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Neural network based approach for determining the shear strength of circular reinforced concrete columns

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ABSTRACT

The objective of this study is to investigate the adequacy of neural networks (NN) as a quicker, more secure and more robust method to determine the shear strength of circular reinforced concrete columns. In the application of the NN model, a multilayer perceptron (MLP) with a back-propagation (BP) algorithm is employed using a scaled conjugate gradient. NN model is developed, trained and tested through a based MATLAB program. The data used for training and testing NN model are gathered from literature. NN based model outputs are compared with ACI, ATC-32, ASCE and CALTRANS codes outcomes on the basis of the experimental results. This comparison demonstrated that the NN based model is highly successful to determine the shear strength of circular reinforced concrete columns.

1. Introduction

It is known that the columns are the most critical element of any RC building. Failure of one of columns could lead the building to collapse. Shear forces have significant effect on the reinforced concrete column subjected to lateral load, e.g., due to an earthquake. Shear failure of reinforced concrete columns can cause to reduce the lateral strength of the building and involve rapid strength degradation. During past severe earthquakes, a number of RC columns failed in shear and eventually collapsed. Therefore, it is very important to estimate the shear strength of reinforced concrete columns [1].

A variety of design codes, such as ACI [2], ATC-32 [3], ASCE [4], CALTRAN [5], presents analytical expressions for the computation of the shear strength of circular columns. Most design codes consist of two components including the contributions of concrete and transverse reinforcement to the shear strength of circular columns. In this study, the neural network (NN) is applied to estimate the shear strength of circular reinforced concrete columns.

In recent years, the NN was widely applied in many engineering applications [6–10] and proved to be very promising. However no research has been come across in the literature regarding NN applications of shear strength of circular reinforced concrete columns. The objective of the study is to evaluate whether the results of NN based model can be more practically applied to circular columns than those obtained from the proposed formulas in current codes. In this study, the data are gathered from literature [1,11–21]. The NN-based estimates are compared with the experimental, numerical and analytical results of different methods. The results are presented in graphical form.

2. The overview to shear strength of circular RC columns

In most of current codes, the shear strength of circular columns is computed from the contributions of concrete and transverse reinforcement (Fig. 1). These codes consider a portion of the design shear force to be carried by the concrete (V_c) and the remaining part carried by the transverse reinforcement (V_s).

$$V_n = V_c + V_s \tag{1}$$

2.1. The ACI code [ACI 318-2005]

The ACI code presents the following equation for calculating (V_c) for members subjected to combined shear, moment and axial compression:

$$V_c = 0.166\left(1+\frac{P}{13.80A_g}\right)\sqrt{f_c'}\mathrm{bd} \quad (\mathrm{Units: MPa}) \tag{2}$$

where P is axial load subjected to the column; A_g is gross cross-sectional area of the column; f_c' is concrete compressive strength; b is the width of column; and d is the effective depth of the column. The transverse reinforcement contribution, V_s, is also calculated as

$$V_s = \frac{A_v f_y d}{s} \tag{3}$$

where A_v is the area of transverse reinforcement f_y is the yield stress of hoops or spirals and s is the spacing of transverse reinforcement.

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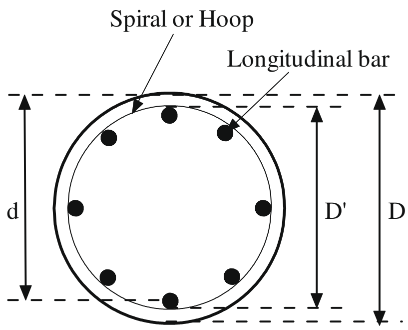

Fig. 1. The general form of circular RC column section.

2.2. ATC-32

In the ATC-32 Report (1996), the concrete contribution is calculated as

$$V_c = 0.167\left(k_1 + \frac{P}{k_2 A_g}\right)\sqrt{f_c'}(0.80A_g) \quad (\text{Units : MPa}) \tag{4}$$

In Eq. (4), $k_1 = 1.0$, except in plastic hinge regions of ductile columns, where $k_1 = 0.50$, and $k_2 = 13.80$ for compressive axial load P and $k_2 = 3.45$ for tensile axial load P. The transverse reinforcement contribution is also calculated as

$$V_s = \frac{\pi}{2}\frac{A_h f_{yh} D'}{s} \tag{5}$$

where D' is the diameter of the spiral or hoop.

2.3. ASCE-ACI 426

In the ASCE-ACI 426, the shear strength carried by concrete, V_c ,is calculated as

$$V_c = v_b\left(1 + \frac{3P}{f_c' A_g}\right)0.628D^2 \tag{6}$$

where D is diameter of circular column and v_b is calculated as

$$v_b = (0.066 + 10\rho_t)\sqrt{f_c\prime} \leqslant 0.20\sqrt{f_c\prime} \quad (\text{Units : MPa}) \tag{7}$$

where ρ_t is the longitudinal tension steel ratio, taken as $0.50\rho_l$ for columns [22] and ρ_l is estimated by the ratio of longitudinal steel area within the column section to gross cross-sectional area of columns. The transverse reinforcement contribution is also calculated as

$$V_s = \frac{\pi}{2}\frac{A_h f_{yh} D'}{s} \tag{8}$$

where D' is the diameter of the spiral or hoop.

2.4. CALTRANS MEMO 20-4

The shear strength carried by concrete, V_c, is calculated as

$$V_c = v_c A_e = F_1 F_2 \sqrt{f_c\prime}(0.80A_g) \leqslant 0.33\sqrt{f_c\prime} A_g \quad (\text{Units : MPa}) \tag{9}$$

In Eq. (7) the terms of $F1$ and $F2$ are related to the shear strength dependent on displacement ductility level, μ_δ, and axial load ratio, P/A_g and these terms can be numerically calculated as

$$F_1 = 0.025 \leqslant 0.08\rho_w f_{yh} + 0.305 - 0.083\mu_\delta \leqslant 0.25 \tag{10}$$

where ρ_w is transverse reinforcement ratio, and f_{yh} is the yield stress of hoops or spirals.

$$\begin{aligned} &F_2 = 0 && \text{for} \quad \tfrac{P}{A_g} < 0 \\ &F_2 = (1 + \tfrac{P}{13.80A_g}) \leqslant 1.50 && \text{for} \quad \tfrac{P}{A_g} = 0 \end{aligned} \tag{11}$$

where P is axial load subjected to the column, and A_g is the gross cross sectional area. The shear strength carried by transverse reinforcement is calculated as

$$V_s = \frac{\pi}{2}\frac{A_{sp} f_{yh} D_{sp}}{s} \tag{12}$$

where A_{sp} is the cross-sectional area of spirals or hoops, D_{sp} is the core diameter of circular column defined by the center-to-center diameter of hoops or spirals, f_{yh} is yield stress of transverse steel, and s is vertical distance between transverse hoops or spirals.

3. Neural networks (NN)

NN is a computational tool, which attempts to simulate the architecture and internal operational features of the human brain and nervous system. NN architectures are formed by three or more layers, including an input layer, an output layer and a number of hidden layers in which neurons are connected to each other with modifiable weighted interconnections. The NN architecture is commonly referred to as a fully interconnected feedforward multilayer perceptron. In addition, there is a bias, which is only connected to neurons in the hidden and output layers with modifiable weighted connections. The number of neurons in each layer may vary depending on the problem.

The most widely used training algorithm for multi-layered feedforward networks is the back-propagation (BP) algorithm. The BP algorithm basically involves two phases. The first one is the forward phase where the activations are propagated from the input to the output layer. The second one is the backward phase where the error between the observed actual value and the desired nominal value in the output layer is propagated backwards in order to modify the weights and bias values. The inputs and the outputs of training and testing sets must be initialized before then the training a feed work network. In the forward phase, the weighted sum of input components is calculated as

$$\text{net}_j = \sum_{i=1}^{n} w_{ij}x_i + \text{bias}_j \tag{13}$$

where net_j is the weighted sum of the jth neuron for the input received from the preceding layer with n neurons, w_{ij} is the weight between the jth neuron and the ith neuron in the preceding layer, x_i is the output of the ith neuron in the preceding layer. The output of the jth neuron out_j is calculated with a sigmoid function as follows:

$$\text{out}_j = f(\text{net}_j) = \frac{1}{1 + e^{-(\text{net}_j)}} \tag{14}$$

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. The goal of the training procedure is to find the optimal set of weights, which would produce the right output for any input in the ideal case. Training the weights of the network is iteratively adjusted to capture the relationship between the input and output patterns.

The most classic training algorithm for the multi-layer feed-forward neural network is back-propagation algorithm. Two back-propagation training algorithms, which are gradient descent and gradient descent with momentum, are slow. Therefore, several adaptive training algorithms for NN have recently been discovered such as conjugate gradient algorithm (CG) and scaled conjugate gradient algorithm (SCG). In this study, SCG is used as optimization algorithm, which is all set to standard values suggested in Moller [23].

The output of the network is compared with a desired response to produce an error. The performance function for feed forward

Table 1
Range of parameters in the database and normalization values.

	Min	Max	Normalization values
Input parameters			
D (mm)	307	610	750
cover (mm)	8.20	33	40
d_h (mm)	2.70	12	15
d_l (mm)	7	24	30
a (mm)	800	1800	2000
s (mm)	14.48	220	250
ρ_l (%)	0.99	3.24	3.50
ρ_w (%)	0.10	1.49	1.50
f_{yl} (MPa)	240	508	550
f_{yh} (MPa)	200	492	500
f_c' (MPa)	22.30	57	60
P (kN)	0	1813	2000
m_d	1	4.40	7.5
Output parameters			
V_{test} (kN)	86	341	800

networks is the sum of the squares error (SSE). The process of feed forward and back-propagation continue until the required sum of the squares error is reached. The SSE is defined as

$$\mathrm{SSE} = \sum_{i=1}^{m} (T_i - \mathrm{out}_i)^2 \tag{15}$$

where T_i and out_i are the target outputs and output of neural network values respectively for ith output neuron, and m is the number of neurons in the output layer.

4. Numerical study

In the study, the NN based model was applied to estimate the shear strength of circular reinforced concrete columns. The data, gathered from literature [1,11–21], are divided into two parts as the training and testing sets. 31 data from database are selected as training set and employed to train NN based model. 16 data, which are not used in the training process, are selected as the testing set and used to validate the generalization capability of NN based model. The training and testing sets are tabulated in Table A1 and Table A2 (appendix A), respectively. Inputs and outputs are normalized in the (0–1) range by using simple normalization methods and values are given in Table 1. The maximum and minimum values of inputs and outputs are also given in Table 1.

The numbers of neurons in input and output layers are based on the geometry of the problem. But, there is no general rule for selection of the number of neurons in a hidden layer and the number of the hidden layers. Hence, they are determined by trial and error method in this study.

In order to determine most appropriate NN model, a lot of different NN models with various numbers of hidden layers and

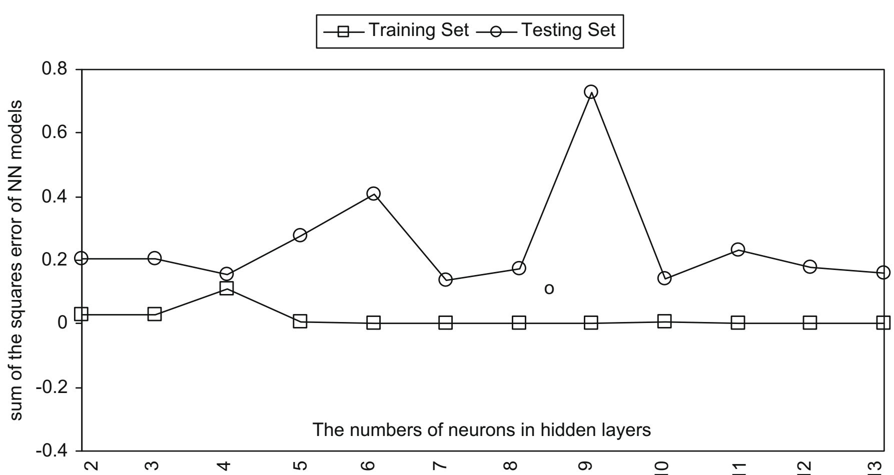

Fig. 2. The SSE of NN models with number of neurons in one hidden layer.

Fig. 3. The SSE of NN models with number of neurons in two hidden layers.

neurons in hidden layers are trained and tested for 1000 epochs. The criterion to establish the most appropriate NN model is selected as the sum of the squares errors (SSE). The required sum of the squares error (SSE) is selected as 10e–5. The most appropriate NN models are chosen corresponding to the performance of both training and testing sets in terms of SSE. The SSE's of the NN models were determined both for one and two hidden layers with various numbers of neurons. While Fig. 2 illustrates the obtained results of SSE values for one hidden layers, Fig. 3 indicates the case where the combinations of two hidden layers are used to get the NN model with the best performance.

Figs 2 and 3 show the effect of the number of hidden layers and neurons in the hidden layers on the NN model accuracy. As can be seen from Figs. 2 and 3, the comparison of the performance of the NN models with both one and two hidden layers revealed the fact that the two layers model resulted in better model accuracy. Consequently, the NN model is selected as having 13 neurons in input layer, 6 neurons in first hidden layer, 3 neurons in second hidden layer and 1 neuron in output layer to define the shear strength (V_n) of circular reinforced concrete columns (Fig. 4).

A MATLAB based program with a graphical user interface (GUI) was developed to train and test the NN model [9]. In the NN model, type of back-propagation is scaled conjugate gradient algorithm (SCGA), activation function is sigmoidal function, and number of epochs (learning cycle) are 20,000. The performance of the NN model showed that the correlations between targets and outputs are consistent as shown in Fig. 5 for training set and in Fig. 6 for

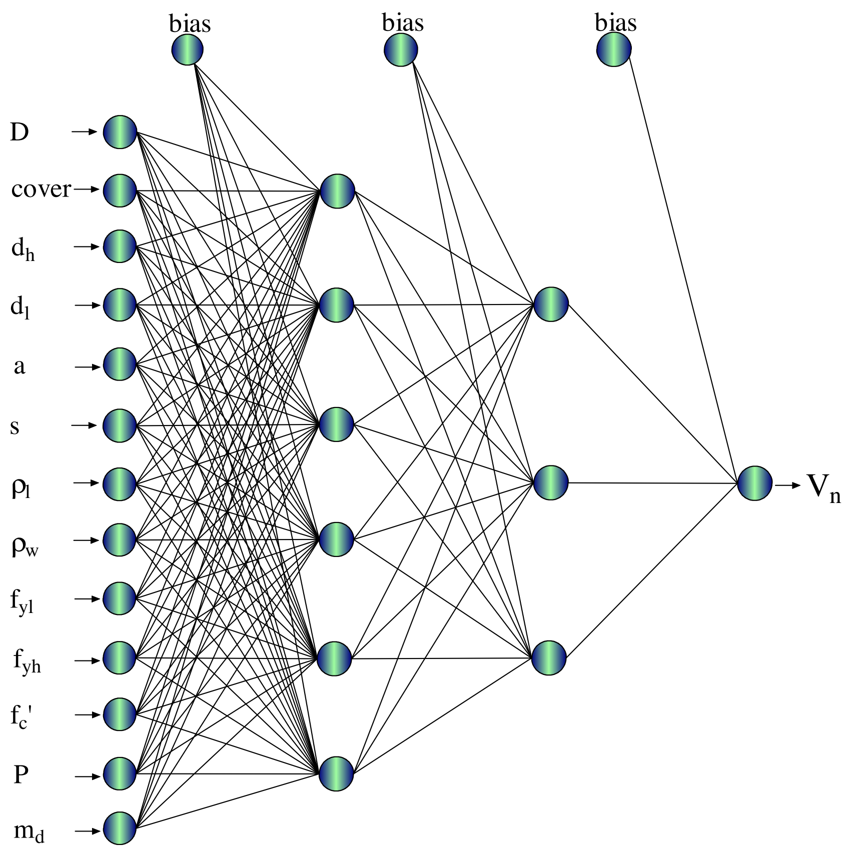

Fig. 4. Architecture of the NN model.

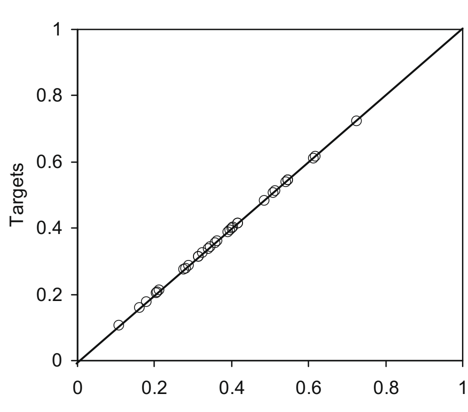

Fig. 5. Performance of NN model for training set.

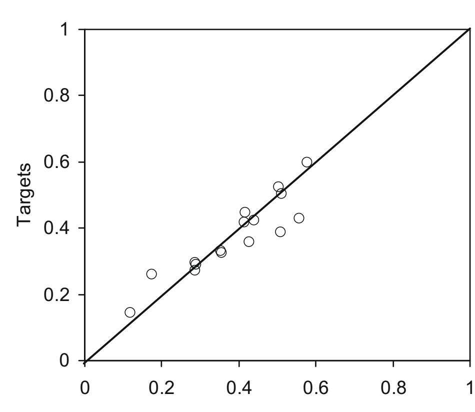

Fig. 6. Performance of NN model for testing set.

testing set. The results of Fig. 5 indicate that the NN based model is successful in learning the relationship between the input parameters and outputs. The results of testing phase in Fig. 6 show that the NN based model is capable of generalizing between input and output variables.

The values of parameters used in this research are summarized as follow:

- Number of input layer unit = 13.
- Number of hidden layers = 2.
- Number of first hidden layer units = 6.
- Number of second hidden layer units = 3.
- Number of output layer units = 1.
- Learning algorithm = scaled conjugate gradients algorithm (SCGA).
- Learning cycle = 20,000.

Table 2
Comparison set of NN based model with some current codes for training set.

Samples	V_n (kN)						$\frac{TEST}{ACI}$	$\frac{TEST}{ATC\text{-}32}$	$\frac{TEST}{ASCE}$	$\frac{TEST}{CALT}$	$\frac{TEST}{NN}$
	TEST	ACI	ATC-32	ASCE	CALT	NN					
Training set											
1	86	138.8	126.1	131.8	87.9	86.003	0.6196	0.6820	0.6525	0.9784	1.0000
2	321	265.5	279.6	299.9	280.8	320.998	1.2090	1.1481	1.0704	1.1432	1.0000
3	221	264.9	279.1	299.4	192.1	221.000	0.8343	0.7918	0.7381	1.1504	1.0000
4	276	262.5	277.5	297.4	215.6	276.005	1.0514	0.9946	0.9280	1.2802	1.0000
5	289	245.2	263.0	281.3	309.1	289.001	1.1786	1.0989	1.0274	0.9350	1.0000
6	437	425.0	445.7	531.6	427.6	437.000	1.0282	0.9805	0.8221	1.0220	1.0000
7	407	323.1	292.3	376.3	349.0	406.999	1.2597	1.3924	1.0816	1.1662	1.0000
8	436	415.1	452.4	508.6	394.5	436.000	1.0504	0.9638	0.8573	1.1052	1.0000
9	316	254.2	273.1	292.4	312.4	316.001	1.2431	1.1571	1.0807	1.0115	1.0000
10	312	294.1	274.0	328.8	355.1	312.000	1.0609	1.1387	0.9489	0.8786	1.0000
11	271	227.4	228.5	247.6	146.2	270.997	1.1917	1.1860	1.0945	1.8536	1.0000
12	285	216.7	218.5	236.9	222.1	285.000	1.3152	1.3044	1.2030	1.2832	1.0000
13	251	277.5	296.7	369.2	348.6	251.002	0.9045	0.8460	0.6799	0.7200	1.0000
14	224	277.3	296.6	368.9	348.3	223.999	0.8078	0.7552	0.6072	0.6431	1.0000
15	230	266.4	269.6	345.0	327.3	229.996	0.8634	0.8531	0.6667	0.7027	1.0000
16	489	416.2	271.4	434.5	233.3	489.001	1.1749	1.8018	1.1254	2.0960	1.0000
17	579	591.4	546.4	709.5	467.1	579.001	0.9790	1.0597	0.8161	1.2396	1.0000
18	143	188.8	157.0	137.1	139.4	143.008	0.7574	0.9108	1.0430	1.0258	1.0000
19	164	188.8	157.0	137.1	191.0	163.993	0.8686	1.0446	1.1962	0.8586	1.0000
20	170	250.8	252.2	225.9	164.5	170.000	0.6778	0.6741	0.7526	1.0334	1.0000
21	493	414.6	283.3	443.5	382.0	493.000	1.1891	1.7402	1.1116	1.2906	1.0000
22	322	258.3	295.7	275.7	284.0	321.999	1.2466	1.0889	1.1679	1.1338	1.0000
23	260	494.5	308.3	286.9	245.1	260.001	0.5258	0.8433	0.9062	1.0608	1.0000
24	252	478.1	300.4	283.1	145.2	251.999	0.5271	0.8389	0.8901	1.7355	1.0000
25	387	691.7	748.5	769.8	571.7	386.998	0.5595	0.5170	0.5027	0.6769	1.0000
26	411	708.6	759.0	778.7	573.5	411.002	0.5800	0.5415	0.5278	0.7167	1.0000
27	433	508.1	326.7	333.5	165.7	433.000	0.8522	1.3254	1.2984	2.6132	1.0000
28	129	478.5	378.8	460.9	415.3	129.001	0.2696	0.3406	0.2799	0.3106	1.0000
29	165	590.4	375.1	549.8	386.4	165.000	0.2795	0.4399	0.3001	0.4270	1.0000
30	332	348.7	268.7	229.8	321.5	332.001	0.9521	1.2356	1.4447	1.0327	1.0000
31	332	372.9	284.6	242.5	324.2	331.998	0.8903	1.1666	1.3691	1.0241	1.0000
St.dev.							0.2887	0.3346	0.2913	0.4649	0.0000
Max							1.3152	1.8018	1.4447	2.6132	1.0000
Min							0.2696	0.3406	0.2799	0.3106	1.0000

Table 3
Comparison set of NN based model with some current codes for testing set.

Samples	V_n (kN)						$\frac{TEST}{ACI}$	$\frac{TEST}{ATC\text{-}32}$	$\frac{TEST}{ASCE}$	$\frac{TEST}{CALT}$	$\frac{TEST}{NN}$
	TEST	ACI	ATC-32	ASCE	CALT	NN					
Testing set											
1	93	145.2	124.8	137.9	83.3	117.394	0.6405	0.7452	0.6744	1.1165	0.7922
2	331	309.4	358.8	377.3	371.5	335.261	1.0698	0.9225	0.8773	0.8910	0.9873
3	281	231.4	241.5	259.6	300.9	265.396	1.2144	1.1636	1.0824	0.9339	1.0588
4	445	394.8	492.7	510.9	538.4	343.235	1.1272	0.9032	0.8710	0.8265	1.2965
5	230	259.3	274.7	271.7	190.5	231.849	0.8870	0.8373	0.8465	1.2074	0.9920
6	352	293.5	274.2	328.0	358.8	338.386	1.1993	1.2837	1.0732	0.9811	1.0402
7	333	309.1	359.4	378.2	406.8	358.719	1.0773	0.9265	0.8805	0.8186	0.9283
8	341	302.7	346.9	366.0	276.8	288.243	1.1265	0.9830	0.9317	1.2319	1.1830
9	228	277.5	296.7	369.2	348.6	217.892	0.8216	0.7685	0.6176	0.6540	1.0464
10	229	266.4	269.6	345.0	327.3	237.121	0.8596	0.8494	0.6638	0.6997	0.9658
11	461	517.0	547.7	638.7	467.4	479.715	0.8917	0.8417	0.7218	0.9863	0.9610
12	403	482.9	640.9	619.3	553.9	421.226	0.8345	0.6288	0.6507	0.7276	0.9567
13	409	454.5	300.8	447.3	371.4	403.346	0.8999	1.3597	0.9144	1.1012	1.0140
14	283	525.0	306.9	297.7	149.3	261.003	0.5391	0.9221	0.9506	1.8955	1.0843
15	138	496.6	379.6	460.7	607.2	209.347	0.2779	0.3635	0.2995	0.2273	0.6592
16	406	365.4	279.6	238.6	98.8	311.557	1.1111	1.4521	1.7016	4.1093	1.3031
St.dev.							0.2571	0.2751	0.2977	0.8637	0.1618
Max							1.2144	1.4521	1.7016	4.1093	1.3031
Min							0.2779	0.3635	0.2995	0.2273	0.6592

Table 4
Statistical value of NN based model with some current codes for training set.

		NN	ACI	ATC-32	ASCE	CALTR
Training set						
V_n	MSE	0.0000	0.0331	0.0262	0.0340	0.0219
	R^2	1.0000	0.2460	0.2618	0.3393	0.2446
	St.dev.	0.0000	0.2887	0.3346	0.2913	0.4649

Table 5
Statistical value of NN based model with some current codes for testing set.

		NN	ACI	ATC-32	ASCE	CALTR
Testing set						
V_n	MSE	0.0030	0.0214	0.0168	0.0254	0.0393
	R^2	0.8330	0.2305	0.3978	0.3483	0.0902
	St.dev.	0.1618	0.2571	0.2751	0.2977	0.8637

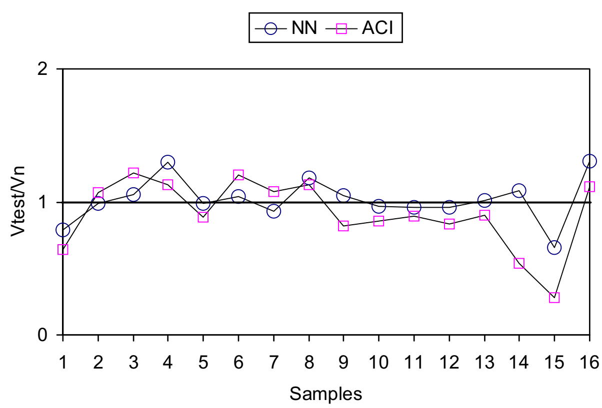

Fig. 7. The comparisons of NN model with ACI.

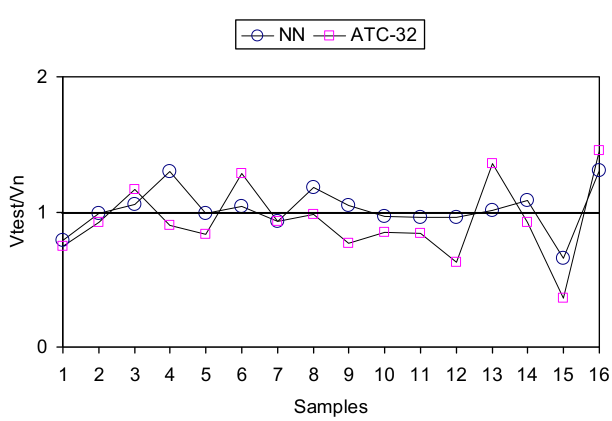

Fig. 8. The comparisons of NN model with ATC-32.

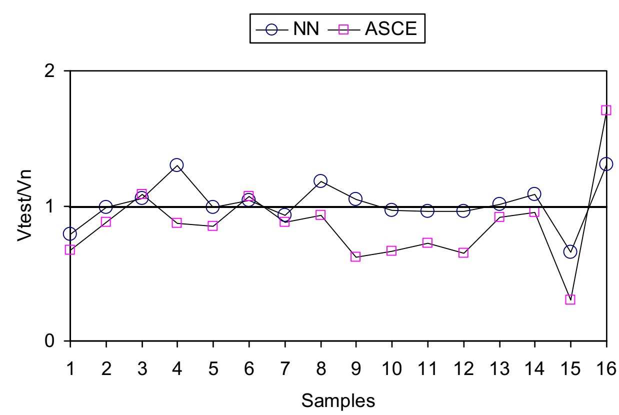

Fig. 9. The comparisons of NN model with ASCE.

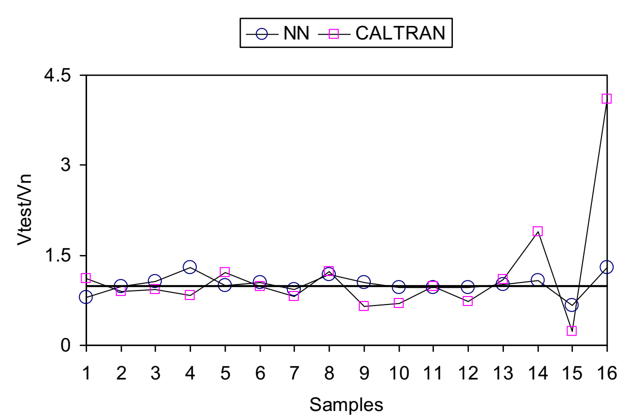

Fig. 10. The comparisons of NN model with CALTRAN.

The normalized results of NN model along with of ACI, ATC-32, ASCE and CALTRANS codes with the experimental results are compared and tabulated in Tables 2 and 3. As can be seen from the results of the training set (Table 2) and the testing set (Table 3), NN results agree well with the experimental results.

The statistical results of mean squared error (MSE), R-square (R^2) and standard deviation (st.dev.) are tabulated for the ACI, ATC-32, ASCE, CALTRANS codes and NN based model in Tables 4 and 5. During the process of training and testing of NN model, the normalization value of the shear strength of circular RC columns (V_n) is selected as 800. The normalized MSE statistical values are also obtained through the same normalization value. As can be seen from Tables 2 and 3, the values of Standard deviation are obtained through the normalized outcomes of NN model and codes with experimental results. The closeness of the standard deviation and MSE to zero and R-square to 1 shows the accuracy of the selected model. It should be pointed out, however, that the statistical values being better for training set does not necessary outline the fact that NN model performs better than the other models. The main performance indicator is the statistical values from the results of testing set. The Tables 4 and 5 below clearly demonstrate that NN based model is superior than the others in terms of the statistical values, MSE, R^2, st.dev.

The normalized values of NN model along with ACI (Fig. 7), ATC-32 (Fig. 8), ASCE (Fig. 9) and CALTRANS (Fig. 10) codes from Tables 2 and 3 are compared. As shown in Figs. 7–10, the shear strength determined by NN based model shows reasonably close values to the measured shear strength of circular reinforced concrete columns.

A careful study of the Figs. 7–10 provides that the results of NN based model are more close to experimental results than the codes.

5. Conclusions

By investigating the shear strength of circular reinforced concrete columns through the NN approach and gathering the training and testing patterns from the literature, the following principal conclusions have been drawn:

- The NN approach is successfully applied to determine the shear strength of circular reinforced concrete columns. Results obtained by the NN based model were truly competent and showed good generalization. A careful study of the results leads to the observations of excellent agreement between NN based model predictions and experimental outcomes.
- It is proven that the NN based approach applied in this study is highly successful for the determination of more accurate values of the shear strength of circular reinforced concrete columns.
- After the well-training of NN based model, a better accuracy is obtained compare to the code results from the literature.
- The results demonstrated that the NN based model is a powerful computational tool to estimate the shear strength of circular reinforced concrete columns. The results of NN based model are compared with the results of the ACI, ATC-32, ASCE and CALTRANS codes on the basis of the experimental results and proven

Table A1

Samples	D (mm)	cover (mm)	d_h (mm)	d_l (mm)	a (mm)	s (mm)	ρ_l (%)	ρ_w (%)	f_{yl} (MPa)	f_{yh} (MPa)	f'_c (MPa)	P (kN)	m_d	V_{test} (kN)
Training set														
1	307	33	6	12	900	75	1.83	0.63	240	240	35.9	145	3.5	86
2	400	15	6	16	800	60	3.2	0.51	436	328	37.5	0	2.7	321
3	400	15	6	16	800	60	3.2	0.51	457	328	37.2	0	4.9	221
4	400	15	6	16	1000	60	3.2	0.51	436	328	36	0	3.9	276
5	400	15	10	16	800	165	3.2	0.51	436	316	30.6	0	1.5	289
6	400	15	12	16	800	120	3.2	1.02	448	332	31.2	784	3.6	437
7	400	15	6	16	800	60	3.2	0.51	448	372	29.9	751	2.6	407
8	400	15	6	16	800	30	3.2	1.02	436	326	36.2	455	4	436
9	400	15	6	24	800	60	3.24	0.51	424	326	33.7	0	1.9	316
10	400	15	6	16	1000	60	3.2	0.51	436	326	34.3	431	1.7	312
11	400	15	6	16	800	80	3.2	0.38	436	326	33.2	0	5.1	271
12	400	15	10	16	800	220	3.2	0.39	436	310	30.9	0	2.5	285
13	400	27	6	13	1350	50	2.02	0.75	377	374	22.4	180	5.1	251
14	400	27	6	13	1350	50	2.02	0.75	377	374	22.3	180	2	224
15	400	27	6	13	1350	60	2.02	0.75	377	374	27.8	180	4.9	230
16	400	15	6	16	800	65	3.2	0.47	475	340	37	1813	3.9	489
17	400	15	10	16	800	60	3.2	1.42	475	300	37	1813	6.5	579
18	406	8.2	4.5	13	1048	171.5	1.37	0.1	459	492	34.5	0	2.7	143
19	406	8.2	4.5	13	1048	171.5	1.37	0.1	459	492	34.5	0	1.6	164
20	406	8.2	4.5	13	1048	63.5	1.17	0.26	459	492	35.4	0	5.1	170
21	460	15.24	6.4	16	910	95.3	2.5	0.25	462	369	29.3	1690	2.1	493
22	460	15.24	6.4	16	910	95.3	2.5	0.25	462	369	35.8	512	2.2	322
23	508	19	4.5	16	1524	102	0.99	0.13	455	455	57	1139	3.1	260
24	508	19	4.5	16	1524	102	0.99	0.13	455	455	52.7	1139	4.4	252
25	600	25.4	9.5	22	1800	97	1.92	0.54	448	431	31.4	400	5.7	387
26	600	25.4	9.5	22	1800	97	1.92	0.54	448	431	34.6	400	5.8	411
27	600	25.4	2.7	7	1500	14.48	1.98	0.68	446	476	25.4	120	3	433
28	610	13.97	6.4	19	1219	127	2.53	0.17	324	359	31	591.9	2.5	129
29	610	13.97	6.4	19	1219	127	2.53	0.17	324	324	34.5	1780	3	165
30	610	16	4.9	16	1219	101.6	1.36	0.13	454	200	26.8	18.8	1.4	332
31	610	16	4.9	16	1219	101.6	1.36	0.13	438	200	31.2	18.8	1.6	332

Table A2

Samples	D (mm)	cover (mm)	d_h (mm)	d_l (mm)	a (mm)	s (mm)	ρ_l (%)	ρ_w (%)	f_{yl} (MPa)	f_{yh} (MPa)	f'_c (MPa)	P (kN)	m_d	V_{test} (kN)
Training set														
1	307	33	6	12	895	75	1.83	0.63	240	240	34.4	254	3.6	93
2	400	15	6	16	800	40	3.2	0.76	436	328	31.1	0	2.4	331
3	400	15	6	16	800	80	3.2	0.38	448	372	29.5	0	1.5	281
4	400	15	6	16	1000	30	3.2	1.02	448	372	29.9	0	3.2	445
5	400	15	6	16	800	60	1.92	0.51	436	326	34.8	0	4.5	230
6	400	15	6	16	800	60	3.2	0.51	436	326	34.4	420	1.3	352
7	400	15	12	16	800	160	3.2	0.76	436	332	32.3	0	1.7	333
8	400	15	10	16	800	110	3.2	0.77	436	310	33.1	0	4.1	341
9	400	27	6	13	1350	50	2.02	0.75	377	374	22.4	180	6.5	228
10	400	27	6	13	1350	60	2.02	1.49	377	374	27.8	180	6	229
11	400	15	10	16	800	60	3.2	1.42	423	300	38	907	7	461
12	457	20	9.5	16	910	80	2.41	0.85	508	448	35.2	490	3.9	403
13	460	15.22	6.4	16	910	95.3	2.5	0.25	462	369	37	1690	2.5	409
14	508	19	4.5	16	1524	102	0.99	0.13	455	455	56.2	1450	4.1	283
15	610	13.97	6.4	19	1219	127	2.53	0.17	469	324	35.9	591.9	1	138
16	610	16	4.9	16	1219	101.6	1.36	0.13	454	200	29.8	18.8	3.5	406

that the NN based approach is highly successful for the determination of more accurate values of the shear strength of circular reinforced concrete columns.

- The data set related experimental values gathered from the literature was 47. Although the more data set would be better in training of the NN model, the obtained data set employed in the proposed model of the paper clearly illustrates the fact that the obtained the shear strength of circular reinforced concrete columns are much better than the current code values.

Appendix A

See Tables A1 and A2.

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