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Application of Artificial Neural Network for Calculation of Axial Capacity of Circular Concrete Filled Steel Tubular Columns

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Abstract: The Concrete Filled Steel Tubular (CFST) columns are highly regarded in recent years as an interesting option in the construction field by designers and structural engineers, due to their exquisite structural performance, with enhanced load bearing capacity and energy absorption capacity. This study presents a new approach to simulate the capacity of circular CFST columns under axial loading condition, using a large database of experimental results by applying artificial neural network (ANN). A well trained ANN- NN7-1-Act_log is established and is used to simulate the axial capacity of CFST columns. The validation and testing of the ANN is carried out. The current study can be used to propose a simplified equation that can predict the ultimate strength of the axially loaded columns with high level of accuracy.

Keywords: *CFST columns, axial loading, Artificial Neural Network and Column capacity*

1. Introduction

The use of concrete filled steel tubular columns have increased in recent years due to their best structural performance, that has the combined advantages of steel and concrete. The steel tube provides confinement to the concrete core, resulting in increased compressive strength and the concrete core resists the inward buckling of the steel tube, resulting in enhancing the load bearing capacity of the CFST columns.

This type of composite columns provides advantages such as high seismic resistance, attractive appearance, fast construction technology, reduction in cross section and fire resistance without external protection. The CFT column provides higher ductility and energy absorption capacity during earthquakes. For a certain design load, a reduced column dimension is arrived and thereby increase in the net usable floor area is high. Additional formwork for pouring concrete is not required as the steel tube acts as formwork and external reinforcement for the concrete core. The external steel section offers the possibility of architectural design with different finishing.

Ahmed Elremaily and Atorod Azizinamini (2002) proved that CFT columns exhibited very high levels of ductility and energy dissipation characteristics. At very high levels of displacement ductility, CFT columns experience axial shortening. The column capacity improved due to the strength gained by the confinement effect of the steel tube. Georgios Giakoumelis and Dennis Lam (2004) presented the findings of short circular CFT columns tested under axial load. The predicted axial strengths using ACI and AS were 35% lower than the results obtained from experiments. A coefficient is proposed for the ACI/AS equations to take into account the effect of concrete confinement on the axial load capacity of CFSTs. The strength and ductility of CFST short columns subjected to different bond and end loading conditions was addressed by Amir Fam, Frank S Qie and Sami Rizkalia (2004). It was observed that the short column behaviour was very ductile after cracking and possessed the strength of composite section based on unconfined concrete strength. Ehab Ellobody and Ben Young (2006) worked on circular CFST columns under axial load conditions and D/t ratio, Concrete strength was the variable parameters considered for the experimental investigations. Lin-Hai Han; Jing-Si Huo and Yong-Chang Wang (2007) evolved a nonlinear Finite Element Analysis procedure. Circular and square CEST specimens were tested. The influence of slenderness ratio, steel ratio, and cross section on P-Δ curves was studied. Mohanraj E K and Kandasamy S (2008) studied the performance of circular CFST columns subjected to axial compression. The stiffness and ductility parameters were studied. A comparison was made with Eurocode 4 (EC4), ACI 318-95 (ACI) and Australian Standards AS3600 AND AS4100 (AS) International Standard Codal Specifications.

Seong-Hui Lee, Brian Uy, Sun-Hee Kim, Young-Hwan Choi, Sung-Mo Choi (2011) estimated the behavior of a circular CFST column subjected to eccentric loading. An experimental test and fiber element analysis on 11 circular stub CFST column specimens were conducted.

The results from the experimental tests and fiber element analysis were compared with AISC, Eurocode 4 to verify the suitability of the analysis in the codes. Zhijing Ou, Baochun Chen P.E., Kai H. Hsieh, Marvin W. Halling S.E., and Paul J. Barr (2011) numerically modelled circular Concrete Filled Steel Tubular laced columns. Codal specifications were compared with the FEM results. The authors proposed a new methodology for the calculation of ultimate load capacity of CFST columns.

Nie Jian-guo, Wang Yu-hang, Fan Jian-sheng (2012) conducted experimental study on the seismic behavior of concrete filled steel tube columns subjected to pure torsion. Based on the test results and available literature, the torsion mechanism of CFST columns was preliminarily analyzed. Suliman Abdalla, Farid Abed and Mohammad Al Hamaydeh (2013) carried out concentric compressive quasi static load tests on circular CFST columns. The concrete compressive strength and D/t ratio, jacketing of CFST columns with GFRP wraps were the variable parameters considered for the study. It was inferred that GFRP wraps improves strength and ductility properties of CFST specimens. Portoles J.M., Serra E. and Romero M.L. (2013) conducted tests on slender circular tubular columns filled with normal, high, and ultra-high strength concrete for plain, bar reinforced and steel fiber reinforced columns. These columns were reinforced and subjected to both concentric and eccentric axial load. The experimental ultimate load of each test was compared with the design load from Eurocode 4 and found that the results were accurate for the eccentrically loaded tests.

It is also worth noting that for slender members an improvement in ductility is easily obtained with eccentricity but not with concrete strength or type of infill. Xiushu Qu, Zhihua Chen and Guojun Sun (2013) carried out Load-reversed push-out tests on 6 rectangular concrete-filled steel tubular (CFST) columns. The investigations focused on the nature of the bond between the concrete infill and the steel tube, the contribution of each bond stress component (i.e. chemical adhesion, microlocking and macrolocking) and the development of macrolocking within four half-cycles of loading. The concept of a critical shear force transfer length was introduced, and its implications on practical design discussed. The critical interface length to ensure full shear transfer was studied, and design recommendations were provided. Ganesh Prabhu and Sundarraja M.C. (2013) investigated experimentally and analytically carbon fibre reinforced Polymer (CFRP) strips composites in strengthening of CFST members under compression. CFRP fabrics were used as horizontal strips (lateral ties) with several other parameters such as the number of layers, width and spacing of strips.

Experimental results revealed that external wrapping of CFRP strips provides restraint against the lateral deformation effectively and delays the local buckling of steel tube. The proposed analytical model for predicting the load bearing capacity of CFRP confined CFST columns was able to capture the results accurately. It was found that external strengthening of CFST columns using normal modulus CFRP strips was a quite effective technique in increasing the load carrying capacity and stiffness of the CFST section.

Lin-Hai Han, Wei Li and Reidar Bjorhovde (2014) carried out a critical review on developments and advancements of concrete filled steel tubular structures. As a scope for future work they proposed that the thorough comparison of advantages and disadvantages of the CFST system with the steel and RC system, the space truss structural system, the connection system, the hybrid system using high performance and sustainable materials as well as the life-cycle performance evaluation should be conducted.

The use of CFST columns has been increased in recent decades, finding important applications in high-rise building and bridges. Other practical applications are industrial buildings, electricity transmitting poles and subways (Zhao, 2010). Some prominent applications of high rise buildings are found in China. The SEG Plaza in Shenzhen, which is the tallest building in China that uses this type of composite construction, is a remarkable example. It has 76-storey office block with a four-level basement and a total height of 361 m. It employs CFT columns of circular shape with diameters ranging 0.9 m to 1.6 m. Another example is the Wuhan International Securities Buildings (WISB) that used CFST columns. A prominent construction found in United States and Canada, is the Museum of Flight at King Country Airport at Seattle, Washington. It uses bar-reinforced concrete filled hollow sections for the columns supporting the roof of the exhibit hall, which permitted the achievement of the required fire resistance. A profound application of this composite construction was done at Fleet Place House, the Montevetro apartment block, the Peckham Library and Queensberry House at London. Fleet Place House is an eight-storey office building using circular CFST columns of 323.9 mm external diameter filled with concrete. The columns are arranged on each longitudinal external face of the building, which has clear span on the inside. The present study focus is on how to calculate the load bearing capacity of CFST columns, under axial loading by the application of an intelligent system, Artificial Neural Network.

***Table 1** statistical property of Experimental Data*

Input Network	D (mm)	t (mm)	f_y (MPa)	f_c (MPa)	L (mm)	P_{exp} (N)
Maximum	1020	13.25	853	108	5000	46000000
Minimum	76	0.52	178.28	9.9	153	211000
Mean	163.6993	4.420498	343.0006	40.32827	937.6668	2194529
Standard Deviation (sample)	96.7207	2.186993	98.84208	19.90406	745.2243	3408954
Standard Deviation (population)	96.64773	2.185343	98.76751	19.88904	744.6621	3406382

2. Artificial Neural Network

Artificial Neural Network (ANN) is a technique that uses existing experimental data to predict the behavior of the same material under different testing conditions.
In the present work, the prediction of the load-carrying capacities for axially cyclic loaded circular composite tubes is evaluated using ANN. To test the validity of using ANN in determining the crushing behaviour of these tubes, the study will compare the predictions obtained to the experimental results using the neural network.

ANN have emerged as a useful concept from the field of artificial intelligence, and has been used successfully over the past decade in modeling engineering problems in general, and specifically those relating to the mechanism behavior of composite materials.

2.1. McCulloch-Pitts-neuron

A first wave of interest in neural networks emerged by McCulloch and Pitts (1943), after the introduction of simplified neurons. These neurons were presented as models of biological neurons and as conceptual components for circuits that could perform the computational tasks. A neural network consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. Artificial neural networks may either be used to gain an understanding of biological neural networks, or for solving artificial intelligence problems without necessarily creating a model of a real biological system (Van Der Smagt and Krose, 1996). A biological neuron has major parts which are of particular interest in understanding an artificial neuron and include: dendrites, cell body, axon, and synapse. A computational neuron has input variable weight, neuron cell, and output. Dendrites are represented by input lines. Every artificial neuron has one output line that represents the axon of the neuron. The biological neuron associated with computational neuron is presented in Fig. 1.

In computational neurons, the net function determines how the network inputs { y_j ; $1 \leq j \leq N$} are combined inside the neuron.

In Fig. 2, a weighted linear combination is adopted:

$$u = \sum_{j=1}^{n} w_j \, y_j + \theta \qquad (1)$$

In which, { w_j; $1 \leq j \leq N$} are parameters known as synaptic weights. The quantity u is called the bias and is used to model the threshold. (M. Ahmadi, H. Naderpour and A. Kheyroddin., 2014).

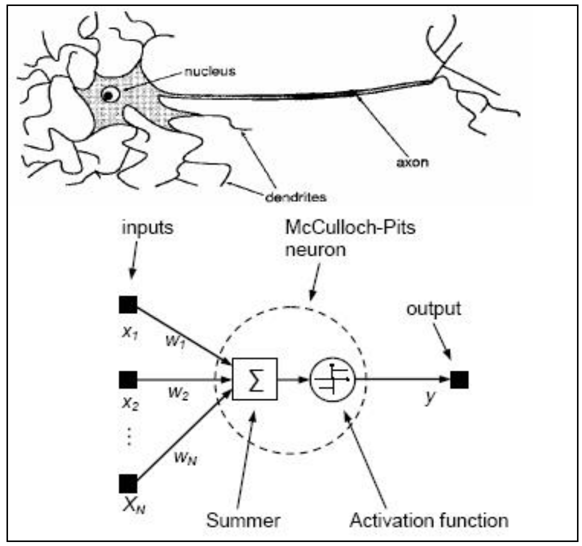

***Figure 1** A biological neuron model, which processes N inputs (xN) to arrive at the output (y). (Source:http://www.controlglobal.com/articles/2006/22)*

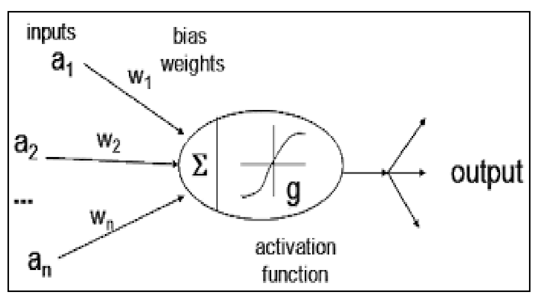

***Figure 2** Schematic Computation of Neuron*

3. Training and Validation of ANN

ANN generally consists of a number of layers: the layer where the patterns are applied is called input layer. This layer could typically include the properties of the composite material under consideration, its layup, the applied load, the tube aspect ratio etc. The layer where the output is obtained is the output layer which contains the resulting load of the tube under the axial loading conditions. In addition, there may be one or more layers between the input and output layers called hidden layers, which are so named because their outputs are not directly observable. The addition of hidden layers enables the network to extract high-order statistics which are particularly valuable when the size of the input is very large. Neurons in each layer are interconnected to preceding and subsequent layer neurons with each interconnection having an associated weight. A training algorithm is commonly used to iteratively minimize a cost function with respect to the interconnection weights and neuron thresholds. The training process is terminated either when the Mean Square Error (MSE) between the observed data and the ANN outcomes for all elements in the training set has reached a pre-specified threshold or after the completion of a pre-specified number of learning epochs. (M.Ahmadi, H. Naderpour and A. Kheyroddin., 2014).

In order to create an efficient network, 633 test results collected from database on the website (http://web.ukonline.co.uk/asccs2), on the axial compressive strength of circular concrete filled steel tube were utilized. The data corresponding to the following parameters were reported: outer diameter (D) if circular cross-section, or breath (B) and depth (H) if rectangular; the thickness (t) of the steel tube; the steel properties (f_y) and for slender or short columns, modulus of elasticity (E_a); the concrete properties (concrete yield strength (f_{cyl}), and, for long columns, its secant modulus of elasticity (E_c) to (0.4 f_{ck})); the length (L) of the column and the maximum load achieved by the column in test (N_u= Test failure load). Statistical properties employed in this study are summarized in Table 1. This table includes:

- Yield strength of steel tube (fy) in MPa.
- The compressive strength of concrete (fc) in MPa.
- Diameter of circular concrete filled steel tube (D) in mm.
- Wall thickness of steel tube (t) in mm.
- Height of circular concrete filled steel tube (L) in mm.

Neural network training reflects efficient results when network inputs and outputs are normalized. In order to scale the whole data from 0.1 to 0.9, minimum and maximum values of data in each group are considered to be 0.1 and 0.9, respectively.

Equations for scaling are given in Table-2. The range of input parameters and reference values used in the present are given in Table-3.

***Table 2** Scaling equations for whole data*

Parameter	**Scaling of equation**
f_y (Mpa)	$f_{y\ scaled}$=[0.8∗(f_(y)−f_(ymin))/ ((f_(y max)−f_(y min))]+0.1
f_c’ Mpa	$f_{c\ scaled}$=[0.8∗(fc)−f_(c min))/ ((f_(c max)−f_(cmin))]+0.1
D (mm)	$D_{scaled} = [(0.8/(D_{max}-D_{min}))*(D - D_{min})]+0.1$
T (mm)	$t_{scaled} = [(0.8/(t_{max}-t_{min}))*(t - t_{min})]+0.1$
L (mm)	$L_{scaled} = [(0.8/(L_{max}-L_{min}))*(L - L_{min})]+0.1$
P (N)	$P_{scaled} = [(0.8/(P_{max}-P_{min}))*(P - P_{min})]+0.1$

***Table 3** Range of input parameters and Reference Values*

Input Parameter	**D (mm)**	**t(mm)**	**fy (MPa)**	**fc (MPa)**	**L (mm)**
Maximum	1020	13.25	853	108	5000
Minimum	76	0.52	178.28	9.9	153
Mean	163.69	4.42	343.00	40.32	937.66
Reference Values	163	4	343	40	937

The Back-propagation training algorithm is used. The network includes biases, a sigmoid layer, and a linear output layer which is capable of approximating any function with a finite number of discontinuities. The term back-propagation refers to the manner in which the gradient is computed for nonlinear multilayer networks. The training of a network by back-propagation involves three stages: the feed-forward of the input training pattern, the calculation and back-propagation of the associated error, and the adjustment of the weights. After training, application of the net involves only the computations of the feed-forward phase. Even if training is slow, a trained net can produce its output very rapidly.

A feed-forward network has a layered structure; each layer consists of units which receive their input from units by a layer directly below and send their output to units in a layer directly above the unit. There are no connections within a layer. The N_i inputs are fed into the first layer of $N_{h,,l}$ hidden units. In the input units, no processing occurs. The output of the hidden units is distributed over the next layer of $N_{h,2}$ hidden units, until the last layer of hidden units, of which the outputs are fed into a layer of N_0 output units (Fig. 3, Source: Van Der Smagt and Krose, 1996). The network which is used in this study is composed of one layers with Act-logistic transfer function in the hidden layer and pure liner transfer function in the output layer.

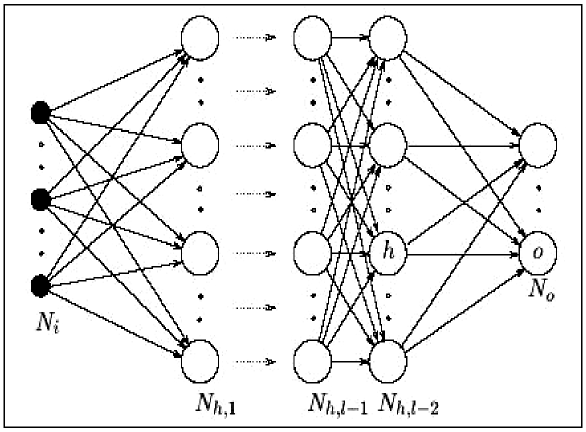

Figure 3 *A Multilayers feed forward network*

Also Backpropmomentum algorithm is used for training but the residuals are higher. The criterion for stopping the training of networks was Mean Square Error (MSE) which is the average squared difference between targets and network outputs, and best value is zero. Regression values measured the correlation between targets and network outputs in the network; regression value of 1 means a close relationship and zero means a random relationship. The regression values are depicted in Figure 4 and Figure 5. The network used 663 data for training. For validation, 20 inputs (Veerabhadragouda. P. Patil, 2012) having the maximum variation in the geometrical properties is used to check the generalization. For testing, 20 data points (Giakoumelis and Lam, 2004) were used independent of the network.

To achieve the proper network, different networks are trained using different learning rate and the activation function with the least sum square error (S.S.E) was chosen for our study. Their regression coefficient is depicted in Figure-4.

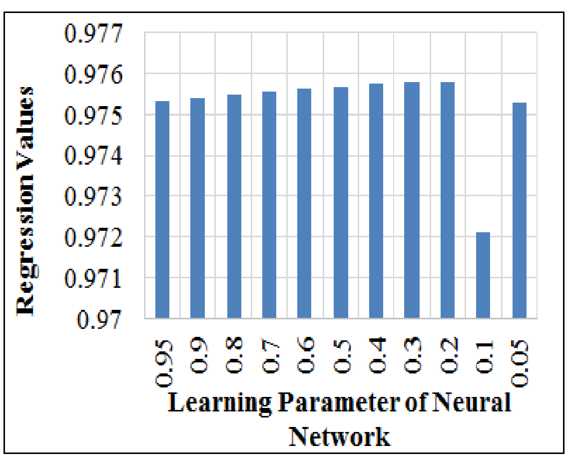

Figure 4 *Correlation coefficient of different learning rate*

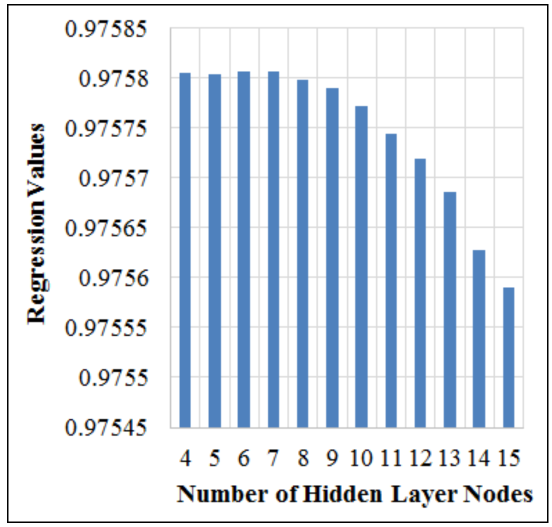

Figure 5 *Regression coefficients of Hidden Nodes*

In order to increase its accuracy and precision different networks were trained using same learning rate, but with the number of hidden neurons between 4 and 15 and their regression coefficient is depicted in Figure 5. Effective parameters to select the appropriate network between different networks have the minimum SSE value and maximum regression values. After the pre-acceptance of desirable networks, network with seven hidden neurons (NN7-1-Act_log) was selected as the best one. Regression values of NN7-1-Act_log network are presented in Fig. 6.

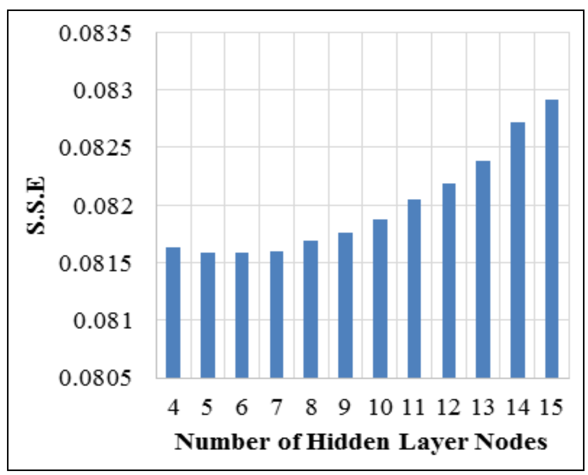

Figure 6 *Sum Square Error for different networks*

The entire process was executed in "Stuttgart Neural Network Simulator". SNNS (Stuttgart Neural Network Simulator) is a software simulator for neural networks on UNIX workstations developed at the Institute for Parallel and Distributed High Performance Systems (IPVR) at the University of Stuttgart. The goal of the SNNS project is to create an efficient and flexible simulation environment for research on and application of neural nets. The SNNS simulator consists of two main components: 1) simulator kernel written in C 2) graphical user interface under X11R4 or X11R5.

The simulator kernel operates on the internal network data structures of the neural nets and performs all operations of learning and recall. It can also be used without the other parts as a C program embedded in custom applications. It supports arbitrary network topologies and, like RCS, supports the concept of sites. SNNS can be extended by the user with user defined activation functions, output functions, site functions and learning procedures, which are written as simple C programs and linked to the simulator kernel.

4. Results and Discussions

The regression value for training is shown in Figure 7, and has coefficient of correlation 0.9758. The regression value for validation is shown in Figure 8, and has coefficient of correlation 0.9810. The regression value for testing is shown in Figure 9, and has coefficient of correlation 0.9366. This shows that there is a high level of correlation between the data sets and the simulated values and the given network can predict the values with high level of accuracy and precision.

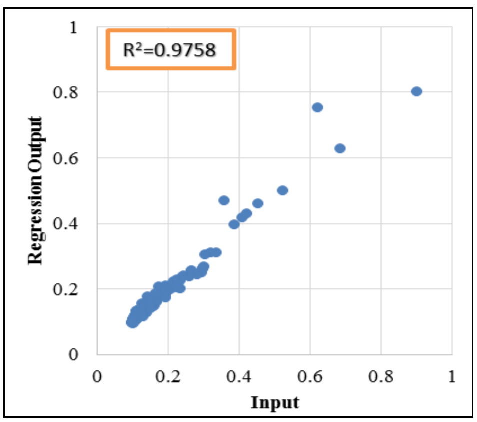

Figure 7 *Regression values of Training*

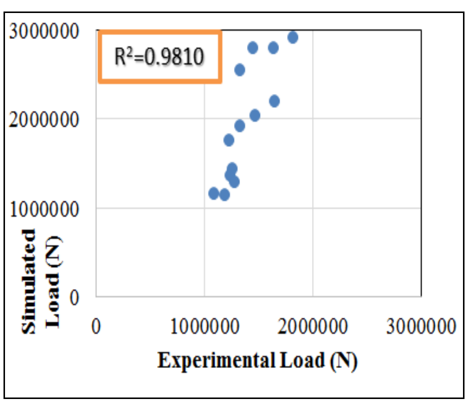

Figure 8 *Comparison of Experimental Load values for Validation Set*

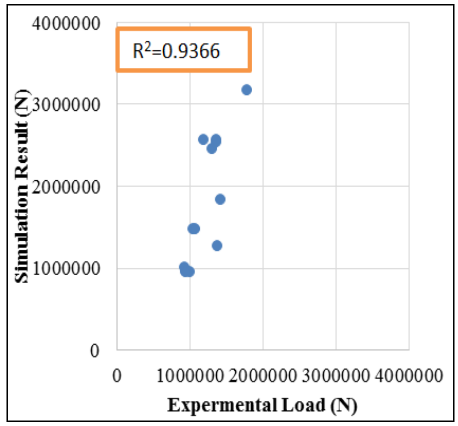

Figure 9 *Comparison of Experimental Load values for Test Set*

Figure 10 shows a dispersion plot that compares the experimental test results with the simulated results obtained from ANN. Figure 11 shows a dispersion plot that compares the experimental test results with the simulated results obtained from ANN and the testing and validation data set. It is found that R^2 =0.9744, which intimates that the ANN is able to depict and simulate the axial capacity of circular CFST columns.

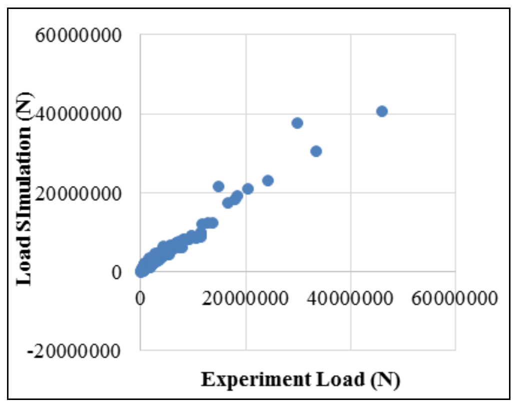

Figure 10 *Comparison of Experimental Data vs Predicted Values*

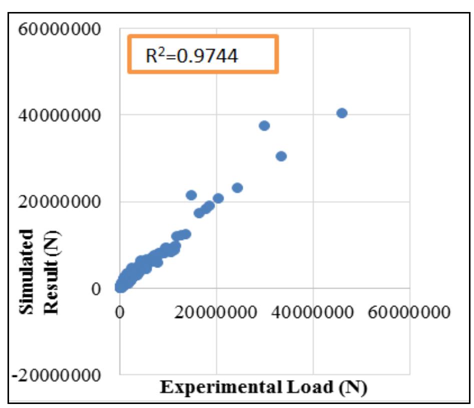

Figure 11 *Comparison of Experimental Load values to Simulated Result for whole data set*

5. Conclusions

In the present study, an experimental database is used for the calculation of axial capacity of circular CFST columns using an intelligent system. By using neural network and input parameters such as yield strength of steel tube, the compressive strength of concrete, diameter and height of circular concrete filled steel tube, and wall thickness of steel tube, a network for strength prediction of columns is proposed. The ANN7-1-Act_log has been established by proper training, validation and testing. The current study and the network developed can be used to examine the variable parameters that govern the load bearing capacity of CFST columns such as compressive strength of concrete, yield strength of steel and D/t ratio. The developed network can be used to propose a new model that can predict the axial capacity of CFST columns with high level of accuracy and precision.

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References

[1] Ahmed Elremaily and Atorod Azizinamini. Behavior and strength of circular concrete-filled tube columns Journal of Constructional Steel Research 2002. (58) pp. 1567–1591.

[2] Amir Fam, Frank S Qie, Sami Rizkalia. Concrete Filled tubes subjected to axial compression and under cyclic loads. *Journal of Structural Engineering* 2004. pp. 631-640.

[3] C.D. Goode, ASCCS Database of Concrete-Filled Steel Tube Columns: Available: http://web.ukonline.co.uk/asccs2/

[4] Ehab Ellobody and Ben Young. Behaviour of normal and high strength concrete-filled compact steel tube circular stub columns. Journal of Constructional Steel Research 2006. (62) pp. 706–715.

[5] G.GaneshPrabhu and M.C.Sundarraja. Behaviour of concrete filled steel tubular (CFST) short columns externally reinforced using CFRP strips composite. Construction and Building Materials, 2013. (47) pp.1362-1371.

[6] Giakoumelis G and Lam D., (2004) "Axial capacity of circular concrete-filled tube columns." *Journal of Constructional Steel Research*, (7):pp 1049–68.

[7] J.M.Portoles, E.Serra, M.L.Romero. Influence of ultra-high strength infill in slender concrete-filledsteeltubularcolumns. Journal of Constructional Steel Research, 2013. (86) pp. 107-114.

[8] Lin-Hai Han, Wei Li and Reidar Bjorhovde, (2014). Developments and advanced applications of concrete-filled steel tubular (CFST) structures: Members. Journal of Constructional Steel Research Journal of Constructional Steel Research, (100) 211–228.

[9] Lin-Hai Han; Jing-Si Huo; and Yong-Chang Wang. Behavior of Steel Beam to Concrete-Filled Steel Tubular Column Connections after Exposure to Fire. Journal of Structural Engineering 2007. pp 800-814.

[10] M. Ahmadi, H. Naderpour and A. Kheyroddin., (2014). Utilization of artificial neural networks to prediction of the capacity of CCFT short columns subject to short term axial load. Archives of Civil and Mechanical Engineering (14) 510-517.

[11] Mohanraj, E.K., and Kandasamy S.,. "Experimental Behaviour of Axially Loaded Hollow Steel Columns In-filled with Concrete*", IE(I) Journal–CV* , 2008. (88) pp. 23-29.

[12] Nie Jian-guo, Wang Yu-hang, Fan Jian-sheng. Experimental study on seismic behavior of concrete filled steel tube columns under pure torsion and compression–torsion cyclic load Journal of Constructional Steel Research 2012. (79) pp. 115–126.

[13] P. VanDer Smagt and B. rose, (1996). An Introduction to Neural Networks, eighth ed., University of Amsterdam, Netherland.

[14] Seong-Hui Lee, Brian Uy, Sun-Hee Kim, Young-Hwan Choi, Sung-Mo Choi, Behavior high strength of circular concrete-filled steel tubular (CFST) Columns under eccentric loading. Journal of Constructional Steel Research, 2011.(67) pp. 1-13.

[15] SNNS (Stuttgart Neural Network Simulator) software simulator for neural networks Available : http://www.ra.cs.uni-tuebingen.de/SNNS/

[16] Suliman Abdalla, Farid Abed and Mohammad Al Hamaydeh, "Behavior of CFSTs and CCFSTs under quasi-static axial compression*", Journal of*

Constructional Steel Research, 2013. pp. 235 –244.

[17] Veerabhadragouda. P. Patil (2012) Finite Element Approach To Study The Elastic Instability Of Concrete Filled Steel Tubular Column Under Axial Loads. International Journal of Emerging Technology and Advanced Engineering, (2) (11) 276-284.

[18] W.S. McCulloch and W.H. Pitts, A logical calculus of ideas immanent in nervous activity Bulletin of Mathematical Biophysics 5 (1943) 115 – 133.

[19] Xiushu Qu, Zhihua Chen, Guojun Sun Experimental study of rectangular CFST Columns subjected to eccentric loading, Thin-Walled Structures, 2013. (64) pp. 83-93.

[20] Zhao XL, Han LH, Lu H. (2010) Concrete Filled Tubular Members and Connections, Spon Press.

[21] Zhijing Ou, Baochun Chen, P.E., Kai H. Hsieh; Marvin W. Halling, S.E., and Paul J. Barr, “Experimental and Analytical Investigation of Concrete Filled Steel Tubular Columns”, *Journal of Structural Engineering*, 2011. pp. 635-645.