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Discussions and Closures

Book Reviews

Modeling Confinement Efficiency of Reinforced Concrete Columns with Rectilinear Transverse Steel Using Artificial Neural Networks

Chao-Wei Tang[1]; How-Ji Chen[2]; and Tsong Yen[3]

Abstract: Artificial neural networks have attracted considerable attention and have shown promise for modeling complex nonlinear relationships. This paper explores the use of artificial neural networks in predicting the confinement efficiency of concentrically loaded reinforced concrete (RC) columns with rectilinear transverse steel. Fifty-five experimental test results were collected from the literature of square columns tested under concentric loading. A multilayer-functional-link neural network was used for training and testing the experimental data. A comparison study between the neural network model and four parametric models is also carried out. It was found that the neural network model could reasonably capture the underlying behavior of confined RC columns. Moreover, compared with parametric models, the neural network approach provides better results. The close correlation between experimental and calculated values shows that neural network-based modeling is a practical method for predicting the confinement efficiency of RC columns with transverse steel because it provided instantaneous result once it is properly trained and tested.

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Introduction

A number of analytical models have been reported that model the behavior of RC columns confined by rectilinear transverse steel over the last 50 years. Since the behavior of RC columns with nonhomogeneous, nonisotropic, and nonlinear material under a multiaxial state of stress may be difficult to establish theoretically, test data are often used to develop empirical or semiempirical approaches. The characteristic parameters for these models have been carefully examined. Generally, a multivariable nonlinear regression analysis is performed so that the major parameters are calibrated to fit the experimental results and to derive the relationships among the involved parameters. However, the factors that affect the column strength, such as residual stresses, material irregularity, initial straightness, etc., make modeling its behavior a hard task. Moreover, applying the statistical approach to a complex nonlinear system is quite difficult, since choosing a suitable regression equation involves considerable technique and experience.

By contrast, the use of artificial neural network (ANN) provides an alternative method that overcomes these difficulties (Hopfield 1982; Murray 1993; Schalkoff 1997). An ANN is a computational tool that attempts to simulate the architecture and internal operational features of the human brain and neurons systems. Much of the success of neural networks is due to such characteristics as nonlinear processing and parallel processing. Neural network modeling techniques have been rapidly applied in engineering, business, psychology, science, and medicine in recent years. In civil engineering, the methodology of neural networks has been successfully applied to a number of areas such as structural analysis and design (Hajela and Berke 1991; Consolazio 2000), structural damage assessment (Elkordy et al. 1993; Mukherjee et al. 1996), structural dynamics and control (Chen et al. 1995), seismic liquefaction prediction (Goh 1994), constitutive modeling (Ghaboussi et al. 1991; Yeh 1999; Zhao and Ren 2002), pavement condition-rating modeling (Eldin and Senouci 1995), and evaluating cone penetration test calibration chamber test data (Goh 1995; Juang et al. 2002).

The intended aim of this study is to explore the feasibility of using a neural network in predicting the confinement efficiency of RC columns with rectilinear transverse steel under concentric compression loading. A database of 55 square columns that includes normal- and high-strength concrete was retrieved from existing literature (Sheikh and Uzumeri 1980; Yong et al. 1988; Cusson and Paultry 1994) for analysis. The results obtained by neural network are compared with the experimental values and with those determined from the Sheikh-Uzumeri (1982), Park et al. (1982), Yong et al. (1988), and Cusson-Paultre (1995) models to assess the performance of the neural network in predicting the confinement efficiency of RC columns with rectilinear transverse steel.

[1]Assistant Professor, PhD, Dept. of Civil Engineering, Cheng-Shiu Institute of Technology, No. 840, Chengching Road, Niaosung Sihsng, Kaohsiung County, Taiwan. E-mail: civiltang@yahoo.com or tang@civil.csit.edu.tw

[2]Associate Professor, PhD, Dept. of Civil Engineering, National Chung-Hsing University, No. 250, Kuo Kuang Road, Taichung, Taiwan.

[3]Professor, PhD, Dept. of Civil Engineering, National Chung-Hsing University, No. 250, Kuo Kuang Road, Taichung, Taiwan.

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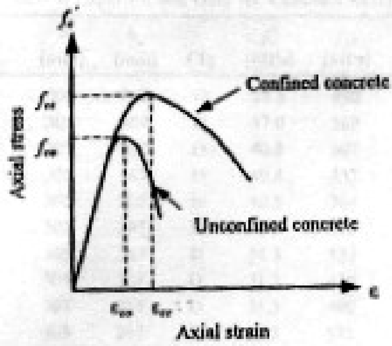


Fig. 1. General stress-strain curves for confined and unconfined concrete

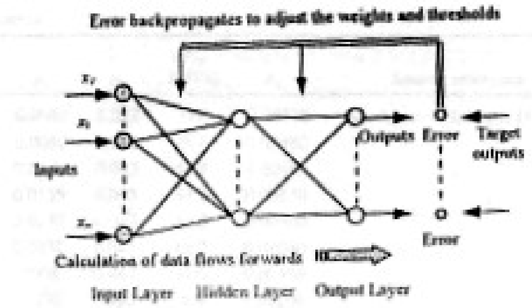


Fig. 2. Architecture of typical back-propagation neural network

Behaviors and Models of Confined Concrete

When a RC column with transverse reinforcement is subjected to an increasing static load, the stress-strain behavior of the column can be described as shown in Fig. 1, in which f_{co} is the maximum strength of unconfined concrete; f_{cc} is the maximum strength of confined concrete; ε_{co} is the strain at the maximum strength of unconfined concrete; and ε_{cc} is the strain at the maximum strength of confined concrete. At the early stage of loading, owing to the fact that the Poisson ratio of concrete is lower than that of steel, the confining steel has no effect on the confined column. With the increase in load, the transverse strain of concrete will cause a lateral expansion of confined concrete core, which will be resisted by the passive confinement provided by transverse reinforcement. At this stage, confinement of the concrete core is gradually achieved due to the so-generated multiaxial state of stress. Accordingly, the strength and strain at the maximum stress of confined concrete are increased. However, the passive lateral confinement is not always uniform, especially in the case of using rectilinear transverse steel (Sheikh and Uzumeri 1980). For instance, in a specimen with four corner bars, the square ties can apply confining pressure only near the corners of the section. Also, at a section midway between ties, the area of effectively confined concrete has the least value (Cusson and Paultre 1994). Therefore, a considerable portion of the concrete may be unconfined.

In order to predict the confinement efficiency of RC columns with rectilinear transverse steel, several analytical models with various degrees of sophistication have been extensively studied in the past two decades. Some prominent methods among them, which were selected and used in this study for comparison with the results from the neural network model, are outlined in the following.

Park et al. Model

According to the modified stress-strain relation for concrete confined by rectangular ties proposed by Park et al. (1982), the maximum axial stress of confined concrete f_{cc} and the corresponding strain ε_{cc} can be computed as follows:

$$f_{cc}=Kf_{co} \tag{1}$$

$$\varepsilon_{cc}=0.002K \tag{2}$$

in which K=strength gain of confined concrete. The expression for K is in the form

$$K=1.0+\frac{\rho_s f_{yh}}{f_c'} \tag{3}$$

where ρ_s=volumetric ratio of transverse steel in concrete core; f_{yh}=yield strength of transverse steel; and f_c'=cylinder compressive strength of concrete.

Yong et al. Model

Yong, Nour, and Nawy (1988) presented an empirical model for the stress-strain curve of rectilinearly confined high-strength concrete. The maximum axial stress of confined concrete and the corresponding strain can be computed as follows:

$$f_{cc}=Kf_{co} \tag{4}$$

$$\varepsilon_{cc}=0.00265+0.0035\left[\frac{(1-0.734s/w)(\rho_s f_{yh})^{2/3}}{\sqrt{f_c'}}\right] \tag{5}$$

The expression for K is in the form

$$K=1.0+0.0091\left(1-\frac{0.254s}{w}\right)\left(\rho_s+\frac{nd_s\rho_g}{8sd_\ell}\right)\frac{f_{yh}}{\sqrt{f_c'}} \tag{6}$$

in which s=spacing of transverse steel in inches; w=length of one side of the transverse steel in inches; n=number of longitudinal steel bars; d_ℓ=nominal diameter of longitudinal steel bars in inches; d_s=nominal diameter of transverse steel bars in inches; ρ_g=volumetric ratio of longitudinal steel ratio in column cross section; and f_c' and f_{yh} in psi.

Sheikh and Uzumeri Model

Sheikh and Uzumeri (1982) introduced the concept of the effectively confined concrete area within the nominal concrete core. The area of the effectively confined concrete is determined by the transverse steel spacing, the distribution of longitudinal steel around the core perimeter, and the configuration of transverse steel. The proposed confinement efficiency of confined concrete can be computed as follows:

$$f_{cc}=Kf_{co} \tag{7}$$

$$\varepsilon_{cc}=80Kf_c'\times10^{-6} \tag{8}$$

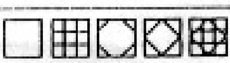
The expression for K is in the form

$$K=1.0+\frac{b_c^2}{140P_{occ}}\left[\left(1-\frac{ns_i^2}{5.5b_c^2}\right)\left(1-\frac{s}{2b_c}\right)^2\right]\sqrt{\rho_s f_{yh}} \tag{9}$$

Table 1. Actual Experimental Data for Confined Reinforce Concrete Columns

Column number	b (mm)	b_c (mm)	Cfg	f'_c (MPa)	f_{yh} (MPa)	s_l (mm)	s (mm)	ρ_s	ρ_l	f_{cc} (MPa)	ε_{cc}	Source reference
2A1-1	305	267	D	37.5	490	133.50	57.20	0.0080	0.022	37.6	0.00360	Sheikh and Uzumeri (1980)
2A1H-2	305	267	D	37.0	269	133.50	57.20	0.0080	0.022	39.6	0.00480	
4A3-7	305	267	D	40.8	507	133.50	75.00	0.0166	0.043	44.4	0.00440	
4A4-8	305	267	D	40.8	533	133.50	28.70	0.0159	0.043	47.2	0.00570	
4A5-9	305	267	D	40.5	364	133.50	75.00	0.0239	0.043	42.3	0.00500	
4A6-10	305	267	D	40.6	470	133.50	35.00	0.0232	0.043	45.2	0.01030	
4A1-13	305	267	D	31.3	533	133.50	57.00	0.008	0.043	34.6	0.00450	
2A5-14	305	267	D	31.3	450	133.50	75.00	0.0239	0.022	36.7	0.01100	
2A6-15	305	267	D	31.3	490	133.50	35.00	0.0232	0.022	39.1	0.02150	
4C1-3	305	267	E	36.3	571	66.75	50.00	0.0076	0.045	37.3	0.00330	
4C6-5	305	267	E	34.9	490	66.75	38.10	0.0227	0.045	48.7	0.01700	
4C1H-4	305	267	E	36.6	288	66.75	50.00	0.0076	0.045	37.3	0.00260	
4C6H-6	305	267	E	34.3	269	66.75	38.10	0.0227	0.045	44.6	0.00930	
4C3-11	305	267	E	40.6	470	66.75	95.00	0.0162	0.045	43.8	0.00510	
4C-12	305	267	E	40.6	723	66.75	25.40	0.0152	0.045	50.4	0.02050	
2C-16	305	267	E	32.5	767	66.75	50.00	0.0076	0.029	37.6	0.00560	
2C5-17	305	267	E	32.5	470	66.75	100.00	0.0237	0.029	37.6	0.01570	
2C-6-18	305	267	E	32.5	533	66.75	38.10	0.0227	0.029	47.0	0.02800	
4B3-19	305	267	B	33.4	470	89.00	100.00	0.0180	0.048	40.6	0.00610	
4B4-20	305	267	B	34.6	526	89.00	38.10	0.0170	0.048	44.7	0.00800	
4B6-21	305	267	B	35.5	490	89.00	47.70	0.0240	0.048	46.5	0.01440	
4D3-22	305	267	B	35.5	470	89.00	82.50	0.0160	0.048	43.5	0.00410	
4D4-23	305	267	B	35.8	526	89.00	28.70	0.0170	0.048	46.9	0.00760	
4D6-24	305	267	B	35.8	490	89.00	38.10	0.0230	0.048	49.6	0.01770	
1A	235	195	A	95.4	410	95.40	50.00	0.0280	0.031	99.74	0.00330	Cusson and Paultre (1984)
1B	235	195	D	95.4	392	97.50	50.00	0.0340	0.032	105.4	0.00480	
1C	235	195	C	95.4	392	65.00	50.00	0.0360	0.032	101.4	0.00470	
1D	235	195	B	100.4	392	65.00	50.00	0.0480	0.032	116.1	0.00570	
1D1	235	195	B	100.4	392	65.00	50.00	0.0480	0.032	124.6	0.00600	
2A	235	195	A	96.4	392	195.00	50.00	0.0200	0.031	91.8	0.00340	
2B	235	195	D	96.4	414	97.50	50.00	0.0220	0.032	91.8	0.00350	
2C	235	195	C	96.4	414	65.00	50.00	0.0230	0.032	99.1	0.00360	
2D	235	195	B	96.4	414	65.00	50.00	0.0310	0.032	98.3	0.00400	
3A	235	195	A	98.1	410	195.00	100.00	0.0140	0.031	81.7	0.00340	
3B	235	195	D	98.1	410	97.50	100.00	0.0250	0.032	85.9	0.00340	
3C	235	195	C	98.1	410	65.00	100.00	0.0260	0.032	90.1	0.00350	
3D	235	195	B	98.1	410	65.00	100.00	0.0350	0.032	93.4	0.00460	
4A	235	195	A	93.1	410	195.00	50.00	0.0280	0.052	96.5	0.00330	
4B	235	195	D	93.1	392	97.50	50.00	0.0340	0.053	102.9	0.00470	
4C	235	195	C	93.1	392	65.00	50.00	0.0360	0.053	106.0	0.00470	
4D	235	195	B	93.1	392	65.00	50.00	0.0480	0.053	111.6	0.00640	
5A	235	195	A	99.9	705	195.00	50.00	0.0280	0.052	99.4	0.00340	
5B	235	195	D	99.9	770	97.50	50.00	0.0340	0.053	104.4	0.00470	
5C	235	195	C	99.9	770	65.00	50.00	0.0360	0.053	110.4	0.00680	
5D	235	195	B	99.9	770	65.00	50.00	0.0480	0.053	128.2	0.00970	
6B	235	195	D	115.9	715	97.50	50.00	0.0490	0.053	122.2	0.00960	
6D	235	195	B	113.6	680	65.00	50.00	0.0480	0.053	126.5	0.00890	
7B	235	195	D	75.9	715	97.50	50.00	0.0490	0.053	107.1	0.01560	
7D	235	195	B	67.9	680	65.00	50.00	0.0480	0.053	100.4	0.01550	
8B	235	195	D	52.6	715	97.50	50.00	0.0490	0.053	89.4	0.03210	
8D	235	195	B	55.6	680	65.00	50.00	0.0480	0.053	90.7	0.02870	
AC1-AC3	152	127	D	88.6	496	63.50	25.40	0.0164	0.035	84.3	0.00512	Yong, Nour, and Nawy (1988)
BC1-BC3	152	127	D	93.5	496	63.50	50.80	0.0082	0.035	80.3	0.00490	
CC1-CC3	152	127	D	88.5	496	63.50	76.20	0.0055	0.035	75.2	0.00344	
NC1-NC3	152	127	D	83.6	496	63.50	50.80	0.0082	0.035	83.9	0.00420	

Notes: cfg = configuration of transverse steel



A B C D E

in which b_c = dimension of concrete core; s_l = distance between the laterally supported longitudinal bars; n = number of laterally supported longitudinal bars; f_{sh} = stress in the transverse reinforcement at the maximum strength of confined concrete; and $P_{occ} = f_{cc}(A_{cc})$, where A_{cc} = area of concrete in the core. In Eq. (8), the linear dimensions are in mm, the stresses in MPa, and P_{occ} in kN.

Cusson and Paultre Model

Cusson and Paultre (1995) proposed a stress-strain model for high-strength concrete tied columns tested under concentric loading. The determination of the strength and ductility of confined concrete is based on the effective confinement pressure, which depends on the stress in the transverse reinforcement at maximum strength of confined concrete and on the effective confined concrete area. The proposed confinement efficiency of confined concrete can be computed as follows:

$$f_{cc} = K f_{co} \tag{10}$$

$$\varepsilon_{cc} = \varepsilon_{co} + 0.21(f_{le}/f_{co})^{1.7} \tag{11}$$

where

$$K = 1.0 + 2.1\left(\frac{f_{le}}{f_{cp}}\right)^{0.7} \tag{12}$$

$$f_{le} = K_e \frac{f_{sh} A_{sh}}{s b_c} \tag{13}$$

$$K_e = \frac{(1 - \Sigma s_i^2/(6 b_c^2))(1 - s'/s)^2}{(1 - \rho_c)} \tag{14}$$

in which f_{le} = effective confinement pressure applied to the nominal concrete core; K_e = effective confinement coefficient; A_{sh} = total cross section of the lateral steel bars; Σs_i^2 = sum of the squares of all the clear spacing between adjacent longitudinal bars in a square section; s' = clear spacing of transverse steel; and ρ_c = volumetric ratio of longitudinal steel in concrete core.

Fundamental Aspects of Neural Networks

As stated previously, there is still a great need to develop tools for modeling the behavior of confined concrete columns that require minimum assumptions. Recent research has shown that artificial neural network-based modeling is a promising method. An artificial neural network consists of a number of processing elements that are arranged logically into two or more layers and interact with each other via weighted connections to constitute a network. The remarkable computational characteristics of neural networks are their ability to learn functional relationships from training examples and to discover patterns and regularities in data through self-organization.

Most neural network applications are based on the error back-propagation algorithm proposed by Rumelhart et al. (1986). The back-propagation algorithm consists of forward propagation of a set of patterns presented as input to the network and, then, backward error propagation beginning at the output layer where errors are propagated back through the intermediate layers toward the input layer. Fig. 2 shows the typical architecture of back-propagation neural networks with an input layer, and output layer, and one hidden layer. The input layer neurons just pass the input pattern values to the hidden layer (with no calculations happening). Each of the hidden layer neurons computes a weighted sum of its input, pass as the sum through its activation function, and presented the activation value to the output layer. The process of forward and backward propagation continues until the error is reduced to an acceptable level.

The learning process primarily involves the determination of connection weight matrices and the pattern of the connections, and application of the learning rule that the neural network obtains the desired relationship embedded in the training data. In addition, the choice of an activation function may significantly influence the applicability of a training algorithm since it defines how the net input received by a unit combines with its current levels of activation to compute a new level of activation. When the activation function is continuous and bounded it is common to use a sigmoid function, the derivative of which is easy to form so that little extra calculation is needed. A detailed explanation of back-propagation networks is beyond the scope of this paper. However, the basic algorithm for back-propagation neural network is described in the literature (e.g., Welstead 1994; Fausset 1994).

Neural Network-Based Modeling of Confined Reinforced Concrete Columns

In this study, a commercially available multilayer-functional-link neural network (MFLN) (Yeh 1997), was used to predict the confinement efficiency of RC columns with rectilinear transverse steel. The MFLN network is a modification of the standard back-propagation neural network, where enhancements with logarithm neurons and exponent neurons in the input and output layers are used to improve the network's performance, including efficiency and accuracy. During the process of learning, several tools, such as the root-mean-square (RMS) (Dayhoff 1990), and weight histograms, monitor the network instantaneously to achieve a better understanding of the network performance. Once the network is trained and converges, a test set is presented to the network sequentially to verify the reliability and accuracy of the network performance. Details on the establishment of neural network models for RC columns, along with sources of the data that are used in the development, are described below.

Generation of Data and System Model

In general, a good training data set should include comprehensive information about the characteristics of the materials behavior,

Table 2. Ranges of Parameters in Database

Parameters	Range
Dimension of concrete core (b_c) (mm)	127–267
Cylinder compressive strength of concrete (f_c') (MPa)	31.3–115.9
Volumetric ratio of transverse steel in concrete core (ρ_s)	0.0080–0.049
Volumetric ratio of longitudinal steel in concrete core (ρ_c)	0.0223–0.0526
Spacing of transverse steel (s) (mm)	25.4–100.0
Yield strength of transverse steel (f_{yh}) (MPa)	269–770
Spacing of longitudinal steel (s_l) (mm)	63.5–195
Maximum strength of confined concrete (f_{cc}) (MPa)	34.6–128.2
Maximum strain of confined concrete (ε_{cc})	0.00329–0.03210

Table 3. Summary of Values of Root-Mean-Square Error and R^2 for All Prediction Models

Model	MAXIMUM STRAIN OF CONFINED CONCRETE (ε_{cc}) Root-Mean-Square Error: Training set	Root-Mean-Square Error: Testing set	R^2: Training set	R^2: Testing set
Multilayer-functional link neural network model	0.00039	0.00077	0.9983	0.9217
Park et al. (1982) model: Eq. (2)	0.00849	0.00289	0.8758	0.7636
Yong and Uzumeri (1988) model: Eq. (5)	0.00551	0.00149	0.7860	0.7797
Sheikh and Uzumeri (1982) model: Eq. (8)	0.00767	0.00254	0.2285	0.4674
Model	**MAXIMUM STRENGTH OF CONFINED CONCRETE (f_{cc}) Root-Mean-Square Error (MPa): Training set**	**Root-Mean-Square Error (MPa): Testing set**	**R^2: Training set**	**R^2: Testing set**
Multilayer-functional-link neural network	1.5483	5.0356	0.9988	0.9911
Park et al. (1982) model: Eq. (1)	8.8820	6.6745	0.9774	0.9842
Yong et al. (1988) model: Eq. (4)	8.5763	7.1533	0.9798	0.9866
Sheikh and Uzumeri (1982) model: Eq. (7)	9.1585	3.4047	0.9771	0.9862

since that the trained neural network will contain sufficient information to quality as a material model. In this study, the experimental data include 55 RC column results, which are taken from the tests carried out by Sheikh and Uzumeri (1980), Cusson and Paultre (1994), and Yong et al. (1988). The complete list of the data is given in Table 1, where the name and the source of each specimen are referenced, and their ranges are listed in Table 2. Among the collected examples, 45 are sampled randomly and used as training examples, and the remaining 10 are regarded as testing examples.

The existing empirical equations, summarized previously, represent a survey of various statistical regression attempts for correlations between the behavior of concrete columns and characteristic parameters. Therefore, selection of input variables for a

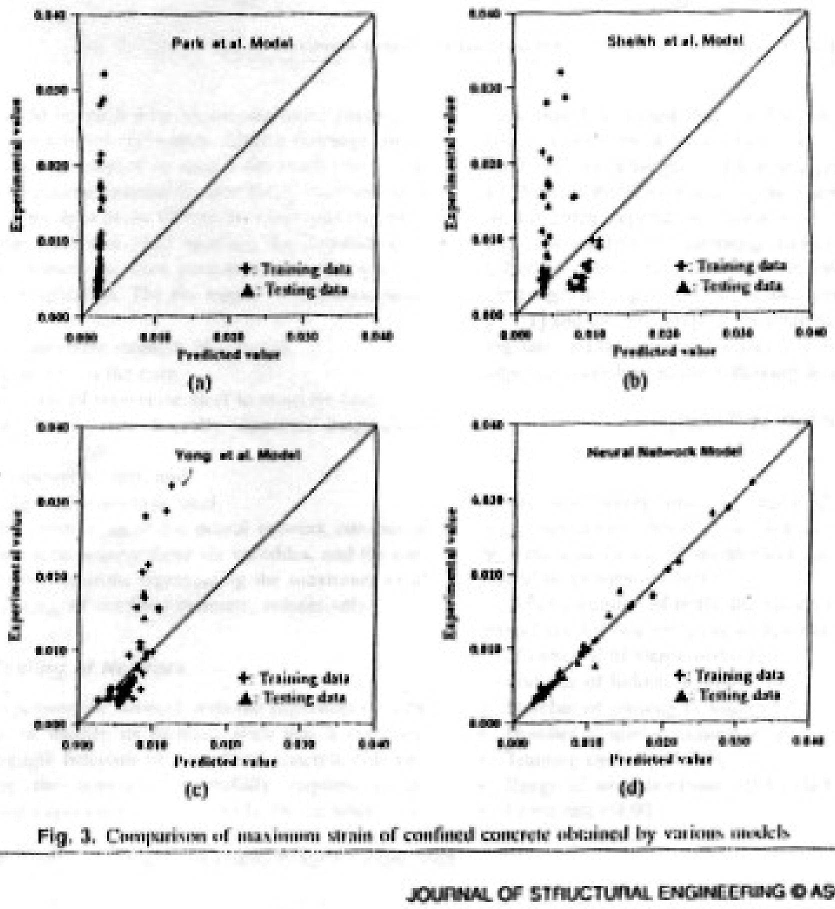


Fig. 3. Comparison of maximum strain of confined concrete obtained by various models

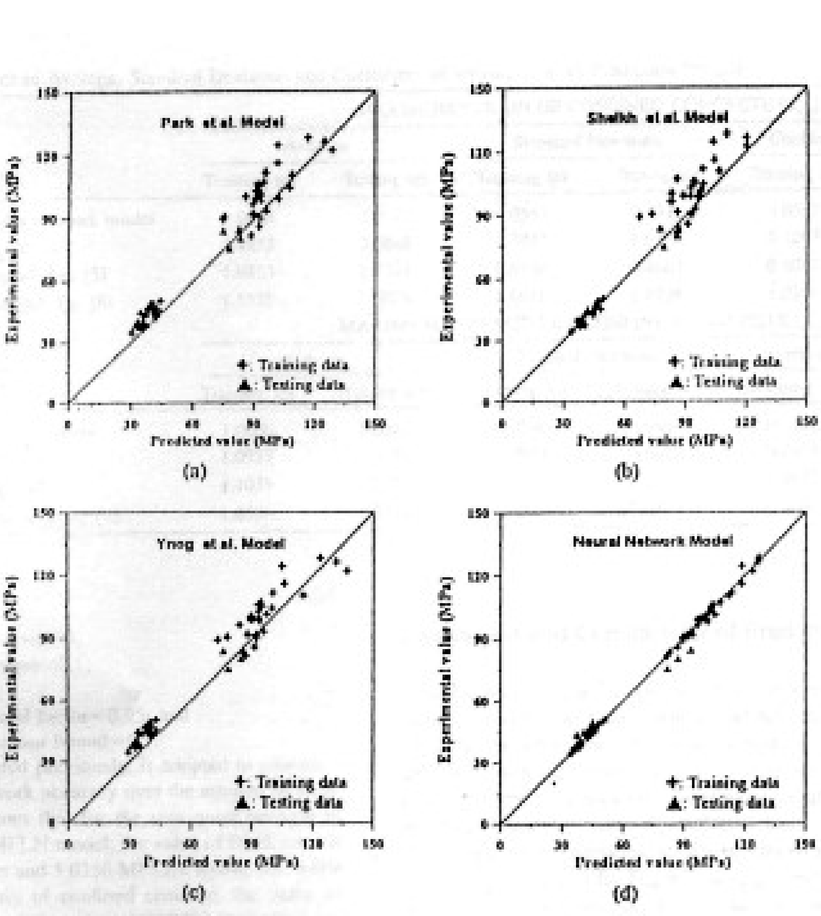


Fig. 4. Comparison of maximum strength of confined concrete obtained by various models

network model could be guided by examining these parameters given in the aforementioned references. After a thorough study, six major variables are adopted to model the confinement efficiency of confined concrete column because these variables could reflect the fact that the area of the effectively confined concrete is determined by the transverse steel spacing, the distribution of longitudinal steel around the core perimeter, and the resulting transverse steel configuration. The six major variables are listed as follows:

- f_c' = cylinder compressive strength of concrete,
- A_{cc} = area of concrete in the core,
- ρ_s = volumetric ratio of transverse steel in concrete core,
- s_l = the distance between the laterally supported longitudinal bars,
- s = spacing of transverse steel, and
- f_{yh} = yield strength of transverse steel.

In other words, the input layer of the neural network consists of six processing units representing these six variables, and the output layer includes two neurons representing the maximum axial stress f_{cc} and strain ε_{cc} of confined concrete, respectively.

Training and Testing of Network

Training means to present the network with the experimental data and have it learn, or modify its weights, such that it correctly reproduces the strength behavior of a confined concrete column. However, training the network successfully requires many choices and training experiences. In this study, the network configuration was arrived after watching the performance of different configurations for a fixed number of cycles. Then, learning parameters were changed and learning processes were repeated. In addition, to avoid over-training the convergence criterion adopted in this study depends on whether the RMS error of the testing data has reached its minimum. Before the neural networks are trained, to avoid the slow rate of learning near the end points of the range, the input and output data were scaled into the interval $[-1,1]$ and the interval $[0.2, 8]$, respectively. Moreover, the learning rate and the momentum factor of the general delta rule were adjusted according to the following formulas:

$$\eta_{t+1} = \gamma_\eta \cdot \eta_t \geq \eta_{min} \tag{15}$$

$$\alpha_{t+1} = \gamma_\alpha \cdot \alpha_t \geq \alpha_{min} \tag{16}$$

where η = learning rate; γ_η = reduced factor of learning rate; η_{min} = minimum bound of learning rate; α = momentum; γ_α = reduced factor of momentum factor; and α_{min} = minimum bound of momentum factor.

After a number of trials, the values of the network parameters considered by this study are as follows:

- Number of hidden layers = 1;
- Number of hidden neurons = 14;
- Number of training examples = 45;
- Number of testing examples = 10;
- Training cycles = 23,700;
- Range of weights = from −0.3 to 0.3;
- Learn rate = 0.90;

Table 4. Summary of Values of Average, Standard Deviation and Coefficient of Variance for All Prediction Models

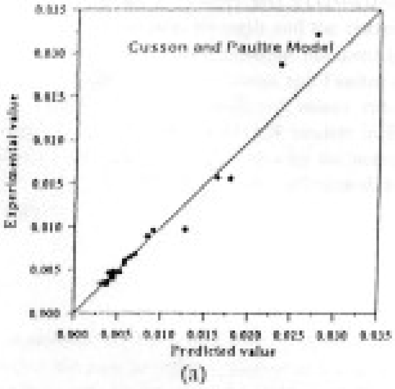
	MAXIMUM STRAIN OF CONFINED CONCRETE (ε_{cc})					
	Average		Standard Deviation		Coefficient of Variance	
Prediction models	Training set	Testing set	Training set	Testing set	Training set	Testing set
Multilayer-functional link neural network model	1.0004	1.0771	0.0547	0.2311	0.0547	0.2145
Park et al. (1982) model: Eq. (2)	3.2853	3.0848	2.3973	1.6778	0.7297	0.5439
Yong and Uzumeri (1988) model: Eq. (5)	1.0853	1.1221	0.6530	0.4164	0.6017	0.3711
Sheikh and Uzumeri (1982) model: Eq. (8)	1.5528	1.6068	1.6011	1.2238	1.0311	0.7616
	MAXIMUM STRENGTH OF CONFINED CONCRETE (f_{cc})					
	Average		Standard Deviation		Coefficient of Variance	
Prediction models	Training set	Testing set	Training set	Testing set	Training set	Testing set
Multilayer-functional-link neural network	1.0000	1.0313	0.0166	0.0864	0.0166	0.0838
Park et al. (1982) model: Eq. (1)	1.0927	1.1255	0.0894	0.1029	0.0818	0.0915
Yong et al. (1988) model: Eq. (4)	1.1035	1.1353	0.0918	0.1241	0.0832	0.1093
Sheikh and Uzumeri (1982) model: Eq. (7)	1.0566	1.0191	0.0944	0.0523	0.0893	0.0513

- Learn rate reduced factor=0.95;
- Learn rate minimum bound=0.1;
- Momentum factor=0.5;
- Momentum factor reduced factor=0.95; and
- Momentum factor minimum bound=0.1.

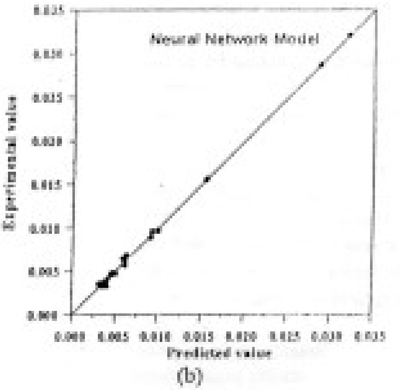
The RMS errors, as stated previously, is adopted to provide a measure of the output network accuracy over the number of training iterations. Table 3 shows that for the maximum strength of confined concrete by the MFLN model, the value of RMS error is 1.5483 MPa for training set and 5.0356 MPa for testing set; while for the corresponding strain of confined concrete, the value of RMS error is 0.00039 for training set and 0.00077 for testing set. These error measurements indicate that the error has been reduced to an acceptable level. In addition, the coefficient of determination (R^2) can be used as an index of how well the independent variables (i.e., f_c', s, s_l, ρ_s, A_{cc}, and f_{yh}) considered account for the measured dependent variables (f_{cc} and ε_{cc}) and thus the accuracy of the trained network. It was found that the values of R^2 are all greater than 0.92 for both the training set and testing set. This indicates a significant correlation between the independent variables and the measured dependent variables.

Discussion and Comparison of Prediction Models

To compare the neural network results with other well-known existing models, the same training and testing data are used to calculate the predicted maximum strength f_{ccp} and the corresponding strain ε_{ccp} of confined concrete columns. Regarding all 55 RC columns, the measured maximum strength and the corresponding strain (f_{cce} and ε_{cce} collected from the literature) are plotted against the predicted values, as shown in Fig. 3 for ε_{cce} versus ε_{ccp} and Fig. 4 for f_{cce} versus f_{ccp}, respectively. To show the overall trend of correlation, the theoretical line with $\varepsilon_{cce}/\varepsilon_{ccp}=1$ or $f_{cce}/f_{ccp}=1$ are drawn on the graphs along with the data points plotted. The nearer the points gather around the diagonal line, the better are the predicted values. Fig. 3 clearly shows that the least scatter of data around the diagonal line confirms the fact that neural network-based model is an excellent predictor for the value of ε_{cc}. While the correlation between the values of ε_{cce} and ε_{ccp}, obtained from Eqs. (2), (5), and (8), is more scattered. For comparison purpose, the values of RMS error and R^2 of the training and testing results for the prediction models



(a)



(b)

Fig. 5. Comparison of maximum strain of confined concrete obtained by the Cusson et al. (1995) and MFLN models

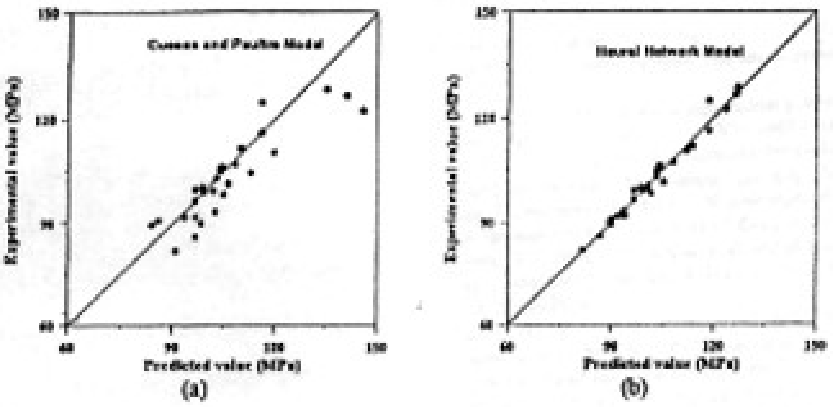


Fig. 6. Comparison of maximum strength of confined concrete obtained by the Cusson et al. (1995) and MFLN models

are also listed in Table 3. It is seen that the MFLN model gives the smallest RMS error and the largest R^2 for both the training and testing sets.

As for the maximum strength values of f_{cce} and f_{ccp}, Fig. 4 shows that for the training set the overall predictions from the MFLN model is better than those of the aforementioned models, namely, Eqs. (1), (4), and (7). However, Table 3 indicates that for the testing set the RMS error values of the Sheikh-Uzumeri model is smaller than that of the MFLN model. This may be attributed to the fact that most of the testing samples are taken from the tests carried out by Sheikh and Uzumeri. In other words, the Sheikh-Uzumeri model had been well calibrated to fit the experimental results of the testing samples and thus resulted in the least value of RMS error. By contrast, the MFLN model is calibrated to fit all the experimental results of the training and testing samples.

In addition, the four prediction models have been compared by means of the average value (AVG), standard deviation (STD), and coefficient of variation (COV) of the ratios of $\varepsilon_{cce}/\varepsilon_{ccp}$ and f_{cce}/f_{ccp}. Table 4 shows that for the ratios of $\varepsilon_{cce}/\varepsilon_{ccp}$, the MFLN model possesses the least COV value of 5.47% (with AVG=1.0004 and STD=0.0547) and 21.45% (with AVG=1.0771 and STD=0.2311) for the training and testing sets, respectively. As for the ratios of f_{cce}/f_{ccp}, the MFLN model possesses the least COV value of 1.66% (with AVG=1.0000 and STD=0.0166) for the training set, while for the testing set, as analyzed previously, the Sheikh-Uzumeri model gives the lease COV value of 5.13% (with AVG=1.0191 and STD=0.0523).

Finally, the measured maximum strength and the corresponding strain of 27 high-strength concrete columns confined by rectilinear transverse steel collected from Cusson and Paultre (1994) are, respectively, plotted against the predicted values calculated by the Cusson and Paultre (1995) and MFLN models in Figs. 5 and 6, which clearly show that the predictions by the neural network model give better results than those calculated by the Cusson-Paultre model.

Conclusions

This study has demonstrated the application of neural network techniques to predict the complicated nonlinear behavior of RC columns with rectilinear transverse steel. Most theoretical models depend on the evaluation of a mathematical expression or solution, while the neural network solution process is not formulated explicitly. Instead, basing its entire process on a set of examples presented to the network, it can reasonably capture the underlying behavior of confined RC columns. Concurrently considering the maximum strength and the corresponding strain, the overall predictions from the neural network MFLN model were found to be better than the aforementioned parametric models. Accordingly, it can be concluded that neural network-based modeling is a practical method for predicting the confinement efficiency of RC columns with rectilinear transverse steel. In light of these promising results, it is believed that the application of neural network techniques to other areas of structural engineering can open new directions for further research.

Notation

The following symbols are used in this paper:

- A_{cc} = area of concrete in the core (mm^2);
- A_{sh} = total cross sections of lateral steel bars (mm^2);
- b = dimension of column cross section (mm);
- b_c = dimension of concrete core (mm);
- cfg = tie configuration;
- d_l = nominal diameter of longitudinal steel bar (in.);
- d_s = nominal diameter of transverse steel bar (in.);
- f_{cc} = maximum strength of confined concrete (MPa or psi);
- f_{cce} = measured maximum strength of confined concrete column (MPa);
- f_{ccp} = predicted maximum strength of confined concrete column (MPa);
- f_{co} = maximum strength of unconfined concrete (MPa or psi);
- f_{le} = effective confinement pressure applied to nominal concrete core (MPa);
- f_{sh} = stress in transverse reinforcement at maximum strength of confined concrete (MPa);
- f_{yh} = yield strength of transverse steel (MPa or psi);
- f'_c = cylinder compressive strength of concrete (MPa or psi);
- K = strength gain of confined concrete;
- K_e = confinement effective coefficient;
- n = number of longitudinal steel bars;
- P_{occ} = $f_{cc}(A_{cc})$ (kN);
- s = spacing of transverse steel (mm or in.);

s_l = distance between laterally supported longitudinal bars (mm);

s' = clear spacing of transverse steel (mm);

w = length of one side of rectilinear transverse steel (in.);

α = momentum;

α_{min} = minimum bound of momentum factor;

γ_{α} = reduced factor of momentum factor;

γ_{η} = reduced factor of learning rate;

ε_{cc} = strain at maximum strength of confined concrete;

ε_{cce} = measured maximum strain of confined concrete column;

ε_{ccp} = predicted maximum strain of confined concrete column;

ε_{co} = strain at maximum strength of unconfined concrete;

η = learning rate;

ρ_c = volumetric ratio of longitudinal steel ratio in concrete core;

ρ_g = volumetric ratio of longitudinal steel ratio in column cross section;

ρ_s = volumetric ratio of transverse steel in concrete core; and

Σs_i^2 = sum of squares of all clear spacing between adjacent longitudinal bars in square section.

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