Structural Engineering and Mechanics, *Vol. 53, No. 5 (2015) 939-956*
DOI: http://dx.doi.org/10.12989/sem.2015.53.5.939

Estimation of ultimate torque capacity of the SFRC beams using ANN

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(Received April 10, 2013, Revised August 21, 2014, Accepted November 6, 2014)

Abstract. In this study, in order to propose an efficient model to predict the torque capacity of steel fiber reinforced concrete (SFRC) beams, the existing experimental data related to torsional response of beams is reviewed. It is observed that existing data neglects the effects of some parameters on the variation of torque capacity. Thus, an experimental research was also conducted to obtain the effects of neglected parameters. In the experimental study, a total of seventeen SFRC beams are tested against torsion. The parameters considered in the experiments are concrete compressive strength, steel fiber aspect ratio, volumetric ratio of steel fibers and longitudinal reinforcement ratio. The effect of each parameter is discussed in terms of torque versus unit angle of twist graphs. The data obtained from this experimental research is also combined with the data got from previous studies and employed in artificial neural network (ANN) analysis to estimate the ultimate torque capacity of SFRC beams. In addition to parameters considered in the experiments, aspect ratio of beam cross-section, yield strengths of both transverse and longitudinal reinforcements, and transverse reinforcement ratio are also defined as parameters in ANN analysis due to their significant effects observed in previous studies. Assessment of the accuracy of ANN analysis in estimating the ultimate torque capacity of SFRC beams is performed by comparing the analytical and experimental results. Comparisons are conducted in terms of root mean square error (RMSE), mean absolute error (MAE) and coefficient of efficiency (E_f). The results of this study revealed that addition of steel fibers increases the ultimate torque capacity of reinforced concrete beams. It is also found that ANN is a powerful method and a feasible tool to estimate ultimate torque capacity of both normal and high strength concrete beams within the range of input parameters considered.

Keywords: reinforced concrete beam; torsion; steel fiber; artificial neural network

1. Introduction

In most of the times, the torque is observed in combination with the bending moment where the effects of axial and shear forces may be significant. Although there are no cases where pure torsion occurs in any frame elements, the behavior of elements under pure torsion needs to be defined explicitly in order to understand the overall combined flexural and torsional response (Ersoy 1999, Nilson and Winter 1991).

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http://www.techno-press.org/?journal=sem&subpage=8 ISSN: 1225-4568 (Print), 1598-6217 (Online)

Since the torque capacity of reinforced concrete (RC) sections affect the response of any structural system subjected to external loadings, it is of crucial to determine the torque capacity accurately. Previous studies focused on the torque capacity of RC sections clearly showed that it is highly dependent on the parameters such as aspect ratio of beam cross-section, strength of concrete, reinforcement ratio, and yield strength of reinforcement.

Being the first experimental study that considered the torsional response of RC sections, Hsu (1968) investigated the effect of transverse reinforcement ratio on the torque capacity of beams. The author had determined in this study that torque capacity and rigidity are nearly the same up to the first crack irrespective of transverse reinforcement ratio; but the torque capacity and rigidity increase with the transverse reinforcement ratio after the occurrence of first crack. In another study, conducted by Narayanan and Kareem-Palanjian (1986), it is revealed that the torque capacity of beam increases as the aspect ratio of beam cross-section increase. In their research, Rasmussen and Baker (1995) performed several experiments with RC beams having various compressive strengths of normal and high strength concrete. Authors found out that torque capacity of RC beams increases with increasing concrete compressive strength. However, they indicated that high strength RC beams present a more brittle behavior compared to normal strength RC beams. Similarly, Fang and Shaiu (2004), focused on the torsional response of beams as a function of the concrete compressive strength together with transverse and longitudinal reinforcement ratios. Fang and Shaiu (2004) concluded that torque capacity of beams increases due to increase in both concrete compressive strength and transverse and longitudinal reinforcement ratios. Moreover, they specified that transverse reinforcement ratio is more effective compared to longitudinal reinforcement ratio on the increase of torque capacity and this behavior is more significant in high strength RC beams. Nevertheless, none of these studies considered the effect of addition of steel fibers to the RC mixtures in terms of torsional response of beams. On the other hand Mansur *et al*. (1989) carried out an experimental study to specify the effect of adding steel fibers on the torsional behavior of normal strength RC beams. Only one type steel fiber aspect ratio is used in the study and it is observed that the cracking torque is nearly the same for all fiber volumetric ratios, whereas the torque capacity increases with the increase of steel fiber volumetric ratio after the first crack. Narayanan and Kareem-Palanjian (1983) took the steel fiber volumetric ratio and beam section's aspect ratio to be the variables. They state that the torque capacity of beam increases with increase of steel fiber volumetric ratio and beam section's aspect ratio. Rao and Seshu (2003, 2005) accomplished torsion tests with concrete beams without transverse and longitudinal reinforcement but having different steel fiber volumetric ratio. It is founded that addition of steel fiber increase the torque capacity and rigidity; besides it makes high strength concrete which is known to present a brittle behavior, more ductile. Yang *et al.* (2013) took steel fiber volume, transverse and longitudinal reinforcement ratio to be the variables in the experiment. Ultra-high performance concrete is used in the study. It is stated that the torque capacity of RC beams made of ultra-high performance concrete increases with the increase of steel fiber volumetric ratio and reinforcement ratio. When studies available in the literature are taken into account, it is seen that most of studies concentrate on the effect of concrete compressive strength, transverse reinforcement ratio and steel fiber volumetric ratio on torque capacity; but the effect of steel fiber aspect ratio and longitudinal reinforcement ratio are disregarded.

The objective of this study is to propose a ANN model to estimate the torque capacity of SFRC beams. This model intends to consider all of the parameters that affect the torsional response of beams. The study consists of two parts as the experimental research and ANN model. In the first part is performed an experimental research in which steel fiber aspect ratio and longitudinal reinforcement ratio are taken into account, and it is seen that their effects on torque capacity have not been addressed in previous studies explicitly. In the second part, experimental results containing parameters like transverse reinforcement ratio, beam section's aspect ratio, transverse and longitudinal reinforcement yield strength, steel fiber volumetric ratio and concrete compressive strength which are all effective on torque capacity, obtained from the experiments performed by Mansur *et al*. (1989), Rasmussen and Baker (1995), Fang and Shaiu (2004). An ANN model is prepared to estimate the torque capacity of SFRC beams by using clustered data from the literature and present study. The accuracy of the proposed model is also tested by comparing the torque capacities of SFRC beams obtained from experiments with the ones obtained by estimations of proposed ANN model.

2. Experimental programme

2.1 Materials and mix proportions

Concrete mixtures are composed of natural sand as fine aggregate, crushed stone as course aggregate and 42.5 MPa strength cement. Since, one of the parameters in the study is the concrete compressive strength, to obtain the desired concrete compressive strengths plasticizer (superplasticizer for normal strength concrete and hyperplasticizer for high strength concrete) is also used as an ingredient for concrete mixtures. The amounts of superplasticizer and hyperplasticizer used to obtain normal strength concrete and high strength concrete are 1.0% and 1.6%, respectively. The corresponding amounts of ingredients for both normal and high strength concrete mixtures are presented in Table 1. In the mixtures, four different steel fiber aspect ratios (l_f/d_f=40, 55, 67, and 80) are used for hook end steel fiber; where l_f is the length and d_f is the diameter of the fiber. These aspect ratios correspond to l_f/d_f ratios of 30/0.75, 30/0.55, 60/0.90, and 60/0.75 in mm. Yield strength for the steel fibers given by the manufacturer is f_{yf}=1200 MPa. Geometry of steel fibers added to the concrete mixtures is given in Fig. 1.

The reinforcement used in the cross-sections is composed of deformed bars. The transverse reinforcement diameter, d_t, is selected as 8 mm. To observe the effect of longitudinal reinforcement on ultimate torque capacity, two distinct longitudinal reinforcement diameters, d_l,

Table 1 Mix proportions

Concrete Content	Concrete Compressive Strength	
	NSC* - 30 MPa (Aim)	HSC** - 60 MPa (Aim)
Water / Cement	0.65	0.37
Water (kg/m^3)	208	203.5
Cement (kg/m^3)	320	550
Course Aggregate (kg/m^3)	1091	982
Sand (kg/m^3)	714	642
Superplasticizer (kg/m^3)	3.2	-
Hyperplasticizer (kg/m^3)	-	8.8
Slump (cm)	24	20

*NSC: Normal Strength Concrete **HSC: High Strength Concrete

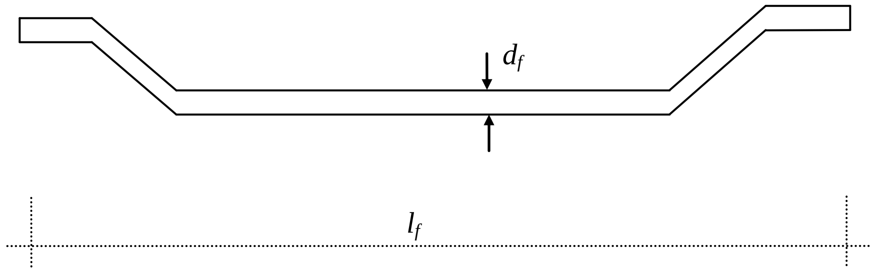


Fig. 1 Geometry of the steel fibers used in the test specimen

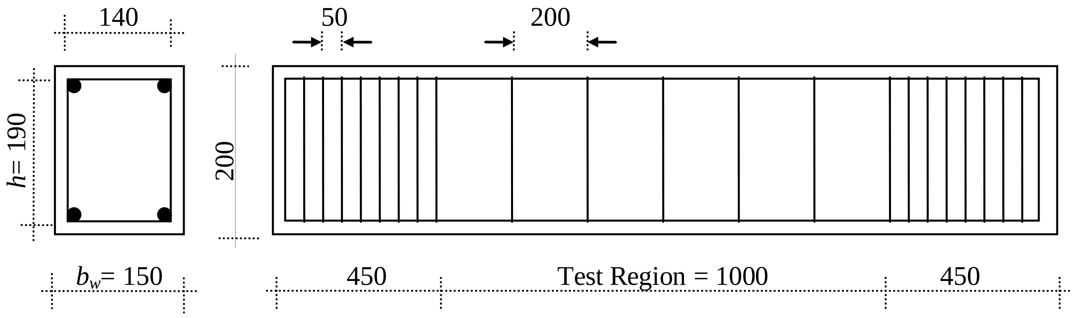


Fig. 2 The reinforcement layout and dimensions of the test specimen. (All dimensions are in mm)

namely, 8 mm and 12 mm, are considered in the cross-sections. The yield strength of the steel used for both transverse and longitudinal reinforcement is 460 MPa.

2.2 Specimen characteristics

The cross sectional dimensions of the test specimens are 150×200 mm with a length of 1900 mm. The first variable is the longitudinal reinforcement ratio ρ_l, which is chosen as 0.0067 (4 pieces of d_l=8 mm) and 0.015 (4 pieces of d_l=12 mm). Transverse reinforcement diameter is 8 mm and their center to center spacing is 200 mm which corresponds to transverse reinforcement ratio of ρ_t=0.006 for all specimens. The transverse reinforcement ratio is kept constant while the other parameters (longitudinal reinforcement ratio, concrete compressive strength, and volumetric ratio of steel fiber) vary accordingly in order to observe their effect on the torque capacity, explicitly. To prevent any failure of the beam except at the test region, spacing of transverse reinforcement outside the test region is decreased from 200 mm to 50 mm. The reinforcement layout and dimension of the test specimen is given in Fig. 2.

In the conducted experiments, the volumetric ratio of steel fiber V_f is chosen as 0.3% and 0.6%. With these two steel fiber ratios (SFRs), it is aimed to observe the behavior of concrete with increasing volumetric ratio of fibers. To identify the specimens, the following alphanumeric procedure is followed: The first character, *C*, followed by numbers designates the concrete compressive strength in MPa, block *L* designates the diameter of the longitudinal reinforcement in mm, block *F* stands for the dimensionless fiber aspect ratio, block *V* represents the volumetric ratio of the fibers added in percentage. Specimen's details are given in Table 2.

Table 2 Specimen details

Beam Designation	Concrete Type	Longitudinal Reinforcement	l_f/d_f	V_f (%)
C30L08F00V0	NSC	4 No. of 8 mm dia.	-	-
C30L08F40V3	NSC	4 No. of 8 mm dia.	40	0.3
C30L08F40V6	NSC	4 No. of 8 mm dia.	40	0.6
C30L08F55V3	NSC	4 No. of 8 mm dia.	55	0.3
C30L08F55V6	NSC	4 No. of 8 mm dia.	55	0.6
C30L08F67V3	NSC	4 No. of 8 mm dia.	67	0.3
C30L08F67V6	NSC	4 No. of 8 mm dia.	67	0.6
C30L08F80V3	NSC	4 No. of 8 mm dia.	80	0.3
C30L08F80V6	NSC	4 No. of 8 mm dia.	80	0.6
C30L12F00V0	NSC	4 No. of 12 mm dia.	-	-
C30L12F40V3	NSC	4 No. of 12 mm dia.	40	0.3
C30L12F80V3	NSC	4 No. of 12 mm dia.	80	0.3
C60L08F00V0	HSC	4 No. of 8 mm dia.	-	-
C60L08F40V3	HSC	4 No. of 8 mm dia.	40	0.3
C60L08F40V6	HSC	4 No. of 8 mm dia.	40	0.6
C60L08F55V3	HSC	4 No. of 8 mm dia.	55	0.3
C60L08F55V6	HSC	4 No. of 8 mm dia.	55	0.6

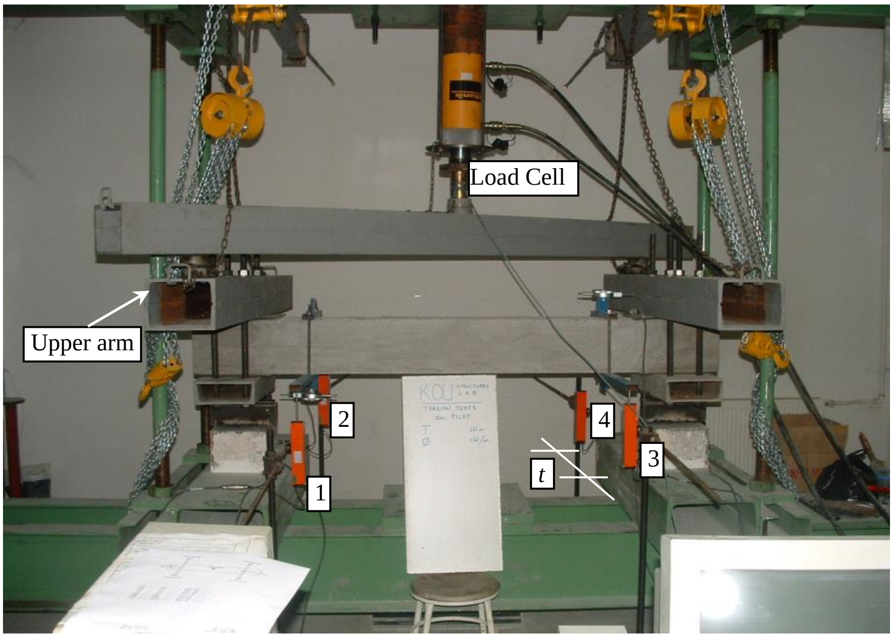


Fig. 3 Test setup, loading and measurement systems

2.3 Test Setup, loading and measurement systems

The test setup where the test specimens are subjected to uniform torsional loading is given in Fig. 3. As shown in the figure, the specimen is placed on roller supports aligned with its axis in order to release both ends of the specimen from free rotation, extension or contraction. The specimen is held in place between the upper arms and lower plates which are connected to roller supports by means of bolts. The variation of the load which is applied to the specimen is measured through the electronic load cell. The torque applied to the beam is obtained by the product of measured load by moment arm (upper arms length/2). Beam's angle of twist is obtained by the division of the addition of the displacements of points 1, 2, 3 and 4 measured by the extensometers, by the distance (t) between the extensometers settled in front and back sides of the beam as shown in Fig. 3. Beam's unit angle of twist is obtained by the division of angle of twist by the length of test region.

3. Test results and discussions

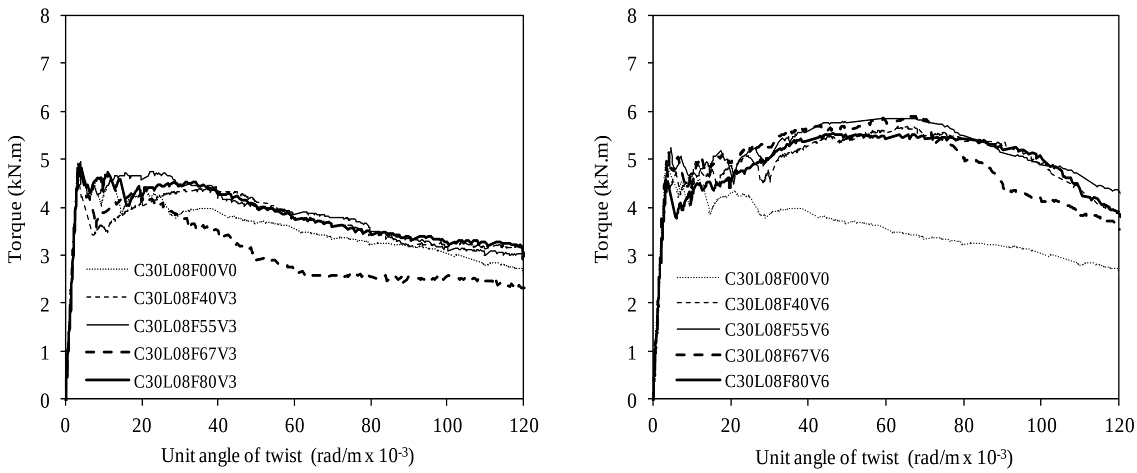
3.1 Test results

Torsion tests are performed on the beams which are produced once for each beam configuration. For each specimen, ultimate torques, T_u, are determined from test results and listed in Table 3. Table 3 also consists of the average values of 28th day compressive strength, f_{ck}, split cylinder tensile strength, f_{cts}, and flexural tensile strength, f_{ctf}, of each test specimen. Torque versus unit angle of twist graphs are plotted for each specimen obtained from pure torsion tests. The graphs are grouped according to experimental parameters. The effect of considered parameters on the torsional capacity of beams is seen clearly by the help of this grouping.

As depicted in Fig. 4(a), the addition of 0.3% steel fiber to normal strength concrete, where longitudinal reinforcement diameter, d_l is equal to 8 mm, results in almost no variation in torsional

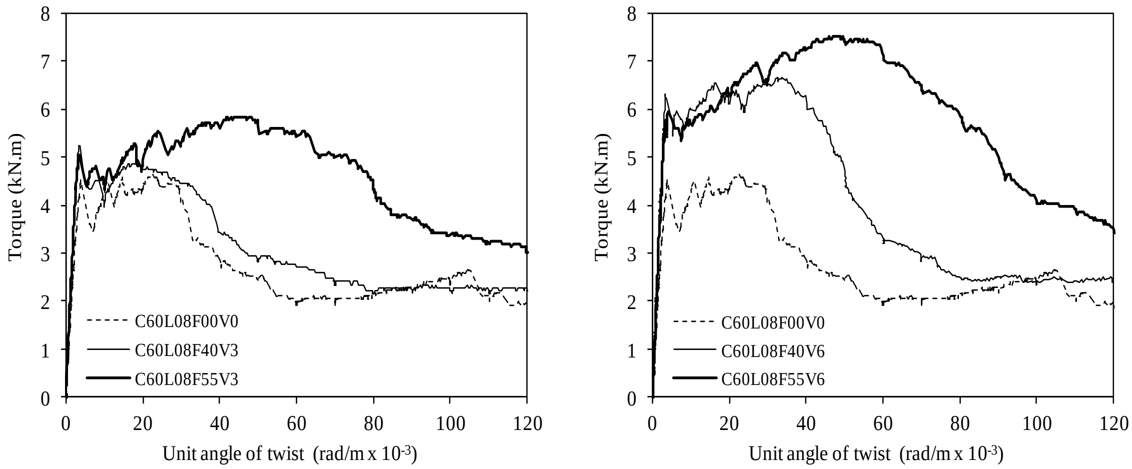
Table 3 Test results

Beam Designation	f_{ck} (MPa)	f_{cts} (MPa)	f_{ctf} (MPa)	T_u (kN.m)
C30L08F00V0	34.8	3.51	4.54	4.93
C30L08F40V3	33.4	3.55	4.96	4.58
C30L08F40V6	31.3	3.35	5.02	5.68
C30L08F55V3	31.0	3.08	4.82	4.94
C30L08F55V6	30.9	3.41	4.57	5.87
C30L08F67V3	32.7	3.42	4.39	4.92
C30L08F67V6	29.5	3.12	4.39	5.88
C30L08F80V3	31.9	3.46	4.56	4.85
C30L08F80V6	30.0	3.10	4.82	5.49
C30L12F00V0	34.8	3.58	4.54	5.07
C30L12F40V3	31.7	3.51	4.46	6.01
C30L12F80V3	31.6	3.56	4.87	6.25
C60L08F00V0	59.0	4.65	6.08	4.63
C60L08F40V3	58.6	4.84	6.23	5.23
C60L08F40V6	59.8	4.80	6.75	6.65
C60L08F55V3	60.8	4.86	5.95	5.83
C60L08F55V6	62.7	5.46	6.63	7.51



(a) Volumetric ratio of steel fiber is 0.3% (b) Volumetric ratio of steel fiber 0.6%

Fig. 4 Torque-unit angle of twist graphs in normal strength beams with d_l=8 mm



(a) Volumetric ratio of steel fiber is 0.3% (b) Volumetric ratio of steel fiber is 0.6%

Fig. 5 Torque-unit angle of twist graphs in high strength beams with d_l=8 mm

capacity compared to cases in which there is no steel fiber presents. However, some increment in the torsional capacities of beams ranging from 11.4% to 19.3% occurs due to addition of 0.6% of steel fiber to normal strength concrete (Fig. 4(b)). Fig. 4(a) also reveals that the change in steel fiber aspect ratios has almost no effect on torsional capacity of specimens. Similar comparisons for specimens with high strength concrete are presented in Figs. 5(a) and (b).

Fig. 5(a) shows that torque capacities of the specimens may increase up to 25% due to addition of 0.3% steel fiber to high strength concrete. Comparisons for the cases where 0.6% steel fiber is added to high strength concrete show that the torque capacities may increase up to 60% (Fig. 5(b)). In addition, there is a significant amount of increment in the energy dissipation capacities of specimens as a function of steel fiber aspect ratio regardless of the concrete strength. To identify the effect of longitudinal reinforcement on the torque capacity of beams, Fig. 6 is depicted. In this figure, variation in the torsional response of SFRC beams with different longitudinal reinforcement ratios is shown. It is clear that, the torque capacity of SFRC beams increases with increasing longitudinal reinforcement. The amounts of increment in torque capacities are 18.5% and 23.3% for d_l=8 mm and for d_l=12 mm, respectively.

Table 4 presents all of the test results in terms of ultimate torque capacities of the specimens. In Table 4, *I* stands for the amount of increment in torque capacity of SFRC beams in percentage.

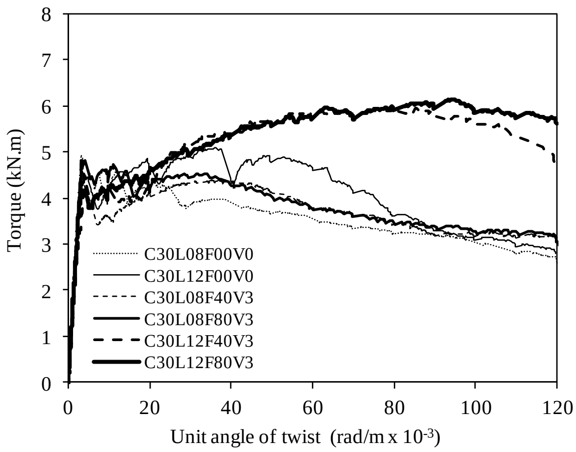


Fig. 6 Torque-unit angle of twist graphs in specimens with d_l=12 mm, different steel fiber aspect ratio of NSC beams

Table 4 Variation in torque capacity of SFRC beams due to addition of steel fibers

Beam Designation	T_u (kN.m)	***I** (%)**
C30L08F00V0	4.93	-
C30L08F40V3	4.58	0.0
C30L08F40V6	5.68	15.2
C30L08F55V3	4.94	0.0
C30L08F55V6	5.87	19.1
C30L08F67V3	4.92	0.0
C30L08F67V6	5.88	19.3
C30L08F80V3	4.85	0
C30L08F80V6	5.49	11.4
C30L12F00V0	5.07	-
C30L12F40V3	6.01	18.5
C30L12F80V3	6.25	23.3
C60L08F00V0	4.63	-
C60L08F40V3	5.23	12.9
C60L08F40V6	6.65	43.6
C60L08F55V3	5.83	25.9
C60L08F55V6	7.51	62.2

* $I = \dfrac{T_{u\,n+1} - T_{u\,n}}{T_{u\,n}} \, x\, 100$

3.2 Discussions on the experimental results

The torque capacity of beams versus unit angle of twist graphs indicates that addition of steel fibers to beams affect the torsional response and it is highly dependent of the concrete compressive strength. Moreover, the variation in torque capacity is also a function of volumetric ratio of steel fiber and steel fiber aspect ratio. In specimens with normal strength concrete, addition of 0.3% steel fiber has almost negligible effect on torque capacity while it is significant for 0.6% cases, regardless of the steel fiber aspect ratio. However, the amount of variation in torque capacity is observed to be affected by steel fiber aspect ratio in specimens with high strength concrete, regardless of the volumetric ratio of steel fiber. It is known that sections subjected to torsional loading are generally dominated by the tensile strength of the concrete (Ersoy 1999). Such conclusion is also in a good agreement with the observations of the present study. Because, the addition of steel fibers enhances the tensile strength of concrete (Song and Hwang 2004, Olivito and Zuccarello 2010), the corresponding torque capacity of SFRC beams increases, accordingly. The reason why addition of steel fibers is more effective in increasing the torque capacity, especially in high strength concrete specimens, can be identified by bonding between steel fibers and concrete. The bond strength between the reinforcement and the concrete is higher in high strength concrete compared to ones in normal strength concrete (Lutz and Gergely 1967, Orangun *et al*. 1977).

4. Application of ANN in engineering problems

Studies on artificial neural networks commonly referred to as “neural networks” and have been motivated right from its inception by the recognition that the human brain computes in an entirely different way from the conventional digital computer (Haykin 1999). ANN learns by sampling just like in human brain. ANN can be constituted for special purpose applications like classification of data and pattern recognition. For these applications the network is subjected to learning process. Learning operation occurs with the help of synaptic connections which are located between neurons. The same learning process is valid in artificial neural networks. ANN produced a general and practical method for real valued, discrete valued and vector valued functions by using the sampling defined to network. Thus, it can easily be used in many applications of engineering branches. ANN is widely used to predict the properties of concrete such as the compressive strength (Altun *et al.* 2008), modulus of elasticity (Demir 2008) and slump of concrete at early age (Öztaş *et al.* 2006). ANN is also used for prediction of the concrete compressive strength with mineral additives such as fly ash (Topçu and Sarıdemir 2008a), ground granulated blast furnace slag (Bilim *et al.* 2009), silica fume (Topçu and Sarıdemir 2008b) and various waste materials (Dantas 2013). After all these studies it is seen that the predictions obtained by using ANN are very close to results of experimental data. Although there exists a lot of ANN-based studies that deal with mechanical properties of concrete, prediction of the ultimate torque capacity of SFRC beams by using the artificial neural networks has not been modeled in literature yet.

5. Artificial neural networks (ANNs)

A neural network can be defined as a matcher to match an input value with an output value in

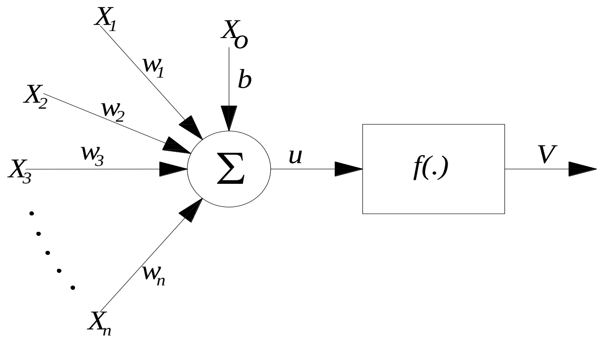


Fig. 7 Schematic diagram for the artificial neural model

engineering applications (Naderpour *et al.* 2010). A network occurs by accumulation of many basic parts that are named as neurons in layer. A neuron has only one output while it has many inputs. The information come to neuron are multiplied by weights of the connections links that they came from, before they are transferred to a neuron. By this means the effect of each input on outputs can be scaled (Alshihri *et al.* 2009). A schematic diagram for an artificial neural model is given in Fig. 7 where $X=(X_1, X_2, . . X_n)$, W_j and b represent the n number of input applied to the neuron, the weight for input X_j and bias, respectively. All of the neurons are connected to each other by the help of connection links and the signals defined to network are transferred from one neuron to another neuron via these links. Every neuron has an activation function in order to determine the output. There exists a numerous number of activation functions in the literature and generally nonlinear activation functions like sigmoid and step are used. ANNs are trained according to the sampling history defined to the network and when an unknown input is entered to the network it produces an output according to the past learning (Bilim *et al.* 2009).

As a beginning, the network structure should be defined in an artificial neural network model. Learning process is performed by the inputs defined to network. The network sets the connection between each input and each output during this process. When the learning process is accomplished, the second process which is called the testing process is performed by entering the inputs that are not defined before. Accuracy of the learning process is tested in testing process. The back-propagation (BP) network is used to perform human tasks such as diagnosis, classification, decision-making, planning and scheduling (Topçu *et al.* 2009). BP is the most applicable gradient descent algorithm which consists of changing weights and bias according to the negative of the error function. This operation must be repeated until the error of the network is minimized.

6. Neural network model and parameters

6.1 Pre-processing of data

An artificial neural network performance depends on selected data. Neural networks learn the physics underlying interest of the system from the training data, which are the cause-effects samples (Alshihri *et al.* 2009). For this reason, the variables used in the artificial neural network should completely define the problem that is to be solved. Torque capacity of a SFRC beam depends on concrete compressive strength, steel fiber aspect ratio, volumetric ratio of steel fibers, longitudinal reinforcement ratio, yield strength of longitudinal reinforcement, transverse reinforcement ratio, yield strength of transverse reinforcement and aspect ratio of beams cross section. The parameters taken as variables of the present experimental study are as follows:

- Concrete compressive strength (f_{ck}) in MPa
- Steel fiber aspect ratio (l_f/d_f) in mm/mm
- Volumetric ratio of steel fiber (V_f) in %
- Longitudinal reinforcement ratio (ρ_l) in %

Learning pats between the input and output values of the neural network should completely define the problem which should be taught. In the light of previous experiments studied by Mansur *et al.* (1989), Rasmussen and Baker (1995) and Fang and Shaiu (2004), further parameters that should be covered to determine the torque capacity of sections are listed below.

- Transverse reinforcement ratio (ρ_t) in %
- Yield strength of the longitudinal reinforcement (f_{yl}) in MPa
- Yield strength of the transverse reinforcement (f_{yt}) in MPa
- Beam section's aspect ratio (b_w/d) in mm/mm

The ultimate torque capacities of specimens taken from the literature are given in Table 5. The parameters that will be defined as an input to ANN model are also given for each considered case in Table 5.

In this section, it is aimed to determine the torsional capacities of SFRC beams subjected to torsion by the help of network model. The parameters that directly affect the pure torsion are considered when the artificial neural network is being constructed. A total of 51 data used in the network, randomly selected 25 are used for training, the remaining 26 are used for testing. The numerical values used in the training set are obtained from 8 specimens belong to present study, 3 specimens belong to Mansur *et al*. (1989), 6 specimens belong to Rasmussen and Baker (1995) and 8 specimens belong to Fang and Shaiu (2004). For this reason, the specimens chosen for training set include all the parameters homogeneously that effect torsion are investigated in study. A sigmoidal transfer function is usually used for the artificial neural networks. A sigmoid transfer function produces output with maximum and minimum limits of signal from generally 1 and 0, respectively. When function limits are considered, it is understood that input and output data should be scaled after preprocessing operation. Scaling increases the learning speed of the network as these values fall in the region of sigmoid transfer function where the output is most sensitive with respect to variations of the input values (Alshihri 2009) and maintains more accurate perception of data at once. For this reason, it is proposed to normalize the input and output data by an appropriate method before they are defined to network. In the network model, all the parameters given in Table 6 were normalized by dividing these terms by the maximum values of each parameter. Statistical data belong to the parameters used for training and testing is given in Table 6.

6.2 Neural network structure

In this study, a computer program was developed by using a computer software program MATLAB, for analyzing the network. Eight input nodes that affect the torsional strength are used to predict the maximum torsional capacity of the sections by using network. Proposed neural network model is shown in Fig. 8.

The multi-layer feed forward back-propagation technique was used for training and testing the neural network. ANN model consist of input, hidden and output layers respectively. Levenberg-

Table 5 Characteristics of the data taken from literature

Aut.	Speci.	f_{ck} (MPa)	l_f/d_f (mm/mm)	V_f (%)	ρ_l (%)	ρ_t (%)	f_{yl} (MPa)	f_{yt} (MPa)	b_w/d (mm/mm)	T_u (kN.m)
Mansur *et al.* (1989)	A-0.0	32.8	60	0	0.0070	0.0087	380.1	380.1	1.00	28.06
	A-0.5	25.8	60	0.005	0.0070	0.0087	380.1	380.1	1.00	27.34
	A-1.0	21.4	60	0.010	0.0070	0.0087	380.1	380.1	1.00	29.01
	A-1.5	28.0	60	0.015	0.0070	0.0087	380.1	380.1	1.00	34.67
	B-1.0	21.4	60	0.010	0.0105	0.0131	380.1	380.1	1.00	36.46
	C-1.0	21.4	60	0.010	0.0140	0.0175	380.1	380.1	1.00	40.86
Rasmussen and Baker (1995)	B30.1	41.7	0	0	0.0351	0.0176	620.0	665.0	0.58	16.62
	B30.2	38.2	0	0	0.0351	0.0173	638.0	669.0	0.58	15.29
	B30.3	36.3	0	0	0.0351	0.0173	605.0	672.0	0.58	15.25
	B50.1	61.8	0	0	0.0351	0.0173	612.0	665.0	0.58	19.95
	B50.2	57.1	0	0	0.0351	0.0173	614.0	665.0	0.58	18.46
	B50.3	61.7	0	0	0.0351	0.0173	612.0	665.0	0.58	19.13
	B70.1	77.3	0	0	0.0351	0.0173	617.0	658.0	0.58	20.06
	B70.2	76.9	0	0	0.0351	0.0173	614.0	656.0	0.58	20.74
	B70.3	76.2	0	0	0.0351	0.0173	617.0	663.0	0.58	20.96
	B110.1	109.8	0	0	0.0347	0.0173	618.0	655.0	0.58	24.72
	B110.2	105.0	0	0	0.0347	0.0173	634.0	660.0	0.58	23.62
	B110.3	105.1	0	0	0.0351	0.0173	629.0	655.0	0.58	24.77
Fang and Shaiu (2004)	H-06-06	78.5	0	0	0.0068	0.0069	440	440	1.00	92.00
	H-06-12	78.5	0	0	0.0116	0.0069	410	440	1.00	115.10
	H-12-12	78.5	0	0	0.0116	0.0139	410	440	1.00	155.30
	H-12-16	78.5	0	0	0.0164	0.0139	520	440	1.00	196.00
	H-20-20	78.5	0	0	0.0196	0.0224	560	440	1.00	239.00
	H-07-10	68.4	0	0	0.0098	0.0077	500	420	1.00	126.70
	H-14-10	68.4	0	0	0.0098	0.0154	500	360	1.00	135.20
	H-07-16	68.4	0	0	0.0164	0.0077	500	420	1.00	144.50
	N-06-06	35.5	0	0	0.0068	0.0069	440	440	1.00	79.70
	N-06-12	35.5	0	0	0.0116	0.0069	410	440	1.00	95.20
	N-12-12	35.5	0	0	0.0116	0.0139	410	440	1.00	116.80
	N-12-16	35.5	0	0	0.0164	0.0139	520	440	1.00	138.00
	N-20-20	35.5	0	0	0.0196	0.0224	560	440	1.00	158.00
	N-07-10	35.5	0	0	0.0098	0.0077	500	420	1.00	111.70
	N-14-10	35.5	0	0	0.0098	0.0154	500	360	1.00	125.00
	N-07-16	35.5	0	0	0.0164	0.0077	500	420	1.00	117.30

Marquardt algorithm is used in this model which is the most common back-propagation training algorithm (Naderpour *et al.* 2010). The sigmoid activation function was used for the training and testing of data. The duty of the neurons in hidden layer is to maintain the relation between inputs and outputs. There is no restriction for determining the number of the neurons that take place in the hidden layer. The dimension of the hidden layer can show a great variation due to the number of inputs and input nodes, characteristics of inputs and type of function used. Optimum number of

Table 6 Statistical properties of training and testing data

Parameters	Training Set			Testing Set		
	Min	Max	Mean	Min	Max	Mean
Concrete compressive strength	21.4	105	48.9	21.4	109.8	51.6
Steel fiber aspect ratio	0	80	21.68	0	80	23.54
Volumetric ratio of steel fiber	0	0.0100	0.0016	0	0.0150	0.0027
Longitudinal reinforcement ratio	0.0067	0.0351	0.0167	0.0067	0.0351	0.0154
Transverse reinforcement ratio	0.0069	0.0224	0.0127	0.0069	0.0224	0.0133
Yield strength of the longitudinal reinforcement	380.1	634	500.3	380.1	638	493.2
Yield strength of the transverse reinforcement	380	672	490	360	669	485
Beam section aspect ratio	0.58	1.00	0.82	0.58	1.0	0.82
Ultimate torque	4.85	196	53.49	4.58	239	51.48

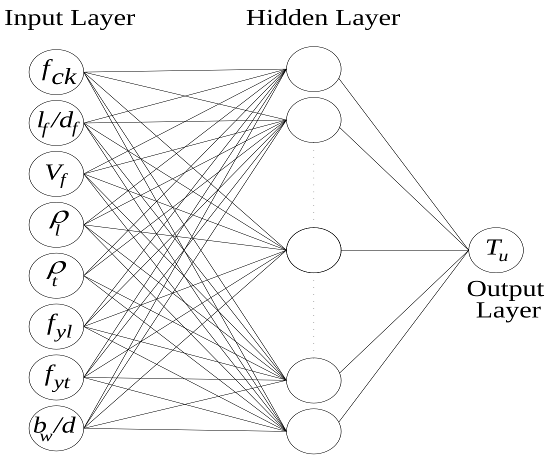


Fig. 8 Proposed ANN model

hidden layers should be correctly determined in order to construct an effective model and to predict the aimed result precisely. The number of neurons in the hidden layer is quite important since it affects the results, although it does not give them directly. For the case that the number of neurons in the hidden layer is less than the required value, the data that should be transferred from different neurons is transferred by a single neuron and this caused an underfitting case. For the contrary case that the number of neurons in the hidden layer is greater than the required value; an overfitting case occurs which causes late learning or lack of learning. Although the number of neurons in the hidden layer is so important, there does not existing a general method for determining the number of neurons. The most appropriate method to model the back-propagation (BP) network which has a stable structure is to try to have a stable network which is obtained by parametrically changing the number of neurons by trial-error method (Alshihri *et al.* 2009). In this study, the numbers of hidden layer neurons were determined by analyzing the network with various numbers of neurons. Fig. 9 illustrates the performance of the networks with various numbers of neurons in hidden layer.

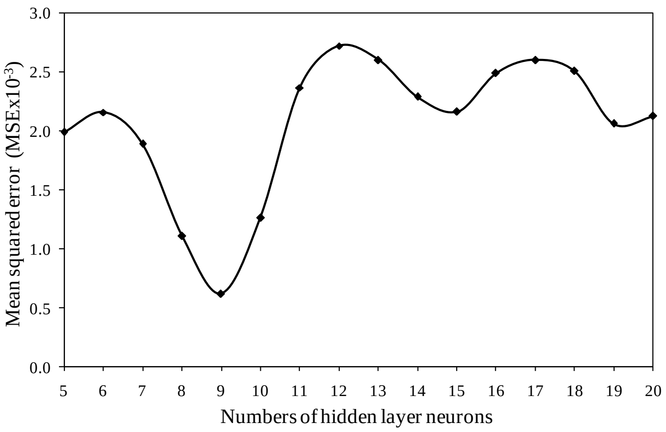


Fig. 9 Performance of the networks with various numbers of neurons in hidden layer

In the Fig. 9 the performance of each network having different number of neurons, is determined by using mean squared error (MSE). Only the performance of the networks having a neuron number between 5-20 is given in the figure, because performance of networks having a number of neurons less than 5 or greater than 20, does not provide satisfactory results. It is known that the error between the estimated and experimental data becomes minimum and consequently more accurate estimates can be done when the ANN model whose MSE is minimum, is chosen (Haykin 1999). Therefore, the case with 9 neurons in one hidden layer selected to create a stable and optimum network.

7. Results of artificial neural network model

Ultimate torque capacity of the steel fiber reinforced concrete beams are predicted by the neural network model. For this purpose, concrete compressive strength, aspect ratio of beam cross-section, fiber aspect ratio, volumetric ratio of steel fiber, yield strength of the longitudinal and transverse reinforcement, longitudinal and transverse reinforcement ratio are used as the input nodes. Hidden layer consists of 9 nodes parallel to the results presented in Fig. 9. Totally 51 data were used for the training and testing the network. The network was started to train with randomly selected 25 data. After the training procedure, the rest of the data were used for the testing the ANN model. The graphs related with the ANN model proposed by Narayanan and Kareem-Palanjian (1986) is given in Fig. 10. These graphs represent the relation between predicted, calculated and experimental results using the linear approaches and best linear equation. Best linear equation obtained from the scatter of the values is given in Fig. 10. The equation can be generalized as $y=a_0x+a_1$. Coefficients of the equation (a_0 and a_1) are closer to the 1 and 0, respectively. The coefficients show that ANN was successful in learning the relationship between input and output parameters. The coefficient of determination (R^2) for the predicted from the ANN model and experimental values was found to be 0.991 after the testing the network. Similarly, R^2=0.964 is obtained for the torsion values calculated from the model proposed by Narayanan and Kareem-Palanjian (1986). It is seen that the results obtained from ANN model and model proposed by Narayanan and Kareem-Palanjian (1986) are consistent with each other.

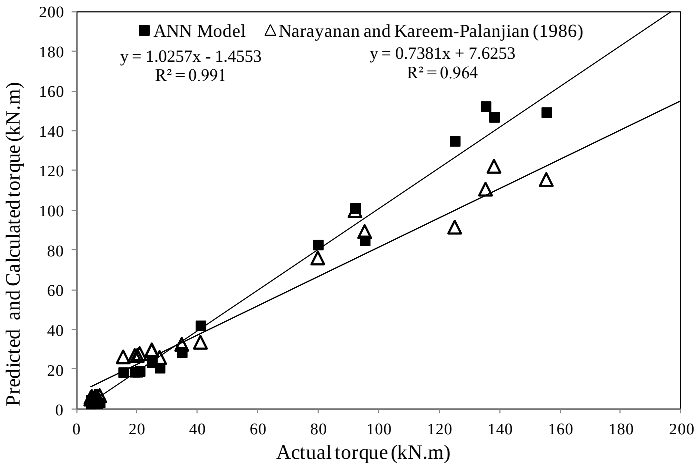


Fig. 10 Relationship between actual torque, calculated and predicted results

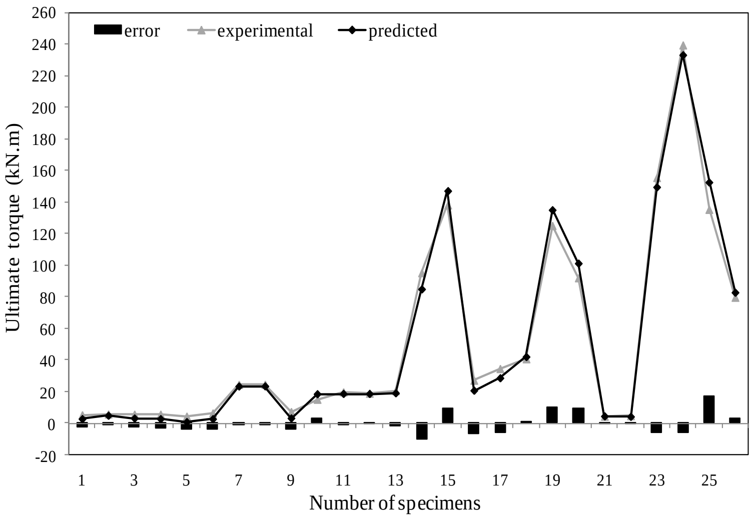


Fig. 11 Error distribution for each specimen

Predicted and experimental ultimate torque values are given for each specimen with error distributions in Fig. 11. In the figure, the torque values obtained from the experiment and estimated values by using ANN model are shown for each specimen one by one and error values represented as differences between the predicted and experimental results in the "kN.m" unit. Estimated and experimental values approach to each other as the error values decrease. It is seen that experimental and predicted results are consistent with each other; since the errors belonging to 26 specimens chosen for the test of network are minimum.

To specify how close the predicted data to the experimental data, various statistical values were examined. To examine the reliability of the ANN model, experimental results and the predicted values obtained from the testing procedure of the network are compared using root mean square

Table 7 The statistical values of the ANN model

	RMSE (kN.m)	MAE (%)	E_f (%)
ANN Model	5.94	4.38	99.50

error (RMSE), mean absolute error (MAE) and coefficient of efficiency (E_f). RMSE, MAE and E_f are calculated by using Eq. (1), Eq. (2) and Eq. (3), respectively.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left|p_i - t_i\right|^2} \tag{1}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|p_i - t_i\right| \tag{2}$$

$$E_f = \left[\sum_{i=1}^{n}\left(t_i - \bar{t}\right)^2 - \sum_{i=1}^{n}\left(p_i - t_i\right)^2\right] \Big/ \left[\sum_{i=1}^{n}\left(t_i - \bar{t}\right)^2\right] \tag{3}$$

In these equations t is the target value, p is the predicted value, n is the total number of data and $\bar{t}$ is the mean value of the target data. The statistical values obtained from the results of testing of the network are shown in Table 7. RMSE, MSE and E_f are found to be 5.94 kN.m, 4.38% and 99.5%, respectively that is determined by using estimated and experimental torque values belonging to 26 specimens that are used for testing the network.

8. Conclusions

In this study, series of parametric analyses were conducted to predict torque capacity of steel fiber reinforced concrete beams. For this purpose, the study is divided into two parts as obtaining the experimental results and preparing an ANN model. In the first part, on the contrary of most previous studies that did not address the effect of steel fiber aspect ratio and longitudinal reinforcement ratio on the torque capacity of normal and high strength reinforcement concrete beams; an experimental research was also performed. According to the experimental research, it is determined that the increase in steel fiber volumetric ratio and longitudinal reinforcement ratio increase the torque capacity in normal and high strength concrete specimens whereas an increase in steel fibers aspect ratio increases the torque capacity of only high strength concrete specimens and does not have a significant effect on normal strength concrete specimens. In the second part, test results obtained from the literature that contain parameters like transverse reinforcement ratio, beam section's aspect ratio, transverse and longitudinal reinforcement yield strength, steel fiber volumetric ratio and concrete compressive strength which all have effect on torque capacity; are added to the results obtained in the first part. All data are grouped in two randomly chosen sets. First set is used to train the ANN model while the second set is used to verify the accuracy of the proposed ANN model to estimate the torque capacity of SFRC beams. The torque capacity of steel fiber reinforced concrete beams can be predicted by using the proposed neural network model. This model is a sufficient tool for estimating the torque capacity, since it takes all the parameters that have effect on torque capacity into consideration. The model can lead the early prediction of the ultimate torque values without additional production cost of experiments.

Acknowledgements

Authors are highly thankful to the authorities of which Kocaeli University, Department of Scientific Research Projects and Beksa Çelik Kord Sanayi ve Ticaret A.Ş. for their invaluable contributions.

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