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Load-deflection Analysis of CFRP Strengthened RC Slab Using Focused Feed-forward Time Delay Neural Network

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Abstract

In this paper, the load-deflection analysis of the Carbon Fiber Reinforced Polymer (CFRP) strengthened Reinforced Concrete (RC) slab using Focused Feed-forward Time Delay Neural Network (FFTDNN) 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 uploaded, normalized, and converted to a time sequence parameter in MATLAB software. Loading, time, and the effect of the different CFRP strip lengths on the slab moment of inertia 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 tapped delay line at the input layer 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 FFTDNN predicted the load-deflection analysis of the slabs in acceptable technique with a correlation of determination of 0.98. The ratio between predicted deflection by FFTDNN and experimental output was in the range of 0.92 to 1.23.

KEYWORD: FFTDNN, RC, CFRP.

1. Introduction

Traditional Load-deflection analysis used for reinforced concrete slabs can be grouped into empirical and rational model. It is observed that the different available calculation methods produce different deflection results (Wium and Eigeaar, 2010). In addition, these models require solving several numerical equations on determining the deflection of RC slabs and beams. Artificial Neural Networks (ANNs) capture the numerical relationship between its nodes and no formal formula utilize within the model. ANNs are trained based on guidelines and relationships between data. They are able to identify relationships between data even when the data are unclear, changeable and insufficient (Dutta and Shekar, 1993).

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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. This depends entirely on the ability to learn, remember, and evaluate multipart data relationships (Medsker and Jain, 2001). 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.

The network output in DNN belongs to the present input data and present or previous inputs, outputs, or status of the network**.** 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; Yasdi, 1999). Tapped-delay line method employs a sequence of delay to state dynamics space within network generation (Lingras, 2001; Yun et al, 1998).

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.

There are really little researches on dynamic neural network using in civil engineering as presented in Table 1.

The limited uses of dynamic neural network in structural engineering are presented as follows:

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.

Table 1: Application of dynamic neural network in Civil Engineering.

No.	References	Network Type	Application
1	(Pan et al, 2007)	Recurrent	To explain the transition of the rainfall–runoff processes
2	(Yun et al, 1998)	Time-delay	Traffic volume forecasting.
3	(Li et al, 1999)	Time series simulation(TSS)	Prediction of amplitude damping in buildings
4	(Chen et al, 1995)	TSS	Identify structural dynamic model
5	(EI-Shafie et al, 2008)	Recurrent	Predicting creep deformation in masonry structures

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 crated 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.

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

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

The main objective of this research is to train FFTDNN to predict load-deflection of

CFRP strengthened RC slab using tapped-delay line to memorize the testing time as sequential or time-varying patterns while in training process. It involves the prediction of load deflection 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

The following five inputs layers are the time dependent parameters utilized for the focused feed-forward time-delay neural network (FFTDNN) generation:

- Layer 1- Loading
- Layer 2- The testing time of each loading
- Layer 3, Layer 4, Layer 5 - The effect of the different CFRP strip lengths on the slab moment of inertia in region a, b, and c respectively (Fig. 1). Loading results in cracks that change the depth of the natural line for the slab and this consequently changes the slab's moment of inertia. The presence of CFRP improves the position of the slab natural line at each loading. The regions a, b and c were selected based on the CFRP length and cross sectional area.

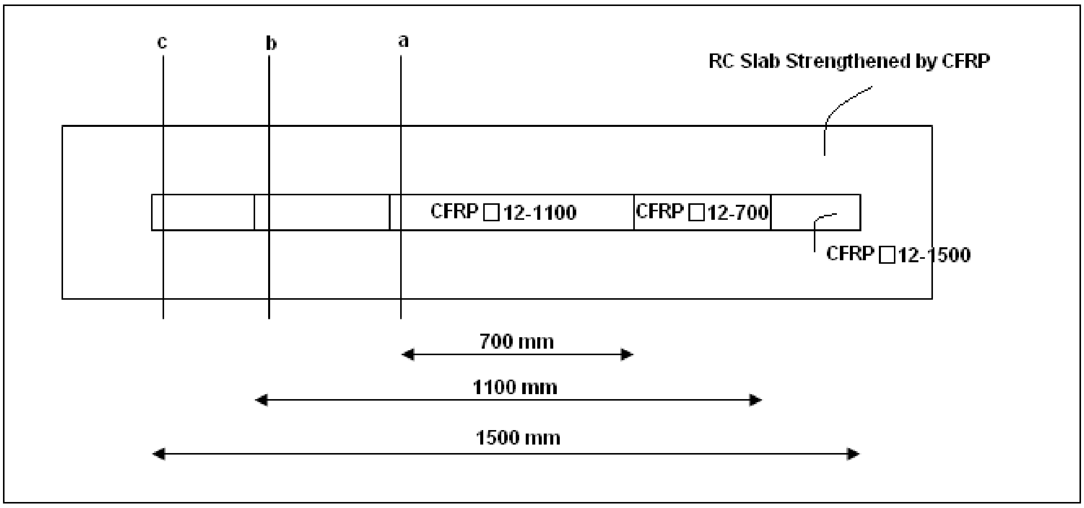

Figure 1: The purposed a, b, & c sections to calculate the effect of CFRP on slabs moment of inertia due to applied loading

The data is uploaded, normalized, and converted to a time sequence parameter in MATLAB software. The relationship between load and testing time for the samples are shown in Fig. 2.

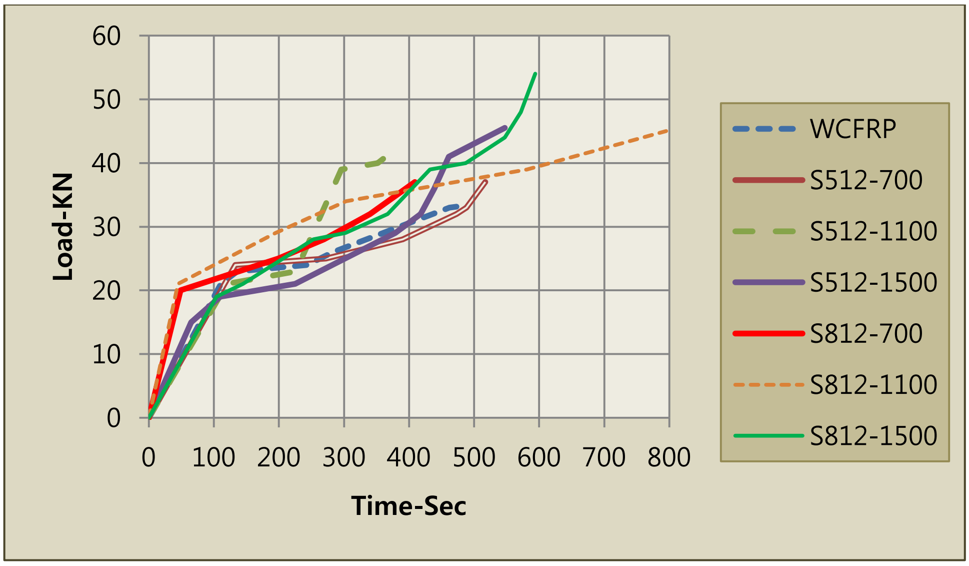

Figure 2: Relationship between applied loading and time for the samples.

The properties of selected network during generation are shown in Table 2.

Table 2: The applied FFTDNN properties

The Number of Data	122
Input Layer	Loading, Time, *Ix(a), Ix(b), & Ix(c)
Time Delay	Testing Time between loading step
The number of Neurons in Hidden Layer	12-7-1
Output Layer	Slab Deflection
Net Architecture	(5-12-7-1-1)
Network Type	Feed-Forward
Net Algorithm	Back-Propagation
Training Function	Trainlm
Learning Function	LEARNGDM
Output Transfer Function	PURELIN
Hidden Transfer Function	Tansig-Logsig-Purelin
Performance Function	MSE

*Moment of Inertia because of CFRP on sections a, b, & c

Where:

A= CFRP cross section area

d = Distance between natural axis and CFRP level

FTDNN consisted of a static feed-forward network with a tapped delay line at the input layer. The process and development details of the FFTDNN modeling is similar to FBNN modeling with a tapped delay line that involves the most recent inputs. In this method, the tapped delay line appears only at the input without any back-propagation to compute the network gradient. The FFTDNN architecture for the CFRP strengthened RC one-way slab is shown in Fig. 3.

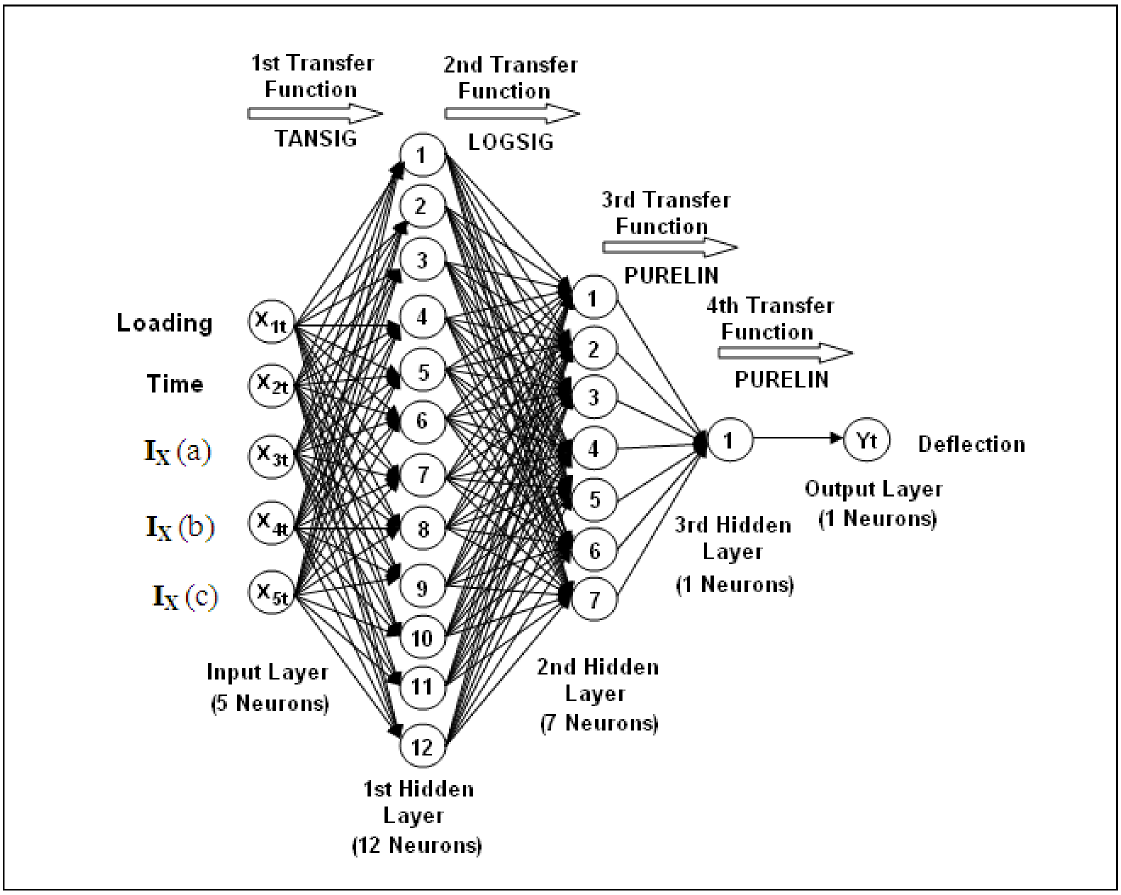

Figure 3: The FFTDNN architecture for the CFRP strengthened RC one-way slab.

$$I_j = \sum_{i=1}^{R} X_i W(X_i) j + b$$

The loading, CFRP length and width as input layers (X1, X2, and X3) are multiplied by an adjustable connection weight (*W(Xi)j*) and then the weighted input signals are summed and a bios (*b*) is added.

This combined input (*Ij*) is then passed through the following LOGSIG and TANSIG transfer function in first and second hidden layer, respectively, to produce the output of the hidden layer.

LOGSIG in first hidden layer:

$$f(x) = \frac{1}{1 + e^{-a(\sum_{i,j=1}^{R} W_{(X_i)j} X_i)}}$$

TANSIG in second hidden layer:

$$g(x) = \frac{1 - e^{-a(\sum_{i,j=1}^{R} W_{(X_i)j} X_i)}}{1 + e^{-a(\sum_{i,j=1}^{R} W_{(X_i)j} X_i)}}$$

Then, each hidden layer sums all the weighted signals from input and applies the PURLIN to calculate the output signals on output layer. The output layer calculates the error by comparing the target patterns and the response of the training pattern in case of supervised training. The back-propagation algorithm revises the weights in each input-output set by propagation the error back to the network using a widely used learning mechanism to change the weights and biases. The effect of back-propagation algorithm starts at the input layer where the input data are presented. The network adjusts its weights on the 87 training data and uses the LEARNGDM as learning rule to find a set of weights that will produce the input/output mapping with maximum accuracy in training. The performance of the generated network has to be validated using testing data.

3. Results and Discussion

3.1 Experimental study

In this part of the 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 3 and Fig. 4). 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).

Table 3: 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

Figure 4: RC one-way slab strengthened by different lengths and width of CFRP.

The slabs were simply supported and were loaded under four point bending load with line load. 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. 5). The structural behavior of the CFRP strengthened RC slabs were compared with similar slab without CFRP.

Figure 5: CFRP debonding at the CFRP/concrete interface under line load.

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 4 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.

Table 4: 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 at First Crack (mm)	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

In Fig. 6, 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 33kN. 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. 7 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

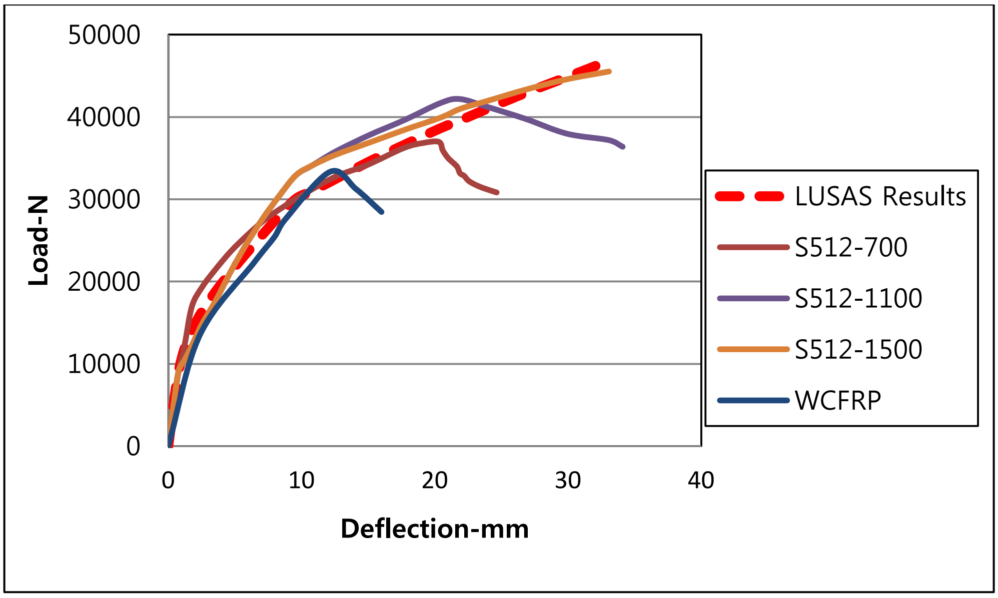

Figure 6: Comparison of load-deflection analysis between CFRP strengthened one-way RC slab with different lengths of CFRP-S512 and non-strengthened slab.

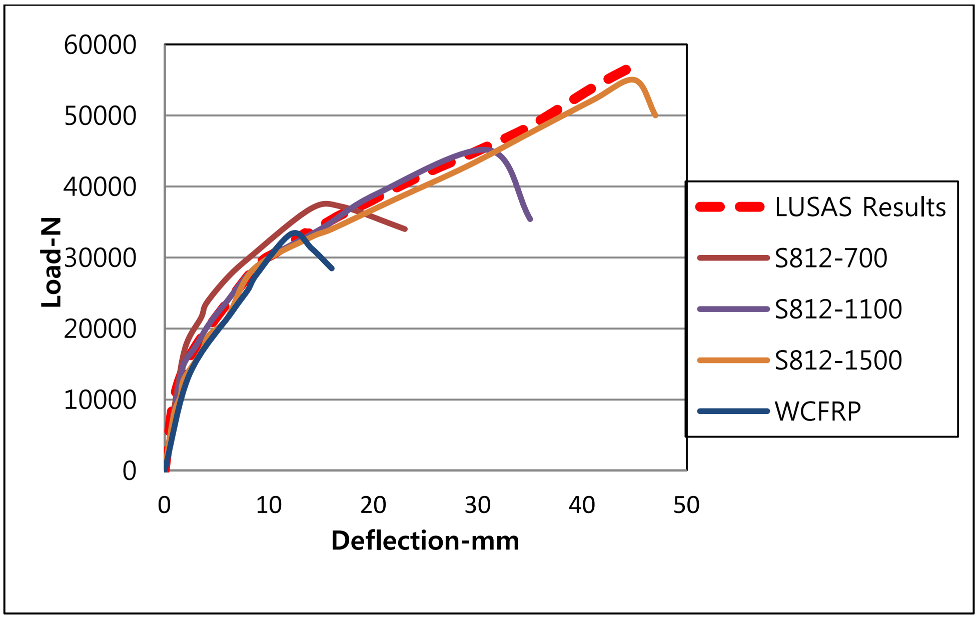

Figure 7: Comparison of load-deflection analysis between CFRP strengthened one-way RC slab with different lengths of CFRP-S812 and non-strengthened slab.

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

3.2 FFTDNN results

In this part, FFTDNN is applied to predict mid-span deflection of CFRP strengthened RC one-way slab. Totally 122 input data were uploaded, normalized, and converted to a time sequence parameter in MATLAB software. Loading, testing time, and the effect of the different CFRP strip lengths on the slab moment of inertia were input layer and mid-span deflection was output layer. The back-propagation algorithm was trained by TRAINLM training function and validated by MSE performance function. The generated network gave MSE of 0.000432 in training stage (Fig. 8).

The network response after training was compared with the training input (Fig. 9). The generated load-deflection analysis by network shows good harmony with the experimental results (Fig. 10).

The correlation coefficient in training phase was 0.987. After training and validation, 11 load-deflection data of samples S812-1100 were utilized for network testing. The network output after training was compared with the input data for testing stage. The testing error and MSE for the eleven neurons in testing stage is shown in Table 5. The MSE between the target and predicted outputs after the testing process was 0.0011. The correlation coefficient of 0.979 is an acceptable relationship between target and created outputs in the testing process (Fig. 11). A comparison between real load-deflection curve and predicted by FFTDNN is shown in Fig. 12.

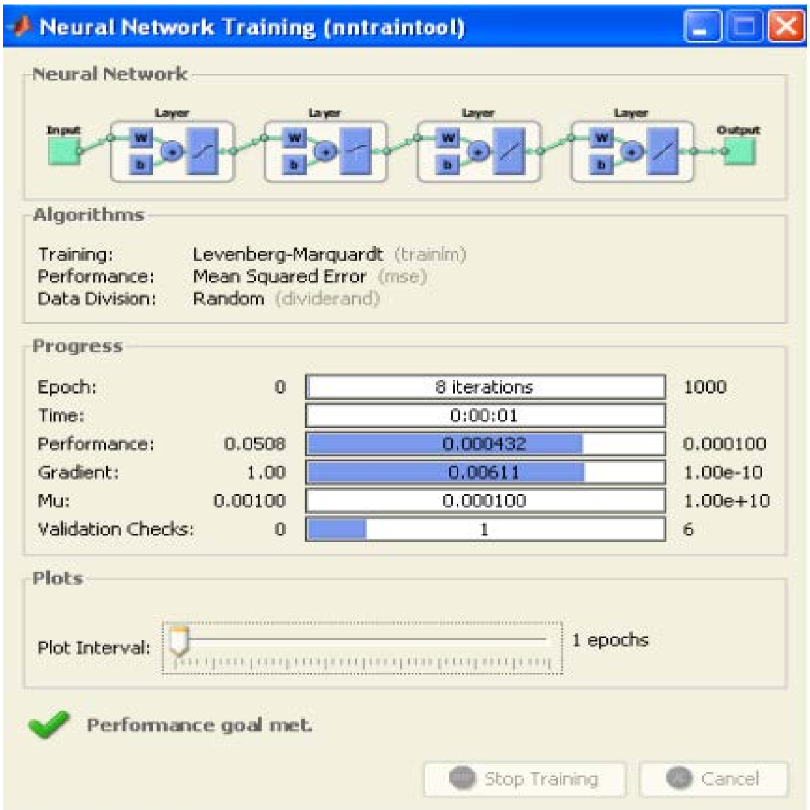

Figure 8: FFTDNN Training process for load-deflection curve prediction on strengthened slab.

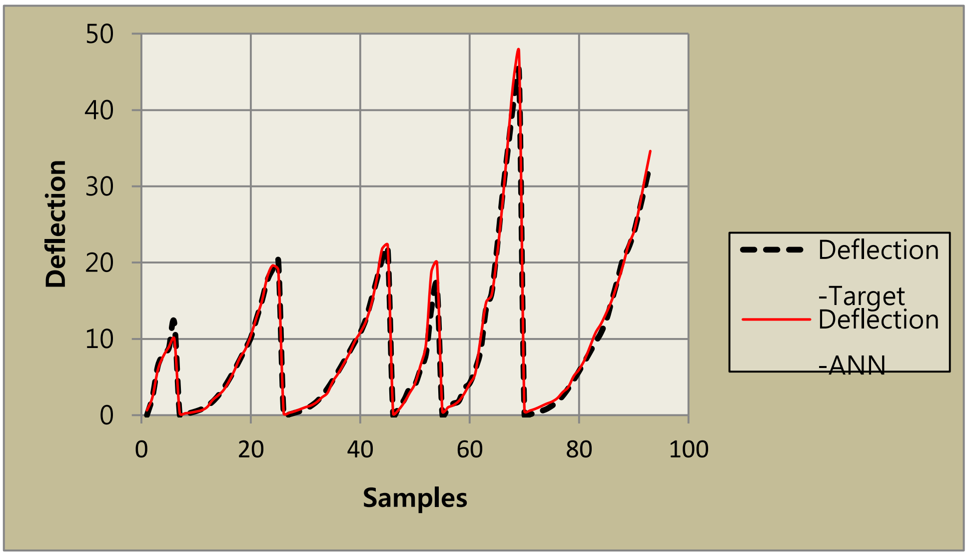

Figure 9: A comparison between net output and experimental results for deflection on the strengthened slab after FFTDNN training.

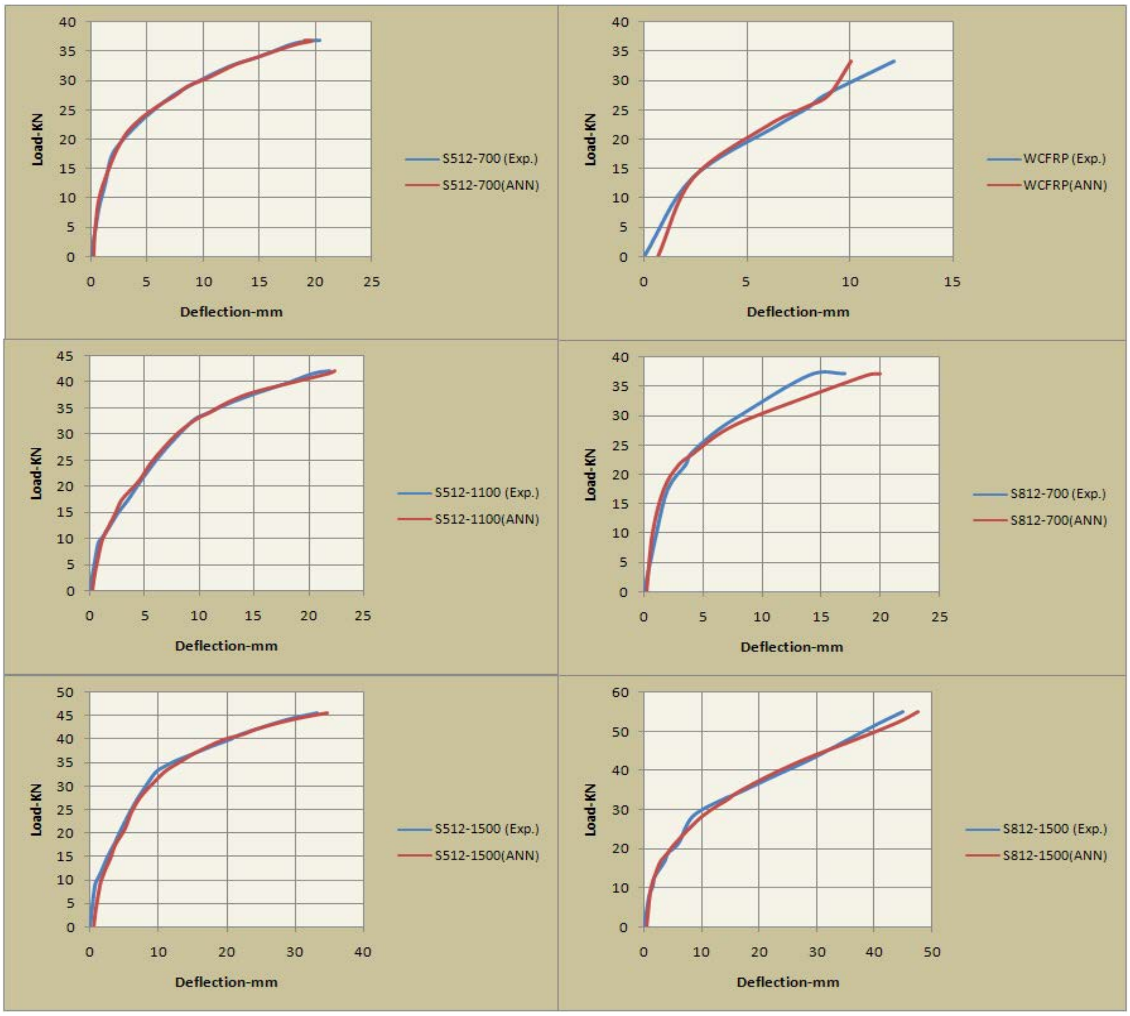

Figure 10: An evaluation between predicted and experimental load-deflection analysis in training phase.

Table 5: MSE calculation for eleven neurons in testing phase of FFTDNN used in prediction of mid-span deflection of S812-1100.

Neurons (n)	Exp. Deflection Δ_{Exp} (mm)		Network Deflection Δ_{Net}(mm)		Δ_{Net} / Δ_{Exp}	E= Δ_{Exp}-Δ_{Net}	E^2
	Real	Normalized	Real	Normalized			
1	0	0.1	0.02	0.001	-	0.0099	9.8×10^{-5}
2	1.32	0.12	1.42	0.08	1.07	0.04	0.0016
3	1.83	0.13	2.25	0.12	1.23	0.01	0.0001
4	3	0.15	3.51	0.18	1.17	-0.03	0.0009
5	4.2	0.17	5.11	0.26	1.22	-0.09	0.0018
6	5.8	0.19	7	0.22	1.21	-0.0204	0.0004
7	9.1	0.25	9.67	0.26	1.06	-0.0097	9.4×10^{-5}
8	15.1	0.36	13.91	0.37	0.92	0.01	0.0001
9	20.3	0.44	18.9	0.5	0.93	0.0579	0.0033
10	31	0.63	29.2	0.59	0.94	0.0311	0.00096
11	35	0.69	38.45	0.75	1.10	-0.0587	0.0034
$MSE=\sum E^2/n$							0.0011

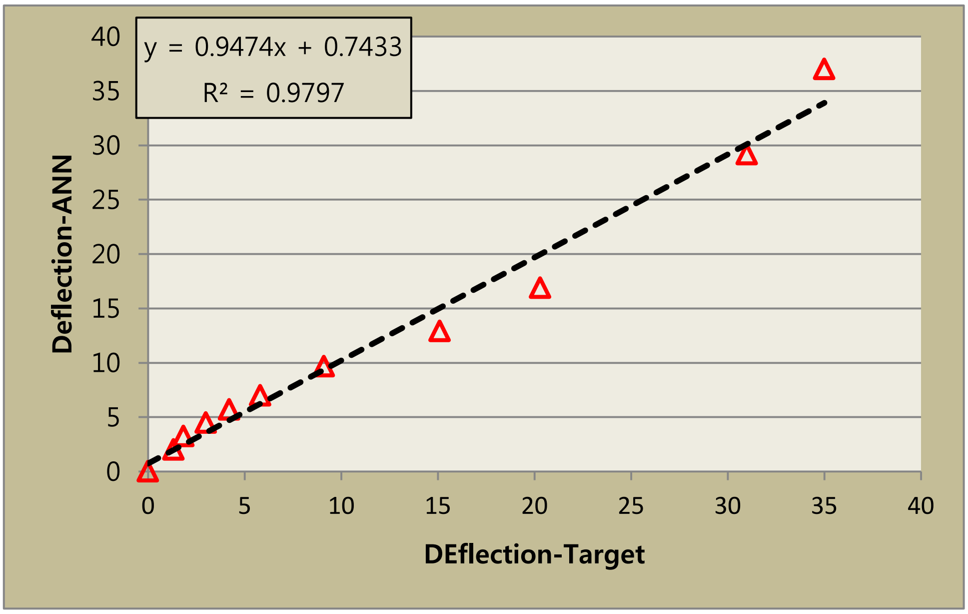

Figure 11: Evaluation between target and predicted deflection after FFTDNN testing stage

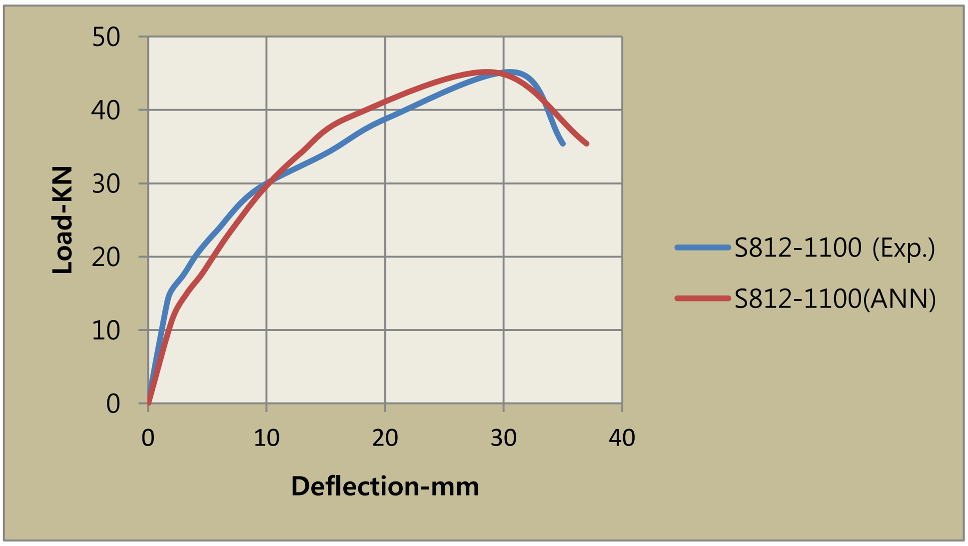

Figure 12: A comparison between target and predicted load-deflection curve after FFTDNN testing process.

4. CONCLUSION

Traditional analysis models for RC structures are reliable and the load-deflection analysis of CFRP strengthened RC slab can be successfully determined by solving several numerical equations. ANN is another alternative analytical modeling method, which capture the numerical equations between its nodes and no formal formula is observable within the network generation. A DNN model using FFRDNN has been developed to predict mid-span deflection of the slabs. The model capability for load-deflection analysis is illustrated by the coefficient of determination of 0.987 and performance function of 0.000432 in network training. The ratio between predicted deflection by FFTDNN and experimental output in network testing on the sample S812-1100 was varied in the range of 0.92 to 1.23.

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