Contents lists available at SCCE

Journal of Soft Computing in Civil Engineering

Journal homepage: www.jsoftcivil.com

Calculation of Torsion Capacity of the Reinforced Concrete Beams Using Artificial Neural Network

M.H. Ilkhani[1], E. Moradi[1], M. Lavasani[2*]

1. Ph.D. Candidate, Faculty of Civil Engineering, Semnan University, Semnan, Iran
2. Ph.D., Florida International University, Miami, FL, USA

Corresponding author: *ssada006@fiu.edu*

https://doi.org/10.22115/SCCE.2017.48685

ARTICLE INFO

Article history:
Received: 13 June 2017
Revised: 12 July 2017
Accepted: 24 July 2017

Keywords:
Neural network;
Torsion;
RC beam.

ABSTRACT

This paper presents a model for calculation of torsion capacity of the reinforced concrete beams using the artificial neural network. Considering the complex reaction of reinforced concrete beams under torsion moments, torsion strength of these beams is depended on different parameters; therefore using the artificial neural network is a proper method for estimating the torsion capacity of the beams. In the presented model the beam's dimensions, concrete compressive strength and longitudinal and traverse bars properties are the input data, and torsion capacity of the reinforced concrete beam is the output of the model. Also considering the neural network results, a sensitivity analysis is performed on the network layers weight, and the effect of different parameters is evaluated on the torsion strength of the reinforced concrete beams. According to the sensitivity analysis, properties of traverse steel have the most effect on torsion capacity of the beams.

1. Introduction

In structural design, usually the effect of the torsional moment is neglected, and members are designed only for stresses due to bending, shear and axial loads. However, the amount of torsion

How to cite this article: Ilkhani MH, Moradi E, Lavasani M. Calculation of torsion capacity of the reinforced concrete beams using artificial neural network. J Soft Comput Civ Eng 2017;1(2):08–18. https://doi.org/10.22115/scce.2017.48685.

2588-2872/ © 2017 The Authors. Published by Pouyan Press.
This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

in lateral beams or the beams connected to a slab or another beam in one side is significant, and even a small amount of torsion can cause high stresses. Since failure due to torsion is a brittle and non-predictable failure, therefore designing against torsion becomes essential.

There are not several studies conducted on the reinforced concrete beams behavior under torsion up to now. H.J. Chiu et al. have studied 13 reinforced concrete beams specimens in two types of high strength concrete and regular concrete. The purpose of this study was to investigate the cracks pattern, torsion strength and deformation of the beams under pure torsion loading. The results showed that hollow beams have less torsion strength against cracking concerning filled rectangular beams and increasing the ratio in the beams section causes lesser torsion strength, cracking and increasing of the cracks widths [1].

Victor and Muthukrishnan have investigated the effect of varying number of stirrups on the torsion capacity of the reinforced concrete beams and presented an empirical relation for the share of stirrups in the torsion capacity [2].

Rasmussen and Baker have studied the behavior of high strength concrete, and ordinary concrete beams under pure torsion [3,4]. The results showed that high strength concrete increases the torsion capacity and stiffness.

McMullen and Rangan have investigated rectangular reinforced concrete beams by varying dimensional ratios and the number of stirrups [5]. Authors concluded that longitudinal stirrups are more effective in controlling traverse cracks than traverse stirrups [6,7].

Although many relations have been presented for reinforced concrete beams under pure torsion, in this study, the behavior of rectangular reinforced concrete beams under pure torsion load has investigated using the neural network, and finally, the weight effect of each of the input parameters on the target function (ultimate torsion capacity) has studied.

2. The artificial neural network model

Neural networks can be assumed as a very simplified electronic model of the human brain neural structure. The learning and training mechanism of the brain is experimental. The electronic neural network models are based on the same pattern, and the analysis method of these models is different from the usual calculation method of computer systems. Artificial neural networks (ANN) are suitable tools for predicting of the non-existing situations based on the existing conditions. In other words, artificial neural networks can interpret the relations between the parameters of one phenomenon and the phenomenon using the training based on experience. In recent years the neural networks have been used by many researchers for many of the civil engineering systems including predicting of surrounded and non-surrounded concrete compressive strength [8,9], predicting of ultimate shear strength of concrete beams reinforced with FRP [10,11] and their free vibration analysis [12] and predicting of shear capacity of concrete beams reinforced with steel plates [13].

In general, artificial neural networks are consisting of three layers including the input layer, middle or hidden layer and an output layer. The presented data to the network including the variables and target function resulted from them are placed in the input and output layers respectively. Then by regulating the weights in the middle layer, a pattern is obtained to achieve the target values from the input data. This trend is called training the network for predicting the target values. The number of data and less number of input variables result in better training of the network and more reliable obtained weights and more accurate network prediction.

Therefore the essential step in modeling a reliable and proper artificial neural network is collecting an appropriate number of experimental accurate and homogenous data (the more number of data used in modeling will result in better specifying relations among variables by the network). In this study, 112 homogenous experimental data have been gathered [1,3–5,7,14–18]. The homogenous data is defined as the data in which the behaviors of the specimens are similar, and shear causes the failure under torsion moment. For example, beams that are failed under a combination of torsion and bending moment cannot be considered for torsion strength study. After gathering suitable data for using in the network, selection of effective parameters in the target values shall be concerned. Studying the existing researches and the relations in the certified regulations [19,20], the following parameters have specified to be effective in torsion capacity of the reinforced concrete beam:

- X: rectangular reinforced concrete beam section width
- Y: rectangular reinforced concrete beam section height
- $f'_{c:}$ concrete compressive strength
- A_L: total cross section of longitudinal bars
- F_{yl}: longitudinal bars yield stress
- A_t: total cross section of traverse bars
- F_{yt}: traverse bars yield stress
- s: distance between traverse bars

To reduce the number of input variables, some of the related parameters are combined with each other, and finally, the following five parameters are introduced to the network as the input variables:

- X: rectangular reinforced concrete beam section width, in mm
- Y: rectangular reinforced concrete beam section height, in mm
- $f'_{c:}$ concrete compressive strength, in MPa

- $A_L F_{yl}$: effect of longitudinal bars, in KN
- $A_t F_{yt}/s$: effect of traverse bars, in N/mm

The ultimate bending moment for the beams (T_u) which is obtained from the experiments is considered as the target value for each input.

The number of the neuron in the hidden layer is considered as 8. The MSE graph of this network is shown in figure 1. As it is seen in the figure, MSE starts from high values and decreases to lower values. This shows the learning process of the network is successful.

At the beginning of learning, the network has a rather high error and with the continuation of learning and changing the used weights in the 31st step the amounts of errors reaches to 0.005, 0.09 and 0.1 for Training, Validation and Test respectively. This graph has three curves, each of them represents a group of Training, Validation, and Test data.

The graphs of procedure of learning and data regression values are presented in Figures 2 and 3 respectively. The reducing of the gradient in figure 2 represents the network procedure of learning. The reduction of gradient continues until MSE value reaches its minimum. From this point on the network, learning stops and the gradient value becomes constant. The amount of regression shown in figure 3 indicates a good network learning and close relation between the target vector and the network output.

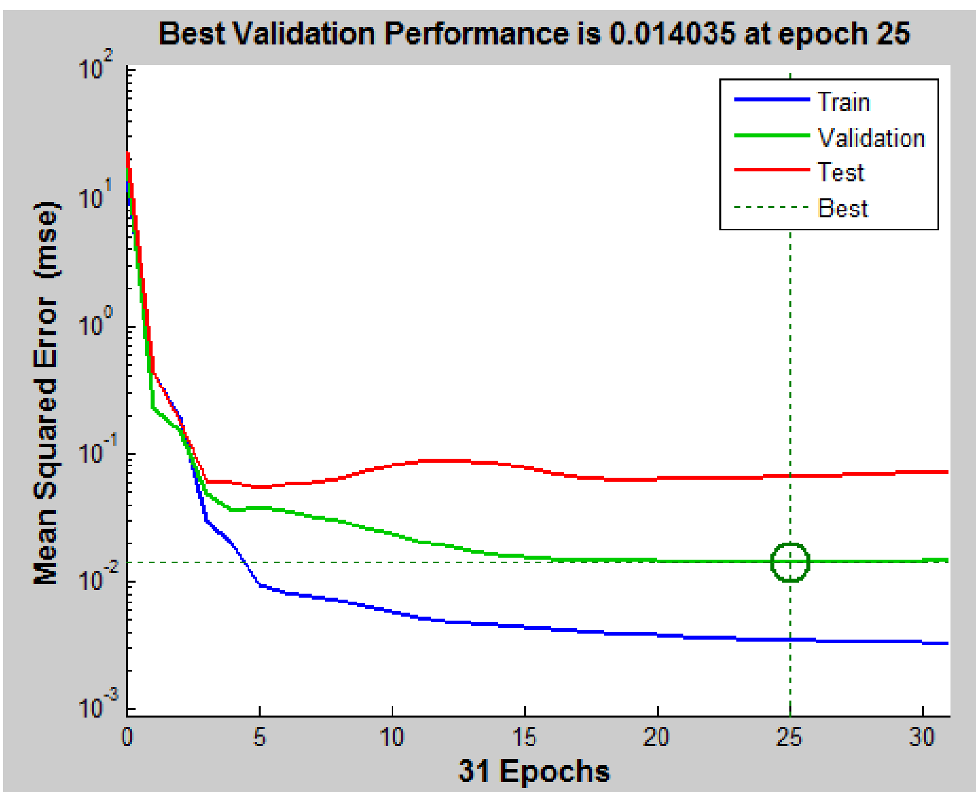

Fig. 1. MSE graph during training of the trained artificial neural network.

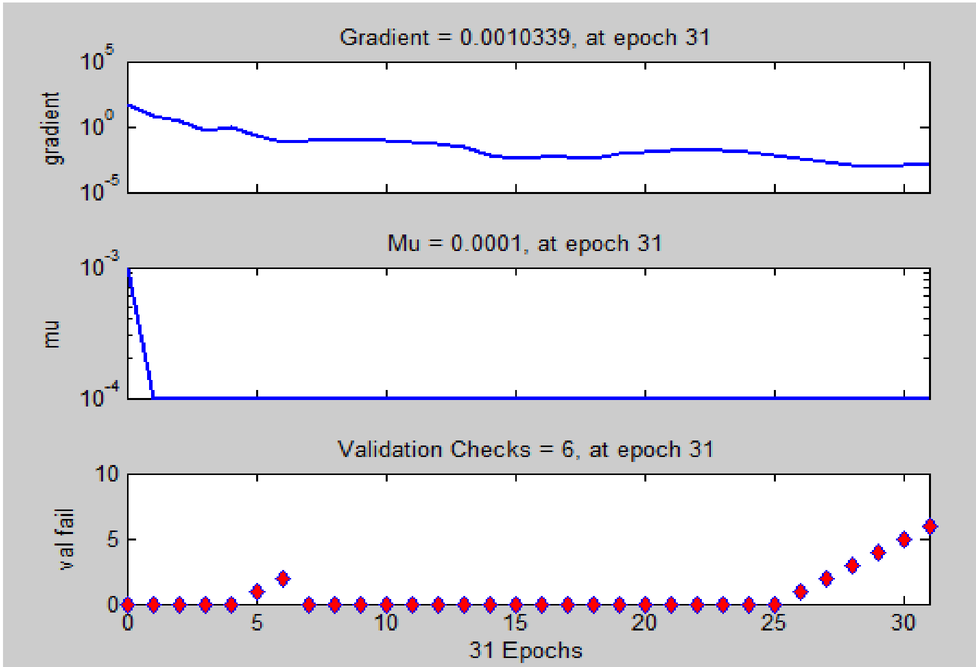

Fig. 2. The learning graph of the trained artificial neural network.

It can be concluded that the modeled network is trained well concerning the input and output data. Therefore, this network is chosen, and its results are compared with the existing relations for ultimate torsion moment.

3. Validation of artificial neural network results

To validate the artificial neural network results, a comparison is made between the experimental results and the network results. Figure 4 shows the experimental results for the ultimate torsion moment, which are the target vector in network training, versus the output values, resulted from neural network simulation. In the presented curves the points corresponding to the 45-degree line, indicate the proper prediction of the model and no difference between the experimental results and the estimated values by the network and distance from this line indicates the error percentage of the model. As it can be seen, most of the points of the network prediction fall in the neighborhood of 45-degree line which indicates the accuracy of the network. %83 of the data has less than 10% error concerning the experimental results. Also, % 97.3of the data has less than 20% error concerning the experimental results. Summary of the network function is presented in Table 1. Considering figure 4 and Table 1, it can be concluded that the maximum error between the experimental results and the network output results is 30%.

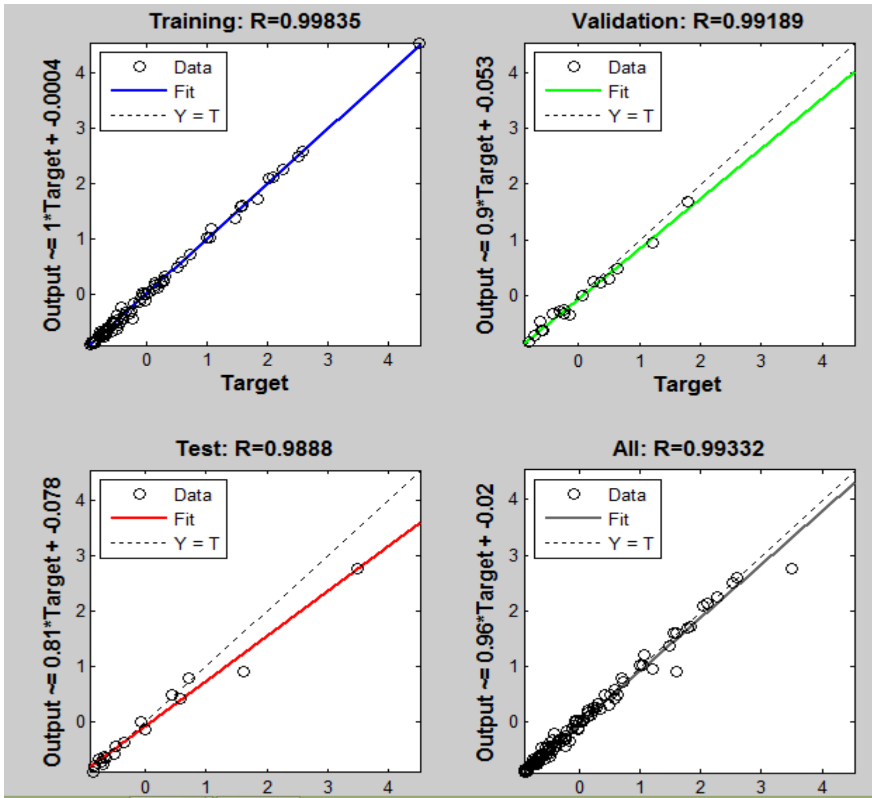

Fig. 3. Fitting of the neural network data related to Training, Validation, and Test

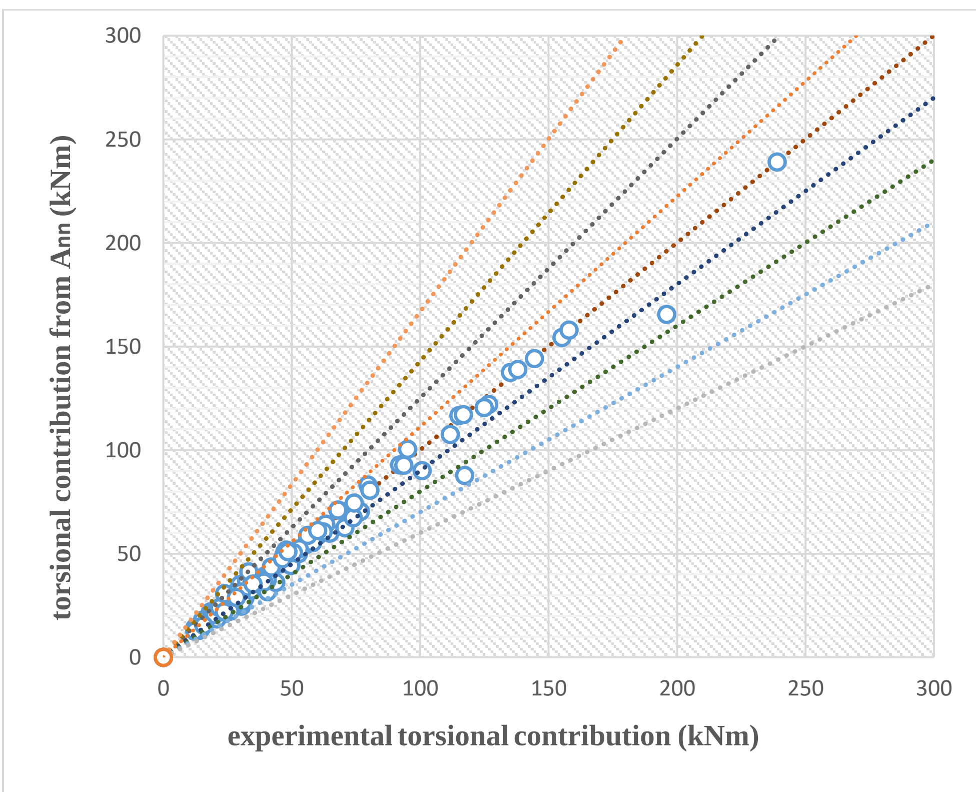

Fig. 4. comparison between artificial neural network data and the experimental results.

Table 1
comparison between artificial neural network error and the existing relations.

The range of error (%)	Number of data in the range of error	Percentage of data in the range of error (%)
±5	60	53.5
±10	93	83
±15	102	91
±20	109	97.3
±25	111	99.1
±30	112	100

4. Effect of network input parameters on output data

In the artificial neural network system, each neuron has an internal weight, which affects the input values of the neuron and directs the weight vectors to the excitation functions. It may be required for a vector to displace in the vector space in addition to changing its weight; this can be done by adding a bias to the weight matrix. Then the weight values are transferred to the excitation functions, and the output function achieves its primary value and considering obtaining a proper response, these values are compared to the target vector, and if there is the difference, the values are returned to select better weights for the vectors.

By increasing the number of input parameters, layers and neurons, the calculation of each parameter effect on the network becomes more complicated. Since 1980, many methods are presented for interpreting the effect of each parameter on the network. In this study analysis concerning the weights, size is used.

Analysis concerning the size of the weight is based on the stored values in the weight matrix to determine the effect of input parameters on outputs. In this study, the presented relation by Garson [21] is used to evaluate the effect of input parameters on outputs (equation 1).

$$Q_{ik} = \frac{\sum_{j=1}^{l}\left(\frac{|w_{ij}|}{\sum_{r=1}^{N}|w_{rj}|} v_{jk}\right)}{\sum_{r=1}^{N}\left(\sum_{j=1}^{l}\left(\frac{|w_{ij}|}{\sum_{r=1}^{N}|w_{rj}|} v_{jk}\right)\right)} \tag{1}$$

Where:

N: the input neurons,

L: the hidden neurons,

$\sum_{r=1}^{N} w_{rj}$: The sum of N input neurons and ***j*** hidden neurons weights

Q_{ik} : the effect percent of input parameter x_i on the output y_k

For the calculation of the effect of input parameters on the outputs, the weight of the hidden layer shall be used. Input and output weights of ANN are presented in Table 2 and 3:

Table 2
The weights of the input layer.

Input nodes	*X* (mm)	*Y* (mm)	*f'c* (MPa)	*Al Fy* (KN)	*At Fyt /S (N/mm)*
Input Weights	0.90496	-0.00676	1.0286	-0.84106	0.16771
	-1.1542	-0.69404	-1.779	-0.82361	-1.3617
	-0.15887	-0.81979	0.80089	0.48162	2.0927
	2.0442	-0.5652	0.88515	5.1367	0.55387
	-2.0988	0.76904	0.44781	1.8936	1.7398
	-0.93063	-1.1389	-1.0987	1.7881	-0.68459
	-0.39337	-0.49757	-0.35269	-0.58626	-1.0928
	-0.06803	0.59484	1.0416	-0.17973	1.6589

Table 3
Weights of output layer

Input nodes	*X* (mm)	*Y* (mm)	*f'c* (MPa)	*Al Fy* (KN)	*At Fyt /S (N/mm)*
Target Weights	-1.8417	1.2028	0.66981	0.86408	-0.88664

Substituting the weight values of the hidden layer in equation (1), the effect of input parameters on network outputs can be determined. The values of relative effect percentage of each of the 5 input parameters are presented in figure 5 and Table 4.

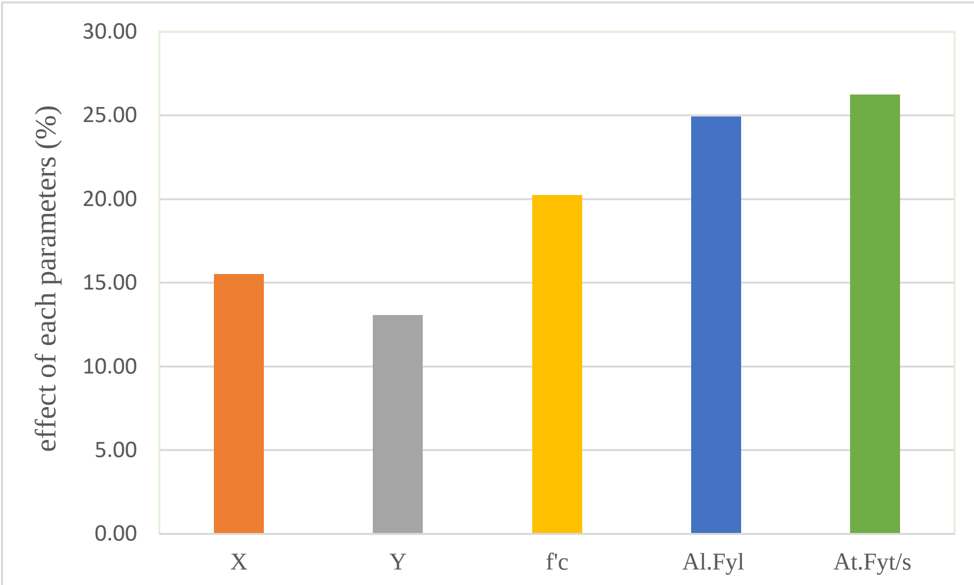

Fig. 5. effect percentage of input parameters on network outputs.

Table 4
Effect percentage of input parameters on network outputs.

Parameter	*X* (mm)	*Y* (mm)	*f'c* (MPa)	*Al Fy* (kN)	*At Fyt /S (N/mm)*
Effect (%)	15.51	13.07	20.25	24.93	26.24

According to the above table, it can be concluded that A_tF_{yt}/s parameter with relative effect percentage of 26.24% has the most effect on network output. It means that the target vector (ultimate torsion moment) has high sensitivity to A_tF_{yt}/s variations. On the other hand, Y (the larger dimension of the beam) parameter with relative effect percentage of 13.07% has the least effect on the ultimate torsion moment.

5. Conclusion

In this study, a model presented for calculation of reinforced concrete beams ultimate torsion moment using artificial neural network algorithm. Using the existing technical data, the results of experiments on 112 reinforced concrete beams under pure torsion have been gathered. After network training for validation of the network outputs, simulation of the existing data was performed and resulted in highly accurate outputs and proved the ability of the trained neural network for estimation of torsion capacity of the reinforced concrete beams. The maximum error between the experimental results and the network output results was 30%.

Also by analyzing the network weights, it was concluded that in reinforced concrete beams, a variation of traverse reinforcements has the most effect on the torsion moment.

Reference

[1] Chiu H-J, Fang I-K, Young W-T, Shiau J-K. Behavior of reinforced concrete beams with minimum torsional reinforcement. Eng Struct 2007;29:2193–205. doi:10.1016/j.engstruct.2006.11.004.

[2] Victor DJ, Muthukrishnan R. Effect of stirrups on ultimate torque of reinforced concrete beams. J. Proc., vol. 70, 1973, p. 300–6.

[3] Rasmussen LJ, Baker G. Assessment of the torsional strength in reinforced normal and high strength concrete beams. Trans Inst Eng Aust Civ Eng 1994;36:165–71.

[4] Rasmussen LJ, Baker G. Torsion in reinforced normal and high-strength concrete beams part 1: experimental test series. Struct J 1995;92:56–62.

[5] E. McMullen A, Rangan BV. Pure torsion in rectangular section-A reexamination. Struct J 1978;75:511–9.

[6] Collins MP, Mitchell D. SHEAR AND TORSION DESIGN OF PRESTRESSED AND NON PRESTRESSED CONCRETE BEAMS. Struct J 1980;25:32–100.

[7] Hsu TTC. Torsion of structural concrete-behavior of reinforced concrete rectangular members. Spec Publ 1968;18:261–306.

[8] Ni H-G, Wang J-Z. Prediction of compressive strength of concrete by neural networks. Cem Concr Res 2000;30:1245–50. doi:10.1016/S0008-8846(00)00345-8.

[9] Naderpour H, Kheyroddin A, Amiri GG. Prediction of FRP-confined compressive strength of concrete using artificial neural networks. Compos Struct 2010;92:2817–29. doi:10.1016/j.compstruct.2010.04.008.

[10] Perera R, Arteaga A, Diego A De. Artificial intelligence techniques for prediction of the capacity of RC beams strengthened in shear with external FRP reinforcement. Compos Struct 2010;92:1169–75. doi:10.1016/j.compstruct.2009.10.027.

[11] Perera R, Barchín M, Arteaga A, Diego A De. Prediction of the ultimate strength of reinforced concrete beams FRP-strengthened in shear using neural networks. Compos Part B Eng 2010;41:287–98. doi:10.1016/j.compositesb.2010.03.003.

[12] Jodaei A, Jalal M, Yas MH. Free vibration analysis of functionally graded annular plates by state-space based differential quadrature method and comparative modeling by ANN. Compos Part B Eng 2012;43:340–53. doi:10.1016/j.compositesb.2011.08.052.

[13] Adhikary BB, Mutsuyoshi H. Artificial neural networks for the prediction of shear capacity of steel plate strengthened RC beams. Constr Build Mater 2004;18:409–17. doi:10.1016/j.conbuildmat.2004.03.002.

[14] Leonhardt F, Schelling G. Torsionsversuche an Stahl betonbalken. Dtsch Ausschuss Für Stahlbet 1974:122.

[15] Mitchell D, Collins MP. Diagonal compression field theory-a rational model for structural concrete in pure torsion. J. Proc., vol. 71, 1974, p. 396–408.

[16] Koutchoukali N-E, Belarbi A. Torsion of high-strength reinforced concrete beams and minimum reinforcement requirement. Struct J 2001;98:462–9.

[17] Fang I-K, Shiau J-K. Torsional behavior of normal-and high-strength concrete beams. ACI Struct J 2004;101:304–13.

[18] Peng X-N, Wong Y-L. Behavior of reinforced concrete walls subjected to monotonic pure torsion—An experimental study. Eng Struct 2011;33:2495–508. doi:10.1016/j.engstruct.2011.04.022.

[19] ACI. Guide for the design and construction of externally bonded FRP systems for strengthening concrete structures, in Rep. No. 440 2R-08. 2008.

[20] FIB. Design and use of externally bonded fibre reinforced polymer reinforcement (FRP EBR) for reinforced concrete structures. 2001.

[21] Garson GD. Interpreting neural-network connection weights. AI Expert 1991;6:46–51.