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AI-Powered GUI for Prediction of Axial Compression Capacity in Concrete-Filled Steel Tube Columns

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Abstract:

In this paper a novel methodology is developed for the characterization of the capacity of rectangular shaped Concrete Filled Steel Tubes (CFST). In the scientific research field, of particular interest is the behavior of long CFST columns under eccentric compressive load. These conditions promote failure mechanisms involving global member buckling. The developed methodologies are based on machine learning techniques found on Artificial Neural Networks (ANN). Furthermore, optimization methodologies, employing the Grey Wolf Optimization algorithm and the Firefly algorithm have been attempted. For the training and validation of the models, a database consisting of 1,641 experimental tests collected from literature sources, has been prepared, containing long and short specimens as well as specimens with or without load eccentricity. As the vast majority of the available experimental tests involves short specimens, the database has been augmented with 216 3D Finite Element Models (FEMs), featuring increased member slenderness values. The calibration of the FEMs has been performed against experimental tests. The performance of the

developed models has been measured through a number of performance indices, and compared with available code procedures. They have been found to provide significant improvements, both for short and long CFST columns, with the ANN model optimized with the Firefly algorithm outperforming the others. Furthermore, a Graphical User Interface (GUI) has been developed which can be readily used to estimate the axial load capacity of CFST columns through the optimal ANN model. The developed GUI is made available as a supplementary material.

Keywords: Rectangular Concrete Filled Steel Tube (CFST); Finite Element Method (FEM); load eccentricity; artificial neural networks (ANNs); CFST; long CFST; ultimate load

1. Introduction

In this paper the behavior of rectangular Concrete Filled Steel Tubes (CFSTs) is investigated, with a particular focus on their ultimate compressive load capacity, taking into account load eccentricity and member slenderness. CFSTs are gaining popularity in modern construction. As columns, subjected to significant compressive actions, they offer a number of valuable advantages compared to either reinforced concrete columns or bare steel ones. For instance, the steel tube provides excellent confinement conditions to the concrete core while at the same time, the concrete core hinders the steel tube from moving inwards, effectively assisting against local buckling failure. In addition, resistance against global buckling is also enhanced, as a result of the stiffness provided by the concrete core and the steel tube combined. Further practical benefits include the increased fire resistance, the speed of execution, since no formwork is needed for casting concrete, the corrosion resistance of the inner tube surfaces and the durability against impact. A disadvantage of CFSTs columns, however, is the need for more complicated detailing and construction of beam-to-column joints.

CFSTs can be manufactured in a number of different cross-section shapes. Circular and square ones are more commonly encountered in practice and have also been widely investigated in the literature. Other shapes, such as octagonal, hexagonal and elliptical cross-sections, are also in use. Circular sections offer better confinement conditions for the concrete, and also prove less prone to delamination between the concrete core and the steel tube, compared to the rectangular ones (Krishan et al. (2016) [1], Bradford et al. (2002) [2], Goel and Tiwary (2018) [3]). On the other hand, rectangular CFSTs present significant advantages in manufacturing and joining with other members, while offering increased bending stiffness (Ren et al. 2019[4], Zhao et al. 2015[5]).

Focusing, at first, on the rectangular CFST concentrically axial compressive capacity, many experimental investigations can be found in the literature, particularly for square sections. A lower number of experimental studies also investigates non-square rectangular sections. Earlier works include Kloppel and Goder (1957) [6], Furlong (1967) [7], Knowles and Park (1969) [8], Gardner and Jacobson (1967) [9] and Tomii et al. (1977) [10]. Most of the studies, investigate short specimens, also called stubs. Testing of stubs cannot capture member buckling, a failure mode that can potentially occur in actual CFST columns. However, they remain a cost-effective solution for studying other aspects, such as section slenderness, material strengths, section aspect ratio, confinement conditions, etc. The term long column, used in this work, describes a column that includes member buckling as a mode of failure, along with other ones, such as local buckling and steel or concrete material failure. The ultimate behavior of long columns, has been tested by Han and Yao (2003) [11], Mursi and Uy (2004) [12], Lue et al. (2007) [13], Yu et al. (2008) [14], Dundu (2016) [15], Khan et al. (2017) [16].

Concentric axial loading is not commonly occurring in practice, especially for members in

frame structures. Typically, eccentric compression of columns is introduced, either directly, due to offset of the beam-to-column joints from the column axis, or indirectly, due to bending moments that are simultaneously carried by the column. Less research studies are available for the experimental testing and characterization of the load capacity in those loading scenarios, in comparison to concentric loading. Earlier experimental studies have been conducted by Knowles and Park (1969) [8], Bridge (1976) [17] and Khalil and Zeghiche (1989) [18]. Cederwall et al. (1990) [19] and Khalil and Al-Rawdan (1996) [20] tested CFSTs with varying steel and concrete strengths under eccentric loading. Similarly, Matsui & Tsuda (1996) [21] tested square CFSTs, both short and long, under varying eccentricities. Nakahara and Sakino (2000) [22] parametrically investigated, through an extensive testing program, square CFSTs with load eccentricity, including high strength ones. Thin-walled CFSTs with load eccentricity were tested by Uy (2000) [23], while later Mursi and Uy (2003) [29] included to the investigation long columns and also proposed a numerical model for the characterization of the entire load-deflection curve, accounting for the eccentricity of the load and the potential for local or global instabilities. Furthermore, Mursi and Uy (2004) [12] extended the scope to high-strength-steel columns. Square CFSTs with varying column length, eccentricity and steel to concrete ratio were parametrically tested by Zhang et al. (2004) [25] and also a non-linear analysis model was presented for the characterization of the load-deflection curve. Rectangular CFSTs with load eccentricity and high strength steel were tested by Liu (2004) [26] as well, with varying aspect ratio of the cross-section and member lengths. Liu (2006) [27] performed more tests, including long columns and developed a numerical model for the complete load-deflection curve. Square CFSTs were tested by Varma et al. (2002) [28], under concentrically axial load and monotonically increasing flexure with varying tube width-to-thickness ratio, axial load and steel yield stress. Varma et al. (2004) [29] expanded the context to cyclic flexural loading. Extended testing results on high strength CFSTs under eccentric loading were reported

by Fujimoto et al. (2004) [30], examining different cross-sectional shapes (including rectangular ones), material strengths and tube section slenderness. Similarly, Zhang and Guo (2007) [31], used high strength concrete and investigated eccentricity, aspect ratio of the cross-section, member slenderness and steel ratio. Furthermore, a numerical modeling procedure was presented for the load-deflection curve, accounting for global buckling. A numerical procedure was proposed for thin-walled rectangular CFSTs by Patel et al. (2012a [32] and 2012b [33]), using fiber-based elements, in order to compute the complete load vs deflection curve, accounting for load eccentricity and local or global buckling. The procedure was later extended in Patel (2020) [34] for rectangular CFST beam-columns with rounded edges. Rectangular CFSTs with axial load combined with uniaxial and biaxial flexure were also tested by Qu et al. (2013) [35], taking into consideration cross-section aspect ratio, material strengths and eccentricity. Rectangular, thin-walled CFSTs, with high strength steel, were tested by Lee et al. (2016) [36], varying the eccentricity, the steel strength and the tube section slenderness. Rectangular, eccentrically loaded CFSTs were tested by Du et al. (2017a) [37] with varying eccentricity, width-to-thickness and aspect ratios of cross-section, and concrete strength. Also, M-N interaction curves were presented for CFSTs under combined axial and flexural actions. Similarly, square, high-strength CFSTs were experimentally investigated by Li et al. (2018) [38], with varying eccentricities and steel ratios. M-N interaction curves were also presented.

A new trend emerged in the recent years, involving soft computing methodologies, for the characterization of the loading capacity of members. Even though such models are analytically formulated, they differ from traditional mechanical, empirical or numerical modeling procedures in the inherently stochastic training or evolution route they are required to pass through. This is achieved using a set of known data, ideally experimental tests, which include all the required input and output variables of the problem. Several soft computing models are available for the characterization of the compressive capacity of CFSTs. For circular CFSTs,

Güneyisi et al. (2016) [39], provided a model using gene expression programming, fine-tuned through a set of 314 data points. Du et al. (2017b) [40] developed a neural network model (ANN) for rectangular CFSTs, trained using a set of 305 data points. Also, Jayalekshmi et al. (2018) [41] quantified an ANN and proposed an empirical formulation. Tran et al. (2019) [42], utilized a database of 300 experimental tests to develop an ANN for square CFSTs and, furthermore, calibrated an empirical formula. Similarly, for square sections, Ren et al. (2019) [4] utilized a mixed algorithm employing a support-vector-machine and particle swarm optimization. Le and Phan (2020) [43] utilized an adaptive neuro-fuzzy inference system for rectangular CFSTs. Also, Zarringol et al. (2020) [44] developed an ANN for rectangular and circular CFSTs and presented empirical equations. For circular CFST long columns, Javed et al. (2020) [45] utilized gene-expression-programming, calibrated through 227 experimental specimens. For rectangular CFST columns, Asteris et al. (2021) [46] presented a hybrid ANN solution, with balancing-motion-composite-optimization, trained through a set of 422 experimental tests. For rectangular and circular CFST columns under concentric or eccentric load, Naser et al. (2021) [47] merged genetic and gene-expression programmings, utilizing an experimental database, totaling 3,103 tests (both circular and rectangular, split in four subgroups). Le et al. (2021) [48], developed an ANN for square and rectangular CFSTs, using 880 experimental data points.

The advantage of soft computing methodologies, compared to analytical, empirical or mechanical modeling approaches, can be summarized in their capacity to compensate for non-linear and irregular patterns in the response of the physical problem, requiring only suitable specimens for their training and no fundamental alteration in modeling process. A major source of nonlinearity in CFST columns is instability phenomena. Either global buckling or local buckling, can lead to radically differentiated response paths that are challenging to incorporate in a single model. Global buckling, in particular, is a failure mode not adequately represented

in soft computing models, available in literature. Even though, there is a plethora of experimental CFST specimens that can be utilized for the training of such models, their vast majority is stub columns, and as a result not representative of the potential for global buckling that may occur in longer columns. In this a study, a soft computing model is developed purposefully targeted for short and long columns alike. In order to train the model, for such a requirement, a considerable number of FEM CFST long columns are developed and presented herein, and are employed together with experimental short and long columns from the literature.

2. Finite Element Modeling

This section presents the development of finite element models, considering the tests E3 [49], E1, E3, E4 and E11 [26] and SS-1[50], as shown in [Table 1](#), in which e is the eccentricity. For each model, buckling and post-buckling analyses were performed, employing ABAQUS software [51]. The initial geometric imperfection is applied with amplitude of $L/300$ [50] for all tests, while $L/1000$ is adopted for SS-1 test [52,53]. Residual stresses are not considered, as they do not influence the overall behavior of CFSTs according to the literature provisions [52]. Next, the materials models will be described, as well as the application of the interaction between the contact surfaces, boundary conditions and discretization.

[Table 1: Data of experimental tests, used for FEM validation](#)

Test	Ref.	B (mm)	H (mm)	t (mm)	L_e (mm)	f_y (MPa)	f'_c (MPa)	e (mm)
E3	[49]	300	300	5	1720	301	70.5	40
E1	[26]	150	150	4.18	870	550	56.6	30
E3	[26]	150	150	4.18	2170	550	56.6	30
E4	[26]	150	150	4.18	2170	550	65.7	60

E11	[26]	160	80	4.18	2310	550	56.6	60
SS-1	[50]	200	200	12.5	3640	465	191.0*	20

* $f'_c = f_{ck} + 8$

2.1 Description of the FE models

The steel tube is modelled with elastic-perfectly plastic behavior assuming that the post-yielding behavior is limited within the yield plateau. The Young's modulus and Poisson's ratio are taken equal 200 GPa and 0.3, respectively. For concrete, the Concrete Damage Plasticity (CDP) model is used [54-56]. The Poisson's ratio is taken equal 0.2. The input parameters of CDP model (i.e., eccentricity, the ratio between initial equibiaxial and uniaxial compressive yield stresses and the ratio of the second stress invariant on the tensile meridian to that on the compressive meridian) are taken as default [50], except for the dilation angle, for which a value of 30° is used [50]. The Carreira and Chu model [57] is used for the stress-strain relationship of concrete in compression (Eqs. 1-2). An important observation is that in the SS-1 test the softening branch of the stress-strain relationship of concrete in compression is not modeled due to its fragile behavior, according to Ref [50]. The fracture energy model by Hillerborg et al. [54] is used for the behavior of concrete in tension and it is calculated according to CEB-FIP Model Code [58] (Eq. 3).

$$\frac{\sigma}{f'_c} = \frac{\beta_c(\varepsilon/\varepsilon_c)}{\beta_c - 1 + (\varepsilon/\varepsilon_c)^{\beta_c}} \quad (1)$$

$$\beta_c = \left(\frac{f_c}{32.4}\right)^3 + 1.55 \text{ (MPa)} \quad (2)$$

$$G_F = G_{F0} \left(\frac{f'_c}{10}\right)^{0.7} \quad (3)$$

Two types of interaction are used between the contact surfaces. The normal and tangential behaviors are modeled between the surfaces of the concrete filled and steel tube. The friction

coefficient is taken as 0.25 [50,59-62]. The tie constraint is applied between the end plates and the CFSTs. This technique simulates a perfect bond between contact surfaces.

The application of boundary conditions and discretization are illustrated in Figure 1. Loading is indirectly applied by imposed displacement. The symmetry of the model along the y axis is considered ($U_y=0$). The boundary conditions and the eccentricity were modeled using kinematic coupling at the reference points, at both ends, similar modeling technique used in [63, 64]. This technique allows to simulate the hinges. In this context, at one end, the displacements in the x, and y axes, as well as the rotation about the z axis, were restrained ($U_x=U_y=U_{Rz}=0$), considering the reference point 1 (RP-1). At that same point, a displacement of 10 mm was applied in the direction of the z axis ($U_z=10$). At the other end, the displacements in the x, y and z axes, as well as the rotation about the z axis, were restrained ($U_x=U_y=U_z=U_{Rz}=0$), considering the reference point 2 (RP-2). It is important to highlight that these boundary conditions are applied considering the eccentricity in relation to the geometric centre of the cross section. The discretization was performed with C3DR8 solid elements, with reduced integration. The element size, with a minimum dimension of 20 mm, is based on similar studies found in the literature [62,65-66].

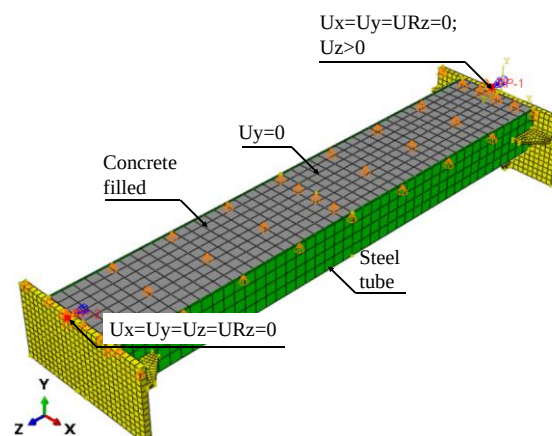


Figure 1. Boundary conditions and discretization of the FE model

2.2 FEM Validation

An example of final configuration of test in comparison with FEM is shown in Figure 2. It can be noted that large deflections are observed on mid-height of CFST at load levels corresponding to capacity. In Figure 3 the load-deflection relationships are shown for two out of the six cases. Similar, behaviour has been achieved by the remaining ones. It can be highlighted that the finite element model can accurately predict the overall behavior of CFSTs with eccentric loading. The validation results for all cases are presented in Table 2.

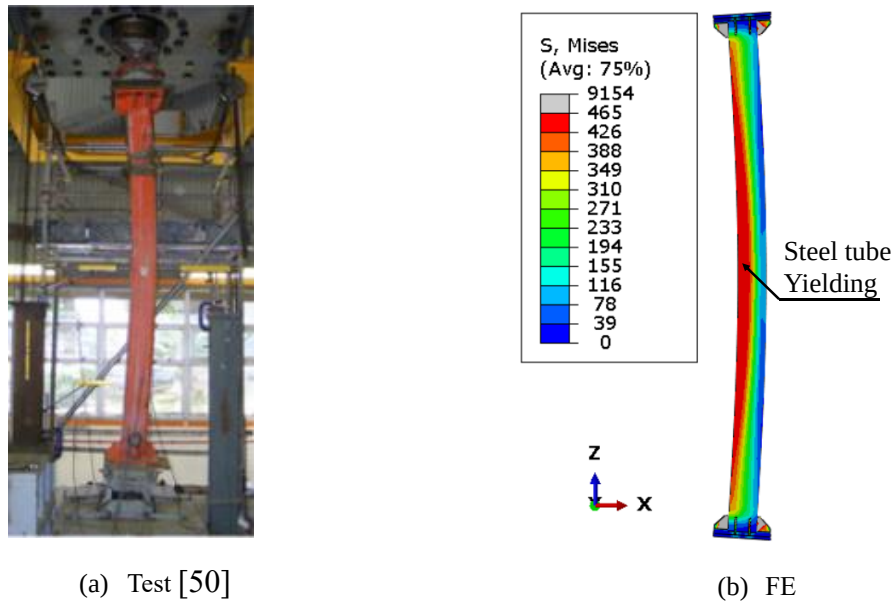


Figure 2. Final configuration of the FE model

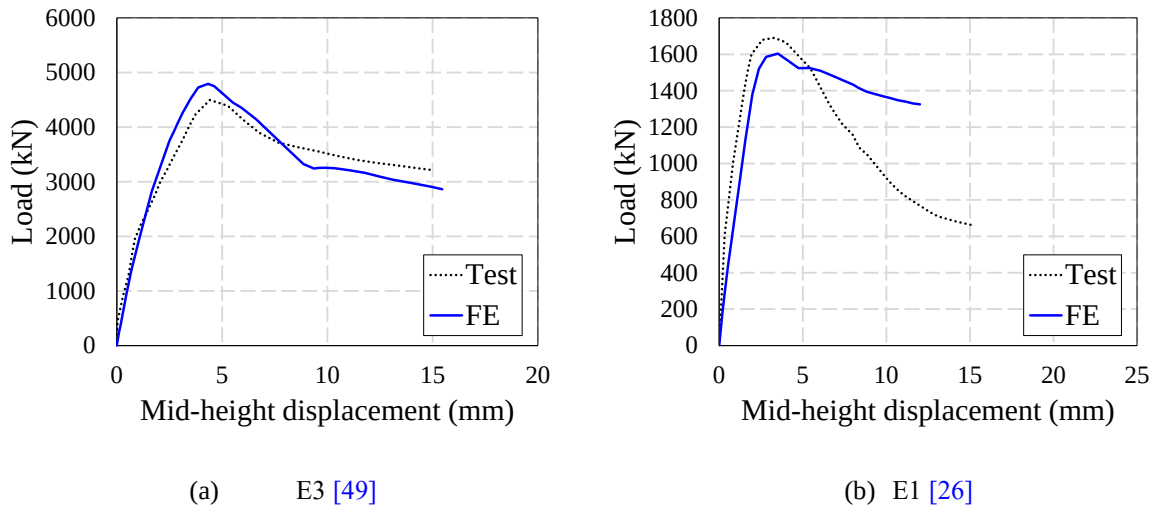


Figure 3. Comparison between FE model results and experimental tests regarding the load-
mid-height displacement relationship

Table 2: Summary of FEM validation results

Test	Ref.	P_{TEST} (kN)	P_{FE} (kN)	P_{TEST}/P_{FE}
E3	[49]	4553	4792	0.95
E1	[26]	1678	1603	1.05
E3	[26]	1330	1291	1.03
E4	[26]	1020	1073.3	0.95
E11	[26]	670	675.6	0.99
SS-1	[50]	5187	4951	1.05

After validating the numerical models, as presented so far, an extensive parametric study was conducted, which is described in the next section.

2.3 Parametric FEA

The parametric study is performed due to the gap of finite element results and tests in the literature. To complement the available data, it was necessary to develop a large amount of additional data. For that purpose, 216 numerical models were established herein, as outlined in Table 3. Parameters under examination were the column length, tube thickness, load eccentricity as well as steel and concrete material strengths. Section slenderness ratios (H/t) in the schedule range between 25 to 50, while length to width ratios (L/B) vary between 7.5 and 22.5, with composite member slenderness L/r (where r the radius of gyration), between 27 and 81.5.

Table 3: FEM parametric analysis schedule

Parameter	Values
-----------	--------

B (mm)	200
H (mm)	200
t (mm)	4;6;8
L (mm)	1500; 3000; 4500
f _y (MPa)	300; 500; 700
f _c ' (MPa)	30; 80
e (mm)	0; 20; 50; 100

3. Materials and Methods

3.1 Database

An extensive database of rectangular (including square) CFST specimens has been prepared in order to provide reliable data for the training of soft computing models. The database contains specimens from both experimental tests that were extracted from the literature, as well as advanced FE models that were developed in this work, as presented in the previous section. Specifically, 1,641 experimental specimens and 216 FEM specimens were included, with a total equal to 1,854 specimens. The FE models were purposefully developed as long columns, with varying lengths, in order to provide a range of input values that are less common in available experimental test setups from the literature. With the inclusion of such long column configurations, the prediction and characterization of compressive strength under member buckling phenomena is looked after. Short specimens are not excluded from the database however, as they still provide data for modes of failure other than member buckling, such as material plasticity or local buckling that remain relevant for physical CFST columns. [Table 4](#) presents a summary of the CFST configurations included in the database. Also, in [Table 5](#), the original sources are presented, where the experimental tests in the database have been extracted from, together with the respective for each source, compressive capacity load ranges.

Specimens with both axial and eccentric compressive loading are included in the database, as well as square and non-square specimens. Regarding the non-square ones, their width, B and height, H dimensions can be inverted without any change in their resulting behavior, in case of concentric loading. When training an ANN however, the two cases (the original and the inverted one) represent two different columns. This way, the training is effectively enriched with more input. For this reason, all non-square specimens have been duplicated and included also with inverted B and H dimensions, resulting in 264 additional cases. For the specimens with eccentric loading however, this duplication was not possible, unless the direction of eccentricity is also changed (which cannot be performed with the selected set of input variables, as outlined hereafter).

Table 4. Summary of the sample configuration in the database

Type	1,641 experimental
	216 FEM
Cross-section	1,182 square
	675 non-square
Loading	1,300 axial compression
	557 eccentric compression
Source	1,593 original
	264 inverted duplicates

In Figure 4, a generic rectangular CFST column layout is shown, presenting the main geometric parameters that are considered in this work. These are:

- the external dimensions of the steel tube, H and B ,
- the thickness of the steel tube walls, t ,
- the effective length of the column member, L_e ,
- the eccentricity of the compressive load (assumed in the direction of B), e .

When a specimen is loaded concentrically, the exact orientation of tube dimensions H and B is not important (i.e., it could be considered as $H \times B$ or $B \times H$ without affecting its output, in fact both configurations are included in the database as explained before). When the load is instead imposed eccentrically, it is assumed that the eccentricity e is parallel to the tube dimension B , as shown in [Figure 4](#). This, assumption makes the definition of H and B dimensions dependent on the orientation of eccentricity (and sometimes H and B are flipped compared to the original source). This approach requires no additional input variables to determine the orientation of eccentricity. This in turn is beneficial for the development of the ANN.

Regarding the effective length of column L_e , the characterization of the imposed constraints on each specimen is required. For short columns, usually no special consideration is given on the characterization of end support conditions during testing, since the emergence of global buckling phenomena is not possible. In these cases, length L_e is set equal to column length L , assuming this way pinned supports. For long columns on the other hand, a more robust approach is followed, so that L_e is properly characterized. In some sources the effective length is measured during testing, so this value is also adopted here. In other cases, end support conditions are described in the text, or presented in illustrations, commonly as knife-edges that implement pinned end support conditions. In these cases, effective length L_e is set equal to physical column length L . If a proper evaluation of effective length L_e of a long column specimen is not possible from the published data, the affected specimen is then excluded from the database.

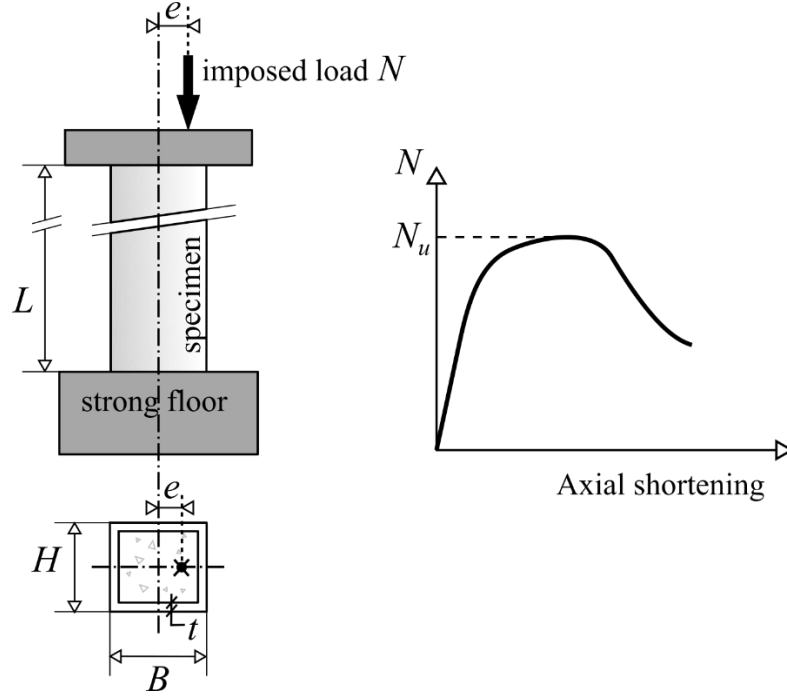


Figure 4. Testing setup definitions

Two more input variables, that characterize the mechanical properties of the CFST, are employed for each specimen in the database as follows:

- yield strength of the steel f_y ,
- cylinder strength of the concrete f'_c .

Specimens with uncommon concrete aggregates are not included in the database. It is important to note, that the concrete cylinder strength (conventionally measured through 150x300 mm molds) is included for all specimens in the database. Correction is performed for those specimens with concrete strengths measured differently. Specifically, a 0.85 correction factor is used for strengths measured with cubic molds, whereas a 0.92 factor is used for strengths measured through 100x200 mm cylindric molds. Steel yield strength f_y is assumed uniform for the entire tube section. Tests with stainless steels or other types beyond carbon steel are not included in the database. Effects of steel strength variance due to manufacturing process over the tube section are ignored. Due to work hardening, corner regions of cold-formed tubes are typically expected to present higher values of yield and ultimate strength, which can lead to an overstrength of affected CFSTs [67-69]. This

effect is not modeled in our database. Concluding, only specimens with experimentally evaluated material properties are allowed in the database. CFSTs with nominal concrete or steel strength values are rejected.

Together, the seven aforementioned variables (five geometric and two material ones) represent the set of input data for each specimen in the database. A single output variable is employed for each specimen, which is the ultimate compressive load, N_u . This is easily obtained when the force-deformation curve features a critical point, followed by a softening branch (typical when instabilities govern behavior). However, some experimental setups feature a stable hardening branch and no critical point is reached. In these cases, the experiment is typically stopped at some point due to excessive deformation, even though additional load capacity may be available. For these tests the maximum recorded load is assigned to N_u , assuming that any further hardening would be rather limited at high deformations and not practically useful.

It is expected that CFSTs tested by different laboratories, at different times exhibit statistical discrepancies in their outcome. Factors such as workmanship, manufacturing procedures, source of materials etc. that are hard to quantify, influence the experimental result, potentially affecting the reliability of any database. However, with increasing number of independent experimental sources and number of specimens, such discrepancies are cancelled out in the context of AI training, producing as result a smoothed output. The large number of sources in our database in our database together with the overall specimen count, better facilitates this key capability of AI technique and reinforces the reliability of the developed models.

In Table 6, a statistical outline of the input and output variables, is shown. Considering material strengths, the database covers an extensive range including both mild steel and high strength steels and also both normal concrete and high strength concrete Regarding column effective length, L_e , a wide range is also present in the database that includes both stub columns and long columns (the range of column slenderness ratios, $L_e / \min \{B; H\}$, found in the database extends from 0.6 to 49).

Table 5. Original sources and data included in the database

Nr.	Reference	Number of Samples			Axial Load (kN)	Eccentricity (mm)
		Eccentricity		Total		
		without	with			
1	Zhang 1984 [70]	50	-	50	660-2800	0
2	Lu et al. 1999 [71]	6	-	6	2061-4872	0
3	Guo 2006 [72]	6	5	11	347-1785	0-40
4	Liu & Gho 2005 [73]	20	-	20	1566-3996	0
5	Liu et al. 2003 [74]	12	-	12	1490-4210	0
6	Liu Dalin 2005 [75]	12	-	12	1657-2828	0
7	Ye Zaili 2001 [76]	66	-	66	1150-2700	0
8	Guo et al. 2006 [77]	8	-	8	635-1785	0
9	Wei & Han 2000 [78]	20	21	41	333.20-2058	0-80
10	Zhang & Zhou 2000 [79]	36	-	36	588-1323	0
11	Tomii & Sakino 1979 [80]	8	-	8	497.40-667	0
12	Inai & Sakino 1996 [81]	46	-	46	1153-7780	0
13	Nakahara & Sakino 1998 [82]	4	-	4	3899-6645	0
14	Lu & Kennedy 1992 [83]	6	-	6	1906-4208	0
15	Yamamoto 2000 [84]	16	-	16	411-6494	0
16	Lam & Williams 2004 [85]	15	-	15	680-2000	0
17	Han & Yao 2004 [86]	6	10	16	14154-2594	0-30
18	Matsui et al. 1995 [87]	5	-	5	1143-1598	0
19	Wei & Han 2000 [78]	8	-	8	754.2-2082.5	0
20	Furlong 1967 [7]	10	-	10	488-1601.36	0
21	Grauers 1993 [88]	14	-	14	1440-2680	0
22	Schneider 1998 [89]	20	-	20	819-2069	0
23	Chung et al. 2001 [90]	5	-	5	1144-1598	0
24	Han 2002 [91]	8	-	8	740-880	0
25	Ghannam et al. 2004 [92]	26	-	26	491-1248	0
26	Han & Yao 2004 [86]	5	-	5	1986-2280	0
27	Guo et al. 2005 [93]	14	-	14	1558-2636	0
28	Luo 1986 [94]	28	-	28	600-1740	0
29	Liu & Gho 2005 [73]	24	-	24	1725-2291	0
30	Liu et al. 2003 [74]	30	-	30	1425-2970	0
31	Liu Dalin 2005 [75]	24	-	24	1735-2124	0
32	Ye Zaili 2001 [76]	46	-	46	1068-2700	0
33	Knowles & Park 1969 [8]	6	4	10	156.35-511.55	0-25.40
34	Lin 1988 [95]	18	-	18	558-1268	0
35	Shakir-Khalil & Mouli 1990 [96]	28	1	29	407.20-1370	0-8
36	Matsui & Tsuda 1996 [21]	5	18	23	276.55-1597.5	0-125
37	Han & Yao 2003a [11]	34	12	46	500-1140	0-31
38	Han & Yang 2003 [97]	8	-	8	490-825	0
39	Han & Yao 2003b [98]	6	13	19	390-816	0-31
40	Ghannam et al. 2004 [92]	36	-	36	240-1248	0
41	Han & Yao 2004 [86]	11	-	11	1986-2594	0
42	Sakino et al. 2004 [99]	46	-	46	1153-7780	0

43	Yu et al. 2008 [14]	10	4	14	390-1220	0-30
44	Aslani et al. 2015 [100]	12	-	12	1367-3882	0
45	Du et al. 2016a [101]	11	-	11	3090-3575	0
46	Du et al. 2016b [102]	16	-	16	1960-3150	0
47	Dundu 2016 [15]	27	-	27	105.4-1516	0
48	Khan et al. 2017a [16]	39	-	39	286-6329	0
49	Khan et al. 2017b [103]	16	-	16	1636-7506	0
50	Mursi and Uy 2004 [12]	4	4	8	1481-3950	0-25
51	Vrcelj and Uy 2002 [104]	13	-	13	269-684	0
52	Xiong et al. 2017 [105]	5	3	8	5078-7276	0-50
53	Zhu et al 2017 [106]	6	-	6	2730-3980	0
54	Lue et al. 2007 [13]	44	-	44	1281.3-2196.4	0
55	Liew et al. 2016 [107]	5	3	8	4997-7276	0-50
56	Chen et al. 2018 [108]	9	-	9	987-2051	0
57	Ibanez et al. 2018 [109]	8	-	8	824.5-1882.5	0
58	Zhu and Chan 2018 [110]	7	-	7	3452-6298	0
59	Uy 1998 [111]	5	-	5	950-2519	0
60	Uy 2000 [23]	8	12	20	619-4581	0-100
61	Tao et al. 2009 [112]	4	-	4	1993-3190	0
62	Tao et al. 2008 [113]	6	-	6	2140-4080	0
63	Cederwall et al. 1990 [19]	14	12	26	610-2680	0-20
64	Chen and Jin 2010 [114]	11	-	11	1980-2360	0
65	Han et al. 2005 [115]	24	-	24	318-3400	0
66	Nakahara & Sakino 2000 [22]	-	21	21	259-4100	45-300
67	Uy 1997 [116]	-	6	6	619-1133	20-84
68	Shakir-Khalil and Al-Rawdan 1996 [20]	-	15	15	273-882	6-75
69	Zhang et al. 2004 [25]	-	26	26	823-2636	0.90-72
70	Liu Dalin 2004 [26]	-	12	12	660-1950	20-70
71	Guo & Zhang 2007 [117]	-	2	2	655-983	30-40
72	Bridge 1976 [17]	-	3	3	513-1956	38-64
73	Shakir-Khalil & Zeghiche 1989[18]	-	4	4	210-393	16-60
74	Mursi & Uy 2003 [24]	-	4	4	1481-3062	8-23
75	Fujimoto et al. 2004 [30]	-	21	21	267-4045	45-300
76	Tao et al. 2007 [118]	-	4	4	1130-1760	30-60
77	Zhang & Guo 2007 [31]	-	26	26	823-2636	0.90-72
78	Hernandez-Fig. et al. 2012a [119]	-	10	10	220.33-573.32	20-50
79	Hernandez-Fig. et al. 2012b [120]	-	12	12	244-935	20-50
80	Qu et al. 2013 [35]	-	9	9	750-3450	10-70
81	Lee et al. 2017 [36]	-	3	3	3873-6491	20-40
82	Du et al. 2017c [121]	-	12	12	2020-2660	13-41.50
83	Liu 2006 [27]	-	20	20	617-1491	15-60
84	Li et al. 2018 [38]	-	12	12	1244.1-2129.7	20-65
85	Ren et al. 2022[122]	4	-	4	1076-1414	0
86	Zhang et al. 2021[123]	2	-	2	3228	0
87	Nguyen 2021[124]	6	-	6	2216-3154	0
88	Huang et al. 2020 [125]	10	6	16	1357.6-4250.1	0-97.50
89	Lee et al. 2019[126]	2	-	2	6602-8686	0

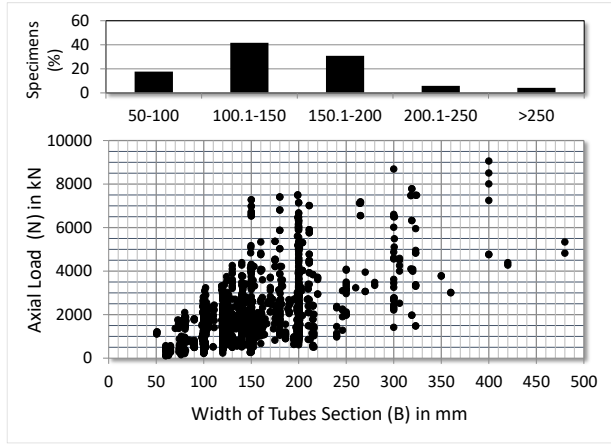
90	Nguyen et al. 2022[127]	-	8	8	1278-2390	15.75-60.75
91	Ibanez et al. 2021[128]	12	-	12	824.5-1882.5	0
92	Lu et al. 2021[129]	4	-	4	7246-9057	0
93	Yan et al. 2021[130]	6	-	6	2247-4310	0
94	Du et al. 2021[131]	6	-	6	2700-6010	0
95	Yang et al. 2021[132]	-	2	2	1092.3-1448.4	27-36
96	Zhang et al. 2021[133]	48	-	48	1735-5334	0
97	Li et al. 2021[134]	-	24	24	981.5-2199.5	20-65
98	Li et al. 2021b[135]	8	-	8	3363.5-4257.5	0
99	Cai et al. 2021 [136]	30	-	30	1112-4062	0
100	Zhang et al. 2020 [137]	2	10	12	259-2213	0-171
101	Ren et al. 2022 [138]	-	1	1	1187	13.01
102	This work (FEM)	54	162	216	608.82- 6674.84	0-100
Total		1300	557	1857	105.4-9057	0-300

An investigation of the relationship between the several input variables and output is also performed, using the Pearson coefficient, R . Specifically, [Table 6](#) presents the value of R between all pairs of input and output variables. In principle, a coefficient close to unity characterizes an almost linear relationship between the involved pair. Considering the reported R coefficients in [Table 6](#), no strong correlation is present between pairs of input variables. In fact, for all pairs, the R coefficient is smaller than 0.5, except for that between the B and H dimensions, which is 0.58. Even though such a value does not describe a strong correlation, it is also justifiable by the physical problem, since the aspect ratios B/H employed in construction are practically bounded (typically below 2.5). Examining the relationships between input and output pairs of variables, most correlation factors are comparable (around 0.5) except for those involving the column effective length L_e and the eccentricity e , which are quite lower. Regarding effective length L_e , it affects the compressive load only when its value is larger, and therefore the weak correlation with output is justified by the fact that a large proportion of specimens in the database features a lower length, thus it is not susceptible to global buckling phenomena. Similarly, regarding eccentricity, e , its weak correlation with output is justified by the fact that not every specimen in the database involves eccentric loading.

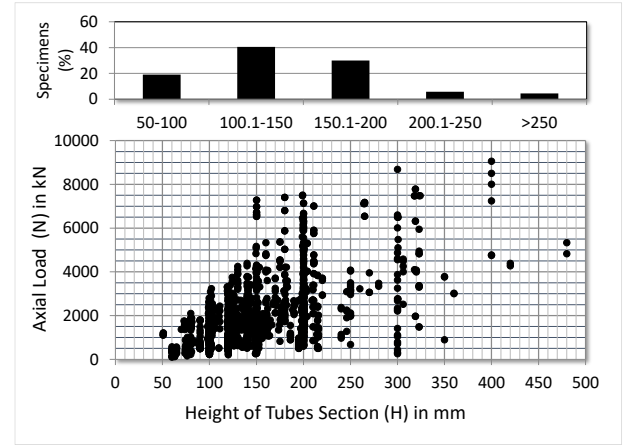
Table 6. Correlation coefficients R between the selected input and output variables

Category	Variable	Input						Output	
		B	H	t	L_e	f_y	f'_c	e	N
Input	B	1.00							
	H	0.58	1.00						
	t	0.23	0.23	1.00					
	L_e	0.14	0.15	0.16	1.00				
	f_y	0.01	-0.01	0.28	0.08	1.00			
	f'_c	-0.07	-0.07	0.13	0.03	0.38	1.00		
	e	0.24	0.23	0.15	0.27	0.07	0.01	1.00	
Output	N	0.55	0.52	0.47	-0.12	0.44	0.34	-0.18	1.00

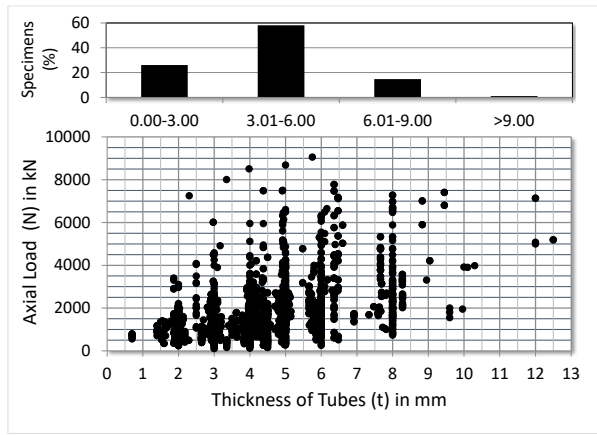
Next, a more in-depth investigation of the correlation between input variables and the output is performed. Specifically, [Figure 5](#) and [Figure 6](#) illustrate the mapping between each of the variables and the output, in the form of scatter plots, for every specimen in the database. Alongside, a histogram is presented, which illustrates the density of specimens in the input space of each variable. Tube thickness t ranges mostly between 3-6mm, while a significant proportion utilizes thicknesses below 3mm, indicating an increasing interest for thin-walled tube sections. Generally, the distribution of specimens throughout the range of available input values is not continuous, but some concentrations on certain key values are observed. The preference to these values could be attributed either to availability reasons of commercially obtained steel tubes, or a preference for external dimensions (to the nearest 50 mm) for manufactured tubes. The preference for certain input values seems more prevailing for the tube thickness t . Regarding effective length L_e , 60% of the specimens employ lengths below 1 m, which probably represent tests on stub columns. There is a good number of specimens, however (around 15%), with effective lengths in the 2-3 m range, which is close to the actual length of a column in building construction. A smaller but considerable number of specimens is available for longer effective lengths.



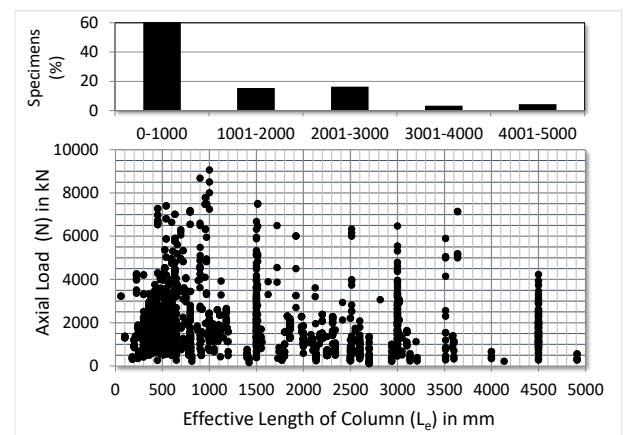
(a)



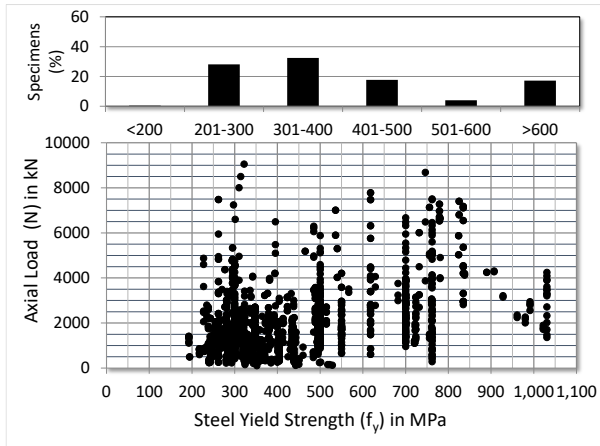
(b)



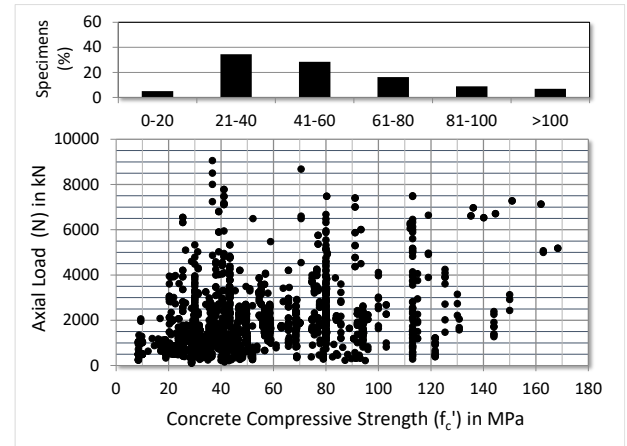
(c)



(d)



(e)



(f)

Figure 5. Relationship with output and histograms of the input variables: a) tube width B; b) tubes height H; c) tube thickness t; d) effective member length Le; e) steel yield strength f_y and f) concrete strength f_c'

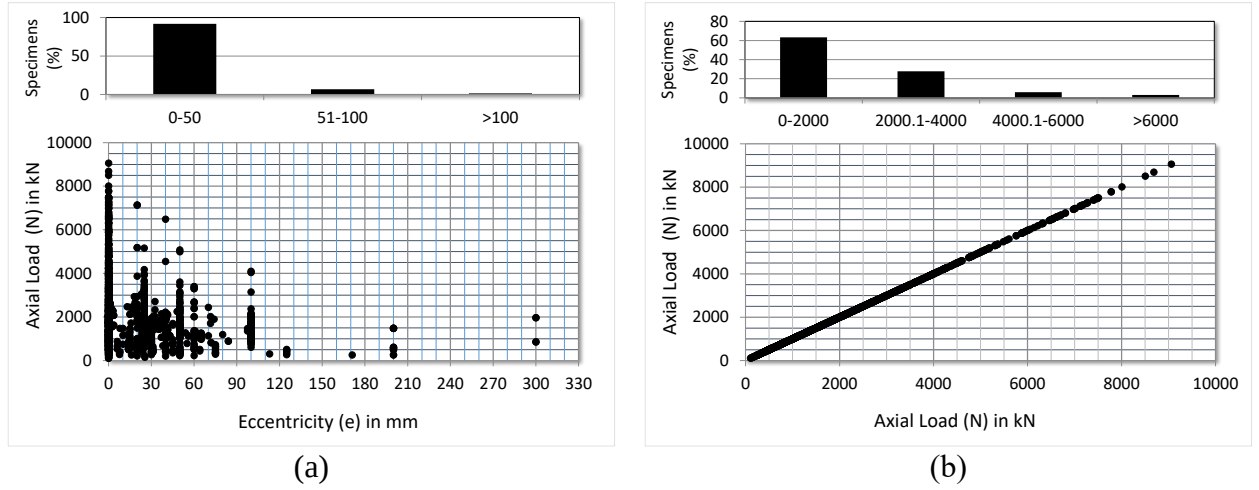


Figure 6 Relationship with output and histograms of the variables: a) eccentricity e and b) axial load (N)

Regarding steel yield stress f_y , approximately 60% of the specimens utilize mild steel (201-300 MPa and 301-400 MPa ranges). A significant portion utilizes high strength steel, most commonly within 401-500 MPa. Similarly, for the concrete strength f'_c , a preference for normal concrete is observed (mostly within 21-40 MPa), however there is a significant proportion employing high strength concrete. For the eccentricity e , the vast majority features values in the 0-50 mm range, which also includes the cases with zero eccentricity (axially loaded). A little number of specimens uses eccentricities over 50 mm (around 5% of the specimens). A clear negative influence on the output axial load N_u , is observed with increasing eccentricity.

In order to verify statistically the relevance for the selection of training and testing datasets from the original database, probability density functions for all data points, training dataset and testing dataset, respectively, are plotted together and shown in Figure 7. It is seen that for each variable in the database, the statistical correlation between the three datasets is very strong. Linear statistical correlation between each pair of datasets was also computed and its value is always larger than 0.99 in all cases. The results of these analyses indicate that the selection of training and testing datasets is relevant.

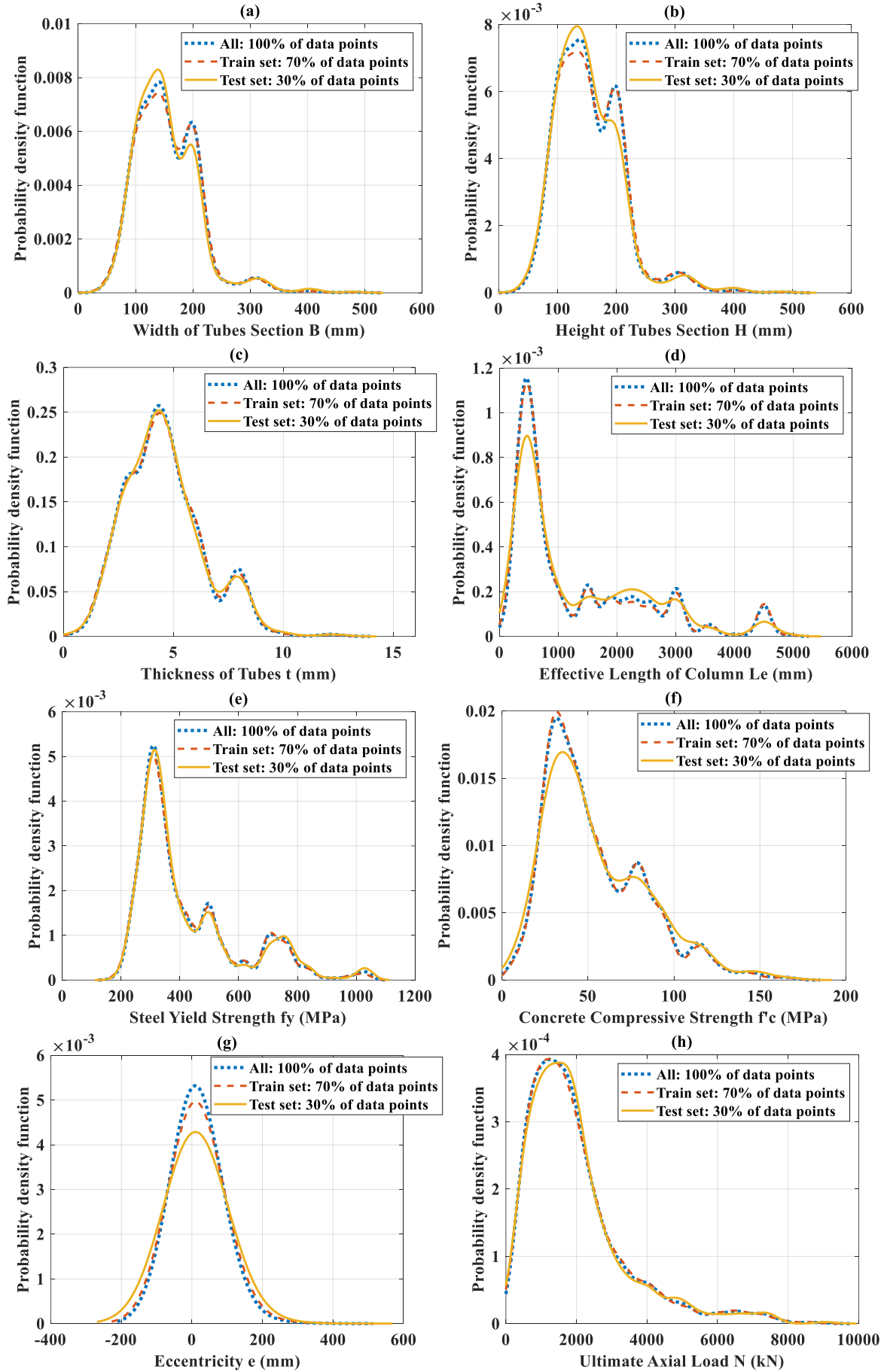


Figure 7. Relevant selection of training and testing datasets

3.2 Soft Computing and Metaheuristic Optimization Methods

3.2.1 Artificial Neural Network

An Artificial Neural Network, also known as ANN, is a type of biomimetic network, imitating biological brain neurons and their connections. Since the groundbreaking work that McCulloch and Pitts [139] presented in 1943, this technique has been improved with a range of structures and successes in the field of information technology [140,141]. As the processing capacity of computers continues to increase and more databases become accessible, artificial neural networks (ANN) have emerged as one of the most important components of machine learning [142]. Along with fuzzy logic and optimization algorithms, artificial neural networks (ANN) are essential components of soft computing, the overarching goal of which is to develop an approximation system capable of handling difficult real world problems [143,144].

A traditional feedforward artificial neural network (ANN) is composed of layers of nodes or neurons. Information or signals are passed from one layer to the next, beginning with the input layer. This process continues until the information reaches the output. The last layer is responsible for providing the dependent variables(s) and checking them against the labels of the associated samples in the input space. A prime architecture of ANN, which is built of one hidden layer, is shown in Figure 8.

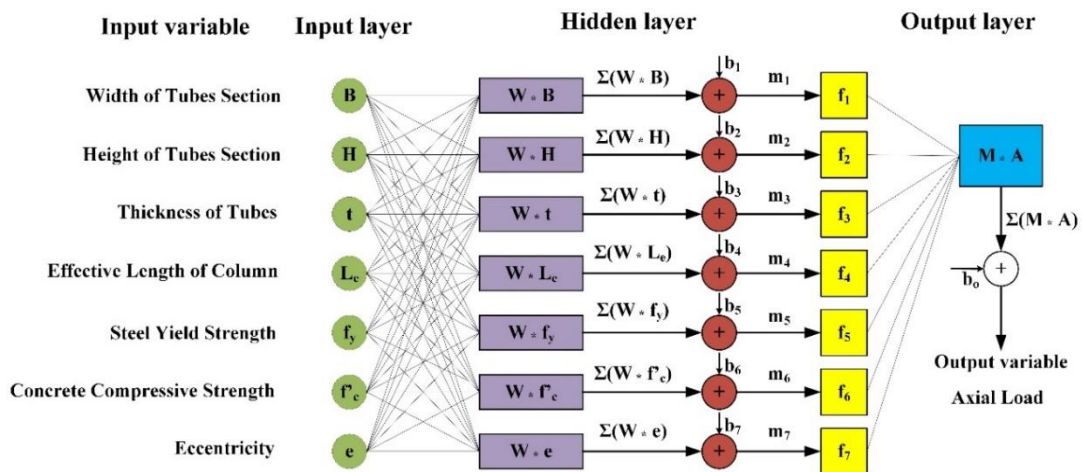


Figure 8. Typical architecture of ANN model including one hidden layer.

The principle of operation of neurons in a biological brain served as the inspiration for artificial neural networks (ANN). One of the primary benefits of ANN is its capability to model complicated phenomena, such as those in which the link between independent and dependent variables is non-linear [145,146]. ANN does not require preconditions during the training process, unlike other techniques [147-149]. In addition to this, ANN is able to process any kind of data, whether it be full or incomplete, and it can also handle complex interactions between parameters in the database [150,151]. From a computational standpoint, ANN is an excellent candidate for parallel computing, which has the potential to considerably cut down on the cost of computation [152-155].

There are a variety of different algorithms available for training ANN. Some, like the Levenberg-Marquardt backpropagation algorithm, use a lot of memory to handle a lot of classification problems [156], and its convergence rate is slow [157]. A number of different strategies have been suggested as potential solutions to these challenges. One such strategy is to build ANN models on the concept of gradient descent [158], also known as the first-order conjugate gradient algorithm. Despite this, the cost of this strategy is still high because the line search has to be performed on each iteration.

3.2.2 Grey Wolf Optimization Algorithm

Grey Wolf Optimization Algorithm (GWO), proposed by Mirjalili et al. [159], is a swarm intelligence algorithm inspired by wolves' hierarchy system and predation process. In GWO, the fittest solution is named alpha (α), the second and third-best solutions are named beta (β) and delta (δ). The other candidate solutions are assumed to be omega (ω). In the GWO algorithm, the hunting (optimization) is guided by α , β and δ . The ω wolves follow the above three kinds of wolves.

There are several advantages in the technique, such as that it has a simple structure, it needs less storage and processing power, it converges faster because the search space gets smaller over time and has fewer decision variables. It can also avoid local minima and has only two control

parameters, which makes it more stable and robust. Increasing the number of goals and communication ranges can make a big difference in how well the GWO system works, which in turn makes the algorithm work better [160]. The GWO's algorithm is presented in Figure 9.

GWO algorithm

```

Initialize the grey wolf population  $X_i$  ( $i = 1, 2, \dots, n$ )
Initialize  $a, A, C$ 
For  $X_i$  ( $i = 1, 2, \dots, n$ ) do
    Calculate fitness
End for
Save the first three best wolves as  $X_\alpha, X_\beta$  and  $X_\delta$ 
While ( $t < \text{Max number of iterations}$ )
    For each search agent
        Update the position of the current search agent
    End for
    Update  $a, A$ , and  $C$ 
    For  $X_i$  ( $i = 1, 2, \dots, n$ ) do
        Calculate fitness
    End for
    Update  $a, X_\alpha, X_\beta$  and  $X_\delta$ 
     $t = t + 1$ 
End while
Return  $X_\alpha$ 

```

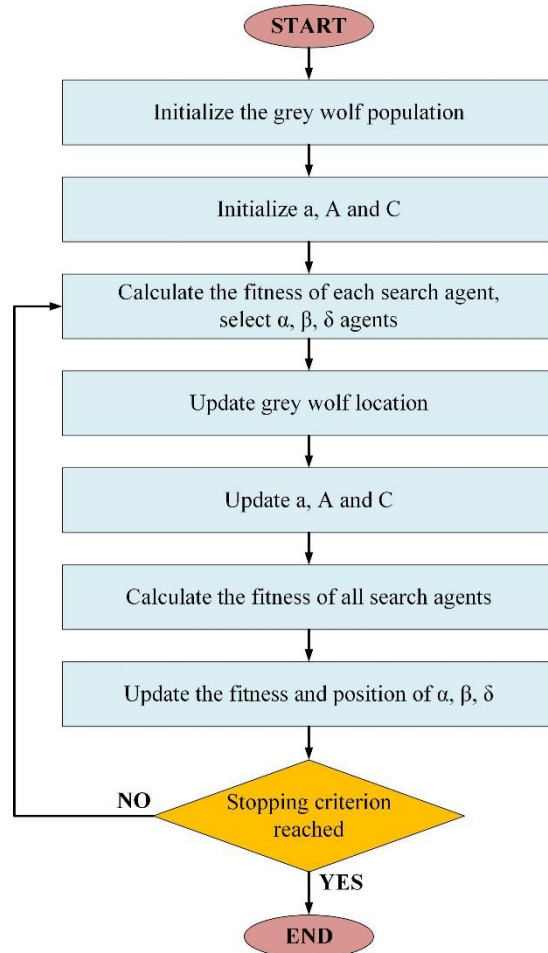


Figure 9. Pseudo code of the GWO algorithm [161] (left) and the respective flow chart (right) (A is the convergence coefficient vector, C is the random coefficient vector, and a is the convergence factor).

3.2.3 Firefly Algorithm

The firefly algorithm (FA), is a recently discovered nature-inspired metaheuristic method [162], inspired by the flashing characteristics and behavior of tropical fireflies. For both global and local optimizations, this meta heuristic technique is extremely accurate. FA adheres to a set of three idealized guidelines, as outlined below[163]:

- Fireflies' gender is unisex, therefore they can be attracted to either male or female fireflies.

- The less bright firefly will be lured to the brighter ones, since attractiveness and brightness are linked.
- The landscape of the objective function determines the brightness of a firefly.

The objective function can be used to determine the brightness in order to solve minimization challenges. Another approach to describe brightness is in terms of the fitness function, which is used in genetic algorithms.

There are several advantages of the technique. FA is able to locate both the global and local optima at the same time and with equal efficiency. This benefit will be demonstrated in greater depth later in the process. FA also has the benefit of allowing various fireflies to operate practically independently one from another. As a result, it is particularly well-suited for parallelization. Fireflies gather around each optimum more tightly than in genetic algorithms or particle swarm. Parallel implementation should have minimum interactions between distinct subregions. The FA's algorithm is presented in Figure 10.

Firefly algorithm

```

Starting the population of fireflies  $X_i$  ( $i = 1, 2, \dots, n$ )
Outlining the coefficient of light absorption  $\gamma$ 
While ( $t < \text{Max number of iterations}$ )
  For  $i = 1:n$  all  $n$  fireflies
    For  $j = 1:n$  all  $n$  fireflies
       $f(x_j)$  is used to ascertain the light intensity  $I_j$  at  $x_j$ 
      If  $I_j > I_i$ 
        The firefly  $i$  approaches firefly  $j$  in all  $d$  dimensions
      End if
      Attractiveness fluctuates within the distance  $r$  by  $\exp[-\gamma r]$ 
      Assess new solutions and update the intensity of the light
    End for  $j$ 
  End for  $i$ 
  Devoting ranks to butterflies and obtaining the current best
End while
Analyzing the results and visualization
  
```

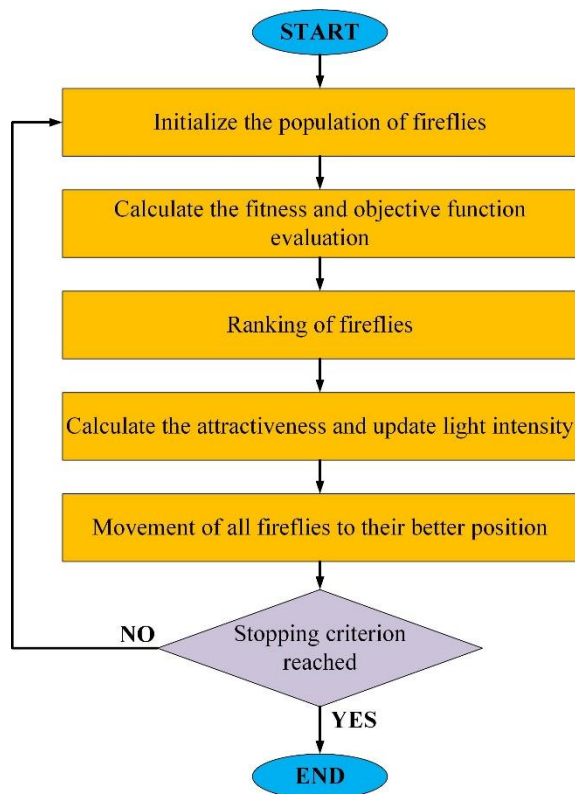


Figure 10. Pseudo code of the FA algorithm [164] (left) and the respective flow chart (right)

3.3 Performance Indices

For the ranking of the trained and developed soft computing models, the following five well-known and established performance indices have been used:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - y_i)^2} \quad (4)$$

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{x_i - y_i}{x_i} \right| \quad (5)$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^n (x_i - y_i)^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \right) \quad (6)$$

$$\text{VAF} = \left(1 - \frac{\text{Var}(y - x)}{\text{Var}(y)} \right) \times 100\% \quad (7)$$

$$\text{a20-index} = \frac{n20}{n} \quad (8)$$

where, x, y the vectors to be compared, namely the experimental and predicted CFST loads. Also, $\bar{x}$ is the mean value of x , while var is the variance of a given vector and $n20$ the number of specimens, with $0.8 \leq y_i/x_i \leq 1.2$.

3.4 Methodology

Rather than relying to intuition or former expertise, the selection of configuration parameters for the ANN in this paper is methodologically performed, evaluating numerous alternative architectures, and ranking them according to their performance. To this end, multiple values of the configuration parameters (listed in supplementary material), were examined in combination. These are the number of hidden layers, the neurons in the hidden layers, the transfer function for hidden and output layers, the training function and the cost function. The combination of these alternatives (including 100 random generations for each

configuration) resulted to 198,460 alternative ANN configurations. For the training and evaluation of these configurations, randomly selected subsets of specimens from the entire database were utilized. Specifically, the entire database was randomly (following a uniform distribution) split into 3 smaller datasets: the first one, with 66.7% of the specimens (967) was used for training alternative ANNs; the second one with 16.7% of the specimens (242) was designated for validating the alternative ANNs; and the third one, with the remaining 16.6% of the specimens (241), was left for comparing the optimum ANN configuration against other methodologies.

4. Results and Discussion

4.1 Optimum developed model

4.1.1 Hidden layers and number of neurons

A number of hidden layers in an ANN design, between 1 and 3, was examined, according to the selection of the configuration parameters explained previously. The influence of hidden layer count and neuron count in each hidden layer is investigated, using a number of quality measures such as R^2 , RMSE, and the a20-index. A parametric investigation was conducted for this reason, and [Table 7](#) offers a summary of the information that was obtained from it. The number of neurons within each hidden layer ranged between 5 and 25. The activation function for the hidden layer is a log-sigmoid function, while the activation function for the output layer is a linear function. In order to train the ANN, the Levenberg-Marquardt method is implemented, and the mean square error function serves as the basis for the cost function. From this evaluation, the best performing architecture was selected as the 7-14-21-19-1 (three hidden layers, with first one having 14 neurons, the second one 21 and the third 19). [Figure 11](#) illustrates the selected architecture.

Table 7. ANN's parameters.

Parameter	Value and description
Number of input variables / number of neurons in input layer	7
Number of output variables / number of neurons in output layer	1
Number of hidden layers	3
Number of neurons in hidden layers	14;21;19
Activation function for hidden layer	Log-sigmoid
Activation function for output layer	Linear
Training algorithm	Levenberg-Marquardt
Cost function	Mean square error

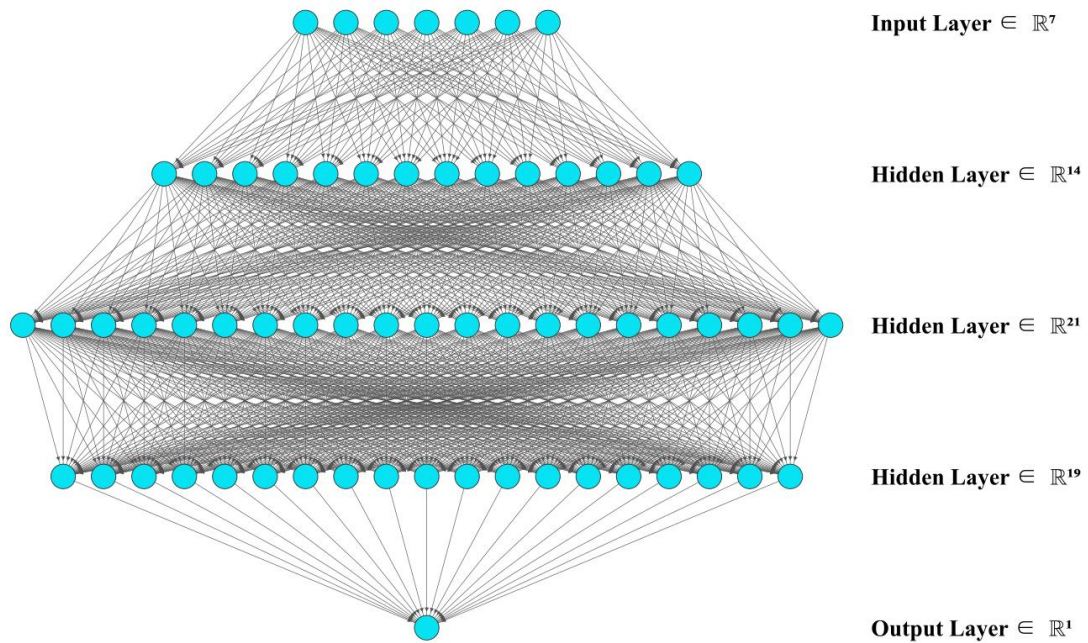


Figure 11. The best performing ANN architecture consists of 3 hidden layers.

4.1.2. Activation functions for hidden layers

Using as a basis the 7-14-21-19-1 architecture (as determined above), 13 alternative activation functions have been examined (listed in supplementary material). All other configuration parameters have been fixed to the default values, defined in Table 7. ANN's have been trained and their RMSE, MAE, R^2 and a20-index indices have been evaluated. Figure 12, depicts the probability distribution of RMSE over the course of 100 random sample runs, along with the average and standard deviation of those metrics. Average values seem to statistically converge over the performed 100 runs. Similar behavior was observed for the other performance indices too.

According to the findings, the *poslin* function, delivered superior performance for the 7-14-21-19-1 ANN model and as a result, was selected as optimal.

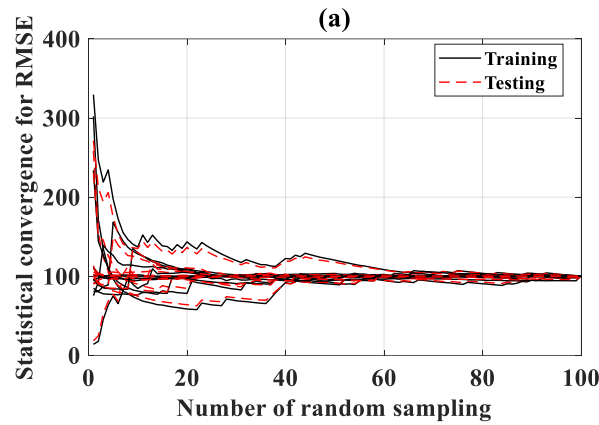


Figure 12. Statistical convergence for RMSE when evaluating the influence of activation functions for hidden layers (over 100 random runs).

4.1.3. Activation function for output layer

Output activation functions have a significant impact on the performance of the prediction model. The selection was performed among the 13 alternatives listed in supplementary material. All the remaining parameters, were fixed on their default values, as defined in Table 7. Ranking the resulting ANN's according to their performance indices, the *purelin* function emerged as better for the 7-14-21-19-1 ANN model, and as a result, was selected as optimal. Again, the number of 100 random sample runs, was sufficient to achieve convergence.

4.1.4. Training algorithm

Training algorithm was selected among the 11 alternatives, listed in supplementary material. All the remaining parameters, were fixed on their default values, as defined in Table 7. A number of 100 random sample runs was performed which proved adequate to achieve converged performance. Ranking the resulting ANN's according to their performance indices, the Conjugate gradient with Fletcher-Reeves updates Algorithm (CGF) was selected, as best suited for the 7-14-21-19-1 ANN model.

4.1.5. Cost function

Cost function was selected performed among the 3 alternatives, listed in supplementary material. All the remaining parameters, were fixed on their default values, as defined in Table 7. From the evaluation, *sae* function was selected as optimal, over 100 random sample runs.

4.2. Metaheuristic techniques

4.2.1. Grey Wolf Optimization

An ANN model of 7-14-21-19-1 utilizing GWO approach is discussed in this part. The weights of the prediction model defined in Section 4.1 were utilized as a starting guess for this optimization. A number of 50 search agents were used in the GWO algorithm, together with the parameters shown in Table 8. Figure 13 shows the cost function for a given number of iterations, as a function of the mean square error (over almost 1,000,000 iterations).

Table 8. Parameters used for GWO.

Parameter	Value
Numbers of search agents	50
Dimension	865
α _score	inf
α _pos	0
β _score	inf
β _pos	0
δ _score	inf
δ _pos	0

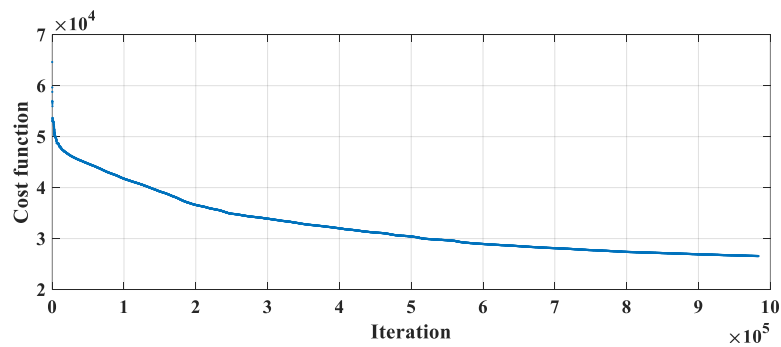


Figure 13. Cost function when using GWO technique

4.2.2. Firefly Algorithm

An ANN model of 7-14-21-19-1 utilizing FA approach is discussed in this part. The weights of the prediction model defined in Section 4.1 were used as a starting guess for this optimization. A number of 50 fireflies were used, together with the parameters shown in Table 9. Figure 14 shows the cost function for a given number of iterations, as a function of the mean square error. Section 5.3 summarizes the results of the ANN model that FA was able to improve.

Table 9. Parameters used for FA.

Parameter	Value
Firefly size	50
Dimension	865
Mutation Coefficient α	0.2
Attraction Coefficient Base Value β	2
Light Absorption Coefficient γ	1
Mutation Coefficient Damping Ratio	0.98

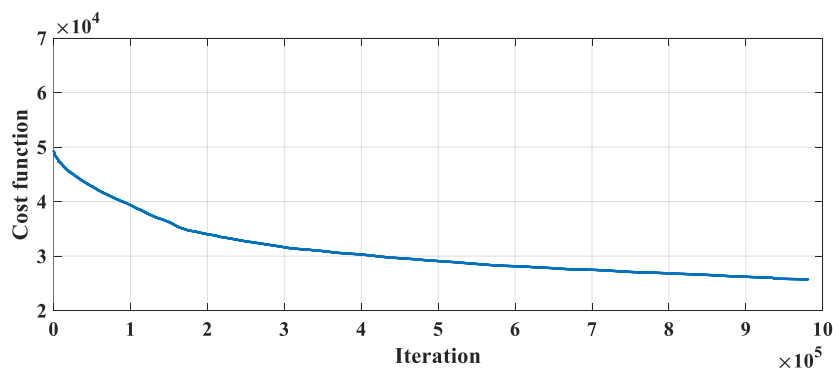


Figure 14. Cost function when using FA technique

4.3. Comparison of performance and optimum model

Herein, the effectiveness of three prediction models, namely ANN, ANN-GWO, and ANN-FA is assessed. Figure 15 depicts the regression prediction performance, while Table 10 lists the related quality metric values.

For the training dataset, the outputs of ANN, ANN-GWO, and ANN-FA in relation to the actual value can be seen in Figure 15a, Figure 15c, and Figure 15e. In Figure 15b, Figure 15d, and Figure 15f, the testing dataset is depicted using ANN, ANN-GWO, and ANN-FA, respectively, in

the same way. For determining the accuracy of the regression results, each of the plots includes linear fitting equations having the form "predicted = slope * (actual) + intercept."

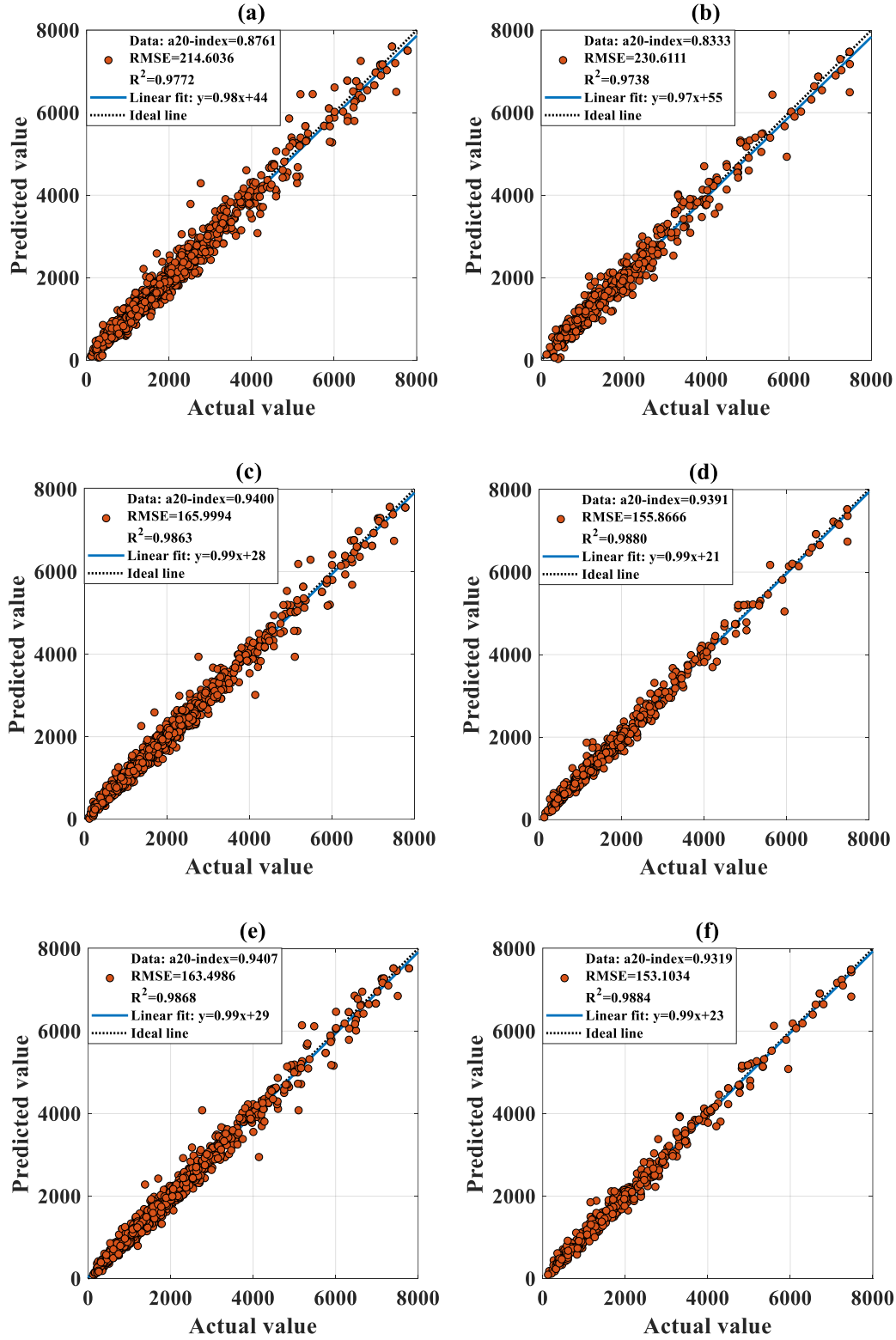


Figure 15. Regression graphs for the training part using (a) ANN, (c) ANN-GWO, and (e) ANN-FA; for the testing part using (b) ANN, (d) ANN-GWO, and (f) ANN-FA, respectively.

As shown in the training portion of Table 10, ANN-FA achieves the highest a20-index, R^2 , and VAF, but also the lowest RMSE, MAE, and MAPE. It may be concluded that ANN-FA is the most appropriate model for the training data. Looking at the testing data, ANN-FA model seems again more accurate. When looking at the linear fit equation, a similar conclusion can be drawn. ANN-FA has a slope of 0.99 for the testing dataset, which indicates that it is superior to ANN and ANN-GWO. Table 10 also includes the gain values between the outcomes of the ANN-FA and those of other models, calculated using Equation (9). A positive gain indicates that the ANN-FA model outperforms other models. Table 10 clearly shows that the ANN-FA model indeed outperforms the other two models, for all performance indices.

$$\%Gain = \begin{cases} ((\lambda^{others} - \lambda^{ANN-ICA}) / \lambda^{others}) \times 100 & \text{in case of: RMSE, MAE and MAPE} \\ ((\lambda^{ANN-ICA} - 1) - (\lambda^{others} - 1)) \times 100 & \text{in case of: a20-index, } R^2, \text{ and VAF} \end{cases} \quad (9)$$

Table 10. Performance assessment of the optimum developed models

Model/%Gain	Dataset	R^2	RMSE	MAE	a20-index	VAF	MAPE
ANN	Train	0.9772	214.6	151.8	0.8761	97.66	10.85
	Test	0.9738	230.6	170.3	0.8333	97.30	16.50
	All	0.9761	219.5	157.3	0.8632	97.55	12.55
ANN-GWO	Train	0.9863	166.0	112.9	0.9400	98.63	7.60
	Test	0.9880	155.9	111.2	0.9391	98.80	7.63
	All	0.9868	163.0	112.4	0.9397	98.68	7.61
ANN-FA	Train	0.9868	163.5	112.7	0.9407	98.67	7.62
	Test	0.9884	153.1	107.1	0.9319	98.84	7.46
	All	0.9873	160.4	111.0	0.9381	98.72	7.5745
%Gain _{ANN}	Train	+1.0	+23.8	+25.8	+6.5	+1.0	+29.7
	Test	+1.5	+33.6	+37.1	+9.9	+1.5	+54.8
	All	+1.1	+26.9	+29.5	+7.5	+1.2	+39.6
%Gain _{ANN-GWO}	Train	+0.0	+1.5	+0.2	+0.1	+0.0	-0.3
	Test	+0.0	+1.8	+3.7	-0.7	+0.0	+2.2
	All	+0.0	+1.6	+1.2	-0.2	+0.0	+0.5

5. Graphical User Interface and Closed Form Equation for the optimum developed model

The closed form, explicit equations for the prediction of eccentric ultimate load of CFST columns, are provided herein. Through these equations the optimum developed ANN-FA model, that was previously presented can be reproduced. The proposed mathematical formula in a matrix form is:

$$\begin{aligned} N_u^{scaled} &= ([L_3] \times poslin([L_2] \times poslin([L_1] \times (poslin([I_w] \times [x_n] + [b_i]) + [b_1]) + [b_2]) + [b_o])) \\ N_u^{predicted} &= \alpha_{Nu} \times N_u^{scaled} + \beta_{Nu} \end{aligned} \quad (10)$$

where $[x_n]$ is a 7×1 input vector. $[I_w]$ is a 14×7 matrix containing weight parameters of the hidden layer. $[L_1]$, $[L_2]$ and $[L_3]$ are 14×7 , 21×14 and 19×21 matrices, containing the weight parameters of the first, second and third hidden layers, respectively. $[b_i]$, $[b_1]$, $[b_2]$ and $[b_o]$ are 14×1 , 21×1 , 19×1 , and 1×1 vectors respectively, containing the bias parameters of the hidden and output layers. Parameters α_{Nu} and β_{Nu} are used for scaling N_u , with $\alpha_{Nu} = 1421.6912$ and $\beta_{Nu} = 1969.976$, respectively. The activation function *poslin* is defined as:

$$poslin(x) = \begin{cases} x, & \text{if } x \geq 0 \\ 0, & \text{if } x < 0 \end{cases} \quad (11)$$

Vector $[x_n]$ is given by:

$$[x_n] = \begin{bmatrix} x_B \\ x_H \\ x_t \\ x_{L_e} \\ x_{f_y} \\ x_{f'_c} \\ x_e \end{bmatrix} = \begin{bmatrix} \frac{B - \beta_B}{\alpha_B} \\ \frac{H - \beta_H}{\alpha_H} \\ \frac{t - \beta_t}{\alpha_t} \\ \frac{L_e - \beta_{L_e}}{\alpha_{L_e}} \\ \frac{f_y - \beta_{f_y}}{\alpha_{f_y}} \\ \frac{f'_c - \beta_{f'_c}}{\alpha_{f'_c}} \\ \frac{e - \beta_e}{\alpha_e} \end{bmatrix} \quad (12)$$

where

$$\begin{bmatrix} \alpha_B \\ \alpha_H \\ \alpha_t \\ \alpha_{L_e} \\ \alpha_{f_y} \\ \alpha_{f'_c} \\ \alpha_e \end{bmatrix} = \begin{bmatrix} 54.3285 \\ 55.4963 \\ 1.7735 \\ 1146.5019 \\ 175.0098 \\ 28.9420 \\ 32.2492 \end{bmatrix} ; \quad \begin{bmatrix} \beta_B \\ \beta_H \\ \beta_t \\ \beta_{L_e} \\ \beta_{f_y} \\ \beta_{f'_c} \\ \beta_e \end{bmatrix} = \begin{bmatrix} 155.3946 \\ 154.8177 \\ 4.5937 \\ 1297.3472 \\ 422.1301 \\ 53.7843 \\ 14.6871 \end{bmatrix} \quad (13)$$

It should be noted that the implementation of the above equations to a computer program requires only simple algebraic and matrix operations. No iterative process is needed, neither complicated branching. To the contrary, analytical methodologies, such as those provided by design codes impose multiple calculation branches for different input cases and often require iterations in order to determine internal equilibrium (i.e. EN1994 [165], AIJ [166], AS-NSZ-2327 [167]). A friendly Graphical User Interface (GUI) based on Microsoft Excel has been created, that demonstrates an actual implementation Equation (10), for the prediction of compressive capacity of eccentric CFST. [Figure 16](#) illustrates this GUI, which can also be

found as supplementary material in the paper. The use of the GUI is rather straightforward. The independent variables are set firstly to the desired values (by typing them or through the sliders), and the prediction of capacity load is automatically presented in the output cell (green cell to the right). The input sliders limit the user to values between the minimum and maximum ones present in the database for the respective input variable. However, the user may still overcome these limits, by typing directly to the input fields at the left.

This GUI can be useful for the research community, facilitating the evaluation of our model against different methodologies. Furthermore, it demonstrates that the final model, as derived from a challenging ANN training, validation and testing procedure, can be fairly simple to implement in a program.

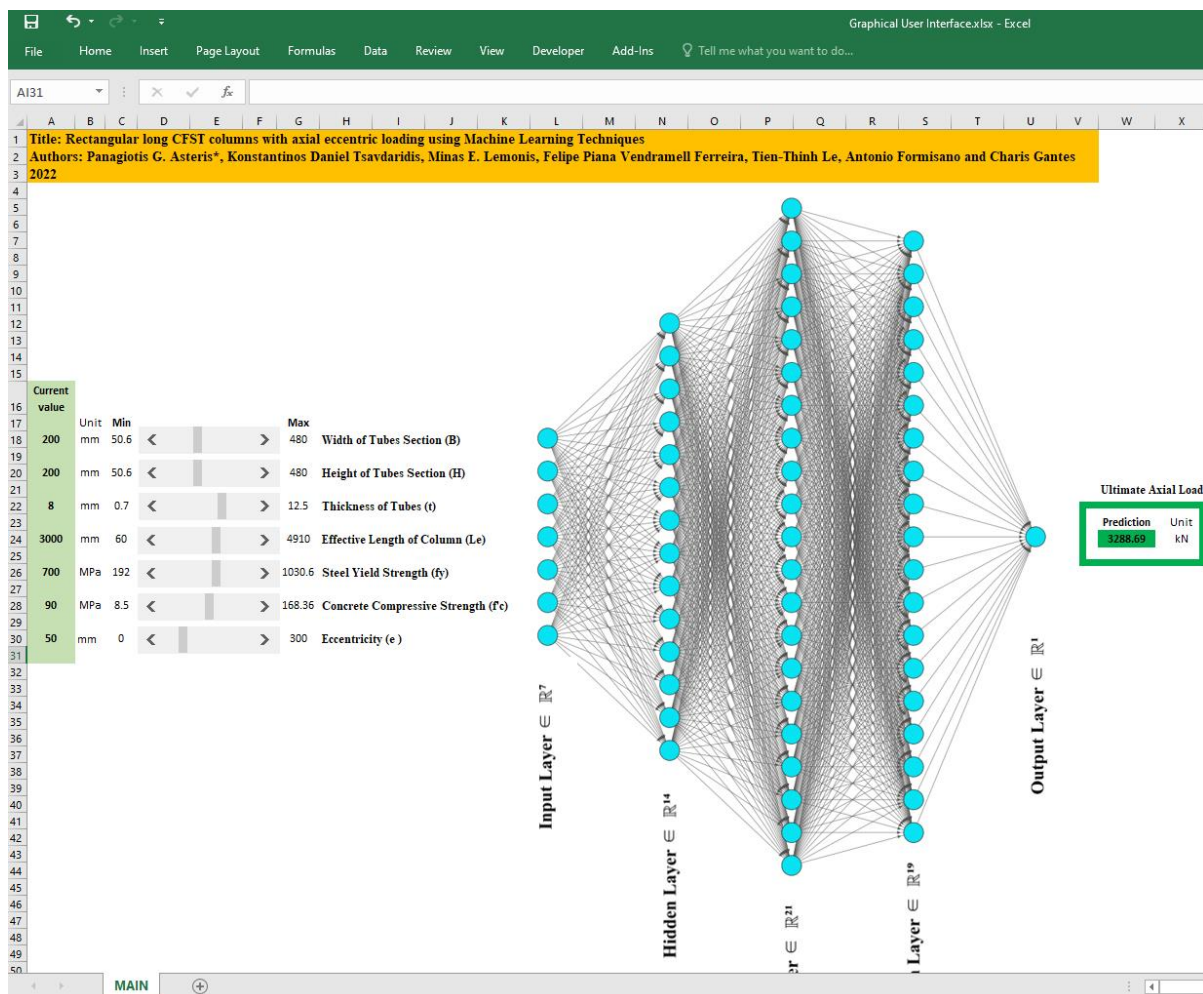
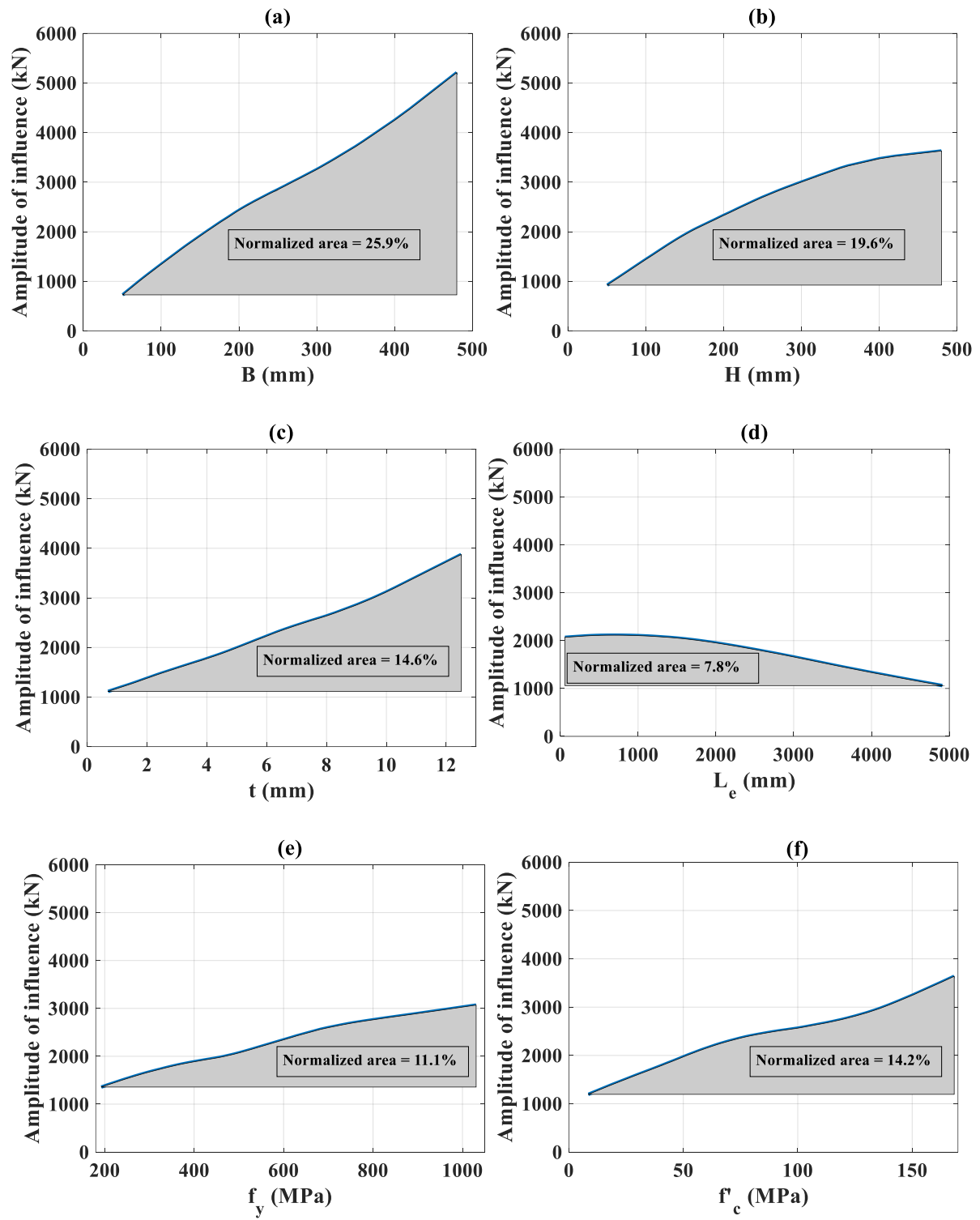


Figure 16. GUI for the prediction of CFST compressive capacity (included as supplementary material of the paper)

6. Sensitivity analysis of compressive capacity on the input parameters

In order to investigate the impact of each input variable on the ANN model's output response, sensitivity analysis based on Individual Conditional Expectation (ICE) [165] is introduced in this section. A change in an input variable will be reflected in the ICE output response. For each input variable, the raw curve created by ICE is shown in Figure 17, as well as the normalized area. It can be seen that the axial load of columns is affected by all input variables, but to varying degrees and with varying outcomes, including either positive or negative effect. The axial capacity of columns rises with increasing B , H , t , f_y , and f'_c ; however, it drops for increasing L_e and e , which is in compliance with physical intuition. From each curve, the normalized covered surface percentages have been deduced such as 25.9%, 19.6%, 14.6%, 7.8%, 11.1%, 14.2%, and 6.8% for B , H , t , L_e , f_y , f'_c , and e , respectively. The ranking of these values is also presented in Figure 18. This indicates that the steel tube's geometric parameters and the concrete core's compressive strength are the most important input variables. These remarks are in agreement with evidence from experimental research in the literature. The sensitivity analysis also shows that linear correlation does not adequately capture the relationship between inputs and ultimate axial load, particularly when it comes to cross-sectional geometry variables. Observations like these are well supported by the literature from a physical standpoint, as long as the cross-sectional areas of the steel tube and concrete core are taken into account. It is possible to identify the relationships between independent variables and output response using an ANN model without having to solve complex equations, thereby reducing excessive processing costs.



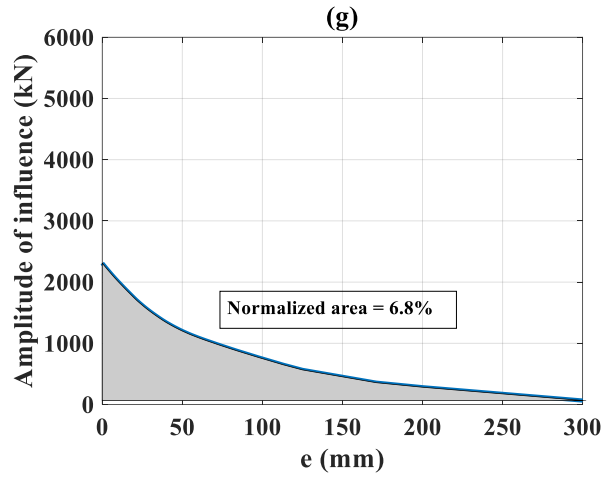


Figure 17. Sensitivity analysis of (a) B , (b) H , (c) t , (d) L_e , (e) f_y , (f) f'_c and (g) e , on the output response from the ANN model.

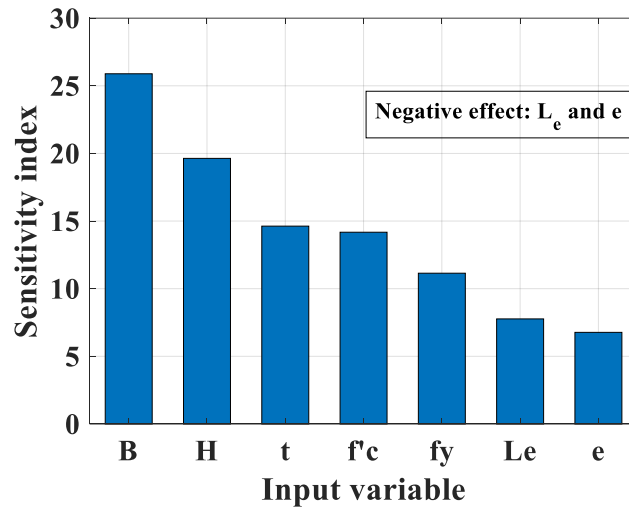


Figure 18. Ranking of sensitivity index

7. Comparison of optimum ANN model with codes

In Table 11, the performance of the developed ANN model is presented, in terms of the statistical metrics described previously (i.e., RMSE, a20-index, R, MAPE, VAF), calculated for the sample in the Testing Dataset (specimens not used during the ANN training and development stages). Alongside, the same performance metrics are recorded for the code standards (i.e., EN1994 [165], AISC 360 [169], AIJ [166], AS-NSZ-2327 [167]) codes. Regarding AISC 360, two M-N interaction diagrams are given, one more simplified (method 1), ignoring the influence of concrete

to steel strength ratio, and another more accurate that takes it into account, through coefficients c_p and c_m (method 2). Code safety or capacity factors, are not applied.

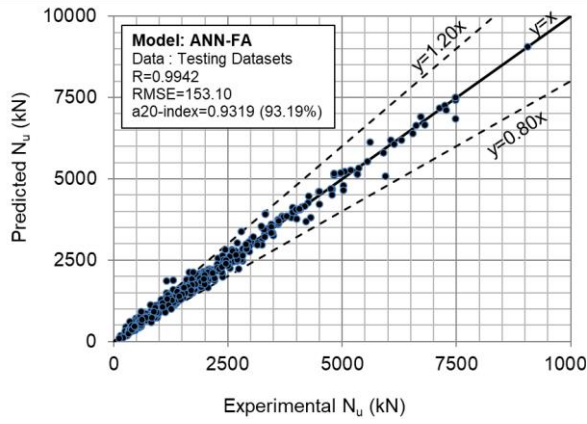
The results are shown in Table 11, sorted by their RMSE index. A significant improvement for the ANN-FA, in every performance metric can be observed. RMSE index is 47% lower compared to the best performing code, which in this context proves the EN1994 [165], closely followed by AIJ [166]) and AS-NSZ-2327 [167]. In terms of the a20-index, the ANN-FA achieves a 20% error margin for 93% of the testing specimens. Equally significant improvements are observable for the other statistical metrics.

In terms of RMSE, there are no big differences among the various codes. Eurocode (EN1994 [165]) achieves the best RMSE with a slight edge (approximately 4%) over the Japanese (AIJ [166]) and the Australian/New Zealand (AS-NSZ-2327 [167]) codes. The two latter ones achieve almost identical RMSE. Comparing the a20-indices however, the performance of the various codes presents remarkable differences. Best performing code now proves the Australian/New Zealand (AS-NSZ-2327 [167]), managing to predict the ultimate load for 74% of the specimens, within a 20% error margin. Similar, but slightly worst a20-indices have been also achieved by the Eurocode (EN1994 [165]) and the Japanese (AIJ [166]) codes. These differences are considered rather small and as a result, the three mentioned codes are considered equivalent in terms of general prediction accuracy. For the American code (AISC 360 [169]), the a20-index is 64% using method 2 and 61% using method 1. These values are 13-18% worse than Eurocode (EN1994 [165]) a20-index.

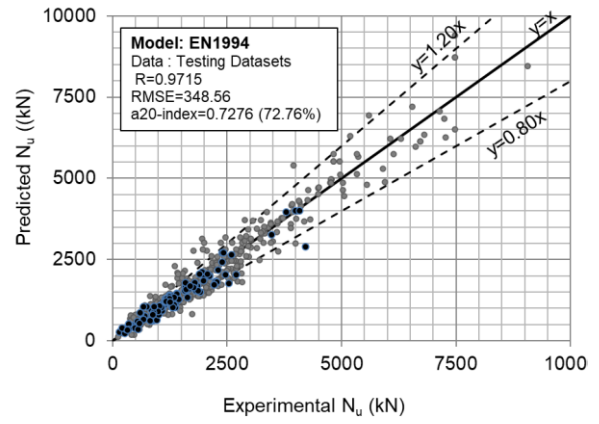
Table 11. Ranking of developed soft computing ANN-FA model and the available in literature proposal based on Testing Datasets

Ranking Nr.	Model	Performance Indices					
		a20-index	R	R ²	RMSE	MAPE	VAF
1	ANN-FA	0.9319	0.9942	0.9884	153.10	7.4620	98.84
2	EN1994	0.7276	0.9715	0.9438	348.56	0.1473	94.12
3	AIJ	0.7079	0.9735	0.9476	364.35	0.1668	94.72
4	AS/NZS 2327	0.7419	0.9679	0.9369	364.71	0.1382	93.44
5	AISC 360 (Method 2)	0.6434	0.9727	0.9461	395.50	0.1878	94.50
6	AISC 360 (Method 1)	0.6093	0.9715	0.9439	414.53	0.2107	94.31

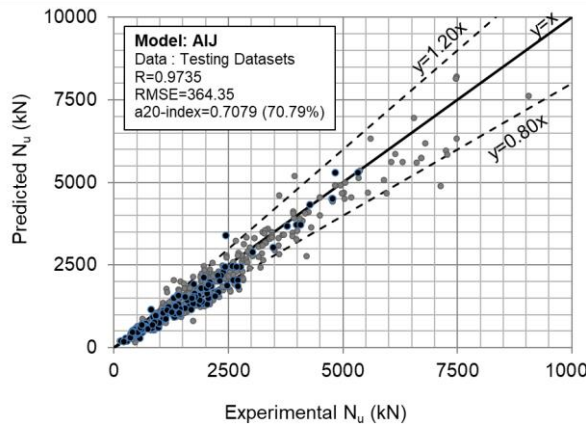
Figure 19, displays the scatter plots for the developed ANN-FA model and also for each design code [165-167, 169] comparing the experimental against the predicted compressive capacity (Testing Dataset only). The ANN-FA model seems to systematically converge to the experimental values for the entire range of compressive loads in the sample, achieving a considerably closer fit to the experimental/FEM values, compared to the codes. For the majority of the specimens in the sample, the prediction didn't exceed the 20% error margin. Among the codes, the Eurocode (EN1994 [165]), the Australian/New Zealand (AS-NSZ-2327 [167]) and the Japanese (AIJ [166]) ones, perform in a balanced way against the experimental values. However, for the American code (AISC 360 [169]) a rather slight underestimation is observed for the predicted load, either through method 1 or 2. It should be noted that the plots for the design codes include all specimens in the Testing Dataset, even though the respective code application limits are not fulfilled for some of them. In this context, the dots are differentiated in color. Those in blue color, correspond to specimens that fulfil the respective code application limits (see appendix A), whereas those in gray color do not fulfill them. For all the design codes, the deviation pattern from the experimental value looks similar over the entire range of available loads and also for both gray dots and blue dots in the plots (in other words for both invalid and valid specimens, considering the code application limits). This suggests that the field of application of all codes could be expanded without affecting the accuracy.



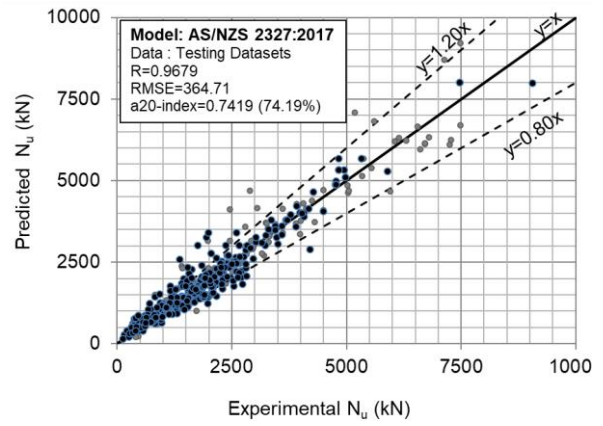
(a)



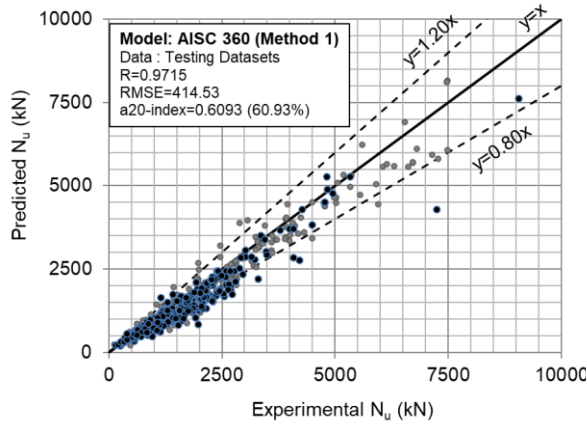
(b)



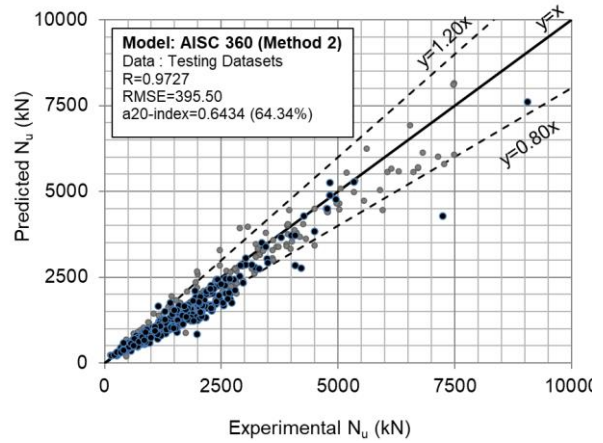
(c)



(d)



(e)



(f)

Figure 19. Evaluation of the predictions by ANN-FA model (top left) and design code methodologies [165-167, 169] for the specimens in Testing Dataset.

In Table 12, the mean absolute relative errors, using the developed ANN-FA model and examined codes, for the prediction of the FEM ultimate capacity, for various combinations of column lengths and load eccentricities, are presented. Also, for each code and the ANN, the

maximum absolute relative error is provided (in parentheses) for every examined column length. The proposed ANN-FA model provides a consistent prediction capability, without exceeding 10% error on average, for all combinations of long columns and eccentricities. The mean errors for the 100mm load eccentricity are larger than those for lower eccentricities, however. The maximum error over the various FE specimens is moderate at 20%. Regarding the EN1994 [165] and the AS/NZS 2327:2017 [167] codes, a severe deterioration in their predictions is confirmed from the results in Table 12, for the longer, eccentrically loaded columns (lengths 3000mm and over). Maximum relative errors around 90% are recorded for the higher column length. On the other hand, AISC360-16 [169] and AIJ [166] appear to produce lower errors without severely affected by load eccentricity levels.

Table 12. Mean absolute relative errors in predicting the FE models ultimate compressive capacity for various combinations of column length and load eccentricity.

Column Length L_e (mm)	Load eccentricity e (mm)	Mean absolute relative error (%) (Maximum absolute relative error %)					
		ANN	EN1994	AIJ	AS/NZS 2327	AISC360 Method 1	AISC360 Method 2
1500	0	5.53	6.84	9.77	7.80	13.17	13.17
	25	3.27	7.73	7.74	3.43	16.16	12.76
	50	4.62	4.77	13.55	7.22	18.03	13.25
	100	6.10	8.16	13.61	5.32	23.45	17.34
	ALL	4.88 (14.61)	6.88 (17.94)	11.17 (29.83)	5.94 (25.64)	17.70 (44.13)	14.13 (36.26)
3000	0	3.93	8.61	11.40	9.44	13.89	13.89
	25	4.48	11.02	7.51	19.19	10.32	6.94
	50	3.28	15.49	5.96	24.95	13.25	8.25
	100	8.27	11.81	9.36	18.74	16.39	10.82
	ALL	4.99 (20.29)	11.73 (36.64)	8.56 (22.67)	18.08 (41.35)	13.46 (30.78)	9.97 (27.24)
4500	0	2.54	7.83	9.18	6.39	7.71	7.71
	25	3.58	36.96	9.24	47.97	7.69	9.42
	50	3.82	51.93	7.75	64.11	7.57	10.64
	100	7.78	40.18	6.36	51.57	9.13	11.44
	ALL	4.43 (19.26)	34.23 (88.25)	8.13 (20.26)	42.51 (89.69)	8.03 (26.62)	9.80 (27.6)
ALL	ALL	4.77 (20.29)	17.61 (88.25)	9.29 (29.83)	22.18 (89.69)	13.06 (44.13)	11.30 (36.26)

8. Concluding remarks

In this paper three alternative models for the prediction of the compressive ultimate load of rectangular CFST columns with load eccentricity were developed. The models relied upon the artificial neural network technique with an optimization stage using the Grey Wolf Optimization Algorithm and the Firefly Algorithm. For the training and validation of the models, a hybrid database of relevant experimental tests and advanced finite element models was utilized, amounting to 1,857 specimens in total (1,641 experimental and 216 FEM). To the authors' knowledge, this is the largest database of rectangular CFSTs ever compiled in the available literature. The FE models were designed as long columns, so that global buckling can emerge as a possible failure mode, with varying length, tube thickness, steel yield limit, concrete strength and load eccentricity, covering an extended area of input space, where available experimental tests are rather scarce.

An optimum ANN architecture has been selected through an exhaustive process of evaluating alternative combinations of key configuration parameters, including number of neurons, cost functions and transfer functions. The model features 7 input variables, including steel tube dimensions (height, width and thickness), column length, concrete strength, steel yield limit and load eccentricity. An analytical expression has been formulated that reproduces the output of the optimum ANN model, with the given input variables.

The developed models were compared with analytical methodologies using 5 alternative procedures provided by 4 different design codes. They were found capable to provide significantly improved accuracy in their predictions.

Particularly, the following concluding remarks highlight the significance of the proposed methodology:

- The optimized ANN models outperformed the non-optimized ones by a considerable amount. The model optimized with the Firefly Algorithm (ANN-FA) achieved a reduced RMSE index by 34%, for the testing datasets, compared to the non-

optimized ANN models. The model optimized with the Grey Wolf Algorithm (ANN-GWO) achieved a similar performance (32% reduction). The ANN-FA model proved slightly more capable than the ANN-GWO, for all other performance indices, as well.

- All developed ANN models, optimized or not, outperformed code methodologies. Focusing on the ANN-FA model, the RMSE index was more than halved for the specimens in the testing dataset (specimens not used for training), compared to the best performing code, while the a_{20} -index was elevated by a 20% difference.
- The improved performance of the ANN-FA model was found consistent even for the longer columns, where global buckling is probable. This was not the case for some of the examined codes (namely EN1994 [165] and AS/NZS 2327:2017 [167]), which provided deteriorated predictions for the longer FEM specimens with eccentricity.
- Using the analytical formulation of the optimum ANN model, it is possible to implement the model in a computer program, using only simple algebraic and matrix operations. A GUI has been developed this way in MS Excel, demonstrating a possible implementation. This GUI is available as supplementary material.

The ultimate compressive load of CFSTs is influenced by several nonlinear phenomena, including material nonlinearities, local buckling, and delamination. The problem becomes even more challenging for long columns with load eccentricity, where global buckling and interaction with flexure is also involved. The development of strictly analytical formulations for all these, potentially interacting phenomena, capable to produce accurate and reliable predictions of the ultimate load, remains a difficult task. On the contrary, the use of machine learning techniques, as demonstrated in this work, can efficiently overcome these difficulties, provided that an adequately large number of training data is available.

Data Availability: The raw/processed data required to reproduce these findings will be made available on request.

Funding Statement: This research received no external funding.

Supplementary material: The Graphical User Interface (GUI) in excel form for the estimation of axial load of rectangular long steel tube columns with axial eccentric loading, based on the optimum the ANN-FA model as well as the Codes are included as supplementary material to this paper.

Conflicts of Interest: The authors declare that there is no conflict of interest regarding the publication of this paper.

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