Nonlinear Finite Element Analysis and Artificial Intelligence (ANN)-Based Predictions for RC Beam Members Strengthened with CFRP Laminates

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1 Introduction

Fibre-reinforced polymers (FRP) belong to a class of composite materials. The majority of FRP materials are composed of continuous fibres of high strength embedded in a polymer matrix (resin). The embedded fibres serve as the primary reinforcing components, while the polymer matrix acts as a binder, preserving the fibres and facilitating load transmission to and between them. Fibre-reinforced polymer (FRP) materials exhibit a wide range of behaviours based on the fibre type and polymer matrix. Retrofitting reinforced and unreinforced masonry walls, retrofitting earthquake-resistant bridges and other structures, repairing or improving concrete structures, metal-and-timber girders, or slabs, and restoring historic monuments and offshore platforms are all possible applications for FRP materials. Concrete surfaces must be prepped before FRP plates and sheets may be attached to them using grinding, sandblasting or water jetting. This method of external reinforcement can be swiftly applied due to its simplicity.

Neural networks are made up of neurons, also known as nodes or units, which are the basic computational units. It receives input from other nodes or an external source. Weight (w) for each input in the equation is assigned based on how significant it is in relation to other inputs. The main components of neural network are input nodes (layer), hidden nodes (layer) where most of the calculations take place and the output nodes (layer).

Experiments on the influence FRP have on flexural, shear, torsional and axial reinforcement in reinforced concrete structural component have garnered attention in recent years from both academic and industry researchers. In 1998, Ritchie et al. [1] tested adhesively bonded GFRP and CFRP plates to failure on 2.75 m long

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reinforced RC beams that were exposed to flexural impacts. Meier [2] conducted a study in 1992 on 60 small-scale RC beams in a four-point bend configuration. CFRP sheets of 200 mm in width and 0.3 mm thick were used to reinforce these beams. There were experiments performed by Arduini and Nanni [3] that involved the use of CFRP sheets to reinforce pre-cracked RC beams. Hussain et al. [4] conducted research on RC-columns of three distinct forms wrapped with GFRP. El-Gamal's et al. [5] research work involved casting 10 full-scale RC beams and reinforcing them in flexure with different FRP materials. Anil et al. [6] in 2013 conducted tests on 12 FRP-strengthened reinforced concrete slabs. Ceroni et al. [7] carried out flexural tests on 21 RC beams reinforced with NSM bars and CFRP plates.

Researchers have shown that artificial neural networks (ANNs) may be used to calculate displacement in reinforced concrete beams as an alternative to traditional techniques. For example, Naderpour et al. [8] predicted concrete's compressive strength; Ahmadi et al. [9] predicted the axial strength of composite columns; and Khademi [10] evaluated the displacement of RC buildings using ANN. Using ANN, Kaczmarek and Szyma'nska [11] calculated displacement in reinforced concrete and the findings were highly accurate. An investigation conducted by Tuan Ya et al. [12] found that the result was extremely accurate when using the ANN technique to forecast displacement in cantilever beams.

Although previous work has been carried out on strengthening beams with FRP, the area to be laminated and the position of placing the FRP over the beam can be a scope of study. How the different strength parameters, crack pattern and other behavioural changes occur with the positioning of the FRP, and varying the area of lamination can be further studied. Prediction of the behaviour of these kinds of beams can be done using ANN and will help the structural engineering professional to assess the extent of improvement that can be achieved by the strengthening process. But to understand the behavioural changes due to FRP, it requires a huge number of numerical experiments. It can be avoided if ANN models can predict those parameters based on some developed data.

2 Numerical Modelling

2.1 Finite Element Modelling

A nonlinear analysis is performed when applied forces and displacements for a structural component are not linearly related. As a result, unlike in linear analysis, the stiffness matrix does not remain constant during the load application process. Thus, the nonlinear analysis requires a different solution method and, consequently, a separate solver. Loading of a structure results in varying stresses at different places in the structure. With the help of modern analytic software tools, nonlinear issues can now be analysed. In this work, the commercial software package ABAQUS has been used for nonlinear analysis of RC beam strengthened with FRP laminates.

The concrete damage plasticity model has been used for analysis of concrete and reinforcement, and the Hashin damage model for analysis of CFRP. The concrete damaged plasticity model in ABAQUS can simulate behaviour of concrete and other quasi-brittle materials in various kinds of constructions (beams, trusses, shells and solids). It is also used with rebar to model concrete reinforcement. The CDP model has been developed for applications where concrete is subjected to monotonic, cyclic and/or dynamic loads.

Concrete elements are modelled using C3D8R meshing, i.e. 8-node linear brick, reduced integration and hourglass control. Reinforcements are meshed using T3D2: a 2-node linear 3-D truss is used, and for CFRP element S4R (a 4-node doubly curved thin or thick shell, reduced integration, hourglass control, finite membrane strains) mesh is used.

2.2   ANN Modelling

It is the neurons in the model that process input data and predict output in artificial neural networks (ANNs) or deep learning models. Neurons can have more than one layer. The model predicts the output using weights and other activation functions that are sent through the model's neurons along with each input. This is known as "forward propagation". The training dataset is a pair of (x, y) where x denotes the features and y denotes the expected output. The predicted output is evaluated against the expected output "y". Now we evaluate the performance of the model using a loss function between the predicted output and "y" (actual output). The loss function is the measure of the difference between the actual and predicted outputs. The loss function could be log-loss, mean-squared-error or any other function. The weights associated with the input and other neural network layers are randomly initialised and are adjusted repeatedly with the help of the loss function. The weights are so adjusted to minimise the loss function. The gradient of the loss function with respect to the parameters is computed. Using this gradient, the weights in each layer are adjusted. This process of adjusting weights, starting from the last layer to the input layer, is known as "back-propagation". There is a learning rate associated with the weight gradients that determine the influence of the gradients in adjusting weights. Once the weights are adjusted, the model is again evaluated to get the loss function and the weights are readjusted. This process goes on till the loss functions are minimised.

3   Results and Discussion

3.1   Loading Condition 1: Beam Subjected to Concentrated Load at Mid-Span

A sample RCC beam with the following specification has been taken for modelling:

Cross section: 100 mm × 200 mm, Length: 2 m.

Reinforcement: Main reinforcement: Top-12 mm @ 2 Nos, Bottom-12 mm @ 2 Nos. Stirrups: 8 mm @ 150 *c/c* (Fig. 1).

   On the given beam, incremental load has been induced at the centre till the RCC beam reached the plastic state. Carbon fibre-reinforced polymer (CFRP) has been wrapped at different places on the beam (Figs. 2, 3, 4, 5, 6 and 7).

   When the load is low, the lines almost completely overlap (Fig. 8), but as the load increases, the difference in displacement widens significantly. It is seen in this graph that the deflection values for the two configurations, *S*2 and *S*3, are nearly identical across the whole region. 125 kN yielded a deflection of 4.69 mm on *S*3 sides and
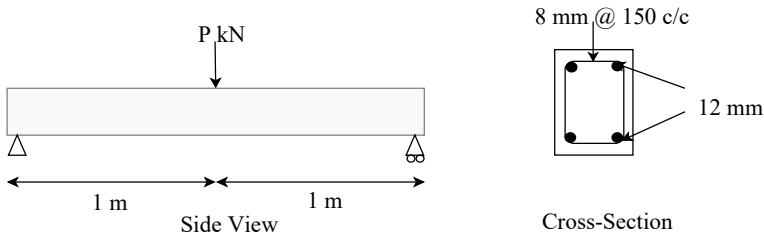
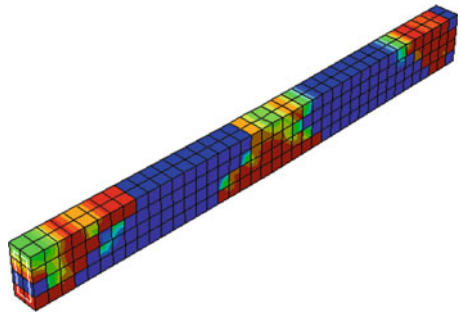**Fig. 1**   Sketch of simply supported beam

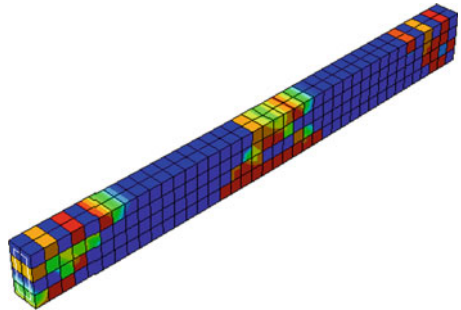**Fig. 2** Different combinations of CFRP strengthening
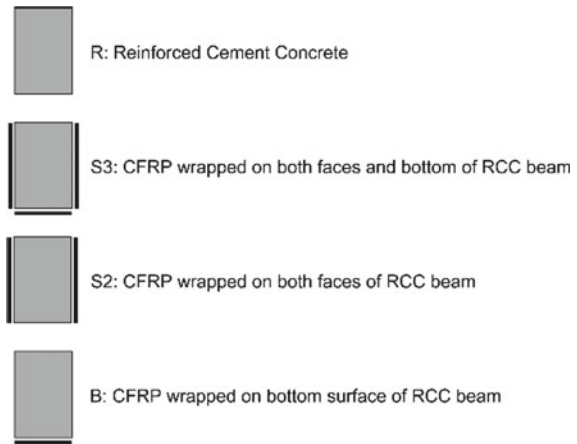
Fig. 3 Stress flow in CFRP in *B* (top), *S*2 (centre) and *S*3 (last*)*
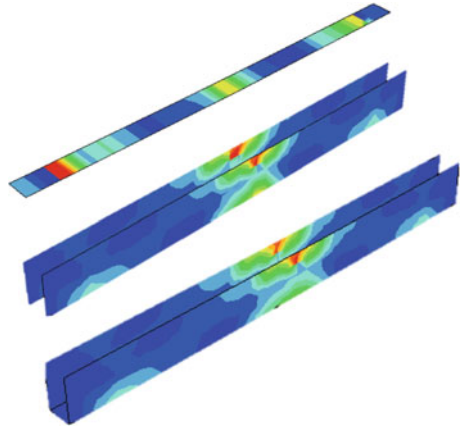
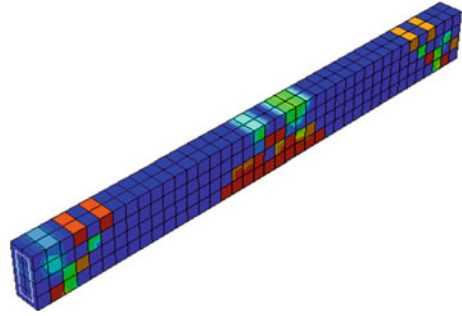**Fig. 4** Crack propagation for RCC

**Fig. 5** Crack propagation for CFRP at bottom (*B*)

4.96 mm on *S*2. Even at a larger load, the change is only 0.27 mm, which is not that significant. As a result, it is preferable to use CFRP on both sides (*S*2) rather than all three, which makes it less cost-effective (Table 1).

It may be deduced that one of the most efficient ways to apply CFRP is to wrap it on both faces. Further different combinations of wrapping of CFRP on both sides of the beam have been done, which are depicted below (Fig. 9).

Fig. 6 Crack propagation
for CFRP on both sides (*S*2)

Fig. 7 Crack propagation
for CFRP on 3 sides (*S*3)
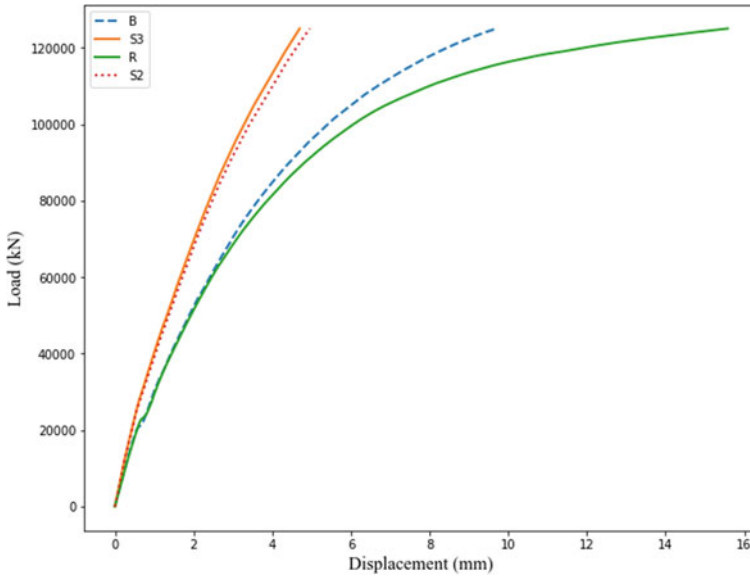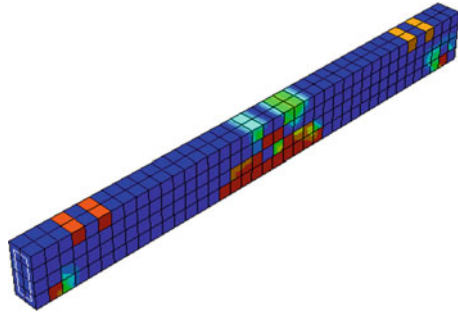
Fig. 8 Load–displacement graph under concentrated loading for different CFRP strengthening
modes

Table 1 Comparison of load–deflection responses

	125 kN		100 kN	
	Δ (mm)	% reduction in Δ	Δ (mm)	% reduction in Δ
R: RCC	15.58	–	6.25	–
B: CFRP on bottom	9.7	38	5.58	11
S2: CFRP on both faces	4.96	68	3.44	45
S3: CFRP on 3 sides	4.69	70	3.28	48
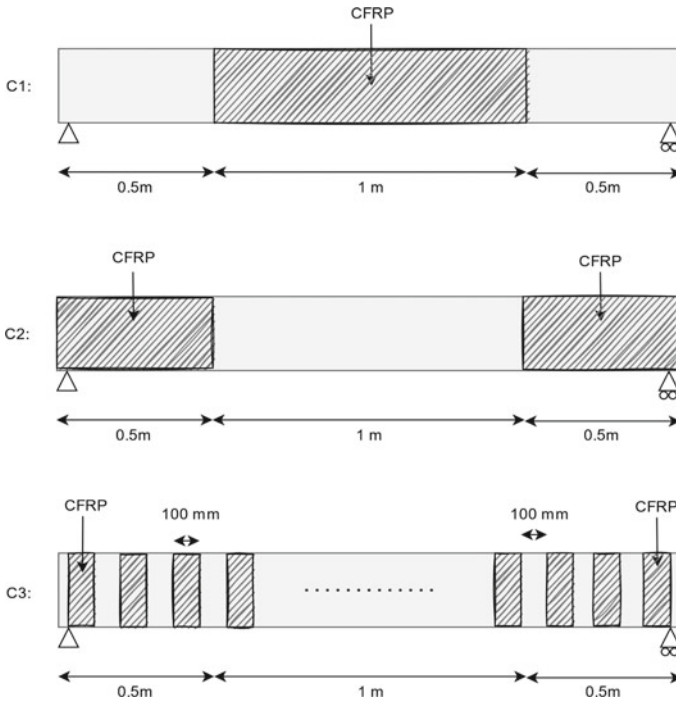
Fig. 9 Different combinations of CFRP wrapping on sides

C1: CFRP of total length L/2 wrapping at mid-section.
C2: CFRP of total length L/2, with L/4 wrapped at two ends.
C3: CFRP of total length L/2, with each segment having a width of 100 mm and 100 mm spacing in between.

Except for S2, the same length of CFRP has been applied on all the other combinations, i.e., C1, C2 and C3, but the difference in deflection is quite significant. While the best possible combination is C1, which has a merely 7.2% increment from S2, C2 is the worst combination with a drastic 90.9% increment over S2 (Table 2).

Table 2 Load–deflection comparison of $C1$, $C2$ and $C3$ with respect to $S2$

|	P = 125 kN	
	Δ (mm)	% increment in Δ w.r.t $S2$
R: RCC	15.58	–
$S2$: CFRP on sides	4.96	–
$C1$: CFRP $L/2$ middle	5.31	7.2
$C2$: CFRP $L/4$ both edges	9.47	90.9
$C3$: CFRP gap graded	8.26	66.5

Gain in Strength of RCC beam may be represented as: $S3 > S2 > C1 > C3 > C2 > B$.

## 3.2 Loading Condition 2: Beam Subjected to Pressure Load of Different Magnitude

Pressure load of different magnitude applied on the same simply supported beam (mentioned earlier) (Figs. 10 and 11).

$S3$ and $S2$ give the best results (Table 3) with maximum reduction in deflection,

Fig. 10 Abaqus model of RC beam under pressure loading
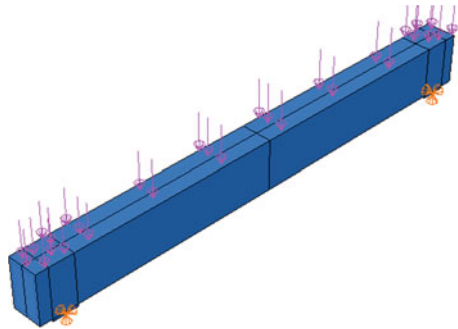
**Fig. 11** Crack propagation of RC beam under pressure load
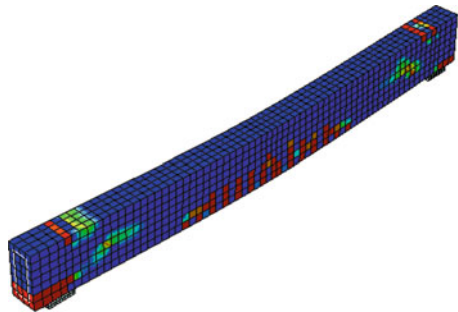
Table 3
Pressure–displacement
comparison

	Pressure = 1.8 MPa	
	Δ (mm)	% Reduction in Δ
R: RCC	9.91	–
B: CFRP on bottom	6.28	36.7
*S*2: CFRP on both faces	3.99	59.7
*S*3: CFRP on 3 sides	3.65	63.1
*C*1: CFRP @ *L*/2 middle	7.50	24.3
*C*2: CFRP @*L*/4 on both edges	4.07	58.9
*C*3: CFRP gap graded	4.41	55.5

but one major difference that has been found is that *C*2 and *C*3 perform better when
pressure load is applied, unlike in concentrated loading at the midpoint (Figs. 12, 13).
So, it can be concluded that for pressure loading *S*3, *S*2 performs the best, followed
by *C*2 and *C*3. *C*2 will be the most economical way of strengthening for pressure
loading.
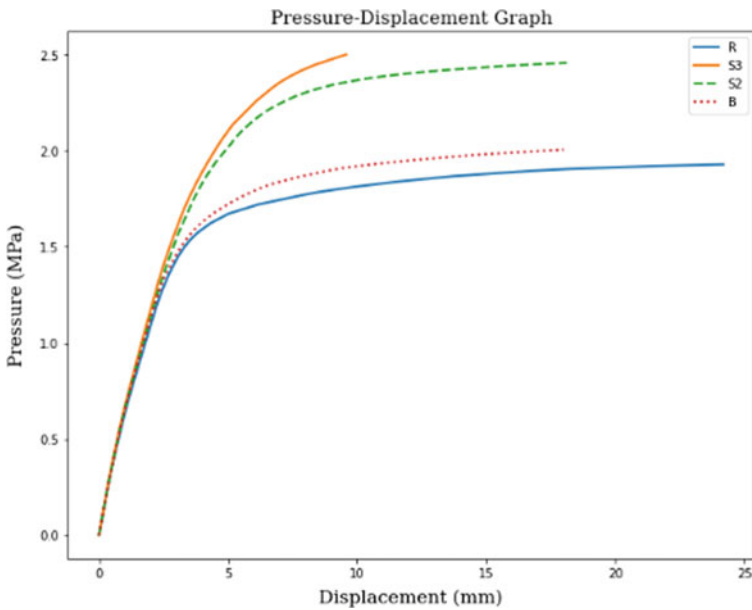
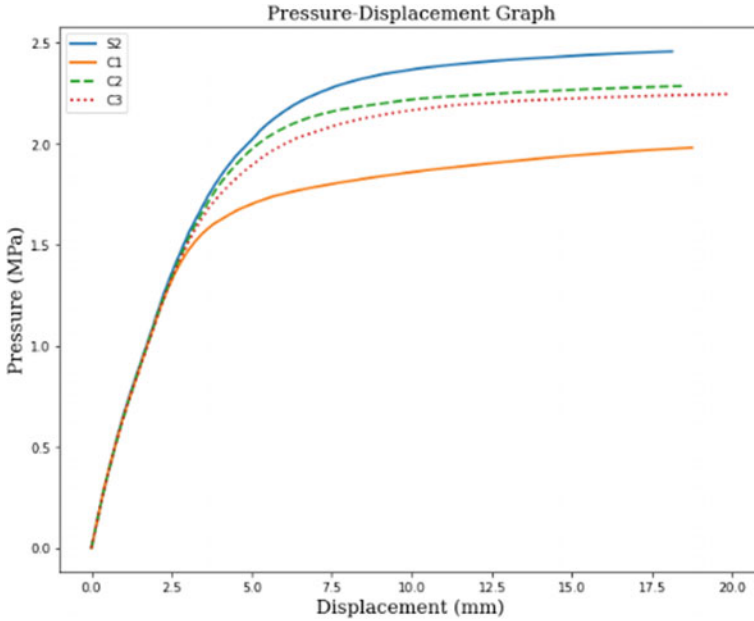**Fig. 12** Pressure–displacement graph for *R*, *B*, *S*2 and *S*3

Fig. 13 Pressure–displacement graph for $S2$, $C1$, $C2$, $C3$

Gain in strength of RCC beam may be represented as: $S3 > S2 > C2 > C3 > B > C1$.

Variation of Load and Deflection of Beam With Thickness of CFRP
The thickness of CFRP has also been changed and the variation in loading capacity and reduction in deflection has been observed. The ultimate loading capacity of the beam increases significantly as the thickness of the CFRP increases (Fig. 14). The deflection of the beam reduces if the thickness is increased. Though the reduction is greater initially, the rate of reduction in deflection decreases after 2.4 mm (Figs. 15, 16, and 17). The slope of the graphs decreases with an increase in thickness, which signifies that the rate of reduction decreases.

Validation of FEM Model Using Artificial Neural Network
FEM data obtained from Abaqus was trained with the deep neural network (DNN) model, to learn the constitutive law of the carbon fibre-reinforced composite. DNN learns the constitutive law in a form-free manner. The learned result automatically satisfies the equilibrium and kinematics equations, which avoids inaccuracies associated with the presumed functions in the constitutive laws. All the models were trained for different combinations of CFRP wrapping in Python (using Keras) and MATLAB. The dataset consists of one feature, i.e. load or pressure, and one target variable, i.e. displacement. The splitting of dataset has been done into training (70%), testing (20%) and validation (10%) using train_test_split () function from sklearn. Training
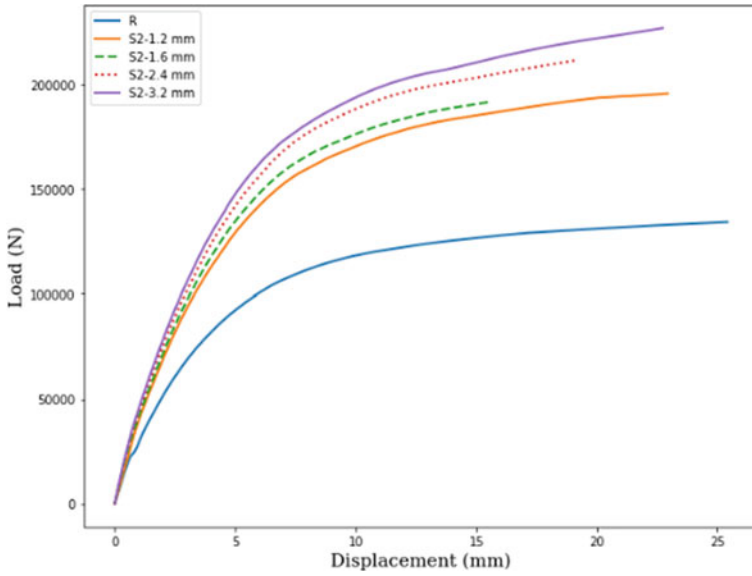
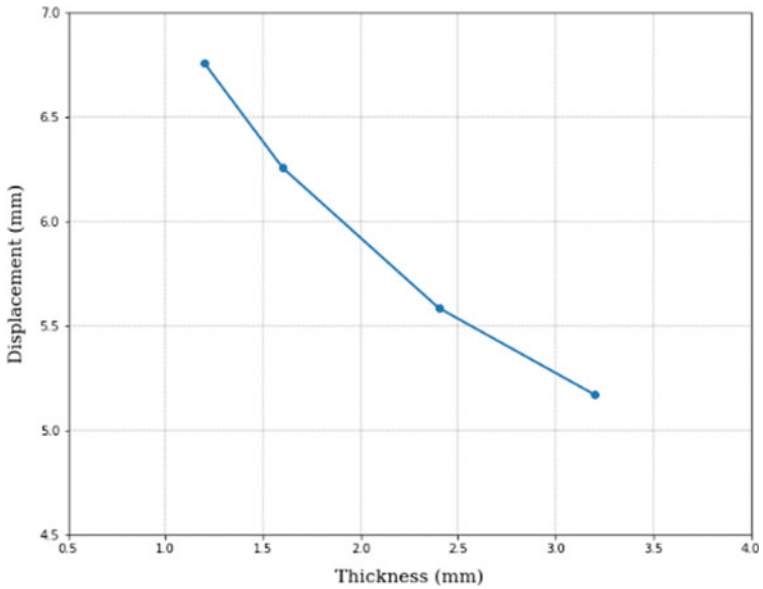**Fig. 14** Load–displacement curve of *S*2 for different thickness of CFRP

Fig. 15 Thickness (CFRP)–displacement graph for *S*2 model at 150 kN load
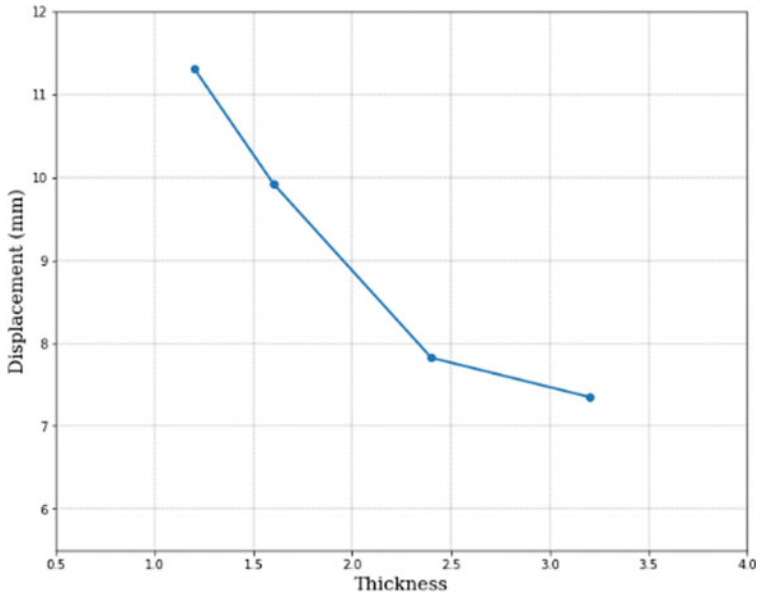
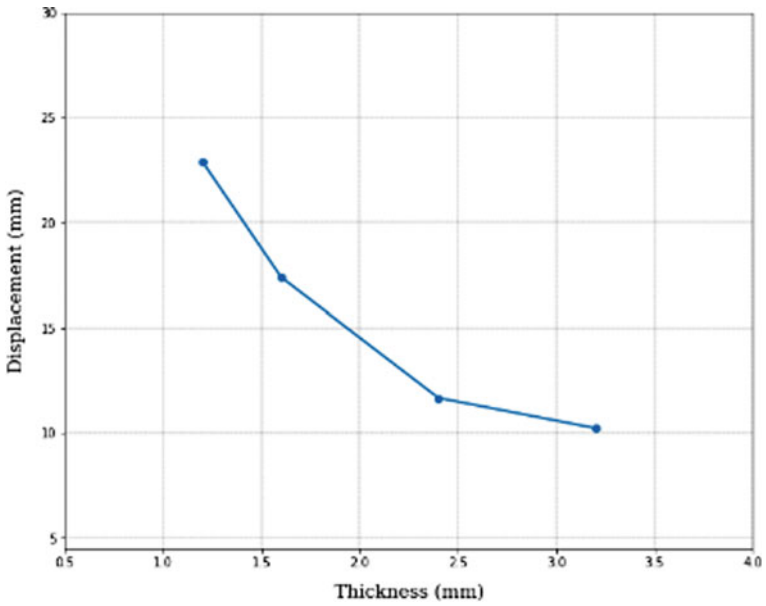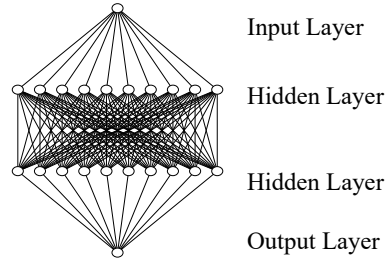**Fig. 16** Thickness (CFRP)–displacement graph for $S2$ model at 175 kN load

Fig. 17 Thickness (CFRP)–displacement graph for $S2$ model at 195 kN load

Fig. 18 ANN architecture

of the neural network with different hyper-parameters has shown that the best activation function is "tanh" and the best optimization function is Adam. Two hidden layers were used with 10 and 20 nodes. The model architecture is given in Fig. 18. The input node consists of one node (since the dataset has one feature), then there are two hidden layers of 10 neurons followed by one output node. In MATLAB, two different neural network models have been used, cascade forward back-propagation (CFB) and Elman back-propagation (EB). The difference in displacement values for FEM and both the ANN models have been calculated (Tables 4, 5) and the values have been plotted (Figs. 19, 20, 21, 22, 23 and 24) to get an idea of the variations from FEM model.

The average R-square value for ANN is 0.99. There is a strong correlation between the two results. With an error rate of less than 1% on average, ANN's predictions reveal a very low and acceptable level of precision in prediction. Moreover, the plots also show that predicted values follow a nonlinear trend (Figs. 21, 22, 23, and 24). Most of the predicted values are in agreement with the Abaqus data.

Table 4 Relative error of ANN model (load-Δ) for $C1$

C1	FEM	ANN		% Error	
Load (N)	Δ (mm)	CFBΔ (mm)	EB Δ (mm)	CFB	EB
0	0.00	0.02	0.04	–	–
12,500	0.26	0.25	0.23	0.36	9.81
25,000	0.55	0.55	0.56	0.12	1.55
50,781	1.38	1.38	1.39	0.07	0.20
60,290	1.73	1.73	1.73	0.34	0.18
75,276	2.31	2.31	2.31	0.02	0.20
100,364	3.60	3.64	3.61	1.30	0.28
120,013	5.08	5.08	5.09	0.02	0.26
125,000	5.58	5.54	5.49	0.69	1.51

Table 5 Relative error of ANN model (pressure-Δ) for $C1$

C1	FEM	ANN		% Error	
Pressure (MPa)	Δ (mm)	CFB Δ (mm)	EB Δ (mm)	CFB	EB
0.00	0.00	0.00	0.01	-	-
0.20	0.27	0.27	0.27	0.00	0.48
0.63	0.95	0.95	0.95	0.01	0.18
1.01	1.77	1.77	1.77	0.00	0.03
1.41	2.82	2.81	2.83	0.24	0.41
1.61	4.51	4.51	4.48	0.02	0.65
1.72	7.66	7.66	7.64	0.00	0.18
1.80	11.86	11.82	11.83	0.30	0.26
1.90	21.82	21.80	21.87	0.11	0.21
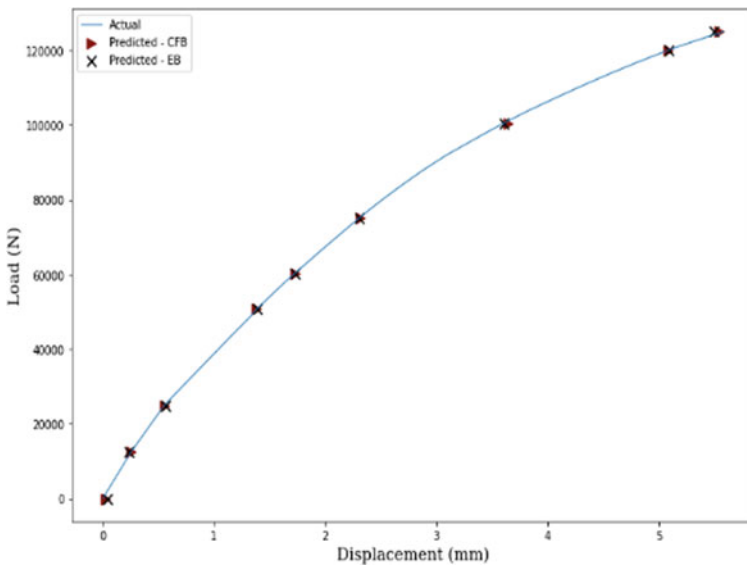
Fig. 19 Actual versus predicted load–displacement curve for $C1$

4   Conclusion

- Under concentrated loading, 48% and 45% reductions in displacement over the control RC beam have been found for CFRP wrapped on three sides ($S3$) and CFRP wrapped on both faces ($S2$), respectively.
- In the case of the RC beam under concentrated load, CFRP of length $L/2$ wrapped on both sides at mid-span ($C1$) has shown to be one of the most effective and
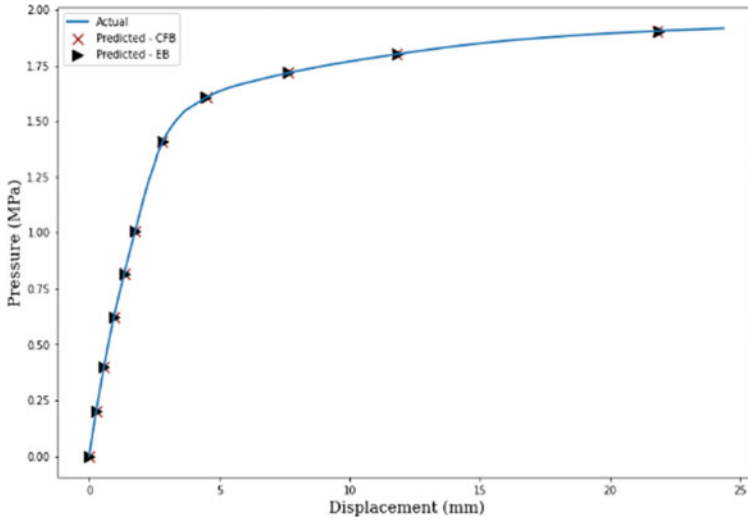
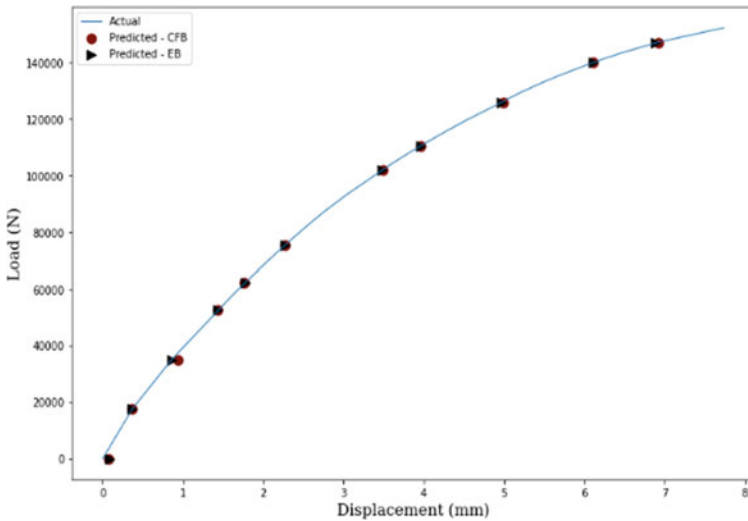**Fig. 20** Actual versus predicted pressure–displacement curve for $C1$

Fig. 21 Actual versus predicted load–displacement curve for $S2$

economical means of wrapping since the increase in deflection was only 7.2% compared to S2 (fully wrapped on both faces).

- Under pressure loading, it has been observed that $S3$ and $S2$ perform best, with a reduction in the displacement of 63.1% and 59.7% over the control beam, respectively. Apart from full-length wraps, $C2$ (wrapped $L/4$ at edges on both sides of
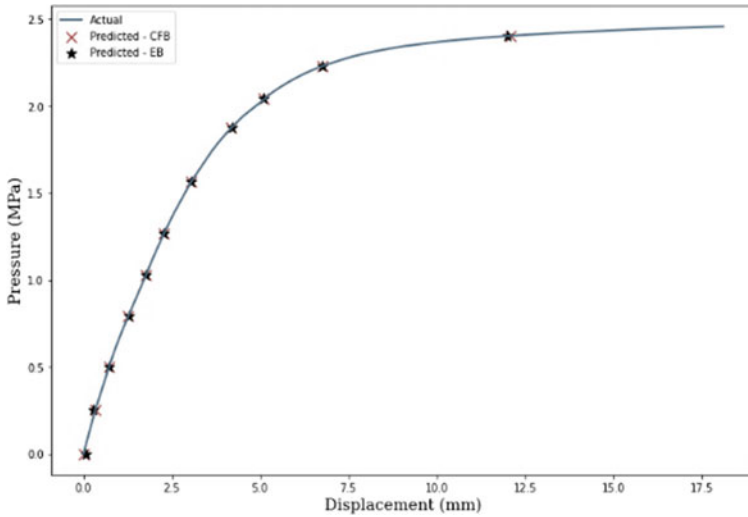
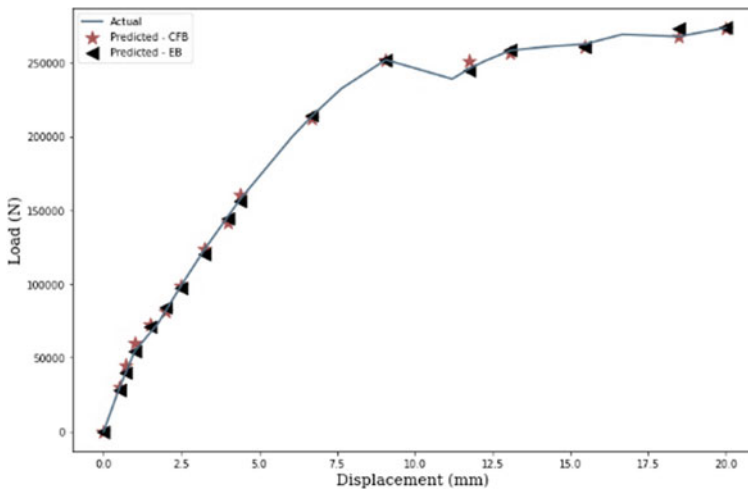**Fig. 22** Actual versus predicted pressure–displacement curve for $S2$

Fig. 23 Actual versus predicted of ultimate load for RCC

the beam) and $C3$ (CFRP gap graded) produce better results, with a reduction of 58.5% and 55.5% over the control beam, respectively.

- With an increase in the thickness of CFRP, there is a considerable amount of reduction in the deflection of the beam, but the rate of reduction in deflection decreases after a certain point even if the thickness of CFRP is kept on increasing.
- It can be concluded that when the load is concentrated at the mid-span of a beam, then the most efficient way of strengthening is to wrap CFRP of length $L/2$ at the
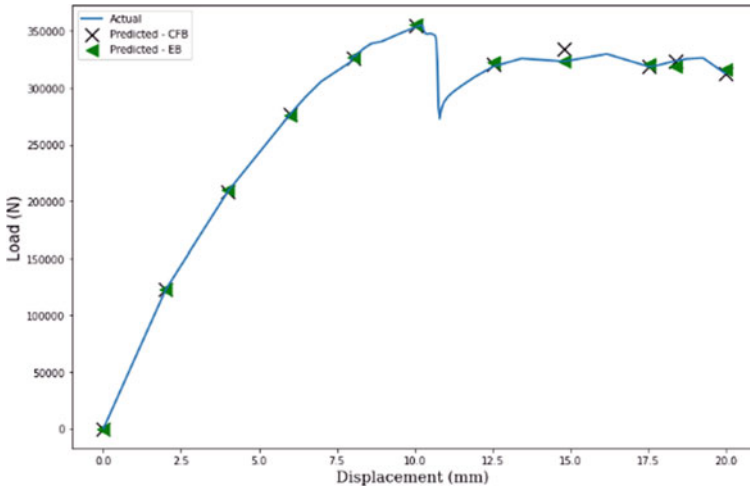
Fig. 24 Actual versus predicted ultimate load for $S2$

mid-span on opposite faces. But when the beam is under pressure load then CFRP of length $L/4$ wrapped near the ends is the most efficient way of strengthening.

- The ANN model predicts the nonlinearity of the models with very high accuracy. An average value of R score of 0.999 indicates that the two results are consistent. Both the ANN model could predict the ultimate load as well as unknown deflection with high accuracy.

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