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Neural Network for Performance of Glass Fibre Reinforced Polymer Plated RC Beams

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Abstract: Prediction of the properties other than moment carrying capacity of GFRP plated RC beams does not have any straight forward mechanism. This study presents a General Regression Neural Network (GRNN) based computational model for predicting the yield load, ultimate load, yield deflection, ultimate deflection, deflection ductility and energy ductility of such beams. Results from experimental investigations carried out on nine RC beams with steel ratios of 0.419, 0.603 and 0.905% plated 0, 3 and 5 mm thick GFRP laminates were used for generating the GRNN model. The predictions of the model closely agreed with experimental results.

Key words: GFRP, GRNN, GUI

INTRODUCTION

Fibre Reinforced Polymer (FRP) plating of reinforced concrete beams has become a common technique for repair and retrofit of RC structures. This investigation seeks to find out the yield load, ultimate load, yield deflection, ultimate deflection, deflection ductility and energy ductility of RC beams with steel ratio of 0.419, 0.603 and 0.905% and Glass Fibre Reinforced Polymer (GFRP) plating at 0, 3 and 5 mm thicknesses. The results obtained from experimental investigation were used as the basis for the generation of a General Regression Neural Network (GRNN) model.

Neural Networks were successfully used for several Civil Engineering problems to predict system behaviour. ANN was used for providing preliminary design of concrete box girders[2]. The neural networks served to filter the noisy data, extract knowledge and synthesize fitting candidates. Radial Basis network was chosen for the study after careful analysis of the comparative performance of several other alternative networks, including the traditional back-propagation networks. Fuzzy network was also employed to deal with integer data. The system provided several design configurations and overwriting of some design parameters to provide a flexible system of preliminary design for concrete box girders.

Neural network was employed for estimating creep and shrinkage deflections in concrete frames[3]. The ANN based approach was formulated as a computationally efficient but approximate alternative to replace the rigorous procedure used for computing the deflection due to creep and shrinkage. A sensitivity study was performed to identify influential parameters. The trained ANN was validated using data available from several buildings.

ANN was used for the assessment of the parameters controlling the longitudinal shear strength of furrowed steel plated composite slabs[4]. It was observed that training the ANN with the input parameters of pitch of ties to width of slab in the top portion and depth of the profile resulted in accurate prediction of the empirical factors used for determining the shear resistance of composite slabs.

Research significance: The experimental work was aimed at investigating the combined effect of internal steel reinforcement and external FRP plating on the performance of reinforced concrete beams. The study parameters included yield strength, ultimate strength, yield deflection, ultimate deflection, maximum crack width, deflection ductility and energy ductility. The results obtained from the investigation were used for generating a GRNN model for predicting the general properties of GFRP plated RC beams. Prediction systems for properties like yield load, yield deflection and ductility are not commonly available. Hence, a computational model could make it easy to estimate the properties of GFRP plated RC beams.

MATERIALS AND METHODS

Material properties: The concrete used for the investigation had mix ratio of 1:1.54:3.01:0.5 (cement:

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FA: CA: Water) and attained characteristic compressive strength of 23.54 MPa. The longitudinal steel reinforcement was provided using rolled tar steel rods having 415 MPa yield strength. The shear stirrups were fabricated using Fe250 grade steel with yield strength of 250 MPa.

The Glass Fibre Reinforced Polymer (GFRP) laminates had Woven Rovings fibres running in mutually perpendicular directions, with fibre density of 450 gram per square metre. The properties of GFRP plates were ascertained from tests conducted in an independent laboratory. The 3 mm thick laminates had tensile strength of 140.40 MPa, ultimate tensile strain of 0.0215 and elasticity modulus of 6855.81 MPa. The 5 mm thick GFRP laminate had tensile strength of 178.09 MPa, ultimate tensile strain of 0.0198 and elasticity modulus of 8994.44 MPa.

Two part epoxy adhesive was used for bonding the plate on to the soffit of the beams. The adhesive was strong enough to resist interfacial shear stresses and ensure perfect composite action between the beam section and the GFRP plate up to the point of failure.

Specimen details: Nine beams having dimensions of 150×250×3000 mm were cast. Three steel reinforcement ratios were adopted at 0.419, 0.603 and 0.905%. The steel reinforcement ratio was calculated as the ratio between area of longitudinal steel and the gross cross sectional area of the beam section. For each steel ratio, one beam was tested without any laminate, one beam with 3 mm thick GFRP laminate and the third with 5 mm thick GFRP laminate. The specimen designations and details are presented in Table 1.

Testing of beams: The beams were tested under two point loading over a span of 2800 mm. The load was applied in increments of 2.50 kN, on two loading points located at 933 mm from each other. The centre point of loading system was coincident with the mid span of the beam. Figure 1 shows the loading and instrumentation setup for the beams.

RESULTS AND DISCUSSION

The experimental results relating to the first crack load, yield load, ultimate load, first crack deflection, yield deflection, ultimate deflection, deflection ductility and energy ductility values for the beams are shown in Table 2 and Fig. 2-10.

The first crack loads were 29.43, 36.79 and 41.69 kN (increase of 71.43, 114.29 and 70.00% over the corresponding reference specimens) for 3 mm thick laminates and 34.34, 49.05 and 53.96 kN (increase of

Table 1: Specimen details

Sl. No.	Beam designation	Steel reinforcement ratio (%)	Thickness of GFRP laminate (mm)
1	B1	0.419	-
2	B2	0.603	-
3	B3	0.905	-
4	B1F3	0.419	3
5	B2F3	0.603	3
6	B3F3	0.905	3
7	B1F5	0.419	5
8	B2F5	0.603	5
9	B3F5	0.905	5

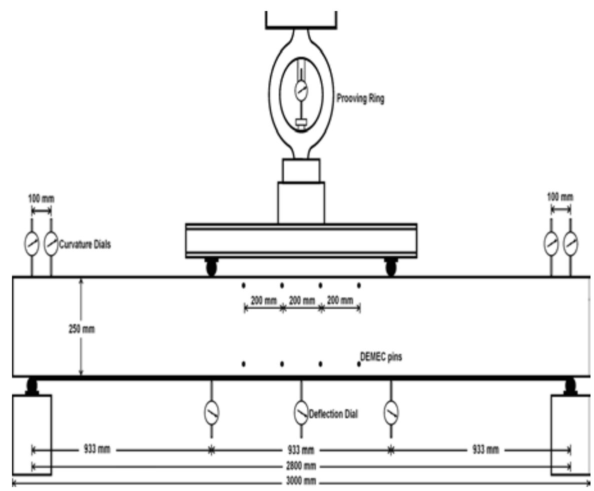

Fig. 1: Loading and Instrumentation Setup

Table 2: Test results and discussion

Sl. No.	Beam designation	First crack load (kN)	Yield load (kN)	Ultimate load (kN)	Deflection at first crack (mm)	Yield deflection (mm)	Ultimate deflection (mm)	Maximum width (mm)	Deflection ductility	Energy ductility
1	B1	17.17	17.17	34.34	4.52	11.17	30.20	1.20	2.70	3.83
2	B2	17.17	34.34	41.69	3.29	10.91	33.70	1.04	3.09	4.77
3	B3	24.53	36.79	63.77	3.75	10.40	33.89	0.90	3.26	5.82
4	B1F3	29.43	44.15	58.86	7.77	11.58	32.83	0.82	2.84	4.94
5	B2F3	36.79	49.05	73.58	6.32	9.85	35.05	0.66	3.56	6.38
6	B3F3	41.69	74.80	78.48	7.47	9.86	37.52	0.54	3.81	8.07
7	B1F5	34.34	51.50	63.77	7.39	7.98	35.49	0.62	4.45	8.05
8	B2F5	49.05	56.41	88.29	11.72	10.63	44.38	0.58	4.17	9.33
9	B3F5	53.96	58.86	105.46	9.20	9.20	45.64	0.52	4.96	14.06

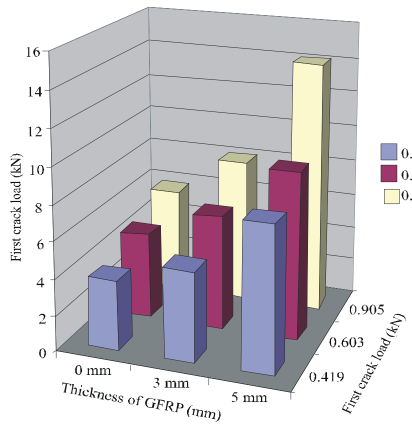

Fig. 2: First crack loads

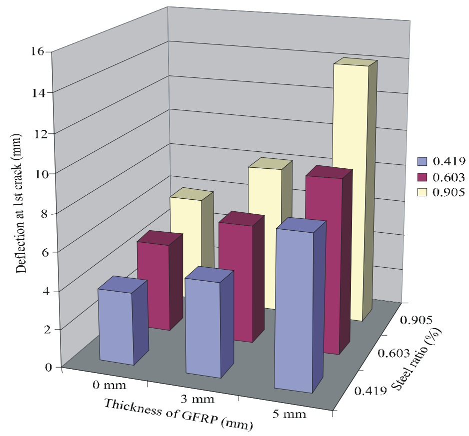

Fig. 5: Deflection at first crack

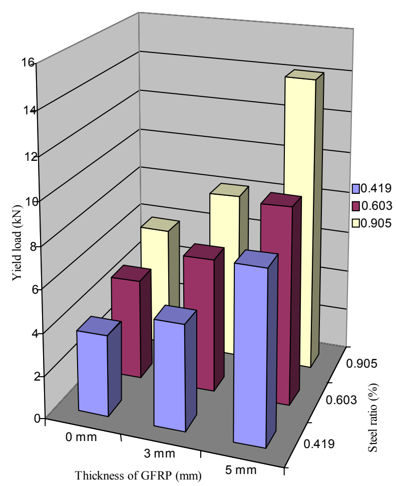

Fig. 3: Yield loads

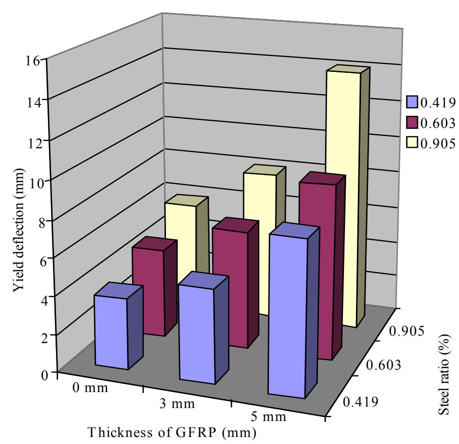

Fig. 6: Deflection at yield

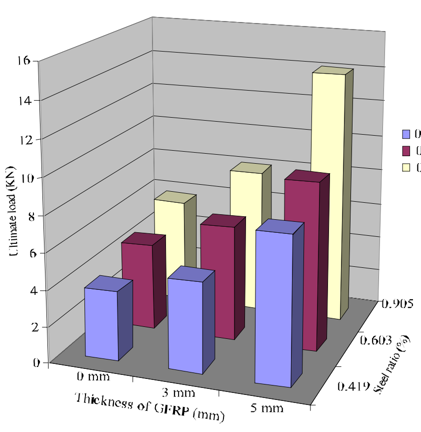

Fig. 4: Ultimate loads

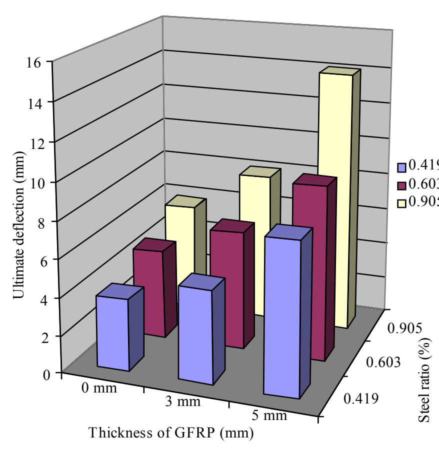

Fig. 7: Ultimate deflection

100.00, 185.71 and 120.00% over the corresponding reference specimens) for 5 mm thick laminates, the triplet data being representative of steel reinforcement ratios of 0.419, 0.603 and 0.905%. Increasing thickness

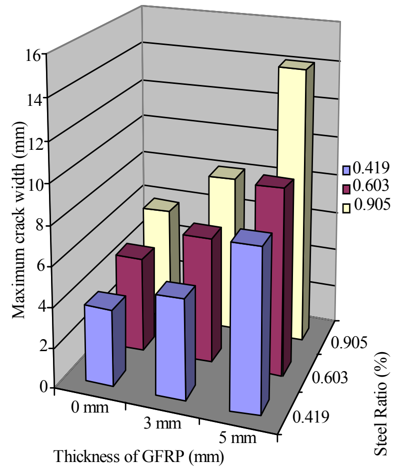

Fig. 8: Maximum crack width

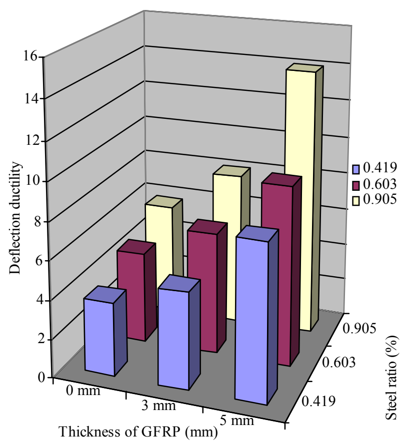

Fig. 9: Deflection ductility values

of GFRP plating resulted in increase in the first crack load.

The 3 mm thick GFRP plated beams of B1F3, B2F3 and B3F3 showed increase in yield load by 57.14, 42.86 and 103.33% respectively. The 5 mm thick GFRP plated beams of B1F5, B2F5 and B3F5 showed increase in yield loads by 200.00, 64.29 and 60.00% respectively.

As the steel reinforcement ratio increased from 0.419-0.603 and 0.905%, the ultimate load carried by control specimens increased from 17.17-34.34 kN (100.00%) and 36.79 kN (114.27%). Beams with 3 mm thick GFRP plating showed ultimate loads of 44.15, 49.05 kN (11.10%) and 74.80 kN (69.42%) and those with 5 mm thick GFRP plating showed increase from 51.50-56.41 kN (9.53%) and 58.86 kN (14.29%) for increase in steel ratio from 0.419-0.603 and 0.905%.

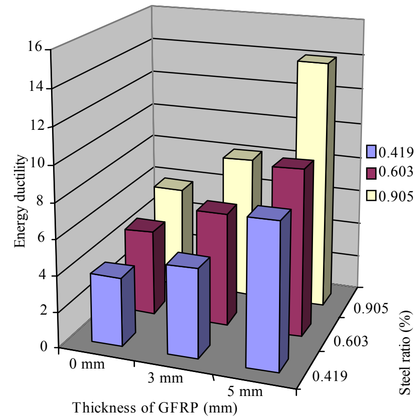

Fig. 10: Energy ductility values

Ultimate load for 3 mm thick GFRP plated beams increased by 71.40, 76.49 and 23.07% when compared to the reference beams. The ultimate load for 5 mm thick GFRP plated beams increased by 85.70, 111.78 and 65.38%. The results indicate that the application of GFRP provides effects similar to the provision of more percentage of internal steel reinforcement on strength.

The beams with 3 mm thick GFRP plating cracked at 171.90, 192.10 and 199.20% of the deflections of their corresponding control beams (B1, B2 and B3). For the beams B1F5, B2F5 and B3F5 (5 mm thick GFRP plating), first crack deflection was 163.50, 356.23 and 245.33% of that for corresponding control specimens of B1, B2 and B3 respectively.

For 3 mm GFRP plated specimens of B2F3 and B3F3, the yield deflection showed a reduction of 9.72, 5.19%, while it showed a marginal increase by 3.67% for B1F3. The 5 mm GFRP plated beams of B1F5, B2F5 and B3F5 showed a reduction of 28.54, 2.57 and 11.54% in yield deflection.

The increase in ultimate deflection was observed to be 8.71, 4.01 and 10.71% for 3 mm thick GFRP laminated beams and 17.52, 31.69 and 34.67% for 5 mm GFRP plated beams.

The deflection ductility values of beams with steel ratio of 0.419% (B1 series) were 4.86 and 64.49% higher for 3 mm and 5 mm thick GFRP plating, those for beams with steel ratio of 0.603% (B2 series) were 15.20 and 35.16% and those for beams with steel ratio of 0.905% (B3 series) were 16.77 and 52.24% for 3 mm and 5 mm thick GFRP plating respectively.

The energy ductility values of 3 mm thick GFRP plated beams B1F3, B2F3 and B3F3, were 29.02, 33.60 and 38.61% higher and those of 5 mm thick GFRP plated beams B1F5, B2F5 and B3F5 were 110.37, 95.43 and

141.63%, than the energy ductility values for the beams B1, B2 and B3 respectively.

General Regression Neural Network (GRNN) model: Modelling with General Regression Neural Network (GRNN) is a flexible way for generalizing experimental results even when the number of data points available for training is very low. The difference between the traditional feed forward network and GRNN is that the feed forward network requires large number of input data for training, structure of the feed forward network requires many arbitrary modifications to achieve low error levels while GRNN becomes ready for prediction works as soon as data points fed, number of data points need not be too many, structure of the network for given data is well defined and the error levels are usually very low and do not depend upon the expertise of the GRNN developer. Hence, GRNN is highly suitable for generalizing the results obtained from experimental investigations.

Basics of general regression neural network: GRNN belongs to the family of radial basis neural network. GRNN contains two processing layers, one radial basis layer and the next linear layer. Radial basis layer contains neuron count equalling the number of elements in the input vector. The linear layer consists of neurons equalling the number of results to be predicted by the GRNN. The implementation of the model was provided using MATLAB® software and a Graphical User Interface was also developed for easily accessing the prediction tool. Figure 11 shows the structure of GRNN.

The steel reinforcement ratio and the thickness of GFRP laminate were chosen as the input parameters for the GRNN model, which was named GFRPBeamNet. The predictions from the model were first crack load, yield load, ultimate load, deflection at first crack, yield deflection, ultimate deflection, maximum crack width, deflection ductility and energy ductility. A graphical user interface named GFRPBeamPrediction was provided for the model.

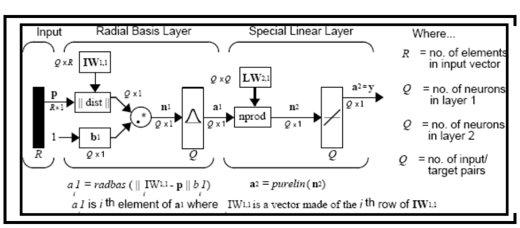

Fig. 11: Structure of general regression neural network

Modelling procedure:

- The input values for each beam were organized in the form of percentage steel ratio and thickness of GFRP laminate. The input consisted of two rows
- The experimental data presented in Table 2 was transposed into row wise representation to provide target and test values for the GRNN model. Two of the nine results were used for testing the model and the remaining seven results for generating the model. The input consisted of ten rows
- The model was generated using the nntool (neural network tool) available in MATLAB® software and the input and target values for the training and testing were entered into the appropriate positions
- The network was generated using the training input and target values (Fig. 12)
- The network was exported to the MATLAB® workspace and saved into a disk file called GFRPBeamNet.mat
- A Graphical User Interface called GFRPBeamProperties was created. It could predict the desired properties for given input values (Fig. 13)

Error levels in GRNN model predictions: The performance of the GFRPBeamNet (GRNN model) was measured using root mean squared error for the training data as well as test data. Since the input and target values for the network are not normalized (values between 0 and 1), the errors reported are actual deviations. These values could be normalized by

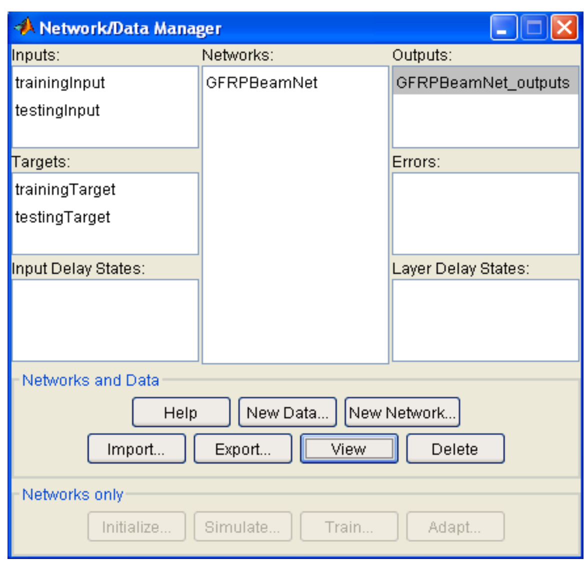

Fig. 12: Creation of neural network

Table 3: Error values of GRNN prediction against training and testing data

Sl. No.	Item	RMS error for training target	RMS error for testing target	Normalized RMS error for training target	Normalized RMS error for testing target
1.	First crack load (kN)	6.0454	4.8431	0.1779	0.1463
2.	Yield load (kN)	9.8073	5.3552	0.2066	0.1180
3.	Ultimate load (kN)	13.6156	6.2868	0.1993	0.0967
4.	Deflection at first crack (mm)	0.6373	2.5753	0.0961	0.3431
5.	Yield deflection (mm)	0.6357	1.3398	0.0635	0.1244
6.	Ultimate deflection (mm)	2.9250	3.3189	0.0817	0.0850
8.	Maximum width (mm)	0.1054	0.0084	0.1403	0.0104
9.	Deflection ductility	0.3242	0.3057	0.0887	0.0842
10.	Energy ductility	1.7638	0.8983	0.2414	0.1274

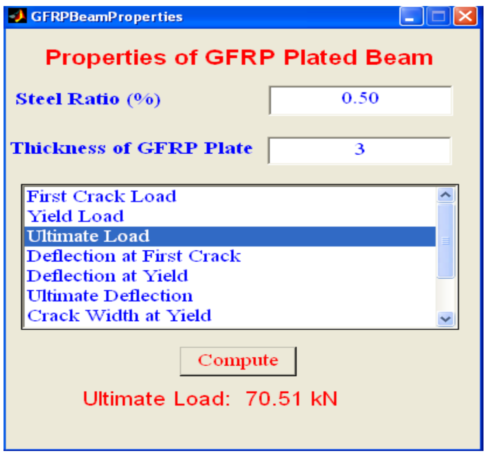

Fig. 13: Prediction of properties

dividing them with the mean values of appropriate target data. The Root Mean Squared (RMS) errors and their normalized values for the prediction parameters are presented in Table 3.

The error levels in prediction are in good agreement with the experimental results for all parameters. The normalized Root Mean Squared Error (RMSE) values should remain as close to 0 as possible, indicating that the network predictions agreed well with target values.

CONCLUSION

The following conclusions are drawn on the basis of the experimental work and GRNN modelling carried out for this investigation. The results obtained from the experimental investigation corroborate the results previously published in the literature. The GRNN model can provide an easy and low error alternative to the traditional regression and finite element techniques of modelling:

- The strength of GFRP plated beams was higher than corresponding unplated beams. The yield strength increased by a maximum of 76.49 and 111.78% for 3 and 5 mm thick GFRP plating
- The maximum deflection levels achieved by the GFRP plated beams were up to 10.71 and 34.67% higher for 3 mm and 5 mm thick GFRP plating, when compared to the unplated reference beams
- The ductility values for beams increased by a maximum of 38.61 and 141.63% for 3 and 5 mm thick GFRP plating respectively
- The General Regression Neural Network (GRNN) model can be used for predicting the properties of GFRP plated RC beams. The normalized RMS error values were in the range of 0.0635-0.2414 for training data and in the range of 0.0104-0.1274 for testing data. The Graphical User Interface is provided to the model suitable for easy prediction of the performance of GFRP plated beams

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