

A streamlined deep-learning algorithm for predicting the ultimate axial load of self-stressed columns

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Abstract. In light of their confinement effect, composite columns were frequently chosen in modern construction procedures over reinforced concrete columns. The outer confining tube was made of various materials, which are primarily distinguished through their mechanical characteristics. The fundamental purpose of this research is to evolve an ingenious artificial neural network simulation that is more straightforward and can be utilized to calculate the ultimate load carrying capacity of self-stressed columns irrespective of the category of impounding tube deployed. The most recent experimental findings associated with the composite columns were utilized in the creation of a database. This database is employed for training, testing, and validating the machine learning model. Following the contemporaneous experimental research, several composite columns were chosen for further examination, and the model that was developed was utilized to validate the ultimate axial load of the columns.

Keywords: ANN; expansive cement, PVA fibers; self-stressed; shrinkage

1. Introduction

Concrete has been widely used as the dominant construction material worldwide for a very long time because of its exceptional capacity to withstand compression and its long-lasting nature. Due to its inherent brittleness, this concrete demonstrates a relatively low tensile strength (Liu *et al.* 2021). Concrete is being optimized to reduce its vulnerability to segregation and bleeding. Numerous investigations have been conducted to enhance the durability and functionality of concrete, as it has become an essential component in all construction projects. Due to the inevitable occurrence of shrinkage in concrete, efforts were made to eliminate shrinkage cracks and develop high-performance concrete. It has become very necessary to develop high-performance concrete that possesses enhanced properties while maintaining its quality and strength. The susceptibility of

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concrete to shrinkage has been reduced through the utilization of a variety of techniques, such as the application of Shrinkage Diminution Admixtures, Expansive Agents (EA), surface conditioning, fiber integration, and other operations.

An attempt was undertaken to enhance the durability of concrete by juxtaposing regular Portland cement with Expansive Cement (EC) of the Sulpho - Alumino type, with the aim of reducing the occurrence of cracks. Compared to traditional concretes, it displays exceptional resistance to environmental threats. The encompassment of expansive cement to concrete has been evinced to offer many supplementary advantages, such as increased resistance to shrinkage (Mo *et al.* 2014), an improved bond between the cement paste and aggregate, and a robust and congruent material. The introduction of this enhanced cement paste was considered one of the most compelling advancements in concrete technology (Yu *et al.* 2018).

The proliferation of innovative architectural designs with tall, wide-span, and heavily laden structures has raised the demand for columns that possess enhanced load-bearing capability and rigidity. Reinforced concrete columns are utilized as structural elements to support and transmit axial loads. The load bearing capacity of columns is influenced by several factors, including the grade of concrete (compressive strength), the strength of materials, the geometry of the section, and the technology used to transfer the loads (Xu *et al.* 2018). However, to enhance the performance of columns, it has been encountered that using infilled concrete columns with concrete infill confined within tubes can be a worthwhile solution. This method provides support and reinforcement to the infill concrete, consequently inhibiting the occurrence of local buckling in the columns.

This coalescence culminates in the optimal utilization of material strength, a high load-bearing capacity, increased member stiffness and ductility, and enhanced seismic resistance in buildings. The outstanding features of CFST are attributed to the correlatively favorable coupling of steel tube and concrete (Lu *et al.* 2017). Polyvinyl Alcohol (PVA) fiber is a type of cement-based composite that serves as a novel reinforcement. It was developed in Japan 50 years ago, and Polyvinyl acetate (PVA) is generated over the hydrolysis of vinyl acetate, which is subsequently cleaved to yield PVA (Lu *et al.* 2018). A variety of investigations have been executed to examine the mechanical properties of Polyvinyl Alcohol fibers reinforced Engineered Cement-based Composites (PVA-ECC) in terms of tensile, flexural, and compressive strength, comparing them to alternative varieties of fibers used as reinforcement in cement-based composites (El-Ghazaly *et al.* 2019). The capacity of concrete to avert fatigue including fibers was superior to that of concrete without fibers, and this capacity could be attributed to the distribution of the fibers (Yurtseven *et al.* 2006). The tensile stress exhibited a significant increase of over 5 MPa, although the crack diameter was less than 60 mm. On the contrary, the flexural stress exceeded 75 MPa and the compressive stress was greater than 15 MPa. El-Ghazaly *et al.* (2019) found that increasing the ratio and length of polyvinyl alcohol (PVA) fibers resulted in a decrease in the air content, slump, and other features of concrete.

Despite being the most effective method, experimental studies are conducted with a restricted range of parameter adjustments and entail more time and expenses. To optimize efficiency and retain expenses, it is possible to utilize prediction models based on Artificial Intelligence (AI) to obtain the desired outcomes. McCulloch and Pitts were pioneers in 1943, being the first to create simpler neurons specifically to build neural networks. Soft computing approaches have garnered increasing attention and found applications across various domains in recent years. Instead of allocating resources to conduct experimental investigations, there are several statistical approaches available to forecast the outcomes of these tests. The Artificial Neural Network (ANN) is an

emerging technology in the field of Artificial Intelligence (AI) that is utilized for resolving diverse technical issues. Among the statistical tools, Artificial Neural Networks (ANN) are widely used because of their exceptional accuracy compared to other techniques. The ANN approach is applicable for studying complex interactions that traditional mathematical methods struggle to handle. The ANN operates similarly to a biological neural network, with interconnected neurons that undergo training, testing, and data validation processes. The learning process in ANN can be classified into two categories: (a) Presided learning, where the target is directly compared with the output, and (b) Emancipated learning, where the inputs are correlated.

By feeding existing experimental data into neural networks for training, the ANN approach is able to make predictions about the outcomes (Output). ANN has been used on concrete structures, steel, RC members, shear connections, seismic resilience, resilience to fire, structure resonance, and structural health monitoring (Kaveh and Khalegi 2000, Alli *et al.* 2003, Mansour *et al.* 2004, Duan *et al.* 2013, Chojaczyk *et al.* 2015, Kotsovou *et al.* 2017, Morfdis and Kostinakis 2017, Tran-Ngoc *et al.* 2019, Abambres and Lantsoght 2020, Charalampakis and Papanikolaou 2021, Moradi *et al.* 2021). Nevertheless, ANN was used by researchers to design and analyze transmission lines, large-scale space structures, and double-layer grids. Among these, researchers found that counter-propagation performed better than back-propagation (Kaveh and Iranmanesh 1998, Kaveh and Servati 2001, Kaveh *et al.* 2008). Some of the modern works utilized deep learning techniques such as multivariate adaptive regression splines, relevance vector machines, support vector regression, grey-wolf optimization, and Gaussian process regression (Yuvaraj *et al.* 2014, Chitra *et al.* 2016, Mansouri *et al.* 2016, Behnood and Golafshani 2018, Prasanna *et al.* 2018, Avci-Karatas 2019, Ngo *et al.* 2021, Le 2022). The work by (Miceli *et al.* 2024) highlights how non-linear numerical analyses (NLNA) of RC structures, account for epistemic uncertainties such as limitations in model accuracy or measurement errors to accurately estimate global safety factors and ensure robust design practices. Gino *et al.* (2024) discuss how epistemic uncertainties play a critical role in determining the reliability of models used for structural assessment.

The main intention of this study is to evolve an underlying ANN model that can precisely ascertain the ultimate axial load of self-stressed columns. Assorted experimental data were gathered from the published works and subsequently utilized for training, testing, and validation purposes. Experiments were performed in actual time on self-stressed columns subjugated under axial compressive loading, and the accuracy of the obtained data was confirmed by comparing them with the established model. Expansive cement exhibits a tendency to undergo an increase in volume during the process of hydration. When the expansion is limited by external confinement using steel tubes, tensile stress is generated on the inner surface of the tubes, resulting in pre-stressing (Krithika Paramesh *et al.* 2023). By confining concrete, the structure can better withstand large deformations (Miceli *et al.* 2024). Such self-stressed columns were tested under axial loads experimentally and were compared with the ANN prediction model. Additionally, this model can be deployed for predicting the final axial load of the self-stressed columns.

2. Development of database

Multiple studies were carried out regarding the axial behavior of the CFST column. From the pool of works, only the most relevant ones were meticulously chosen to enhance the efficiency of the model. A comprehensive database containing data pertaining to 158 CFST columns featuring various diameters and heights has been assembled. The key parameters, such as the inner diameter

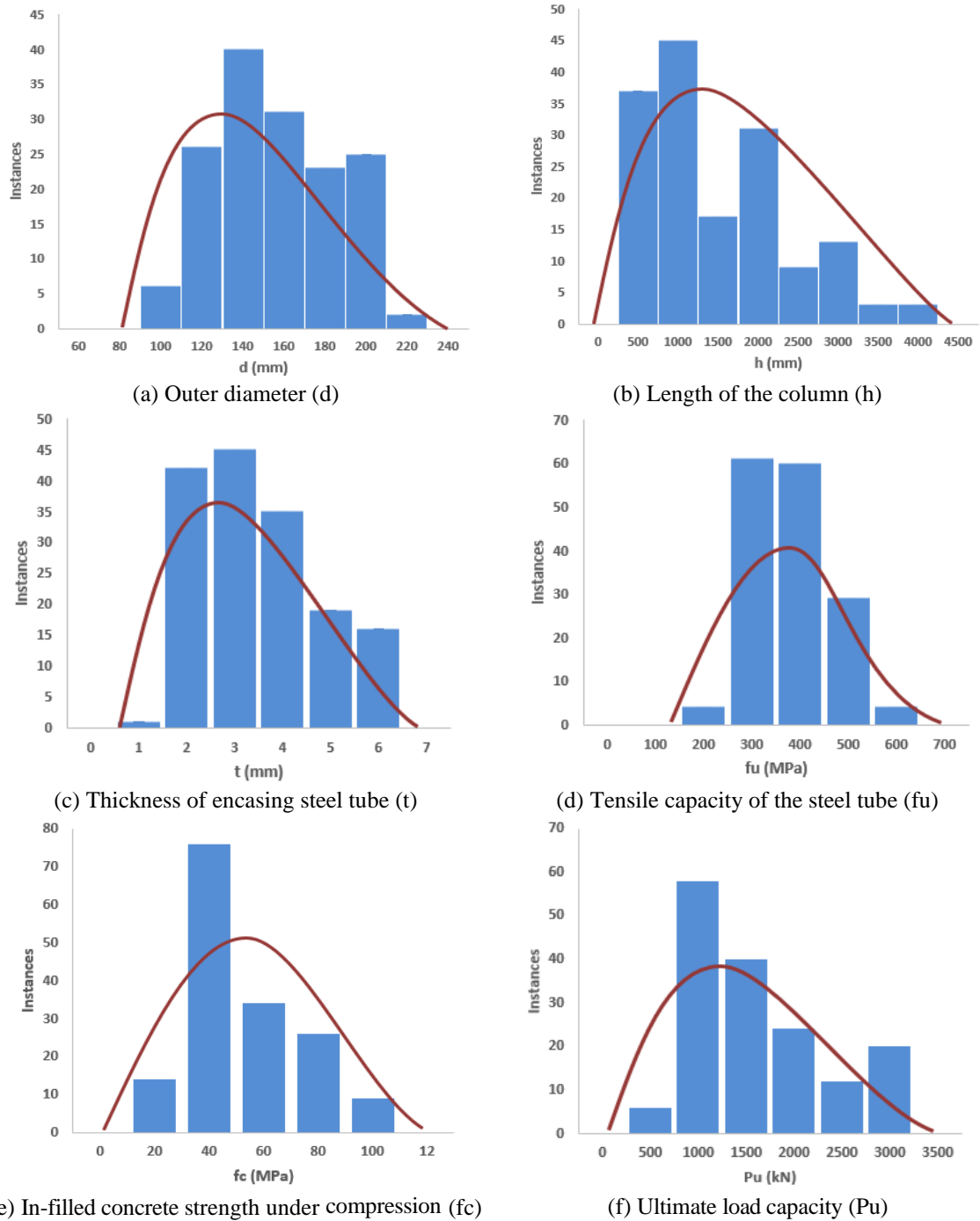


Fig. 1 Histogram for the distribution of the statistical data

(d) and height (h) of the column, the thickness of the outer tube (t), the tensile strength of the outer confining tube (f_u), compressive strength of the in-filled concrete (f_c), and axial load (P_u), have

Table 1 Statistical data on the variables

Variables	Outer diameter (d) (mm)	Length of the column (h) (mm)	Thickness of the encasing steel tube (t) (mm)	Tensile capacity of the steel tube (fu) (N/mm ²)	In-filled concrete strength under compression (fc) (N/mm ²)	Ultimate load capacity (Pu) (kN)
Minimum	101.50	300.00	1.13	185.70	14.44	305.00
Maximum	210.00	3720.00	5.99	604.67	102.43	2870.00
Mean	132.10	1145.42	3.34	323.38	41.61	996.00
SD	26.1036	827.8266	1.1074	52.5037	19.0802	498.5905
COV	0.1976	0.7227	0.3313	0.1624	0.4586	0.5006

been retrieved from several studies. (Huang *et al.* 2002), (Han and Yao 2004), (Giakomelis and Lam 2004), (Sakino *et al.* 2004), (Yu *et al.* 2007), (de Oliveira 2009). The findings from statistical analysis for the aforementioned variables are outlined in Table 1 and Fig. 1 displays the histogram for the statistical data distribution.

3. Modeling - ANN Architecture

The structure and function of actual neural networks in the brain serve as inspiration for the architecture and operation of artificial neural networks, which are simulated computer models. In a neural network, every node in one layer is linked to every node in the layer below it, irrespective of whether it is the input, hidden, or output layer. The strength of these linkages is determined by the weights that are linked with them. To train the network to produce the desired output with as little variation as possible, repeated adjustments are made to these weights using methods like gradient descent and back-propagation. A neural network would also be incomplete without the activation function. It allows the network to learn complicated patterns in the data by introducing non-linearity.

3.1 Input, output, and hidden layers of ANN

The input layer receives the initial data or features of the problem you're trying to solve. Each node in this layer represents a feature or input variable. The values from the input layer are passed to the nodes in the subsequent hidden layer. The main function of the input layer is to simply pass the input data forward to the hidden layers without any computation. Hidden layers are where the majority of the computation in a neural network occurs. Every neuron across a hidden layer acquires input from each of the nodes comprising the preceding layer (either the input layer or another hidden layer). For each node in the hidden layer, the input values are multiplied by weights (which are initially random) and summed up. This weighted sum also includes a bias term.

Once the weighted aggregate is calculated, an activation function is used to bring non-linearity to the network. This enables the network to acquire intricate patterns and correlations within the data. Each node in the hidden layer produces an output that is used as input for every node in the following layer, whether it is a hidden layer or an output layer. The selection of the assortment of hidden layers and the multitude of nodes in each hidden layer is a decision that is contingent upon the intricacy of the problem at the time along with the extent of available data. The output layer

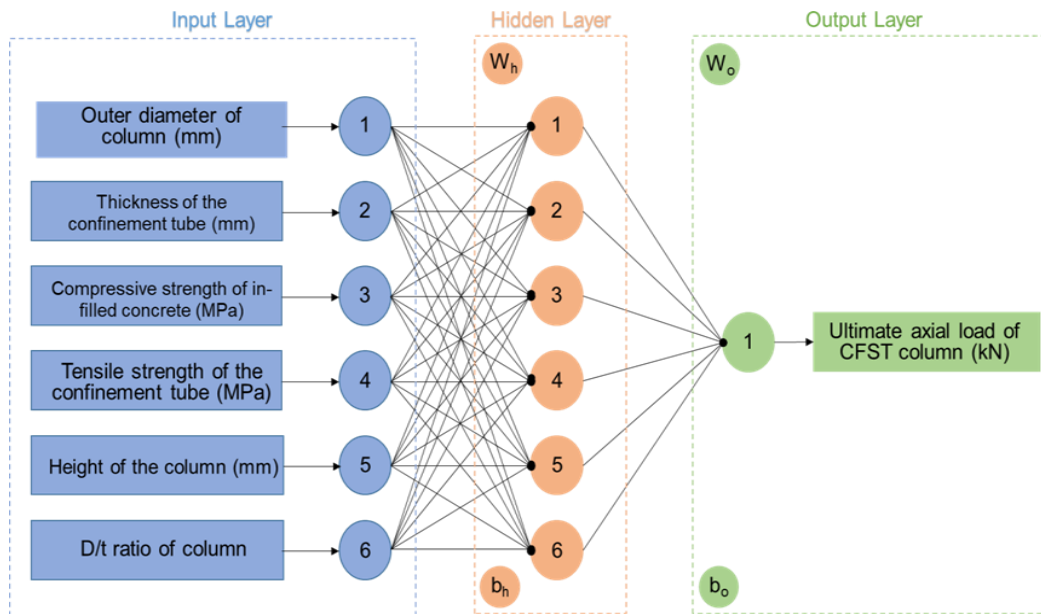


Fig. 2 The architecture of the designed ANN model

produces the final result or prediction of the neural network. Like the hidden layers, each node comprising the output layer receives input from every node in the preceding layer (which could be a hidden layer or another output layer). The nature of the problem at the moment dictates the optimal number of output layer nodes. Similar to the hidden layers, the output layer applies an activation function to its input. The choice of activation function in the output layer depends on the nature of the problem. During the training phase, the network modifies the weights and biases of the connections amongst nodes using optimization procedures such as gradient descent and back-propagation. The process of adaptation enables the algorithm to acquire knowledge from the input data and enhance its capacity to generate precise predictions or classifications.

Fig. 2 depicts the architectural design of the proposed ANN model used to forecast the highest possible load capacity of the self-stressed columns. The proposed ANN model encompasses six input layers, including the outside diameter, steel tube thickness, in-filled concrete strength under compression, the tensile capacity of encasing steel tube, column height, and the diameter-to-thickness (D/t) ratio of the column. The model consists of a single output layer that allows for the conjecture of the axial load capacity of the column. This research study utilized a total of 6 hidden layer neurons, with each of the six input layers interacting with a hidden neuron to get the desired goal output.

The Tangent-Sigmoidal (tansig) function is used as the activation function for the hidden layer, as depicted in Fig. 3a. This function is similar to the sigmoid or logistic function and has the same S-shape with an output range of -1 to 1. The hyperbolic tangent function, Tanh, approaches a value of 1 when the input is high (+) and -1 when the input is a deficit (-). The purelin function is utilized as the activation function for the output layer, as shown in Fig. 3b. It corresponds to the input as a linear activation function, sometimes referred to as “no activation” as well as the “identity function.” The function outputs the provided data without affecting the weighted aggregate of the input.

Table 2 Design parameters for the ANN model

Parameters	Methods/value
MATLAB tool	Nftool
Network type	Scaled conjugate gradient
Training function	Trainscg
Data division	Dividerand
Performance analysis	Mean Squared Error (MSE)
Number of hidden layers	1
Number of hidden neurons	6
Number of epochs	74
Maximum fail	6
Minimum gradient	$1.50 \times e^{+03}$

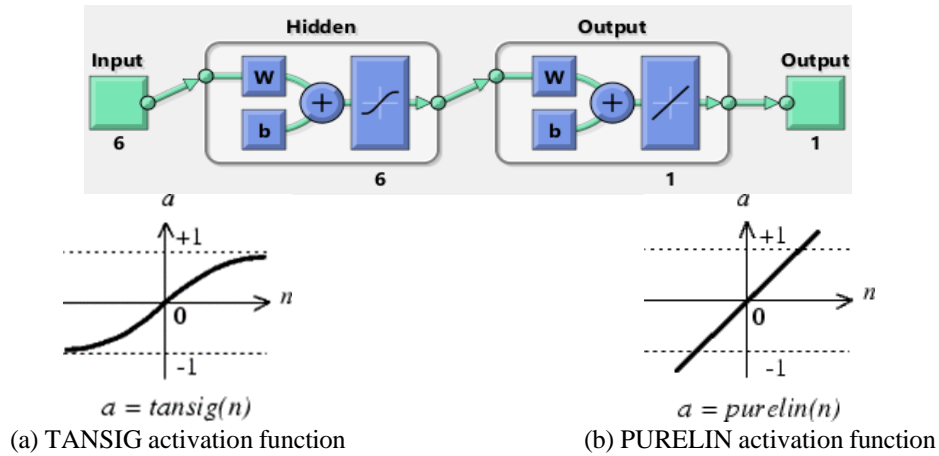


Fig. 3 Activation functions

The MATLAB R2018a application, which is a flexible tool for soft computing, is used to create an ANN model and is now being explored. A total of 158 experimental instances of steel composite columns were utilized in the development of the ANN simulation.

The Scaled Conjugate Gradient (SCG) technique was utilized for training the network. The data were partitioned randomly into three groups using the SCG algorithm, with 80% designated for training, 10% for validation, and 10% for testing. The activation function used in the output layer is PURELIN, which is a linear transfer function that sustains the input values. Both layers are defined by their weight and bias, as depicted in Fig. 3. The design parameters for the presented artificial neural network (ANN) model are set forth in Table 2.

3.2 Training, validation and testing of ANN model

Approximately 75% of the entire archives are utilized for training the Artificial Neural Network (ANN), while the remaining datasets are employed for testing and validating the created model, respectively. The training phase of the Artificial Neural Network (ANN) reaches convergence after approximately 74 epochs or iterations for Pu. This interpretation utilized the “Mean Squared Error” (MSE) criterion to evaluate the accuracy of ANN structure by assessing correlations between training, testing, and validation data.

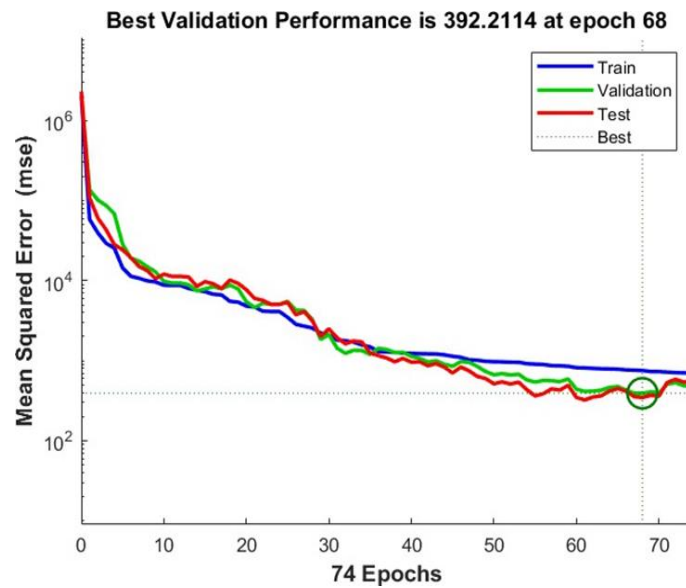


Fig. 4 Performance of the proposed ANN model during the Training, Validation, and Testing process

Fig. 4 illustrates the performance of the proposed ANN model throughout the training, testing, and validation stages. It demonstrates that the error frequently diminishes as training epochs go. However, when the network excessively adapts to the training data, the error may increase on the validation data set. The optimal performance is achieved by selecting the epoch with the lowest validation error while using the default configuration. Training is stopped after six consecutive rises in the validation error. The highest validation performance achieved is 392.2114, which occurred at epoch 68. The performance plot exhibits the fluctuations of mean square error for all datasets, utilizing a logarithmic scale. The validation and test mean squared error (MSE) should mirror the training MSE, which exhibits a consistent decrease, indicating an optimal training process.

Fig. 5 displays additional training statistics in the Training State plot. The gradient corresponds to the logarithmic representation of the back-propagation gradient at each iteration. The result $1.50 \times e^{+03}$ signifies that the local minimum of the objective function has been achieved.

Validation failures are defined as iterations in which the validation mean squared error (MSE) increased. Multiple failures suggest excessive training, yet in this case, it is deemed appropriate. The software automatically stops training after six consecutive failures.

The error histograms illustrating the residual errors in forecasting optimal capacity of the self-stressed columns were depicted in Fig. 6. The error histogram is derived from the amalgamation of the training, validation, and testing datasets. The histogram displays the relationship between errors and instances, revealing that the error value is considerably lower in key areas. This indicates the level of precision of the presented model.

The Regression graphs for the training, validation, testing, and overall process showcasing an exemplary model are exhibited in Fig. 7. The Regression (R) values achieved for Training, Validation, and Testing were 0.99194, 0.99861, and 0.99879, respectively. The approach has an overall regression value of 0.99411, signifying excellent performance in training, validating, and testing the advocated ANN model.

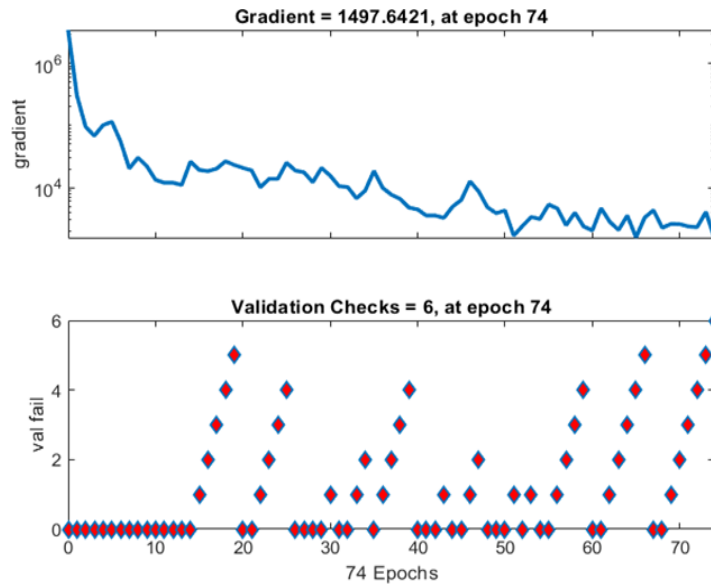


Fig. 5 The Architecture of the Designed ANN Model

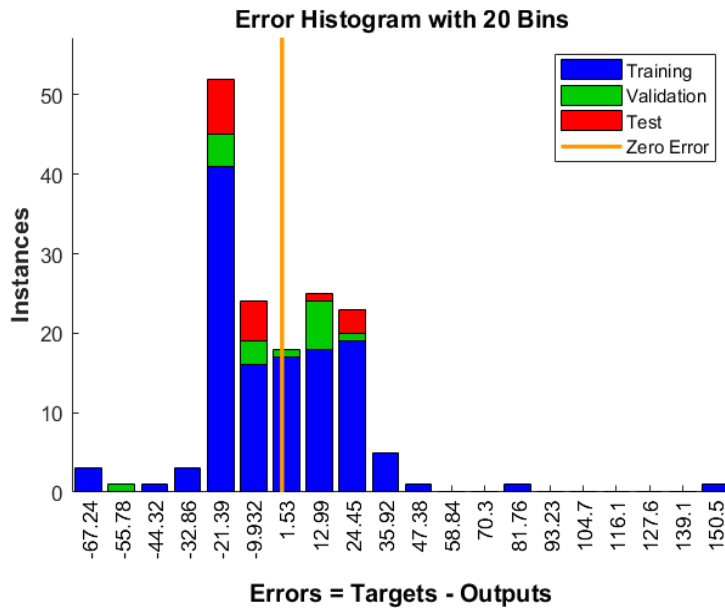


Fig. 6 Error Histogram in Predicting Ultimate Load Capacity of Self-stressed Columns

3.3 ANN-based formulation

Based on the data gathered from the preceding subsection, the outlined artificial neural network (ANN) model is adept at accurately predicting the maximum axial load capacity of composite columns. Given the challenges associated with finding analytical answers, the proposed ANN model can be used to build a clear and useful empirical formula that disentangles the process of

applying it in practical design. By employing the activation functions and parameters (weights and biases), the constructed ANN model promptly produced the precise expression for the maximum axial load capacity. The equation for the target value of the optimal load capacity (P_u), derived from the recommended ANN model which is a function of the considered parameters is provided by Eq. (1),

$$p(\text{kN}) = b_0 + (\tanh \sum W_h x_i + b_h) W_0 \quad (1)$$

where $n = 6$ (hidden layer neurons);

W_h, b_h = the weights (6×6) and bias (6×1) of the hidden layer as in Eq. (2) and (3);

x_i = the inputs (6×1) parameter as in Eq. (4).

$W_0, b_0 = 0.4507$ are the weights (6×1) as in Eq. (5) and bias of the output layer;

$$[W_h]_{6 \times 6} = \begin{bmatrix} 1.0488 & 0.9213 & 1.4451 & -0.8037 & 0.0185 & -0.1303 \\ -0.0795 & -1.5981 & 0.5983 & 0.4735 & -0.0716 & -0.5799 \\ 0.4153 & 0.8880 & -0.8694 & 0.8109 & 1.1592 & 0.5217 \\ 0.6544 & 1.1780 & -0.7210 & -1.2752 & -0.9568 & 0.6720 \\ -1.1187 & -2.3085 & -0.5143 & 0.0630 & 1.5777 & -0.6806 \\ -0.0265 & 0.8329 & -0.8335 & -0.8365 & -0.8303 & -0.8478 \end{bmatrix} \quad (2)$$

$$[b_h]_{6 \times 1} = \begin{bmatrix} -1.4142 \\ 1.6483 \\ -0.7906 \\ -0.6841 \\ 0.7772 \\ 2.0413 \end{bmatrix} \quad (3)$$

$$[x]_{6 \times 1} = \begin{bmatrix} D \\ t \\ fc \\ fy \\ L \\ D/t \end{bmatrix} \quad (4)$$

$$[W_0]_{6 \times 1} = \begin{bmatrix} -1.1689 \\ 0.1685 \\ 0.3791 \\ -0.5476 \\ -0.3900 \\ -0.1581 \end{bmatrix} \quad (5)$$

3.4 Experimental validation

The implied artificial neural network (ANN) model is assessed and validated against the experimental findings (Krithika Paramesh *et al.* 2023). Experiments were conducted in actual time using self-stressed columns under axial compression loads. The load set-up is depicted in Fig. 8. The final load carrying capacity (LCC) of the CFST columns achieved in the experiments was juxtaposed with the values derived from the constructed artificial neural network (ANN) model. The percentage divergence between the experimental and ANN outcomes was computed and illustrated in Table 3.

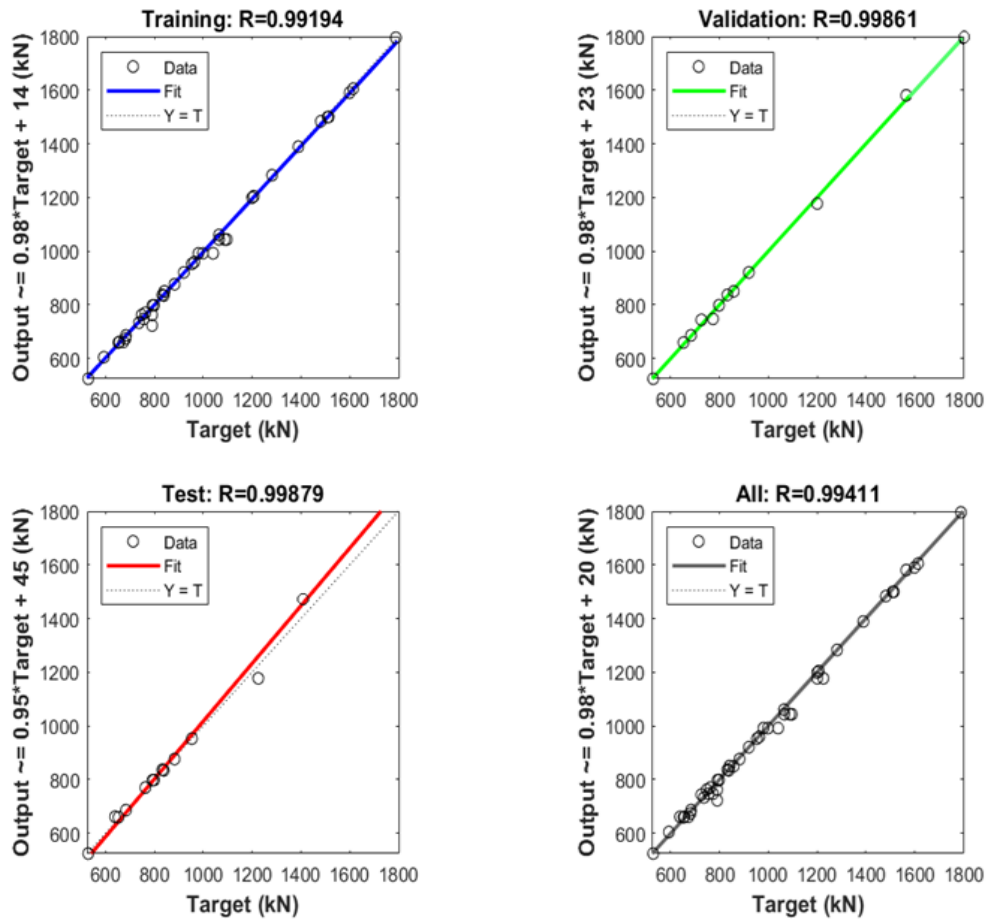


Fig. 7 Regression plots of the training, validation, and test process

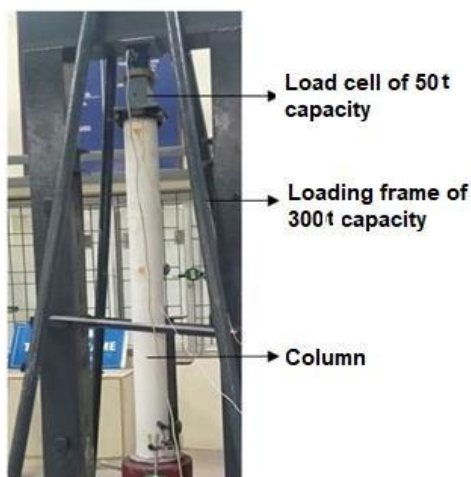


Fig. 8 Loading Set-up of the Columns (Krithika Paramesh *et al.* 2023)

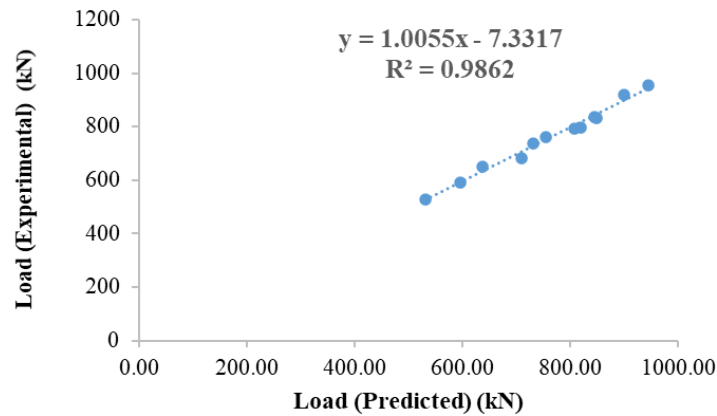


Fig. 9 Load comparison (Experimental versus Predicted)

Table 3 Comparison of experimental results of self-stressed columns with results of the ANN Model

Specimen Label	Height 'H' (mm)	ANN Model (Ultimate Load, kN)		
		Experiment	ANN Predicted	% Deviation
S1-40G2*	600	592	596.85	0.82
S2-40G2	600	528	530.27	0.43
S3-40G2	1000	762	754.09	1.04
S4-40G2	1000	736	731.81	0.57
S5-40G2	1500	832	847.85	1.91
S6-40G2	1500	798	819.18	2.65
S7-50G1.5	600	683	709.53	3.88
S8-50G1.5	600	652	636.52	2.37
S9-50G1.5	1000	838	843.84	0.70
S10-50G1.5	1000	791	807.85	2.13
S11-50G1.5	1500	953	945.21	0.82
S12-50G1.5	1500	920	899.39	2.24

*S1-40G2 – for Self-stressed columns with Concrete of grade 40 and 2% of PVA fibers for D/t ratio 56

The 'xy'-graphs in Fig. 9 display the ultimate load, correlating the experimental and predicted values. The load generated from the suggested ANN model closely matched the experimental results. The R^2 value for the load comparison between the experimental and predicted values is 0.9862. This indicates that the created ANN model accurately predicts the ultimate axial load capacity of CFST columns with a precision of 98.62%. In regression analysis, the accuracy is improved when the results closely align with the straight line.

The results indicate that the created artificial neural network (ANN) model accurately predicted the axial load capacity of self-stressed columns in all situations and aligned closely with the experimental findings. The findings obtained from the proposed Artificial Neural Network (ANN) model demonstrated a maximum deviation of 3.88% when compared to the experimental data. Nevertheless, the model is constructed using the Scaled Conjugate Gradient technique, while alternative approaches can accurately forecast the ultimate Load Carrying Capacity (LCC) of the

CFST columns. Additional investigations can be conducted using alternative techniques, such as the Levenberg-Marquardt algorithm, to assess the precision of the outcomes obtained by these methods. A comparative analysis using these various algorithms to compare the accuracy differences between the models can be performed.

4. Conclusions

The main objective of the study is to develop a streamlined ANN model for accurately predicting the optimal axial load capacity of self-stressed columns. The model was constructed using the experimental database derived from the relevant literature. A combined empirical model and ANN model are proposed to get an appropriate agreement with the database. The subsequent research discoveries can be inferred from the study presented,

- The suggested model undergoes training with different numbers of trials. However, the ANN model, specifically with 6 neurons in the hidden layer, demonstrates greater efficiency in terms of experimental data, achieving a regression value of $R = 0.9862$.

- The suggested experiential equation demonstrates a strong correlation with both present and real-time experimental findings, making it suitable for precisely estimating the axial load of self-stressed columns.

- The constructed model is assessed and confirmed using coexistent experimental research with self-stressed columns, yielding a percentage error of less than 3.8%.

- Therefore, the unambiguousness of the simulation will suffice to forecast the axial load of the self-stressed columns with minimal errors.

- The created ANN model leverages an empirical equation for reckoning the axial load of self-stressed columns. This assessment is independent of factors such as the type, diameter, height, and thickness of the encasing material, along with the compressive strength of the unconfined concrete.

- D/t is used as an input variable in addition to the other five variables to train the ANN model and to precise the predictive nature of model which will enhance the ANN performance, while L/r is excluded to prevent unnecessary noise (i.e., error) and overfitting, thereby improving the model's accuracy and generalization. In future research, L/r will be used to analyze the model performance.

- The training phase of the ANN model may face limitations such as overfitting due to complex architectures and significant computational demands, which can lead to longer training times and resource constraints. Additionally, challenges in hyper-parameter tuning and data quality issues can hinder optimal performance and generalization. Whereas in this model, the input variable is limited to six to avoid the above mentioned problems. In future research, more variables can be used in the training phase to train the ANN model.

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