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PROCENA GRANIČNE NOSIVOSTI VITKIH CCFST STUBOVA PRIMENOM VEŠTAČKIH NEURONSKIH MREŽA

Summary:

U radu je predložena primena algoritama veštačkih neuronskih mreža (ANN) za procenu granične nosivosti pri pritisku vitkih kružnih stubova od čeličnih cevi ispunjenih betonom (CCFST). Skup podataka od 1051 uzorka je primenjen za generisanje odgovarajućeg prognostičkog ANN modela. Empirijske jednačine su takođe razvijene iz najbolje neuronske mreže, a njihovi rezultati su upoređeni sa rezultatima dobijenim standardom Evrokod 4 (EC4). Analize pokazuju da se izlazni rezultati predloženog ANN modela bolje slažu sa eksperimentalnim rezultatima od onih koji su kreirani primenom odredbi EC4 standarda.

Key words: Mašinsko učenje, CFST stubovi, Empirijske jednačine, Predikcija

ESTIMATION OF ULTIMATE STRENGTH OF SLENDER CCFST COLUMNS USING ARTIFICIAL NEURAL NETWORKS

Summary:

This paper proposes the use of artificial neural network (ANN) algorithms to estimate the ultimate compressive strength of slender circular concrete-filled steel tubular (CCFST) columns. A dataset of 1051 samples was applied to generate an appropriate ANN prognostic model. Empirical equations were also developed from the best neural network, and their results were compared with those obtained by Eurocode 4 (EC4) design code. Analyses show that the proposed ANN model has a better agreement with experimental results than those created with provisions of the EC4 design code.

Key words: Machine learning, CFST columns, Empirical equations, Prediction

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1. INTRODUCTION

Machine learning (ML) is a category of artificial intelligence (AI) that contains a series of algorithms capable of adapting to certain situations and predicting outcomes with high accuracy, based on experience. ML has found applications in many branches including civil engineering.

Concrete-filled steel tubular (CFST) columns play an important role in structural engineering due to their numerous advantages. There are different guidelines for their modelling proposed by several design codes such as Eurocode 4 (EC4). To find better agreement with experimental results than the EC4 design code has, many authors have tried different approaches to predict the axial capacity of CFST columns. The efficient application of the support vector machine (SVM) and artificial neural network algorithms (ANN) for the prediction of the ultimate strength of CFST columns was proposed by Zarringol et al. [1]. Nguyen and Kim [2] recommended a hybrid particle swarm optimization-based artificial neural network (PANN) algorithm on a limited number of specimens (241 experiments). Many accurate surrogate models for a similar problem such as gradient tree boosting (GTB) algorithm [3], adaptive neuro-fuzzy inference system (ANFIS) model [4], and gene expression programming (GEP) method [5] were successfully employed, but without established empirical equations. Đorđević and Kostić [6] found on a small dataset that EC4 design code works better for stub CCFST columns (236 samples) than for slender columns (272 samples), using Decision tree (DT) and Random forest (RF) algorithms. A similar conclusion was provided in [7], using ANN with Levenberg-Marquardt (LM) algorithm for square CFST columns (685 stub columns and 337 slender columns), by the same authors.

This paper proposes an improved LM algorithm with Bayesian Regularization (BRA) for predicting the ultimate compressive strength of slender circular CFST columns (CCFST). Also, this study aims to develop empirical equations. The best ANN model with fine-tuned hyperparameters was developed using a K-fold cross-validation technique. Obtained results show that the ANN model better simulates the behaviour of the axially loaded CCFST columns than the more conservative EC4 design code. Using the regularization method, even with a simpler architecture the results are better than those obtained with the basic LM algorithm [7].

2. EXPERIMENTAL DATASET

In this study, a total of 1051 tests on slender CCFST columns subjected to pure compression were retrieved from various researchers, including Denavit [8] (387 samples), Goode [9] (330 samples), Thai et al. [10] (188 samples), Belete [11] (121 samples), Zeghiche et al. [12] (15 samples), Schneider [13] (8 samples), and Zhichao et al. [14] (2 samples). Table 1 presents major distribution features of the following input and output parameters: outer diameter (D), the thickness of the steel tube (t), length of column (L), steel yield stress (f_y), concrete compressive strength (f_c'), ultimate compressive strength (N_{exp}). It can be seen that wide ranges of all features were considered, even beyond the EC4 design code limitations described in section 3.

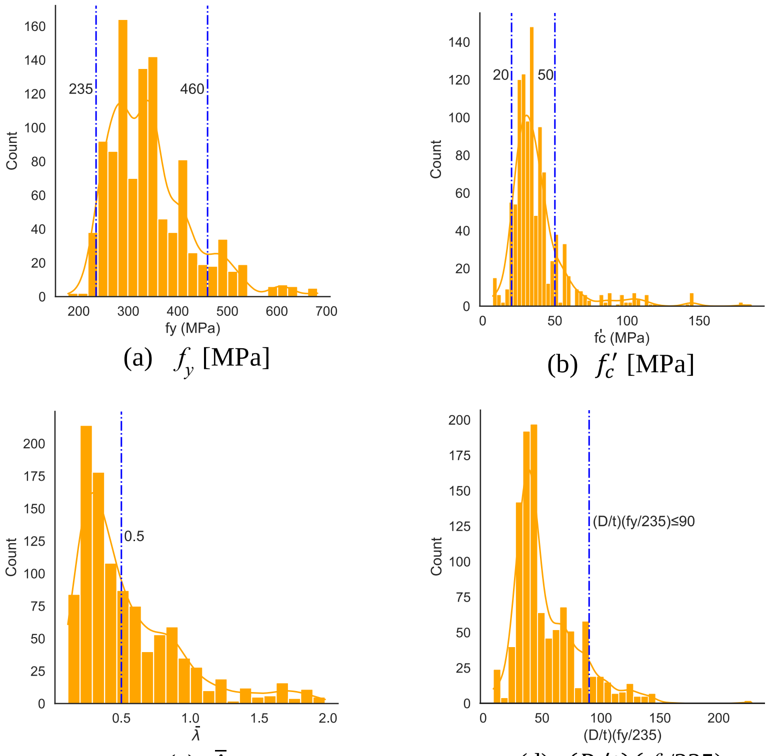
CCFST members are categorized as slender columns for $L/D > 4$ [6], [7], [15]. Since in some references, the concrete compressive cube strength (f_{cu}) is reported, these values are converted on the cylinder strength (f_c') according to the following expression proposed by L'Hermite [16]:

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

Table 1. Distribution values of the test parameters

Parameter	Unit	Mean	St.Dev.	Min.	Max.
D	mm	135.9	61.08	38.1	500
t	mm	4.27	2.34	0.7	16
L	mm	1562.23	1035.88	350	5000
f_y	MPa	343.5	83.45	178.28	682
f_c'	MPa	38.44	21.18	6.99	186
N_{exp}	kN	1329.88	1577.94	45.2	12838

Since a pre-processing phase is very important for training ANN, to disqualify bias due to different units possessing variables, input and output values were normalized to fall in the interval [-1,1]. The distributions of the database with respect to the steel yield stress, concrete compressive strength, and relative and section slenderness, are graphically presented in Figure 1. It can be seen that a large number of samples have standard geometrical and material properties, but some data exceeds the EC4 limits, marked with dash-dot blue lines.



(a) f_y [MPa] (b) f_c' [MPa]

(c) $\bar{\lambda}$ (d) $(D/t)(f_y/235)$

Figure 1 – Distribution of the dataset referred to: (a) steel yield stress, (b) concrete compressive strength, (c) relative slenderness, (d) section slenderness

Figure 2 illustrates the heatmap of Pearson correlation coefficients between parameters. It is visible that the highest correlation is obtained between the dimensions of the section and the ultimate compression strength of CCFST columns (0.828 for outer diameter and 0.621 for the thickness of the steel tube). These variables have the strongest relation with each other, and a similar conclusion was derived by Zarringol et al. [1].

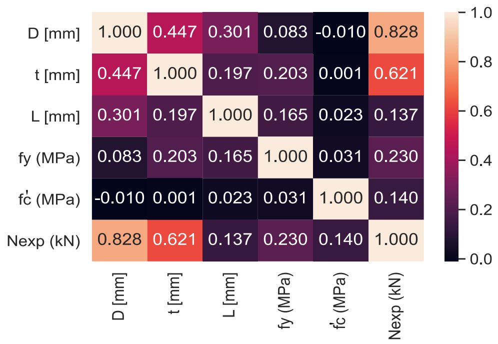


Figure 2 – Heatmap of Pearson correlation coefficients between parameters

3. EUROCODE 4 PROVISIONS

Axial compressive strength of doubly symmetrical CFST columns using a simplified method, with a condition of relative slenderness $\bar{\lambda} \leq 2$, calculates as follows:

$$N_u^{EC4} = \chi \cdot N_{pl,Rd} = \chi \cdot (A_s \cdot f_y + A_c \cdot f_c') \quad (2)$$

For circular CFST columns where relative slenderness does not exceed 0.5 and without eccentricity of the force, the increase in strength caused by the confinement effect can be taken into account:

$$N_u^{EC4} = \chi \cdot N_{pl,Rd} = \chi \cdot \left(A_s \cdot f_y \cdot \eta_s + A_c \cdot f_c' \cdot \left(1 + \eta_c \cdot \frac{t}{D} \cdot \frac{f_y}{f_c'} \right) \right) \quad (3)$$

where $N_{pl,Rd}$ is the plastic resistance to compression, χ is the reduction factor for relevant buckling mode, η_s describes the reduction of the steel yield stress due to expansion of concrete and η_c describes the increase of concrete compressive strength due to the confinement effect

$$\eta_s = \eta_{s0} = 0.25(3 + 2\bar{\lambda}) \leq 1.0 \quad (4)$$

$$\eta_c = \eta_{c0} = 4.9 - 18.5\bar{\lambda} + 17\bar{\lambda}^2 \geq 0 \quad (5)$$

Factor χ and relative slenderness $\bar{\lambda}$ are calculated as follows:

$$\chi = 1 / [\Phi + \sqrt{\Phi^2 - \bar{\lambda}^2}\,] \leq 1 \quad (6)$$

$$\Phi = 0.5 \cdot [1 + 0.21 \cdot (\bar{\lambda} - 0.2) + \bar{\lambda}^2] \quad (7)$$

$$\bar{\lambda} = \sqrt{N_{pl,Rd} / N_{cr}} \quad (8)$$

where N_{cr} is the elastic critical force for relevant buckling mode calculated with effective flexural stiffness EI_{eff} defined as:

$$EI_{eff} = E_s \cdot I_s + 0.6 \cdot E_c \cdot I_c \tag{9}$$

Limitations of geometrical and material properties shown in Table 2 are prescribed by EC4 and denoted in Figure 1. The first condition in Table 2 refers to the possibility of neglecting the impact of local buckling.

Table 2. Limitations of geometrical and material properties prescribed in EC4 design code

Design code	Limitations
Eurocode 4	$D/t \leq 90 \cdot 235/f_y$
	$235 \leq f_y \leq 460\ MPa$
	$20 \leq f_c' \leq 50\ MPa$

An additional limitation of the EC4 is the steel contribution ratio δ, which should satisfy the following condition:

$$0.2 \leq \delta = A_s \cdot f_y \,/\, N_{pl,Rd} \leq 0.9 \tag{10}$$

4. ARTIFICIAL NEURAL NETWORKS

In this study, a feedforward neural network with one hidden layer and eight neurons was developed. This network was trained using a backpropagation algorithm based on the modification of the LM algorithm, named BRA. Steps for exploring and creating an ANN model with the best generalization are described in the following sections.

4.1. BAYESIAN REGULARIZATION

Oppose to the basic LM algorithm based on the early-stopping rule, Bayesian improvement of LM belongs to the regularization techniques. The classical LM algorithm modifies the second-order Hessian matrix using the first order Jacobian matrix [7]. Bayesian regularization has proven to make a better generalization less prone to the possible overfitting, even with a simpler ANN architecture. It uses an adapted performance function without the need for the validation subset [17].

The approximation of the Hessian matrix using BRA is described as follows:

$$H = 2 \cdot \beta \cdot J^T \cdot J + 2 \cdot \alpha \cdot I \tag{11}$$

$$\alpha = \gamma \,/\, (2 \cdot E_W(x)) \tag{12}$$

$$\beta = (n - \gamma) \,/\, (2 \cdot E_D(x)) \tag{13}$$

where J is the Jacobian matrix, I is the identity matrix, α and β are the regularization parameters, n is the total number of ANN parameters, E_W is the sum of the squared weights and E_D is the selected performance measure. Parameter γ is equal to n in the first iteration, and, in the next iterations, is calculated from Eq.14:

$$\gamma = n - 2 \cdot \alpha \cdot tr(H)^{-1} \tag{14}$$

The ANN parameters (weights and biases) are determined to minimize the performance function *F(x)* (Eq.15):

$$F(x) = \beta \cdot E_D(x) + \alpha \cdot E_W(x) \tag{15}$$

$$E_D(x) = MSE = 1 / n_{tot} \cdot \sum_{i=1}^{n_{tot}} (y_i - \overline{y}_i)^2 \tag{16}$$

$$E_W(x) = 1 / n_{tot} \cdot \sum_{i=1}^{n_{tot}} (w_i)^2 \tag{17}$$

where MSE is the mean squared error, y_i is a target value, $\overline{y}_i$ is the predicted value, n_{tot} is the number of samples and w_i are the network weights.

4.2. QUALITY ASSESSMENT

To make a comparison between predicted and experimental results, in addition to the MSE defined in the previous section, other performance indicators as coefficient of determination (R^2) and root mean squared error ($RMSE$) have also been calculated, Eqs.18-19:

$$R^2 = \left(\frac{n_{tot} \cdot \sum_{i=1}^{n_{tot}} (y_i \cdot \overline{y}_i) - \sum_{i=1}^{n_{tot}} y_i \cdot \sum_{i=1}^{n_{tot}} \overline{y}_i}{\sqrt{\left[n_{tot} \cdot (\sum_{i=1}^{n_{tot}} y_i^2) - (\sum_{i=1}^{n_{tot}} y_i)^2 \right] \cdot \left[n_{tot} \cdot (\sum_{i=1}^{n_{tot}} \overline{y}_i^2) - (\sum_{i=1}^{n_{tot}} \overline{y}_i)^2 \right]}} \right)^2 \tag{18}$$

$$RMSE = \sqrt{1 / n_{tot} \cdot \sum_{i=1}^{n_{tot}} (y_i - \overline{y}_i)^2} \tag{19}$$

It is important to note that from the initial dataset, by random selection, 70% of the data are used for the training and 30% for the testing. Outputs from the hidden and output layer are generated through the hyperbolic tangent and simple linear activation functions respectively, which are mathematically defined as (Eqs.20-21):

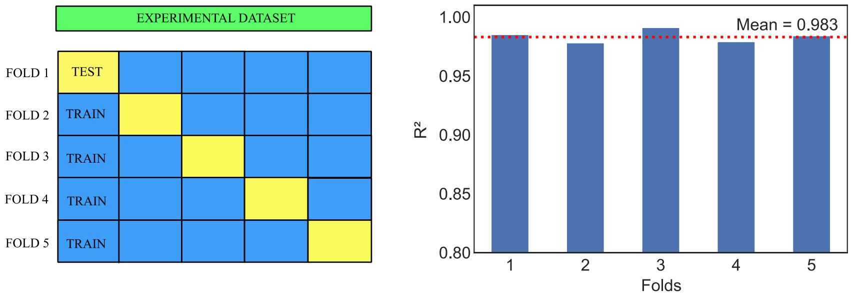
$$f(x) = (e^{x} - e^{-x}) / (e^{x} + e^{-x}) \tag{20}$$

$$f(x) = x \tag{21}$$

4.2.1. Hyperparameters tuning

To evaluate the performance of the ANN model, a 5-fold cross-validation technique is employed. This procedure reduces the chance of overfitting and bias due to the random splitting of the dataset. The experimental dataset is divided into 5 subsets with an equal amount of data, where each time one subset is used for the testing, while others are used for training. After 5 runs of the ANN, the independent performance scores of each fold and average accuracy of each model is reported. Figure 3a illustrates the split of the dataset.

The tested ANN architectures include 5-4-1, 5-5-1, 5-8-1, 5-10-1, 5-12-1, 5-14-1 networks with a different sets of hyperparameters. After analyses is performed, it is concluded that the network 5-8-1 gives the best results on the 5-fold cross-validation with small fluctuations of R^2 (0.985, 0.978, 0.991, 0.979 and 0.984) and with a high mean value (0.983). Figure 3b presents these results. Also, the best set of hyperparameters are μ=0.1, μ_{dec}=0.001, μ_{inc}=10. The role of these hyperparameters is well described in [7]. Figure 4 presents the best-obtained ANN architecture with one hidden layer and eight neurons.



(a) *5-fold scheme* (b) R^2

Figure 3 – (a) 5-fold cross-validation scheme and (b) R^2 of the test set per each fold

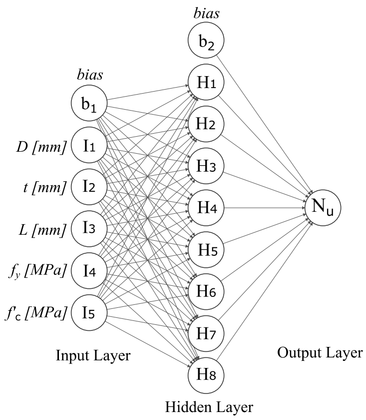


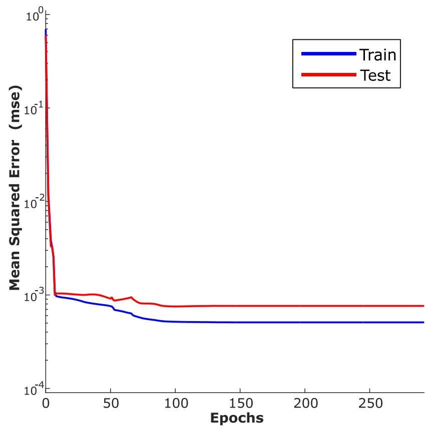
Figure 4 – Proposed ANN model

5. RESULTS

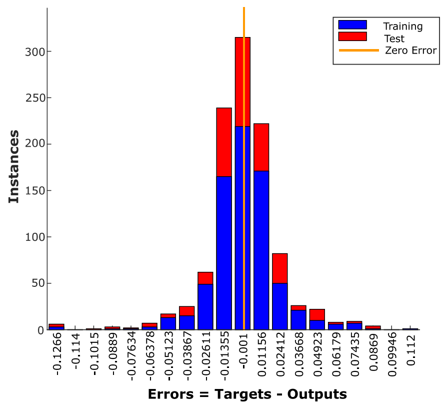
Table 3 compares the computed ultimate compressive strength values of slender CCFST columns with two different approaches: by the presented ANN model and using the EC4 expressions. The recommended ANN model gives more accurate results (R^2=0.992) than EC4 (R^2=0.961) on all samples. It is equally good on the training (R^2=0.992) and test (R^2=0.990) sets. Other performance indicators (*MSE* and *RMSE*) lead to the same conclusion. Figure 5a illustrates that there is no risk of overfitting and the best performance is obtained at the 292nd epoch. Figure 5b shows that a large percentage of errors are close to zero. Several authors have shown similar results for slender columns using various machine learning algorithms as in [6], [7].

Table 3. ANN and EC4 performance scores

Dataset	R^2		*MSE* ($\cdot 10^{-4}$)		*RMSE* ($\cdot 10^{-2}$)	
	ANN	EC4	ANN	EC4	ANN	EC4
Training	0.992	-	4.760	-	2.182	-
Test	0.990	-	5.201	-	2.281	-
All	0.992	0.961	5.069	34.147	2.252	5.844



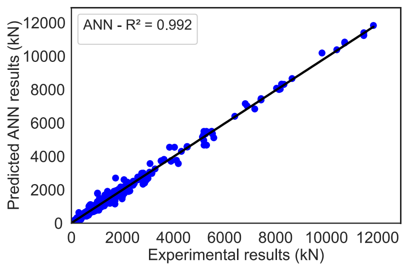
(a) Training set - ANN



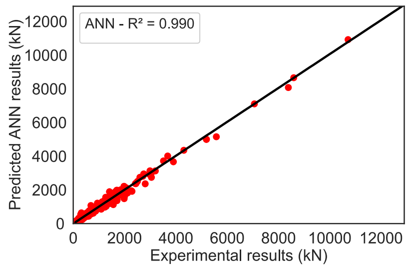
(b) Test set - ANN

Figure 5 –Train and test results (a) performance functions, (b) error distribution

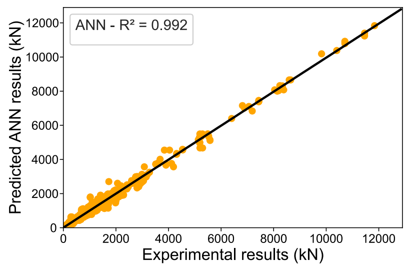
Figure 6 graphically presents the regression lines for training, test and all data. The ANN results have a good agreement with experimental results for all three subsets. On the other side, EC4 shows a scatter of the results, which is especially pronounced for outputs above 3000 kN. ANN model shows that besides giving more accurate results, the derived expressions can be applied to a wider range of data than the EC4 design code.



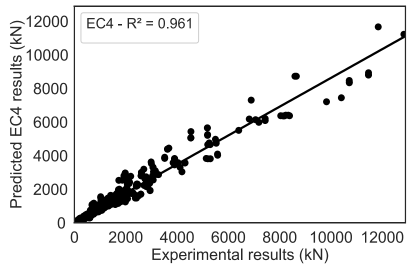
(c) Training set - ANN



(d) Test set - ANN



(e) All data - ANN



(f) All data – EC4

Figure 6 – Comparison of experimental and predicted results (a) Training set, (b) Test set, (c) All data – ANN, (d) All data – EC4

5.1. PROPOSED EQUATIONS

According to the network parameters from the best-trained ANN model, the following empirical equations for calculation of the axial capacity (N_u^{ANN}) of slender CCFST columns are recommended:

$$N_u^{ANN}=N_{u,1\text{-}4}^{ANN}+N_{u,5\text{-}bias}^{ANN} \tag{22}$$

$$N_{u,1\text{-}4}^{ANN} = 2.94144\cdot H_1'+0.14098\cdot H_2'+0.38613\cdot H_3'+1.43560\cdot H_4' \tag{23}$$

$$N_{u,5\text{-}bias}^{ANN} = 1.67761\cdot H_5'-2.38619\cdot H_6'-0.70682\cdot H_7'-1.13363\cdot H_8'-1.65957 \tag{24}$$

$$H_1'=Tanh(-1.54932\cdot D-0.14438\cdot t+0.75599\cdot L-0.53019\cdot f_y-0.23926\cdot f_c'+0.36257) \tag{25}$$

$$H_2'=Tanh(3.0702\cdot D+1.10493\cdot t-1.22707\cdot L+0.88028\cdot f_y+0.47573\cdot f_c'+3.42817) \tag{26}$$

$$H_3'=Tanh(2.77720\cdot D-0.23581\cdot t+0.90585\cdot L-0.70207\cdot f_y+1.17248\cdot f_c'+0.02708) \tag{27}$$

$$H_4'=Tanh(3.24453\cdot D+1.11523\cdot t-2.00113\cdot L+1.23696\cdot f_y+0.58214\cdot f_c'-0.46130) \tag{28}$$

$$H_5'=Tanh(-0.59108\cdot D-1.35953\cdot t-1.47492\cdot L+0.29325\cdot f_y-1.17222\cdot f_c'+1.44294) \tag{29}$$

$$H_6'=Tanh(-2.94726\cdot D-1.24046\cdot t-0.19169\cdot L-1.57374\cdot f_y-1.18168\cdot f_c'+1.17002) \tag{30}$$

$$H_7'=Tanh(-3.14082\cdot D-0.49002\cdot t+1.39387\cdot L-1.01158\cdot f_y-0.63854\cdot f_c'-1.40464) \tag{31}$$

$$H_8'=Tanh(-0.86469\cdot D+1.26690\cdot t-0.94459\cdot L+1.12318\cdot f_y+1.00749\cdot f_c'-2.04153) \tag{32}$$

6. CONCLUSIONS

The presented ANN model is highly accurate and robust. On the dataset of 1051 samples, the applied LM algorithm with BRA has shown the outstanding prediction performance of the axial capacity of slender CCFST columns. Outputs from the proposed empirical equations have a better agreement with experimental results (R^2=0.992) than those recommended by the EC4 design code (R^2=0.961), even for the wider range of test parameters. The proposed ANN model based on one hidden layer and eight neurons can precisely capture the nonlinear behaviour of CFST columns. As opposed to the LM algorithm, there is no need for the validation set of data, which makes the BRA algorithm more efficient with better generalization and with less risk of the possible overfitting. On the other side, analyses also indicate the importance to make a wider dataset for upcoming research. In general, similar surrogate models could be very useful for the engineering practice in the future.

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