

Load-deflection analysis prediction of CFRP strengthened RC slab using RNN

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(Received July 3, 2014, Revised June 25, 2015, Accepted June 26, 2016)

Abstract. In this paper, the load-deflection analysis of the Carbon Fiber Reinforced Polymer (CFRP) strengthened Reinforced Concrete (RC) slab using Recurrent Neural Network (RNN) is investigated. Six reinforced concrete slabs having dimension 1800×400×120 mm with similar steel bar of 2T10 and strengthened using different length and width of CFRP were tested and compared with similar samples without CFRP. The experimental load-deflection results were normalized and then uploaded in MATLAB software. Loading, CFRP length and width were as neurons in input layer and mid-span deflection was as neuron in output layer. The network was generated using feed-forward network and a internal nonlinear condition space model to memorize the input data while training process. From 122 load-deflection data, 111 data utilized for network generation and 11 data for the network testing. The results of model on the testing stage showed that the generated RNN predicted the load-deflection analysis of the slabs in acceptable technique with a correlation of determination of 0.99. The ratio between predicted deflection by RNN and experimental output was in the range of 0.99 to 1.11.

Keywords: CFRP; RC; RNN; MATLAB

1. Introduction

Traditional analysis models for reinforced concrete (RC) structures are reliable and the behavior of structural elements can be successfully determined by solving several numerical equations. It is observed that the different available calculation methods produce different deflection results (Wium and Eigeaar 2010). Neural networks (NNs) model the impact of input parameters on a set of output conclusions. They apply the influential learn-by-example technique and generalization system to identify the hidden relationships linking the input to their outputs (Hegazy *et al.* 1996). The goal of ANNs is to emulate the human brain's ability to adapt to changing circumstances based on past experiences and the knowledge acquired there from.

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This depends entirely on the ability to learn, remember, and evaluate multipart data relationships (Medsker and Jain 2001). NNs have the capability to totally identify any complex nonlinear relationship between the dependent and independent variables (Hinton 1992 and White 1989). The data could be from a market research effort in the form of questionnaires, an assembly procedure of variable working conditions and guidelines, or the result of experimental and observation works in various industries.

The network connections are divided in static and dynamic network connection. In static or feed-forward connection, the information moves in only forward direction from input to output. In dynamic or feedback connection, the signal moves in both directions, forward and backward. The network with feedback connection, namely Dynamic Neural Network (DNN), is very powerful and can get extremely complicated. DNN is a kind of artificial neural network that can modify its own topology to acceptable and also changeable data. In the other word, learning process in DNN never finishes. The workflow generation of dynamic neural networks is similar to feed-forward neural networks. The major differentiation between dynamic neural network and static feed-forward neural network happen in the design development because of the defined input in dynamic networks as time sequences. In the other word, dynamic neural networks have memory and can be generated to learn time-varying or sequential prototypes.

Previous researches of ANNs in Structural Engineering mainly focused on static neural network using Feed-forward Back-propagation Neural Network (FBNN). Mehmet (2007) tried to model FBNN to predict ultimate deformation capacity of RC columns. Different network architecture investigated on the 682 column tests in un-axial bending with or without axial force and the N 9-12-1, N 9-14-1, N 9-16-1, N 9-18-1 and N 9-20-1 were the best five networks when MSE of testing data was considered. The results from the generated network presented the feasibility of using ANN models for deformation prediction of RC columns. Cevik and Guzelbey (2008) employed 101 data to generated FBNN to predict mechanical strength of cylindrical samples reinforced by CFRP. The training algorithm was quasi-Newton back propagation with 4–15–1 NN architecture and hyperbolic tangent sigmoid transfer function (tansig).

Jamal *et al.* (2007) applied FBNN with different transfer functions to predict the shear resistance of rectangular RC beams. The sigmoid function was the last iteration to predict the shear strength of RC beam accurately.

Generally, dynamics can be communicated by using an external, internal dynamics, and tapped-delay line (Nelles 2001). External dynamics method applies the historical information of output to demonstrate dynamics and makes autoregressive type neural network. The internal dynamics type takes in a nonlinear condition space model without any information regarding the true process state (Ishak 2003 and Yasdi 1999). Tapped-delay line method employs a sequence of delay to state dynamics space within network generation (Lingras 2001 and Yun *et al.* 1998).

In a research, the traditional neural network (TNN) and time delay neural network (TDNN) has been employed to detect damage in bridge structures (Barari and Pandey 1996). A multilayer perceptron with the back-propagation learning algorithm has been implemented to train TDNNs and TNNs. The architecture for TDNN and TNN was 345-(21-21)-21 and 69-(21-21)-21 with two hidden layers and 21 nodes in each hidden layer. It is found that the results of generated TDNN are more effective than TNN to detect damage in the bridge structure.

Graf *et al.* (2010) showed a numerical prediction for future structural responses in dependency of uncertain load processes and environmental influences using ANN. The generated ANN was based on RNN trained by time-dependent measurement results. The approach presents a capability for prediction of the long-term structural behavior of a reinforced concrete plate strengthened by a

textile reinforced concrete layer.

Abed *et al.* (2010) applied Focused Feed-forward Time Delay Neural Network (FFTDNN) to consider the time dependency of creep in masonry structures. The architecture of the generated network was 4-8-4-1. It means, the produced network consisted of an input layer with four neurons, two hidden layers with eight, four neurons respectively and an output layer with one neuron. They compared the capability of the created network for creep prediction with the other model which is employed Recurrent Neural Networks (RNNs) by El-Shafie *et al.* (2008). They presented that the created model in FFTDNN has a comparatively small prediction error compared to the RNN model and other theoretical model. In this research, FTDNN and RNN are applied for load-deflection and crack width prediction of RC slab strengthened by CFRP.

Freitag *et al.* (2011) introduced a model for prediction of time-dependent structural behaviour using RNN. The time-dependent data for RNN generation was obtained from measurements or numerical analysis. The RNN new approach was verified by a fuzzy fractional rheological material model to predict the long-term behaviour of a textile strengthened reinforced concrete structure

The main objective of this research is to train RNN to predict load-deflection of CFRP strengthened RC slab using internal dynamic space to memorize the input data while in training process. It involves the prediction of load deflection of 7 CFRP strengthened RC one-way slabs under four point line loads. The results of experimental works were compared with finite element analysis.

2. Methodology

2.1 Experimental work

Six reinforced concrete slabs having dimension 1800×400×120 mm with similar steel bar of 2T10 and strengthened using different length and width of CFRP were tested and compared with similar samples without CFRP (Table 1 and Fig. 1). All the slabs were designed as under-reinforced section based on rectangular stress block of ISIS (Intelligent Sensing for Innovative Structures) Canada Research Network (2001).

The slabs were simply supported and were loaded under four point bending load with line load. The loading and instrument setup are shown in Fig. 2.

Table 1 The characteristics of samples for the CFRP strengthened RC one-way slab under four point loads

No.	Slab	CFRP width (mm)	CFRP length (mm)
1	S512-700	50	700
2	S512-1100	50	1100
3	S512-1500	50	1500
4	S812-700	80	700
5	S812-1100	80	1100
6	S812-1500	80	1500
7	WCFRP*	-	-

*Without CFRP



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

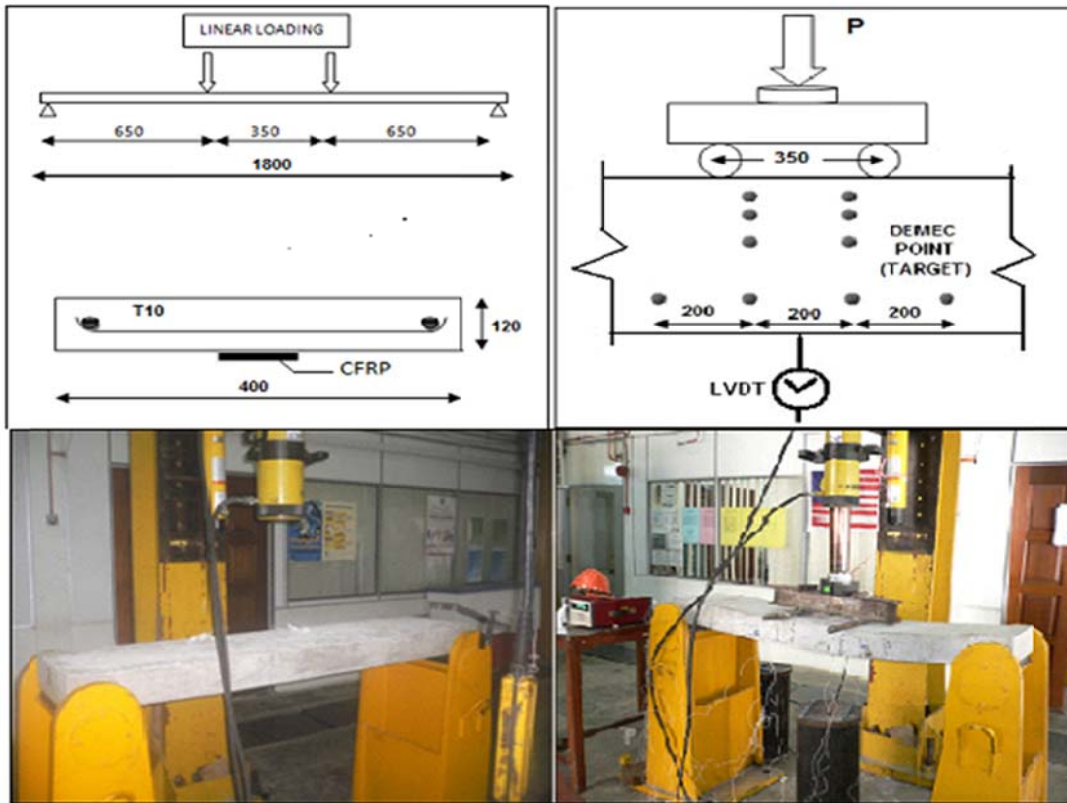


Fig. 2 Instrument setup for CFRP strengthened one-way RC slabs under linear load

Table 2 The applied RNN properties

The Number of Data	103
Input Layer	Loading, CFRP Length and Width
The number of Neurons in Hidden Layer	11
Output Layer	Slab Deflection
Net Architecture	(3-11-1)
Network Type	Feed-Forward
Net Algorithm	Back-Propagation
Training Function	Trainlm
Learning Function	LEARNGDM
Output Transfer Function	PURELIN
Hidden Transfer Function	Tansig- Purelin
Performance Function	MSE

2.2 RNN modelling

The load-deflection analysis of the CFRP strengthened RC one-way slab can be quantitatively modeled in a number of different methods. The philosophy of modeling using ANN is similar to a number of conventional statistical models in the sense that both are challenging characteristics to find the relationship between inputs and corresponding outputs. ANNs modeling do not need any prior knowledge between input and output data, which is one of the benefits that ANNs have compared with most empirical models.

The data is loaded and normalized in MATLAB software. The properties of selected network during generation are shown in Table 2.

The architecture of selected RNN is consisted of one hidden layer with 11 neurons as well as shown in Fig. 3. The transfer function in hidden layer and output were TANSIG and PURELIN respectively.

The loading, CFRP length and width as three input layers (X_1 , X_2 , and X_3) are multiplied by an (11×3) weight matrices. The results of combined input are then passed through the TANSIG transfer function in the hidden layer to produce the output of the hidden layer using PURELIN activation function. In the RNN, the neurons in hidden layer have feedback connection to neurons in input layer by context unit. The number of neurons in context unite is equal to neurons in hidden layer. The neurons in hidden layer feedback and then the activation vector of hidden layer is updated using following equation

$$H(t+1) = \frac{1}{1 + e^{-a(W^{in}X(t+1) + W^{hi}H(t) + W^{back}Y(t))}}$$

Where:

$H(t+1)$, is the updated hidden layer

W^{in} , is the input weight matrices

$X(t+a)$, is the input layer

W^{hi} , is the hidden layer weight matrix

W^{back} , is the output feedback connection of 11×1 weight matrix

The updated neurons in hidden layer make again the output layer using PURELIN activation function and then feedback to context unit to update the activation vector of hidden layer. The cycle between hidden layer and input layer is repeated to maximize the accuracy in network training.

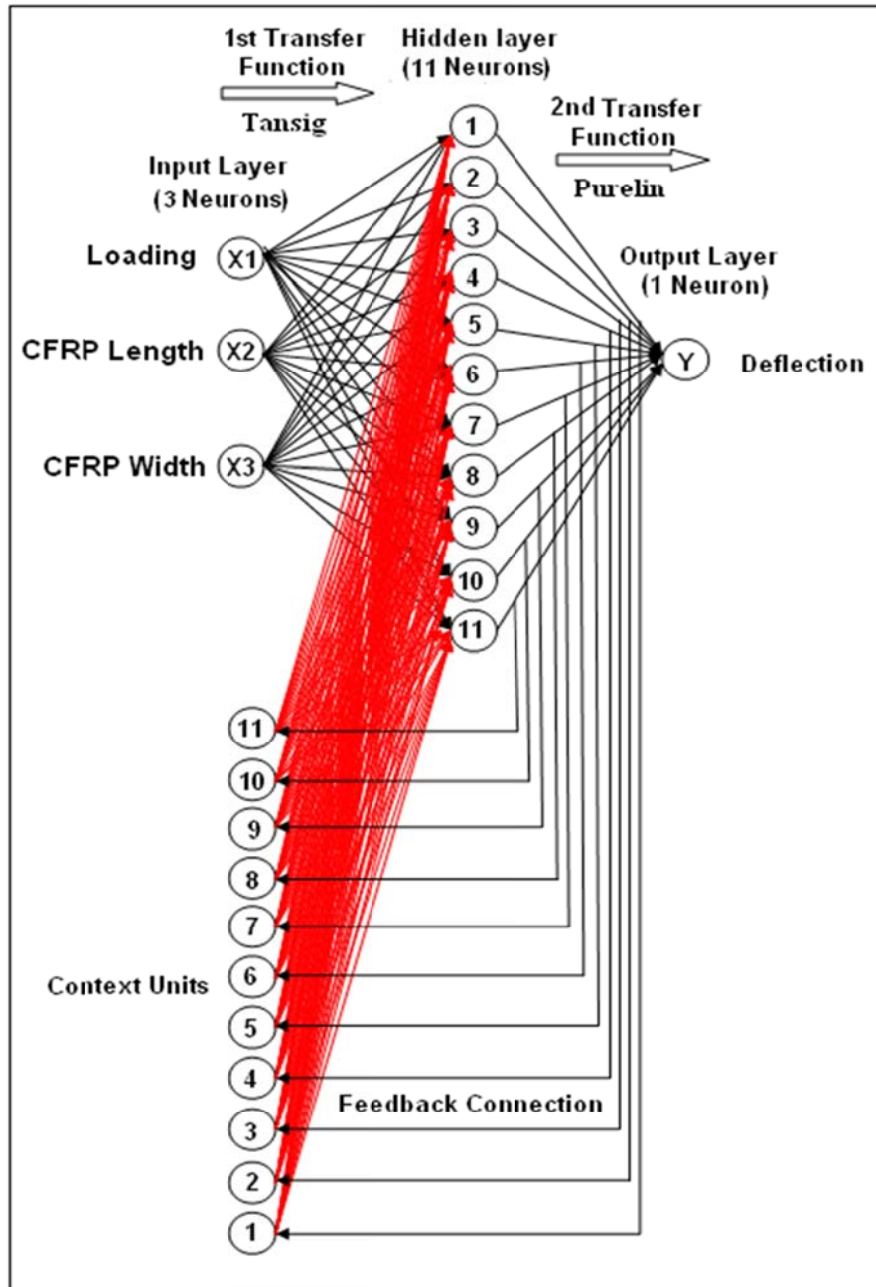


Fig. 3 The RNN architecture for the CFRP strengthened RC one-way slab



Fig. 4 CFRP debonding at the CFRP/concrete interface under line load

3. Results and discussion

3.1 Experimental results

In the failure mode of the slabs, the yielding of the steel took place before the failure of concrete in the compression zone. Debonding of the CFRP plate was occurred at the CFRP/concrete interface before the yielding of the steel reinforcement (Fig. 4). The structural behavior of the CFRP strengthened RC slabs were compared with similar slab without CFRP.

The load-deflection curve of the CFRP strengthened slabs obtained from the experimental work is validated with the corresponding finite element analysis using LUSAS software.

Table 3 gives the mid-span deflection at the first crack and ultimate load for each slab. The mid-span deflection of CFRP strengthened slab at failure load ranged between 20.3 mm and 45 mm, corresponding to a deflection-to-clear span ratio of 1/2674 and 1/1086, respectively.

In Fig. 5, the load-deflection of the one-way RC slab strengthened by CFRP S512 with lengths 700, 1100 and 1500 mm have been compared with the non-strengthened one-way RC slab. The non-strengthened one-way slab failed at load 33 kN. After the strengthening using CFRP, the one-way RC showed an increased failure load of 37 kN, 42 kN, 45.5 kN for S512-700, S512-1100 and S512-1500 respectively. These results indicated that using CFRP for strengthening improves the failure load. It also shows that by increasing the lengths of CFRP, the failure load increases by 10.8%, 21.5% and 27.5% for the 512-700, S512-1100 and S512-1500 respectively.

Also noted on Fig. 6 is that the experimental results of load-deflections analysis are in agreement with the results of the LUSAS finite element analysis. This is therefore, an acceptable finding. The comparison between the results of the experimental work on the strengthened one-way RC slab using CFRP-S812 with CFRP lengths 700 mm, 1100 mm and 1500 mm and the non-strengthened one-way RC slab are presented in Fig. 5. By increasing the lengths of the CFRP, the

loading capacity improved by 13.2%, 26.7% and 40% for S812-700, S812-1100 and S812-1500 respectively.

The experimental results of load-deflection analysis of the CFRP strengthened RC slab were applied for RNN generation.

Table 3 Experimental deflection at the first crack and ultimate load for the CFRP strengthened RC one-way slabs

Slab	Exp. First crack load (kN)	Exp. Deflection First (mm)	Exp. Deflection at Crack	Predicted deflection (mm) ISIS	Span/Def	Exp. Ultimate load (kN)	Exp. Deflection near ultimate load (mm)
S512-700	7.5	0.62		1.11	2674	37	20.3
S512-1100	10	1.22		1.11	1352	42	21.89
S512-1500	10	1.25		1.11	1320	45.5	29.9
S812-700	9.5	1.05		1.14	1571	37	17
S812-1100	10.3	1.19		1.14	1387	45	31
S812-1500	10.5	1.52		1.14	1086	54	45
WCFRP	7	1.17		1.15	1404	33.3	12.14

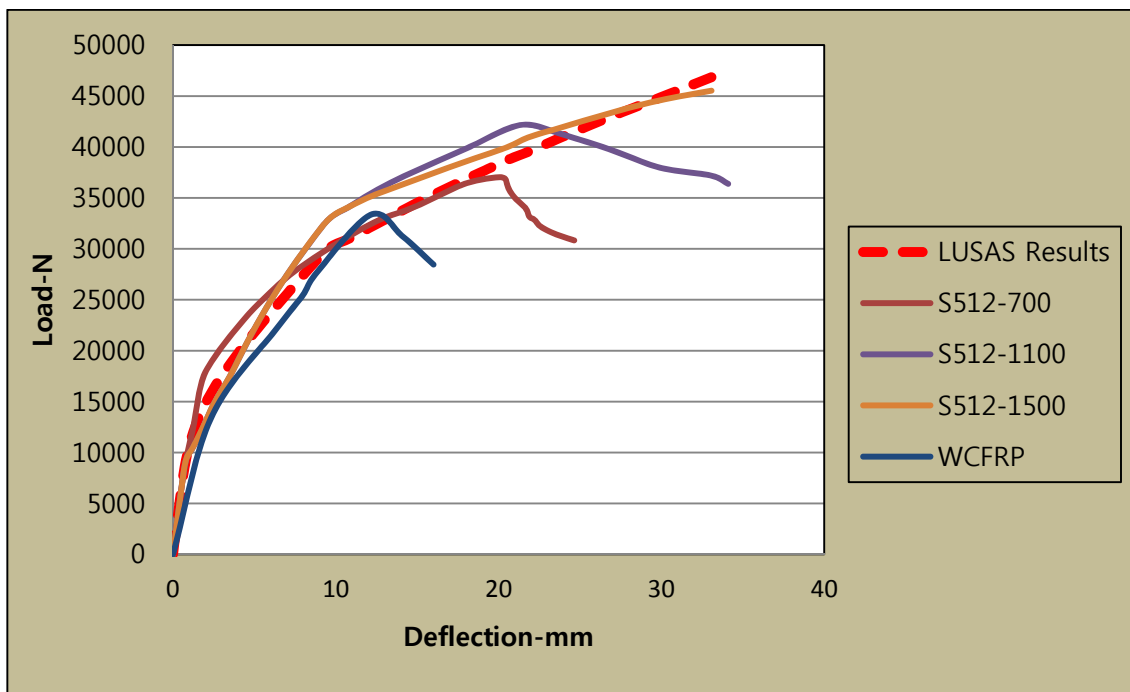


Fig. 5 Comparison of load-deflection analysis between CFRP strengthened one-way RC slab with different lengths of CFRP-S512 and non-strengthened slab

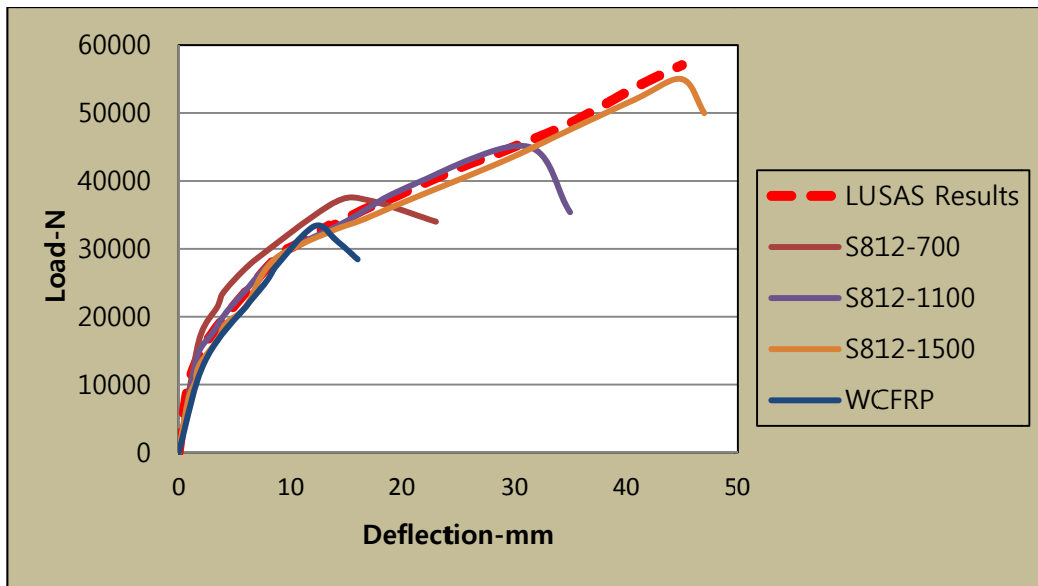


Fig. 6 Comparison of load-deflection analysis between CFRP strengthened one-way RC slab with different lengths of CFRP-S812 and non-strengthened slab

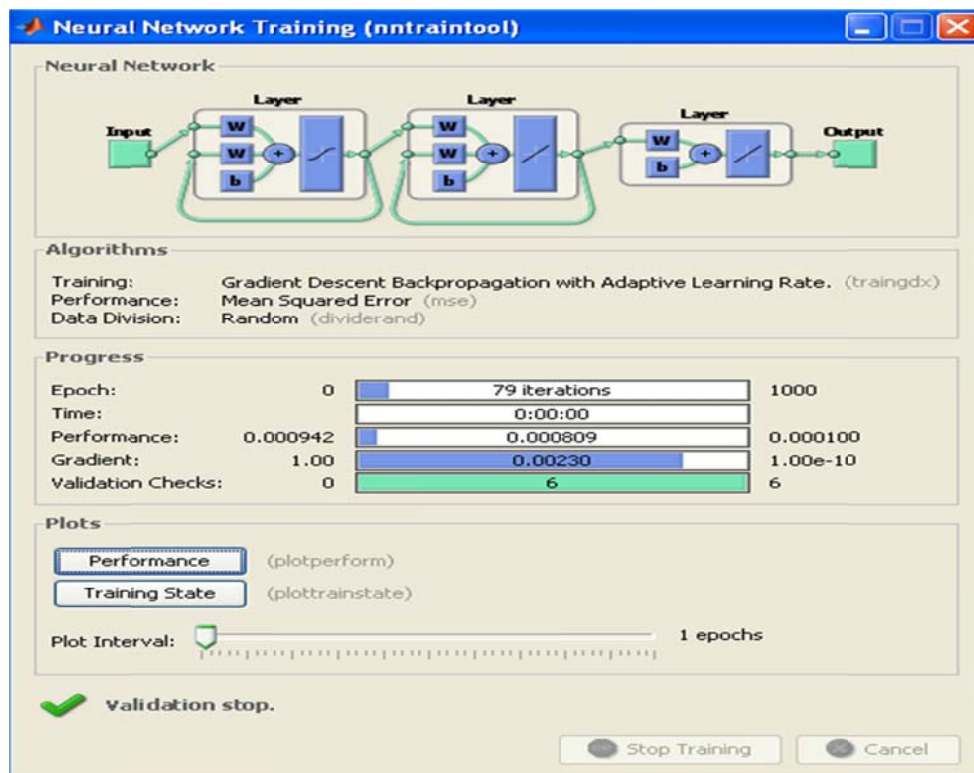


Fig. 7 RNN training for load-deflection prediction of CFRP strengthened RC slab

3.2 RNN results

In this part, RNN is applied to predict mid-span deflection of CFRP strengthened RC one-way slab. Totally 122 input data were normalized and uploaded in MATLAB software. Loading, CFRP strip lengths and width was input layer and mid-span deflection was output layer. The training process is presented in Fig. 7 with a MSE performance function of 0.000809.

The correlation of determination between experimental results and predicted deflection in training phase was 0.990 (Fig. 8). The load-deflection data for sample S812-1100 were applied to simulate for the testing network. The RNN testing MSE between for predicted deflection in testing phase was 0.0018 (Table 4). Fig. 9 shows the evaluation between experimental and predicted deflection of slab S812-1800 that indicated a correlation of determination equivalent to 0.998.

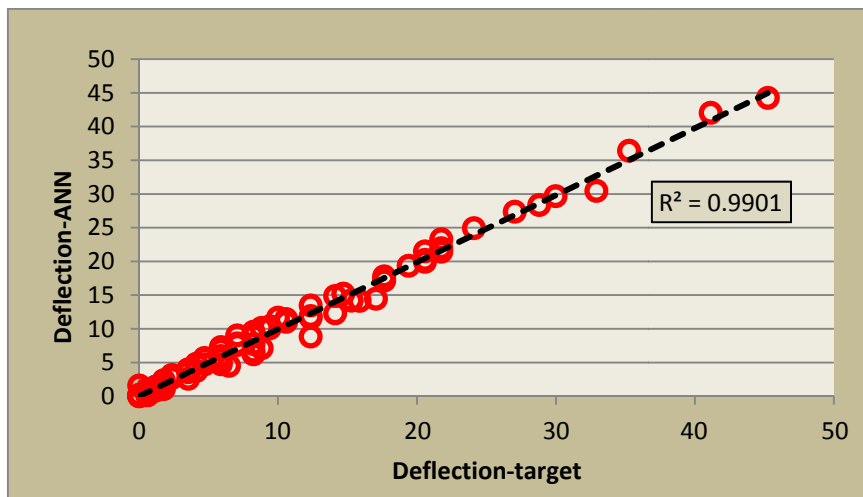


Fig. 8 Evaluation between experimental and predicted deflection on CFRP strengthened RC slab after RNN training phase

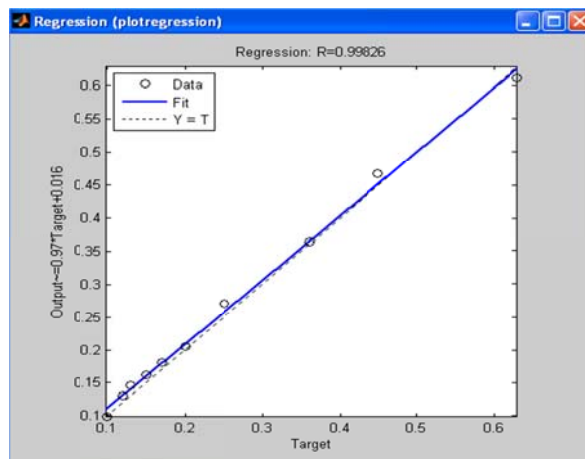


Fig. 9 Evaluation between experimental and predicted deflection of slab S812-1100 after RNN testing phase

Table 4 The RNN testing MSE for predicted mid-span deflection of slab S812-1100

Neurons (n)	Exp. Deflection Δ_{Exp} (mm)		Network Deflection Δ_{Net} (mm)		$\frac{\Delta_{Net}}{\Delta_{Exp}}$	E= $\Delta_{Exp}-\Delta_{Net}$	E ²
	Real	Normalized	Real	Normalized			
1	0	0.1	-0.10	0.10	-	0.0017	0.000003
2	1.32	0.12	1.45	0.13	1.19	-0.0102	0.000103
3	1.83	0.13	2.03	0.14	1.16	-0.0100	0.000100
4	3	0.15	3.61	0.16	1.05	-0.0115	0.000133
5	4.2	0.17	4.76	0.18	0.96	-0.0111	0.000123
6	5.8	0.19	6.19	0.21	0.88	-0.0153	0.000235
7	9.1	0.25	10.06	0.27	0.87	-0.0213	0.000454
8	15.1	0.35	15.56	0.36	0.91	-0.0149	0.000221
9	20.3	0.44	21.59	0.47	1	-0.0275	0.000758
10	31	0.63	30.06	0.61	0.92	0.0183	0.000336
MSE= $\sum E^2/n$							0.0018

4. Conclusions

In this study a DNN model using RNN has been developed to predict mid-span deflection of the CFRP Strengthened RC slabs. The following conclusions are obtained from current research

1. The model capability for load-deflection analysis is illustrated by the coefficient of determination of 0.99 and performance function of 0.00081 in network training. The ratio between predicted deflection by RNN and experimental output in network testing for the sample S812-1100 was varied in the range of 0.97 to 1.11.

2. RNN predicted the load-deflection analysis with mean error 8.4. This results show that by creating DNNs using internal dynamic space give more accurate result in compare to SNN method.

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