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An Innovative Forecasting Formula for Axial Compression Capacity of Circular Steel Tubes Filled with Concrete through Neural Networks

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ABSTRACT

The manufacturing industry widely employs concrete and steel as building materials. These materials can be cleverly combined to create an efficient and innovative system, commonly referred to as a composite system. Despite the advantages and high performance of circular concrete filled steel tube (CCFST), there is a lack of reliable and accurate relationships for estimating their ultimate capacity. To address this issue, a wide range of valid experimental tests have been collected as a reference for actual data. By utilizing intelligent systems, such as artificial neural networks (ANN), the data can be effectively used to estimate the ultimate capacity of CCFST columns. Selecting the appropriate algorithm is critical for ANNs to eliminate unnecessary errors and produce optimal outputs. This study proposes a relation created by ANN to determine the ultimate capacity of CCFST columns and assesses its accuracy. Finally, a comparison with existing formulas has been conducted. The proposed network introduced enough accuracy compare to other existing methods.

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1. Introduction

Choosing the appropriate materials for a structure is a critical decision for structural designers today. This decision is influenced by various factors such as the type and application of the structure, its economics, and its strength. Among the commonly used construction materials, concrete and steel are prevalent. Their combination through a composite system provides an effective and efficient solution. Composite columns that utilize concrete and steel together are increasingly popular worldwide due to their ability to cooperate and enhance structural systems. CFST columns are a specific type of composite column that combine steel and concrete in various cross-sectional shapes. Two primary types of composite columns (illustrated in Figure 1) are the concrete-filled steel tube (CFST) and the steel reinforcement concrete column. The former utilizes a steel hollow section filled with concrete, while the latter embeds or encases a steel section in concrete [1–4]. The steel part of the column is circular, square, and rectangular, in the core of which concreting is done. Also, for the type of column concrete, self-compacting concrete or ordinary concrete is used. The combination columns have better structural performance than steel or reinforced concrete structural columns. Interaction between concrete and steel tube is one of the most important parameters that influenced the performance of composite columns. Although extensive studies were carried out on the axial strength of the concrete-filled steel tube (CFST) columns, it is not well known. Now, the designers of such structures will need comprehensive and accurate information from researchers, so using high-accuracy results is very important. To achieve accurate structural data in research, different laboratory devices will be needed, only materials, manpower assistance, etc. will be needed. Therefore, in such structural research, we will deal with cases that are costly and we will also face many problems. But with the help of appropriate research methods and tools, the desired result can be achieved with the least cost and these problems can be overcome. One of these suitable methods is the intelligent systems method, which is one of the most popular and most practical of these structures, Artificial neural networks (ANN), whose role in solving the problems of today's world cannot be overlooked [5–25].

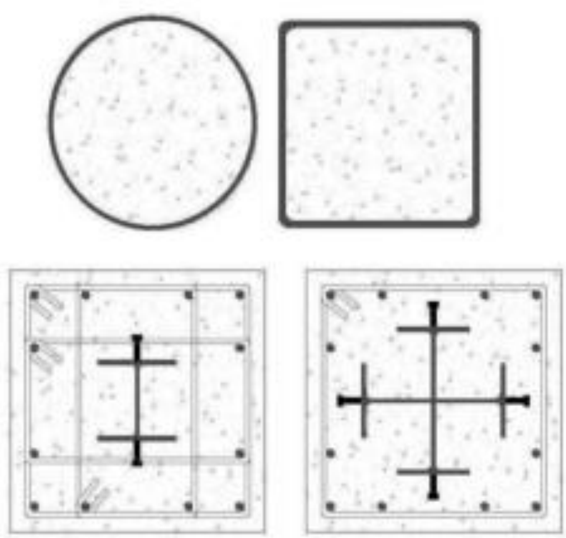

Fig. 1. Cross-section configuration in composite members.

2. Research significance

According to a series of studies, the ultimate axial strength assessment of CCFST columns is a vital issue in design and strengthening of structures. There is a limited available equation that are able evaluate the ultimate strength such members accurately. Consequently, the primary objective of the present study is to construct soft-computing models based on ANN to establish equations for estimating the ultimate strength of CCFST columns that are more precise than the equations now in use. A dependable database is required for this objective. The given database [26–32] was utilized for training and testing the developed model based on the ANN technique. A portion of 192 sample records were utilized for generating the network.

3. Methods

3.1. Artificial neural networks

Looking back in time, the origins of neural networks may seem recent, but in reality, they existed long before computers. Artificial neural networks (ANNs) are tools for processing information, inspired by biological nervous systems like the human brain. The defining characteristic of ANNs is their unique structure, consisting of numerous interconnected processing units known as neurons that work together to solve specific problems. Like humans, ANNs learn by example and are trained for specific applications such as pattern recognition or data classification. Just as biological systems adjust synaptic connections between neurons, ANNs also undergo a learning process. Due to their ability to model real-valued, discrete-valued, and vector-valued functions from examples, ANNs have been widely adopted in various engineering applications [5,6,17,19,20].

The ANN model is a computational tool that mimics the structure of biological neurons, which comprise dendrites, cell bodies, and axons. Each neuron receives information from previous neurons through dendrites and transfers processed information to the next neuron through axons. The design process for neural networks involves five key steps: creating the network, configuring the network, initializing weights and biases, training the network, and validating the network [7–15,20,22–24].

4. Results

4.1. Network modeling

Artificial neural networks (ANNs) modify their architecture during the learning process, utilizing internal or external data to construct models of intricate input-output relationships. By the links that process the input data, the desired output can be generated. The artificial neural network algorithms create coordination between the variables and in the network training stage it is adapted based on matching and matching between the input and the target until the network output and our desired output are matched, so the extent Laboratory data is very necessary. In various types of ANN algorithms, the process of network creation, network training, and network simulation is usually performed. In this research, four processes of laboratory data collection, creating a suitable network, network training, and simulation will be used to use ANNs. To create an efficient network, 192 samples of experimental tests, which include the dimensions and mechanical characteristics of the section and the ultimate capacity, are from the authoritative articles of O'Shea [26], Yu Z [27], Gupta [28], Giakoumelis [29], Abed [30] , Yu Q [31], Ellobody [32], has been extracted and collected. All of these columns are stub and buckling does not occur in them. The maximum axial compressive-capacity of CCFST columns is determined by several parameters as per the researchers' models, including:

Tensile yield stress of the steel tube (f_y) measured in MPa

Compressive strength of unconfined concrete (f'_c) measured in MPa

Length of the column (L) measured in mm

Wall thickness of the steel tube (t) measured in mm

Outer diameter of the column (D) measured in mm

The 5 parameters together with the D/t ratio form a total of 6 network input nodes, and also the experimental ultimate capacity of the columns is specified as the target vector. It should be noted that the 6 input nodes of the network form a 192×6 matrix and the target vector forms a 192×1 matrix. The modeling algorithm utilized in this study is the post-diffusion network, which operates by decreasing the slope of the performance function through weight adjustments in the opposite direction. This network consists of multiple layers and utilizes the Wiedro-Hoff learning rule with a nonlinear transfer function. The term post-diffusion refers to the network behavior in calculating the slope in multilayer nonlinear networks. The transfer functions for these networks are sigmoidal logarithm and the transfer function in the output layer is linear. Using this method, due to the bias of a sigmoid layer and a linear output layer, it is possible to estimate any function with finite discontinuities. Well-trained post-broadcast networks tend to respond with high accuracy when dealing with input data they have not seen before. In the simplest post-diffusion learning implementation, weights and biases are updated in the direction that the performance function decreases, that is, against its slope. A repetition of this process can be written as follows.

$$x_k + 1 = x_k - a_k\, g_k \tag{1}$$

The vector x_k represents the current weights and biases, while g_k denotes the current slope and a_k represents the learning rate. Neural networks composed of multiple layers of neurons with nonlinear transmission functions enable the system to learn both linear and nonlinear relationships between inputs and outputs. As shown in (Fig. 2), a tansig-purelin bilayer network is shown.

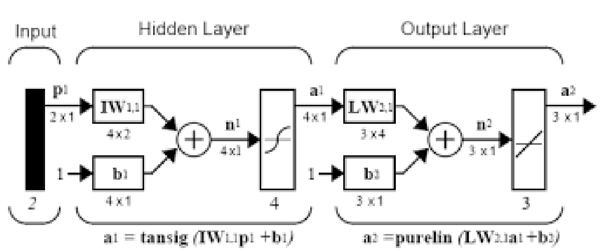

Fig. 2. A two-layer post-release network.

Input vectors and target vectors are divided into three sets of training, validation set, and network test set. Changing the percentage ratio of these sets will have a small effect on the network learning process. In this study, the selected relative percentage of these sets is 70% of the data allocated to education, 15% of the data to accuracy, and 15% of the data to testing. Choosing the right number of layers and neurons is very important and can affect the quality of the network. To increase the efficiency of the network, data must be written in the continuation of the process. Here there are 6 input data and one output data and each data is written with a mapping to the interval [-1 1] and after training the network, the results can be converted to real data by inverse mapping. To select the optimal number of neurons, the number of these neurons is changed between 3 and 15, and the 13 networks produced are tested. To teach all networks, the post-publication method and Levenberg-Marquardt algorithm have been used, and after training the networks, the most optimal network should be selected. The performance of the 13 networks was assessed based on two criteria. The first criterion is the mean square error (MSE), which is the average square difference between the target and the output values. The training was stopped when the MSE reached a sufficiently low value, indicating good network performance. The second criterion is the regression value (R) of the networks, which measures the correlation between the target and the output. A value of R = 1 represents complete correlation, while a value of R = 0 indicates a random relationship. There are two criteria of regression and mean square error as two acceptable principles for selecting the best network. A very important criterion in selecting the appropriate network is the mean square error, which is the value for networks with 3 to 15 neurons in the hidden layer for training, validation, testing, and data sets in the (Fig. 3) it has been shown

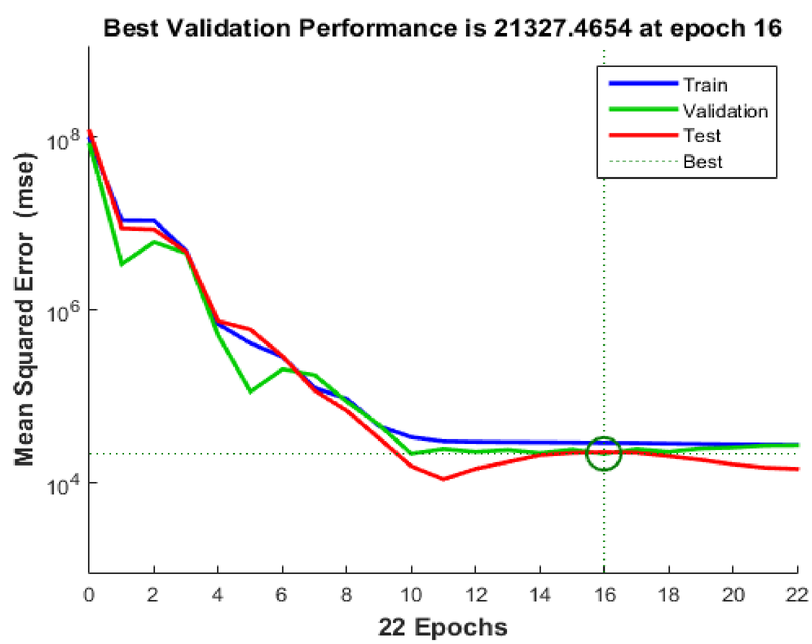

Fig. 3. Network efficiency changes with increasing repetitions (Epochs).

From the above diagram, it is clear that by increasing the number of neurons, the training data error decreases. Because as the number of neurons increases, the degrees of freedom increase, and the network can achieve fewer errors. But because the network focuses on reducing training data error, overfitting occurs, and test data error increases. It is well known that most networks have an error of less than 0.002, which proves that the networks are well trained and the error rates are small. The highest network error with 9 and 10 neurons is hidden in the layer and the lowest network error with 6 and 12 neurons. According to the mean square error diagram, we select a network with 12 neurons and it is appropriate. With this number of neurons, the network is trained and the changes in network efficiency are in the form of (Fig. 4), which is clear to have reached a very small amount. The correlation coefficient and correlation diagram for test, training, validation data, and total data are shown in (Fig. 5).

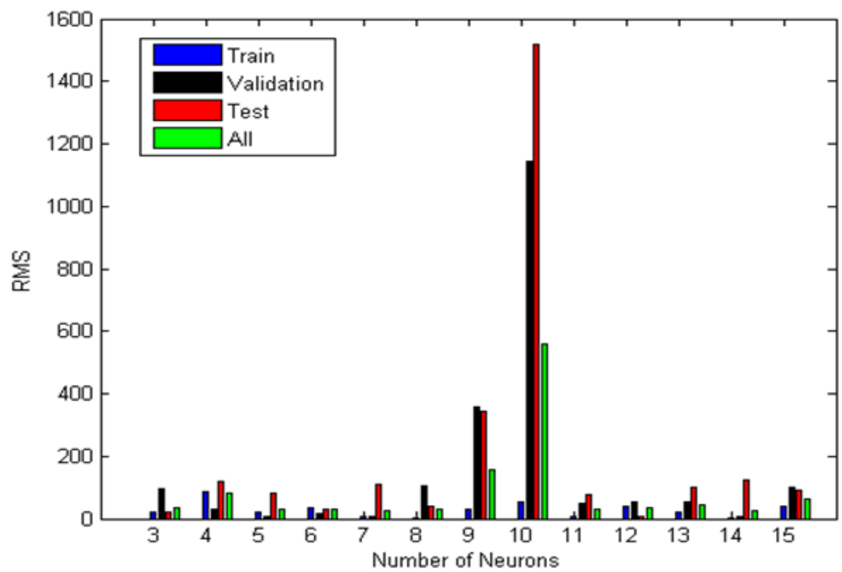

Fig. 4. Changes in the sum of error squares with different lattice neurons in the hidden layer.

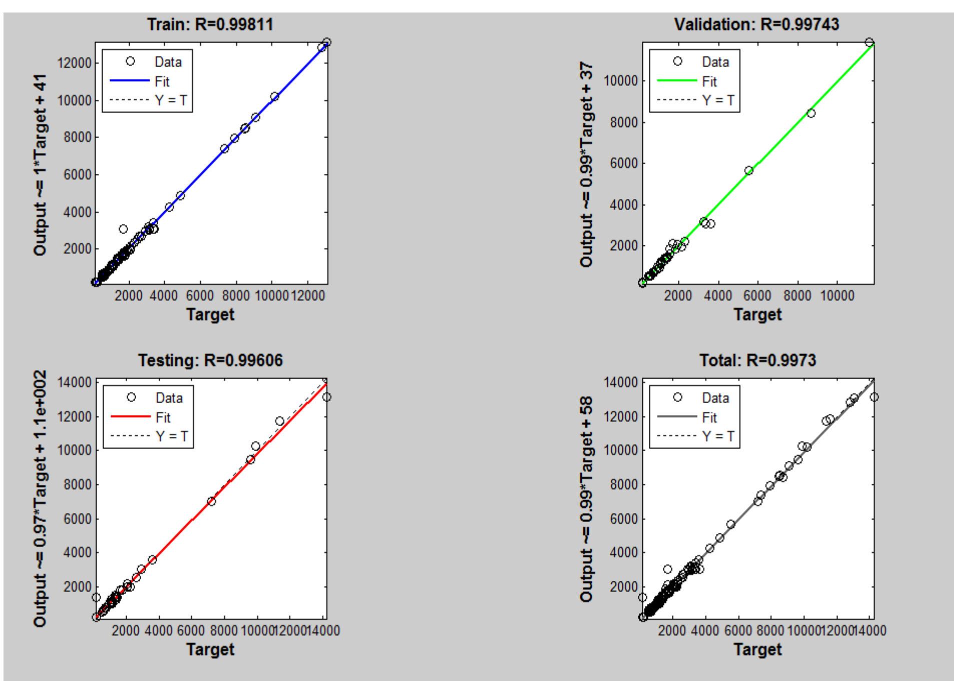

Fig. 5. Data correlation diagram for a monolayer network with 12 neurons.

Upon reviewing Figure 6, it is evident that the correlation coefficients of the network for the training, validation, and test data are 0.99811, 0.99743, and 0.99606, respectively. These values indicate that the correlation coefficient is greater than 0.99 in all cases, which is highly favorable. Figure 7 compares the output of the network for the training, validation, and test data with the experimental data, demonstrating a strong agreement between the two. Additionally, Figure 7 displays the data error, which confirms that the errors are negligible.

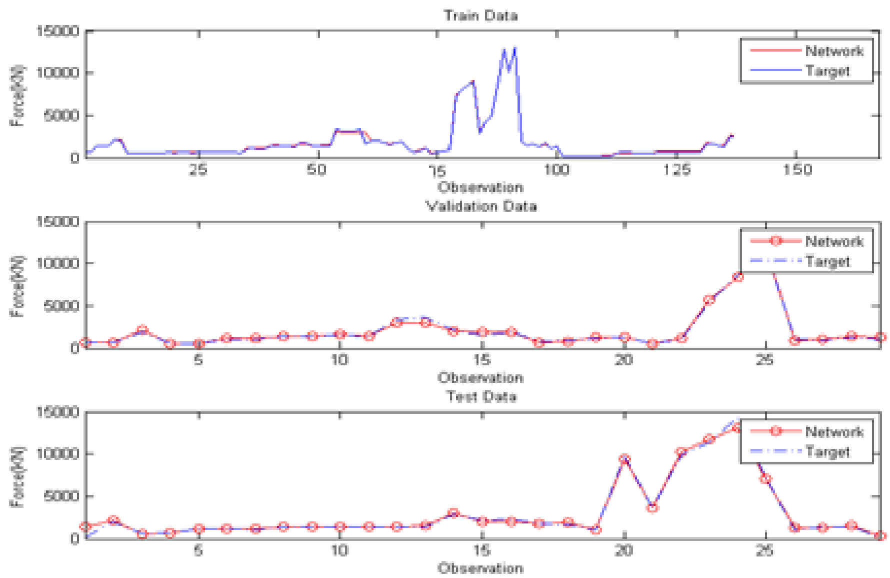

Fig. 6. Single-layer network output with 12 neurons for training, validation, and testing data.

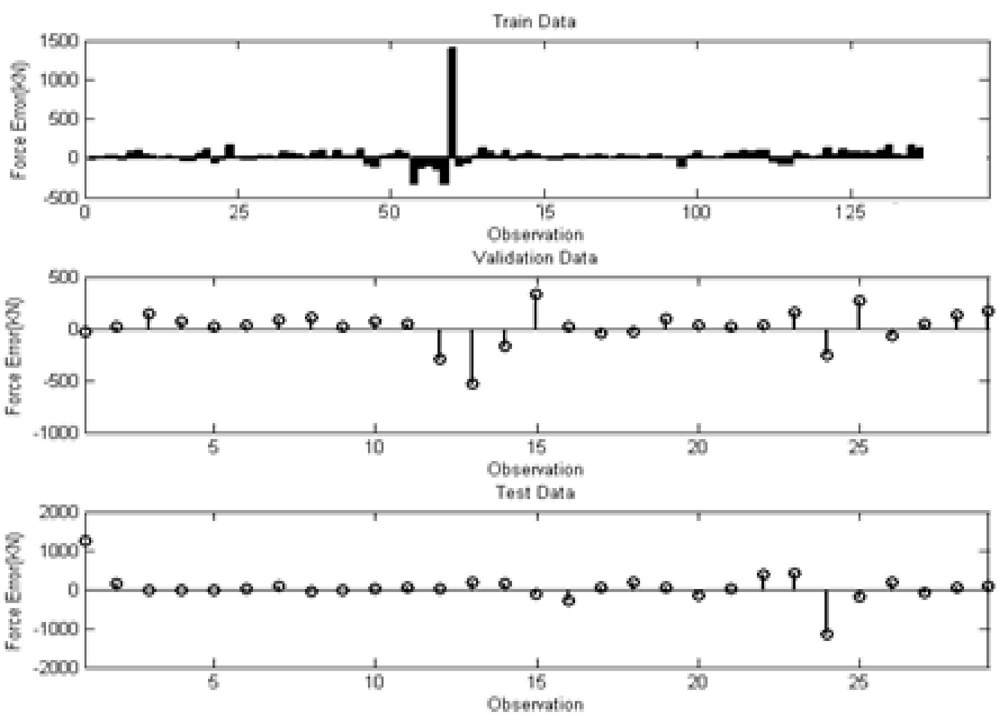

Fig. 7. The error of training data, validation, and testing.

5. Discussion

5.1. Ultimate capacity assessment of the CCFST columns using ANN

There is now a neural network that, with the input of the column parameters, predicts its ultimate capacity with great accuracy, but the use of the network is tedious. In this section, we try to provide an analytical relationship for ultimate capacity predicting using ANN results. Based on this, it was decided to use the model suggested by Leung [33]. First, it was assumed that the area of change of the 5 main parameters is as shown in Table (1).

Table 1
Area of change of 5 input parameters.

	f_y (MPa)	f_c (MPa)	L (mm)	t (mm)	D (mm)
Max	185.5	22.6	250	0.86	47
Min	525	110	1080	11.9	360

The following is a set of reference data approximately around the average of this data as shown in Table (2):

Table 2
Reference data.

f_y (MPa)	f_c (MPa)	L (mm)	t (mm)	D (mm)
318.781	106.788	506.846	1.8830	228.829

Now to present the analytical relation, we have to enter the cross-section changes, the thickness of the steel layer as well as the yield stress of steel and concrete in the equation. For this purpose, a relation as the following was presented:

$$P_{\text{Equation}} = C_{\text{D}}\, C_{\text{L}}\, C_{\text{T}}\, C_{\text{fc}}\, C_{\text{fy}}\, P_{\text{Simulation}} \tag{2}$$

The coefficients of this relationship must be determined in such a way that changes in other parameters can be included in the ultimate capacity assessment. The process of finding these coefficients is that, as an example, we fix all the parameters to reference values and change the *D* parameter. For the input parameters, we obtain the network output and by dividing it by the stored value of the network output, we obtain the value of this coefficient. By performing this procedure for the *L* parameter, changes in this coefficient are obtained as shown in Fig. 8.

It is known that with changes in the *L* parameter, the compressive strength of the column can change between 0.7 and 2.5. If the value of L/L_o is equal to 1, the value of this parameter is equal to the reference value and the coefficient is equal to 1. To be able to mathematically model the obtained diagram, we use the fit of a polynomial to it and increase the order of the polynomials so that a good result is obtained. By fitting a 3rd order curve to Fig. 9, and Fig. 10 is obtained as follows:

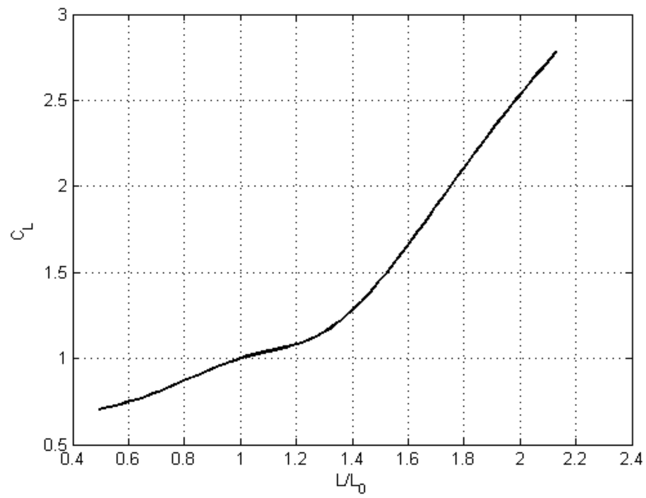

Fig. 8. C_L parameter changes.

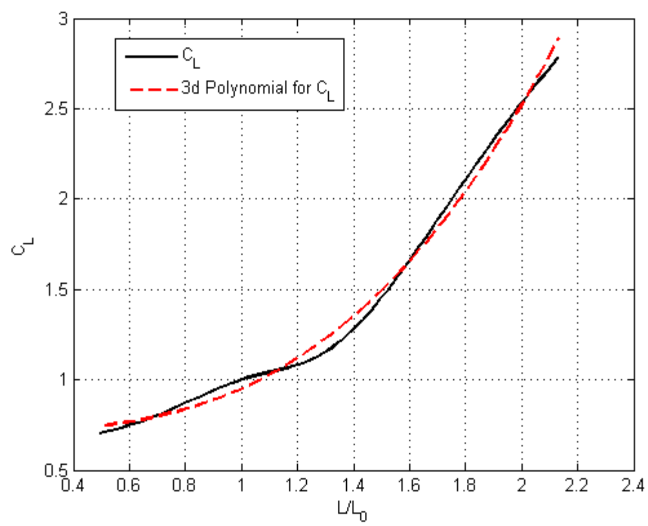

Fig. 9. C_L parameter changes with fitted curve output.

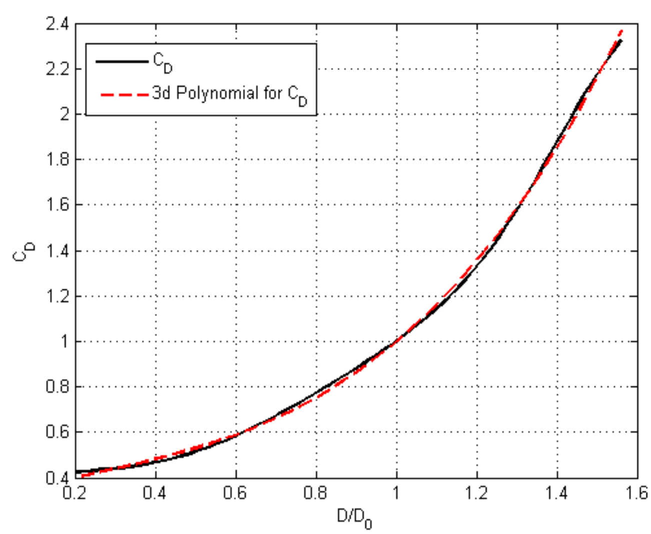

Fig. 10. C_D parameter changes with fitted curve output.

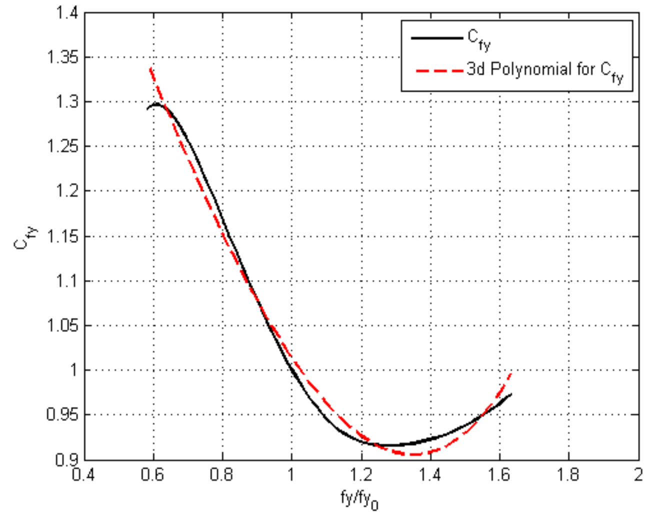

Fig. 11. Changes in the C_{fy} parameter with the output of the fitted curve.

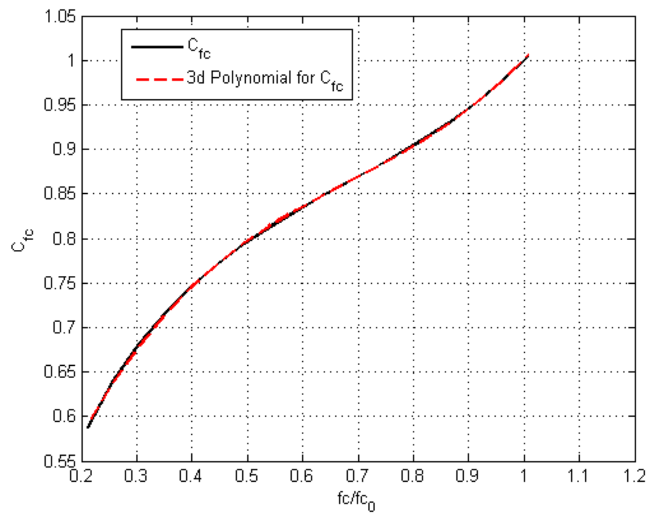

Fig. 12. Changes in the C_{fc} parameter with the output of the fitted curve.

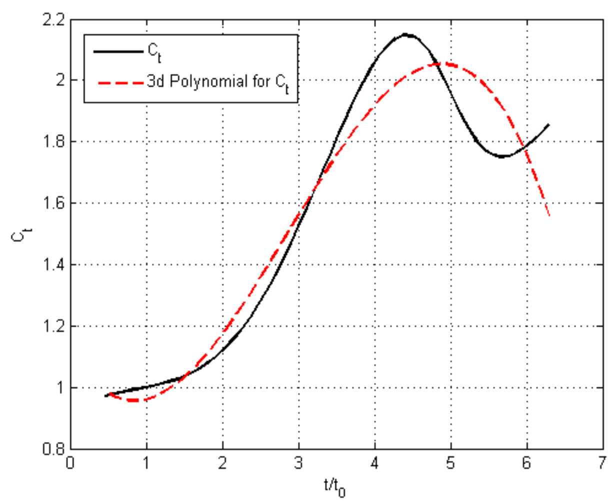

Fig. 13. Changes in the C_t parameter with the output of the fitted curve.

Now obtain the changes of the parameters of the reference data on the output and fit a 3rd-degree polynomial to it and the results are obtained as (Figs. 11-13). After plotting the fitted curve diagrams, the coefficients are obtained as shown in Table 3.

Table 3
The resulting coefficients of the fitted curve.

C_L	0.6791	- 2.0991	3.2727	- 0.8718
C_D	- 0.1075	0.4574	- 0.6396	1.2709
Ct	-0.0426	0.2361	0.0801	0.7083
C_{fc}	- 0.0108	- 0.1318	0.8368	0.3034
C_{fy}	3.8576	- 7.0833	4.2939	- 0.0420

Finally, by fitting the 3rd order curve to the diagrams (9), (10), (11), (12), (13) and according to the coefficients produced in Table 3, the governing equations are obtained as follows:

$$C_L = 0.6791(L/L_0)^3 - 2.0991(L/L_0)^2 + 3.2727(L/L_0) - 0.8918 \quad (3)$$

$$C_D = -0.1075(D/D_0)^3 + 0.4574(D/D_0)^2 - 0.6396(D/D_0) + 1.2709 \quad (4)$$

$$C_t = -0.0426(t/t_0)^3 + 0.2361(t/t_0)^2 + 0.0801(t/t_0) + 0.7083 \quad (5)$$

$$C_{fc} = -0.0108(fc/fc_0)^3 - 0.1318(fc/fc_0)^2 + 0.8368(fc/fc_0) + 0.3034 \quad (6)$$

$$C_{fy} = 3.8576(fy/fy_0)^3 - 7.0833(fy/fy_0)^2 + 4.2939(fy/fy_0) - 0.0420 \quad (7)$$

5.2. Validation

To validate the developed network and the proposed equation, a comparison between the aforementioned algorithms and experimental values was made and the results was tabulated in Figs. 14 and 15.

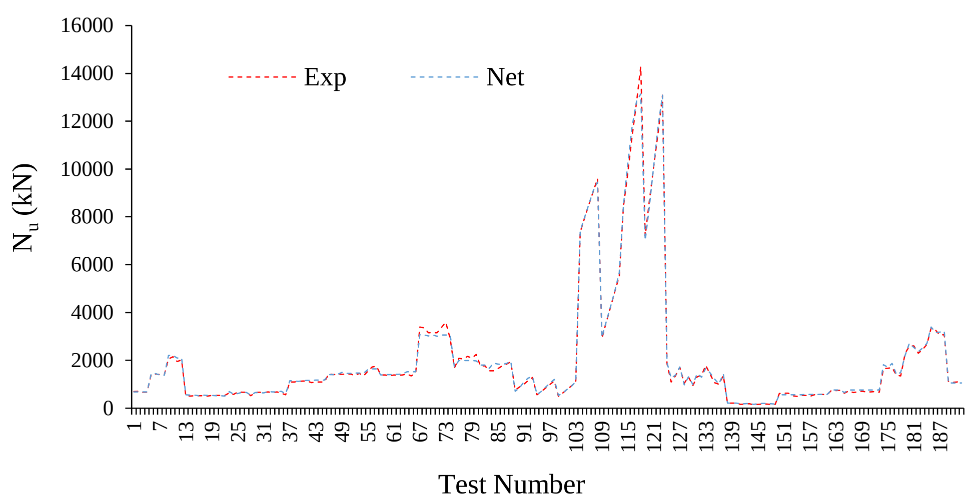

Fig. 14. Comparison of the developed network vs. the experimental values.

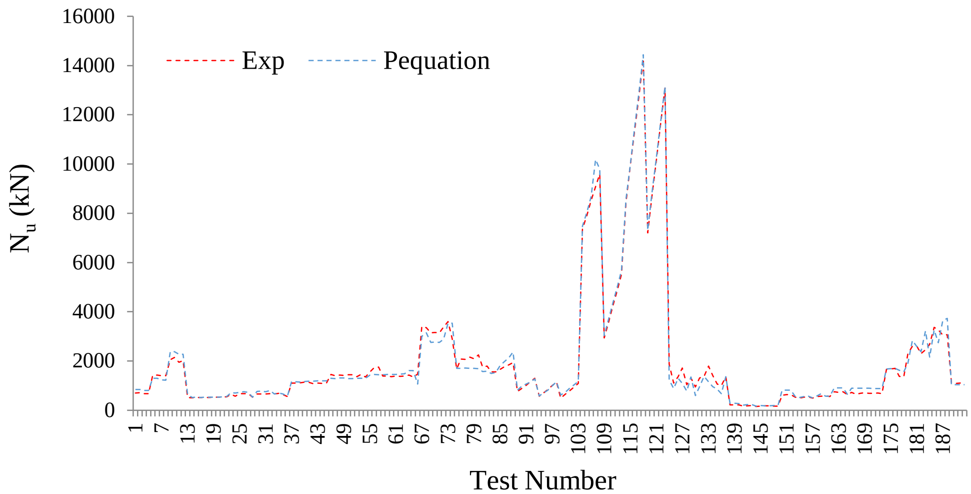

Fig. 15. Comparison of developed formula vs. the experimental values.

Using Equation (8), we can obtain the error rate for the network and the proposed relation. The mean error difference is the sum of the mean error that can be seen in the two Figs (14) and (15) based on experimental tests.

$$Err = ((|N_m - N_{exp}|)/N_{exp}) \times 100 \tag{8}$$

where *Err* is error percentage; N_m is the ultimate capacity of the models and N_{exp} is the actual ultimate capacity of the columns. The average error rate of the proposed network-based model according to 192 experimental data is equal to 95.4% and the average error of the proposed relationship is 10.45%, 63 of the data with an error of less than 4%, and 100 cases predict with an error of less than 10%, which means that the proposed relationship predicts 52% of the data with an error below 10% and is highly desirable. Therefore, the proposed equation can predict the axial compressive capacity of the CCFST column with appropriate accuracy.

5.3. Equations compared to existing ones

Figs. 16 and 17 show the strengths and proficiency of the proposed models as well as proposed by Eurocode 4 and AISC 2010. Figs. 16 and 17 allow us to draw the conclusion that the offered formulas, which are based on the ANN model, have a precise accuracy. The generated formulae may produce the most accurate results among others because the same samples were used. However, the offered equations show the highest precision during testing since the utilized samples were not taken into account when formulas were developed. Given this, the suggested formulas may provide an accurate and useful evaluation of the ultimate strength of CCFST columns.

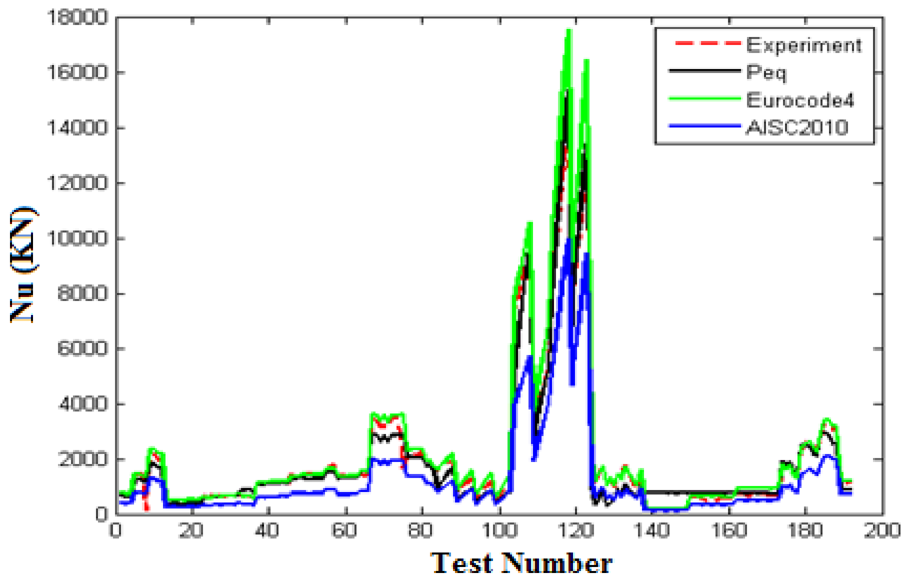

Fig. 16. Comparison of existing codes provisions vs. the experimental values.

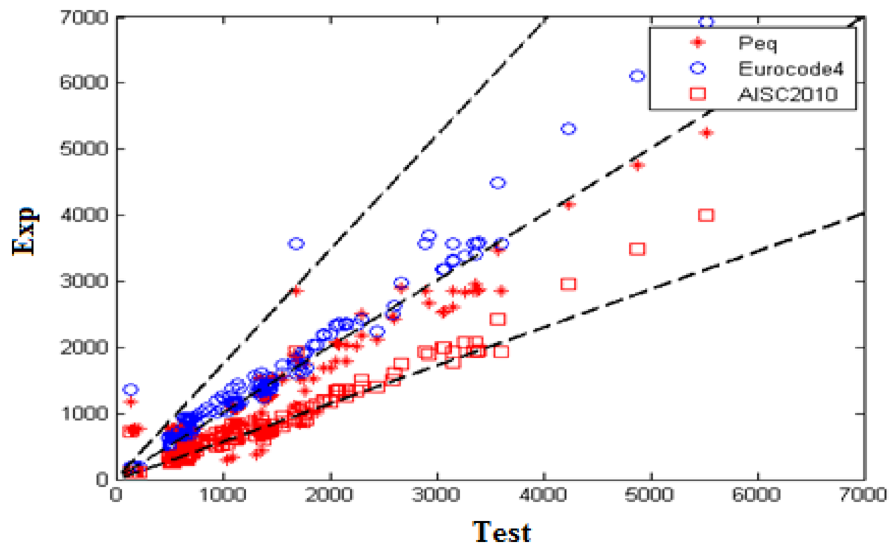

Fig. 17. Comparison of existing codes provisions vs. the experimental values.

6. Conclusions

The study referred to above led to the following conclusions:

1- It is very important to use a large number of laboratory data, of which a total of 192 column samples are considered. Because ANN algorithms create coordination between variables, and in the network training phase, it is adapted based on the match between input and output, until the desired output is matched. Therefore, the breadth of data plays an important role.

2- The network used in this research for education is the post-publication network. The ability of the algorithms of this network to reduce the total square of errors in each iteration is desirable and is the fastest training algorithm for neural networks.

3- To select the optimal neuron, change the number of neurons between 3 and 15 neurons and measure the 13 networks created based on the maximum regression close to 1 and the minimum square mean error close to zero, and the best network with 12 We select the neurons.
4- The output of the network with 12 neurons and based on 192 laboratory data for training, validation and testing data is very consistent with the output of laboratory data and the number of correlations is 0.99811, 0.99743, and 0.99606, respectively. It is clear that this correlation coefficient is higher than 0.99 for all cases and is very suitable.
5- Using the neural network results and based on the proposed Leung model [10], the proposed relation for the final axial load capacity of the CCFST column was proposed and validated. Also, the average error rate of the proposed model based on the network according to 192 basic laboratory data is equal to 95.4% and the average error of the proposed relationship is 10.45%, which is 63 cases of data with an error of less than 4%. And predicts 100 items with an error of less than 10%, which means that the proposed relationship predicts 52% of the data with an error of less than 10% and is highly desirable. Therefore, the proposed equation can obtain the axial bearing capacity of CCFST columns with very appropriate accuracy.

Conflicts of Interest

The authors declare no conflict of interest.

Authors Contribution Statement

Yasser Sharifi: Conceptualization; Ehsan Karamizadeh: Data curation; SA: Formal analysis; FA, SA: Investigation; FA, SA: Methodology; Mohamad Reza Javaheri-Tafti: FA: Resources; Ehsan Karamizadeh: Software; Yasser Sharifi: Supervision; FA, SA: Validation; Mohamad Reza Javaheri-Tafti: Visualization; Ehsan Karamizadeh, Mohamad Reza Javaheri-Tafti: Roles/Writing – original draft; Yasser Sharifi: Writing – review & editing.

References

[1] Kheyroddin A, Naderpour H, Ahmadi M. Compressive Strength of Confined Concrete in CCFST Columns. J Rehabil Civ Eng 2014;2:106–13. https://doi.org/10.22075/jrce.2014.12.

[2] Chitawadagi M V., Narasimhan MC, Kulkarni SM. Axial strength of circular concrete-filled steel tube columns — DOE approach. J Constr Steel Res 2010;66:1248–60. https://doi.org/10.1016/j.jcsr.2010.04.006.

[3] Fakharian P, Rezazadeh Eidgahee D, Akbari M, Jahangir H, Ali Taeb A. Compressive strength prediction of hollow concrete masonry blocks using artificial intelligence algorithms. Structures 2023;47:1790–802. https://doi.org/10.1016/j.istruc.2022.12.007.

[4] Ahmadi M, Naderpour H, Kheyroddin A. ANN Model for Predicting the Compressive Strength of Circular Steel-Confined Concrete. Int J Civ Eng 2017;15:213–21. https://doi.org/10.1007/s40999-016-0096-0.

[5] Sharifi Y, Lotfi F, Moghbeli A. Compressive Strength Prediction Using the ANN Method for FRP Confined Rectangular Concrete Columns. J Rehabil Civ Eng 2019;7:134–53. https://doi.org/10.22075/jrce.2018.14362.1260.

[6] Ghanizadeh AR, Ghanizadeh A, Asteris PG, Fakharian P, Armaghani DJ. Developing bearing capacity model for geogrid-reinforced stone columns improved soft clay utilizing MARS-EBS hybrid method. Transp Geotech 2023;38:100906. https://doi.org/10.1016/j.trgeo.2022.100906.
[7] Sharifi Y, Tohidi S. Lateral-torsional buckling capacity assessment of web opening steel girders by artificial neural networks — elastic investigation. Front Struct Civ Eng 2014;8:167–77. https://doi.org/10.1007/s11709-014-0236-z.
[8] Sharifi Y, Tohidi S. Ultimate capacity assessment of web plate beams with pitting corrosion subjected to patch loading by artificial neural networks. Adv Steel Constr 2014;10:325–50.
[9] Tohidi S, Sharifi Y. A new predictive model for restrained distortional buckling strength of half-through bridge girders using artificial neural network. KSCE J Civ Eng 2016;20:1392–403. https://doi.org/10.1007/s12205-015-0176-8.
[10] Tohidi S, Sharifi Y. Load-carrying capacity of locally corroded steel plate girder ends using artificial neural network. Thin-Walled Struct 2016;100:48–61. https://doi.org/10.1016/j.tws.2015.12.007.
[11] Sharifi Y, Moghbeli A, Hosseinpour M, Sharifi H. Neural networks for lateral torsional buckling strength assessment of cellular steel I-beams. Adv Struct Eng 2019;22:2192–202. https://doi.org/10.1177/1369433219836176.
[12] Sharifi Y, Moghbeli A, Hosseinpour M, Sharifi H. Study of Neural Network Models for the Ultimate Capacities of Cellular Steel Beams. Iran J Sci Technol Trans Civ Eng 2020;44:579–89. https://doi.org/10.1007/s40996-019-00281-z.
[13] Sharifi Y, Hosseinpour M, Moghbeli A, Sharifi H. Lateral Torsional Buckling Capacity Assessment of Castellated Steel Beams Using Artificial Neural Networks. Int J Steel Struct 2019;19:1408–20. https://doi.org/10.1007/s13296-019-00217-3.
[14] Hosseinpour M, Sharifi Y, Sharifi H. Neural network application for distortional buckling capacity assessment of castellated steel beams. Structures 2020;27:1174–83. https://doi.org/10.1016/j.istruc.2020.07.027.
[15] Sharifi Y, Moghbeli A. Shear capacity assessment of steel fiber reinforced concrete beams using artificial neural network. Innov Infrastruct Solut 2021;6:89. https://doi.org/10.1007/s41062-021-00457-5.
[16] Khademi A, Behfarnia K, Kalman Šipoš T, Miličević I. The Use of Machine Learning Models in Estimating the Compressive Strength of Recycled Brick Aggregate Concrete. Comput Eng Phys Model 2021;4:1–25. https://doi.org/10.22115/cepm.2021.297016.1181.
[17] Ghanizadeh AR, Delaram A, Fakharian P, Armaghani DJ. Developing Predictive Models of Collapse Settlement and Coefficient of Stress Release of Sandy-Gravel Soil via Evolutionary Polynomial Regression. Appl Sci 2022;12:9986. https://doi.org/10.3390/app12199986.
[18] Naderpour H, Sharei M, Fakharian P, Heravi MA. Shear Strength Prediction of Reinforced Concrete Shear Wall Using ANN, GMDH-NN and GEP. J Soft Comput Civ Eng 2022;6:66–87. https://doi.org/10.22115/SCCE.2022.283486.1308.
[19] Rezazadeh Eidgahee D, Jahangir H, Solatifar N, Fakharian P, Rezaeemanesh M. Data-driven estimation models of asphalt mixtures dynamic modulus using ANN, GP and combinatorial GMDH approaches. Neural Comput Appl 2022;34:17289–314. https://doi.org/10.1007/s00521-022-07382-3.
[20] Naderpour H, Rezazadeh Eidgahee D, Fakharian P, Rafiean AH, Kalantari SM. A new proposed approach for moment capacity estimation of ferrocement members using Group Method of Data Handling. Eng Sci Technol an Int J 2020;23:382–91. https://doi.org/10.1016/j.jestch.2019.05.013.
[21] Sharifi Y, Hosainpoor M. Compressive Strength Assessment of Concrete Containing Metakaolin Using ANN. J Rehabil Civ Eng 2020;8:15–27. https://doi.org/10.22075/jrce.2020.19043.1358.

[22] Naderpour H, Rafiean AH, Fakharian P. Compressive strength prediction of environmentally friendly concrete using artificial neural networks. J Build Eng 2018;16:213–9. https://doi.org/10.1016/j.jobe.2018.01.007.

[23] Naderpour H, Nagai K, Fakharian P, Haji M. Innovative models for prediction of compressive strength of FRP-confined circular reinforced concrete columns using soft computing methods. Compos Struct 2019;215:69–84. https://doi.org/10.1016/j.compstruct.2019.02.048.

[24] Tohidi S, Sharifi Y. Neural networks for inelastic distortional buckling capacity assessment of steel I-beams. Thin-Walled Struct 2015;94:359–71. https://doi.org/10.1016/j.tws.2015.04.023.

[25] Tohidi S, Sharifi Y. Inelastic lateral-torsional buckling capacity of corroded web opening steel beams using artificial neural networks. IES J Part A Civ Struct Eng 2015;8:24–40. https://doi.org/10.1080/19373260.2014.955139.

[26] O'Shea MD, Bridge RQ. Design of Circular Thin-Walled Concrete Filled Steel Tubes. J Struct Eng 2000;126:1295–303. https://doi.org/10.1061/(ASCE)0733-9445(2000)126:11(1295).

[27] Yu Z, Ding F, Cai CS. Experimental behavior of circular concrete-filled steel tube stub columns. J Constr Steel Res 2007;63:165–74. https://doi.org/10.1016/j.jcsr.2006.03.009.

[28] Gupta PK, Sarda SM, Kumar MS. Experimental and computational study of concrete filled steel tubular columns under axial loads. J Constr Steel Res 2007;63:182–93. https://doi.org/10.1016/j.jcsr.2006.04.004.

[29] Giakoumelis G, Lam D. Axial capacity of circular concrete-filled tube columns. J Constr Steel Res 2004;60:1049–68. https://doi.org/10.1016/j.jcsr.2003.10.001.

[30] Abed F, AlHamaydeh M, Abdalla S. Experimental and numerical investigations of the compressive behavior of concrete filled steel tubes (CFSTs). J Constr Steel Res 2013;80:429–39. https://doi.org/10.1016/j.jcsr.2012.10.005.

[31] Yu Q, Tao Z, Wu Y-X. Experimental behaviour of high performance concrete-filled steel tubular columns. Thin-Walled Struct 2008;46:362–70. https://doi.org/10.1016/j.tws.2007.10.001.

[32] Ellobody E, Young B, Lam D. Behaviour of normal and high strength concrete-filled compact steel tube circular stub columns. J Constr Steel Res 2006;62:706–15. https://doi.org/10.1016/j.jcsr.2005.11.002.

[33] Leung CK, Ng MY, Luk HC. Empirical Approach for Determining Ultimate FRP Strain in FRP-Strengthened Concrete Beams. J Compos Constr 2006;10:125–38. https://doi.org/10.1061/(ASCE)1090-0268(2006)10:2(125).