Use of Neural Networks to Predict Ultimate Strength of Circular Concrete Filled Steel Tube Beam-Columns

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Abstract

Artificial neural networks (ANNs) are useful computing system which can be trained to learn complex relationship between two or more variables. It learns from examples and storage the knowledge for future use. In this study, a model for predicting the ultimate strength of circular concrete filled steel tube (CCFST) beam-columns under eccentric axial loads has been developed in ANN. The available experimental results for 181 specimens obtained from previous studies were used to build the proposed model. The predicted strengths obtained from the proposed ANN model were compared with the experimental values and current design provision for CCFST beam-columns (AISC and Eurocode4). Results showed that the predicted values by the proposed ANN model were very close to the experimental values and were more accurate than the AISC and Eurocode4 values. As a result, ANN provided an efficient alternative method in predicting the ultimate strength of CCFST beam-columns.

Keywords: beam-columns, artificial neural networks, concrete filled steel tube.

استخدام الشبكات العصبية في تقدير المقاومة القصوى للعتبات ـ الاعمدة ذات مقطع انبوب حديدي دائري مملوء بالخرسانة

المستخلص

ان الشبكات العصبية نظام مفيد ممكن تدريبه ليتعلّم العلاقات المعقدة بين عدة متغيرات من خلال إدخال مجموعة من الامثلة الحقيقية. ان الهدف الرئيسي من الدراسة الحالية هو بناء شبكة عصبية لتقدير مقاومة العتبات ـالأعمدة ذات مقطع انبوب حديدي دائري مملوء بالخرسانة والمعرّضة الى أحمال ضغط لامركزية. وقد استعملت النتائج المختبرية لـ(١٨١) عيّنة (مستخلصة من بحوث سابقة) في بناء الشبكة المقترحة. وقورنت القيم المقدّرة من هذه الشبكة مع القيم المختبرية ومع القيم المحسوبة على ضوء شرط التصميم في الكودين العالميين AISC و Eurocode4. لقد أظهرت النتائج أن القيم المقدّرة من الشبكة المقترحة كانت قريبة جداً من القيم المختبرية وكانت أدقّ من القيم المحسوبة حسب مواصفات الكودين المذكورين. وبالتالي فانه من الممكن استخدام الشبكات العصبية في تقدير مقاومة مثل هذا النوع من العتبات ـ الأعمدة.

1. Introduction

Beam-columns are members that are subjected simultaneously to axial forces and bending moments. Thus, their behavior falls somewhere between that of a pure axially loaded column and that of a beam with only moments applied. Also, their behavior must include the effects of the axial loads on the flexural stiffness. This is usually referred to as the second-order elastic analysis. To understand the behavior of beam-columns, it is common practice to look at the response as predicted through an interaction equation between axial loads and moments.

Numerous different structural systems are used today to meet performance or functional requirements in structures. Composite construction is widely used in structural systems to achieve long spans, lower story heights, and provide additional lateral stiffness. Composite construction uses the structural and constructional advantages of both concrete and steel. Concrete has low material costs, good fire resistance, and is easy to place. Steel has high ductility and high strength-to-weight and stiffness-to-weight ratios. When properly combined, steel and concrete can produce synergetic savings in initial and life-cycle costs. Currently composite floor systems are widely utilized in steel buildings in the form of composite beams and joists/trusses. There are two basic kinds of composite beams or columns: steel sections encased in concrete (steel-reinforced concrete sections or SRC) and steel sections filled with concrete (concrete filled tubes or CFT). The latter can be either circular (CCFT) or square/rectangular (RCFT) in cross-section. In composite columns additional synergies between concrete and steel are possible: (a) in concrete-filled tubes, the steel increases the strength of the concrete because of its confining effect, the concrete inhibits local buckling of the steel, and the concrete formwork can be omitted; and (b) in encased sections, the concrete delays failure by local buckling and acts as fireproofing while the steel provides substantial residual gravity load-carrying capacity after the concrete fails.

The structural behavior of circular concrete filled steel tube (CCFST) beam-columns has been investigated through many experimental tests [1-5]. The main objective of these tests was to determine the different parameters that influence the beam-columns structural behavior.

For the last two decades, different modeling methods based on artificial neural networks (ANN) have become popular and have been used by many researchers for a variety of civil engineering applications [6-10]. ANNs are natural complementary tools in building intelligent systems and are low level computational structures that perform well when dealing with raw data. The basic strategy for developing ANN systems based models for material behavior is to train ANN systems on the results of a series of experiments using that material. If the experimental results contain the relevant information about the material behavior, then the trained ANN systems will contain sufficient information about material's behavior to qualify as a material model. Such trained ANN systems not only would be able to reproduce the experimental results, but also they would be able to approximate the results in other experiments through their generalization capability.

The aim of this study is to propose a model using ANN to predict the ultimate strength of CCFST beam-columns under eccentric axial loads (Fig. (1)).

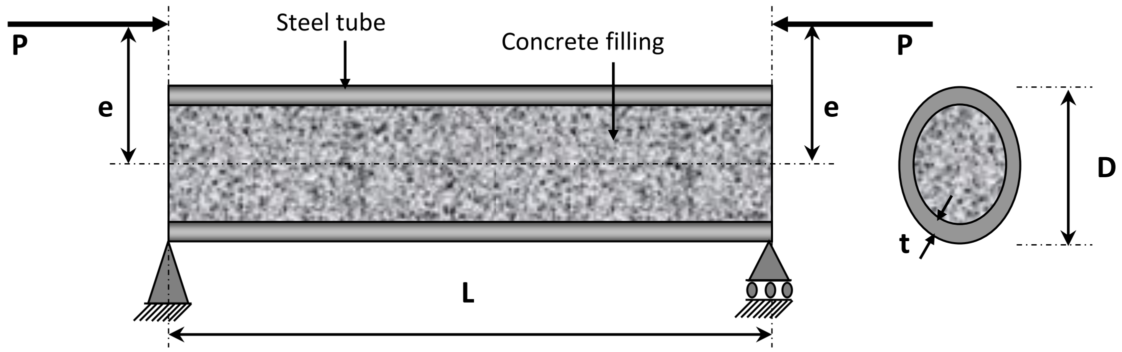

Fig. (1) CCFST beam-column under eccentric axial loads

2. Artificial Neural Networks (ANN)

2.1. General

An Artificial Neural Network (ANN) is a computational tool that attempts to simulate the architecture and internal features of the human brain and nervous system. Comparing ANN with other digital computing techniques, ANNs are advantageous because of their special features such as the possibility of non–linear modeling relationship between input and target specially for problem where the relationships are not very well known and low sensitive to error.

The first structural engineering application of ANN goes back only to the year 1990. Since then a wide range of applications have emerged. These applications include [11]:-

- Mapping of input–output data of non–linear relation for materials and structures.
- Damage identification of structures and structural control against dynamic loads.
- Preliminary design of structure.
- Optimum design and analysis.

ANNs are enormously parallel systems composed of many processing elements connected by links of variable weights. Generally, ANNs are made of an input layer of neurons, sometimes referred to as nodes or processing units, one or several hidden layer of neurons and output layer of neurons. The neighboring layers are fully interconnected by weight. The input layer neurons receive information from the outside environment and transmit them to the neurons of the hidden layer without performing any calculation. Layers between the input and output layers are called hidden layers and may contain a large number of hidden processing units. All problems, which can be solved by a perceptron can be solved with only one hidden layer, but it is sometimes more efficient to use two or three hidden layers. Finally, the output layer neurons produce the network predictions to the outside world.

Figure (2) shows a symbol neuron model with input, sum function, sigmoid activation function and output. The input to a neuron from another neuron is obtained by multiplying the output of the connected neuron by the synaptic strength of the connection between them. The weighted sums of the input components $(net)_j$ are calculated by using the following equation:

$$(net)_j = \sum_{i=1}^{n} W_{ij} Y_i + b, \tag{1}$$

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 in the preceding layer, Y_i is the output of the ith neuron in the preceding layer. The quantity b is called the bias and is used to model the threshold. The output signal of the neuron, denoted by Y_j in Fig. (2), is related to the network input $(net)_j$ via a transformation function called the activation function. The most common activation functions are sigmoid and Gaussian function due to their nonlinearity property. The output of the jth neuron Y_j is calculated by using Eq. (2) with a sigmoid function as follows:

$$Y_j = f(net)_j = \frac{1}{1 + e^{-a(net)_j}}, \tag{2}$$

Where α is a constant used to control the slope of the semi-linear region. The sigmoid function represented by Eq. (2) gives outputs in the range (0,1).

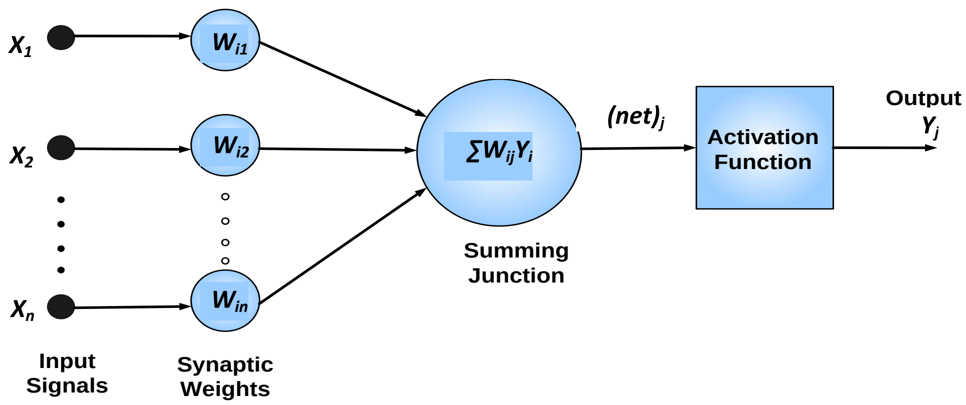

Fig. (2) A simple neuron model.

2.2. Feed-forward Neural Networks

Feed-forward NNs are the most popular and most widely used models in many practical applications. They are known by many different names, such as multilayer feed-forward and multilayer perceptrons. In a feed-forward NN, the artificial neurons are arranged in layers, and all the neurons in each layer have connections to all the neurons in the next layer. However, there is no connection between neurons of the same layer or the neurons which are not in successive layers. In general, the feed-forward NN consists of one input layer, one or two hidden layers and one output layer of neurons. The input layer receives input information and passes it onto the neurons of the hidden layer(s), which in turn pass the information to the output layer. The output from the output layer is the prediction of the net for the corresponding input supplied at the input nodes. Each neuron in the network behaves in the same way as discussed in Eqs. (1) and (2). There is no reliable method for deciding the number of neural units required for a particular problem. This is decided based on experience and a few trials are required to determine the best configuration of the network. In this study, the multilayer feed-forward type of neural networks, as shown in Fig. (3), is considered.

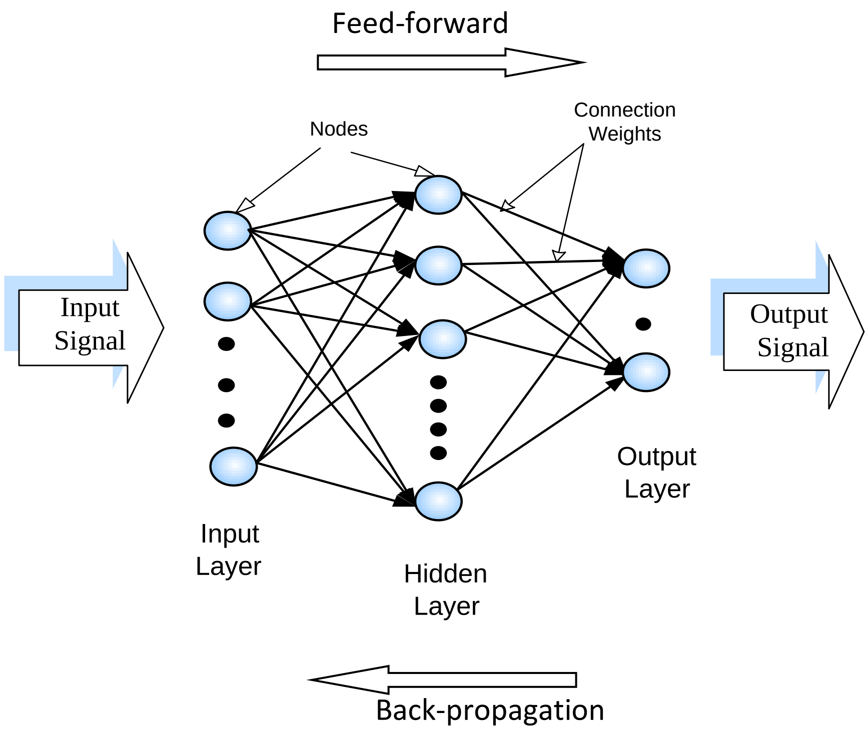

Fig. (3) Architecture of Neural Network

2.3. Back-propagation Algorithm

Multi-layer perceptrons are trained with supervised learning rules. Hopefully, a network that produces the right output for a particular input will be obtained. The most widely used supervised learning algorithm for neural networks is the back propagation, also known as error back propagation. Training is implemented by adjusting the weights according to the error (the distance between the target and the actual output vector) in the output layer. The learning error for *r*th example is calculated by the following performance function usually called the mean-square error:

$$E_r = \frac{1}{2} \sum_j (T_j - Y_j)^2 , \tag{3}$$

Where T_j is the target output at neuron j and Y_j is the output predicted at neuron j. As presented in Eqs. (1) and (2) the output Y_j is a function of synaptic strength and outputs of the previous layer. In the back-propagation phase, the error between the network output and the desired output values is calculated using the so called generalized delta rule, and weights between neurons are updated from the output layer to the input layer. These operations are repeated for each example and for all the neurons until a satisfactory convergence is achieved for all the examples present in the training set. The training process is successfully completed, when the iterative process has converged. The connection weights are captured from the trained network, in order to use them in the recall phase. There are several different back propagation training algorithms. They have a variety of different computation and storage requirements and no one algorithm is best suited to all locations. The resilient back propagation (RPROP) is an algorithm for feed forward networks that often provides faster convergence; therefore it is used in this study.

3. ANN for Beam-columns:

The computer program "MATLAB version 7.0 Neural Network Toolbox" is employed for the proposed ANN model in this study. The advantage of using this program is that many types of networks are included in the program and many training algorithms with different properties can be used for a specific network model. An ANN model was developed to predict the ultimate strength of CCFST beam-columns under eccentric axial loads.

3.1. Selection of Training and Testing Data

The experimental data that are used to build the NN model are obtained from a database developed by Kim [12]. The data used to build the NN model should be divided into two subsets: training data and validating or testing data. The testing data contains approximately 20% from total database. The training phase is needed to produce a NN that is both stable and convergent. Therefore, selection of what data to use for training a network is one of most important steps in building a NN model. The total number of (181) test beam-columns were utilized. The training data contained (147) samples and the testing data comprised of (34) samples which were selected randomly. ANNs interpolate data very well. Therefore, patterns chosen for training set must cover upper and lower boundaries [13].

3.2. Input and Output Layer

The nodes in the input layer and output layer are usually determined by the nature of the problem. In this study the parameters which may be introduced as the components of the input vector consist of yield stress of steel tube (f_y), cylinder concrete compressive strength (f'_c), outside diameter of circular steel tube (D), thickness of steel tube (t), laterally unbraced length of member (L), and eccentricity of applied load (e). The output vector is the ultimate axial load (P). Table (1) summarizes the ranges of each different variable.

Table (1) Range of input parameters

Parameters	Range
Yield stress of steel tube (f_y) (MPa)	185-435
Cylinder concrete compressive strength (f'_c) (MPa)	20-113
Outside diameter of circular steel tube (D) (mm)	95-324
Thickness of steel tube (t) (mm)	0.9-12.8
Laterally unbraced length of member (L) (mm)	360-4968
Eccentricity of applied load (e) (mm)	0.3-337

3.3. Proposed ANN Model

A multilayered feed-forward NN with a resilient back-propagation algorithm was employed in the present study. The NN architecture developed has six neurons in the input layer and one neurons in the output layer as demonstrated in Fig. (4). Two hidden layers were used in the architecture of multilayer feed-forward NN due to its minimum absolute percentage error values for training and testing sets. In the first hidden layer eight and in the second hidden layer two neurons were determined. The transfer (activation) functions used are hyperbolic tangent (tansig) function in first hidden layer and linear (purelin) function in both second hidden and output layer.

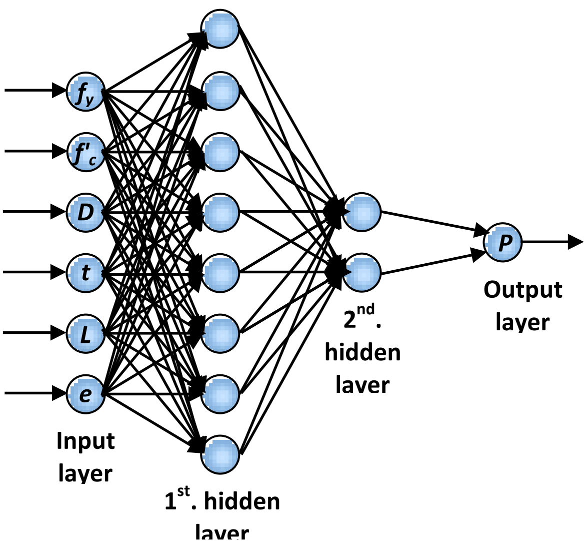

Fig. (4) Architecture of proposed ANN

4. Results and Discussion

An important aspect of developing ANNs is determining how well the network performs once training is complete. The performance of a trained network is checked by involving two main criteria:

(1) How well the NN recalls the predicted response from data sets used to train the network (called the recall step). A well trained network should be able to produce an output that deviates very little from desired value.

(2) How well the NN predicts responses from data sets that were not used in the training (called the generalization step). A well generalized network should be able to sensible the new input patterns.

The performance of the proposed ANN is tested by the regression analysis between the output of this network (predicted values) P(ANN) and the corresponding targets (experimental values) P(exp) for both training and testing data as shown in Figs. (5) and (6), respectively. The coefficient of correlation (R^2) is a measure of how well the variation in the output is explained by the targets. If this number is equal to 1, then there is a perfect correlation between targets and output. In these figures, the coefficient of correlation R^2= 0.984, 0.979 for training and testing data respectively. These values indicate an excellent agreement between the predicted values and the experimental values.

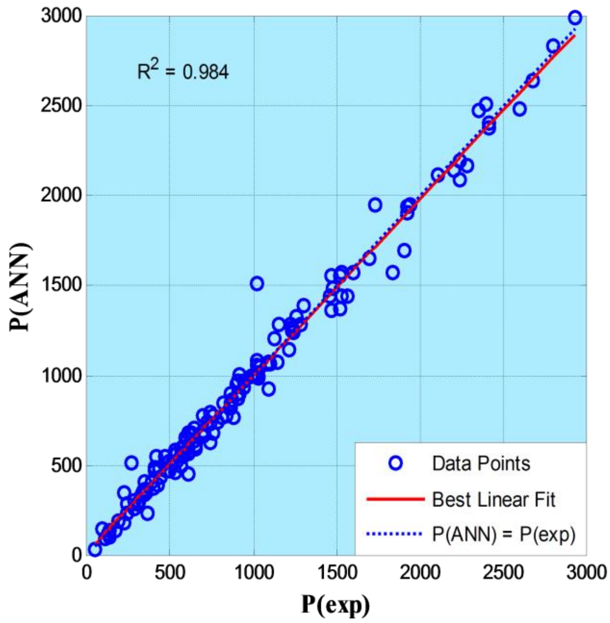

Figure (5) Regression analysis between predicted and actual values for training data

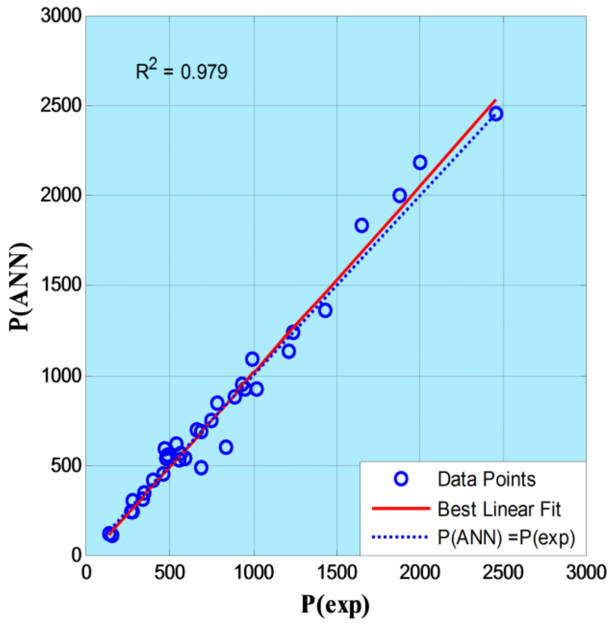

Figure (6) Regression analysis between predicted and actual values for testing data

Table (2) presents the actual and predicted values for testing data. As seen from this table, the values obtained are very close to the experimental results. The average value of ratios of actual to predicted ultimate loads is 1.028 with a standard deviation of 0.147. This result demonstrates that ANN can be successfully applied to establish accurate and reliable prediction models.

Table (2) Actual (experimental) and predicted values for testing data

Column designation	f_y (MPa)	f'_c (MPa)	*D* (mm)	*t* (mm)	*L* (mm)	*e* (mm)	*P(exp)* (kN)	*P(ANN)* (kN)	*P(exp)/ P(ANN)*
#1	415	29	114.3	3.2	914.4	30	400	415.5	0.963
#2	330	21	152.4	1.5	1016	111.3	135	117.7	1.147
#3	290	35.2	127	2.4	1066.8	66	267	238.6	1.119
M2	305	43.2	169.4	5.3	3327.4	38.1	689	684.8	1.006
M8	270	33.2	140.2	9.6	3327.4	31.8	538	621.6	0.866
C7	190	60.1	127	1.7	1714.5	6.4	836	601.9	1.389
C11	190	42.6	127	1.6	2032	22.4	338	309.7	1.091
#4	220	67.4	101.6	1.6	1313.2	10	350	346.9	1.009
9	220	67.4	101.6	1.6	1818.6	10	280	242.0	1.157
PB1-4	315	41.1	166.1	5	665.5	40	1245	1242.7	1.002
PB2-2	300	41.1	166.1	5	1496.1	20	1431	1364.0	1.049
PB2-6	300	41.1	166.1	5	1496.1	100	568	565.2	1.005
PC1-1	285	27.9	166.1	5	2989.6	20	1022	924.9	1.105
8	275	20.3	95	12.8	1420	2.3	938	949.9	0.987
13	275	20.3	95	12.7	861.1	2.3	886	884.2	1.002
42	385	25	95	3.7	861.1	0.5	686	491.9	1.395
49	335	25	95	3.5	1981.2	3.3	488	558.1	0.874
69	390	22.9	215.9	6	2220	2.8	2462	2457.2	1.002
74	335	24.1	95	3.4	1981.2	1.5	473	588.4	0.804
84	330	21.1	120.9	3.7	1049	5.3	746	753.7	0.990
89	345	21.1	120.9	5.6	1049	4.6	998	1088.7	0.917
101	345	21.1	120.9	5.7	2311.4	3.6	786	850.2	0.924
S2	240	71.1	250	2	2200	46	2002	2187.7	0.915
SC-16	410	96	101.6	2.4	2175	50	157	108.5	1.447
C4-5	355	31.9	165.4	4.1	660.4	103.3	555	533.3	1.041
C8-3	355	31.9	165.4	4.1	1323.3	62.1	659	699.3	0.942
C12-1	355	31.9	165.4	4.1	1983.7	20.7	948	925.7	1.024
C18-3	355	31.9	165.4	4.1	2976.9	62.1	460	460.0	1.000
C24-5	355	31.9	165.4	4.1	3967.5	103.3	277	304.7	0.909
C30-1	355	31.9	165.4	4.1	4968.2	20.7	479	540.2	0.887
L-1	340	36	119.9	2.6	1400	14	590	541.1	1.090
S10E250A	210	41	190	0.9	662.9	7.4	1218	1132.7	1.075
S30E180A	365	80.2	165.1	2.8	579.1	17.8	1652	1841.1	0.897
S30E110B	365	112.7	165.1	2.8	579.1	15.5	1879	2004.8	0.937
								Average	1.028
								Standard Deviation	0.147

Based on these results, the proposed ANN architecture (6-8-2-1) with activation functions (tansig, purelin, purelin) with (RPROP) is used for this study. Table (3) shows the properties of this network.

Table (3) Values of parameters used in the proposed ANN model

Number of input layer neurons	Number of hidden layer	Number of first hidden layer neurons	Number of second hidden layer neurons	Number of output layer neuron	Error after learning	Learning cycle
6	2	8	2	1	0.003	10000

5. Comparison with Design Strengths

The predicted strengths, of the CCFST beam-columns in Table (2), obtained from the proposed ANN model are compared with unfactored design strengths predicted using the design procedure specified in the American Institute of Steel Construction (AISC) [14] and the Eurocode4 [15] for CCFST beam-columns as calculated by Kim [12]. The predicted strengths of the proposed ANN model P(ANN) are compared with the design strengths calculated using AISC specifications P(AISC) and the design strengths calculated using Eurocode4 specifications P(Euro) as shown in Table (4). The values of P(exp)/P(ANN), P(exp)/P(AISC) and P(exp)/P(Euro) ratios with the corresponding averages and standard deviations are shown also in this table.

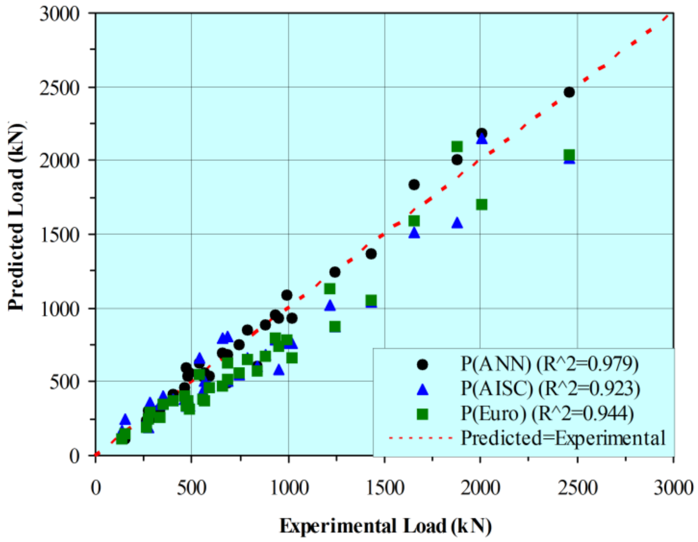

Fig. (7) Regression analysis between predicted and actual values

It can be seen, from Table (4), that the average ratio of actual to predicted loads is 1.028 for ANN, 1.168 for AISC, and 1.249 for Eurocode4, and that the standard deviation is 0.147 for ANN, 0.236 for AISC, and 0.179 for Eurocode4. Therefore the design strengths calculated using AISC and Eurocode4 specifications are generally conservative.

Table (4) Comparison between actual (experimental) and predicted values

Column designation	*P(exp)* (kN)	*P(ANN)* (kN)	*P(AISC)* (kN)	*P(Eurocode)* (kN)	*P(exp)/ P(ANN)*	*P(exp)/ P(AISC)*	*P(exp)/ P(Euro)*
#1	400	415.5	377.4	373.8	0.963	1.06	1.07
#2	135	117.7	163.9	107.9	1.147	0.83	1.26
#3	267	238.6	249.5	185.4	1.119	1.07	1.44
M2	689	684.8	801.2	632.1	1.006	0.86	1.09
M8	538	621.6	656.1	543.4	0.866	0.82	0.99
C7	836	601.9	601.4	572.6	1.389	1.39	1.46
C11	338	309.7	344.9	262	1.091	0.98	1.29
#4	350	346.9	402.3	350	1.009	0.87	1
9	280	242.0	354.4	291.7	1.157	0.79	0.96
PB1-4	1245	1242.7	870.6	876.8	1.002	1.43	1.42
PB2-2	1431	1364.0	1034	1052.2	1.049	1.38	1.36
PB2-6	568	565.2	507.1	364.1	1.005	1.12	1.56
PC1-1	1022	924.9	762.7	655.1	1.105	1.34	1.56
8	938	949.9	788.2	794.9	0.987	1.19	1.18
13	886	884.2	681.5	666.2	1.002	1.3	1.33
42	686	491.9	508.1	519.7	1.395	1.35	1.32
49	488	558.1	332	319	0.874	1.47	1.53
69	2462	2457.2	2018	2034.7	1.002	1.22	1.21
74	473	588.4	337.9	330.8	0.804	1.4	1.43
84	746	753.7	548.5	565.2	0.990	1.36	1.32
89	998	1088.7	761.8	779.7	0.917	1.31	1.28
101	786	850.2	655	644.3	0.924	1.2	1.22
S2	2002	2187.7	2152.7	1696.6	0.915	0.93	1.18
SC-16	157	108.5	241.5	151	1.447	0.65	1.04
C4-5	555	533.3	437	385.4	1.041	1.27	1.44
C8-3	659	699.3	794	470.7	0.942	0.83	1.4
C12-1	948	925.7	581.6	740.6	1.024	1.63	1.28
C18-3	460	460.0	383.3	400	1.000	1.2	1.15
C24-5	277	304.7	189.7	251.8	0.909	1.46	1.1
C30-1	479	540.2	386.3	371.3	0.887	1.24	1.29
L-1	590	541.1	464.6	460.9	1.090	1.27	1.28
S10E250A	1218	1132.7	1015	1127.8	1.075	1.2	1.08
S30E180A	1652	1841.1	1515.6	1588.5	0.897	1.09	1.04
S30E110B	1879	2004.8	1579	2087.8	0.937	1.19	0.9
				Average	1.028	1.168	1.249
				Standard Deviation	0.147	0.236	0.179

In Fig. (7), the predicted strengths P(ANN) and the design strengths P(AISC) and P(Euro) are plotted against the experimental strengths. As shown in this figure, the coefficient of correlation R^2 = 0.979, 0.923 and 0.944 for ANN, AISC, and Eurocode4, respectively. These values indicate that the proposed ANN model can predict more accurate results than AISC and Eurocode4 methods and that ANN provided an efficient alternative method in predicting the ultimate strength of CCFST beam-columns.

6. Conclusions

The most important conclusions that can be drawn from the present study are the followings:

1. The ultimate strength of CCFST beam-columns can be predicted by the proposed ANN model in a quite short period of time with tiny error rates.
2. The predicted ultimate strength values were very close to the experimental results.
3. It was noticed that the design strengths calculated using AISC and Eurocode4 specifications are generally conservative.
4. The predicted strengths obtained from the proposed ANN model were compared with current design provision for CCFST beam-columns (AISC and Eurocode4). It was found that the proposed ANN model can predict more accurate results than AISC and Eurocode4 specifications.
5. The above conclusions have demonstrated that ANN provided an efficient alternative method in predicting the ultimate strength of CCFST beam-columns.

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Notation

The following symbols are used in this paper:

α = constant;

b = bias (used to model the threshold);

D = outside diameter of circular steel tube (mm);

E = mean-square error;

e = eccentricity of applied load (mm);

f'_c = cylinder concrete compressive strength (MPa);

f_y = yield stress of steel tube (MPa);

L = laterally unbraced length of member (mm);

$(net)_j$ = weighted sums of the input components;

P = ultimate eccentric axial load;

R^2 = coefficient of correlation;

T_j = target output at neuron j;

t = thickness of steel tube (mm);

W_{ij} = weight between the jth neuron in the preceding layer; and

Y_i = output predicted at neuron i.