions for the test results using the previous strain models. Thus, those sample points were removed from the database so that the saturation of root mean square error (RMSE) could be avoided. The statistical information of all the parameters (height H, and diameter D) included in the database was given in Table 1.

Table 1. The statistical details of the database

Parameter	Unit	Min.	Max.	Diff.	Avg.	St. Deviation	COV
D	(mm)	51.00	406	154.17	41.98	41.98	0.28
H	(mm)	102.0	812	308.0	84.46	84.46	0.28
nt	(mm)	0.09	5.90	0.89	1.060	1.06	1.20
E_f	MPa	10.00	663	163.08	121.33	121.33	0.75
f'_{co}	MPa	12.41	188.2	45.98	23.26	0.51	12.41
ε_{co}	(%)	0.17	1.53	0.27	0.150	23.24	0.51
ε_{cc}	(%)	0.33	4.62	1.40	0.650	34.83	0.47

2.2 Architecture of ANN

For each layer, there were selected activation functions (AF) between the input layer (IL) and the hidden layer (HL), the total neurons available in every layer, along with the activation functions between the output layer (OL) and hidden layers. The construction of ANNs is governed by the problem in hand and automatically selected by hit and trial method. All the architectures of the ANNs adopted in current study were presented in Table 2. Six artificial neural network (ANN) models were created, each varying in the number of activation functions, hidden layers, and neurons.

Table 2. The design of various ANN models in the present study

Models	**Inputs**	**AF between IL and HL**	**No. of neurons in HL**	**AF between HL and OL**	**Output**
ANN_1	d, h, t, E_f, ε_{co}	Sigmoid	5	Tanh	ε_{cc}
ANN_2	d, h, t, E_f, ε_{co}	Sigmoid	10	Tanh	ε_{cc}
ANN_3	d, h, t, E_f, ε_{co}	Sigmoid	5-5	Tanh	ε_{cc}
ANN_4	d, h, t, E_f, ε_{co}	Sigmoid	10-10	Tanh	ε_{cc}
ANN_5	d, h, t, E_f, ε_{co}	Sigmoid	5-5-5	Tanh	ε_{cc}
ANN_6	d, h, t, E_f, ε_{co}	Sigmoid	10-10-10	Tanh	ε_{cc}

2.3 Normalization of Constructed Database

The ANNs are significantly affected by the normalization of the developed database. The procedure regulates all the variables by making them unit less despite numerous units for the added input variables. To minimize the concerns of the reduced rate of learning of the ANNs, all the added variables should be normalized by re-assigning the most appropriate highest values [23]. In the current work, all the input parameters were normalized by using Eq. (3) between 0.8 and 0.2 instead of 1 and 0.

$$X = [0.9 - (0.6/\Delta)x_{max} + (0.6/\Delta)x] \tag{3}$$

where x is the experimental value of the input parameter, X is the value of the input parameter obtained after normalization, Δ designates the difference between x and X, and x_{max} is the highest value of the input parameter.

2.4 Calibration of Proposed ANN Model

Established ANN models must be calibrated by the experimental outcomes to simulate the most accurate results. The adopted ANN model employed both the (MLFFBP) procedure [23] and using test results to fine-tune the proposed model. For better results, and to minimize over-fitting, the entire data was classified into three groups: one to validate, the other to train, and the last to test. The ANN modelling was carried out in MATLAB [24]. The model utilized almost 60% of sampling data for training purposes, 20% for validation while, remaining 20% were employed for the testing. Each ANN model was trained with 100 sessions, where the MLFFBP process ran until meeting one of three conditions: (i) during the validation phase of iteration, there were 20 instances of failure, (ii) the performance target becoming equivalent to the discrepancy of output and target value, i.e. 0.0001 (iii) The least performance gradient being equivalent to 10^{-10}. The built ANN considers both the highest correlation factor (R) and the mean squared error (MSE) between the output and target. Furthermore, the ANN models were assessed by using R, mean absolute error (MAE), and MSE given by Eq. (4), Eq. (5) and Eq. (6), respectively[25-27]. Table 3 presents predictions and their statistical details of all ANN models.

Table 3. The values of $\varepsilon_{cc}/\varepsilon_{co}$ for various ANN models

Model	Min.	Max.	Diff.	Avg.	St. Deviation	COV
Exp $\varepsilon_{cc}/\varepsilon_{co}$	1.375	17.2727	15.8977	5.56	2.73	0.49
ANN_1	1.223	13.5319	12.3087	5.48	2.08	0.38
ANN_2	1.650	14.3371	12.6871	5.58	2.07	0.37
ANN_3	0.469	12.2890	11.8197	3.70	2.08	0.56
ANN_4	0.171	16.0476	15.8762	5.58	2.50	0.45
ANN_5	1.411	14.1429	12.7323	5.58	2.13	0.38
ANN_6	-0.818	14.6667	15.4848	5.59	2.38	0.43

Here, n depicts the total sample points, T_i is testing value obtained from experiments, O_i is the value predicted by the ANN models, $\bar{T} = \sum_1^n T_i/n$ is the average value of T_i, and $\bar{O} = \sum_1^n O_i/n$ is the average value of O_i. The statistical details of the estimates of the established six ANN models and the experimental measurements were presented in Table 3. Moreover, the predictions and performances of ANN models for $\varepsilon_{cc}/\varepsilon_{co}$ were presented in Figure 3 and the statistical error functions (MSE, MAE, and R) of the predictions of ANN models were presented in Figure 4. That ANN model was selected to be the most optimal model which presented the minimum values of R, MSE and MAE [21, 22]. The ANN_4 portrayed a value of 85% for R, 4.62% for MAE and 0.42% for MSE which were the best predictions. Therefore, ANN_4 was selected as the most reliable ANN model to estimate axial compression strain of FRP-confined concrete elements subjected to compression loadings.

$$R = \frac{\sum_{i=1}^{n} (T_i - \bar{T})(O_i - \bar{O})}{\sum_{1}^{n}(T_i - \bar{T})^2 \sum_{1}^{n}(O_i - \bar{O})^2} \tag{4}$$

$$MAE = \frac{\sum_{i=1}^{n}|T_i - O_i|}{n} \tag{5}$$

$$MSE = \frac{\sum_{i=1}^{n}({T_i}^2 - {O_i}^2)}{n} \tag{6}$$

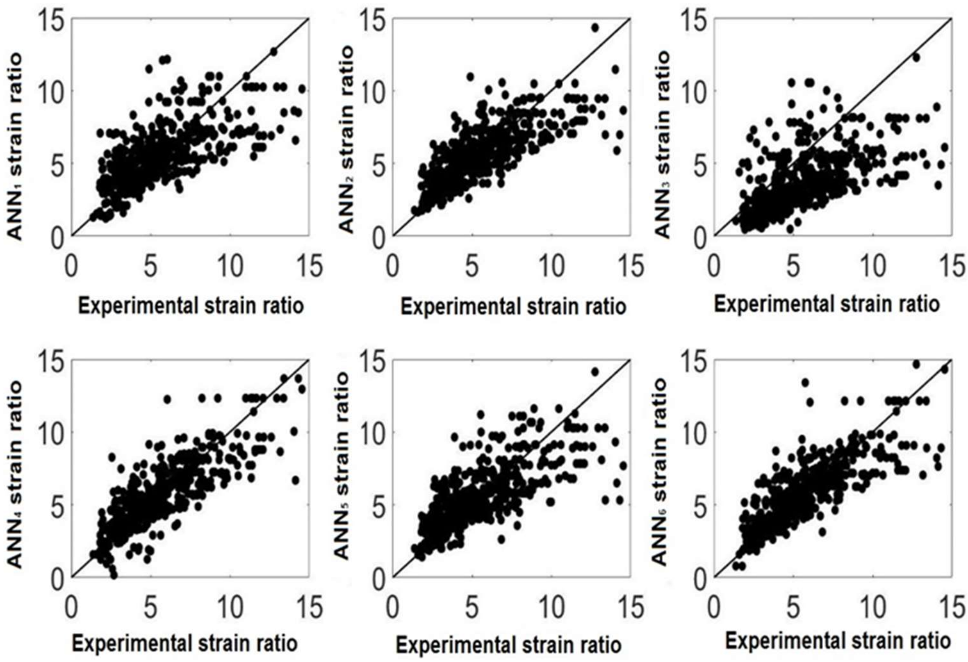

Fig. 3. Predictions of proposed six ANN models

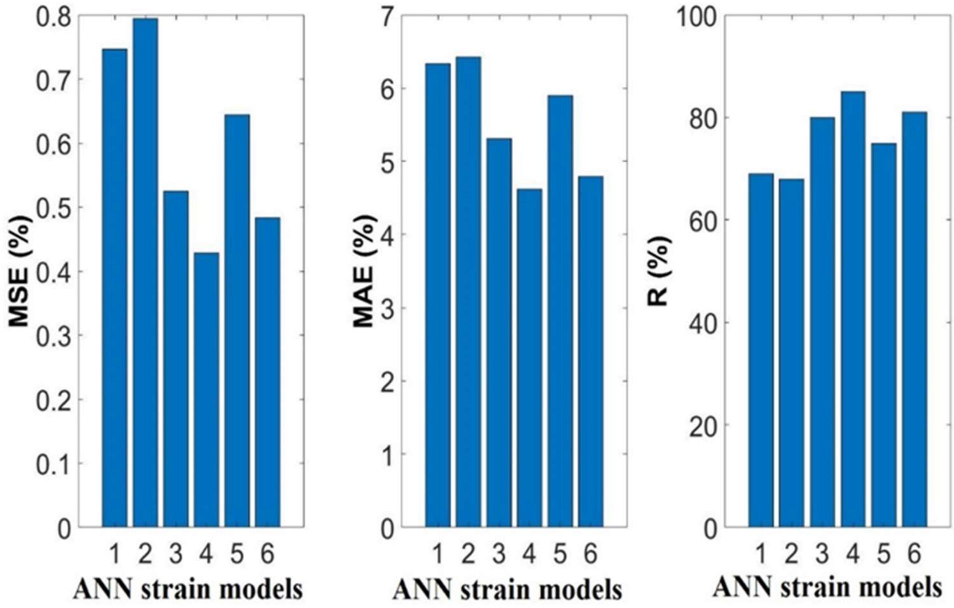

Fig. 4. Statistical error variables presented by proposed ANN models

3. CONCLUSION

The current work performs a reliability analysis of the strain models proposed using artificial neural networks with a large database of 570 testing results. The accuracy of the newly developed ANN model was superior to the previously suggested models with RMSE of 1.42 and R^2 of 0.85. Thus, these statistical parameters substantiate the superiority of newly developed strain model over the previous models.

4. ACKNOWLEDGEMENTS

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