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Evaluation of Ultimate Torsional Strength of Reinforcement Concrete Beams Using Finite Element Analysis and Artificial Neural Network

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ABSTRACT

Calculation of torsional strength of reinforcement concrete members due to the lacks of the theory of elasticity is a difficult task. Therefore, the finite element analysis could be applied to determination of strength of concrete beams. As well, for modeling of complicated, highly nonlinear and ambiguous phenomena, artificial neural networks (ANN) are appropriate tools. The main purpose of this paper is an evaluation of ultimate torsional strength of rectangular concrete beams. A three-dimensional finite-element model (FEM) along with establishing the artificial neural network is used for achieving this aim. The finite element model utilizes the brittle failure criterion for concrete fracture, and experimental data are applied for training of the ANN.The commercial software is used for numerical modeling, and existing experimental tests are used in validation of the proposed failure criterion. In order to apply the data for training of the network, they are divided into three categories: training, testing and validating data. For training of the proposed network, three-layer perceptron network with a back propagation error algorithm is used. Comparison of accuracies for applied failure criterion in the numerical modeling, and neural network predictions are carry out using the experimental tests.

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NOMENCLATURE

BR	*V*	*BR*	*V*
T_u	Ultimate torsional strength	N_p	Number of input patterns
X,y	Dimension of cross-sectional area of the beam	T, O	Target and network output values
X_1,y_1	Dimension of closed stirrups	N_{out}	Number of the output neurons
ρ_l	Steel ratio of longitudinal reinforcement	d_m^p	Actual output of network
ρ_t	Steel ratio of stirrups	y_m^p	Desired output of neural network
f_{yl}	Yield strength of longitudinal torsional reinforcement	net_j	The weighted sum of the j-th neuron
f_{yv}	Yield strength of closed stirrups	W_{ij}	Weight between the j-th neuron and the i-th neuron in the preceding layer
A_t	The cross-sectional area of one-leg of closed stirrup	x_i	Output of the i-th neuron in the preceding layer
A_l	Total area of longitudinal torsional reinforcement	out_j	Output of the j-th neuron
S	Stirrup spacing	S_x	Normalized value of the variable *Z*
R^2	Correlation coefficient	Z_{min}, Z_{max}	Minimum and maximum values of Z
MSE	Mean Squared Error	f'_c	Compressive strength of concrete
E_{rate}	Error rate		

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1. INTRODUCTION

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 [1]. 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 [2]. 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 [2]. 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 [3]. 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 [4].

In the case of cracking appearance, using finite element is an appropriate tool in calculation of failure torque of concrete members. So far, two different philosophies for representing cracks in numerical implementations have been proposed. The first one is the discrete crack model, originated by Ngo and Scordelis [5], which reflects the localized nature of cracks. The second approach is the smeared crack model, which was introduced by Rashid [6].

Karayannis and Chalioris [7, 8] comprehensively survived the smeared crack analysis for behavior of plain concrete beams, and the experimental data had been used to numerical modeling validations. Chiu et al. [9] studied the effects of the ratio of cross-sectional area and the rate of the transverse reinforcement to the longitudinal reinforcement on the cracking pattern and ultimate torsional strength. William and Tanabe [10] studied the torsional behavior of reinforcement beams using the nonlinear finite element analysis. Pourhoseini et al. investigated the behavior of RC beams only for longitudinal reinforcement effects. The commercial software is applied to the finite-element analysis, and the experimental data have been used to confirm the obtained results. Mohammad, N.M [11] survived the predictions of nonlinear behavior of the cantilever beams under pure torsion.

Heretofore, in the literature, no comprehensive studies have been reported for studying all the significant parameters in the ultimate tosional strength. Accordingly, here the exhaustive study has been carried out for taking into account of the important variables. In the present paper, three-dimensional finite element study is used in order to calculate the failure torque of RC beams. Brittle failure criterion for concrete is utilized for fracture of the beams. This behavioral model is applied when the tension-cracking in the concrete is dominant, and the compressive failure is not significant. Finite element validating for proposed failure criterion is confirmed using experimental data.

Moreover, for complicated, highly nonlinear and ambiguous phenomena such as torsional behavior of concrete members, artificial neural networks are appropriate tools. Rakhshan & Akbari [12] utilized three-layer perceptron network with a back propagation error algorithm, and the generalized regression network to predict the ultimate torsional strength. Arslan [13] applied different neural networks algorithms and building codes for estimating of failure torque. Cevik et al. [14] used the genetic programming method to calculate the torsional strength of rectangular RC beams. Tang developed a radial basis function neural networks to predict the ultimate torsional strength of RC beams.

The capabilities of the artificial neural network (ANN) in prediction of torsional strength of RC beams investigated here. To achieve this goal, experimental data of 76 reinforced concrete beams subjected to torsion are used from the existing database [3, 14-17] . Ultimate predictions of RC beams using soft computational methodologies have been investigated by many researchers using the data [12-18].

The samples have a range from normal strength concrete to high-strength concrete. The test specimens have been rectangular beams, and they have been subjected to pure torsion. As well, none of them were deep beams. In the ANN model, the input parameters consist of 12 parameters. The parameters are: the cross-sectional area of beams, dimensions of closed stirrups, concrete compressive strength, spacing of stirrups, cross-sectional area of one-leg of closed stirrup, total area of longitudinal torsional reinforcement, yield strength of stirrup and longitudinal reinforcement, the steel ratio of stirrups and a steel ratio of longitudinal reinforcement. The output parameter of the ANN model is the torsional strength of the RC 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. After training of the neural network using experimental data, parametric studies are accomplished using FEM and ANN tools. Finally, the accuracies of obtained results are confirmed using the experimental data.

2. FINITE ELEMENT MODELING OF TORSION

Among the numerical methods for studying the failure behavior of concrete, the finite element method is predominant. Because it has high flexibility in the modeling of structures with complex geometries, various boundaries and loading conditions, and complicated cracking patterns. In the present paper, the commercial finite element software (ABAQUS) is utilized for estimating of the ultimate torsional strength of (RC) beams. In order to examine the capabilities of the brittle failure criterion in torsion modeling, this criterion is applied in the finite element analysis.

This criterion is a crude way of modeling failure and should be used carefully. Using of the brittle failure criterion based on an incorrect user assumption will lead to the inappropriate simulation. In the application of the failure criteria, issues such as rebar interactions with concrete, crack initiation, cracking directions and detection, stress-strain relation should be taken into account carefully. Typically, reinforcement in concrete beams is provided by rebars. Here, they are applied by elasto-plastic material behavior and are superposed on a mesh of standard element types are used to model the plain concrete. With this modeling approach, the concrete cracking behavior is considered independently of the rebar.

Cracking model has been fixed with the maximum number of cracks at a material point limited by the number of direct stress components present at that material point (a maximum of three cracks in the three-dimensional beam). A simple Rankine criterion is used to detect crack initiation. This criterion states that a crack forms when the maximum principal tensile stress exceeds the tensile strength of the concrete.

The embedded element technique is used to specify that steel reinforcement elements are embedded in host concrete elements.

2. 1. Finite Element Model Specifications For steel, the perfect elastic-plastic behavior with isotropic hardening and same behavior in tension and compression is considered. The used elements in the finite element modeling of this study are as follows:

B31: for rebar and stirrup in which has a capability to modeling shear deformations.

C3D8R: for three-dimensional hexahedral elements with linear approximation of displacements and reduced integration with hourglass control.

At the free end of the beam, all the nodes are released for any deformation. In order to prevent the stress concentrations in the location of loading on the beam, the rigid segment is used with a cross-section equal to the beam dimension. Loading pattern in the finite element modeling is the gradual rotation at the free end of the samples. A typical finite element mesh for the beam is illustrated in Figure 1.

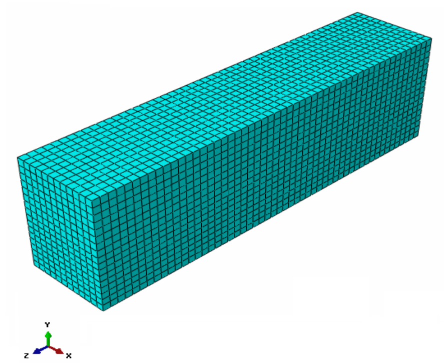

Figure 1. Finite element mesh for the rectangular beams

3. ARTIFICIAL NEURAL NETWORKS (ANNs)

ANN is an information-processing ssystem, which consists of highly interconnected processing neurons. There are mainly two stages in ANN models. In the first stage, the ANN model is developed, and then trained to learn the relationships between provided input and output data. In the second stage, this learning mechanism is used to predict the outputs for the input data, which are included in the input set in the first stage. Its effectiveness depends mainly on the quality of the database used for its training in the first stage. Among many types of ANNs, feed-forward networks are commonly used in engineering applications (see Figure 2.)

The network performance maybe evaluated quantitatively in terms of the correlation coefficient, mean squared error and the error rate. Error rate is defined as Equation (1).

$$E_{rate} = \frac{1}{N_p} \sum_{i=1}^{N_p} Er_i \tag{1}$$

where, Er_i is calculated as Equation (2).

$$Er_i = \sum_{j=1}^{N_{out}} \sqrt{(T_j - O_j)^2 / N_{out}} \tag{2}$$

For a network with one output neuron, as in this study, Equation (2) reduces to Equation (3)

$$E_{rate} = \sum_{i=1}^{N_p} (|T_j - O_j| / N_p) \tag{3}$$

$$M_{SE} = 0.5 \sum_m (d_m^p - y_m^p)^2 \tag{4}$$

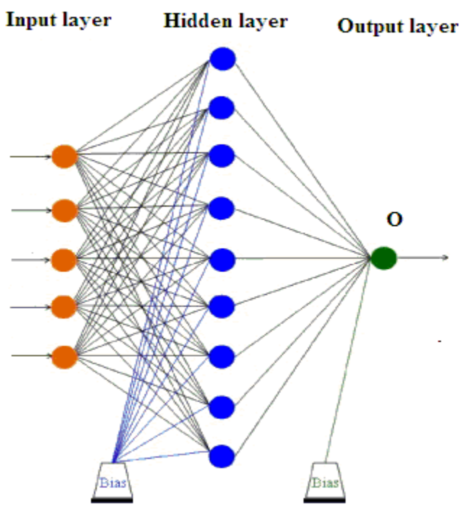

Figure 2. Structure of three-layered feed-forward network

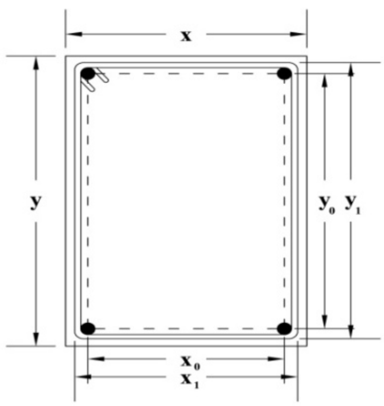

Figure 3. The cross section of the RC beams and geometrical Variables

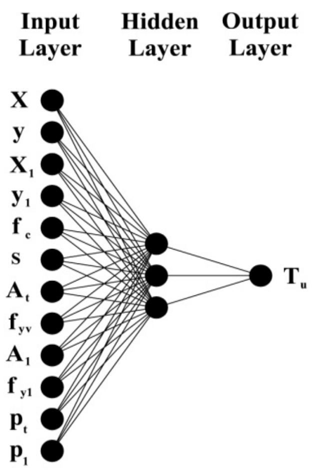

Figure 4. Feed forward multilayer network (inputs according to Table 1)

3. 1. Error Back-Propagation Algorithm (BPNN)

Error back-propagation algorithm is accepted as the best training algorithm of the multi-layer perceptron network. In this algorithm, the weights are adjusted in order to make the minimum standard errors. In the forward phase, the weighted sum of input components is calculated as Equation (5)

$$net_j = \sum_{i=1}^{n} w_{ij} x_i + bias_j \tag{5}$$

The output of the j-th neuron is calculated with a sigmoid function as follows:

$$out_j = f(net_j) = \frac{1}{1+e^{-net_j}} \tag{6}$$

The training of the network is achieved by adjusting the weights and is carried out through a large number of training sets and training cycles. Data scaling is another important step for network training. In this study, the simple linear normalization function with values between 0–1 is used as Equation (7).

$$S_x = \frac{(Z - Z_{min})}{(Z_{max} - Z_{min})} \tag{7}$$

3. 2. Neural Network Model

In the ANN model, the inputs consist of 12 parameters, which including the cross-sectional area of the beams, dimensions of closed stirrups, concrete compressive strength, spacing of stirrups, cross-sectional area of one-leg of closed stirrup, yield strength of stirrup, total area of longitudinal torsional reinforcement, yield strength of longitudinal reinforcement, the steel ratio of stirrups and the steel ratio of longitudinal reinforcement.

In Figure 3, some of the geometrical parameters are illustrated. The output parameter of the model is torsional strength of the beams. The range of data sets for training of the network is presented in Table 1. As well, in Table 2 for maximum and minimum values of T_u, experimental values of the mentioned 12 parameters are presented.

As illustrated in Figure 4, a feed-forward multilayer network with error back-propagation model is utilized. Here, neural network toolbox of MATLAB [19] is applied for prediction of torsional strength of RC the beams.

In the first step, the three-layered feed-forward neural network is used and trained with error back-propagation algorithm (Levenberg- Marquardt). According to Figure 4, general structure of the neural network consists of an input layer, one hidden layer with three neurons and an output layer. Logarithmic sigmoid function is used in hidden layer and hyperbolic tangent function is applied to the output layer. Among the 76 experimental data, 53 data sets are selected randomly for network training, 15 data sets for testing and 8 data sets for validating.

TABLE 1. Data range of effective parameters in the ANN model [13]

Variable	x (mm)	y (mm)	x_1 (mm)	y_1 (mm)	f'_c (MPa)	s (mm)	A_t (mm^2)	f_{yv} (MPa)	A_l (mm^2)	f_{yl} (MPa)	ρ_t (%)	ρ_l (%)
Minimum	160	275	130	216	26	50	71	319	381	310	0.22	0.3
Maximum	350	508	300	469	110	215	127	672	3438	638	2.56	3.51

TABLE 2. Specifications of experimental data for maximum and minimum torsional strength [13]

-	x (mm)	y (mm)	x_1 (mm)	y_1 (mm)	f'_c (MPa)	s (mm)	A_t (mm^2)	f_{yv} (MPa)	A_l (mm^2)	f_{yl} (MPa)	ρ_t (%)	ρ_l (%)
Tu(min)	254	508	215.9	215.9	27.0	215.9	71.3	341.3	381	341.3	0.22	0.30
Tu(max)	350	500	300	450	78.5	55	126.7	440	3438	560	1.97	1.96

The number of neurons in the hidden layer is changed from 2 to 20 by trial-and-error process, and the optimum number of nodes is determined. According to Figures 5 and 6, the optimum number of neurons in hidden layer of the proposed network is three, because these neurons have minimum MSE and maximum correlation coefficient (R^2). Maximum training cycles are 5000 cycles.

In the second step, from the set of 76 design data, 53 data sets are selected randomly for network training and 23 data sets for testing. In order to avoid over training of the network, the spread constant is changed such that the error of testing data became close to error of training data. Here, 0.5 is assigned to the spread constant by trial and error.

In the error back-propagation algorithm, the correlation coefficient for training, testing and validating data are 0.979, 0.993 and 0.995, respectively. Mean squared error (MSE) for training, testing and validating data are 3.93%, 0.66% and 0.297, respectively. The error rates for these data are 0.024, 0.021 and 0.023, respectively.

Figure 7 shows the mean squared error of the network that starts with a large value and decreases to a small one. In the other words, the figure displays that the network is properly learning.

3. 3. Sensitivity Analysis of Parameters

For torsional strength prediction, using a multi-variable linear regression model the following equation is drawn.

$$T_u = -52.62 - 2.92x - 0.05y + 3.41x_1 + 0.08y_1 + 0.40f_c - 0.05s + 0.03A_t + 0.03f_{yv} + 0.05A_l + 0.14f_{yl} + 14.99\rho_t - 40.53\rho_l \quad (8)$$

According to Equation (8), torsional strength of the beams has direct relation with dimensions of closed stirrups, concrete compressive strength, area of one-leg of closed stirrup, yield strength of stirrup, total area of longitudinal torsional reinforcement, yield strength of longitudinal torsional reinforcement and the steel ratio of stirrups. As well, this equation shows that T_u has inverse relation with the cross- sectional area of the beam, spacing of stirrups and steel ratio of longitudinal reinforcement.

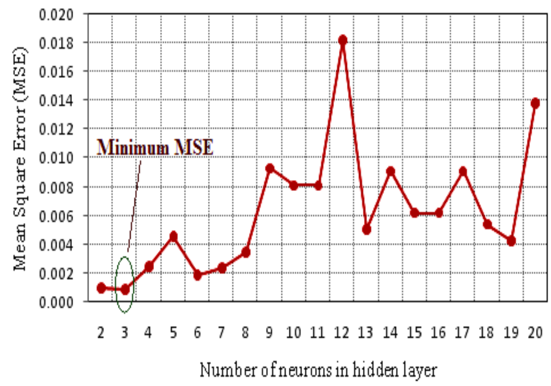

Figure 5. Values of the mean square error versus the number of neurons in the hidden layer

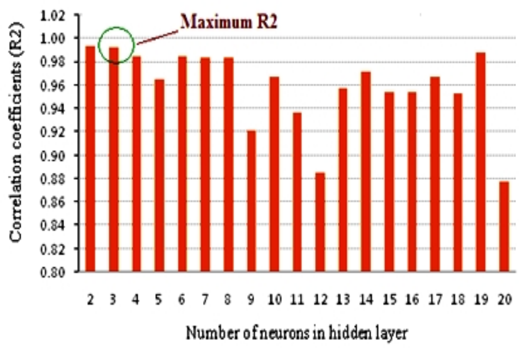

Figure 6. Values of the correlation coefficient versus the number of neurons in the hidden layer

TABLE 3. Specifications of experimental samples in the numerical studies

Sample no.	$T_{u\,(EXP)}$ (KN.m)	ρ_l (%)	ρ_t (%)	f_{yl} (MPa)	A_l (mm^2)	f_{yv} (MPa)	A_t (mm^2)	s (mm)	f'c (MPa)	y_1 (mm)	x_1 (mm)	y (mm)	x (mm)
6	**126.7**	0.98	0.68	500.0	1719	420.0	71.3	90	68.4	450	300	500	350
7	**135.2**	0.98	1.36	500.0	1719	360.0	126.7	80	68.4	450	300	500	350
12	**138.0**	1.64	1.22	520.0	2865	440.0	71.3	50	35.5	450	300	500	350
37	**24.8**	3.51	1.49	629.0	1544	655.0	78.5	90	105.1	245	130	275	160
57	**60.1**	2.36	2.09	317.9	2288	340.6	126.7	70	29.4	343	216	381	254
64	**40.3**	0.49	0.63	322.7	635	333.7	71.3	120	30.9	470	216	508	254

TABLE 4. Results of T_u for six samples with experimental, numerical and artificial neural network methods

Sample no.	T_uEXP (KN.m)	T_uFEM (KN.m)	T_uANN (KN.m)	E_{Num} (%)	E_{ANN} (%)
6	126.7	135.0	150.0	6.6	**20.6**
7	135.2	142.2	130.0	5.2	10.6
12	138.0	131.8	135.0	4.5	0.91
37	24.8	25.0	23.0	0.8	0.71
57	60.1	54.9	50.0	8.7	10.1
64	40.3	47.0	45.0	**16.6**	0.12

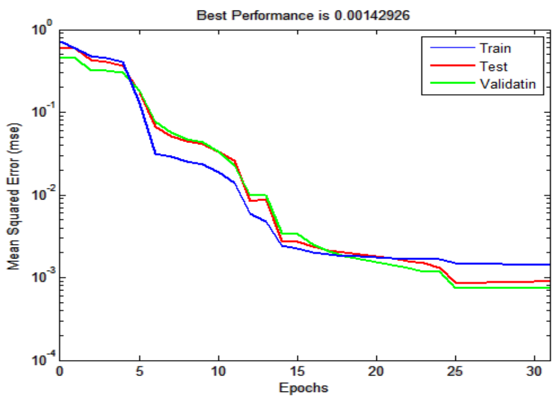

Figure 7. Performance of the BPNN algorithm

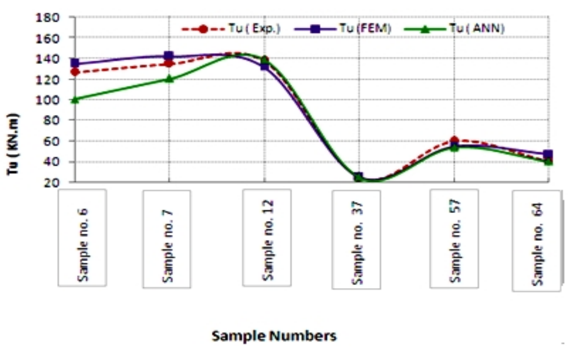

Figure 8. Comparison of ultimate torsional strength by experimental, numerical and neural network methods

4. RESULTS

In order to validate the finite element model, six samples in the experimental data are selected. According to Table 3, these samples are the representatives of all the 76 experimental samples. These data are also used for validating of the trained neural network.

As shown in the Figure 8, good agreement between finite element modeling, artificial neural network and experimental results are observed. As seen from this figure, the results of numerical modeling are close to the experimental values. Errors for each sample in compare with the experimental data are shown in Table 4.

In sample 6, error in the ANN is high, and also for sample 64, error of the finite element modeling is relatively large. Presumably, the reason for large value of error for sample 64 in numerical modeling is that the behavior of the sample is similar to plane concrete behavior. In this sample, the spacing of stirrups is large, and the amounts of longitudinal torsional reinforcement and steel ratio of stirrups are low. Large error for sample 6 for neural network predictions is apparently related to the initial stages of the network training. By continuing of training, the performance of the network is improved and the errors became smooth.

4. 1. Parametric Studies The parametric studies upon the finite-element model validation are fulfilled. To reveal of the effects of the significant variables on torsional strength, six finite element models are established. The effects of the spacing of stirrups (s), the concrete compressive strength (f'_c) and the total area of longitudinal torsional reinforcement (A_l) are studied, individually. For parametric studying of the effect of the stirrups spacing, values 80, 100, 150 and 200 mm are assigned to this parameter. In order to considering the effect of concrete compressive strength, values 28, 40, 60 and 68.4 MPa are included in the models. Values 1719, 2574.6, 3432.8 mm^2 are also assigned to examine the effect of the total area of longitudinal torsional reinforcement. Figures 9, 10 and 11 shows the results of the parametric studies.

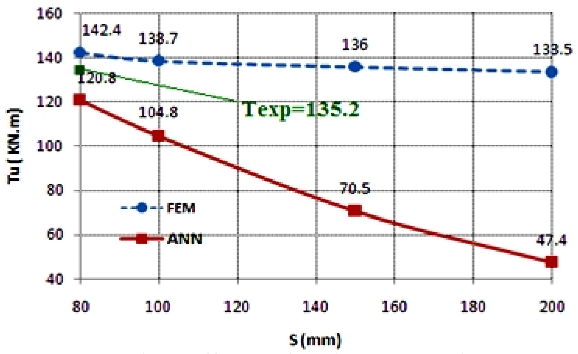

Figure 9. The effect of stirrups spacing on T_u ($\text{for } S=80\text{ mm}, T_{exp}=135.2\text{ (KN.m)}$)

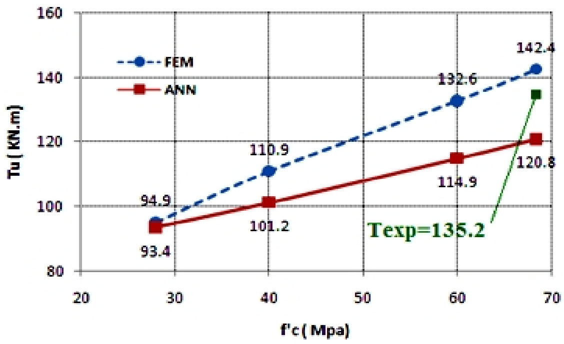

Figure 10. The effect of concrete strength on T_u ($\text{for } f_c'=68.4\text{ MPa}, T_{exp}=135.2\text{ (KN.m)}$)

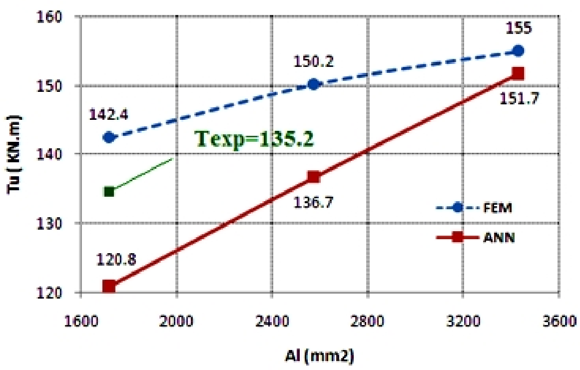

Figure 11. The effect of longitudinal reinforcement on T_u ($\text{for } A_l=1719\text{ mm}^2, T_{exp}=135.2\text{ (KN.m)}$)

According to these figures, usually the predicted values of torsional strength by ANN method are less than FEM values. As seen from Figure 9 for s=80 mm, the error of the FEM is %5.3 and the error of the ANN prediction is % 10.7.Therefore, the results of the FEM are reliable than the results of the ANN. For s= 100, 150 and 200 mm, there are not experimental data to compare the accuracies of the FEM and ANN results. However, the variation of T_u against stirrups spacing for ANN method is considerable, and for FEM, the variation is negligible. The reason is that, the ANNs have not any ability to extrapolate solutions for problems outside the network training domain. Therefore, it seems that the results of the ANN have lower accuracies in compare with the FEM results for large variations of S, because the values maybe become outside of the training data. In Figure 10 for f_c' = 68.4 MPa, the errors of FEM and ANN are %5.3 and % 10.7, respectively. As well, for f_c' = 28, 40 and 68.4 MPa, there are no experimental data to evaluate the accuracies of the FEM and ANN observations. However, the variations of T_u for FEM and ANN methods versus f_c' are same. It is noticed that the distances between values of ANN and FEM are increasing when increasing the values of f_c' . The predicted values of torsional strength by ANN method are usually less than FEM values, and it seems that the results of the FEM have better accuracies. According to Figure 11, by increasing the values of A_l , the values of T_u for FEM and ANN are increasing. It is observed that by increasing the values of A_l distances between values of ANN, and FEM are decreasing because ANNs have not the ability to extrapolate solutions for problems outside the network training domain.

5. CONCLUSION

In this paper, using the nonlinear FEM and ANN tools torsional strength of the reinforcement concrete beams have been estimated. The adequacy of brittle failure criterion is confirmed. As well, the capability of feed-forward multilayer network with the error back-propagation algorithm is proven. Using the experimental data, the obtained results from the FEM and the ANN have been compared. Based on the present study, the following conclusions are drawn:

- ❖ In the literature, the smeared crack model was utilized in plain concrete, though for reinforcement concrete members, this model is inadequate. It has been shown that under pure torsion, the brittle failure criterion is an appropriate tool for studying of the behavior of RC beams.
- ❖ By surveying the results, it can be concluded that the numerical modeling has better accuracy than artificial neural network predictions. Probably, the reason is that the 76 data sets are not sufficient for proper training of the network.
- ❖ Neural network results indicate that the number of layers and neurons in hidden layer, and number of iterations are assigned correctly.
- ❖ It seems that the results of the FEM are reliable than the results of ANN. The reason is that in some cases values of parameters might be in the outside of training data. Therefore, the networks are not able to extrapolate solutions for problems outside the network training domain. As a result, the ANN predictions might have the accuracy problems.

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Evaluation of Ultimate Torsional Strength of Reinforcement Concrete Beams Using Finite Element Analysis and Artificial Neural Network

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چکیده

محاسبه مقاومت پیچشی نهایی اعضای بتنی مسلح به دلیل نقص تئوری الاستیسیته، کاری دشوار می باشد. بنابراین، تحلیل المان محدود برای تعیین مقاومت پیچشی روش مناسبی است. همچنین، شبکه‌های عصبی مصنوعی ابزاری کارآمد برای مدلسازی مسائل پیچیده، مبهم و با رفتار غیرخطی می باشند. هدف این تحقیق، محاسبه مقاومت پیچشی نهایی تیرهای بتنی مسلح مستطیلی است. این مهم، با مدلسازی سه بعدی تیر با روش المان محدود و ایجاد یک شبکه عصبی مصنوعی محقق شده است. معیار شکست ترد در مدل المان محدود برای شکست بتن و داده‌های آزمایشگاهی برای آموزش شبکه عصبی مورد استفاده قرار گرفته‌اند. برای مدلسازی عددی از یکی از نرم‌افزارهای تجاری و برای اعتبار سنجی مدل عددی از داده‌های آزمایشگاهی موجود استفاده شده است. بمنظور آموزش شبکه عصبی، داده های در نظرگرفته شده به سه دسته آموزشی، آزمایشی و اعتبارسنجی تقسیم شده‌اند و شبکه پرسپترون سه لایه با الگوریتم پس‌انتشار خطا بکار گرفته شده است. دقت نتایج مدل سازی عددی، و نتایج پیش بینی شبکه عصبی با استفاده از داده های آزمایشگاهی موجود در ادبیات فنی مقایسه شده‌اند.

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