Scientific Research and Essays Vol. 6(23), pp. 5609-5627, 9 November, 2011
DOI: 10.5897/SRE11.737
Available online at http://www.academicjournals.org/SRE
ISSN 1992-2248 © 2011 Academic Journals

Full Length Research Paper

Artificial neural network for structural behavior prediction of RC one-way slab strengthened by CFRP

S. V. Razavi*, M. H. Ayazi and P. Mohammadi

Department of Civil Engineering, Islamic Azad University, Dezful Branch, Iran.

Accepted 28 September, 2011

In this project, 6 Reinforced Concrete (RC) slabs with various length and thickness of carbon fiber reinforced polymer (CFRP) in comparison with the plain RC slab have been used to generate Artificial Neural Networks (ANNs) for structural behavior prediction. The slab dimension was 1800 × 400 × 120 mm and the length of the CFRP was 700, 1100 and 1500 mm in two different cross section area of 60 and 96 mm^2. The results of this experimental work are noted in each testing process. The general regression neural network (GRNN) was the first practical approach that has applied for structural analysis prediction. The feed forward back-propagation (FFB) was the second method with a per regression method for data collection to increase the number of data for training, verifying and testing. The two used method had minimal error and maximum correlation coefficient. The amounts of MSE and RMSE in GRNN and FFB system were in the acceptable ranges. The correlation coefficient is closed to 1 for output data.

Key words: Artificial neural networks, carbon fiber reinforced polymer, general regression neural network, feed forward back propagation, mean squared error, root mean squared error.

INTRODUCTION

Damaged elements of structures due to accident or material degradation need to develop and strengthen. Fiber reinforced polymer (FRP) is a suitable material for repairing and rehabilitation of the structures because of good qualities in strength and easy installation with minimum failure usually. The carbon (CFRF), aramid (AFRP) and glass (GFRP) are three kinds of material in FRP that are as matrix saturated in resin. Normally, CFRP had used for rehabilitation of RC structures because of high strength and stiffness-to-weight ratio, corrosion resistance, using in a different point of design, easy to prepare the surface before using, reduced the duration of the construction period and long time remaining after strengthening scheme (Taljsten and Elfgren, 2000; Clarke, 1996). The first use of CFRP was in Switzerland (1990) to service of failed RC bridge due to an accident.

After that, FRP has studied for strengthening and rehabilitation in a different part of RC structures. The different using of FRP in RC structures is shown in Table 1. CFRP is the essential characteristics to review of mechanical strength of RC elements with applying debonding failure controlling (Li et al., 2005). They have carried out the first crack load, ultimate load, stiffness, ductility, and CFRP stress in an experimental work and finite element analysis of varying length and thickness (single and dual layer) of CFRP in rectangular beam samples and compared with debonded ones. Christopher et al. (2002), performed a laboratory research on different small area of concrete with steel ratio of 0.01 and different layer of CFRP to achieve the same CFRP/concrete ratio. The samples have tested for closure loading in comparison with similar samples without CFRP. Later study arranged independent experiments on strengthened flat slab using CFRP to achieve load capacity (Smith and Kim, 2008; Ola et al., 2007; Amen et al., 2008). In current experimental research, the different length and thickness of CFRP have been used in one-way slab. In this case, all of

*Corresponding author. E-mail: Vahidrazavy@yahoo.com.

Table 1. Different application of CFRP in civil engineering.

Writer	Description
Toutanji and Balaguru (1998)	The performance issue of the RC column wrapped with CFRP and GFRP on the wet-dry and freeze thaw condition were carried out.
Stijn and Luc (2000)	The one-way slab using FRP grid was investigated under concentrated loading.
Christopher et al. (2002)	In this research, the similar RC beam with steel ratio of 0.01, different depth from 0.2 m to 0.8 m, and different layer of CFRP from 2 to 8 with same CFRP to concrete area ratio were tested and compared with same RC beam without CFRP.
Harajili and Soudki (2003) and Ehab et al. (2004)	The CFRP are studied in RC column-slab edge connection against punching shear.
Carlos et al. (2006)	Different kinds of FRP are used for failure prediction of RC beam.
Marco and ASCE (2006)	The load-carrying capacity of the strengthened RC beams was studied.
Chami et al. (2007)	The 26 RC beams with dimension of 100* 150* 1800 mm with and without bonded CFRP were studied for their creep behavior.
Smith and Kim (2008)	The results of experimental work of the strengthened one way slab were reported.

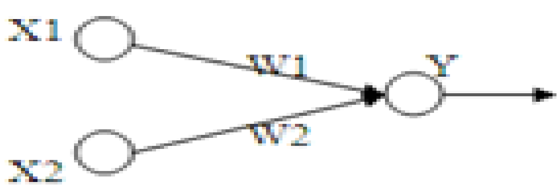

Figure 1. A simple ANNs.

experimental study lost a lot of time for concreting, curing, CFRP installing and testing process. Actually, a scientific programming near to experimental results with minimal error helps us to save time.

Artificial neural networks (ANN) is a method to predict experimental results with minimal error. In fact, ANN presents the nervous system performance with using mathematical formulation to build a relationship between information. A signal layer of ANN is shown in Figure 1. It shows a single ANN with two input neurons (x1, x2) and one output (y). The effect of an internal link has called the weight of the connection, have been given by w1 and w2. In a single layer net, there is a single layer of weighted interconnections. The ANNs may be multi layer that the structure and formula of a multi input neuron as well as in Figure 2 and the following formula respectively:

$$n = \sum_{i=1}^{R} X_i W(1,i) + b = WX + b \quad (1)$$

$$Y = f(WP + b) \quad (2)$$

Where W = weight of interior link and n= the conclusion of input layer that is defined pure input.

In recent years, the application of ANNs in a different part of civil engineering such as inspection, design and existing technology has been accomplished. Yeh (1998); Kasperkiewics et al. (1995); Lai and Sera (1997) and Lee (2003) applied the ANN for predicting properties of normal and high performance concretes. Fatih et al. (2008) have used ANN to predict the compression strength of lightweight concrete by steel fiber. The steel fiber, water, water–cement ratio, cement, pumice sand, pumice gravel and super plasticizer were the input data and the test results obtained from the ANN have compared with 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 have been carried out with a relative absolute mean error of 6.75%. Jamal et al. (2007) have done a research about shear resistance of RC beam by using ANN. They have used 160 and 30 experimental data for training and testing respectively, and the predicted data has compared with the shear strength predictions of ACI318 and BS8110. In another study, Naci et al. (2008) have applied the dynamic response of 165 different buildings for training and testing in ANN and compared with the results of numerical analysis. Mehmet (2007) has developed the ANN with 237 experimental data to predict ultimate

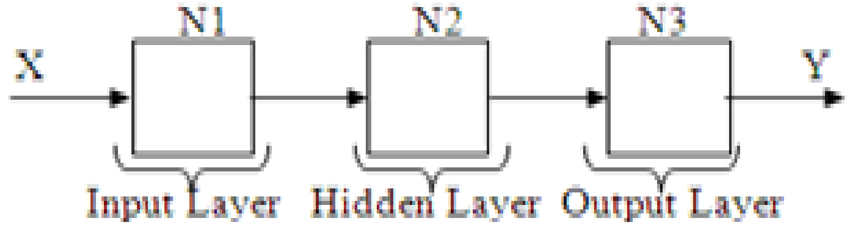

Figure 2. A three layers of multi input layer.

deformation capacity of RC rectangular column. The compared results have been found to perform well. In previous researches, it has been considered that we need a lot of information to produce the best ANN with minimal error for prediction. ANN system will be extremely difficult for prediction of high-scale elements, due to difficulty data gathering. General regression neural network system (GRNN) is a way to generalize results when the number of data for training is extremely small. Pannirselvan et al. (2008) have utilized GRNN system to develop neural network for prediction of first crack load, yielding load, ultimate load and their deflection, and energy ductility due to the results of strengthened RC beam with GFRP. The three cases of steel percent in concrete (0.419, 0.603 and 0.905) and two thickness size of GFRP laminate (3 and 5 mm) used on 6 beam samples is compared with 3 beams without GFRP and similar steel percent were input data. The prediction details of the model were close to experimental results.

In the first part of this research, it has tried to create GRNN for prediction due to 7 strengthened one-way slab samples with different length, width and cross section area of CFRP. In the second quarter, it has created some more non experimental results by using regression function and generated feed forward backprop network for prediction. The dimension of the slab is 1800 × 400 × 120 (mm) that has been loaded by two linear loading.

MATERIALS AND METHODS

The amount of cement, fine aggregate (FA), coarse aggregate (CA) and water have been calculated in BS1881 method. The compressive strength of cubic (150* 150* 150 mm) samples, tensile strength of prismatic (100 × 100 × 500 mm) samples and elasticity of cylindrical (150 × 300 mm) samples has been measured in experimental work session from 5 same samples for each part. The rebar with high strength tested for tensile stress and elasticity before concreting. The used CFRP had similar quality but different dimensions with the same adhesive for installation in below of specimens. The property of used materials is shown in Table 2.

Specimen and testing method

Six slabs having dimension 1800 × 400 × 120 mm with the same steel percent and different length and width of CFRP, as well as in Table 3 have been tested and compared with the similar samples without CFRP. Before sampling, the strain gauges have pasted on the rebar and covered by silicon adhesive for isolation. The steel has put in the timber formwork with the covering consideration. The samples have cured by gunny and water for 28 days after casting in the concrete lab. Then, the CFRP has been attached on the tensile surface of the concrete. Finally, the strain gauges have been attached on the CFRP and compressive side of the concrete before test. The loading and instrument setups is shown in Figure 3.

EXPERIMENTAL RESULTS

The experimental results of first crack loading and deflection, yielding load and deflection, failure load and deflection, strain on concrete, CFRP and rebar for different cross section area and length of CFRP are shown in Table 4 and Figure 4 to 18. The first crack load for S512-70, S512-110, S512-150, S812.70, S812-110 and S812-150 were 23.52, 24.12, 24.72, 29.3, 29.58 and 30.19 KN with 8, 10, 13, 34, 35.9 and 38.74% increase in capacity than reference sample (WCFRP) respectively. The results exposed that by increasing in cross section area of CFRP for the different length of CFRP, the first crack load will be improved. For example, in the strengthen slab by using S512-70 (60 mm^2 cross section area) and S812-70 (96 mm^2 cross section area), the first crack load was added 8 and 34% than reference sample respectively. The results were found 10 and 35.9% for S512-110 and S812-110 and 13 and 38.74% for S512-150 and S812-150. 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 S512-70, S512-110, S512-150, S812-70, S812-110 and S812-150 respectively. In the strengthened slabs, the stress in the rebar, concrete and CFRP were 1990, 567 and 2750 for S512-70, 1941, 573 and 2678 for S512-110, 1881, 792 and 2615 for S512-150, 2226, 661 and 3239 for S812-70, 2201, 666 and 3199 for S512-110, 2158, 982 and 3183 for S812-150 correspondingly. Indeed the stress in the rebar and CFRP were decreased and the stress in the compressive area of the concrete was increased by increasing of the length of CFRP by 700, 1100 and 1500 mm. As we see in the first crack load part, the load,

Table 2. The used materials.

Concrete	Mix ratio of 1: 1.47: 2.64: 0.5 (cement: FA: CA: water), Mean compressive strength (fcu = 45.5 MPa), tensile strength (ft = 6.19 MPa) Elasticity (Ec = 25881 MPa)
Steel	Rebar T10, (fy = 828.5 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 in 35°C temperature.)
Strain gauge for steel	Type: PFL-10-11, (used in the center 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 center top of slab) (length 30 mm)n(resistance 120 ± 0.3Ω) Araldite epoxy adhesive for installation on the smooth surface of concrete in compressive part
DEMEC Pin	Demountable mechanical strain gauge and pin Araldite epoxy adhesive for installation on the concrete
Mold	Timber formwork, interior dimension: 2800 x 400 x 12 mm

Table 3. The tested samples.

Samples market	Steel	CFRP		
		Thickness (mm)	Width (mm)	Length (mm)
S512-70	2T10	12	50	700
S512-110	2T10	12	50	1100
S512-150	2T10	12	50	1500
S812-70	2T10	12	80	700
S812-110	2T10	12	80	1100
S812-150	2T10	12	80	1500
WCFRP*	2T10	-	-	-

*Without carbon fiber reinforced polymer CFRP.

deflection, and stress were improved by increasing the length and cross section area and width of CFRP. After first crack, the loading on the samples were continued and the width of cracks was increased and so the rebar in the slab was yielded. The yield load and deflection $[P_y(KN), \Delta_y(mm)]$ of specimens were [37.61, 16.21], [41.27, 14.17], [43.11, 9.46], [37.91, 15.71], [45.16, 9.3] and [48.49, 7.1] for S512-70, S512-110, S12-150, S812-70, S812-110 and S812-150 correspondingly compared with [33.34, 22.14] for sample without CFRP.

As we know, using CFRP in RC flexure element cause increasing in the yielding load and decreasing in the deflection. For the best case (the reinforced concrete slab by CFRP with 1500 mm in length), the yield load and deflection had 22.66% rise and 67.9% reduction for S512 and the results for the S812 had 31.24% increase and 67.93% reduction in the yield load and deflection.

P_{cr} = First crack loading.

Δ_{cr}= First crack deflection.

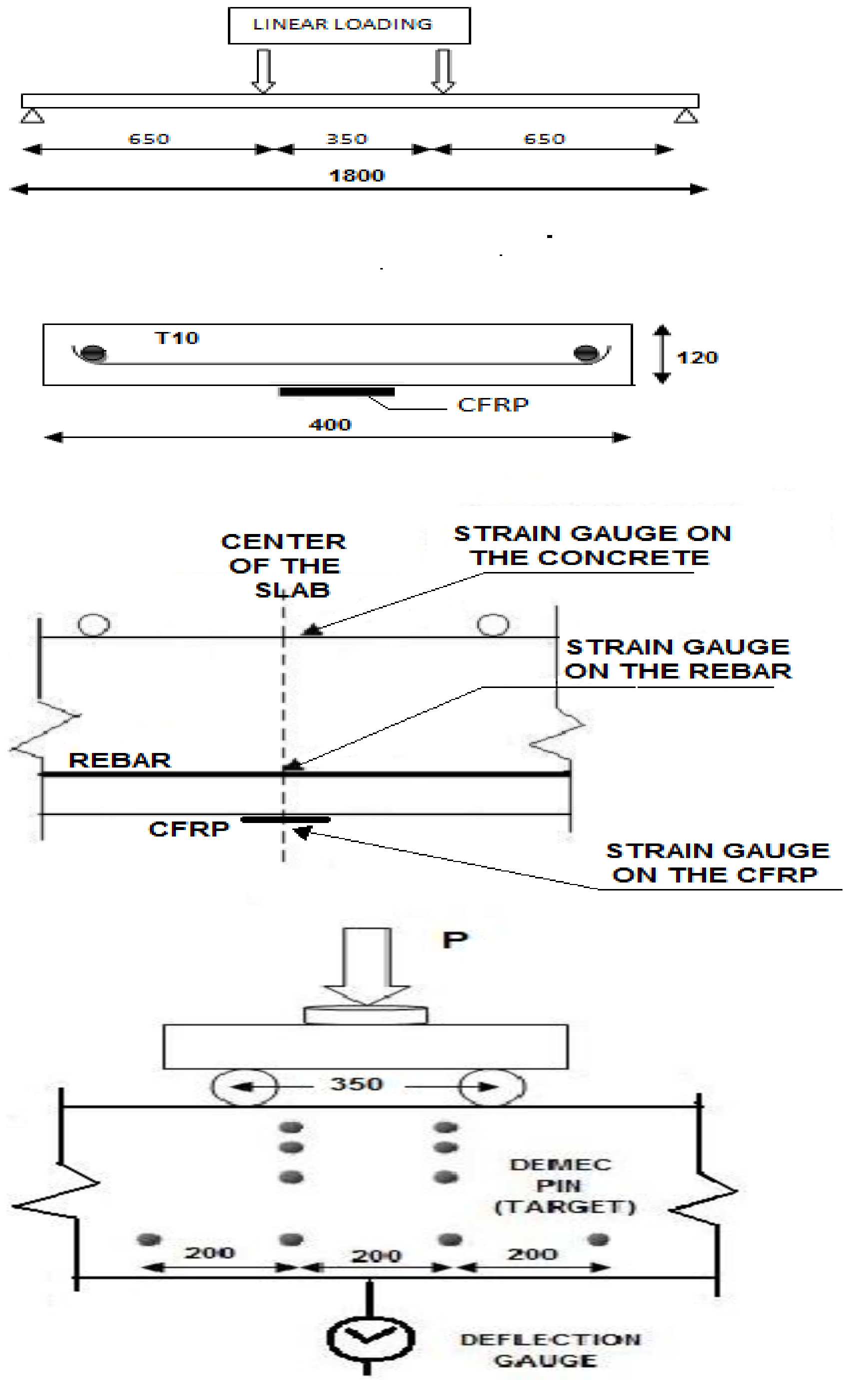

Figure 3. Loading and instrument setup.

ε_s = First crack tensile strain in steel bar.

ε_C = First crack compressive strain on concrete.

ε_{CF} = First crack tensile strain in CFRP

P_y = Yielding load

Δ_y = Yielding deflection

P_f = Failure load

Δ_{Max} = Maximum deflection before failure

In the last part of loading, the samples have fractured. The experimental results have shown the failure load 43.82, 45.14, 48.39, 46.12, 53.2 and 57 KN for S512-70 ~

Table 4. The experimental result for structural behavior of the plain RC one-way slab and strengthened by CFRP.

Slab market	First crack					After first crack			
	Crack load	Crack deflection	Steel Strain	Concrete strain	CFRP Strain	Yield load	Yield deflection	Failure load	Maximum deflection
	P_{cr}_KN	Δ_{cr}_mm	ε_{s}_μ	ε_{c}_μ	ε_{CF}_μ	P_{y}_KN	Δ_{y}_ mm	P_{f}_KN	Δ_{Max}_mm
WCFRP	21.76	6.46	2430	494	-	33.34	22.14	42.53	31.16
S512-70	23.52	5.94	1990	567	2750	37.61	16.21	43.82	24.58
S512-110	24.12	5.04	1941	573	2678	41.27	14.17	45.14	19.22
S512-150	24.72	4.95	1881	792	2615	43.11	9.46	48.39	12.34
S812-70	29.3	4.7	2226	661	3239	37.91	15.71	46.12	20.78
S812-110	29.58	4.6	2201	666	3199	45.16	9.3	53.2	13.62
S812-150	30.19	4.46	2158	982	3183	48.49	7.1	57	9.52

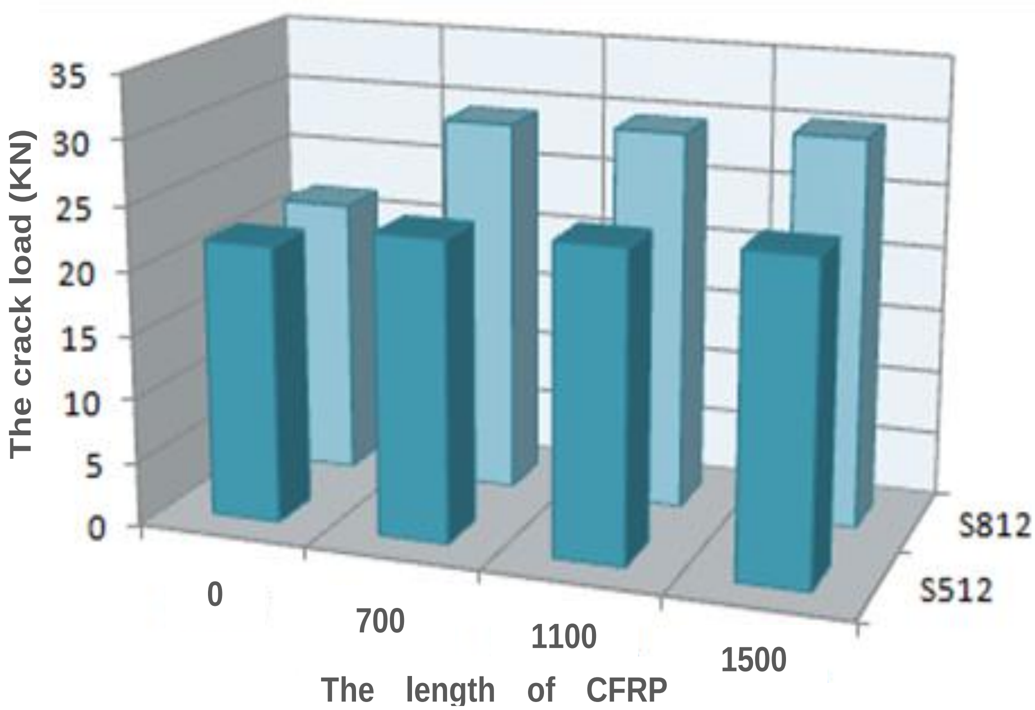

Figure 4. First crack loading.

S812-150 respectively in comparison with 42.53 KN for the original sample (WCFRP). The maximum load in current experimental testing had 25.5% increasing by using CFRP with 80 mm width, 12 mm thickness and 1500 mm length. The maximum deflection has improved over. The maximum deflection was 24.58, 19.22, 12.34, 20.78, 13.62 and 9.52 mm for S512-70 ~ S812-150 respectively in compared with 31.16 mm maximum deflection for slab without CFRP. The results have shown that the maximum deflection deceased 69.44% by using CFRP S812-150.

DISCUSSION

In this part, artificial neural network (ANN) has used for prediction of experimental results. The generalized regression and feed forward backprop are two different networks that have been applied to expect of data and compared with experimental results. MATLAB and EXCEL software has been used for the performance of the prediction. Firstly, the data has gathered in the EXCEL software and then has copied in the MATLAB software. The NNTOOL part of the MATLAB software has

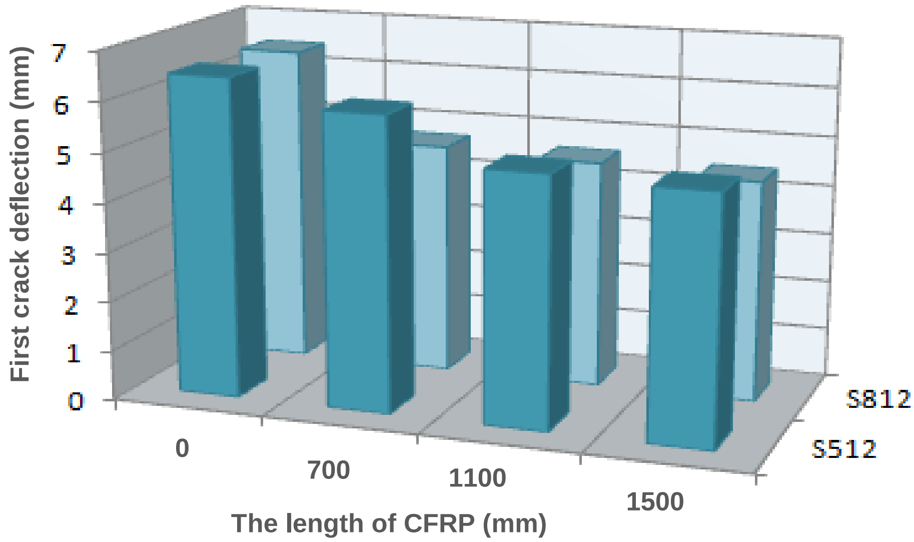

Figure 5. First crack deflection.

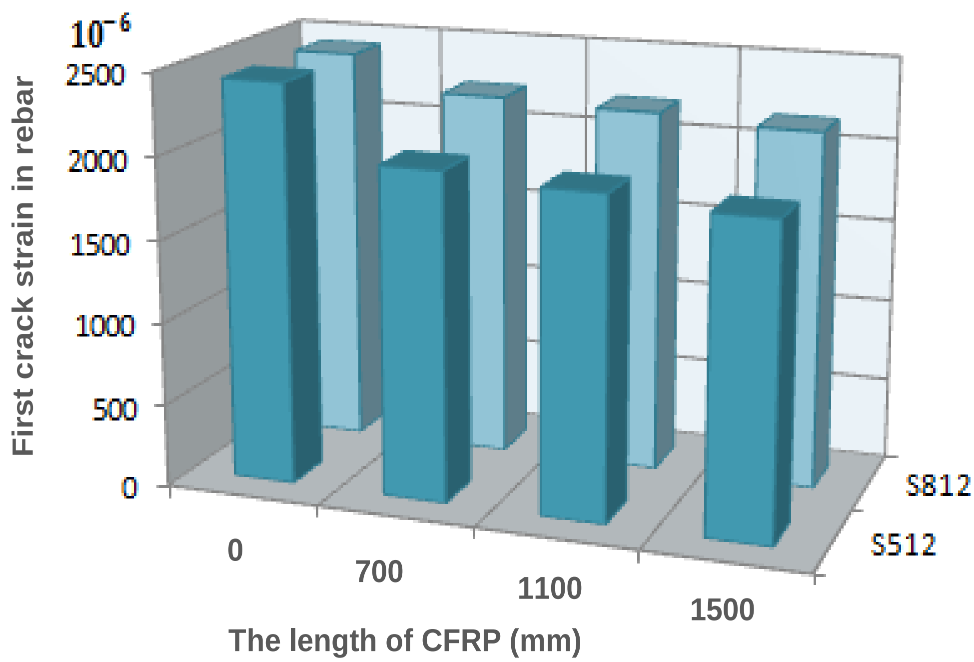

Figure 6. First crack strain on rebar.

been used to describe different parameters of the networks. After simulation, the predicted results have copied in EXCEL software for diagramming and comparing. The minimum error in training information and the quality of the correlation coefficient of data were two main elements to differentiation between actual and predicted results.

General regression neural network (GRNN)

The GRNN belongs to the class of radial basic neural network with two layers of radial basis and linear layer. When the number of data is extremely little, GRNN will be useful for prediction. Five details of seven experimental results (S512-70, S512-150, S812-110, S812-150 and

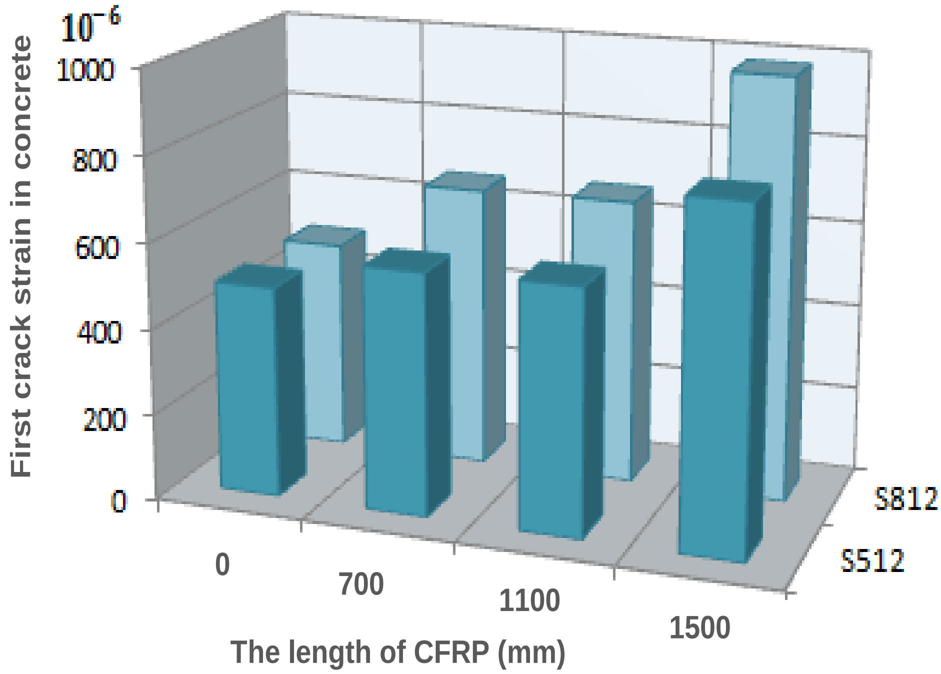

Figure 7. First crack strain on concrete.

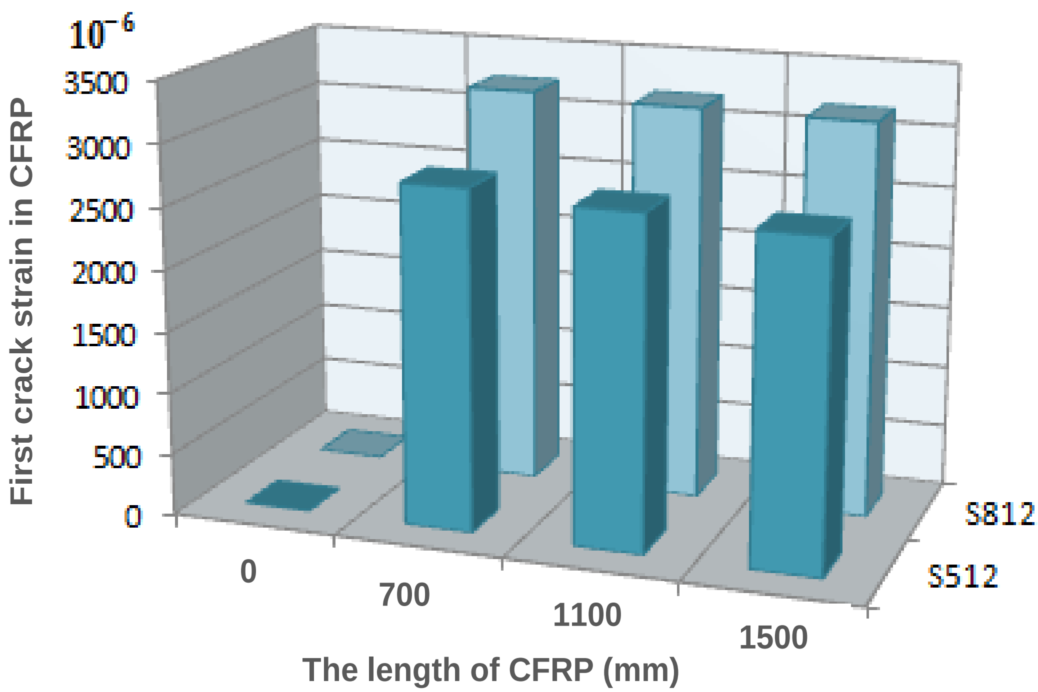

Figure 8. First crack strain on CFRP.

WCFRP) have been used for training and simulate and 2 data (S512-110 and S812-70) have been compared with the predicted results. The predicted results for S512-110 and S812-70 in two parts of crack load parameters and

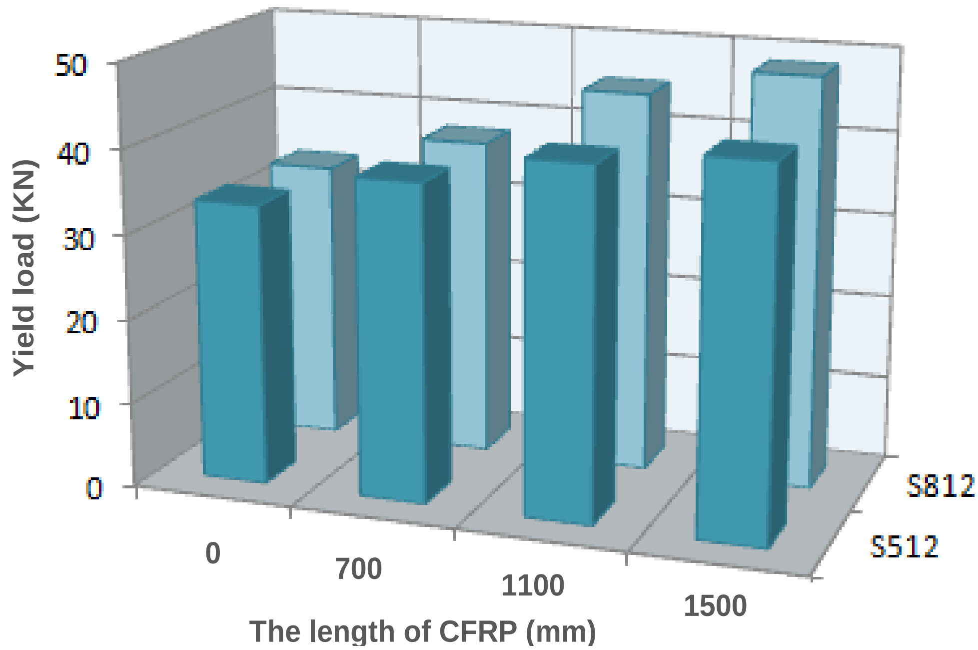

Figure 9. Yield load.

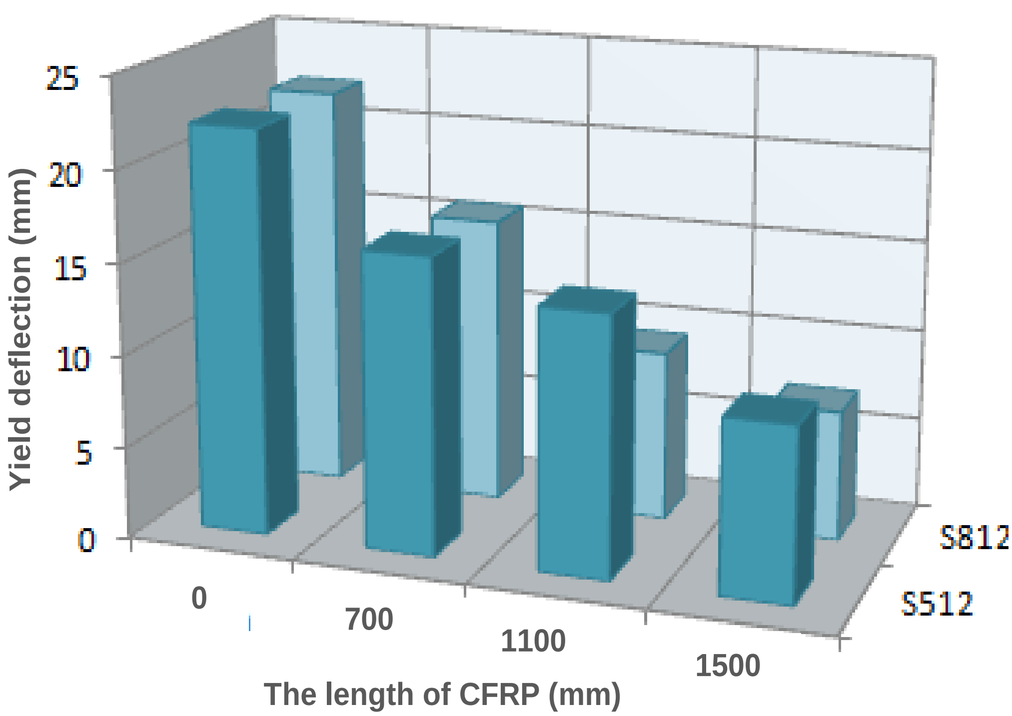

Figure 10. Yield deflection.

after cracking have been shown in Figures 17 to 20. The predicted and original results have been closed together before and after cracking with minimal error and maximum correlation coefficient. The mean square error (MSE) and the root mean square error (RMSE) of the predicted results than actual results have been shown in

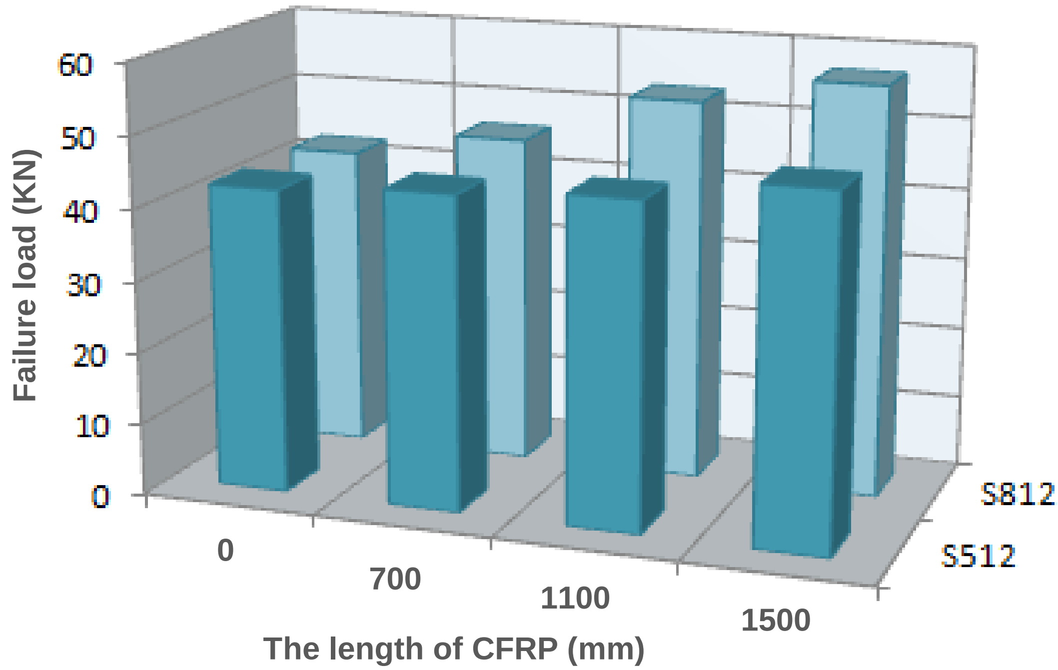

Figure 11. Failure load.

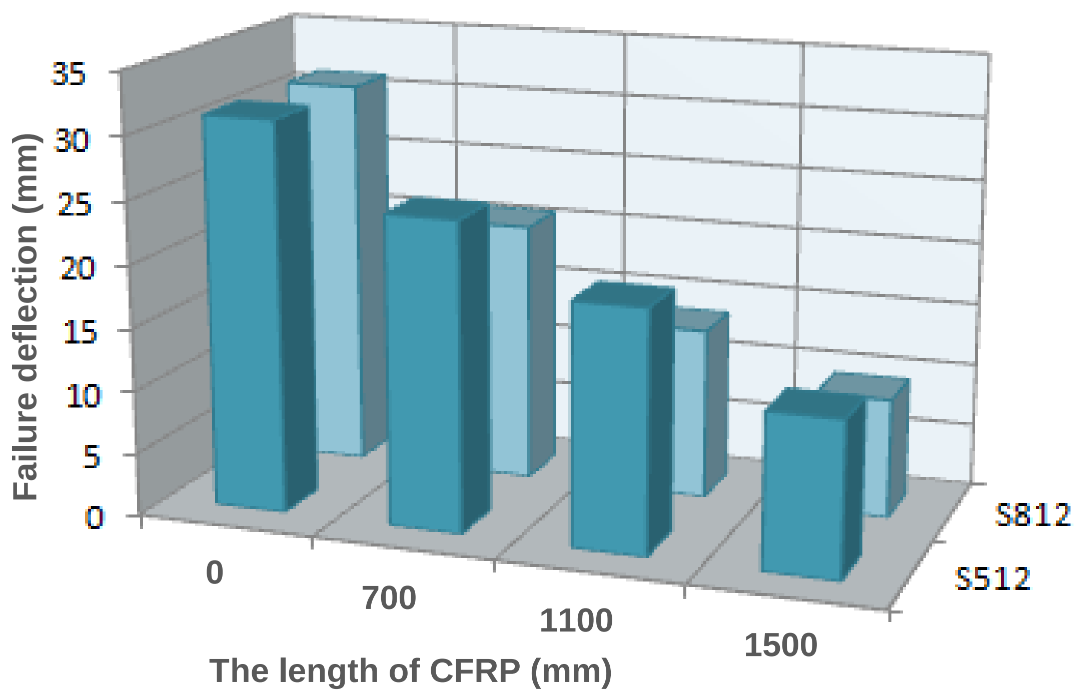

Figure 12. Maximum deflection.

Table 5. As we see, the error of constructed network is extremely low. In the Figures 21 and 22, the first crack load (1), deflection (2), steel bar strain (3), strain in concrete (4), strain in CFRP (5), yielding load (6), yielding

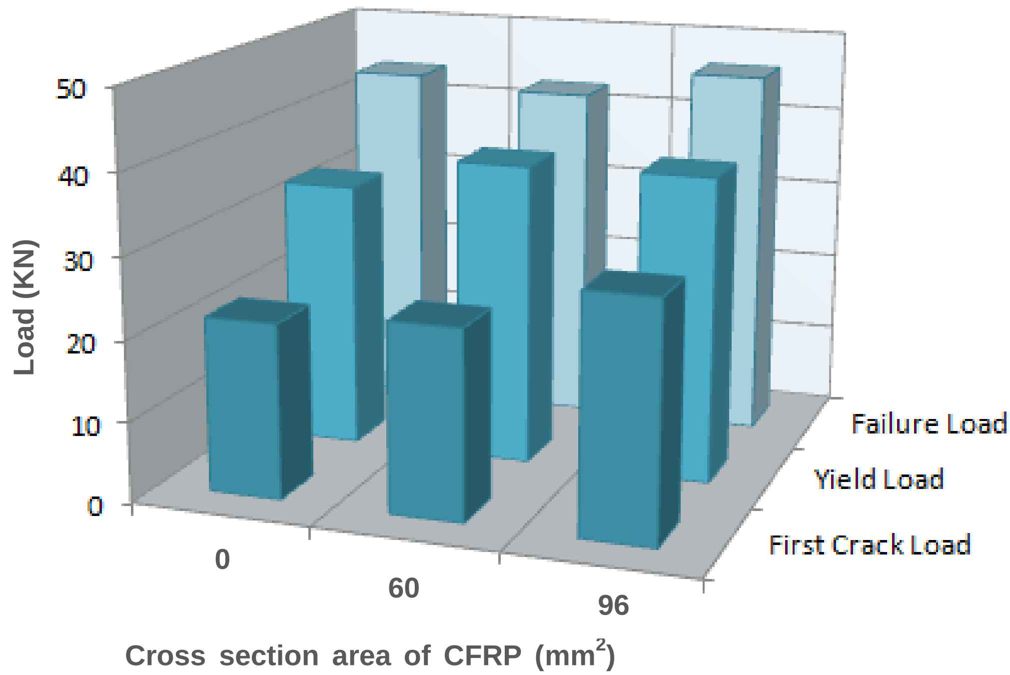

Figure 13. Experimental loading result of S512 & S518-70.

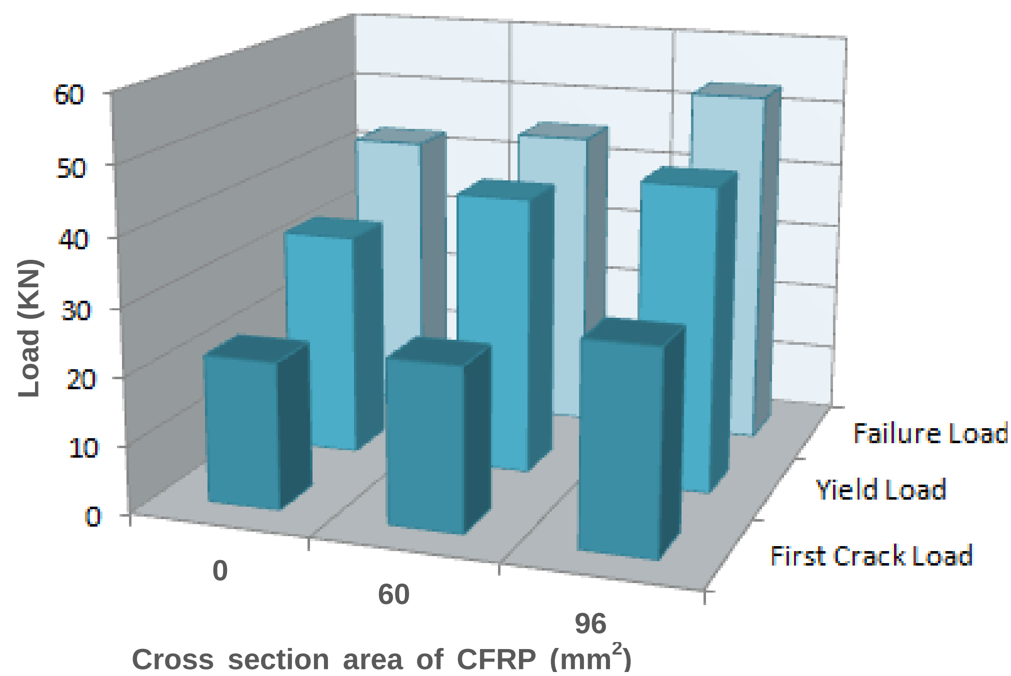

Figure 14. Experimental loading result of S512 & S518-110.

deflection (7), failure load (8), and maximum deflection (9) of the network output and the experimental data for S512-110 and S812-70 have compared together.

The results have been closed together with the highest correlation coefficient as well as in Figures 19 and 20.

The amount of coefficient correlation was 0.992 and

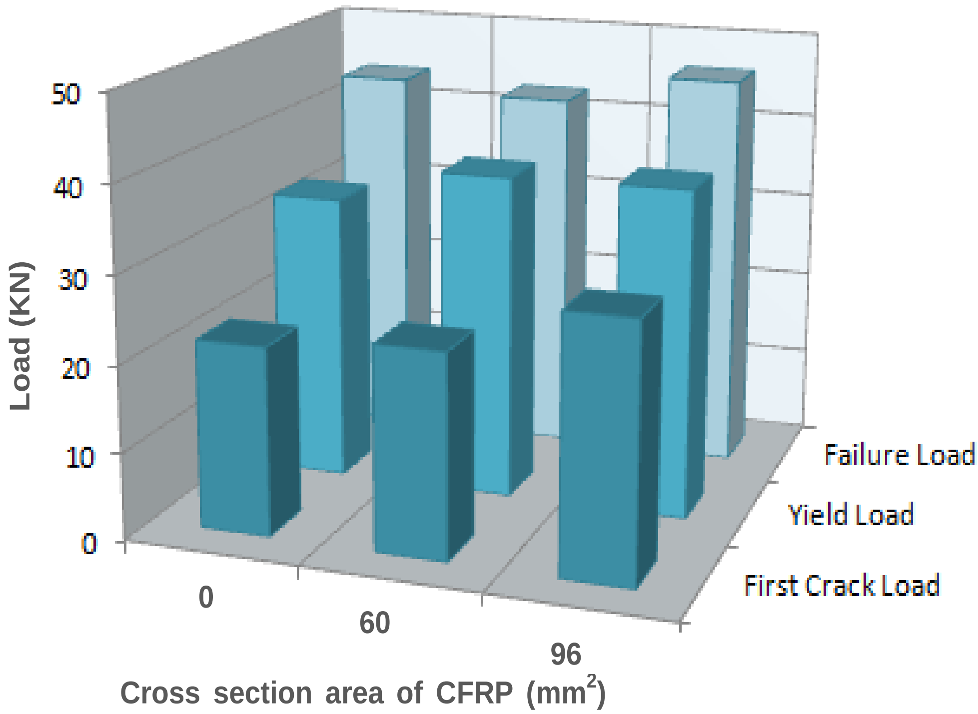

Figure 15. Experimental loading result of S512 & S518-150.

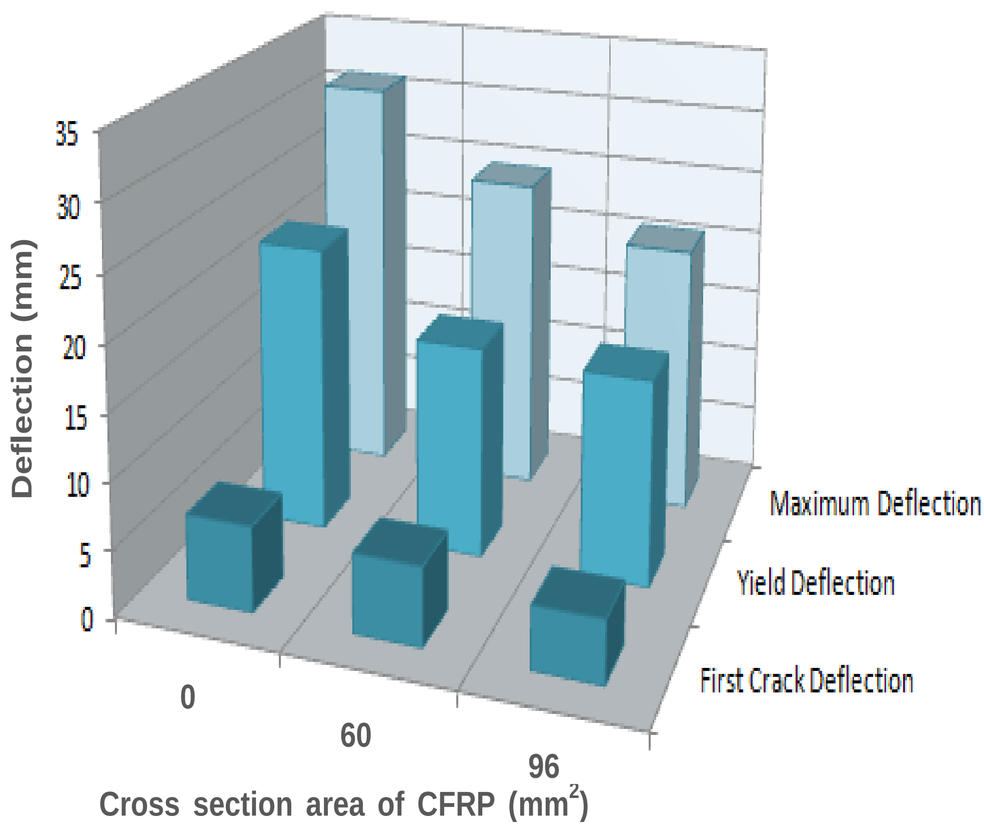

Figure 16. Experimental deflection result of S512 & S518-70.

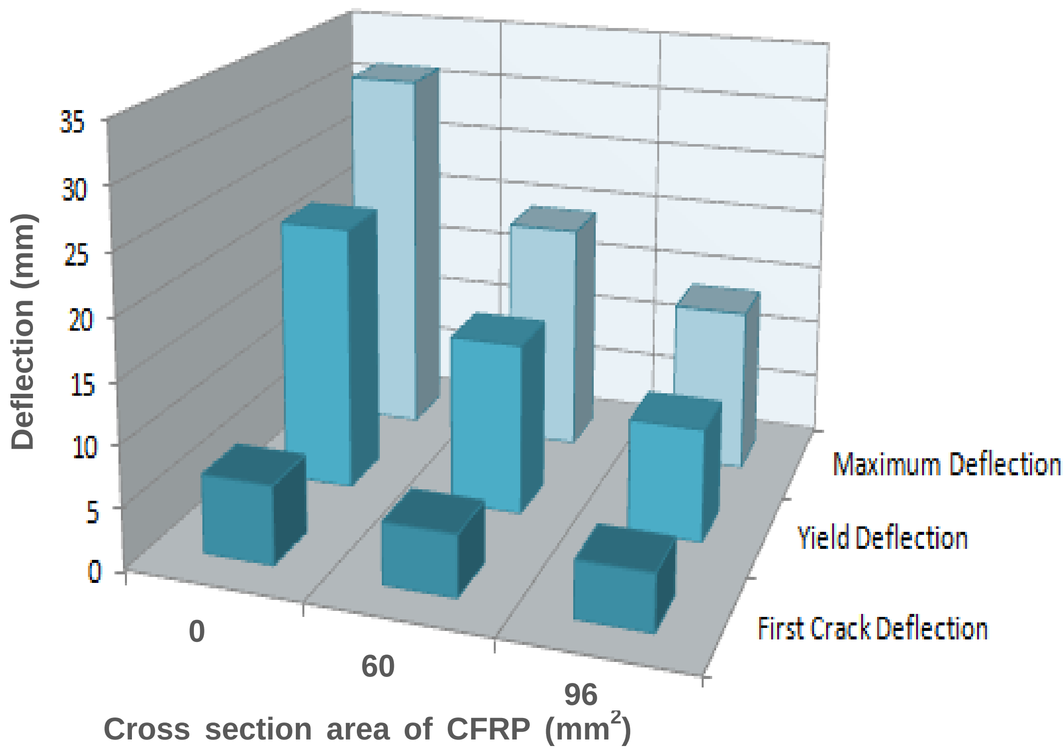

Figure 17. Experimental deflection result of S512 & S518-110.

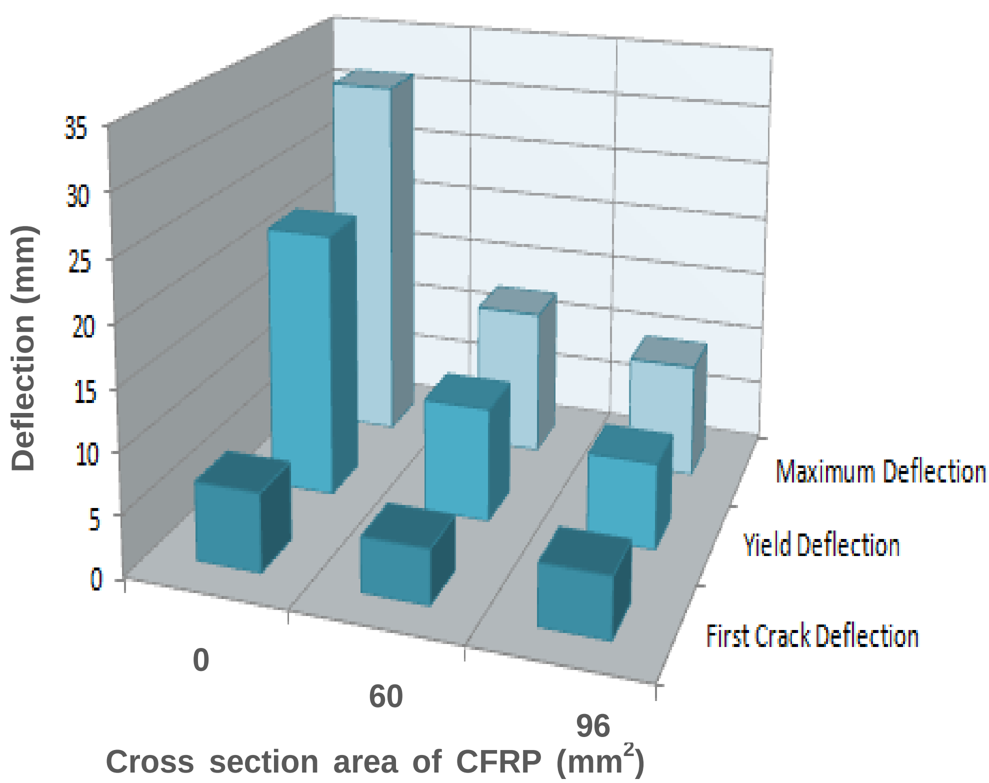

Figure 18. Experimental deflection result of S512 & S518-150.

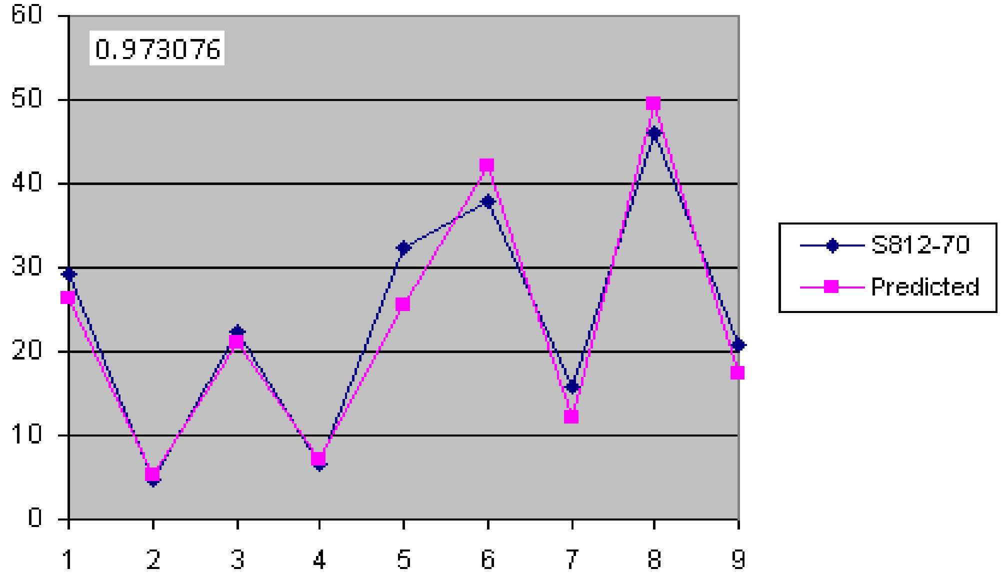

Figure 19. The predictive results compared with experimental results for S512-110.

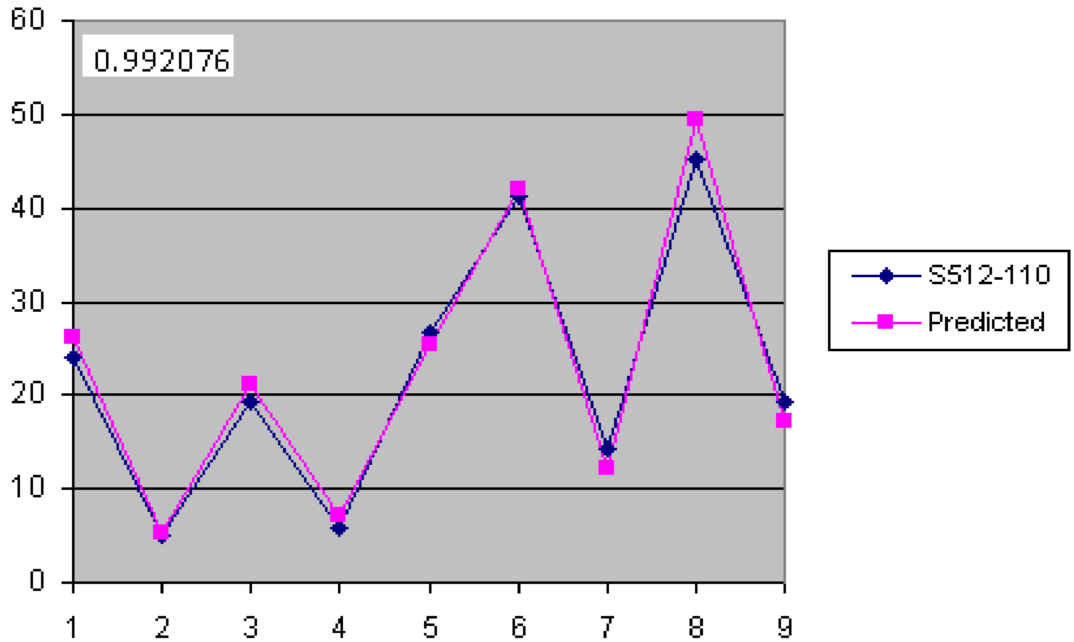

Figure 20. The predictive results compared with experimental results for S518-70.

0.973 for S512-110 and S812-70 respectively.

Feed forward backprop (FFB)

When the number of information is not enough, the FFB cannot be an advantage in prediction and the output results will be out of real data set. In regard to the small numbers output results in current research, some information has gathered between real data by creation regression function before making network. The created data have referenced in Table 6. The S512-90, S812-90

Table 5. The MSE & RMSE amounts of the predicted outputs for structural analysis of slab in GRNN technique.

	P_{cr}	Δ_{cr}	ε_s	ε_c	ε_{CF}	P_y	Δ_y	P_f	Δ_{Max}
MSE	0.000298	6.02E-06	8.86E-05	4.96E-05	0.001081	0.000411	0.000368	0.000655	0.00038
RMSE	0.017255	0.002453	0.009411	0.007045	0.032886	0.020281	0.019193	0.025603	0.018382

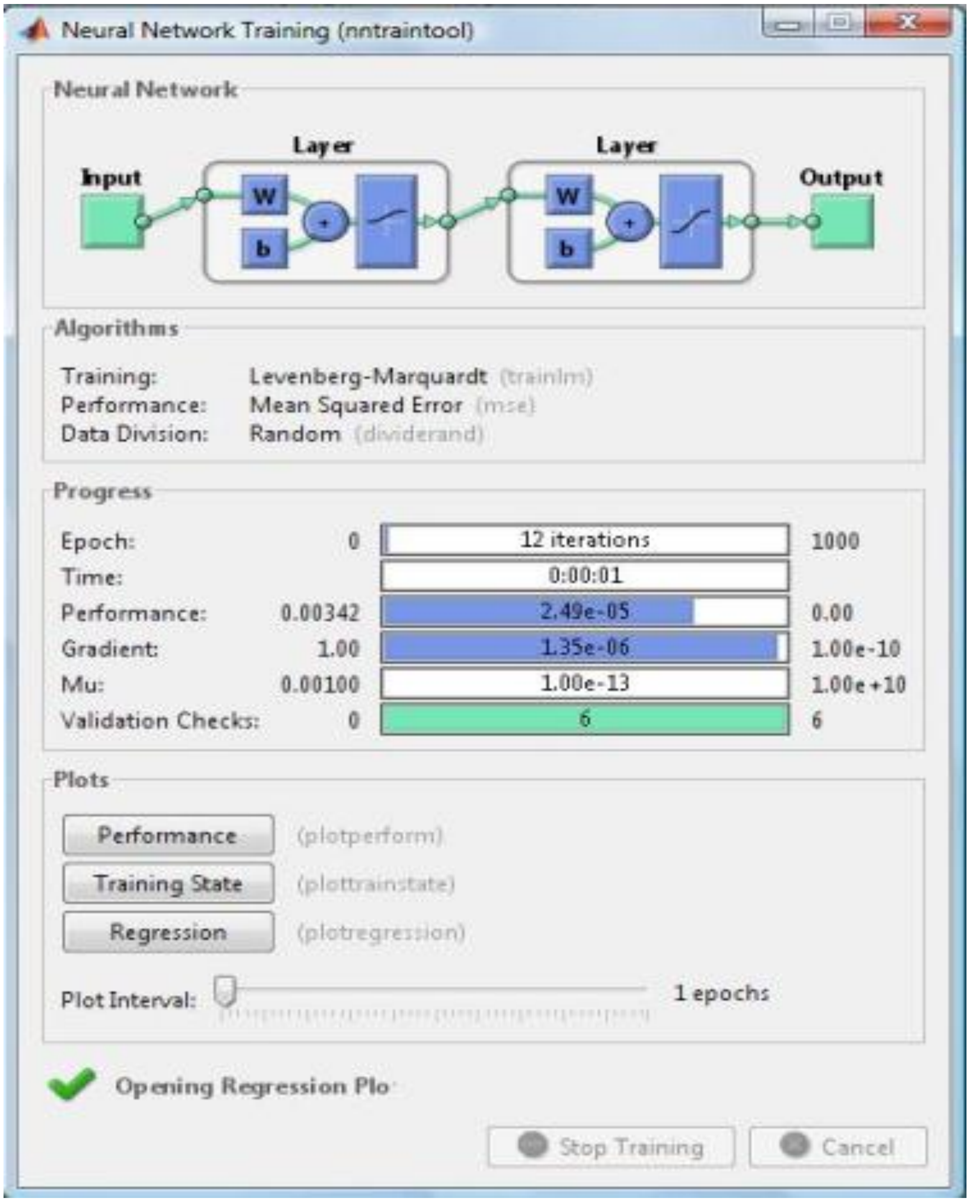

Figure 21. Neural network training.

(L = 900 mm) and S512-130, S812-130(L = 1300 mm) variable in length are four new information that have been collected from regression function of experimental results. The modeling of the applied network is consisted from Table 7.

The best network architecture

The best architecture is estimated by testing of different number of neuron in the hidden layer. In this order, MSE method is used to determine minimum error. The (3-10-9)

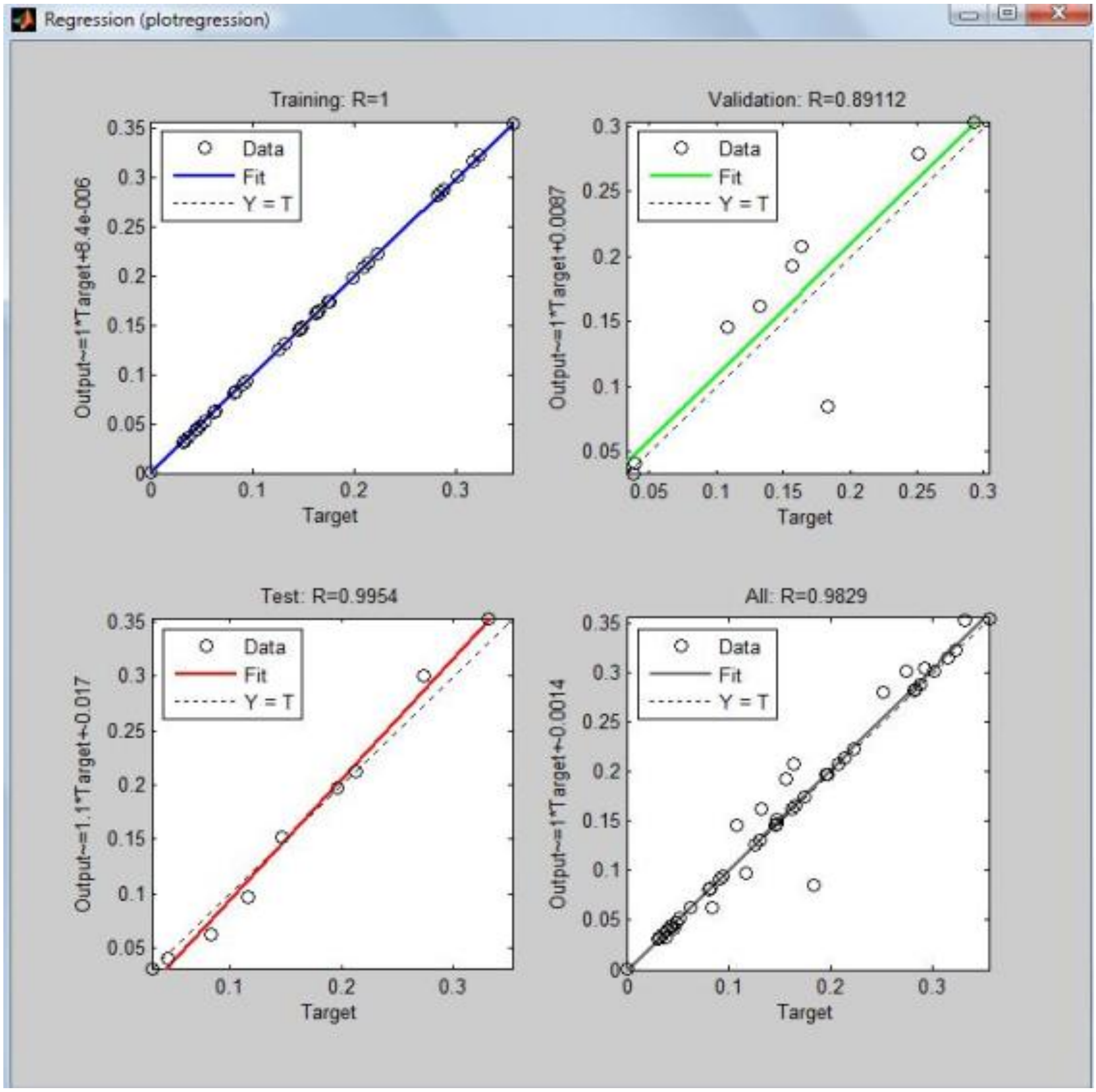

Figure 22. The regression function for training, validation and testing.

architecture has been accepted in the end of the calculation. The (3-10-9) meaning is 3 inputs, 10 hidden layers and 9 outputs.

Training

In this part, 6 details of three kinds of information, such as the thickness, the length and the width of CFRP have been applied.

Verifying

For network structures checking in different series of training, 3 data as verifying input and output have been used to time break of computation. This operation has continued until the error in the verifying has decreased (Figure 21).

Testing

Two sets data have used for testing in the next step after training and verifying. The selected data were similar with GRNN method. The regression function of training, validation, testing and for all is shown in Figure 22. The MSE and RMSE of selected network are exposed in Table 8. The generated network has a correlation coefficient close to 1. The first crack load (1), deflection

Table 6. The created data due to regression function from experimental results.

Slab market	First crack						After first crack		
	Crack load	Crack deflection	Steel strain	Concrete strain	CFRP strain	Yield load	Yield deflection	Failure load	Maximum deflection
	P_{cr}_KN	Δ_{cr}_mm	ε_{s}_μ	ε_{c}_μ	ε_{CF}_μ	P_{y}_KN	Δ_{y}_ mm	P_{f}_KN	Δ_{Max}_mm
S512-90	23.82	5.77	1997	605	2687	39.4	15.36	44.9	20.04
S512-130	24.42	5.37	1957	725	2607	42.2	12.16	47.3	14.04
S812-90	29.37	4.65	2199	688	3194	41.01	12.64	49.75	17.52
S812-130	29.77	4.53	2159	848	3154	46.21	8.24	55.35	11.92

Table 7. ANN modeling.

Training algorithms	Function	Network architecture	Training, verifying and testing
Levenberg Marquardet	LOGSIG	3-10-9	6, 3 and 2 data

Table 8. The MSE & RMSE amounts of the predicted outputs for structural analysis of slab in FFB technique.

	P_{cr}_KN	Δ_{cr}_mm	ε_{s}_μ	ε_{c}_μ	ε_{CF}_μ	P_{y}_KN	Δ_{y}_ mm	P_{f}_KN	Δ_{Max}_mm
MSE	7.575E-05	0.0001297	0.0001297	0.0001297	0.000203	0.001158	0.001585	0.000995	0.0003818
RMSE	0.0087	0.00099	0.0114	0.0053	0.014	0.034	0.0398	0.0315	0.0195

(2), steel bar strain (3), strain in concrete (4), strain in CFRP (5), yielding load (6), deflection (7), failure load (8), and maximum deflection (9) have displayed in the evaluative graphs between predicted output and real result (Figures 23 and 24).

Conclusion

The first part of this current research is on the base of practical results but, in the second part, carried out two theoretical methods for prediction of information with minimal error and maximum correlation coefficient.

i) By increasing the length, width and cross section area of CFRP in tensile side of the slab, the analysis limitation of RC slab has improved. The results have shown the first crack load, yield load, and failure load has increased to 34.74, 31.24 and 25.5% respectively. The reduction in the development practice has shown that the samples could not have a maximum load issue because of debonding defect. The first crack deflection, yield deflection, and maximum deflection have decreased 31, 67.93 and 69.44% respectively.
ii) The first analytical method was general regression neural network (GRNN) that has generated predictive data with minimal error and maximum correlation coefficient. The calculated errors for testing data were in the field of 6E-6~ 0.0011 for MSE and 0.0024~0.03 for RMSE. The correlation coefficients for S512-110 and S812-70 were 0.992 and 0.973.
iii) The next analytical method was ‘feed forward backprop’. In this method, 6 data have been used for training, 3 information for verifying and 2 data for testing. The selected data were similar to used data in GRNN process but, the additional information data have created due to regression function between experimental results.

The MSE and RMSE was in the field of 9.91E-7 ~

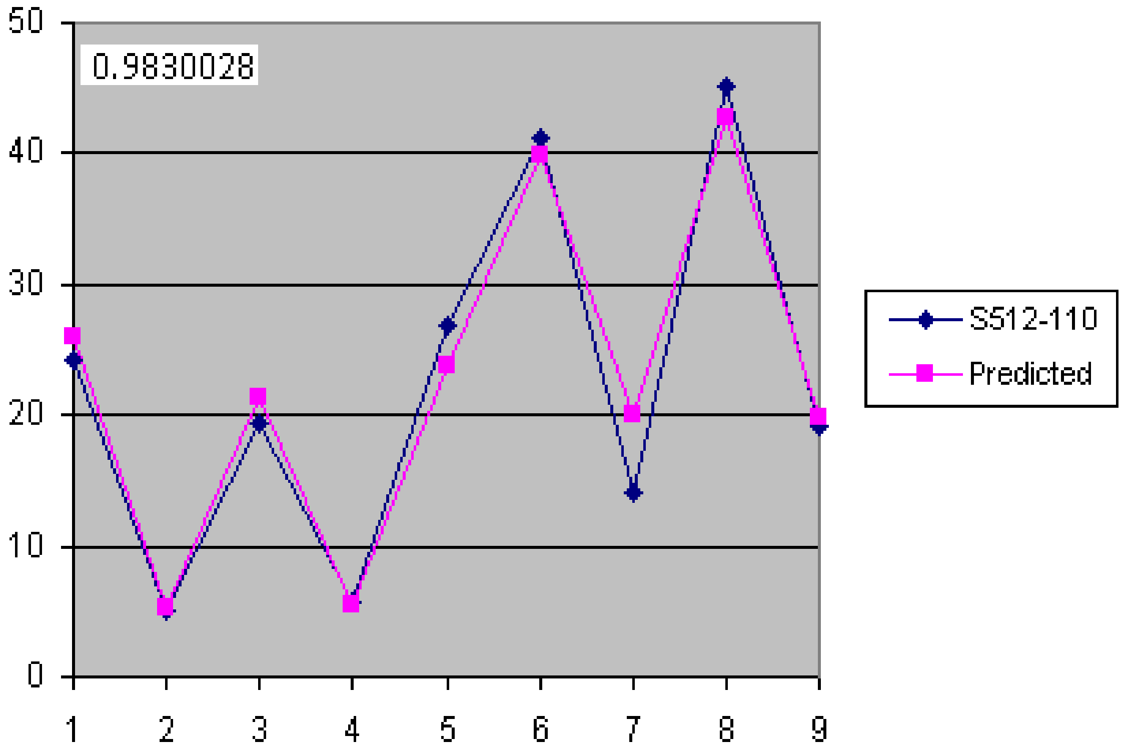

Figure 23. The predictive results compared with experimental results for S512-110.

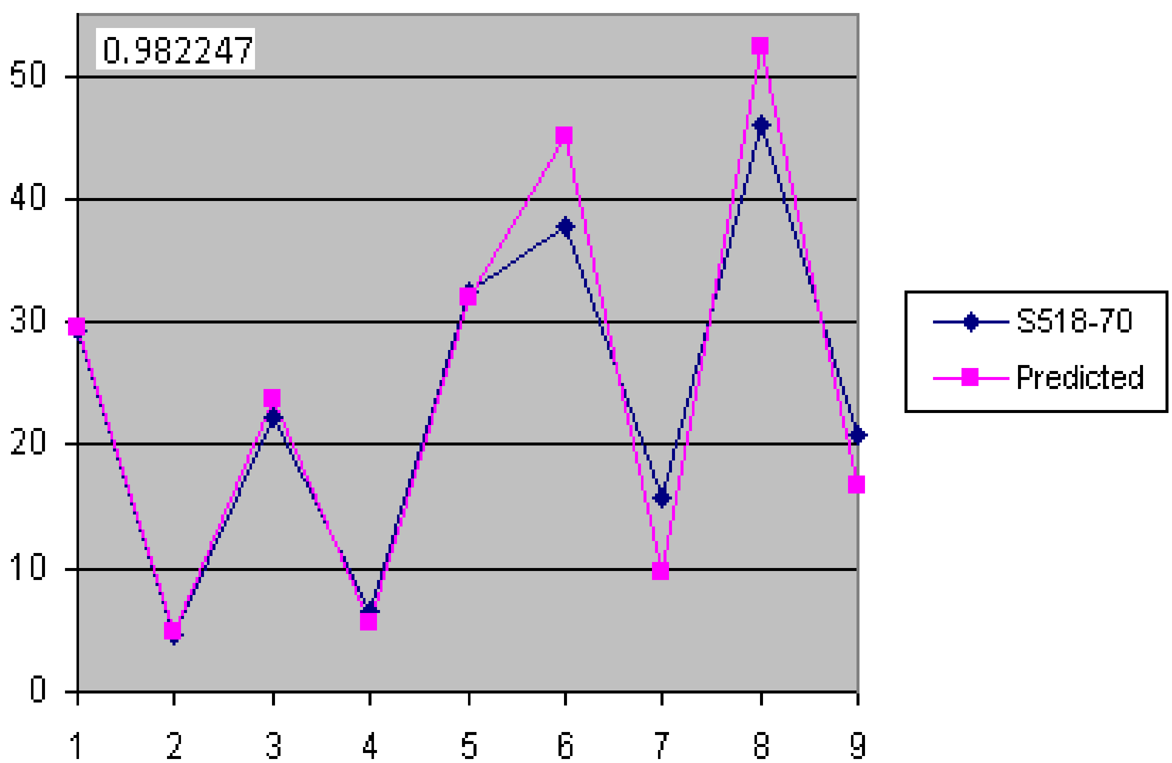

Figure 24. The predictive results compared with experimental results for S518-70.

0.00158 and 0.00099~0.0398. The correlation coefficient for S512-110 and S812-70 were 0.983 and 0.982 respectively.

REFERENCES

Amen A, Laurent M, Manuel L, Patric H (2008). Strengthening slab using externally-bonded strip composite. Composite, 39: 1125-35.

Carlos AC, Maria ML (2006). Sensitivity analysis of reinforced concrete beams strengthened with FRP laminates. Cem. Concrete Comp., 28: 102-114.

Chami GA, Thériault M, Neale KW (2007). Creep behavior of CFRP-strengthened reinforced concrete beams. Constr. Build. Mater., 23(4): 1640-1652.

Christopher KY, Zhongfan CS, Lee KL (2002). Effect of size on the failure of FRP strengthened reinforced concrete beams. Adv. Build. Technol., pp. 797-801.

Clarke JK, Waldron P (1996). The reinforcement of concrete structures with advanced composites. Struct. Eng., 74(17/3): 283-288.

Ehab ES, Khaled S, Maria AP (2004). Punching Shear Behavior of Flat Slabs Strengthened with Fiber Reinforced Polymer Laminates. J. Comp. Constr., ASCE., pp. 384-392.

Fatih A, Özgür K, Kamil A (2008). Predicting the compressive strength of steel fiber added lightweight concrete using neural network. Comput. Mater. Sci., 42: 259-265.

Harajili MH, Soudki AK (2003). Shear Strengthening of Interior Slab–Column Connections Using Carbon Fiber-Reinforced Polymer Sheets. J. Comp. Constr., ASCE., pp. 145-153.

Jamal AA, Elsanosi A, Abdelwahab A (2007). Modeling and simulation of shear resistance of R/C beams using artificial neural network. J. Franklin Instit., 344: 741-756.

Kasperkiewics J, Racz J, Dubrawski A (1995). HPC strength prediction using ANN. ASCE J. Comput. Civil Eng., 9: 279-284.

Lai S, Sera M (1997). Concrete strength prediction by means of neural network. Constr. Build. Mater.,11: 93-98.

Lee SC (2003). Prediction of concrete strength using artificial neural Networks. Eng. Struct., 25: 849-857.

Li LJ, Guo YC, Liu F, Bungey JH (2005). An experimental and numerical study of the effect of thickness and length of CFRP on performance of repaired reinforced concrete beam. Constr. Build. Mater., 20: 901-909.

Marco A, Pisani M (2006). Evaluation of Bending Strength of RC Beams Strengthened with FRP Sheets. J. Comp. Constr. ASCE., pp. 313-320.

Mehmet I (2007). Modeling ultimate deformation capacity of RC columns using artificial neural networks. Eng. Struct., 29: 329-335.

Naci C, Elmas M, Yaman ZD, Saribiyik M (2008).Neural networks in 3-dimensional dynamic analysis of reinforced concrete buildings, Constr. Build. Mater., 5(22): 788-800.

Ola E, Lundqvist J, Ta¨ljsten B, Rusinowski P, Olofsson T (2007). CFRP strengthened openings in two-way concrete slabs – An experimental and numerical study. Constr. Build. Mater., 21: 810-826.

Pannirselvam N, Raghunath PN, Suguna K (2008). Neural Networks for performance of Glass Fiber Reinforced polymer plated RC beam. Am. J. Eng. Appl. Sci., 1: 82-88.

Smith ST, Kim SJ (2009). Strengthening of one-way spanning RC slabs with cutouts using FRP composites. Constr. Build Mater., 23: 1578-90.

Stijn M, Luc T (2000). Concrete Slabs Reinforced with FRP Grid, Punching Resistance, J. Comp. Constr., 154-161.

Taljsten B, Elfgren L (2000). Strengthening of concrete beams for shear using CFRP-materials: Evaluation of different application methods. Composites Part B: Eng., 31:87-96.

Toutanji H. and Balaguru P (1998). Durability Characteristics of Concrete Columns Wrapped with FRP Tow Sheets. J. Mater. Civil Eng., 52-57.

Yeh IC (1998). Modeling of strength of HPC using ANN. Cem. Concr., 28: 1797-1808.