Full Length Research Paper

Nonlinear analysis of load-deflection testing of reinforced one-way slab strengthened by carbon fiber reinforced polymer (CFRP) and using artificial neural network (ANN) for prediction

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Load-deflection curve is the most important part of the structural analysis of RC beam and slab. The load-deflection analysis of the RC one-way slab strengthened by CFRP using experimental work, finite element analysis (FEA), artificial neural network (ANN), and a comparison of them together are the important objective of this study. The dimension of the one-way slab was 1800×400×120 mm which was strengthened by different length and width of carbon fiber reinforced polymer (CFRP). The experimental results sufficiently adapted with FEA and ANNs output. The feed forward back-propagation (FFB) was the best ANN for prediction of load-deflection curve with minimum error below 1%, and maximum correlation coefficient close to 1.

Key words: Carbon fiber reinforced polymer (CFRP), finite element analysis (FEA), artificial neural network (ANN), feed forward back-propagation (FFB).

INTRODUCTION

Damaged parts of structures require strengthening and also upgrading due to disaster or material degradation. Normally, carbon fiber reinforced polymer (CFRP) was used for strengthening of RC structures due to high strength and stiffness-to-weight ratio, corrosion resistance, utilization within various factors of design, simple organization of the surface just before applying, decreased duration of the construction time and lots of time remaining after strengthening scheme (Taljsten and Elfgren, 2000; Clarke and Waldron, 1996). CFRP has the essential requirement characteristics which make it usable for installation on the RC elements for structural behavior strengthening by considering debonding failure management (Li et al., 2005). The first crack load, final load, stiffness, ductility and CFRP stress have been carried out in an experimental work, and the finite element analyses of various length and thickness (single and dual layer) of CFRP, carried out in rectangular beam

samples, were compared with the debonded ones. Another study completed a laboratory research on different small areas of concrete with a steel ratio of 0.01 and different layers of CFRP to achieve the same CFRP/concrete ratio (Christopher et al., 2002). The samples were tested for closure loading in contrast to having similar samples without CFRP. Later, a study prepared independent experiments on reinforced flat slab applying CFRP to accomplish load capacity (Amen et al., 2008; Naci et al., 2007; Smith and Kim, 2008). As we know, load-deflection analysis is the essential and important factor used to make design formulation for structures. So, in this research, by using different length and cross section areas of CFRP attached below the slab, the load-deflection analysis of the strengthened slab is compared with the plain reinforced concrete slab. As this research progresses, artificial neural network is applied for load-deflection prediction of the one-way slab strengthened by different length and cross section areas of CFRP, after which nonlinear analysis of the samples, using LUSAS software, is compared with the experimental results and artificial neural network (ANN) outputs.

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Table 1. Application of ANN in civil engineering problems.

No.	Reference	Objective
1	Kasperkiewicz et al. (1995)	Predicting strength of high-performance concrete- ANN
2	Ilker and Mustafa (2008)	Mechanical properties of recycled aggregate concretes containing silica fume- ANN and FL
3	Yeh (1998)	Modeling of strength of HPC using ANN
4	Jamal et al. (2007)	R/C beams shear resistance using ANN

Table 2. The dimension of attached CFRP on the RC one-way slab.

CFRP (mm)	Sample market					
	S512-700	S512-1100	S512-1500	S812-700	S812-1100	S812-1500
Length	700	1100	1500	700	1100	1500
Width	50	50	50	80	80	80
Thk	1.2	1.2	1.2	1.8	1.8	1.8

For the last two decades, the different modeling techniques, based on ANN systems were used by many researchers in different branches of Civil Engineering applications (Akbulut et al., 2004). Some of the applications of the ANN are explained in Table 1.

Bimal and Mutsuyoshi (2006) applied ANN models to predict the ultimate shear strength in steel fiber RC beams. The back-propagation was utilized as a learning algorithm in the feed-forward neural network. The studied on the effect of the number of input layer upon the net accuracy in regard to comparison with the analytical formulation given in literature. The analysis shows that the generated ANN with five input layers can predict the ultimate shear strength more accurately than the network with 4 input layers. Also the results show that ANN model present the underlying shear behavior very well in beam.

In other research by Jamal et al. (2007), back propagation neural network (BPNN) with different transfer functions is applied for shear resistance of rectangular R/C beams predicting and compared together. The BPNN with sigmoid function was the last iteration to predict the shear strength of RC beam accurately. Kerh and Yee (2000) applied energy function as minimization key in dynamic back propagation neural networks to analyze the deformed behaviors for culvert structure under a static loading. The stiffness matrix and force vector of the structure were replaced with weighting matrix and bias vector in the neural networks calculations. Naci et al. (2007) utilized the dynamic analysis results of 165 buildings to generate a multilayer perception (MLP) with a back-propagation (BP) algorithm. Different properties in network employed to find the optimum network. The output results specified that the produced ANN can determine the 3D response of buildings subjected to earthquake as a user friendly computational tool.

METHODOLOGY

Construction of the experimental work

The slab having a similar dimension of 2800×400×120 (mm), an equal steel bar percentage of 2T10, and strengthened by different length (700, 1100 and 1500 mm) and cross section area (60 and 96 mm^2) of CFRP, was tested and compared with similar samples without CFRP, and is shown in Table 2. The samples loading and instrument setup is shown in Figure 1, while the property of the used materials is shown in Table 3.

Nonlinear analysis using LUSAS software

LUSAS is a finite element analysis (FEA) software that can evaluate all kinds of complex models using linear or non linear analysis. In LUSAS software, the model geometry is defined as features which are then sub-divided into finite elements in order to do the analysis. By increasing the number of elements in the meshed member, the accuracy of the analysis is usually increased, and the time required for analysis is also increased. The elements are modeled in LUSAS software as the following statements: In considering the linear strain distribution over the depth, no slip was found between the concrete and steel bar and external CFRP, thereby the adhesive tensile strength was ignored and tensile stress was not carried by concrete after cracking. The concrete feature assumptions in the current study are as follow:

1. The first crack maximum stress in concrete is equal to $0.3f_c'$
2. The strain on the ultimate concrete compressive is equal to 0.0035.
3. The relationship between stress and strain after first crack and ε_0 is defined by the following formula:

$$\frac{f_c}{f_c'} = \frac{2\varepsilon_c}{\varepsilon_0} - \left(\frac{\varepsilon_c}{\varepsilon_0}\right)^2$$
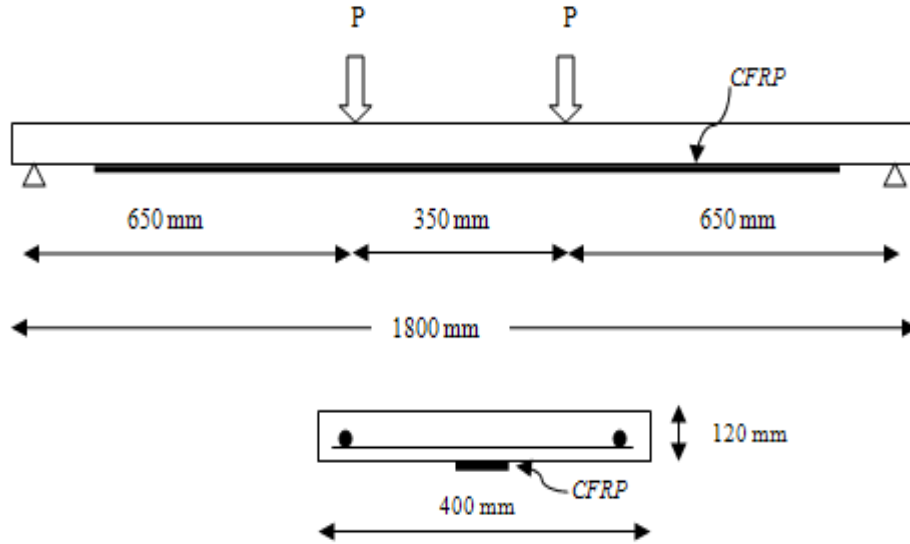
Figure 1. Loading and instrument setup.

Table 3. The properties of the used material.

Material	Properties
Concrete	Mix ratio of 1: 1.47: 2.64: 0.5 (Cement: FA: CA: Water); Mean compressive (300 Kg/cm^2), tensile strength (45 Kg/cm^2); Elasticity (E_c = 258811 Kg/cm^2)
Steel	Rebar T10 (f_y = 4000 Kg/cm^2), (E_s = 2150000 Kg/cm^2)
CFRP	-Sika CarboDur- MY S 512 (width 50 mm, thickness 12 mm), (Cross section area = 60 mm^2)
Adhesive	Sikadur -30 m (Compressive, shear and tensile strength are 90, 17.5 and 28.6 Mpa, respectively after 7 days curing in 35°C temperature)

$$\varepsilon_0 = \frac{1.8 f_c'}{E_c}$$

4. The relationship between stress and strain after ε_0 and before ε_{cu} is defined by the following formula:

$$\frac{f_c}{f_c'} = 1 - K(\varepsilon_c - \varepsilon_0)$$

$$K = \frac{0.15}{0.0038 - \varepsilon_0}$$

where: f_c = stress in concrete; f_c' = ultimate stress in concrete; ε_c = compressive strain in concrete; ε_0 = strain in maximum compressive stress, and E_c = concrete module of elasticity.

Artificial neural networks (ANNs)

Artificial neural networks (ANNs) are extremely simplified models of biological neural systems, displaying capabilities such as learning, abstraction and generalization (Wasserman and Bentur, 1996). Neural networks are kinds of data information used to give out the method, whose architecture is enthused by the construction of human nervous structure (Caudill and Butler, 1990). Actually, the fundamental purposes of biological neurons are simulated by artificial neurons (Hawley et al., 1990).

A network is performed by lot of nodes that are connected together by function. The nodes inside the input and output layers are named sensory and responding nodes, respectively. The nodes in the interior layer between input and output layers are named hidden nodes. The information data are entered into the network
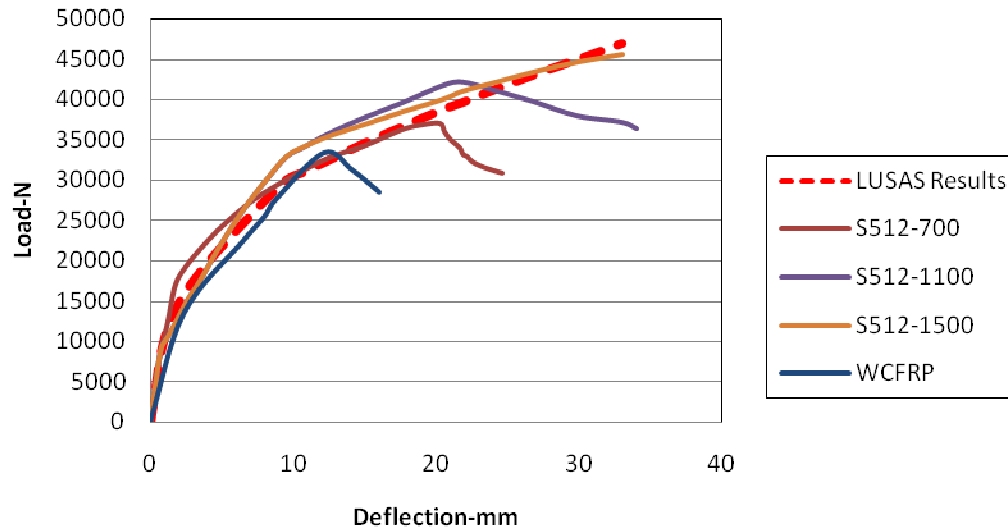
Figure 2. Load-deflection relationship for slab with CFRP S512 as compared to that without CFRP.

named input nodes, after which they are connected to hidden nodes by function, and finally the network output is concluded from the output layer nodes. The selection of the network type is the first and important part of modeling by artificial neural network, after which the input parameters will be selected adequately to the output data. Then, the network architecture means of the number of layers, the neurons in each layer and their connection together, the kind of transfer function for neurons, and the network training and learning function will be determined. After determining the network type and net architecture, there is need for some gathered data to generate network. The gathered data, which must be for the network generation, are divided into three phases (Ripley, 1996):

1. Training phase: Using all training data set for network learning to fit the weight of the classifier.
2. Validation phase: A set of data used to adjust the parameters of a classifier, such as the number of hidden layers and neurons in each hidden layer. Actually, in this phase, the necessary training iteration is determined to avoid overtraining.
3. Test phase: A set of data is used for full assessment of the network performance.

In the current research, Feed-forward back-propagation neural networks (FBNNs) were applied for load-deflection prediction of the plain RC one-way slab and were strengthened by CFRP. In recent years, the FBNN efficiently attracted researchers from many areas of civil engineering applications, such as prediction of compressive concrete strength (Hong-Guang and Ji-Zong, 2000), prediction of shear strength of RC beams (Mansour et al., 2004), structural analysis and design (Consolazio, 2000; Hadi, 2003), damage detection of bridges (Lee et al., 2005; Yeung and Smith, 2005), structural dynamics and control (Chen et al., 1995).

RESULTS AND DISCUSSION

Experimental results versus nonlinear analysis

Here, the results of the experimental work are compared with that of the analytical output. In Figure 2, the one-way

RC slab strengthened by CFRP S512 (width = 50 mm and thickness = 1.2 mm) and different length (700, 1100 and 1500 mm) were compared with the similar one way RC slab without CFRP. As it is considered, the experimental result for load-deflection analysis follows the result of the finite element analysis (FEA) output. By using CFRP installed on the slab structure, the value of load-deflection set (KN, mm) for the sample without CFRP changed from 33 and 12 to 37 and 19, 42 and 22, and 45.5 and 33 for S512-700, S512-1100 and S512-1500, respectively. These results indicated that by increasing the length of CFRP (such as 700, 1100 and 1500 mm), the loading capacity increased by 10.8, 21.5 and 27.5%, respectively.

The results of the experimental work on the one-way RC slab strengthened by S812 (width = 80 mm and thickness = 1.2 mm) and the different length (700, 1100 and 1500 mm) in comparison with the sample without CFRP are indicated in Figure 3. By increasing the length of the installed CFRP, the loading capacity improved by 13.2, 26.7 and 40% for S812-700, S812-1100 and S812-1500, respectively.

By increasing the CFRP cross section area from 60 (S512-1500) to 96 mm^2 (S812-1500), the maximum load capacity increased from 45.5 to 55 KN (Figure 4).

Artificial neural networks

The modeling of the network consists of the following five parameters:

1. Training algorithms: Back-propagation algorithm is applied as the training phase in the feed forward neural network. The back-propagation neural networks (BPNNs) consist of an input layer, one or more hidden layers, and
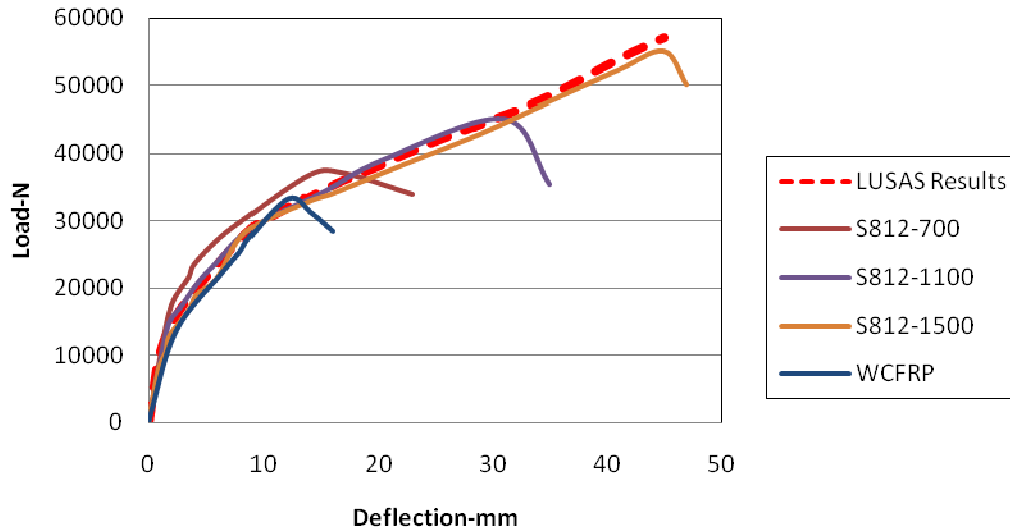
Figure 3. Load-deflection relationship for slab with CFRP S812 as compared to that without CFRP.
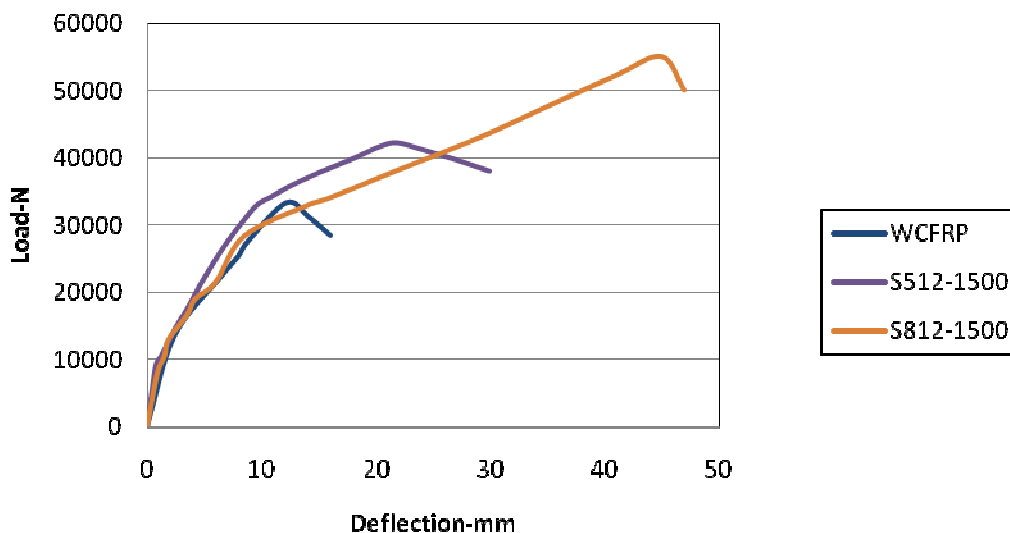

Figure 4. Load-deflection analysis comparison between the samples strengthened by CFRP512-1500 and CFRP S812-1500 and the samples without CFRP.

an output layer (Rajagopalan et al., 1973).

2. Network training and learning function: Training and learning functions are numerical measures used for automatically changing the weights and biases of the system.

3. Network architecture: The number of hidden layers and neurons in each hidden layer is defined in this part. The number of hidden layers can be randomly selected and changed to find the best one in each trial. Normally, one or two hidden layers with a random number of neurons should be sufficient to estimate any function (Haykin, 1994).

4. Network transfer function: An appropriate transfer function should be selected for numerical representation of the relation between the input and output of a network. Linear, threshold and sigmoid are three applicable transfer functions (Ripley, 1996).

5. Network performance function: The mean square error (MSE) was used to calculate the percentage of different values between actual and network output. The properties of the selected network are shown in Table 4.

The optimum network is selected based on minimum error and maximum correlation coefficient between data.

Table 4. The network properties.

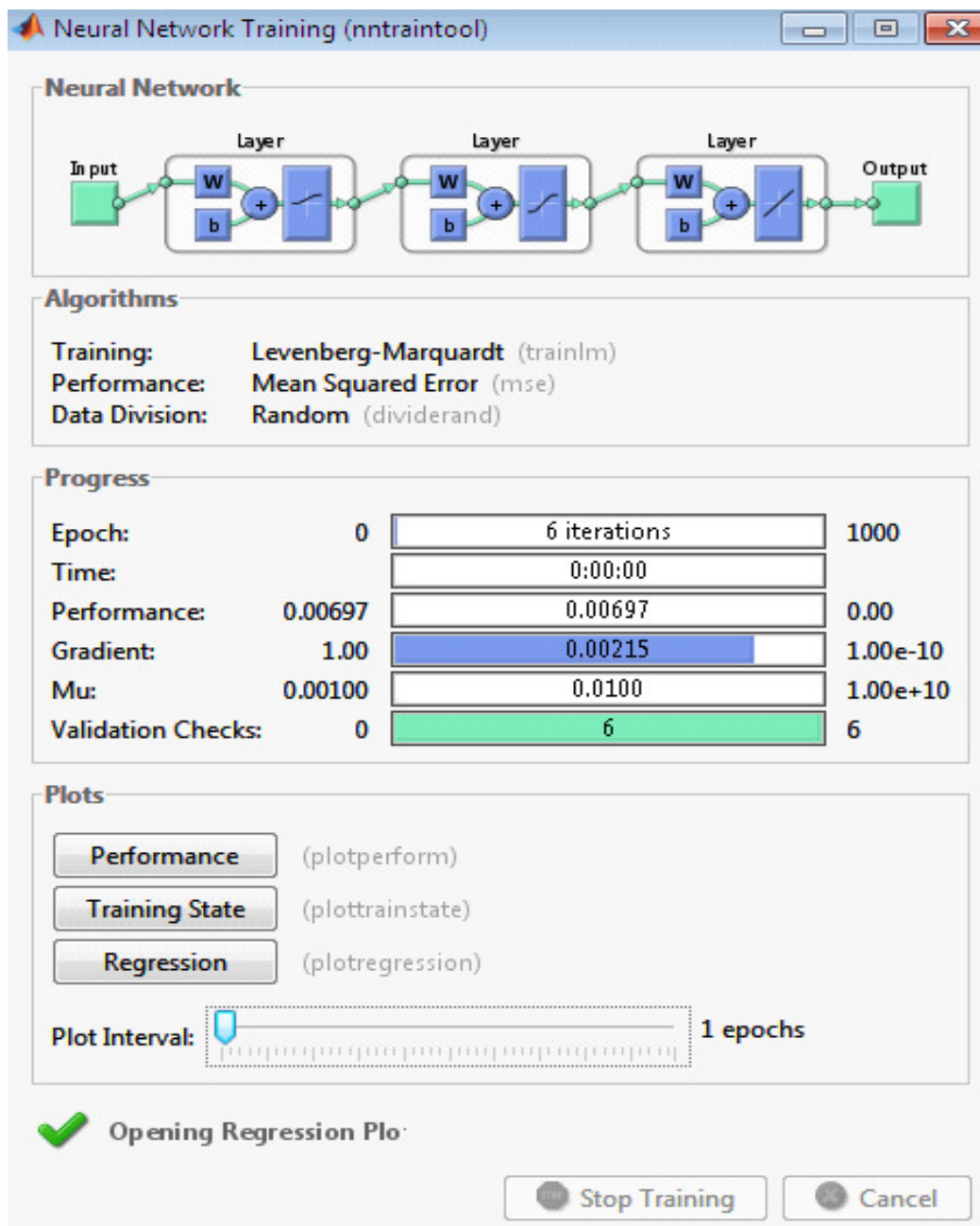| No.	Parameter	Property
1	Training algorithms	Lonberg-Markorat
2	Network transfer function	LOGSIG-TANSIG-PURELIN
3	Network architecture	3-15-5-1
4	The number of training data	87
5	The number of verifying data	24
6	The number of testing data	11
7	Network function	Feed forward backdrop

Figure 5. Architecture, algorithm and training progress for the selected network.
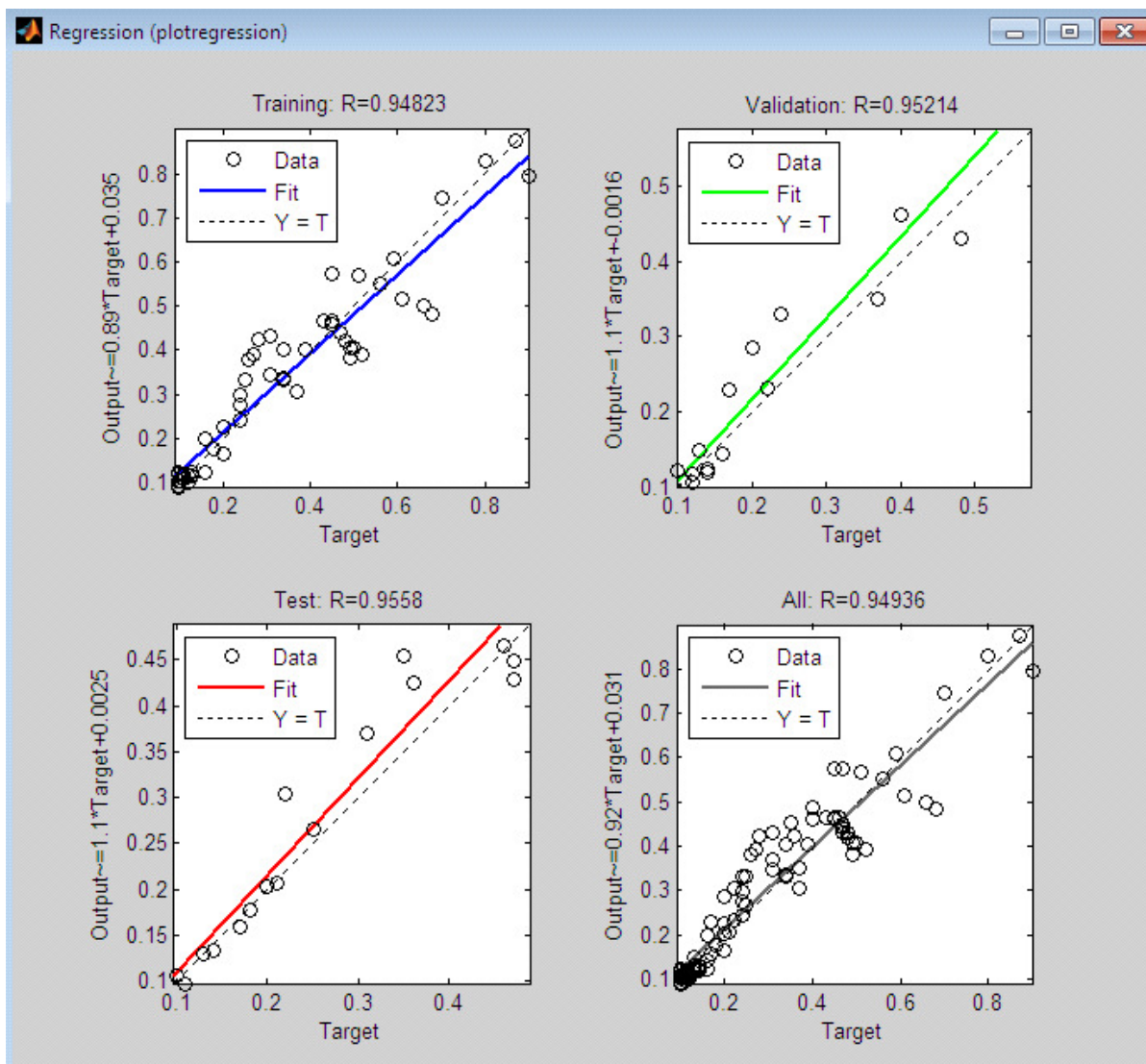
Figure 6. Network submission for the RC slab strengthened by CFRP.

The minimum training error, equal to 0.00697 (less than 1%), is extracted by the MSE method from the networks and is shown in Figure 5. However, the correlation coefficient, which is equal to 0.95 in training, verification and the testing process, is shown in Figure 6. The evaluation between the experimental results and network results is shown in Figure 7. Nonetheless, the load-deflection curve, concluded by ANN, is close to the experimental output with the minimum error below 1% as the testing output error.

Conclusion

The results of the current study are summarized as follows:

1. CFRP caused improvement on the load-deflection diagram.
2. The experimental results are sufficiently adapted to FEM, and are compared together.
3. By increasing the length of CFRP (such as 700, 1100 and 1500 mm) for the slab strengthened by S512, the loading capacity increased by 10.8, 21.5 and 27.5%, respectively.
4. By increasing the length of CFRP (such as 700, 1100 and 1500 mm) for the slab strengthened by S812, the loading capacity increased by 13.2, 26.7 and 40%, respectively.
5. For the two networks, the best architecture is 3-15-5-1.
6. For the two networks, the training, verification and testing of data had minimum error below 1%.
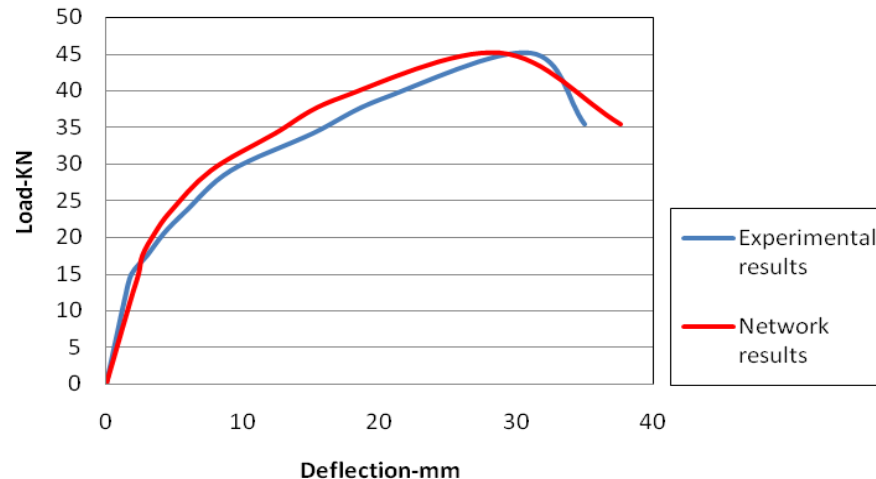7. For the two networks, the correlation coefficient was equal to 0.95.

Figure 7. Experimental and network results comparison of slab with CFRP.

8. The feed forward back-propagation is the best network function with minimum error and maximum correlation coefficient close to 1.

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