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Full Length Research Paper

General regression neural network (GRNN) for the first crack analysis prediction of strengthened RC one-way slab by CFRP

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In this study, six strengthened RC one-way slabs with different lengths and thicknesses of CFRP were tested and compared with a similar RC slab without CFRP. The dimensions of the slabs were1800 x 400 x 120 mm and the lengths of CFRP used were 700, 1100, and 1500 mm, with different thicknesses of 1.2 and 1.8 mm. The results of the experimental operation for the first crack were used to generate general regression neural networks (GRNNs). Concerning the limited data for training and testing, the different data were extracted seven times for use as training and testing data. In this case, the optimum run was evaluated and compared with the experimental results. The results indicate that the amount of MSE and RMSE was acceptable and the correlation coefficient was close to 1.

Key words: CFRP, GRNN (general regression neural network), MSE, RMSE.

INTRODUCTION

Due to disasters or material deprivation, the damaged parts of structures need to be rehabilitated and made stronger. CFRP has been used for the rehabilitation of RC structures because of its high strength and stiffness-to-weight ratio, corrosion resistance, use in different points of design, easy preparation of surface before use, reduced duration of the construction period and the prolonged life after the strengthening scheme (Taljsten and Elfgren, 2000; Clarke and Waldron, 1996). Different studies have conducted independent testing on strengthened flat slabs using CFRP to evaluate the load capacity (Smith and Kim, 2008; Ola et al., 2007; Amen et al., 2008). Actually, all practical research requires considerable time for the concreting, curing, CFRP installation, and testing process. Therefore, a technical method that has practical outcomes helps us to reduce the time. Artificial neural networks (ANN) is a system for predicting practical results with minimum error. Indeed, ANN demonstrates the nervous system performance using numerical equations to create a relationship between information data. In recent years, ANN has been applied in different parts of civil engineering such as inspection, design, environment, and concrete technology. For example, Yeh (1998), Kasperkiewics et al. (1995), Lai and Sera (1997), and Lee (2003), applied more than one hundred data to generate ANN for predicting concrete properties for normal and high performance concrete. Altun et al. (2008) applied 126 practical data sets to make an ANN to predict the compression strength of lightweight concrete by using steel fibre]. The input data for network generation were steel fibre, water, water-cement ratio, cement, pumice sand, pumice gravel, and super plasticizer. They evaluated the output obtained from the ANN using the multi linear regression (MLR) technique based on mean square error, mean absolute error, and correlation coefficient criteria. The predicted results of ANN for compressive strength were carried out with a relative absolute mean error of 6.75%. Jamal et al. (2007) conducted research concerning the shear resistance of RC beams by using ANN. They used 160 and 30

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Table 1. The materials used.

Steel bar	Rebar T10, (fy = 620 MPa), (Es= 215000 MPa)
CFRP	-Sika CarboDur –MY S 512 (width 50 mm, thickness 12 mm), (Cross section area=60 mm^2) -Sika CarboDur –MY S 812(width 80 mm, thickness 12 mm), (Cross section area=96 mm^2) (E = 170000 MPa)
Adhesive	Sikadur -30 m (Compressive, shear, and tensile strength 90, 17.5, and 28.6 Mpa, respectively, after 7 days curing at a temperature of 35℃.)
Strain gauge for steel	-Type: PFL-10-11, (Used in the centre of slab) (Length 10 mm) (Resistance 120±0.3Ω) -Cyanoacrylate adhesive for installation on the steel -Silicon for isolation
Strain gauge for concrete	-Type: PFL-30-11, (Used in the centre top of slab) (Length 30 mm)n(Resistance 120±0.3Ω) -Araldite epoxy adhesive for installation on the smooth surface of the concrete in the compressive part

experimental data for training and testing, respectively, and the predicted data was compared with the shear strength predictions of ACI318 and BS8110. In another study, Naci et al. (2007) applied the dynamic response of 165 different buildings for training and testing ANN and compared them with the results of numerical analysis. Mehmet (2007) developed an ANN using 237 experimental data to predict the ultimate deformation capacity of RC rectangular columns. The results, when compared, were found to perform well. Also, ANNs have been used for prediction in water-related areas, including evaporation (Sudheer et al., 2002), water resource research (Ahmed et al., 2009), and hydrograph simulator (Lange, 1999). More than 100 data have been used to generate ANN for results prediction.

In prior studies, it was found that considerable data is required to generate the optimum ANN for prediction. But, data gathering for high-scale elements of structures is not simple. The general regression neural networks method (GRNNs) is a way of generalizing results when the number of data for training is extremely small. Pannirselvan et al. (2008) utilized the GRNN system to generate a neural network for the analysis and comparison of 6 RC beams strengthened with glass FRP and 3 beams without GFRP. The prediction details of the model were close to the experimental results.

In the current practical study, the first crack loading, deflection, and strain of 6 strengthened one-way RC slabs with different lengths, widths and thicknesses of CFRP were considered. The dimensions of the slab were 2800 x 400 x 12 mm, which was subjected to two linear loads. The results of the experimental and analytical analysis of 6 strengthened slabs were evaluated by the RC slab without CFRP. The technical outcome for the first crack was utilized to generate GRNN for prediction.

MATERIALS AND METHODS

Materials

The concrete mixture ratio for the cement, fine aggregate (FA), coarse aggregate (CA), and water were, 1: 1.47: 2.64: 0.5, respectively, based on the BS1881 method. The compressive strength of the cubic (150 x 150 x 150 mm) samples; tensile strength of the prismatic (100 x 100 x 500 mm) samples; and the elasticity of the cylindrical (150 x 300 mm) samples were measured in the experimental work session using 5 same samples each time. The mean compressive strength, tensile strength, and elasticity of the samples were 45.5, 6.19, and 25881 MPa, respectively. The steel bar used inside the concrete slab was tested for tensile stress and elasticity before concreting. The CFRP used, had similar qualities but different dimensions of the same adhesive for each of the specimens further mentioned. The properties of the materials used are shown in Table 1.

Methods

Six slabs with dimensions of 2800 × 400 × 120 mm, with an equal percentage of steel bars and different lengths and width of CFRP, as shown in Table 2 and Picture 1, were tested and compared with a similar sample without CFRP. Before sampling, the strain gauges were installed on the bending region of the steel bar and covered by silicon adhesive for water isolation. After casting, the samples were cured using gunny bags and water for 28 days. Then, the CFRP was attached on the tensile surface of the concrete. Finally, the strain gauges were attached on the CFRP and the compressive side of the concrete before testing. The loading and instrument setups are indicated in Figure 1.

DISCUSSION

Experimental results

The experimental results for first crack loading for the

Table 2. The tested samples.

Samples market	CFRP type	Steel	CFRP (mm)		
			Thickness	Width	Length
CFRP-1	S512	2T10	12	50	700
CFRP-2	S512	2T10	12	50	1100
CFRP-3	S512	2T10	12	50	1500
CFRP-4	S812	2T10	12	80	700
CFRP-5	S812	2T10	12	80	1100
CFRP-6	S812	2T10	12	80	1500
CFRP-0	WCFRP*	2T10	-	-	-

*Without CFRP.

Picture 1. RC one-way slab strengthened by different lengths and width of CFRP.

different slabs are shown in Table 3 and Figures 2 to 6. The first crack load for CFRP-1, -2, -3, -4, -5, and -6 were 23.52, 24.12, 24.72, 29.3, 29.58, and 30.19KN with 8, 10, 13, 34, 35.9, and 38.74% increase in capacity, respectively, in comparison with the slab without CFRP (CFRP-0). The results indicate that by increasing the length and thickness of the CFRP, the first crack load will improve. The deflections in the first crack load were 5.94, 5.04, 4.95, 4.7, 4.6, and 4.46 mm with 8, 21.8, 23.25, 27.24, 28.8, and 31% reduction for CFRP-1, -2, -3, -4, -5, and -6, respectively. In the strengthened slabs, the stress on the steel bar, concrete, and CFRP were 1990, 567, and 2750 µ for CFRP-1, 1941, 573, and 2678µ for CFRP-2, 1881, 792, and 2615 µ for CFRP-3, 2226, 661, and 3239 µ for CFRP-4, 2201, 666, and 3199 µ for CFRP-5, and 2158, 982, and 3183 µ for CFRP-6, respectively. Indeed, by increasing the length of the CFRP, the stress on the steel bar and CFRP were decreased and the

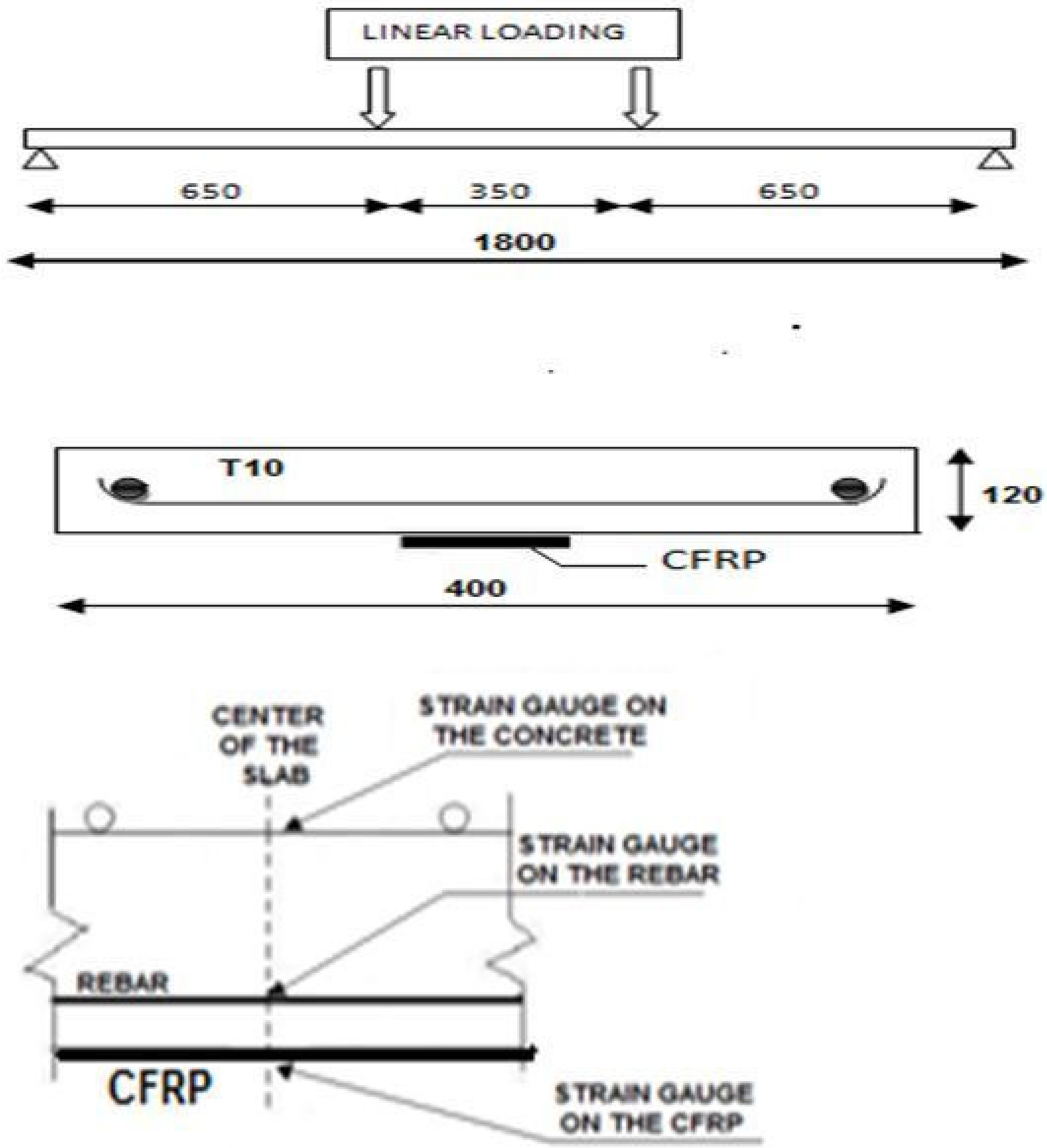

Figure 1. Loading and instrument setup.

Table 3. The experimental result.

Slab market	First crack				
	Crack load (P_{cr}_KN)	Crack deflection (Δ_{cr}-mm)	Steel strain (ε_s_μ)	Concrete strain (ε_c_μ)	CFRP strain (ε_{CF}_μ)
CFRP-0	21.76	6.46	2430	494	-
CFRP-1	23.52	5.94	1990	567	2750
CFRP-2	24.12	5.04	1941	573	2678
CFRP-3	24.72	4.95	1881	792	2615
CFRP-4	29.3	4.7	2226	661	3239
CFRP-5	29.58	4.6	2201	666	3199
CFRP-6	30.19	4.46	2158	982	3183

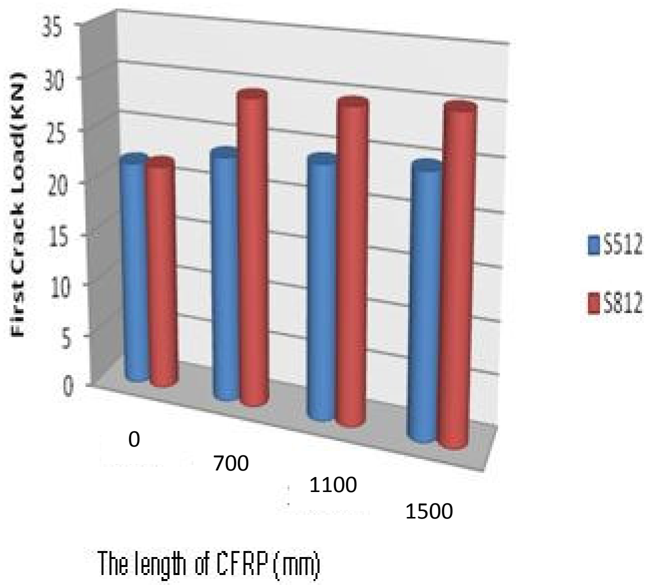

Figure 2. The first crack loading.

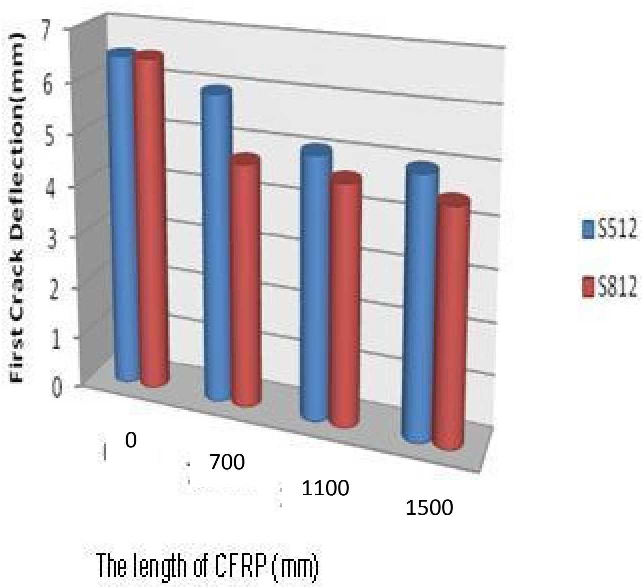

Figure 3. The first crack deflection.

stress on the compressive surface of the concrete was increased. As can be seen in the first crack loading, the load, deflection and strain were improved by increasing the length, thickness and width of CFRP.

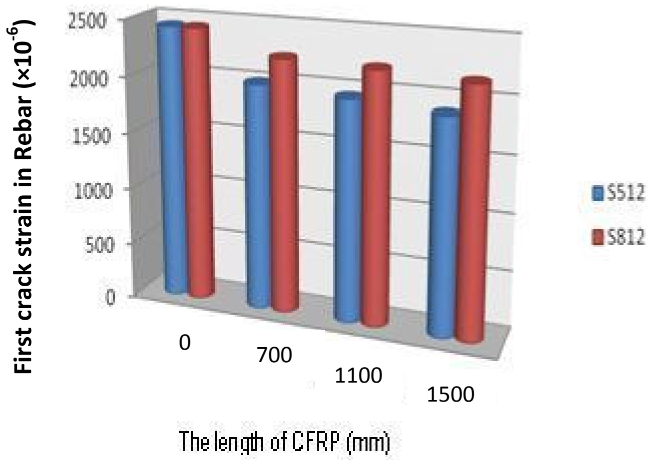

Figure 4. First crack strain in rebar.

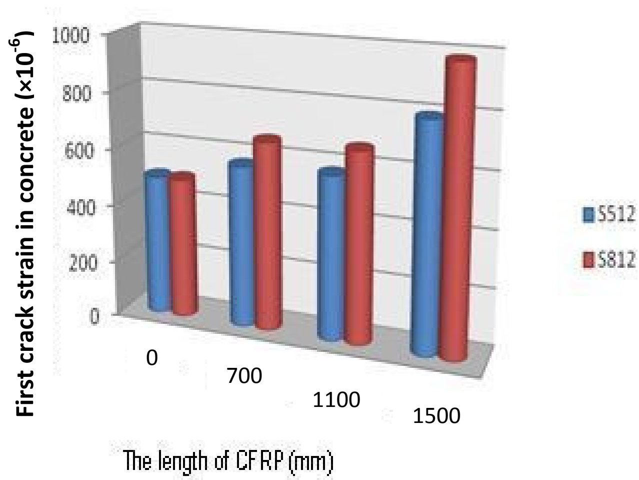

Figure 5. First crack strain on concrete.

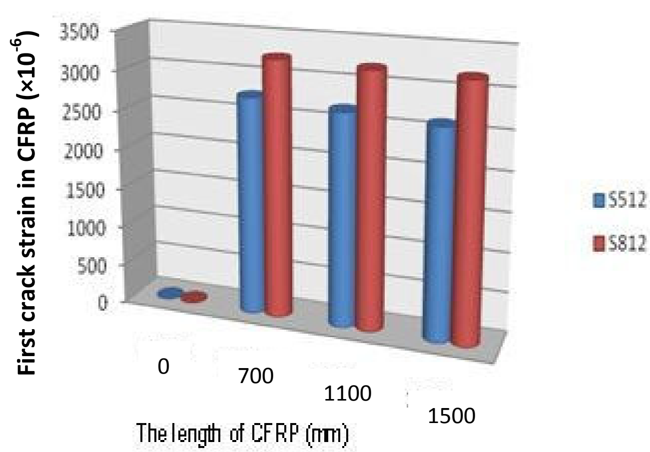

Figure 6. First crack strain on CFRP.

General regression neural network (GRNN)

GRNN classify into probabilistic neural networks (PNN)

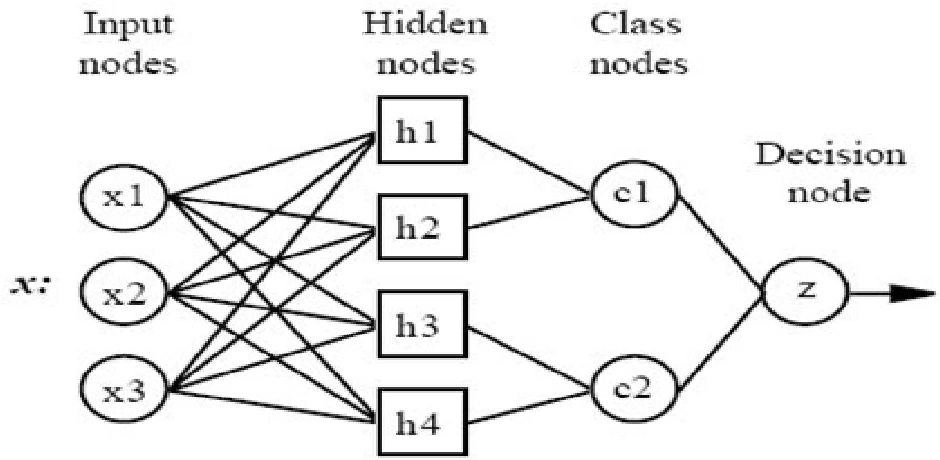

Figure 7. A model of PNN/GRNN.

Table 4. The different extracted data for network generation.

Set No.	Training data	Testing data
1	CFRP-0, CFRP-1, CFRP-2, CFRP-3 and CFRP-4	CFRP-5 and CFRP-6
2	CFRP-0, CFRP-1, CFRP-3, CFRP-5 and CFRP-6	CFRP-2 and CFRP-4
3	CFRP-2, CFRP-3, CFRP-4, CFRP-5 and CFRP-6	CFRP-0 and CFRP-1
4	CFRP-1, CFRP-2, CFRP-3, CFRP-5 and CFRP-6	CFRP-0 and CFRP-4
5	CFRP-0, CFRP-1, CFRP-3, CFRP-5 and CFRP-6	CFRP-2 and CFRP-4

and the sample model of PNN/GRNN is given in Figure 7. When the data available from measurements of an operating system for a back propagation neural network is not enough, the probabilistic neural network is particularly useful due to its ability to connect to the underlying function of the data with only a few training samples available (Specht, 1990). This makes GRNN an extremely useful tool to achieve predictions and comparisons of system performance in practice. GRNN is a neural network architecture that can solve any activity approximation problem. GRNN networks have four layers which are discussed further.

Input layer: For each predictor variable, one neuron is in the input layer. In the case of categorical variables, “n-1” neurons use where, “n” is the number of categories. The input neurons standardizes the field of the values by subtracting the median and dividing by the inter quartile range. The input neurons then send the values to each of neurons in the hidden layer.

Hidden layer: There is one neuron for each case in the training information collection. The neuron supplies the values of the predictor variables for the case along with the object value. The resulting value will shift to the neurons in the pattern layer.

Pattern layer/summation layer: There are two neurons in the pattern layer. One neuron is the numerator summation section, and another is the denominator summation section. The denominator summation section inserts the weight values coming from each of neurons in the hidden layer. The numerator summation section applies the weight values multiplied by the real target value for each neuron in the hidden layer.

Decision layer: The decision layer separates the value accumulated in the numerator summation section by the value in the denominator summation section and uses the result as the predicted target value.

The learning method is similar to finding a table in a multidimensional space that provides a perfect fit to the training data. The generalization corresponds to the use of this multidimensional way to include the test data. Five sets of extracted data were considered to generate an optimum network. The five different attempts to extract data for training and testing are indicated in Table 4. For example, for the best generated network, set number 5, the predicted results of network for the CFRP-2 and -4

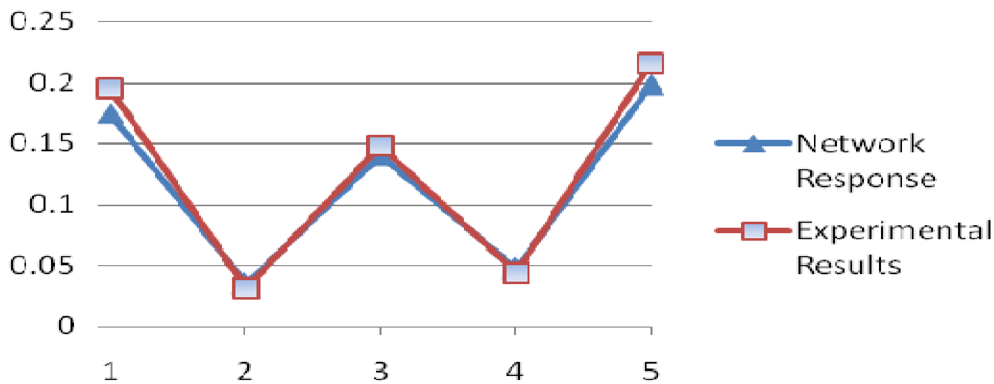

Figure 8. Network response in comparison with experimental results for CFRP-2 in set number 5.

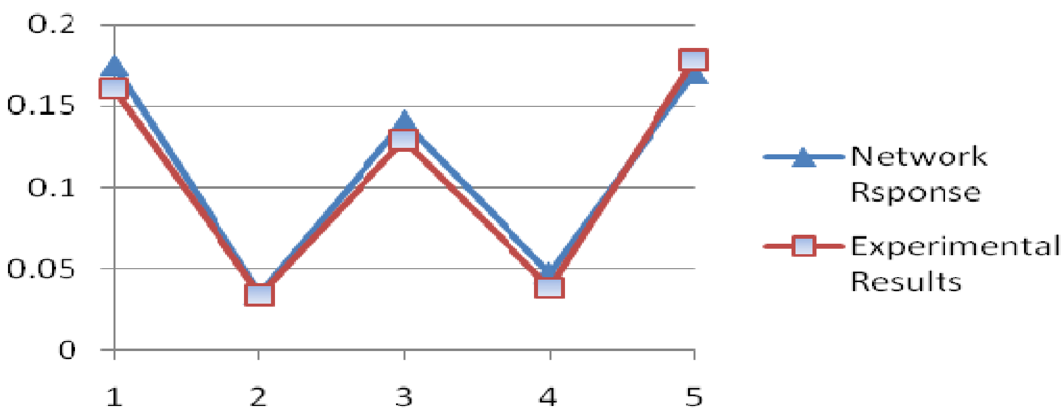

Figure 9. Network response in comparison with experimental results for CFRP-4 in set number 5.

Table 5. The MSE and RMSE in GRNN method.

Method	P_{cr_KN}	Δ_{cr_mm}	$\varepsilon_{s\_}\mu$	$\varepsilon_{c\_}\mu$	$\varepsilon_{CF\_}\mu$
MSE	0.000298	6.02E-06	8.86E-05	4.96E-05	0.001081
RMSE	0.017255	0.002453	0.009411	0.007045	0.032886

are indicated in Figures 8 and 9, respectively, and compared with the experimental results. In these figures, the GRNN results for five parameters of analysis – loading, deflection, steel bar strain, strain on concrete, and strain on CFRP – in the first crack are shown and compared with the experimental results. The network predicted and the experimental results are close with minimum error and maximum correlation coefficient. In addition, the mean square error (MSE) and the root mean square error (RMSE) of the predicted results for set number 5 are shown in Table 5. As we see, the error for the constructed network is extremely low.

The mean amount of the five extracted sets for RMSE is shown in Table 6. The output results of the generated GRNNs produced experimental results of 2.89, 1.45, 1.98, 1.23, and 3.45% root mean squared error for the first crack loading, deflection, steel bar strain, strain on concrete, and strain on CFRP, respectively.

Conclusion

In the current research, 6 RC slabs strengthened with CFRP were compared with a similar RC slab without

Table 6. The mean amount of the five extracted sets for RMSE.

Error	P_{cr}_KN	Δ_{cr}_mm	ε_{s}_μ	ε_{c}_μ	ε_{CF}_μ
RMSE	0.02891	0.01456	0.01981	0.012356	0.03451

CFRP and the experimental results were applied to create a general regression neural network. In this case, 5 different extracted data sets were tested on the generated network and the mean amount of 5 sets in the first crack analysis, were compared with the experimental results by determining the root mean squared error (RMSE).

By increasing the length, width, and cross sectional area of the CFRP, which was fixed on the tensile surface of RC slab, the analysis parameters of the RC slab improved. The first crack load for, CFRP-1, -2, -3, -4, -5, and -6 increased 8, 10, 13, 34%, 35.9, and 38.74% in capacity, in comparison with the slab without CFRP (CFRP-0), respectively. The deflections in the first crack load decreased 8, 21.8, 23.25, 27.24, 28.8, and 31% for CFRP-1, -2, -3, -4, -5, and -6, respectively, in comparison with CFRP-0. In the strengthened slabs, the stress on the steel bar, concrete, and CFRP were 1990, 567, and 2750 microns for CFRP-1, 1941, 573, and 2678 microns for CFRP-2, 1881, 792, and 2615 microns for CFRP-3, 2226, 661, and 3239 microns for CFRP-4, 2201, 666, and 3199 microns for CFRP-5, and 2158, 982, and 3183 microns for CFRP-6, respectively. Indeed, by increasing the length of the CFRP, the stress on the steel bar and CFRP were decreased and the stress on the compressive surface of the concrete was increased.

General regression neural network (GRNN) was the analytical method used to predict the analysis parameters of the first crack. The generated network was tested on five different extracted data sets to justify the created method for first crack analysis prediction. The calculated errors for testing data were in the field 0.012356~0.03451 for RMSE. The correlation coefficient was close to 1.

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