Predicting Of Torsional Strength Of Prestressed Concrete Beams Using Artificial Neural Networks

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Abstract—In this paper, the artificial neural networks (ANNs) model in predicting the torsional strength of prestressed concrete beams is done. Experimental data of eighty two rectangular prestressed concrete beams under pure torsion from an existing available literature were used to develop ANN torsion model. The input parameters affecting the torsional strength of prestressed concrete beams were selected as dimensions of beams, steel ratio of transverse reinforcements, spacing of stirrups, steel ratio of longitudinal (main) reinforcement, prestressing force, concrete compressive strength, also flexural and splitting strengths. An algorithm of back propagation neural network (BPNN) with the log-sigmoid activation function is adopted due to its accuracy and results enhancement of predictions the torsional model. In addition to the ANN model is compared with ACI- 318 building code provisions for the design of prestressed concrete beams under pure torsion. The study illustrates that the ANN models give a very good predictions of the ultimate torsional strength of prestressed concrete beams.

Index Terms— Prestressed concrete beam, Torsional Strength, and Artificial neural networks.

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1. INTRODUCTION

In civil engineering practice, horizontally curved beams, members of a space frame, eccentrically loaded beams, spandrel beams, and spiral staircases are typical examples of structural elements subjected to predominant torsional moments and hence torsion cannot be neglected in design of such members. Torsion is produced when a member carries a force that does not act through its shear center. Hence, special care must be taken for the structural systems governed by equilibrium torsion, to prevent catastrophic failures being taken place. For many years, torsion in prestressed and reinforced concrete structures was regarded as a secondary effect, and was not considered explicitly in design. The design for torsion has received an increasingly greater importance after 1960's. The torsion provisions in the ACI Building Code ACI 318-89 were proposed in a series of papers by ACI Committee 438, in 1968 and 1969 and included for the first time in the 1971 [1].

In the literature, many analytical, numerical and experimental studies have been reported for torsional behavior of concrete elements under pure torsion. The behavior of homogeneous members under torsion in the elastic domain is expressed very well by Saint Venant's theory and its complementary one by Cowan [2]. This theory has been extended to describe the behavior of non-homogeneous elements and to predict their torsional strength. However, this theory seems to be unsatisfactory since concrete exhibits the complex structural response with various important nonlinearities. Tests of concrete elements under torsion have shown that this theory underestimates the failure strength of plain concrete members. In the examined cases, the actual strength proved to be roughly 50% greater than the predicted one by the elastic theory. Whereas Saint Venant's theory underestimates the torsional strength of concrete elements, the plastic and the skew bending theories have been proposed to estimate the failure torque of them. Nevertheless, the plastic theory is not quite satisfactory and overestimates the failure strength [3]. The skew bending theory describes the failure of concrete elements with a rectangular cross section very well, but it is useless in practice in the case of flanged sections due to mathematical complexity [4]. The procedure for the torsional analysis and design of concrete adopted by the American Concrete Institute (ACI) is based on the skew bending theory and mainly covers rectangular beams [1].

Many application of neural networks in civil engineering, Vanluchene and Sun, proposed the first prototype application of neural networks as a tool for structural design in 1990 [5]. Several applications of neural networks in civil engineering problems such as: modeling the capacity of pin-ended RC columns [6], prediction of shear strength of RC deep beams [7], size effect on shear strength of reinforced concrete beams [8], predicting structural properties of Elasto-Plastic plates [9], predicting nonlinear response of uniformly loaded fixed plates[10], predicting thickness of rectangular plates[11], prediction of strength of concrete mix [12,13], and torsion of reinforced concrete beams [14-16].

In this paper, the collected specimens have a range from normal strength concrete to high-strength concrete. The test specimens have been solid rectangular beams, and they have been subjected to concentric pure torsion. In the ANN model, the input parameters consist of nine parameters. The parameters are: the cross sectional dimensions of beams(b and h), concrete compressive strength, rapture

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strength of concrete, splitting strength of concrete, spacing of stirrups, the steel ratio of stirrups , the steel ratio of longitudinal reinforcement, and prestressing force. The output parameter of the ANN model is the torsional strength of the prestressed concrete beam. The error back propagation algorithm (Levenberg-Marquardt) is used for training of the network. Then, training, testing and validating errors and correlation coefficients are calculated for these data. Also in this paper a parametric study is established to obtain the importance of different input parameters on the behavior of prestressed concrete beams under pure torsion load using the trained ANN.

2. TORSIONAL STRENGTH OF PRESTRESSED CONCRETE BEAMS

Characteristics of prestressed concrete beams are essentially similar to the plain concrete beams unless additional torsional reinforcement is provided. It is well known that subjecting the concrete members to axial prestress results in a substantial increase in their torsional capacities. However, the addition of axial prestress force alone will not add any post-cracking ductility index of the member. In prestressed concrete members subjected to torsion, there exists a state of triaxial stresses [17,18]. Cracking occurs when the combined stress produced by the torsional shear and prestress exceeds the concrete strength as defined by an appropriate failure criterion, where (T_n)shall be determined the lesser value get from equation(1) or equation(b): [19,20].

$$T_n = \frac{2A_oA_tf_{yt}}{s} \times \cot\theta \quad (1)$$

$$T_n = \frac{2A_oA_\ell f_{yt}}{p_h} \times \cot\theta \quad (2)$$

Tests on prestressed concrete members in pure torsion were first carried out by many researchers [21-27], where some researchers are tested for normal concrete specimens and others for high strength concrete prestressed rectangular beams with a concentric prestressing force. The prestressed members are observed their it has been established that the member was increased significantly when subjected to axial compression. Moreover, it has been found that the direction of the failure cracks depended on the level of prestressing.

3. NEURAL NETWORK MODELING BACKGROUND:

Multilayer feed-forward neural network model is the most widely used network for its efficient generalization capabilities [8,28]. Figure(1) presents typical multi-layer feed-forward neural networks.

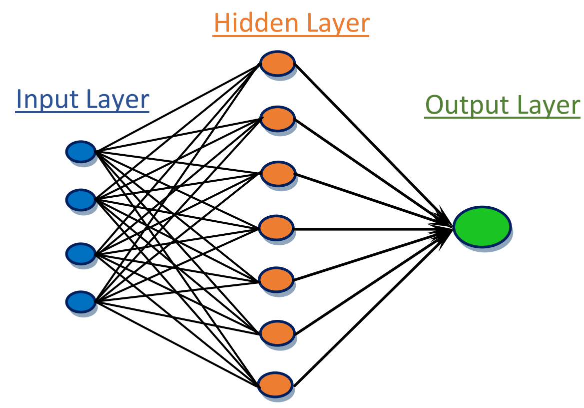

Fig.1 Structure of three-layered feed-forward network

This type of neural network consists of an input layer, one or more hidden layer(s) and an output layer. Layers are fully connected by arrows, and comprise a number of processing units, the so-called nodes or neurons. The strength of connections between neurons is represented by numerical values called weights. Each neuron has an activation value that is a function of the sum of inputs received from other neurons through the weighted connections [7,29]. The optimum number of hidden layers and the number of neurons in each hidden layer is problem specific. Therefore, trial and error should be carried out to choose an adequate number of hidden layers and the number of neurons in each hidden layer [10,30].

A Back propagation is the most successful and widely used in neural network applications. In this method, the input is propagated from the input layer through the hidden layers to the output layer. The network input is connected to every neuron in the first hidden layer while each network output is connected to each neuron in the last hidden layer. In this case this would call full connection ANN. The network weights were originally set to random values and new values of the network parameters (weights) are computed during the network training phase. The neurons output are calculated using:

$$O_i = F\left(\sum_j I_j \times W_{ij} + b_i\right) \quad (3)$$

Where Oi is the output of the neuron i, Ij are the input of j neurons of the previous layer, Wij are the neuron weights, bi is the bias for the modeling, and F is the activation function. The activation function is the portion of the neural network where all the computing is performed. The activation function maps the input domain (infinite) to an output domain (finite). The range to which most activation functions map their output is either in the interval [0, 1] or the interval [-1, 1]. There are several activation functions used over the years, however, the most common activation functions belong to five families as follows: (1) linear activation function; (2) step activation function; (3) ramp activation function; (4) sigmoid activation function; and (5) Gaussian activation function.

The network error is then back propagated from the output layer to the input layer in which the connection weights are adjusted. This process is repeated until the error is minimized to a preference level. The error incurred during the learning can be expressed as Mean squared error and is calculate using Eq. (4)

$$MSE = \frac{1}{nm}\sum_{i=1}^{n}\sum_{j=1}^{m}\left(t_{ij} - y_{ij}\right)^2 \quad (4)$$

Where t is the target value, y is the output value.

4. NEURAL NETWORK DESIGN AND TRAINING

The use of ANN provides an alternative way to estimate torsional strength of reinforced concrete beams[15,16]. However, this paper deals with estimate torsional strength of prestressed concrete solid rectangular beams. In this study 82 samples were extracted from experimental tests conducted by previous publishing papers [4,21,26,and31-34]. The selected test specimens were of solid rectangular beams which were subjected to pure torsion. The ranges of torsional strength of samples are 2.25 to 55.8 kN.m, while those of input data are shown in Table(1).

To train the ANN models, first, the entire training data file is randomly divided into training and testing data sets. A (70) sets were used to train the different network architectures. The remaining (12) patterns were used for testing to verify the prediction ability of each trained ANN models, where the testing data are shown in Table (2). The multilayer feed forward back-propagation technique is used to develop and train the neural network model of this study where the sigmoid transform function adopted.

A good prediction for these cases is the ultimate verification test for the ANN models. These tests have to be applied for (input and output) response within the domain of training. Preprocessing of data by scaling was carried out to enhancement the training process of the neural network. Then, to avoid the slight speed of learning near the end points specifically of the output range due to the property of the sigmoid function, therefore, the input and output sets were scaled between the interval (0.1 to 0.9). The scaling of the training data sets was carried out using the equation(5):

$$y = \left(\frac{0.8}{x_{max}-x_{min}}\right)x + \left(0.9 - \frac{0.8\,x_{max}}{x_{max}-x_{min}}\right) \quad (5)$$

The back-propagation learning algorithm was employed for learning in the MATLAB program [29]. Each training of the network consisted of one pass over the entire 82 training data sets. The 12 testing data sets were used to monitor the training progress. Different training functions available in MATLAB program were experimented for the current application.

TABLE 1

RANGES OF INPUT PARAMETERS IN DATABASE

Input parameters	Ranges	
	Minimum	Maximum
b (mm)	75	240
h (mm)	125	420
f'_c (MPa)	24.25	95.6
f_r (MPa)	3.69	9.1
f_t (MPa)	2.46	7.17
ρ_l (MPa)	0.004	0.0352
ρ_s (MPa)	0.004	0.0247
S (mm)	65	220
f_p (MPa)	0.0	29.19

The scaled conjugate gradient (SCG) techniques built in MATLAB proved to be efficient training function, and therefore, was used to construct the neural network model. This training function is one of the conjugate gradient algorithms that start training by searching in the steepest descent direction (negative of the gradient) on the first iteration. The network architecture or topology is obtained by identifying the number of hidden layers and the number of neurons in each hidden layer. The network learns by comparing its output for each pattern with a target selected output for that pattern, after that the process of calculating the error and propagating an error function backward through the neural network is done. To use the trained neural network, new values for the input parameters are presented to the network. The network then calculates the neuron outputs using the existing weight values developed in the training process.

TABLE 2
INPUTS OF TESTING DATA

Speci men	f'_c MPa)	f_r MPa)	f_t MPa)	b (mm)	h (mm)	ρ_l MPa)	ρ_s MPa)	S (mm)	f_p (MPa)	TEXP (kN.m)
HIAR	94.67	8.41	6.98	240	240	0.0152	0.0140	90	6.39	38.44
H1B	89.78	8.07	6.92	240	240	0.0117	0.0054	120	4.27	31.33
B2.75-A1	43.30	9.10	6.08	85	187	0.0060	0.0040	220	2.48	2.92
Hum3	48.20	5.55	4.17	125	125	0.0060	0.0040	220	4.15	2.93
Hum14	48.20	5.55	4.17	125	125	0.0060	0.0040	220	5.87	2.90
Hum19	48.20	5.55	4.17	125	250	0.0060	0.0040	220	9.15	6.74
Hum23	48.20	5.55	4.17	125	250	0.0060	0.0040	220	11.82	8.30
Hum33	48.20	5.55	4.17	125	375	0.0060	0.0040	220	17.92	14.15
Hum43	48.20	5.55	4.17	75	300	0.0060	0.0040	220	21.99	7.64
Hum46	48.20	5.55	4.17	75	300	0.0060	0.0040	220	24.41	8.13
Hum52	48.20	5.55	4.17	125	125	0.0060	0.0040	220	0.00	2.49
Nyl_04	24.25	3.69	2.46	200	200	0.0060	0.0040	220	8.50	5.16

5. ARCHITECTURE OF NEURAL NETWORK

In this work a multilayered feed-forward neural network with a back-propagation algorithm was adopted. The ANN was developed using the popular MATLAB software package [29]. To train the ANN models, first the entire experimental data file was randomly divided into training and testing data sets. The seventy patterns were used to train the different network architectures. The remaining twelve patterns were used for testing to verify the prediction ability of each trained ANN model. The network model was constructed. The model has nine input parameters and one output parameter.

The rationale behind this is to study the significance of parameter on torsional strength of prestressed concrete beams. The models has two hidden layers with seven nodes each, and output layer with one node giving torsional strength of prestressed concrete beams. Since the sigmoid function is used as transfer function, however the inputs as well as the output are scaled in the range of (0.1–0.9). The convergence of the models in training is based on minimizing the error of tolerance for mean squared (MSE) error during the training cycles and monitoring the overall the performance of the trained networks by comparing the outputs. Figure(2) was illustrated the minimum error could be issued by selected architecture (9-7-7-1). The architecture of the developed ANN model and its properties are shown in Table (3).

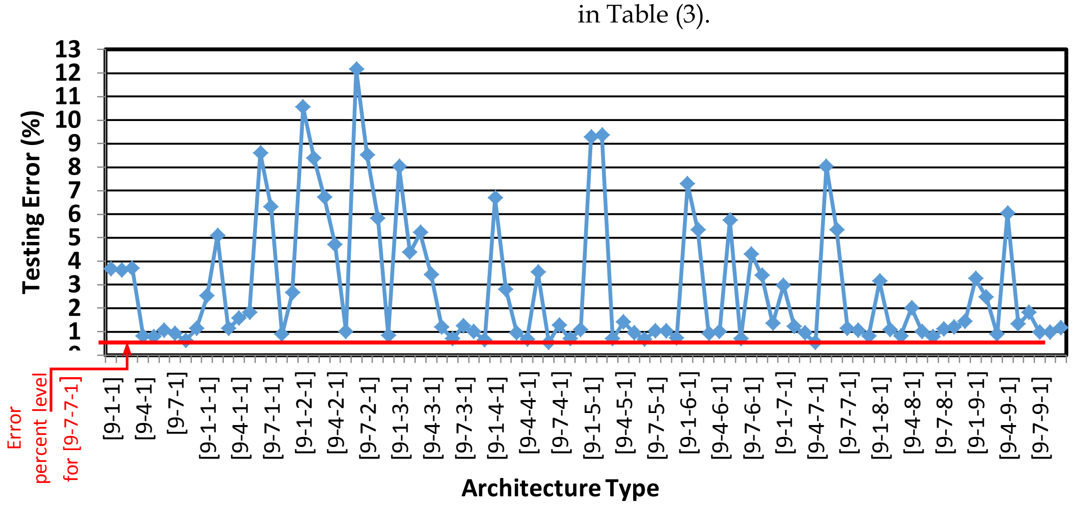

Fig.2 Illustrated the errors of many trail architectures

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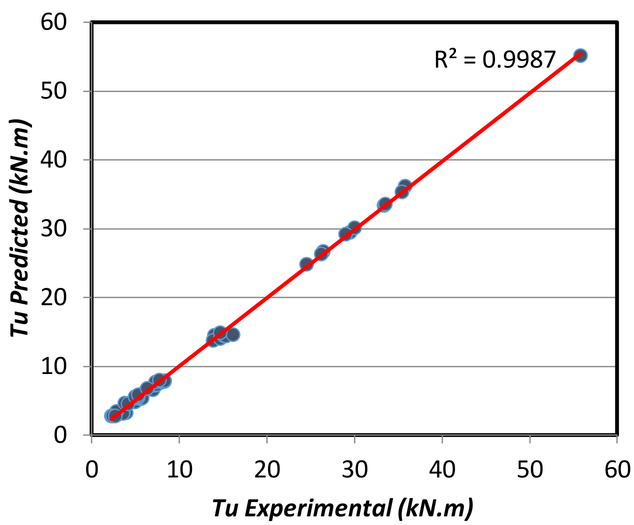
TABLE 3

ARCHITECTURE OF THE DEVELOPED ANN MODEL AND ITS PROPERTIES

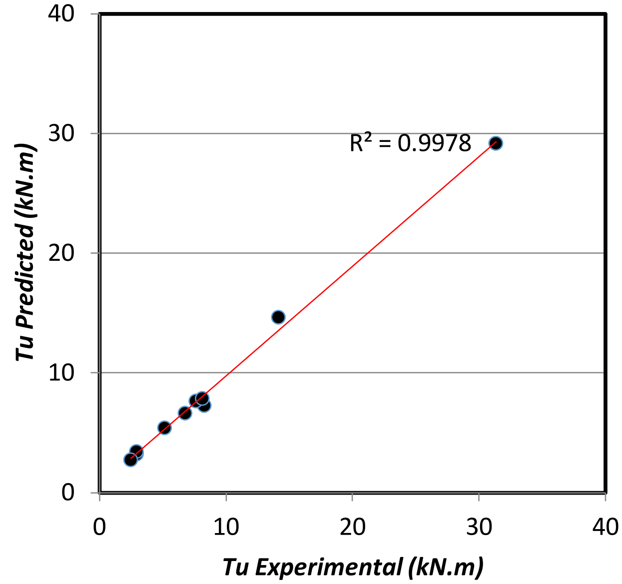
ANN Used Model	
Architecture	9-7-7-1
Performance function in terms of MSE	0.01
Learning Algorithm	(LM) Levenberg–Marquardt
Activation Function	Logsig- Logsig- Logsig

6. RESULTS AND DISCUSSION

The predictions of the selected ANN model as compared to the experimental values are illustrated in figure(3-a, b) for both choosing training and testing data. The coefficient of correlation (R) was equaled to 0.998, and 0.997 for both training and testing data set, respectively. Table(4) represents the details of test data which used in ANN model and the ratio of experimental torsional strength (Tu,exp) with computed values from analytical equations ACI318 model. In addition to suggested ANN model. The accuracy of the predicted ANN values of the torsional strength is shown in Fig. (3a-b), this model, predict the training sets and testing sets quite well. The coefficient of variation (COV) was equaled to (0.118) for the ANN model, compared to COV equal to 0.37 for the ACI model, and the standard deviation was equal to (0.116) for the ANN model, compared to COV equal to 0.355 for the ACI model. From these results, it can be seen that the neural network model predict the torsional strength of prestressed concrete beams more accurately than other ACI model and concluded that the neural network model can successfully predicted the torsional strength for prestressed concrete beams. On the other hand, the ANN model shows least scattering of the results.



a. ANN predicted training data



b. ANN predicted testing data

Fig. 3. Predictions of the ANN model as compared to the experimental values

7. PARAMETRIC STUDY

One of the advantages of neural network models is that parametric studies can be easily done by simply varying one input parameter and all other input parameters are set to constant values. Through parametric studies, it can verify the performance of model in simulating the physical behavior of prestressed concrete beams due to the variation in a certain parameter values.

7.1. Effect of Beam Depth.

The effect of beam depth on torsional strength is illustrated in the Fig. (4).While the width of section remain constant (b=100mm). Regardless of other parameters the figure show that the torsional strength of the prestressed concrete beams increases in (130%) with increasing the beam depth from 100 mm, to 300mm for the compressive strength was equaled to 50MPa (as average value). Also the figure indicated that the increases rate of the torsional strength which reach (23%) when the compressive strength of the beam changes from 20MPa, to 80MPa, for the beam depth equal to (300mm). This fact is due to the effect of slender coefficient becomes clearer when the depth increased.

7.2. Effect of Main Reinforcement Ratio (ρ_l)

Fig. (5) Shows the effect of main reinforcement ratio on the torsional strength of the prestressed concrete beams. The range of main reinforcement ratio values were 1.2% to 3%, and the range of compressive strength values were 20 to 80MPa, with a constant section dimensions (100x200)mm. It can be seen that the torsional strength increase with increasing the main reinforcement ratio, and its effects become more obvious as the main reinforcement ratio increases. When the main reinforcement ratio increases from 1.2% to 3%, the torsional strength increases by (170%) for compressive strength equal to 50MPa, while torsional strength increase in rate (14.6%) when the compressive strength of the beam increased from 20MPa, to 80MPa, the main reinforcement ratio equal to (3%).

7.3. Effect of Secondary Reinforcement Ratio

Figure (6) illustrated the relationship between the torsional strength and concrete strength with different secondary reinforcement ratios (as a function of stirrups spacing) of prestressed concrete beams. The ranges of spacing of stirrups were 80 to 200mm. When the other parameters kept constant as shown in figure (6) the torsional strength increases with decreasing spacing of steel stirrups. Thus, the concrete compressive strength increase from 20 to 50MPa, given rate of increase in torsional strength is (180%), and (340%) for the prestressed concrete beams with spacing of steel stirrups 200mm, and 80mm, respectively.

Table (4)
Comparison with test results

Specimen	T_{EXP} (kN.m)	T_{ANN} (kN.m)	T_{ACI} (kN.m)	T_{ANN}/T_{EXP}	T_{ACI}/T_{EXP}
HIAR	38.44	30.2	30.15	0.786	0.784
H1B	31.33	29.39	22.61	0.938	0.722
B5-A1	2.92	2.43	2.06	0.832	0.705
Hum3	2.93	3.22	2.06	1.099	0.703
Hum14	2.90	3.43	2.6	1.183	0.897
Hum19	6.74	6.62	7.48	0.982	1.110
Hum23	8.30	7.27	10.6	0.876	1.277
Hum33	14.15	14.63	7.40	1.034	0.523
Hum43	7.64	7.64	6.37	1.000	0.834
Hum46	8.13	7.86	6.37	0.967	0.784
Hum52	2.49	2.73	4.02	1.096	1.614
Nyl_04	5.16	5.41	8.11	1.048	1.572
Mean ($\bar{X}$)				0.987	0.960
Standard Division (SD)				0.116	0.355
Variance Coefficient (COV)				0.118	0.370

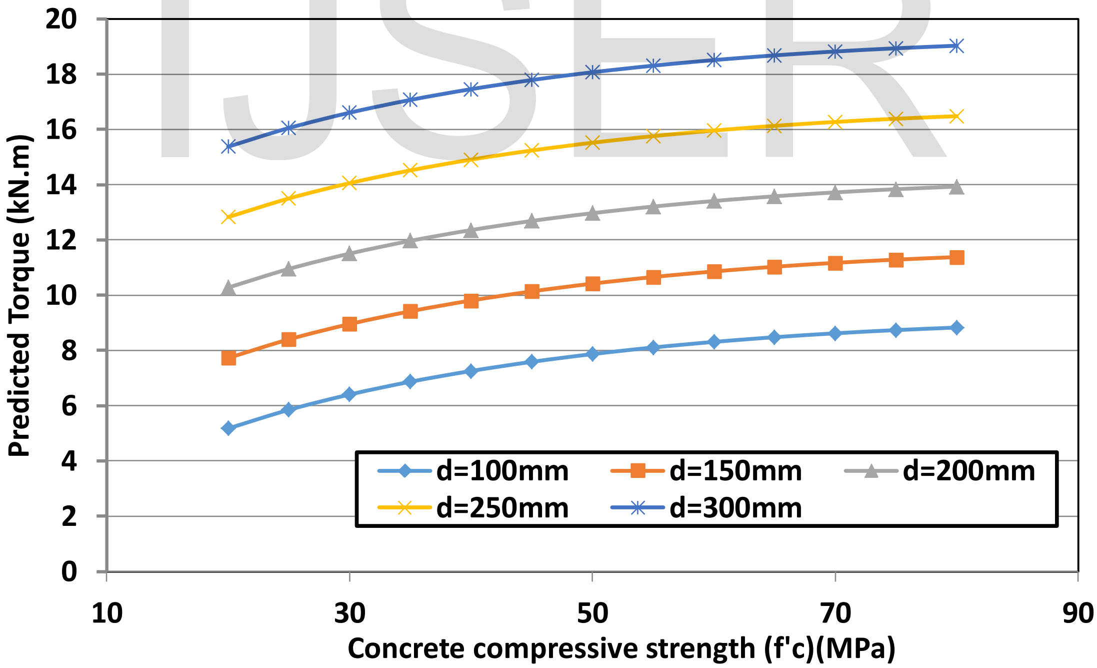


Fig. 4. Torsional strength versus compressive strength for different values of section depth (h)

7.4 Effect of Prestressing Force

The relationship between the torsional strength and the prestressing concentric axial force of prestressed concrete beams for different values of compressive strength, as shown in fig.(7). The ranges of prestressing forces were $0.1f'_c$ to $0.5f'_c$. When the other parameters kept constant, the torsional strength increases with increasing prestressing force. It can be seen that the prestressing force increases from $0.1f'_c$ to $0.5f'_c$, the torsional strength increases by (45%) for compressive strength equal to 50MPa, while torsional strength increase in rate (46.5%) when the compressive strength of the beam increased from 20MPa, to 80MPa, the prestress force was equal to ($0.5f'_c$.).

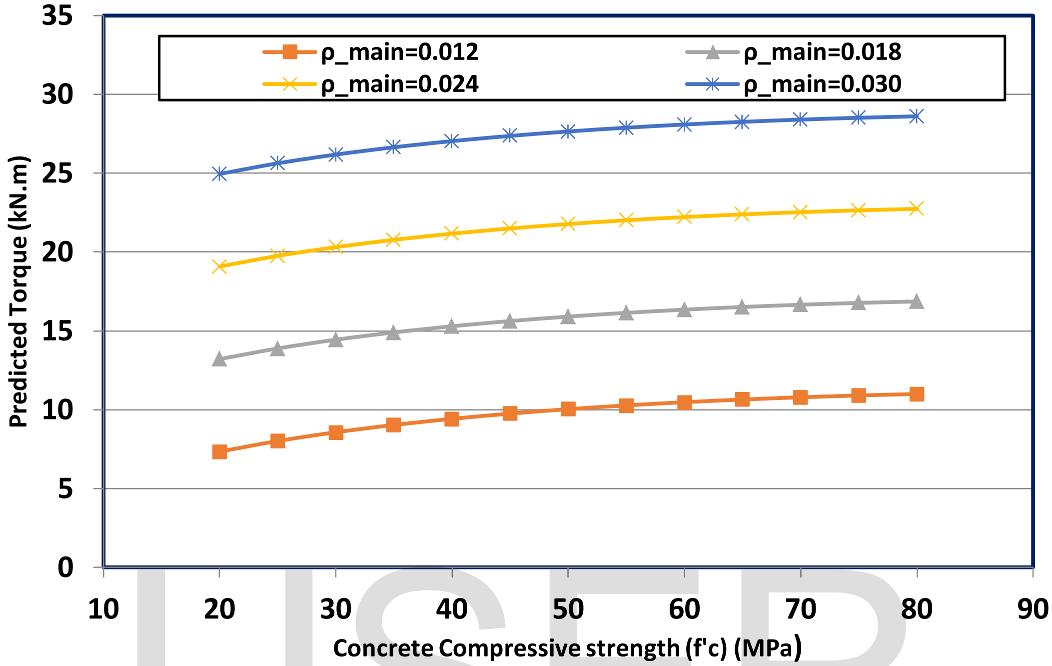


Fig. 5. Torsional strength versus compressive strength for different values of main reinforcement ratios (ρ_l)

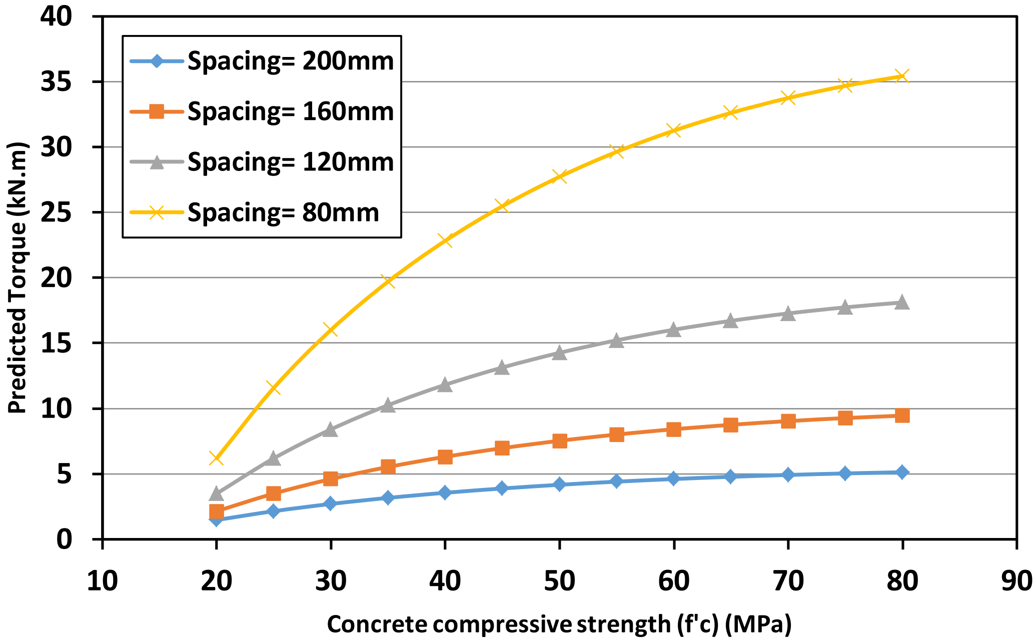


Fig.6. Torsional strength versus compressive strength for different values of steel stirrups spacing

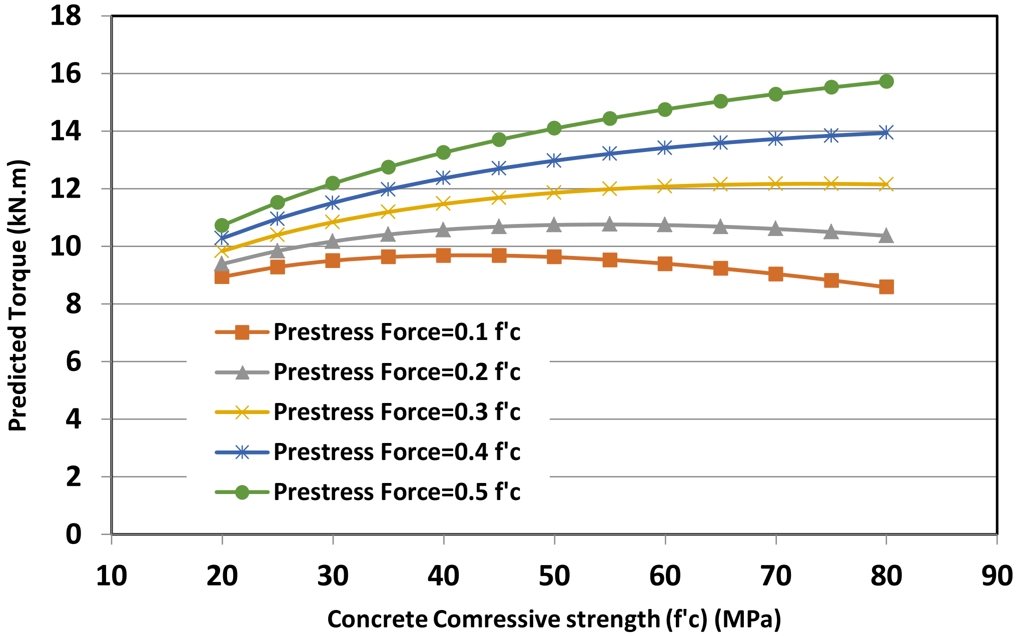


Fig. 7. Torsional strength versus compressive strength for different values of prestressing forces

8. CONCLUSIONS

In this study, the ANN model was developed to simulate the behavior of prestressed concrete beams. A back-propagation neural network (BPNN) was used. The measured experimental values are compared with the torsional strength calculated from ANN model, the ACI318-14 code formula. A parametric study was carried out to explain the effects of various parameters on the behavior of prestressed concrete beams. It can be concluded from this study the following:

- The ANN model is stronger and valid to simulate the behavior of prestressed concrete beams, the ANN predictions are accurate provided that the input data are within the ranges used for training the network.
- ANN algorithm is an effective and inexpensive tool for carrying out parametric study among several parameters that affect physical phenomenon in engineering as demonstrated for the case of torsional strength of prestressed concrete beams.
- All design models developed using ANN show the differences in performance of ANN predictions but has an advantage to build a family of models of varying complexity and significant accuracy.
- From parametric study the beam depth, main reinforcement ratio secondary reinforcement ratio and prestressing concentric forces are the major factors effect on the torsional behavior of prestressed concrete beams. Also, from the parametric study the compressive strength of concrete has a little enhancement in torsional strength of prestressed concrete beams.

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