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AXIAL STRENGTH PREDICTION OF SQUARE CFST COLUMNS BASED ON THE ANN MODEL

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Abstract:

Due to numerous advantages, concrete-filled steel tubular (CFST) columns have an increasingly important role in the civil engineering industry. Because of the expensive experimental testing of these members, it is beneficial to provide prognostic models. In this study, an artificial neural network (ANN) model for predicting the axial compressive strength of square CFST columns has been developed. A dataset of 1022 samples (685 stub columns and 337 slender columns) was collected from available literature in order to compare the accuracy of the fast predictive Levenberg-Marquardt algorithm (LM) and Eurocode 4 (EC4) design code. Analyses showed that the ANN model has better accuracy than EC4. Over a whole domain, the ANN model has higher coefficient of determination (R^2), and lower root mean squared error (RMSE). The same conclusion is valid when two separate datasets are considered: one for stub columns and the other for slender columns. The benefit of the ANN model is its applicability in a broader range of column parameters. At the same time, EC4 puts several limitations on its use and gives satisfactory results only in limited circumstances. Empirical equations have also been proposed from the best ANN model, which is useful for engineering practice.

Keywords: machine learning, artificial neural network, Levenberg-Marquardt algorithm, backpropagation, Eurocode 4, empirical equations

1. Introduction

In recent years, artificial intelligence (AI) and machine learning (ML) techniques have found increasing application in many research areas. In the first place, the reasons for that are less computational efforts for solving different kinds of problems and good correspondence between price and required performance, which may be a very significant obstacle in some branches.

Many authors have tried to implement various AI techniques to predict the ultimate compressive strength of rectangular or circular concrete-filled steel tubular (CFST) columns. ML algorithms such as Decision tree (DT) and Random forest (RF) were employed by Đorđević and Kostić [1] for the prediction of circular CFST columns, but with a relatively small amount of data (236 stub columns and 272 slender columns), and with coefficients of determination (R^2) of 0.989 and 0.985 for stub and slender columns, respectively. For the same problem, efficient implementation of artificial neural networks (ANN) was done by Zarringol et al. [2] with better performance for circular than for rectangular columns, but with two hidden layers. Also, Zarringol et al. [3] made analyses with a different number of neurons in one hidden layer using ANN and support vector regression (SVR). Vu et al. [4] developed a gradient tree boosting (GTB) predictive algorithm with similar size of a dataset as in our study (1017 samples) and compared it with the support vector machines (SVM), RF and DT models with obtained (R^2) values of 0.999, 0.965, 0.971, 0.963 respectively for all data. Additional alternative methods for successful determination of the axial capacity of CFST columns, such as fuzzy logic (FL) or multivariate adaptive regression splines (MARS), were recommended by Moon et al. [5] and Luat et al. [6], but with a small database in both cases (123 and 141 samples). This work aims to develop a fast and efficient prognostic model using ANNs with the Levenberg-Marquardt (LM) algorithm, whose accuracy for the prediction of square CFST columns may exceed the current limitations given by Eurocode 4 (EC4). Besides, the empirical equations obtained from the most suitable ANN model are proposed.

2. Dataset description

In order to compare the results of two different approaches for calculation of ultimate compressive strength of square CFST columns and appropriate training and testing of developed ANN models, an experimental dataset with 1022 samples is collected from the available literature. A larger part of the database was extracted from Denavit [7] (470 samples), and Thai et al. [8] (263 samples), and the other parts were from Goode [9] (166 samples) and Belete [10] (123 samples).

The database consists of the samples exposed to pure compression only, without load eccentricity and steel reinforcement.

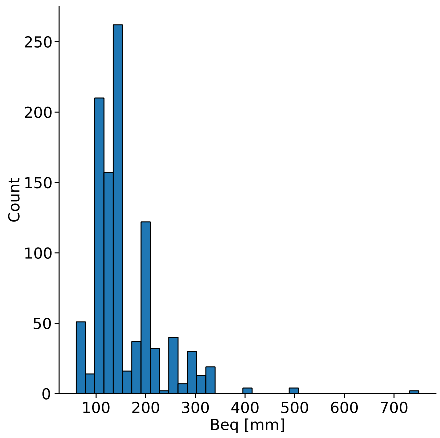
Table 1 shows the ranges and distributions of parameters B_{eq}, t, L, f_y, f_c' in the experimental tests. Values of square section width (B_{eq}), the thickness of the steel tube (t), length of column (L), steel yield stress (f_y) and concrete compressive strength (f_c'), are in the range: 60-750 mm, 0.7-16 mm, 180-4500 mm, 115-835 MPa, 6.99-164.1 MPa, respectively. As can be seen, the database contains a broad range of test samples, according to both geometric and material properties. It is important to note that some references reported concrete compressive strength obtained from the cube samples (f_{cu}). In that case, these values are converted to a cylinder (f_c') using the equation proposed by L'Hermite [11]:

$$f_c' = \left[0.76 + 0.21 \cdot log_{10}(f_{cu} / 19.6)\right] \cdot f_{cu} \tag{1}$$

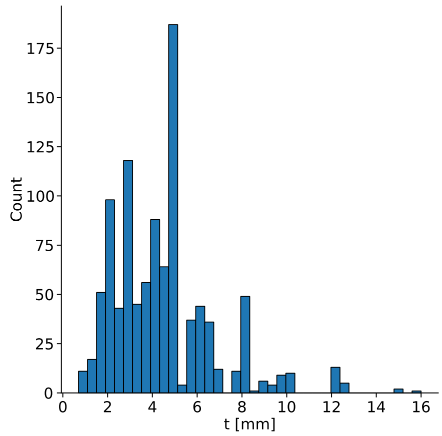
Parameter	Unit	Mean	Std.Dev.	Min.	Max.
B_{eq}	mm	157.71	70.32	60	750
t	mm	4.47	2.25	0.70	16
L	mm	936.85	859.47	180	4500
f_y	MPa	388.22	162.06	115	835
f_c'	MPa	52.10	31.01	6.99	164.1
N_{exp}	kN	2318.13	2302.55	105.40	24294

Table 1. Range and distribution of test parameters

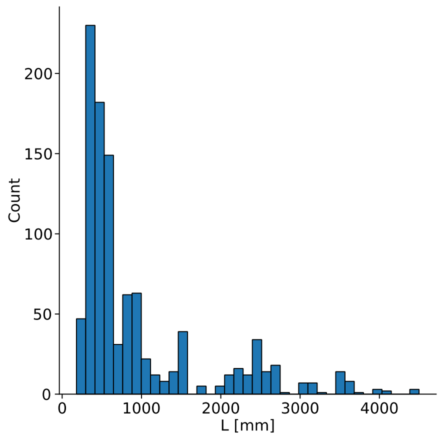
Figure 1 illustrates the distribution of the parameters through histograms of the dataset. It is visible from the Figure 1, that the highest density of the data for each parameter fulfils the Eurocode 4 (EC4) requirements for mechanical and geometric properties.



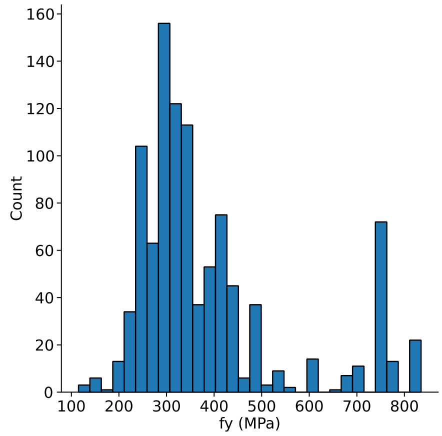
(a) B_{eq} [mm]



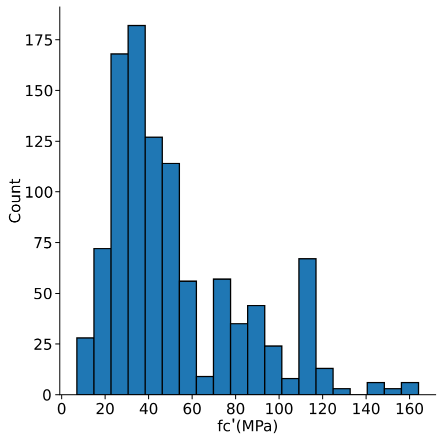
(b) t [mm]



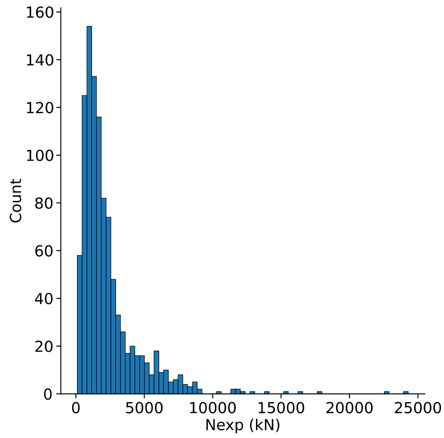
(c) L [mm]



(d) f_y [MPa]



(e) f_c' [MPa]



(f) N_{exp} [kN]

Figure 1. Distribution of dataset parameters

Goode [9] and Thai et al. [8] proposed conditions to separate CFST members into stub and slender columns. Square CFST members belong to the stub columns for length-to-width ratio less or equal to 4 (i.e. $L/B_{eq} \leq 4$) and to slender columns for the ratio higher than 4 (i.e. $L/B_{eq} > 4$). Since each of the parameters from the database has different units and ranges, before training the artificial neural networks (ANNs) it is recommended to normalize the data in a preprocessing phase to avoid favouritism of the parameters with a greater range as in [3].

Following the applied activation function in the ANN model, features were normalized to lie in the range between -1 and 1 using the mapminmax function [12]:

$$y = (y_{max} - y_{min}) \cdot (x - x_{min}) / (x_{max} - x_{min}) + y_{min} \tag{2}$$

where y is a normalized value of x, x_{max} and x_{min} are maximum and minimum original values, y_{max} and y_{min} are expected maximum and minimum values, 1 and -1.

3. Methodology

3.1 Eurocode 4

Eurocodes are a series of standards that provide different procedures for designing buildings, structural members, etc. EC4 [13] design code is referenced in this work, related to the design of composite structures, which are the subject of this research. The plastic resistance to compression $N_{pl,Rd}$ for rectangular and square columns, defined in Section 2, is calculated according to the EC4 provisions as follows:

$$N_{pl,Rd} = A_s \cdot f_y + A_c \cdot f_c' \tag{3}$$

where A_s and A_c are the area of the structural steel section and cross-sectional area of concrete, respectively.

The design value of ultimate compressive strength N_u^{EC4} should satisfy the following condition:

$$N_u^{EC4} = \chi \cdot N_{pl,Rd} \tag{4}$$

where χ is the reduction factor for the flexural buckling mode, defined as:

$$\chi = 1 / [\Phi + \sqrt{\Phi^2 - \bar{\lambda}^2}\,] \leq 1 \tag{5}$$

Parameter Φ and the relative slenderness $\bar{\lambda}$ are calculated as:

$$\Phi = 0.5 \cdot [1 + 0.21 \cdot (\bar{\lambda} - 0.2) + \bar{\lambda}^2] \tag{6}$$

$$\bar{\lambda} = \sqrt{N_{pl,Rd} / N_{cr}} \tag{7}$$

where N_{cr} is elastic critical force for flexural buckling mode calculated with the effective flexural stiffness EI_{eff} obtained without reinforcement steel.

$$EI_{eff} = E_s \cdot I_s + 0.6 \cdot E_c \cdot I_c \tag{8}$$

One of the mentioned limitations of the EC4 is that steel contribution ratio δ should satisfy the following conditions:

$$0.2 \leq \delta = A_s \cdot f_y / N_{pl,Rd} \leq 0.9 \tag{9}$$

According to the Eurocode 4 (EC4) provisions, Table 2 presents geometrical and mechanical limitations for estimating the axial compressive strength of CFST columns. The first limitation from Table 2 refers to the condition when the local buckling of the steel tube can be neglected.

Design code	Equation	Limitation
Eurocode 4 (EC4)	$N_{pl,Rd} = A_s \cdot f_y + A_c \cdot f_c^{'}$	$B_{eq}/t \leq 52 \cdot \sqrt{235/f_y}$
		$235 \leq f_y \leq 460\ MPa$
		$20 \leq f_c^{'} \leq 50\ MPa$
		$0.2 \leq \delta \leq 0.9$

Table 2. Ranges of the geometric and mechanical properties in EC4 design code

3.2 Artificial neural networks

People have strived to create intelligent devices using the human nervous system as a model for many years. The first system based on the principle of the nervous system was applied by McCulloch and Pitts [14]. Further development was accompanied by constructing a multilayer neural network, the so-called multilayer perceptron, which was used in this work [15]. The basic structure of the artificial neural network consists of three layers, input, hidden and output layers with the corresponding number of neurons. The number of layers and neurons determines the model's performance and may be the possible cause of potential overfitting with a low training error and high testing error. In general, to develop a model with the best performance, firstly, it is necessary to tune the hyperparameters using the trial-and-error method.

Within the hidden layers, it is necessary to define the activation function, thus obtaining the following connection between the neurons in a feed-forward network:

$$z_i^l = \sum_{k=1}^{m} w_{ik}^l \cdot a_k^{l-1} + b_i^l \tag{10}$$

$$a_i^l = f^l(z_i^l) \tag{11}$$

where z_i^l is the input signal in the current layer l, w_{ik}^l are the weights, a_k^{l-1} are the outputs from the previous layer, b_i^l are the biases of the current layer and a_i^l is an output signal.

Tuning the hyperparameters according to the Levenberg-Marquardt (LM) algorithm is described in the following section.

3.3 Levenberg-Marquardt algorithm

The Levenberg-Marquardt (LM) algorithm belongs to the high-performance algorithms based on the numerical optimization technique such as conjugate gradient and quasi-Newton methods. LM is several times faster than a classic backpropagation (BP) algorithm based on gradient descent. Opposed to a standard BP algorithm, LM was designed to skip the calculation of the second-order derivatives of the Hessian matrix, using an approximation with the first-order (Jacobian) matrix, and update the network as follows [16]:

$$x_{k+1} = x_k - [J^T \cdot J + \mu \cdot I]^{-1} \cdot J^T \cdot e \tag{12}$$

where J - Jacobian matrix, μ - adaptive (damping) parameter, I – identity matrix, $J^T \cdot e$ – gradient, x_k – current value of variable x, x_{k+1} – updated value of variable x

Besides the damping parameter μ, two additional and important parameters (μ_{inc} and μ_{dec}) allow the reduction of performance function at each iteration. The ANN was trained with the dataset divided into the training, validation and test set with the following percentage amount of data (70%, 15%, 15%). The hyperparameters of the best neural network, tuned by a random search and by detecting the error in the validation set are:

- Architecture of the network: 5-12-1
- Activation functions: hyperbolic-tangent for the hidden layer and linear for the output layer

- μ=0.1, μ_{dec}=0.01, μ_{inc}=10

Activation functions used for hidden and output layers are shown in the following equations:

$$f(x) = (e^{x} - e^{-x}) / (e^{x} + e^{-x}) \tag{13}$$

$$f(x) = x \tag{14}$$

During the analysis of different ANN models, several sets of hyperparameters and architectures were examined, and the best three architectures, according to the error values of the validation set, were further explored (5-10-1, 5-12-1, 5-14-1). A detailed description of the search for an appropriate model is described in Section 5. Figure 2 graphically presents the adopted artificial neural network architecture with one hidden layer and 12 neurons, finally endorsed by measuring the performance function of the test set. Figure 3 shows applied activation functions for the hidden and the output layers. The input features are parameters B_{eq}, t, L, f_y, f_c', as explained before in the text.

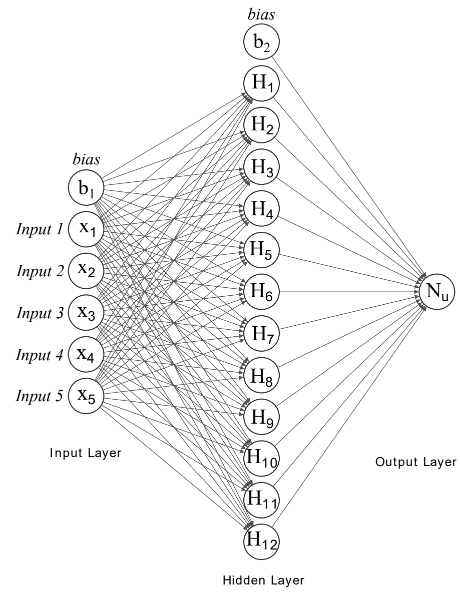
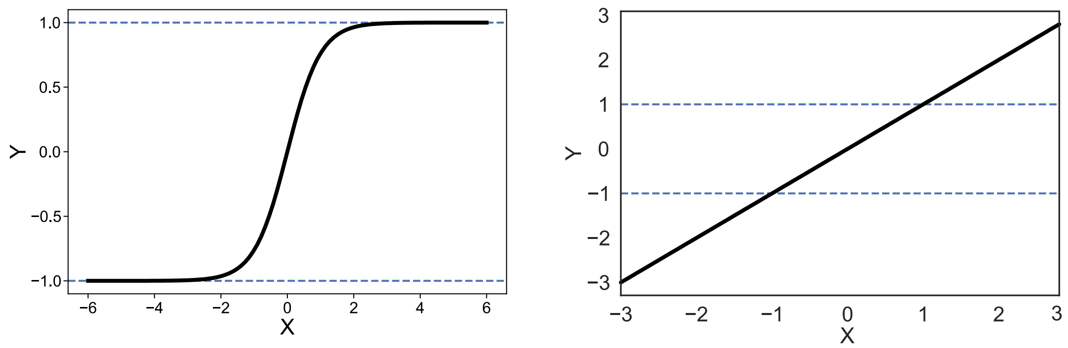


Figure 2. The architecture of the ANN model



(a) Hyperbolic tangent (b) Linear

Figure 3. Activation functions: (a) for the hidden layer and (b) for the output layer

4. Quality evaluation

For evaluation of the performance of the best ANN model and comparison with the EC4 design code, the performance functions: coefficient of determination (R^2) as a square of a linear correlation coefficient, mean squared error (MSE), and root mean squared error (RMSE) are calculated:

$$R^2 = \left(\frac{n \cdot \sum_{i=1}^{n}(y_i \cdot \bar{y}_i) - \sum_{i=1}^{n} y_i \cdot \sum_{i=1}^{n} \bar{y}_i}{\sqrt{\left[n \cdot (\sum_{i=1}^{n} y_i^2) - (\sum_{i=1}^{n} y_i)^2\right] \cdot \left[n \cdot (\sum_{i=1}^{n} \bar{y}_i^2) - (\sum_{i=1}^{n} \bar{y}_i)^2\right]}} \right)^2 \tag{15}$$

$$\text{MSE} = \frac{1}{n} \cdot \sum_{i=1}^{n} (y_i - \bar{y}_i)^2 \tag{16}$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} (y_i - \bar{y}_i)^2} \tag{17}$$

where y_i is a target value, $\bar{y}_i$ is the predicted value and n is a number of samples.

These indicators express a level of agreement between the experimental and the predicted results. Namely, lower values of MSE and RMSE error and the higher value of R^2 show a better agreement with the experimental results.

5. Results

Two approaches for predicting the axial capacity of square CFST columns were used with different data subsets. Both methods are validated by comparison with the experimental results. Table 3 shows the performance scores (R^2, MSE, RMSE) for all data. It can be seen that ANN has a good performance for training, validation and test data, with a high value of R^2 and minor values of error functions.

Data	Set	R^2		MSE ($\cdot 10^{-4}$)		RMSE ($\cdot 10^{-2}$)	
		ANN	EC4	ANN	EC4	ANN	EC4
All	Training	0.984	-	6.104	-	2.471	-
	Validation	0.980	-	8.634	-	2.938	-
	Test	0.976	-	6.082	-	2.466	-
	All	0.982	0.953	6.480	20.789	2.546	4.559

Table 3. Performance scores of ANN and EC4 for all data

The power of the LM algorithm is visible from the diagram of performance functions for training, test and validation data in Figure 4 and where all functions are very close to each other. Figure 5(a) shows the error distribution. The error values are very close to zero for the significant part of data.

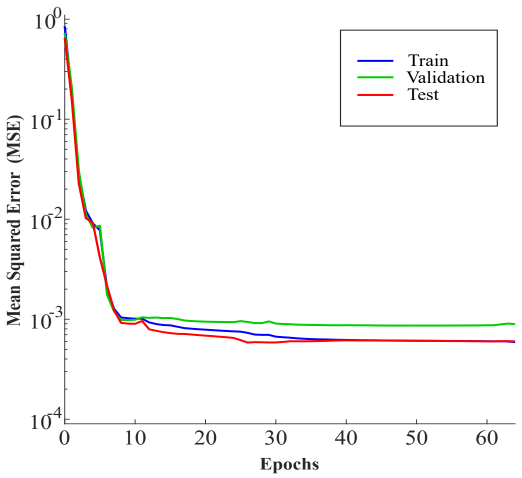
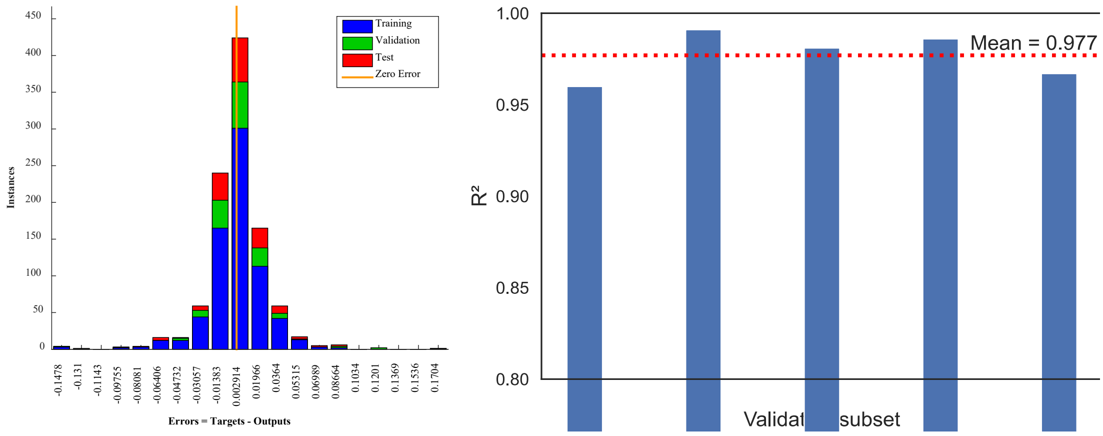


Figure 4. Performance functions of the best ANN model

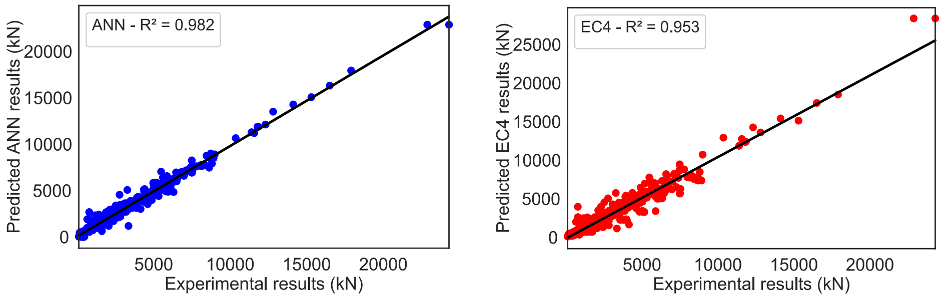
By looking for a relevant ANN model with associated hyperparameters, there is a tendency to reduce the bias of the training set. In the phase of tuning the hyperparameters, the initial dataset was divided into the five subsets. In each step, one subset was used for validation and the other four for building the model. With the appropriate number of repetitions of this action, the average performance of the validation set was obtained. The whole procedure is illustrated in Figure 5(b), with marked coefficients of determination (R^2) for the selected set of hyperparameters. Even with certain oscillations of the R^2 value for each subset, the model maintained a high global accuracy.



(a) Error distribution (b) Validation subset R^2

Figure 5. Performance of the best ANN model: (a) error distribution and (b) validation subset R^2

Figure 6 illustrates the regression lines for the whole dataset of 1022 samples, with coefficients of determination presented in Table 3. Obviously, the ANN model with LM algorithm better agrees with experimental results ($R^2 = 0.982$) than EC4 equations ($R^2 = 0.953$), with lower value of the MSE and RMSE errors.



(a) ANN model (b) EC4

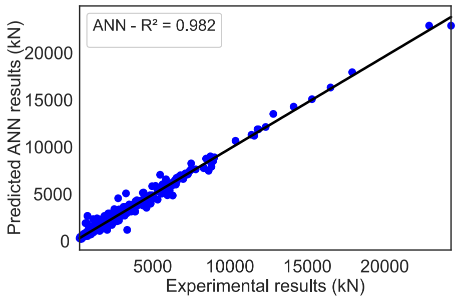
Figure 6. Regression lines for axial capacity of all data: (a) ANN model and (b) EC4

Under conditions for a categorization of stub and slender columns given in Section 2, Table 4 shows the performance scores of the adopted ANN model when the dataset is split into two datasets: one for stub columns and one for slender columns. For both types of columns, the ANN model gives more accurate results than EC4. This is especially significant for slender columns. A similar conclusion about the performance of the EC4 design code is proposed by Đorđević and Kostić [1] and Nguyen et al. [17].

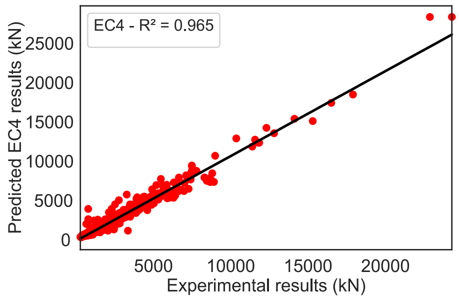
	Stub columns		Slender columns	
Score	ANN	EC4	ANN	EC4
R^2	0.982	0.965	0.976	0.901
MSE ($\cdot 10^{-4}$)	7.765	21.707	3.867	18.925
RMSE ($\cdot 10^{-2}$)	2.787	4.659	1.966	4.350

Table 4. Performance scores of ANN and EC4 for stub and slender columns

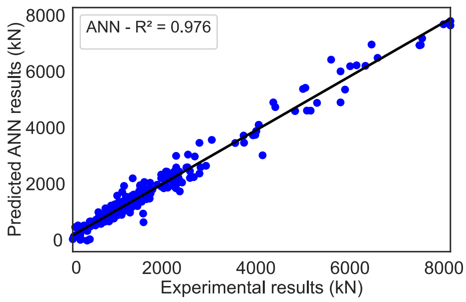
Significant improvement in the prediction of the column axial strength obtained by the ANN model compared to EC4 is visible in Figure 7. This figure illustrates the results from Table 4, and presents the model's accuracy for predicting the compressive strength of stub (685 samples) and slender (337 samples) columns. An important note is that only 276 samples meet all of the EC4 requirements given in Table 2, but even for that narrow range of data, the ANN model has better accuracy ($R^2 = 0.985$) than the EC4 design code ($R^2 = 0.979$).



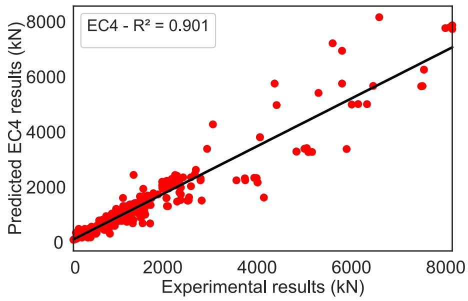
(a) ANN model – stub columns



(b) EC4 – stub columns



(c) ANN model – slender columns



(d) EC4 – slender columns

Figure 7. Regression lines for axial capacity: (a) ANN model – stub columns, (b)EC4 – stub columns, (c) ANN model – slender columns and (d) EC4 – slender columns

The weights and biases obtained by the artificial neural network model with the best performances are used for the expressions of axial capacity. This equation can be used for a wider range of the input parameters than equations recommended by EC4 design code. Empirical equations are given below.

5.1 Empirical equations

In this section, the proposed empirical equations from the best trained ANN model for the calculation of the axial strength of CFST columns (N_u^{ANN}) are presented.

$$N_u^{ANN} = N_{u,1\text{-}6}^{ANN} + N_{u,7\text{-}10}^{ANN} + N_{u,11\text{-}b}^{ANN} \tag{18}$$

$$\mathrm{N}_{\mathrm{u},1\text{-}6}^{\mathrm{ANN}} = 0.36942 \cdot H_1' + 0.17561 \cdot H_2' + 0.85246 \cdot H_3' + 2.11462 \cdot H_4' + 0.25185 \cdot H_5' - 0.75579 \cdot H_6' \tag{19}$$

$$N^{ANN}_{u,7\text{-}10} = -0.72015 \cdot H'_7 - 0.28088 \cdot H'_8 + 0.03985 \cdot H'_9 - 0.22153 \cdot H'_{10} \tag{20}$$

$$N^{ANN}_{u,11\text{-}b} = -0.64204 \cdot H'_{11} + 0.29962 \cdot H'_{12} - 0.19279 \tag{21}$$

$$H'_1 = Tanh(-2.99785 \cdot B_{eq} + 0.03824 \cdot t + 2.30045 \cdot L - 1.22101 \cdot f_y - 1.41724 \cdot f'_c + 1.74681) \tag{22}$$

$$H'_2 = Tanh(0.22214 \cdot B_{eq} - 1.07706 \cdot t - 0.28860 \cdot L + 1.93483 \cdot f_y + 1.57035 \cdot f'_c + 1.25465) \tag{23}$$

$$H'_3 = Tanh(-3.19831 \cdot B_{eq} + 0.19453 \cdot t + 1.49455 \cdot L - 0.26289 \cdot f_y + 1.05999 \cdot f'_c + 2.36753) \tag{24}$$

$$H'_4 = Tanh(1.43075 \cdot B_{eq} + 0.29089 \cdot t - 0.21691 \cdot L + 0.31746 \cdot f_y + 0.38075 \cdot f'_c - 0.42691) \tag{25}$$

$$H'_5 = Tanh(-1.15582 \cdot B_{eq} - 0.59118 \cdot t - 0.32937 \cdot L + 1.44036 \cdot f_y + 0.17081 \cdot f'_c - 2.10676) \tag{26}$$

$$H'_6 = Tanh(-0.51972 \cdot B_{eq} - 1.93479 \cdot t - 0.31072 \cdot L + 0.36646 \cdot f_y - 1.54064 \cdot f'_c - 1.16398) \tag{27}$$

$$H'_7 = Tanh(-0.56840 \cdot B_{eq} - 0.83197 \cdot t - 0.00251 \cdot L + 0.46419 \cdot f_y - 0.73562 \cdot f'_c - 1.76459) \tag{28}$$

$$H'_8 = Tanh(-0.58226 \cdot B_{eq} + 0.86928 \cdot t - 0.65778 \cdot L + 0.53551 \cdot f_y + 0.73365 \cdot f'_c + 0.65797) \tag{29}$$

$$H'_9 = Tanh(-0.77780 \cdot B_{eq} - 1.36496 \cdot t - 1.56830 \cdot L - 0.83646 \cdot f_y + 1.78459 \cdot f'_c - 1.13412) \tag{30}$$

$$H'_{10} = Tanh(-2.69378 \cdot B_{eq} + 1.68626 \cdot t - 0.26690 \cdot L + 0.29521 \cdot f_y + 0.74424 \cdot f'_c - 1.93671) \tag{31}$$

$$H'_{11} = Tanh(0.73053 \cdot B_{eq} + 1.79608 \cdot t + 0.47584 \cdot L - 0.34696 \cdot f_y + 1.85566 \cdot f'_c + 1.45230) \tag{32}$$

$$H'_{12} = Tanh(-1.50786 \cdot B_{eq} + 0.14294 \cdot t - 0.25338 \cdot L + 0.14615 \cdot f_y - 1.86013 \cdot f'_c - 2.67629) \tag{33}$$

6. Conclusions

In this study, the efficient Levenberg-Marquardt algorithm was used to predict the axial capacity of square CFST columns with the application of artificial neural networks. The best ANN model was constructed according to the least measure of the performance function (error), conducted on the validation set. The proposed ANN model is stable for different subsets and conditions with high performance, and the model was verified by comparison with the experimental results.

The results show that the proposed ANN model with recommended empirical equations, based on a one-layer feed-forward network, has a significant advantage over the EC4 design code in predicting the ultimate compressive strength N_u for a wider range of data. The coefficient of determination (R^2) for all data was 0.982. Also, the results achieved for the stub and slender columns are 0.982 and 0.976. Slightly better results were obtained with a relatively restricted dataset (276 samples), that met all EC4 criteria, with the R^2 values of 0.985 for all data, 0.983 for stub and 0.989 for slender columns. Therefore, the ANN is a robust and powerful tool for predicting the axial capacity of square CFST columns.

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