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# A Neural Model to Estimate Carrying Capacity of Rectangular Steel Tubular Columns Filled with Concrete

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**ABSTRACT**

The goal of the current investigation is to construct an artificial neural network (ANN) to estimate the ultimate capacity of the composite columns consisting of a rectangular steel tube filled with concrete (RSTFC) under concentric loads. The experimental results of (222) samples collected from previous researches were used in constructing the proposed network. Totally (45) specimens were randomly chosen for network testing while the remaining (177) specimens were used to train the network. The information used to create the ANN model is arranged into (6) variables represents the different dimensions and properties of the RSTFC columns. Based on the input information, a formulated network was used to estimate the columns' ultimate capacity. Results obtained from the formulated network, available laboratory tests, and Eurocode 4 and AISC equations were compared. The network values were closer to the laboratory values than the calculated values according to the specifications of the mentioned codes. It has been shown that the formulated ANN model has a high ability to estimate the RCFST ultimate capacity under concentric loads



## ١. Introduction

Composite steel tubes are considered one of the structural elements used in civil engineering [1-11], these elements may be used as composite columns or Beam–columns [12]. These columns are made of steel and filled with concrete inside. So that it can take advantage of the properties of steel (high tensile strength and high ductility) and concrete (high compressive strength and stiffness). Consequently, the combination of these two features leads to a member having the best properties of the two materials. There are two categories of composite columns; columns of sections encased with concrete (SEC), Fig. 1, and columns of tubes filled with concrete (TFC), Fig. 2.

Composite columns have some advantages:

- Steel pipes work on an integrated and permanent formwork
- Steel pipes act as external reinforcement

Although composite columns are preferred for tall buildings that might be exposed to earthquakes, their use is restricted due to the poorness of detailed information and their inelastic behavior because of the separation between the design for steel structure and the design for a concrete structure. Whereas, the



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design equations for these columns using the American concrete code (ACI) differ significantly from the method for designing using the design equations of the American Institute of Steel (AISC). As a result, the applications of composite columns have increased significantly over the past few decades.

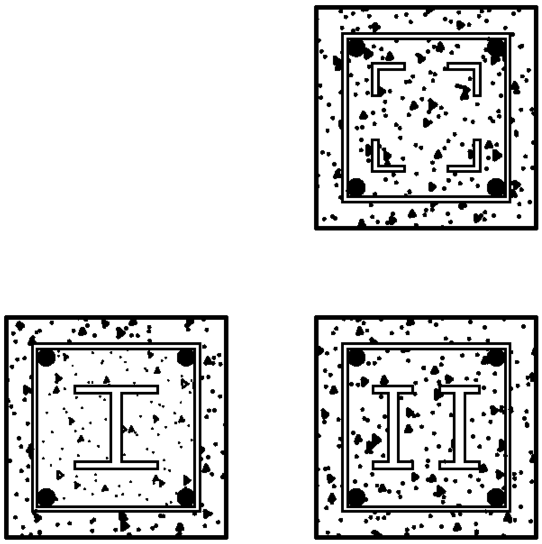

**Figure 1.** Columns of SEC

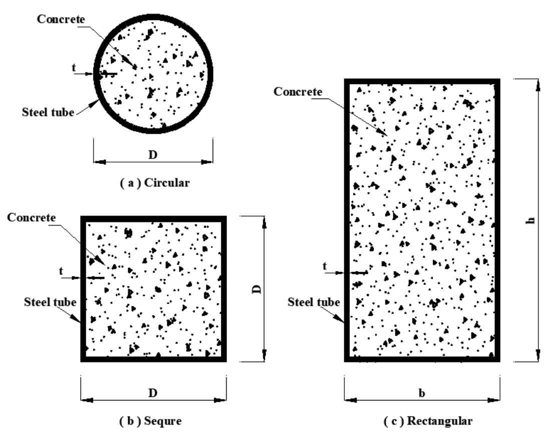


**Figure 2.** Columns of TFC

Various systems adopting artificial neural networks (ANNs) have been utilized by many investigators. Yeh et al. [13] and Yeh [14] used ANNs to study the properties and specifications of high and normal concrete. Nath et al. [15] and Deka and Diwate [16] used ANNs to estimate the concrete strength. Abdollahzadeh et al. [17] developed an ANN model to understand the properties of concrete that contain different proportions of rubber. Ayazi et al. [18] and Alshihri et al. [19] studied the properties of lightweight concrete with Scoria instead of sand by using ANNs. Erfani and Farsangi [20] formulated an ANN model to study the concrete strength after the addition of ground granular blast furnace slag. Basyigit et al. [21] estimated the strength of heavy concrete using ANNs and fuzzy logic. Saridemir [22] built ANN and fuzzy logic models to estimate the strength of metakaolin mortar. Khalaf et al. [23] used ANNs in developing a model to estimate the peak capacity of composite columns.

The main purpose of this article is to formulate a model using ANNs to estimate the peak capacity of RCFST columns under concentric loads.

# ٢. Architecture of ANNs

The ANNs are designed using computers to be similar to natural neural networks. ANNs are simple and small if compared to the human brain and these networks are able to process a wide range by identifying the input information and then collecting sufficient information about the problem by approximating. The job then to predict the results and try to give the best results, and therefore the neural networks can be used to solve many complex issues in which the connection between the input and output data is not clear. Neural networks are computational techniques designed in a manner similar to the work of the human brain. These networks consist of many simple units called (node, neurons) that are grouped by layers. The human being is linked to the outside world by the five-sided senses. Therefore, neural networks need input information and need processing units in which calculations can be performed and can be adjusted using weights in order to gain accurate outputs for each of the network inputs. The input units are grouped together by a layer called the input layer, which is connected to the next layer, the processing layer, which contains the processing units that yield the network products. Also, there are layers, hidden layers, that adjust the weights for each interface. In general, the network contains a network one entry contains more than one processing layer.
As shown in Fig. 3, ANNs contain three layers; the input, hidden, and output layer.

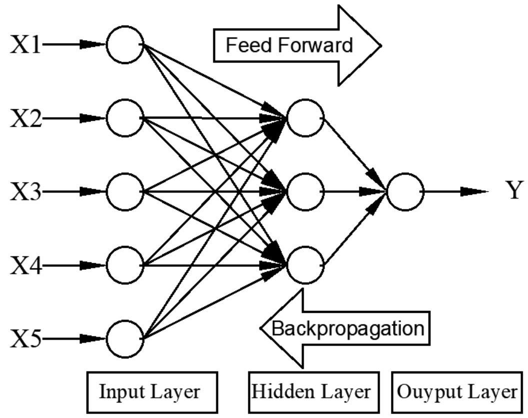


**Figure 3.** Architecture of ANN

The cells in the hidden layer are for the purpose of processing and adjusting weights where the variables are received in the input layer and then passed to the hidden one for the purpose of processing and then reaching the output layer. There are many networks that are used in neural networks, but among these networks that are most used is the "multilayer feed-forward ANN based on a back-propagation algorithm (MFFNN)" [24], which may be considered as the most common networks utilized in many engineering fields and will be used in this research.

## ٣. Structure and Parameters of Formulated Model

For the purpose of constructing the network, there must be sufficient information for the purpose of learning (training) and verifying (testing) the network. For this purpose, a large number of information on the RSTFC composite columns was collected from previous research [25]. The database collected over the past four decades contains (222) specimens for building the model proposed in this study. In this study, a generalized MFFNN was adopted. The backpropagation algorithm and formulating of the formulated ANN model was constructed using the neural network toolbox of MATLAB version 7.0 (R14). In this type of networks the neurons (nodes) are ordered in layers so that the nodes are connected with the nodes in the next layer while there is no interconnection between the nodes of the same layer. The information is entered in the input layer and then transferred to the nodes of the hidden layers which pass their information to the output layer. The individual outputs of each layer are treated as new inputs in the next layer. MFFNN is trained by controlling weights, and the training process takes place through large groups and training series (epochs). The primary purpose for training is to obtain the best set of weights that lead to correct outputs for the proportional with the inputs.

The formulated MFFNN network used in the current research contains (6) variables in the input layer and a single node in the output layer as shown in Fig. 4. For the purpose of constructing this model, the following variables were used in the input layer: Tube yield stress (fy), concrete strength (f'c), length of tube cross-section (h), width of tube cross-section (b), tube thickness (t), and column height (L), while the ultimate capacity was used in the output layer.

Table 1 represents the range of the variables used to create the formulated ANN model.

Among the available (222) samples, (177) actual samples were used for the purpose of network training (learning phase), while (45) samples were used for the purpose of testing (verifying phase) the model.

**Table 1.** Variables' range

| Parameters | Range |
|---|---|
| Yield stress of steel tube (fy) (MPa) | 246-833 |
| Cylinder concrete compressive strength (f'c) | 18-103 |
| Length of rectangular cross-section (mm) | 50-360 |
| width of rectangular cross-section (mm) | 50-333 |
| Thickness of steel tube (t) (mm) | 0.7-12.0 |
| Laterally unbraced length of member (L) (mm) | 150-4503 |

The formulated ANN model in this research includes (6) variables (nodes) as inputs and a single output variable and contains two hidden layers due to obtaining the lowest values of absolute percentages of errors. The first and second hidden layer contains nine and five nodes, respectively. Adjacent layers were entirely linked by weights. The formulated ANN model was learned and tested through repetition and its obtained results were very close to the actual results. The different parameters of the formulated ANN model are listed in Table ٢ while its architecture is depicted in Fig. 4.

**Table 2** Different parameters of the formulated model

| No. of nodes in input Layer | No. of hidden Layers | No. of nodes in first hidden Layer | No. of nodes in second hidden Layer | No. of nodes in output Layer | Error after learning | Learning cycle |
|---|---|---|---|---|---|---|
| 6 | 2 | 9 | 5 | 1 | 0.0034 | 20000 |

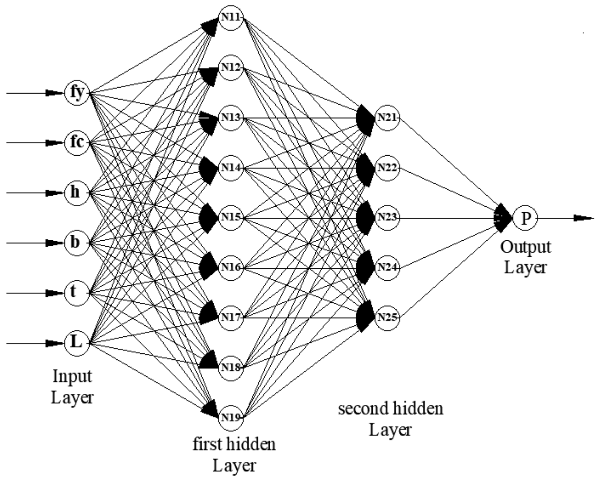


**Figure 4.** Architecture of formulated model

## ٤. . Results and Discussion

For the purpose of estimating the peak capacity of the studied RSTFC columns without resorting to laboratory experiments, smart systems were used to construct a model that is able to find the maximum load through the use of ANNs. For this purpose, it had been relied on a large number of laboratory data to build the model. A model was built with (6) variables as inputs and a single variable as the output.

The estimated, from the formulated model, and actual (laboratory) outputs of the verifying phase are listed in Table 3. As shown in this table, the ratio of the actual value relative to the expected values was 1.008, while the standard deviation rate was 0.103.

The estimated results from the formulated model and the available laboratory (actual) values were compared for both the learning and verifying phase as shown in Figs. 5 and 6, respectively.

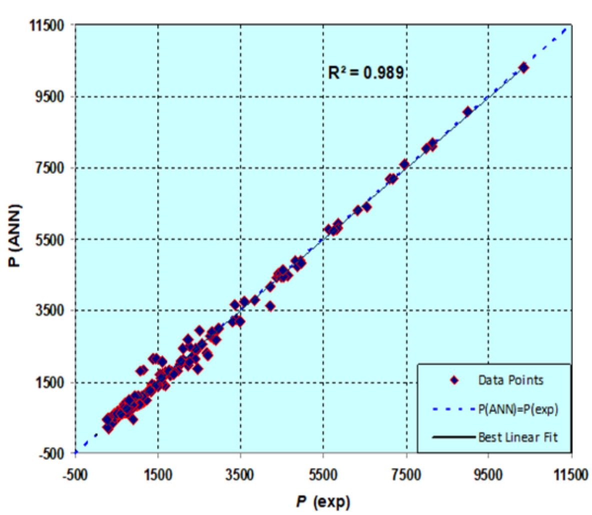


**Figure 5.** Regression of the estimated and actual outputs for learning phase

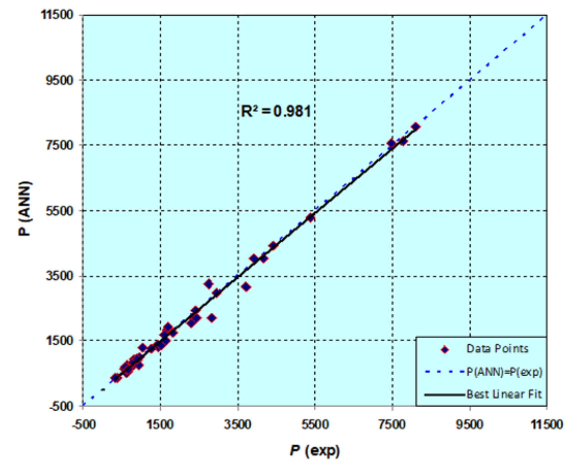


**Figure 6.** Regression of the estimated and actual outputs for verifying phase

After the formulation of the model, it must be tested for the purpose of checking the results and this is done here by using three norms to check the performance of the formulated model. These norms are the "coefficient of correlation (R2)", and "mean absolute percentage error (MAPE)" and "fraction of variance (FV)" which represents a measure of the error rate between the estimated NN values and the experimental (actual) values according to the following equations:

$$R^2 = \frac{(n\Sigma T_i Y_i - \Sigma T_i \Sigma Y_i)^2}{(n\Sigma T_i^2 - (\Sigma T_i)^2)(n\Sigma Y_i^2 - (\Sigma Y_i)^2)} \quad (1)$$

$$MAPE = \frac{1}{n}\left[\Sigma \left|\frac{T-Y}{T}\right|\right] \times 100 \quad (2)$$

$$FV = 1 - \frac{\Sigma (T_i - Y_i)^2}{\Sigma (Y - \bar{Y})^2} \quad (3)$$

In which T is the actual target, Y is the estimation and n is the no. of data. If MAPE is 0 and FV is 1, then this indicates that the formulated model is excellent. The values of the used norms are summarized in Table 4.

**Table 4.** values of statistical norms

| Norm | Learning (training) Phase | Verifying (testing) Phase |
|---|---|---|
| $R^2$ | 0.989 | 0.981 |
| MAPE | 7.78 | 8.52 |
| FV | 0.993 | 0.991 |

As can be seen from Fig. 5 and Fig. 6, the coefficient $R^2$ = 0.989, 0.981 for the learning and verifying phase, respectively, while from Table 4, MAPE = 7.78, 8.52 and FV = 0.993, 0.991 for the learning and verifying phase, respectively. It is evident that the estimations gained using the formulated network are very close to the laboratory records. Depending on these values, ANNs can be used to create a model that is able to produce accurate and reliable results.

## ٥. Comparative Study

In this research, a comparison study was made between the results obtained through the current model with design values, originally calculated by Kim [25], using the equations adopted by the two codes AISC [26] and Eurocode 4 [27] in designing composite columns. The values estimated by ANN and that calculated from the ASIC and Eurocode 4 equations were compared and shown in Table 5.

**Table 3.** Estimated and actual values of verifying phase

| Column designation | fy (MPa) | f'c (MPa) | h (mm) | b (mm) | t (mm) | L (mm) | P(exp) (kN) | P(ANN) (kN) | P(exp)/ P(ANN) |
|---|---|---|---|---|---|---|---|---|---|
| --- | 331 | 28.8 | 102 | 102 | 3.2 | 914 | 676.10 | 626.35 | 1.079 |
| --- | 324 | 34.1 | 76 | 76 | 3.4 | 1422 | 385.20 | 373.73 | 1.031 |
| 1 | 386 | 35.2 | 120 | 80 | 5 | 2939 | 600.10 | 506 | 1.186 |
| 24 | 370 | 31.6 | 331 | 331 | 4.5 | 1318 | 4411.70 | 4423.9 | 0.997 |
| 29 | 390 | 28.5 | 331 | 331 | 10.1 | 1397 | 8088.20 | 8094.8 | 0.999 |
| CR4-A-4-1 | 261 | 40.4 | 148 | 148 | 4.4 | 224 | 1413.60 | 1384.4 | 1.021 |
| CR4-C-4-2 | 261 | 41 | 215 | 215 | 4.4 | 323 | 2392.30 | 2441.1 | 0.980 |
| CR4-D-8 | 261 | 80.1 | 324 | 324 | 4.4 | 485 | 7478.40 | 7570.7 | 0.988 |
| CR6-C-2 | 616 | 25.4 | 211 | 211 | 6.4 | 315 | 3918.40 | 4032.8 | 0.972 |
| CR6-D-4-1 | 616 | 41 | 319 | 319 | 6.4 | 478 | 7777.30 | 7635.4 | 1.019 |
| CR8-A-4-2 | 833 | 40.4 | 120 | 120 | 6.5 | 180 | 2959.80 | 2982.4 | 0.992 |
| CR8-C-8 | 833 | 76.8 | 175 | 175 | 6.5 | 262 | 5364.60 | 5303.8 | 1.011 |
| 1 | 304 | 47 | 120 | 120 | 5 | 249 | 1439.90 | 1307.9 | 1.101 |
| 6 | 300 | 46 | 120 | 120 | 8 | 249 | 1669.90 | 1847.2 | 0.904 |
| 11 | 376 | 93 | 120 | 120 | 8 | 249 | 2820.20 | 2212.3 | 1.275 |
| 16 | 396 | 96 | 120 | 120 | 8 | 249 | 2,340.20 | 2192.3 | 1.067 |
| 24 | 379 | 92 | 120 | 120 | 8 | 249 | 2430.10 | 2197.7 | 1.106 |
| D8 | 246 | 22.5 | 150 | 150 | 0.7 | 800 | 611.60 | 605.92 | 1.009 |
| D16 | 247 | 22.5 | 150 | 200 | 1.4 | 800 | 881.20 | 916.34 | 0.962 |
| E18 | 248 | 35.2 | 150 | 200 | 2.1 | 800 | 1267.70 | 1270.2 | 0.998 |
| C8-0 | 412 | 40.9 | 150 | 150 | 4.3 | 1201 | 1587.60 | 1691 | 0.939 |
| S1 | 356 | 30.5 | 127 | 127 | 3.1 | 610 | 916.80 | 904.16 | 1.014 |
| R1 | 430 | 30.5 | 77 | 152 | 3 | 612 | 818.50 | 937.5 | 0.873 |
| R6 | 358 | 23.8 | 102 | 152 | 7.3 | 610 | 1690.30 | 1925.4 | 0.878 |
| M-2-1 | 340 | 23.1 | 360 | 240 | 2.6 | 1440 | 2299.30 | 2049.4 | 1.122 |
| M-2-2 | 340 | 23.1 | 195 | 130 | 2.6 | 780 | 959.50 | 986.67 | 0.972 |
| H-6-1 | 340 | 23.1 | 195 | 130 | 2.6 | 2339 | 644.50 | 751.81 | 0.857 |
| H-8-2 | 340 | 23.1 | 135 | 90 | 2.6 | 541 | 551.60 | 653.4 | 0.844 |
| HSS2 | 750 | 28 | 110 | 110 | 5 | 3000 | 1831.30 | 1759.5 | 1.041 |
| HSS14 | 750 | 40 | 210 | 210 | 5 | 3000 | 3708.50 | 3174.6 | 1.168 |
| CCM1 | 450 | 52 | 75 | 75 | 3 | 1770 | 343.00 | 381.31 | 0.900 |
| C18-0 | 452 | 96 | 125 | 125 | 3.2 | 2250 | 1650.30 | 1507.8 | 1.095 |
| KOM2001 | 318 | 24.8 | 300 | 300 | 3.2 | 899 | 2749.90 | 3244.1 | 0.848 |
| KOM2001 | 364 | 30.3 | 200 | 200 | 9 | 599 | 4169.80 | 4037.4 | 1.033 |
| --- | 387 | 45 | 100 | 100 | 2.9 | 300 | 794.90 | 764.43 | 1.040 |
| KLM2002 | 277 | 54.2 | 100 | 100 | 3.2 | 300 | 909.70 | 896.35 | 1.015 |
| KLM2002 | 365 | 46.7 | 100 | 100 | 2.3 | 300 | 576.50 | 700.37 | 0.823 |
| LPK2002 | 372 | 55.4 | 100 | 100 | 3.2 | 749 | 883.00 | 862.84 | 1.023 |
| LPK2002 | 354 | 55.4 | 75 | 75 | 3.2 | 274 | 705.90 | 648.35 | 1.089 |
| LPK2002 | 372 | 55.4 | 100 | 100 | 3.2 | 1123 | 798.00 | 842.94 | 0.947 |
| LPK2002 | 354 | 55.4 | 75 | 75 | 3.2 | 549 | 651.20 | 628.39 | 1.036 |
| LPK2002 | 374 | 55.4 | 100 | 100 | 2.3 | 381 | 937.70 | 761.58 | 1.231 |
| SKA2002 | 445 | 64.1 | 125 | 125 | 3 | 1001 | 1517.30 | 1373.6 | 1.105 |
| SKA2002 | 453 | 62.4 | 125 | 125 | 3 | 2250 | 1038.70 | 1302.1 | 0.798 |
| SKA2002 | 436 | 61.3 | 125 | 125 | 3 | 3000 | 894.50 | 940.91 | 0.951 |
| | | | | | | | | Average | 1.008 |
| | | | | | | | | Standard Deviation | 0.103 |

Two norms were used for the purpose of evaluating the proposed network performance and the specifications of the mentioned two codes, ASIC and Eurocode 4. These norms are MAPE and FV given in Eqs. 2 and 3, respectively.

As shown in Table 5, the values obtained using Eqs. 2 and 3 for MAPE and FV are 0.997 and 7.78% for the formulated ANN, 0.968 and 17.01% for Eurocode 4, and 0.983 and 13.19% for AISC, respectively. These norms' values verify that the formulated network can estimate the peak capacities of RSTFC columns in a more accurate sense than the two used codes, ASIC and Eurocode 4.

Figure 7 depicts the estimated column capacity using the formulated ANN and the calculated capacity using the AISC and Eurocode provisions versus the actual experimental capacity. The coefficient $R^2$ = 0.981, 0.933, and 0.947 for the formulated network, Eurocode 4 and AISC, respectively. As it is evident from these values, the formulated model gives more accurate capacities than the equations of the two codes, Eurocode 4 and ASIC. So it can be said that the formulated ANN can outfit an accurate and alternative method for estimating the peak capacity of RSTFC columns.

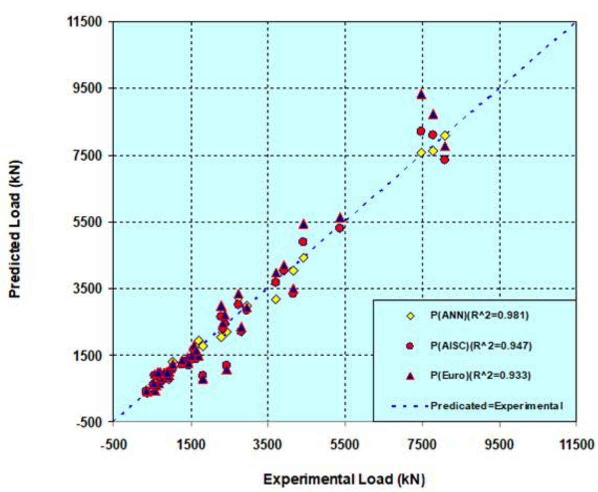


**Figure 7.** Regression of the ANN and codes estimations

## ٦. Conclusions

The current study demonstrates that the formulated model that was designed using ANNs can be utilized to estimate the peak capacity of the RSTFC columns under the action of concentric loads. It has the ability to estimate the peak capacity of this type of column during a very short period and with a slight error rate and this indicates that the neural networks have the ability to solve many problems which take a very long time very quickly. ANNs are made so that they depend mainly on experimental results, and whenever the number of experimental results is large, it gives more accurate results. Thus, this type of system does not need hypotheses about the variables, especially in solving problems that there are several ways to solve them. In this research, an MFFNN model was formulated. The formulated model involves two hidden layers of nine and five nodes in the first and second layers, respectively. The formulated network was trained through (6) input variables. Results indicate that the peak capacities estimated by the formulated model were in good agreement with the laboratory capacities. Also in this study, a comparison was made between the values obtained from the formulated network and the design values of the Eurocode 4 and AISC equations. The comparison verified that the estimations of the formulated network are more accurate than the estimations of the adopted equations by Eurocode 4 and AISC. As a result, ANNs present an accurate and alternative model for estimating the ultimate strength of RSTFC columns.

**Table 5.** ANN and codes estimations

| 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) |
|---|---|---|---|---|---|---|---|
| --- | 676.10 | 626.35 | 609.1 | 656.4 | 1.079 | 1.110 | 1.030 |
| --- | 385.20 | 373.73 | 389.1 | 418.7 | 1.031 | 0.990 | 0.920 |
| 1 | 600.10 | 506 | 458.1 | 428.6 | 1.186 | 1.310 | 1.400 |
| 24 | 4,411.70 | 4423.9 | 4901.9 | 5446.5 | 0.997 | 0.900 | 0.810 |
| 29 | 8,088.20 | 8094.8 | 7352.9 | 7777.1 | 0.999 | 1.100 | 1.040 |
| CR4-A-4-1 | 1,413.60 | 1384.4 | 1321.1 | 1442.4 | 1.021 | 1.070 | 0.980 |
| CR4-C-4-2 | 2,392.30 | 2441.1 | 2441.1 | 2718.5 | 0.980 | 0.980 | 0.880 |
| CR4-D-8 | 7,478.40 | 7570.7 | 8218.0 | 9348.0 | 0.988 | 0.910 | 0.800 |
| CR6-C-2 | 3,918.40 | 4032.8 | 4039.6 | 4213.3 | 0.972 | 0.970 | 0.930 |
| CR6-D-4-1 | 7,777.30 | 7635.4 | 8101.4 | 8738.5 | 1.019 | 0.960 | 0.890 |
| CR8-A-4-2 | 2,959.80 | 2982.4 | 2846.0 | 2930.5 | 0.992 | 1.040 | 1.010 |
| CR8-C-8 | 5,364.60 | 5303.8 | 5311.5 | 5646.9 | 1.011 | 1.010 | 0.950 |
| 1 | 1,439.90 | 1307.9 | 1180.2 | 1263.1 | 1.101 | 1.220 | 1.140 |
| 6 | 1,669.90 | 1847.2 | 1491.0 | 1575.4 | 0.904 | 1.120 | 1.060 |
| 11 | 2,820.20 | 2212.3 | 2203.3 | 2350.2 | 1.275 | 1.280 | 1.200 |
| 16 | 2,340.20 | 2192.3 | 2294.3 | 2463.4 | 1.067 | 1.020 | 0.950 |
| 24 | 2,430.10 | 2197.7 | 1174.0 | 1075.3 | 1.106 | 2.070 | 2.260 |
| D8 | 611.60 | 605.92 | 518.3 | 599.6 | 1.009 | 1.180 | 1.020 |
| D16 | 881.20 | 916.34 | 786.8 | 890.1 | 0.962 | 1.120 | 0.990 |
| E18 | 1,267.70 | 1270.2 | 1207.3 | 1363.1 | 0.998 | 1.050 | 0.930 |
| C8-0 | 1,587.60 | 1691 | 1653.8 | 1783.8 | 0.939 | 0.960 | 0.890 |
| S1 | 916.80 | 904.16 | 916.8 | 996.5 | 1.014 | 1.000 | 0.920 |
| R1 | 818.50 | 937.5 | 826.8 | 880.1 | 0.873 | 0.990 | 0.930 |
| R6 | 1,690.30 | 1925.4 | 1444.7 | 1495.8 | 0.878 | 1.170 | 1.130 |
| M-2-1 | 2,299.30 | 2049.4 | 2642.9 | 2986.1 | 1.122 | 0.870 | 0.770 |
| M-2-2 | 959.50 | 986.67 | 1020.7 | 1115.7 | 0.972 | 0.940 | 0.860 |
| H-6-1 | 644.50 | 751.81 | 895.1 | 976.5 | 0.857 | 0.720 | 0.660 |
| H-8-2 | 551.60 | 653.4 | 599.6 | 648.9 | 0.844 | 0.920 | 0.850 |
| HSS2 | 1,831.30 | 1759.5 | 884.7 | 810.3 | 1.041 | 2.070 | 2.260 |
| HSS14 | 3,708.50 | 3174.6 | 3671.8 | 3987.6 | 1.168 | 1.010 | 0.930 |
| CCM1 | 343.00 | 381.31 | 403.5 | 428.8 | 0.900 | 0.850 | 0.800 |
| C18-0 | 1,650.30 | 1507.8 | 1386.8 | 1650.3 | 1.095 | 1.190 | 1.000 |
| KOM2001 | 2,749.90 | 3244.1 | 3021.9 | 3353.5 | 0.848 | 0.910 | 0.820 |
| KOM2001 | 4,169.80 | 4037.4 | 3335.8 | 3504.0 | 1.033 | 1.250 | 1.190 |
| --- | 794.90 | 764.43 | 771.7 | 836.7 | 1.040 | 1.030 | 0.950 |
| KLM2002 | 909.70 | 896.35 | 798.0 | 874.7 | 1.015 | 1.140 | 1.040 |
| KLM2002 | 576.50 | 700.37 | 873.5 | 945.1 | 0.823 | 0.660 | 0.610 |
| LPK2002 | 883.00 | 862.84 | 919.8 | 1003.4 | 1.023 | 0.960 | 0.880 |
| LPK2002 | 705.90 | 648.35 | 916.8 | 994.2 | 1.089 | 0.770 | 0.710 |
| LPK2002 | 798.00 | 842.94 | 876.9 | 961.4 | 0.947 | 0.910 | 0.830 |
| LPK2002 | 651.20 | 628.39 | 917.2 | 1001.8 | 1.036 | 0.710 | 0.650 |
| LPK2002 | 937.70 | 761.58 | 947.2 | 1030.4 | 1.231 | 0.990 | 0.910 |
| SKA2002 | 1,517.30 | 1373.6 | 1354.7 | 1502.3 | 1.105 | 1.120 | 1.010 |
| SKA2002 | 1,038.70 | 1302.1 | 1093.4 | 1251.4 | 0.798 | 0.950 | 0.830 |
| SKA2002 | 894.50 | 940.91 | 894.5 | 983.0 | 0.951 | 1.000 | 0.910 |
| *VAP* | | 0.997 | 0.983 | 0.968 | | | |
| *MAPE* | | 7.78 | 13.19 | 17.01 | | | |

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