GFRP wrapped concrete column compressive strength prediction through neural network

P. Sangeetha¹ · M. Shanmugapriya²

Received: 4 February 2020 / Accepted: 23 October 2020 / Published online: 20 November 2020
© Springer Nature Switzerland AG 2020

Abstract

Wrapping of fibre over the concrete columns significantly improves the compressive strength and ductility behaviour of columns. In this study the compressive strength of the Glass Fibre Reinforced Concrete (GFRP) wrapped concrete columns were studied under axial compression. The parameters varied are types of GFRP (Surface Mat, Chopped Strand Mat and Woven Roving Mat), number of plies (0, 1 ply and 3 plies) and period of curing (7, 14 and 28 days). Twenty-one standard cylindrical specimens were tested to failure under compression testing machine. The GFRP confined concrete columns increases the compressive strength by 30% for different types of fibres. The change in the number of plies from one to three improves the strength six times. The Artificial Neural Network (ANN) is an alternate tool used to accurately estimate the confined strength of the wrapped columns. The multi-layer neural network has been used with back propagation training algorithm. The predicted strength was compared with the experimental results. A good correlation was obtained between the predicted strength by ANN model and experimental values with correlation coefficient R values of 0.992, 0.999 and 0.999 for training, validation and testing data sets.

Keywords GFRP · Number of plies · Period of curing · Compressive strength · ANN

1 Introduction

Confined of concrete columns using FRP sheet and steel jacketing are the efficient techniques to increase the strength and retrofitting of structures. Many researchers carried out experimental investigation to study the structural behaviour of the confined columns under axial compression [1], wrapped columns under eccentric loading [2], stiffened concrete filled steel column [3] and rectangular columns with composites [4] and concluded that wrapping improves the overall behaviour of the confined columns. The application of ANN in the civil engineering field are enormous and becoming popular. Many researchers reported that prediction of material properties using ANN tool are effective and accurate. The compressive strength

of concrete in existing structures was predicted using ANN model against the published experimental results of non-destructive testing [5]. The prediction of the compressive strength of the hydraulic lime mortar for three different mixes using soft computing techniques and stated that ANNs can predict the strength in a satisfactory manner [6]. ANN prediction of shear strength of concrete beam [7], gives confidence in using ANN tools to predict shear strength of properties of the concrete structures.

The prediction of FRP—confined compressive strength of the concrete using artificial neural network with experimental data and its comparison shows good agreement [8]. The prediction of various strength parameters such as confined compressive strength and crushing strain of FRP wrapped concrete specimens using regression and ANN

✉ P. Sangeetha, sangeethap@ssn.edu.in; M. Shanmugapriya, shanmugapriyam@ssn.edu.in | ¹Department of Civil Engineering, Sri Sivasubramaniya Nadar College of Engineering, Chennai 603 110, India. ²Department of Mathematics, Sri Sivasubramaniya Nadar College of Engineering, Chennai 603 110, India.

model found more accurate and precise [9]. The analytical behaviour of FRP wrapped concrete columns carried by researchers using ANSYS and ANN for varying parameters like shape of the column, type of fiber, number of plies, corner radius and concrete strength with the use of available published experimental results and the predicted values found effective [10, 11]. The study on wrapping of the concrete columns with different GFRP sheets tested under axial compression and concluded that confined compressive strength increases with the increases in number of ply and period of curing [12]. Ninety-five experimental data used to predict FRP-confined circular reinforced concrete columns using soft computing methods and among the many methods, the ANN model showed the highest accuracy [13]. A sensitivity analysis based on Garson's algorithm generated by author for indicating the value of each used variable for predicting the compressive strength of the confined rectangular column [14]. Literature [8] stated the application of neural network in concrete structures and in the field of civil engineering. The proposed NN model are compared with ten different theoretical models proposed by researchers [15] so far and are found to be by far more accurate. Using the ANN model and based on the results of the 2000 experiment, predictive formulas for shear strength of slender FRP-reinforced concrete beam without stirrups were developed for practical application [16]. Author proposed the approach with existing empirical formula and results exhibits a very good precision of the developed artificial intelligence-based model in predicting the lateral confinement coefficient in CFRP wrapped RC columns [17]. The bond strength prediction of GFRP-bar reinforced concrete using ANN and genetic algorithm [18, 19] and fatigue behaviour of GFRP laminates [20], shear strength prediction of FRP reinforced concrete beam [21], optimise the cutting parameters of GFRP composites [22, 23], etc., all the literatures stated that prediction using ANN model found to be satisfactory.

1.1 Research significance

From the previous research, it clear that doing experimental testing to know the properties of materials which involves cost and time, and to predict the life of the existing structures using some non-destructive techniques which gives widely varied output and uneconomical. Prediction of the strength and behaviour of the structures using soft computing tool is feasible and viable. Now-a-days retrofitting and rehabilitation of the existing structures using various techniques like steel jacketing, fibre wrapping, etc., are challenging. The fibre wrapping techniques not only enhance the strength but also has good resistance to earthquake loading. Very few researches in the fibre wrapped concrete with ANN was carried out in

the past 10 years. In this paper, strength enhancement of the twenty-one concrete stub columns wrapped using GFRP sheets, studied experimentally with varying parameters and prediction of the compressive strength using ANN tool are presented. The effect of GFRP fibre on the concrete columns under axial compression for three different types of GFRP sheets of zero, one and three numbers of plies used as input to predict the confined compression strength of the wrapped concrete using Artificial Neural Network. The ANN model used in this study are shown in Fig. 1 and to prove higher accuracy and good agreement with the experimental results were obtained.

2 Materials and methods

2.1 Specimen details and testing

Totally twenty one concrete cylinder of diameter 150 mm and height 300 mm were made using M25 grade and specimens were under curing for 7, 14 and 28 days. All

Fig. 1 Flow chart for the ANN prediction

the specimens were wrapped with GFRP sheets of type Surface Mat, Chopped Strand Mat and Woven Roving Mat with varying the number of wraps. The naming of the specimens was made as Unconfined Cylinder as UC, Surface Mat wrapped Cylinder as SMC, Chopped Strand Mat wrapped Cylinder as CSMC and Woven Roving Mat Cylinder as WRMC. Figure 2 shows the concrete cylindrical specimens after GFRP wrapping. Wrapped specimens were subjected to compression under the compression testing machine of capacity 200 Tons. The specimens after failure were shown in Fig. 3.

2.2 Artificial neural network approach

ANN is a mathematical algorithm developed using the neuro-computing technique. The neural network gains knowledge through learning process and stored within inter neuron connection strengths called synaptic weights. The multilayer feedforward neural network with backpropagation training algorithm has been used. The multilayer perception comprises an input layer, an output layer and a hidden layer. The feedforward neural network passes the data from the input layer. The input layer provides information from outside environment and passes it on to the hidden layer where the information is processed by summing up together with bias term and transfers the results to the output layer as given in Eq. (1)

Fig. 3 FRP wrapped specimens after failure

$$y = f\left(\sum_{i=0}^n x_i w_i - b\right) \quad (1)$$

where f is a nonlinear and is the activation function, x_i and w_i are the i th input neuron and the corresponding weight, n is the number of neurons, b is the bias term and y is the output. The most common nonlinearity function is the sigmoid function, and is expressed as in Eq. (2)

Fig. 2 Cylindrical specimens with FRP wrapping. (a) Surface Mat. (b) Chopped Strand Mat. (c) Woven Roving Mat

(a) Surface Mat

(b) Chopped Strand Mat

(c) Woven Roving Mat

$$f(t) = \frac{1}{1 + e^{-\sigma t}} \quad \text{where } t = \left(\sum_{i=0}^n x_i w_i - b \right) \quad (2)$$

where σ is a constant to manage the gradient of the semi-linear region. The backpropagation training algorithm train the neural network, evaluate the error, update the weights and bias values and the training process continues till the errors are minimized.

2.2.1 Description of data

FRP confined concrete is a nonlinear complex problem since it depends on many variables and that can be easily analysed using ANN. The parameters such as diameter (d) in mm and height (h) in mm of the cylindrical specimen, types of the FRP material (SM, CSM and WRM), number of ply (0, 1 and 3), period of curing (7, 14 and 28 days) were used as input nodes and also one target node was the compressive strength of confined concrete column in the ANN model. Figure 4 shows the schematic diagram of ANN model.

3 Result and discussion

From the experimental study it is observed that the GFRP wrapped concrete gives the compressive strength three times more than that of the concrete columns without wrapping. The GFRP has significantly enhanced the strength by perfect adhesive bond between concrete and the wrapping material. Moreover, care was taken during wrapping to make sure that fibers remain in hoop direction so that it can give proper confinement effects at the time of loading. The overlapping length of 100 mm of the GFRP sheets over the concrete specimen improves the strength significantly. From Fig. 3 it is clear that wrapping of fibre sheet not only increase the strength but also delays the formation of cracks in the cylinder. Confined concrete fails after the formation of multiple cracking and finally crushing of concrete were able to observe.

Curing of concrete is also play an important role to improve the strength of the FRP wrapped concrete. The effect of curing of concrete on to the compressive strength of the single ply and three plies confined concrete were made. Figure 5 shows the bar chart comparison between the strength and GFRP sheet for various curing period. The percentage increase in compressive strength for the specimen UC is 11% and 25% for change of curing period from 7 to 14 days and 7 to 28 days respectively. Similarly, the overall percentage increase in the strength for SMC, CSMC and

Fig. 4 Diagram of ANN model

Fig. 5 Comparison between the compressive strength of the wrapped columns with 1 and 3 plies

WRMC are 33%, 31% and 27% respectively for change in curing period from 7 to 28 days. The change in number of plies from 1 to 3 increases the compressive strength of cylinder by

38%, 73% and 90% for SM, CSM and WRM respectively. The strength attained by the cylinder with woven roving mat is 2.5 times more when compared to Chopped strand mat and surface mat. Figure 6 shows the error bar for the compressive strength of all specimens.

The prediction of confined compressive strength of the cylinder were made using ANN model and shows the satisfactory prediction with the available experimental strength. The validity of the constructed ANN models was compared with various types of errors such as Average Absolute Error (AAE), Variance Accounted For (VAF), Mean Square Error (MSE), Mean Absolute Error (MAE) and Sum Square Error (SSE) given by Eqs. (3)–(7). The coefficient of determination R^2 in Eq. (8), of the linear regression line between the predicted values from the ANN model and the desired output was also used as a measure of performance. The values of R for training, validation and testing stages are 0.992, 0.999 and 0.999 which are very close to one. The results are more accurate and also within the acceptable limit.

$$AAE = \frac{1}{N} \sum_{i=1}^N |M_i^{Exp} - M_i^{ANN}| \quad (3)$$

$$VAF = 100 \left[1 - \frac{\text{var}(M_i^{Exp} - M_i^{ANN})}{M_i^{Exp}} \right] \quad (4)$$

Fig. 6 Error bar for the compressive strength of the specimens

$$MSE = \frac{\sqrt{\sum_{i=1}^N (M_i^{Exp} - M_i^{ANN})^2}}{M_i^{Exp}} \quad (5)$$

$$MAE = \sum_{i=1}^N (M_i^{Exp} - M_i^{ANN}) \quad (6)$$

$$SSE = \frac{\sqrt{\sum_{i=1}^N (M_i^{Exp} - M_i^{ANN})^2}}{N - 1} \quad (7)$$

$$R^2 = \frac{\sum_{i=1}^N (M_i^{Exp} - \bar{M})^2 - \sum_{i=1}^N (M_i^{Exp} - M_i^{ANN})^2}{(\sum_{i=1}^N (M_i^{Exp} - \bar{M})^2)} \quad (8)$$

where N for number of experimental data, M_i^{Exp} for the experimental data dedicated to maximum stress and number of cycles, M_i^{ANN} for predicted value by ANN model and $\bar{M}$ is the mean values of maximum stress and number of cycles.

Figure 7 shows the mean squared error for networks with different number of hidden neurons. It was found that the mean square error was very low for a hidden layer of seven neurons and hence the network was fixed with single hidden layer and seven hidden neurons.

Figure 8 shows the training state of the ANN model and figure gives errors are repeated six times after 5 epochs and the test is stopped at epoch 11.

Figure 9 shows the learning behaviour of ANN model and its mean square error of the network which starts at the large value and get reduces to smaller value at 11 epochs. The three colour line in the plot represents steps of training, validation and test of the ANN model for GFRP

Fig. 7 Mean squared error vs number of hidden layer neurons

Fig. 8 Learning behaviour of ANN model of GFRP confined concrete

Fig. 9 Validation performance in ANN model for GFRP confined concrete

Fig. 10 Error histogram for training, validation and test in ANN model of GFRP confined concrete

Fig. 11 Comparison between the experiment and predicted strength for training set for ANN model for GFRP confined concrete

wrapped concrete specimens. Training until the training vector reduces to zero error and it is also seen that best validation is occurred at epoch 5, the process stopped at epoch 11.

The error histogram for the training, validation and test of the ANN modeling are shown in Fig. 10. The yellow line in Fig. 9 represents the zero error with eight instances in the training set of the ANN model.

Figures 11 and 12 shows the comparison between the experimental and predicted strength of GFRP wrapped concrete specimens for training and validation steps obtained using MATLAB software respectively. Table 1 gives the confined strength of GFRP wrapped concrete specimens for the both experimental and predicted

values and its comparison. The errors such as AAE, VAF, MSE, MAE and SSE was also calculated using Eqs. (3)–(7) and listed in Table 1.

Using the proposed ANN model, the prediction of the compressive strength of the FRP wrapped concrete column against the published experimental strength of 64 specimens [11] was carried out. After comparison between the results, it was found that the error was less than 4% and shows good agreement with the published experimental results. Table 2 shows the experimental, analytical and ANN prediction of the compressive strength of FRP wrapped concrete columns with varying shape, types of fiber, number of plies, strength of concrete and corner radius of the concrete column.

Fig. 12 Comparison between the experiment and predicted strength for validation set for ANN model for GFRP confined concrete

Table 1 Compression between the experimental and predicted strength of GFRP wrapped concrete columns

Sl. no.	Specimen	D (mm)	H (mm)	Period of curing (days)	No of plies	Experiment strength (MPa)	Predicted strength (MPa)	MAE	AAE	VAF	MSE	SSE
1	UC	150	300	7	0	15.84	18.35328	-2.51328	0.11968	90.03065600	0.10084140	0.1256640
2		150	300	14	0	17.52	17.70463	-0.18463	0.008791905	99.95135811	0.024525453	0.0092315
3		150	300	28	0	19.81	19.00946	0.80054	0.038120952	99.19123638	0.045165523	0.0400270
4	SMC	150	300	7	1	16.41	16.77905	-0.36905	0.017573810	99.79250777	0.037019796	0.0184525
5		150	300	14	1	18.68	20.28139	-1.60139	0.076256667	96.56792033	0.067744132	0.0800695
6		150	300	28	1	21.78	21.88661	-0.10661	0.005076667	99.98695398	0.014991362	0.0053305
7		150	300	7	3	23.76	24.87926	-1.11926	0.053298095	98.68187821	0.044526551	0.0559630
8		150	300	14	3	25.23	26.20321	-0.97321	0.046343333	99.06149653	0.039100835	0.0486605
9		150	300	28	3	28.86	30.71433	-1.85433	0.088301429	97.02136196	0.047184264	0.0927165
10	CSMC	150	300	7	1	19.24	20.35974	-1.11974	0.053320952	98.37081904	0.054998840	0.0559870
11		150	300	14	1	22.72	22.92440	-0.20440	0.009733333	99.95402799	0.019899040	0.0102200
12		150	300	28	1	25.18	25.61705	-0.43705	0.020811905	99.81035276	0.026254868	0.0218525
13		150	300	7	3	37.35	37.59493	-0.24493	0.011663333	99.95984558	0.013250443	0.0122465
14		150	300	14	3	38.21	38.10746	0.10254	0.004882857	99.99312062	0.008380494	0.0051270
15		150	300	28	3	39.61	38.73242	0.87758	0.041789524	99.51391905	0.023650401	0.0438790
16	WRMC	150	300	7	1	20.43	20.47232	-0.04232	0.002015238	99.99780839	0.010069420	0.0021160
17		150	300	14	1	23.13	22.83141	0.29859	0.014218571	99.90363598	0.023624466	0.0149295
18		150	300	28	1	26.03	25.65670	0.37330	0.017776190	99.86616127	0.023472256	0.0186650
19		150	300	7	3	42.44	42.34924	0.09076	0.004321905	99.99514763	0.007098586	0.0045380
20		150	300	14	3	43.75	43.24729	0.50271	0.023938571	99.85559009	0.016206182	0.0251355
21		150	300	28	3	45.27	44.74787	0.52213	0.024863333	99.84944790	0.015961688	0.0261065

Table 2 Comparison between the experimental, analytical and predicted stress of the ANN

Sl. no.	Model	Geometry l × b × h (mm)	No. of plies	Concrete strength (MPa)	Published experi- mental axial stress (kN/mm ²)	Analytical axial stress	ANN	Error
1	S-NC-40	152 × 152 × 500	0	40	0.0416	0.0401	0.038789	0.002811
2	S-NC-45	152 × 152 × 500	0	45	0.0423	0.0412	0.041391	0.000909
3	S5-C3-40	152 × 152 × 500	3	40	0.0395	0.0421	0.045052	−0.00555
4	S5-C4-45	152 × 152 × 500	3	45	0.0402	0.0416	0.046621	−0.00642
5	S25-C3-40	152 × 152 × 500	3	40	0.0416	0.0450	0.045052	−0.00345
6	S25-C3-45	152 × 152 × 500	3	45	0.0421	0.0470	0.046621	−0.00452
7	S38-C3-40	152 × 152 × 500	3	40	0.0475	0.0450	0.045052	0.002448
8	S38-C3-45	152 × 152 × 500	3	45	0.0482	0.0475	0.046621	0.001579
9	S5-C5-40	152 × 152 × 500	5	40	0.0427	0.0431	0.053632	−0.01093
10	S5-C5-45	152 × 152 × 500	5	45	0.0439	0.0461	0.045509	−0.00161
11	S25-C4-40	152 × 152 × 500	4	40	0.05	0.0510	0.056222	−0.00622
12	S25-C4-45	152 × 152 × 500	4	45	0.0509	0.0473	0.04894	0.00196
13	S25-C5-40	152 × 152 × 500	5	40	0.0469	0.0417	0.053632	−0.00673
14	S25-C5-45	152 × 152 × 500	5	45	0.0479	0.0427	0.045509	0.002391
15	S-NC-35	152 × 152 × 500	0	35	0.0363	0.0367	0.036372	−7.25E-05
16	S-NC-40	152 × 152 × 500	0	40	0.0375	0.0387	0.038789	−0.00129
17	S25-C4-35	152 × 152 × 500	4	35	0.0523	0.0529	0.055857	−0.00356
18	S25-C4-40	152 × 152 × 500	4	40	0.0543	0.0552	0.056222	−0.00192
19	S25-C4-35	152 × 152 × 500	4	35	0.0576	0.0595	0.055857	0.001743
20	S25-C4-40	152 × 152 × 500	4	40	0.0583	0.0597	0.056222	0.002078
21	S38-C4-35	152 × 152 × 500	4	35	0.0594	0.0502	0.055857	0.003543
22	S38-C4-40	152 × 152 × 500	4	40	0.0612	0.0623	0.056222	0.004978
23	S38-C5-35	152 × 152 × 500	5	35	0.0687	0.058	0.065866	0.002834
24	S38-C5-40	152 × 152 × 500	5	40	0.0693	0.062	0.053632	0.015668
25	R-NC-35	203 × 152 × 500	0	35	0.0389	0.0401	0.038354	0.000546
26	R-NC-40	203 × 152 × 500	0	40	0.042	0.0437	0.041014	0.000986
27	R25-C3-35	203 × 152 × 500	3	35	0.039	0.042	0.040239	−0.00124
28	R25-C3-40	203 × 152 × 500	3	40	0.042	0.0706	0.042401	−0.0004
29	R38-C3-35	203 × 152 × 500	3	35	0.0421	0.0501	0.040239	0.001861
30	R38-C3-40	203 × 152 × 500	3	40	0.0437	0.069	0.042401	0.001299
31	R5-C5-40	203 × 152 × 500	5	40	0.042	0.0482	0.043001	−0.001
32	R5-C5-45	203 × 152 × 500	5	45	0.0443	0.0584	0.04366	0.00064
33	R25-C4-40	203 × 152 × 500	4	40	0.0421	0.043	0.042742	−0.00064
34	R25-C4-45	203 × 152 × 500	4	45	0.0443	0.0449	0.043648	0.000652
35	S5-A3-40	152 × 152 × 500	3	40	0.0489	0.0501	0.045052	0.003848
36	S5-A3-45	152 × 152 × 500	3	45	0.0507	0.0462	0.046621	0.004079
37	S5-A6-44	152 × 152 × 500	6	40	0.0498	0.0412	0.049619	0.000181
38	S5-A6-40	152 × 152 × 500	6	45	0.0516	0.043	0.049941	0.001659
39	S5-A12-40	152 × 152 × 500	12	40	0.0522	0.0612	0.052299	−9.90E-05
40	S5-A12-45	152 × 152 × 500	12	45	0.0542	0.0714	0.052651	0.001549
41	S25-A3-40	152 × 152 × 500	3	40	0.0482	0.0467	0.045052	0.003148
42	S25-A3-45	152 × 152 × 500	3	45	0.0512	0.0466	0.046621	0.004579
43	S25-A6-40	152 × 152 × 500	6	40	0.0501	0.0485	0.049619	0.000481
44	S25-A6-45	152 × 152 × 500	6	45	0.0512	0.0495	0.049941	0.001259
45	S25-A9-40	152 × 152 × 500	9	40	0.0521	0.0461	0.051741	0.000359
46	S25-A9-45	152 × 152 × 500	9	45	0.0533	0.047	0.052436	0.000864
47	S25-A12-40	152 × 152 × 500	12	40	0.0512	0.0451	0.052299	−0.0011
48	S25-A12-45	152 × 152 × 500	12	45	0.0533	0.0463	0.052651	0.000649

Table 2 (continued)

Sl. no.	Model	Geometry l × b × h (mm)	No. of plies	Concrete strength (MPa)	Published experi- mental axial stress (kN/mm ²)	Analytical axial stress	ANN	Error
49	S38-A6-40	152 × 152 × 500	6	40	0.051	0.0485	0.049619	0.001381
50	S38-A6-45	152 × 152 × 500	6	45	0.054	0.0495	0.049941	0.004059
51	S38-A9-40	152 × 152 × 500	9	40	0.0512	0.0452	0.051741	−0.00054
52	S38-A9-45	152 × 152 × 500	9	45	0.0529	0.0469	0.052436	0.000464
53	S5-A9-40	152 × 152 × 500	9	40	0.0511	0.05	0.051741	−0.00064
54	S5-A9-45	152 × 152 × 500	9	45	0.0538	0.0517	0.052436	0.001364
55	C100-C2-40	150 × 300	2	40	0.0734	0.0744	0.070843	0.002557
56	C100-C2-45	150 × 300	2	45	0.0742	0.0752	0.06949	0.00471
57	C150-A3-40	150 × 300	3	40	0.0463	0.0621	0.052827	−0.00653
58	C150-A3-45	150 × 300	3	45	0.0473	0.0728	0.051922	−0.00462
59	C150-A6-40	150 × 300	6	40	0.0552	0.0682	0.052083	0.003117
60	C150-A6-45	150 × 300	6	45	0.0589	0.0737	0.051756	0.007144
61	C150-A9-40	150 × 300	9	40	0.0683	0.0671	0.070838	−0.00254
62	C150-A9-45	150 × 300	9	45	0.0709	0.0706	0.071766	−0.00087
63	C150-A12-40	150 × 300	12	40	0.081	0.07	0.080127	0.000873
64	C150-A12-45	150 × 300	12	45	0.0844	0.0714	0.083661	0.000739

4 Conclusions

In the present work, based on experimental work carried out on GFRP wrapped concrete column under axial compression for varying number of plies, types of mats and curing period, an ANN model was proposed for the estimation of the compressive strength of confined columns. The comparison of the analytical results with experimental findings, the back propagation neural networks was used for the reliable and accurate results of the compressive strength of the GFRP wrapped concrete columns. ANN model was trained for five input layers (diameter, height, period of curing, type of GFRP, number of plies and one output layer (confined compressive strength) and it was found that the good correlation between the input and output variables with the coefficient of correlation R for training, validating and testing are 0.992, 0.999 and 0.999 respectively was achieved. Also, the proposed ANN models can continuously trained for the new set of the experimental data, so it can be used to predict the strength of the GFRP wrapped column in order to expand the range of suitability of the ANN model. Using the proposed neural network and the values of weights of the various inputs, a useful model is developed for researchers and engineers to predict the compressive strength of the confined concrete columns.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflicts of interest.

References

1. Mirmiran A, Shahawy M (1997) Behaviour of concrete columns confined by fiber Composites. *J Struct Eng* 123(5):583–590
2. Parvin A, Wang W (2000) Behaviour of FRP jacketed concrete columns, under eccentric loading. *J Comp Constr* 4(3):146–152
3. Huang CS, Yeh YK, Liu GY, Hu HT, Tsai KC, Weng YT, Wang SH, Wu MH (2002) Axial load behaviour of stiffened concrete filled steel columns. *J Struct Eng* 128(9):1222–1230
4. Rochette P, Labossiere P (2000) Axial testing of rectangular column models confined with composites. *J Compos Constr* 4(3):129–136
5. Asteris PG, Mokos VG (2020) Concrete compressive strength using artificial neural networks. *Neural Comput Appl* 32:11807–11826
6. Apostolopoulou M, Armaghani DJ, Bakolas A, Douvika MG, Moropoulou A, Asteris PG (2019) Compressive strength of natural hydraulic lime mortars using soft computing techniques. *Proc Struct Integr* 17:914–923
7. Armaghani DJ, Hatzigeorgiou GD, Karamani C, Skentou A, Zoumpoulaki I, Asteris PG (2019) Soft computing-based techniques for concrete beams shear strength. *Proc Struct Integr* 17:924–933
8. Naderpour H, Kheyroddin A, Amiri GG (2010) Prediction of FRP-confined compressive strength of concrete using artificial neural networks. *Compos Struct* 92(12):2817–2829

9. Elsanadedy HM, Al-Salloum YA, Abbas H, Alsayed SH (2012) Prediction of strength parameters of FRP-confined concrete. *Compos Part B* 43:228–239
10. Sangeetha P (2007) Analysis of FRP wrapped concrete column under uniaxial compression. *J Sci Ind Res* 66:235–242
11. Sangeetha P, Shanmugapriya M (2019) Numerical study on FRP wrapped concrete columns under compression. *Indian J Sci Technol* 12(15):1–7
12. Sangeetha P, Sumathi R (2010) Behaviour of glass fiber wrapped concrete column under uniaxial compression. *Int J Adv Eng Technol* 1:74–83
13. Naderpour H, Nagai K, Fakharian P, Haji M (2019) Innovative models for prediction of compressive strength of FRP-confined circular reinforced concrete columns using soft computing methods. *Compos Struct* 215:69–84
14. Sharifi Y, Lotfi F, Moghbeli A (2019) Compressive strength prediction using the ANN method for FRP confined rectangular concrete columns. *J Rehab Civil Eng* 7(4):134–153
15. Flood I, Kartam N (1994) Neural networks in civil engineering. I: principles and understanding. *J Comput Civil Eng* 8(2):131–148
16. Lee S, Lee C (2014) Prediction of shear strength of FRP-reinforced concrete flexural members without stirrups using artificial neural networks. *Eng Struct* 61:99–112
17. Doran B, Yetilmezsoy K, Murtazaoglu S (2015) Application of fuzzy logic approach in predicting the lateral confinement coefficient for RC columns wrapped with CFRP. *Eng Struct* 88(1):74–91
18. Yan F, Lin Z, Wang X, Azarmi F, Sobolev K (2016) Evaluation and prediction of bond strength of GFRP-bar reinforced concrete using artificial neural network optimized with genetic algorithm. *Compos Struct* 161(1):441–452
19. Yan F, Lin Z (2016) New strategy for anchorage reliability assessment of GFRP bars to concrete using hybrid artificial neural network with genetic algorithm. *Compos Part B* 92:420–433
20. Leone C, Caprino G, de Iorio I (2006) Interpreting acoustic emission signals by artificial neural networks to predict the residual strength of pre-fatigued GFRP laminates. *Compos Sci Technol* 66(2):233–239
21. Hasanzade-Inallu A, Zarfam P, Nikoo M (2019) Modified imperialist competitive algorithm-based neural network to determine shear strength of concrete beams reinforced with FRP. *J Cent South Univ* 26:3156–3174
22. Behera RR, Ghadai RK, Kalita K, Banerjee S (2016) Simultaneous prediction of delamination and surface roughness in drilling GFRP composite using ANN. *Int J Plastic Technol* 20:424–450
23. Bagci E, Işık B (2006) Investigation of surface roughness in turning unidirectional GFRP composites by using RS methodology and ANN. *Int J Adv Manuf Technol* 31:10–17

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.