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# MODEL PREDICTION FOR COMPRESSIVE STRENGTH OF A FULLY CONFINED CONCRETE CYLINDER WITH CARBON FIBRE REINFORCED POLYMER

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**Abstract**

Nowadays, the application of carbon fibre reinforced polymer (CFRP) composites in engineering works for strengthening of reinforced concrete structures is increase dramatically. CFRP can be used to strengthen the structural elements to increase its performance in load carrying capacity, and subsequently delaying the deterioration rate or reducing the impact of damage, if any. This paper aims to provide an analytical model which is capable to predict the CFRP fully confined concrete compressive strength. This analytical model is developed by using artificial neural network (ANN) which utilised the data from a new database created from the previous experimental works in previous literatures. Four input parameters are selected as the training parameters for the ANN, i.e. the tensile strength of CFRP ($f_f$), thickness of the CFRP layer ($t$), CFRP's Young modulus of elasticity ($E_f$) and compressive strength of unconfined concrete ($f_{co}$). The output of the ANN models is to predict the compressive strength of confined concrete ($f_{cc}$). In addition, a comparison was carried out with the predicted value from the proposed ANN model in this study and the experimental value from literature, and with two other existing mathematical models from previous study. The proposed ANN model showed lowest average error in predicting the experimental results with only a difference of 5.91 MPa as compared to the actual experimental value.

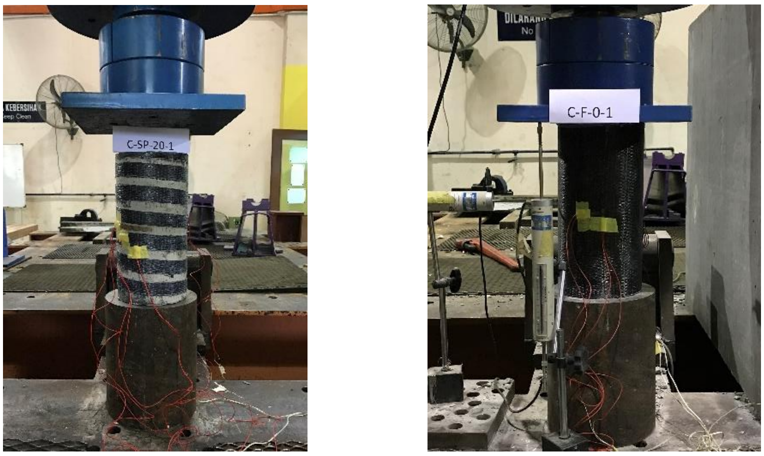
Keywords: Artificial neural network, Carbon fibre reinforced polymer, CFRP confinement, Compressive strength, Resilient building.

## 1. Introduction

Fibre reinforced polymer (FRP) is a composite material composed of a fibre reinforced matrix polymer. The main composite material's name which used to form the matrix polymer is generally used to address the type of FRP in the market. Generally, there are a few types of fibres that are commonly used to form the matrix polymer which are aramid, carbon or glass, and sometimes other fibres such as paper, asbestos, or wood. For example, if glass fibre is utilised as the main ingredient to form the reinforced polymer, then it is calling as glass fibre reinforced polymer (GFRP), and if the carbon fibre is used as the main ingredient, then it is calling as carbon fibre reinforced polymer (CFRP).

Commonly, FRP is applied to provide submissive confinement for reinforced concrete or masonry columns to increase both compressive and ductile strengths [1]. The application of FRP as a strengthening material has been popularly used in the past decade due to its good strength, high modulus of elasticity, easy installation and cost effective compared with other type of fibres. Many studies have been conducted to investigate the behaviour and effect of FRP confinement to the concrete strengths. Earlier study by Hosotani et al. [2] has demonstrated the proposed concrete model confined to the FRP that applied to circular and rectangular columns. Then, more studies have been conducted by other researchers like Kim et al. [3], Lin and Liao [4], Masia et al. [5], Ongpeng [6], Akogbe et al. [7], Li and Wu [8], Ismail et al. [9], Raza et al. [10], Huang et al. [11] and Tang et al. [12] in applying the FRP to confine various shapes of concrete and reinforced concrete columns in investigating their behaviour and strength. All studies concluded that the FRP has shown great potential in improving the concrete performance.

Although many studies have been carried out on investigating the concrete performance of either fully or partially confined concrete cylinder with FRP, but many studies are focusing on the experimental program. Due to the advancement of the technology, the capacity of the numerical software available has also becoming powerful. Different numerical models are proposed in recent years to capture the ultimate compressive strength of such confined concrete columns. Some recent studies involving numerical investigation on the concrete cylinder can be found in Mazzucco et al. [13], Al-Kamaki et al. [14], and Du et al. [15] and Tang et al. [16]. However, there is no study carried out on the model prediction for providing the compressive strength of a fully confined concrete cylinder with CFRP. Hence, this study focuses on creating a database from the previous studies based on the experimental works carried out on CFRP confined concrete column. Fig. 1 shows the sample of partially confined CFRP and fully confined CFRP on a concrete column in a laboratory testing. A collection of a large number of experimental data is therefore essential for this purpose [17]. In this study, a database is created from the data collected based on the testing carried out in previous studies on CFRP confined concrete column. Then, a new prediction model is developed using the artificial neural networks (ANN) using the collected database based on the previous studies to predict the concrete compressive strength.




**Partially confined column with CFRP** **Partially confined column with CFRP**

**Fig. 1. Partially and fully confined column with CFRP.**

## 2.Methodology

ANN is basically a computer system which architecture essentially imitates the human brain working skills and power in memorising [18]. Artificial neurons work similarly to real neurons in the human brain. It is trained to predict the desired result based on data that fed into the learning process. Similar to the biological neuron network, the digital neuron network has an input layer, a neuron layer, and an output layer. Every neuron is typically connected to one another by a link which contains weights which integrate complex information. The types of ANN can be differentiated by its structure, type of neuron, training database and learning algorithms among others [17]. There are evidences that ANN is a powerful tool to employ as a prediction tool in the engineering field as in studies by Asteris and Mokos [19] and Karimipour et al. [20].

In this study, a collection of database on the compressive strengths of CFRP confined circular concrete samples was created. The range of parameters for the proposed database is tabulated in Table 1. The database was employed to provide enough information for the training, validation and testing of ANN model. Overall, the created database contains 243 test results from the related previous studies in the literature. The database collection consisted of four input parameters which was the ultimate tensile strength of CFRP ($f_f$), thickness of the CFRP layer ($t$), CFRP's Young modulus of elasticity ($E_f$), and compressive strength of unconfined concrete ($f_{co}$) while the target output was the compressive strength of confined concrete ($f_{cc}$). The dimension of the concrete cylinder employed in this study was 150 mm × 300 mm with the length-to-diameter ratio (h/d) as 0.5.

**Table 1. Range of parameters for the proposed database**

| **Input parameter** | $t$ **(mm)** | $f_{co}$ **(MPa)** | $f_{cc}$ **(MPa)** | $f_f$ **(MPa)** | $E_f$ **(MPa)** |
|---|---|---|---|---|---|
| **Max** | 1.50 | 82.13 | 146.4 | 4580 | 377 |
| **Min** | 0.11 | 6.2 | 19.4 | 1265 | 82.7 |
| **Mean** | 0.36 | 39.44 | 83.66 | 3502 | 256.46 |

In this study, the ANN model was developed using MATLAB R2018b. The architecture of the proposed model was designed by using trial and error method. Fifteen trials ANN models were trained using different number of neurons to get the best network configuration of the ANN model. The Mean Square Error (MSE) was adopted to determine the best ANN model in this study. MSE is the average squared difference between outputs and targets. Lower values are better. Zero means no error. The neurons with the lowest MSE can be considered as the best network to predict the compressive strength of CFRP fully confined concrete column. Other criteria used to choose the network with best performance was by analysing its regression value (R-value) which measure the correlation between outputs and targets. An R-value of 0 indicate random relationship, while 1 indicate close relationship. Hence, R-values and MSE were used as the main criterion to select the idealised network in this prediction study.

The ANN models were developed with one layer of hidden neurons. In this study, the transfer function used in the ANN model was log-sigmoid for the hidden layer while pureline for the output layer. The training algorithm utilised was Levenberg-Marquardt as according to study by Goh et al. [21], Levenberg-Marquardt algorithm in ANN gave the best generalisation performance in prediction. This algorithm typically requires more memory but less time. Training automatically stops when generalisation stops improving as indicated by an increase in the MSE of the validation samples. The designed network used in this analysis was named NN 4-n-1, where the first digit number representing the inputs while the last digit representing the output of the ANN model as illustrated in Fig. 2. The number of hidden neurons was stated in between in the input and output layers.

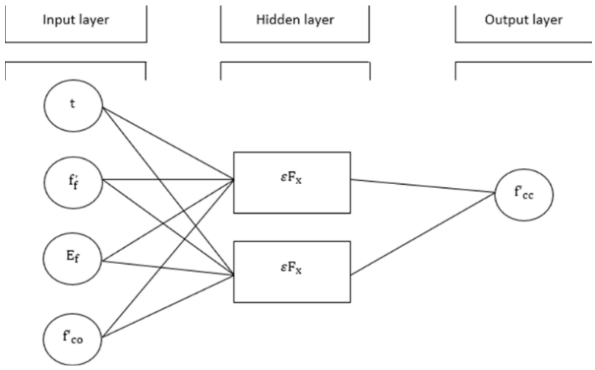



**Fig. 2. Schematic diagram of ANN model.**

The database was normalised before they were fed to train the ANN model. The objective of data normalisation was to reduce the data redundancy if any and minimise the amount of storage space needed to save the data to make it easier to maintain. Sixty percent from the data was randomly selected as the training data to train the network. The network learnt by adjusting the errors automatically during the learning process. Another 20% randomly selected data from the database was specified as validation data which was used to evaluate the data generalisation. The remaining 20% in the database was classified as testing data. The testing data has no influence on training and thus an independent network performance measurement can be provided during and after training.

The values from the ANN output were the used in a comparison study with two existing mathematical models to validate the efficiency of the proposed ANN model. The two existing mathematical models employed for this comparison study were models proposed by Matthys et al. [22] with nonlinear relationship and Mander et al. [23] with second-order relationship. The formulation to calculate the predicted full confinement compressive strength for these two models are presented in Table 2.

**Table 2. Existing mathematical models for FRP confined concrete.**

| Author | Formula |
|---|---|
| Matthys et al. [22] | $\frac{f'_{cc}}{f'_{co}} = 1 + 2.3\left(f_l/f'_{co}\right)^{0.85}$ |
| Mander et al. [23] | $\frac{f'_{cc}}{f'_{co}} = -1.25 - 2\left(f_l/f'_{co}\right) + 2.25\left(1 + 7.94\, f_l/f'_{co}\right)^{0.5}$ |

The following equation which was proposed by Al Abadi et al. [24] was applied to employ to calculate the lateral confining stress ($f_l$).

$$f_l = \frac{2 \times f_f \times t}{d} \tag{1}$$

where, $f_f$ = Ultimate tensile strength of CFRP, $t$ = Thickness of CFRP layer, $d$ = Diameter of concrete cylinder.

## 3. Results and Discussion

As mentioned in the previous section, MSE was employed in this study as the indicator for stopping the network training, while regression value was used to check the correlation between the outputs and targets. Fig. 3 presents the MSE values obtained from the ANN training and validation process using the different number of neurons. From Fig. 3, it is observed that the MSE values for the model training starts with a large value and then continue to decrease to a smaller value. It means that the ANN model was learning well during training. The MSE values for the model validation of the ANN model also showed a large value initially but continue to decrease to the smaller values. However, the MSE values for the model validation started to increase when the ANN model employed more than 10 hidden neurons. Thus, the number of neurons with minimum value of MSE for model validation can be considered as the most efficient ANN model for this study. Another filtering criteria for pre-elimination of ANN model can be seen in Fig. 4 where it shows the R-value for different number of neurons applied.

After analysing the MSE and R-value from Figs. 3 and 4, the best ANN model was selected based on their accuracy and efficiency was NN 4-10-1 as it recorded the lowest value of MSE value, and its R-value exceeded 0.95 which was close to 1. The results for the ANN model training of the NN 4-10-1 are summarised in Figs. 5 and 6.

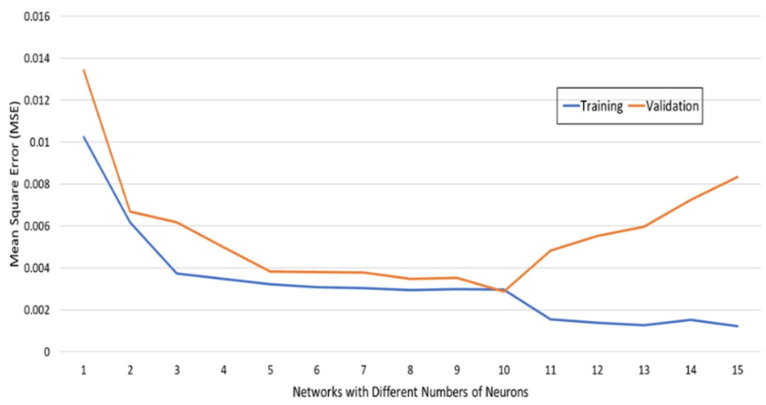



**Fig. 3. MSE value for training and validation for different number of neurons.**

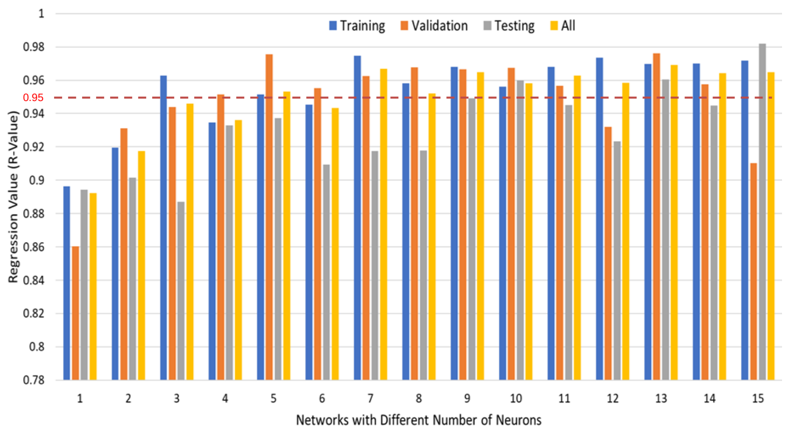



**Fig. 4. Regression value (R-Value) for different number of neurons.**

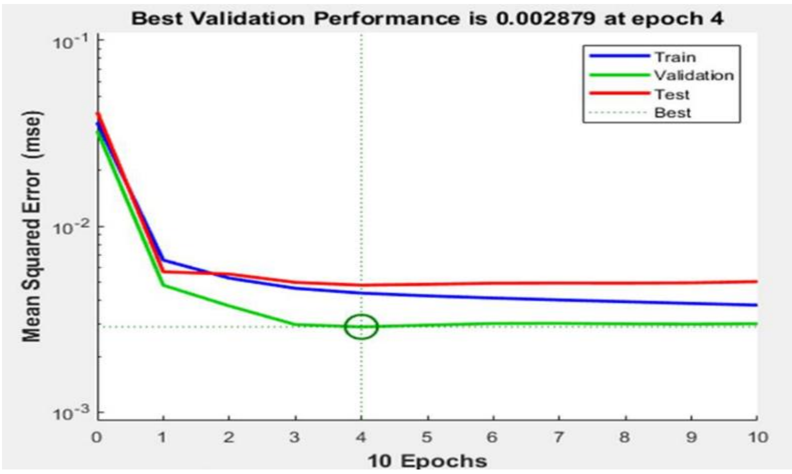



**Fig. 5. Performance of NN 4-10-1.**

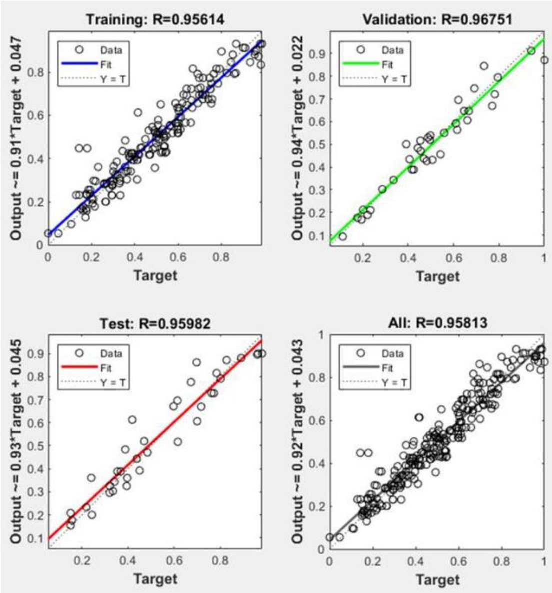



**Fig. 6. R-Value for training, validation, test and all for NN 4-10-1.**

Figure 5 illustrates the ANN model's training performance. The plot in Fig. 5 has three lines as the vectors of the 243 inputs and targets were divided into three sets randomly. Training on the training vectors continues as long as the training reduces the error on the validation vectors from the network. Training is stopped after the network memorises the training set which make it generalise the result more poorly. This technique automatically avoids over-fitting problem which plagues many algorithms for optimisation and learning. Figure 6 depicts the R-value for training, validation, and testing for NN 4-10-1 which the line spread around the 45° which indicate that the result was neither underestimated nor over estimated.

After the best network has been selected, the output of the network was compared with the experimental results and two other models from Matthys et al. [22] and Mander et al. [23] to validate the efficiency of the proposed ANN model in predicting the full CFRP confinement concrete cylinder compressive strength. Figure 6 presents the comparison of proposed model with the mathematical models from previous studies related to experimental works. When there is a perfect agreement between the model and the results from experiment, all points will lie along the 45° line.

From Fig. 7, it can be observed that the point distribution of proposed neural network lies among the 45° line which indicate that it can performs fairly well when it comes to predicting the experimental results. The average error between predicted values and experimental values were then calculated. The percentage error of these three models is shown in Fig. 8.The proposed ANN model recorded the lowest average error of 5.91 MPa to the actual value, followed by model by Matthys et al. [22] with of 10.0 MPa, and model by Mander et al. [23] recorded the highest average error among three prediction value with 18.78 MPa. This demonstrates that the proposed method has good capability to predict the compressive strength of a fully confined concrete cylinder with CFRP.

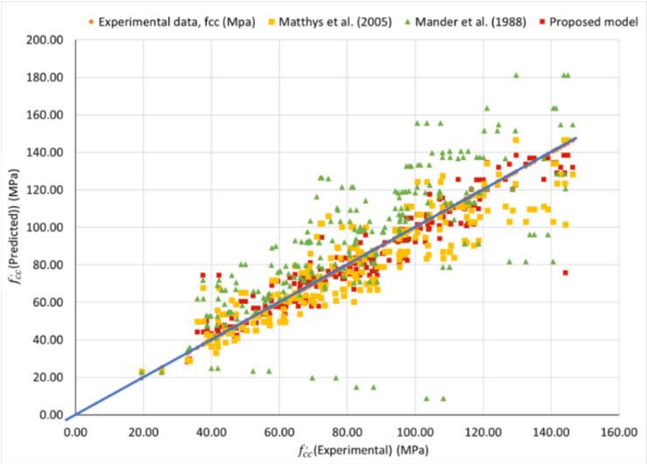



**Fig. 7. Comparison of proposed model and two other empirical models from previous studies with experimental results.**

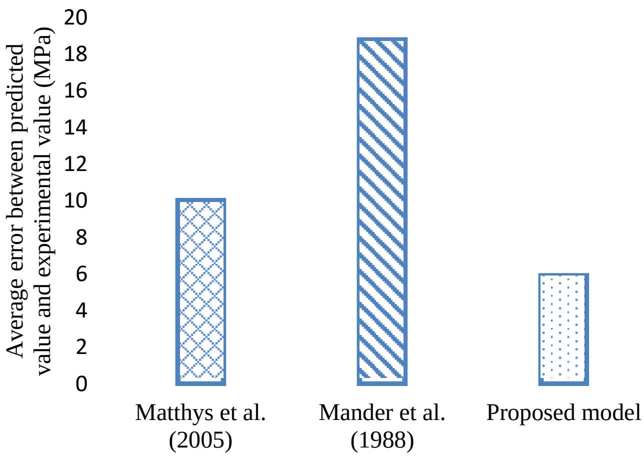



**Fig. 8. Percentage error between proposed model and two other strength models.**

## 4. Conclusions

A collection of database with a total of 243 samples for CFRP confined concrete was gathered from all related previous studies. A training process of the ANN model was carried out with 15 different number of hidden neurons, and one of the best network was selected. The best network selected was NN 4-10-1 based on its performance using the indication of MSE and regression values. In order to verify the performance of the network, the prediction from the ANN model was compared with the actual experimental results and two other existing empirical models from previous studies. The proposed ANN model was capable to provide the lowest average error in predicting the experimental results with only a difference of 5.91 MPa as compared to the actual experimental value, while the other two empirical models were at 10.0 MPa and 18.78 MPa, respectively. In addition, to prove the efficiency of the proposed model, percentage error of these three models were compared. The proposed ANN model gave the lowest percentage of error. In conclusion, this study demonstrated that the proposed ANN model is capable to provide an accurate prediction of CFRP full confinement concrete compressive strength and can be useful as a good prediction tool in the related industry.

## Nomenclatures

| | |
|---|---|
| $E_f$ | CFRP's Young modulus of elasticity |
| $f_f$ | CFRP's Young modulus of elasticity |
| $f_{cc}$ | Compressive strength of confined concrete |
| $f_{co}$ | Compressive strength of unconfined concrete |
| $t$ | Thickness of the CFRP layer |

**Abbreviations**

| | |
|---|---|
| ANN | Artificial Neural Networks |
| CFRP | Carbon Fibre Reinforced Polymer |
| FRP | Fibre Reinforced Polymer |
| GFRP | Glass Fibre Reinforced Polymer |
| MSE | Mean Square Error |

## References


1. Wu, G.; Lü, Z.T.; and Wu, Z.S. (2006). Strength and ductility of concrete cylinders confined with FRP composites. *Construction and Building Materials*, 20(3), 134-148.
2. Hosotani, M.; Kawashima, K.; and Hoshikuma, J.-i. (1998). A stress-strain model for concrete cylinders confined by carbon fiber sheets. *Doboku Gakkai Ronbunshu* (*Japan Society of Civil Engineers*), 1998(592), 37-52.
3. Kim, J.-H.J.; Yi, S.-T., Lee, S.-H.; Park, S.-K.; and Kim, J.-K. (2003). Compressive behaviour of CFS strengthened concrete specimens with various cross-sectional shapes and laminations. *Magazine of Concrete Research*, 55(5), 407-418.
4. Lin, H.-J.; and Liao, C.-I. (2004). Compressive strength of reinforced concrete column confined by composite material. *Composite Structures*, 65(2), 239-250.
5. Masia, M.J.; Gale, T.N.; and Shrive, N.G. (2004). Size effects in axially loaded square-section concrete prisms strengthened using carbon fibre reinforced polymer wrapping. *Canadian Journal of Civil Engineering*, 31(1), 1-13.
6. Ongpeng, J.M.C. (2006). Retrofitting RC circular columns using CFRP sheets as confinement. *Proceedings of the Symposium on Infrastructure Development and the Environment 2006At: Quezon City, Philippines*. 1-10.
7. Akogbe, R.K.; Liang, M.; and Wu, Z.M. (2011). Size effect of axial compressive strength of CFRP confined concrete cylinders. *International Journal of Concrete Structures and Materials*, 5(1), 49-55.
8. Li, P.; and Wu, Y.-F. (2016). Stress-strain behavior of actively and passively confined concrete under cyclic axial load. *Composite Structures*, 149, 369-384.
9. Ismail, R.; Rashid, R.S.M.; Chan, W.C.; Jaafar, M.S.; and Hejazi, F. (2019). Compressive behavior of concrete cylinder fully and partially confined by carbon fibre-reinforced polymer (CFRP). *Construction and Building Materials*, 201, 196-206.

10. Raza, A.; Rafique, U.; Masood, B.; Ali, B.; ul Haq, F.; and Nawaz, M.A. (2021). Performance evaluation of hybrid fiber reinforced low strength concrete cylinders confined with CFRP wraps. *Structures*, 31, 182-189.
11. Huang, L.; Su, L.; Xie, J.; Lu, Z.; Li, P.; Hu, R.; and Yang, S. (2022). Dynamic splitting behaviour of ultra-high-performance concrete confined with carbon-fibre-reinforced polymer. *Composite Structures*, 284, 115155.
12. Tang, W.; Liu, Z.; Lu, Y.; and Li, S. (2022). Hybrid confinement mechanism of large-small rupture strain FRP on concrete cylinder. *Journal of Building Engineering*, 51, 104335.
13. Mazzucco, G.; Salomoni, V.A.; Majorana, C.E.; Pellegrino, C.; and Ceccato, C. (2016). Numerical investigation of concrete columns with external FRP jackets subjected to axial loads. *Construction and Building Materials*, 111, 590-599.
14. Al-Kamaki, Y.S.S.; Al-Mahaidi, R.; Al-Mosawe, A.; and Bennetts, I. (2020). Experimental and numerical study on wrapping concrete cylinders post heating and cooling under preload using CFRP fabrics. *Structures*, 23, 425-436.
15. Du, Y.; Fu, M.; Chen, Z.; Yan, J.B.; and Zheng, Z. (2022). Axial compressive behavior of CFRP confined rectangular CFT columns using high-strength materials: Numerical analysis and carrying capacity model. *Structures*, 36, 997-1020.
16. Tang, H.; Chen, J.; Yue, Z.; Jia, Y.; and Yuan, Z. (2022). Theoretical and numerical analysis on the ultimate bearing capacity of CFRP-confined CFSST stub columns. *Archives of Civil and Mechanical Engineering*, 22(1), 1-15.
17. Naderpour, H.; Kheyroddin, A.; and Amiri, G.G. (2010). Prediction of FRP-confined compressive strength of concrete using artificial neural networks. *Composite Structures*, 92(12), 2817-2829.
18. Cai, Z.-X. (1997). *Intelligent control: principles, techniques and applications:* Volume 7. World Scientific.
19. Asteris, P.G.; and Mokos, V.G. (2020). Concrete compressive strength using artificial neural networks. *Neural Computing and Applications*, 32(15), 11807-11826.
20. Karimipour, A.; Abad, J.M.N.; and Fasihihour, N. (2021). Predicting the load-carrying capacity of GFRP-reinforced concrete columns using ANN and evolutionary strategy. *Composite Structures*, 275, 114470.
21. Dee, G.L.; Bakhary, N.; Rahman, A.A.; and Ahmad, B.H. (2011). A comparison of artificial neural network learning algorithms for vibration-based damage detection. *Advanced Materials Research*, 163-167, 2756-2760.
22. Matthys, S.; Toutanji, H.; Audenaert, K.; and Taerwe, L. (2005). Axial load behavior of large-scale columns confined with fiber- reinforced polymer composites. *ACI Structural Journal*, 102(2), 258-267.
23. Mander, J.B.; Priestley, M.J.; and Park, R. (1988). Theoretical stress-strain model for confined concrete. *Journal of Structural Engineering*, 114(8), 1804-1826.
24. Al Abadi, H.; Abo El-Naga, H.; Shaia, H.; and Paton-Cole, V. (2016). Refined approach for modelling strength enhancement of FRP-confined concrete. *Construction and Building Materials*, 119, 152-174.