Predicting Compressive Strength of CFRP-Wrapped Reinforced Concrete Columns using Soft Computing Techniques

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Abstract

Reinforced concrete columns deteriorate over time, necessitating strengthening methods such as wrapping with carbon fiber reinforced polymer (CFRP) to enhance their strength. Predicting the compressive strength of these columns is vital for structural assessment and design. This study explores the use of soft computing techniques, specifically multivariable linear regression (MLR) and multivariable nonlinear regression (MNLR), to predict the compressive strength of columns confined with CFRP. A dataset comprising 46 experimental observations is utilized to develop and validate the predictive models. The results highlight the effectiveness of soft computing approaches in accurately estimating the compressive strength of CFRP-wrapped reinforced concrete columns, offering valuable insights for structural engineers and practitioners. The diameter-to-height ratio (d/h) of the column, the compressive strength of unconfined concrete (f_c'), number of layer of CFRP (n), thickness of CFRP (t) the elastic modulus (E_{frp}) and tensile strength (f_{frp}) of CFRP, the area of longitudinal steel (A_s), and the yield strength (f_y) of longitudinal steel were considered as input parameters, while the compressive strength of FRP-confined columns was considered as the target. The proposed methods are compared with the existing models and provide great accuracy in predicting the results. Among the utilized methods, the MLR model showed the highest accuracy.

Keywords: Strengthening, Cylinder, Confinement, Modeling, FRP, Failure, MLR, MNLR

1. Introduction

Reinforced concrete columns serve as crucial components, withstanding both horizontal and vertical loads within concrete structures. Consequently, their resilience significantly contributes to the overall structural integrity. Retrofitting these elements often involves employing various conventional methods such as exterior pre-stressing systems, steel collars, or concrete, along with fiber-reinforced polymers (FRP). Among these methods, strengthening reinforced concrete structures using FRP composites has gained widespread acceptance globally due to its ability to enhance resistance significantly without altering the structure's original shape and dimensions [1]. The primary characteristics of polymer composites include corrosion resistance, ease of installation, and their lightweight nature. Additionally, the cost-effectiveness of FRP materials has contributed to their increased utilization. To ensure reinforced concrete columns can sustain significant deformations under load prior to failure, lateral confinement is essential to attain adequate strength. Consequently, FRP is often employed to provide external confinement for reinforced concrete columns, particularly when internal transverse reinforcement is insufficient. Furthermore, FRP materials offer advantages such as the ability to design simpler and more durable structures, high tensile strength, better compatibility with pre-stressing systems, and reduced fatigue compared to steel. A substantial body of experimental studies has been conducted to investigate various FRP strengthening techniques [1–6]. In recent years, there has been a notable expansion in the use of soft computing methods for predicting relationships between parameters in civil engineering. This trend has emerged due to the favorable performance and high accuracy of such methods.

In 1997, Hoshikum et al. [7] formulated a stress-strain model for confined concrete following an experimental investigation. Their study involved the examination of various reinforced concrete columns featuring diverse cross-section shapes (including circular, square, and wall-type) and distinct configurations of hoop reinforcement under compression loading. Their findings led to the determination that the peak stress, accompanied by its corresponding strain and degradation rate, significantly influences the stress-strain relationship.

In 2006, Matthys et al. [8] conducted a study on the stress-strain characteristics of large-scale columns subjected to axial loading and confined with FRP (Fiber-Reinforced Polymer). Their research delved into the efficacy of prevailing stress-strain models in forecasting the performance of these large-scale columns. Notably, they observed that only a limited number of models, primarily derived from small-scale specimens, exhibited satisfactory alignment with the experimental results.

Eid and Paultre (2007) [9] introduced a stress-strain model utilizing the analytical approach, incorporating the renowned Drucker–Prager failure criterion. This model is applicable to both the axial and lateral responses of confined concrete in circular columns, whether reinforced with transverse steel, fiber-reinforced, or a combination of both. Their analysis revealed strong agreement between the proposed analytical model and experimental findings, as well as finite element simulations.

Paultre and Légeron (2008) [10] introduced novel equations aimed at predicting the behavior of columns with circular and rectangular cross-sections. These equations were developed through a comprehensive parametric study, which involved analyzing numerous columns. The study took into account various factors, including the concrete strength, yield strength of transverse reinforcement, axial load level, and spatial distribution of transverse confinement reinforcement. By systematically examining a wide range of column configurations, Paultre and Légeron demonstrated the effectiveness and accuracy of their equations. They validated their findings by comparing them against extensive experimental data sets. This rigorous validation process underscored the reliability and applicability of the proposed equations in accurately predicting the behavior of columns under various conditions.

In 2009, Caglar [11] employed artificial neural networks (ANN) to predict the shear strength of circular reinforced concrete columns under constant axial load and cyclic lateral loading conditions. Utilizing ANN allowed for a more flexible and adaptive approach in estimating shear strength compared to traditional methods. Caglar conducted a thorough analysis by comparing the results obtained from the neural network with those derived from various design codes. This comparison involved calculating the ratios between the outputs from the neural network and the outcomes predicted by the design codes. Ultimately, Caglar demonstrated the superior performance of the neural network model in accurately determining the shear strength of circular columns. The excellent performance of the ANN model showcased its effectiveness as a predictive tool for assessing the shear behavior of reinforced concrete columns, particularly under the specified loading conditions.

In 2010, Naderpour et al. [12] proposed an equation for prediction of the FRP-confined compressive strength of concrete using an extensive number of experimental data by applying artificial neural networks.

Chastre and Silva (2010) [13] carried out an experimental investigation on twenty-five circular reinforced concrete columns confined with CFRP subjected to axial compression. The variable parameters in their study were the column diameter, space of stirrups and number of CFRP layers. They proposed a stress-strain model with consideration of CFRP and transversal reinforcement effect on compressive strength based on their experimental study. Their proposed model predicts the compressive strength of the confined concrete, the maximum bearing capacity and the axial or the lateral failure strain.

In 2012, Wang et al. [14] conducted an experimental study by testing thirty large-scale circular columns subjected to various compression loading (monotonic and cyclic). The variable parameters in their study were column diameter and height, longitudinal bars, stirrups spacing and number of CFRP layers. They also proposed a cyclic stress-strain model based on their experimental work.

In 2015, Shirmohammadi et al. [15] presented a stress-strain model for circular concrete columns with existence of FRP and transverse steel when they act simultaneously based on the experimental database.

Cascardi et al. (2017) [16] proposed an analytical model to predict the strength of FRP-confined concrete for circular columns which revolves new effectiveness parameter as opposed to current models using Artificial Neural Networks by considering a large experimental database.

Also many researches have been conducted using soft computing methods such as prediction of the strength of CCFT short columns subject to axial load [17], in which a model to predict the compressive capacity of circular concrete-filled steel tube was suggested [18]; Furthermore, prediction of shear contribution of FRP-confined RC beams by externally bonded method using ANFIS was also investigated [19]. Estimation of compressive strength in environmentally friendly concrete [20], determining compressive strength of concrete by ANN and ANFIS models [21] and prediction of compressive strength of mortars having calcium inosilicate minerals [22] were among other studies.

There are two types of models for predicting the maximum compressive strength of FRP confined concrete. In the first type, only the FRP confinement effect, and in the second type, the simultaneous effect of FRP confinement and transverse steel is considered. In this study for the sake of simplicity the effect of transverse steel was not considered. In addition, based on 46 validated experimental data, several models using 8 input data including the diameter to height ratio (d/h) of the column, the compressive strength of unconfined concrete (f_c'), number of layer (n) of CFRP, thickness (t) of CFRP the elastic modulus of CFRP (E_{frp}) and tensile strength (f_{frp}) of CFRP, the area of longitudinal steel (A_s), and the yield strength (f_y) of longitudinal steel were used to predict the maximum stress sustain by the FRP-confined column using soft computing methods such as MLR, and MNLR. Therefore, the main objective of this work is to establish soft computing models to estimate the confined compressive strength of plain concrete cylinders. Furthermore, several statistical tools have been utilized to assess the models. In this regard, a model with the best performance to predict the fc'c can be identified and the applicability of the models in the real world can also be discussed.

2. Assembled experimental database

The experimental database, which consists of 46 specimens, assembled from five different experimental works (Chastre and Silva 2010; Eid et al. 2006; Benzaid et al. 2010; Abdelrahman and El-Hacha 2016; Demers and Neale 1999). All of the specimens were confined with full FRP and tested under monotonic loading, consecutively. The height-to-diameter ratio (aspect ratio) of the samples (H/D) is less than 5, for which the diameter is ranging 150–300 mm and height from 320 to 1200 mm. The strength of unconfined concrete f_{c0} varies between 26 and 62 Mpa. Accordingly, the property of FRP sheets and steel reinforcement varies considerably. Furthermore, the type of the FRP which was used for all of the specimens was carbon FRP type. The strength of FRP sheets varies between 450 and 3339 MPa, The area and yield strength of steel reinforcements varies between 169.5 mm^2 and 2492 mm^2 and 391 MPa and 550 MPa, respectively. Table 1 Statistical properties of the assembled data provides a summary of the statistics for the experimental database assembly.

3. Methodology

In total, datasets from 46 samples were gathered in some studies. In the studies, reinforced concrete confined were strengthened by CFRP. The samples were tested under uniaxial compressive strength and the maximum strength of the samples were recorded. In this work, some input parameters than might have the influence on the confined compressive strength of reinforced concrete columns were included, such as, diameter-to-height ratio (d/h), compressive strength of the concrete (fc' MPa), the thickness of the FRP (tf mm), number of wrapped layers (n), the modulus of elasticity of the FRP (Ef MPa), the ultimate tensile strength of the FRP (f_{fu} MPa), the area of longitudinal reinforcement and the yield strength of steel reinforcement. Afterward, soft computing models, including multivariable linear regression (MLR), and multivariable non-linear regression (MNLR), were employed to predict the confined compressive strength of the reinforced concrete column. Table 1 shows the ranges of the data collected from the literature. The input parameters were utilized in the process of developing the models, and the performance of the models was evaluated by comparing the predicted values with the actual values of the output parameter. It was determined whether or not the models were accurate by using the testing datasets. Finally, statistical tools were utilized to evaluate the performance of the models. Table 2 contains the statistical values of the parameters on both the input and the output.

Table. 1: The ranges of the data from the collected samples.

Reference	No	d/h	f'_{co}	t_f	n	E_f	f_{fu}	A_s	f_y	f'_{cc}
Chastre and Silva 2010	8	0.2 - 0.33	35.2 - 38	0.167 - 0.176	1, 2, 3 and 4	226000	3339	169, 678	391, 458	56.4 - 98.4
Benzaid, et al., 2010	6	0.5	26 - 62	1	1, 3	34000	450	452	500	49.9 - 100.4
Eid et al. 2009	21	0.25	29.4 - 50.8	0.381	2, 4	78000	1050	1205	424	40.6 - 98
Abdelrahman and El-Hacha 2016	1	0.25	40	0.381	1	67220	865	2077	444	72
Demers and Neale, 1999	16	0.25	25 and 40	0.3	3	84000	1270	501 - 2492	400	31.3 - 55.7

Table 2: Statistical summary of input and output parameters of experimental data.

Mean	0.29	36.86	0.40	2.50	101.15	1494.33	1048.51	431.28	62.06
Standard Error	0.01	1.40	0.04	0.12	9.37	152.57	92.04	6.32	2.81
Median	0.25	36.00	0.30	3.00	84.00	1270.00	1205.76	423.00	57.46
Mode	0.25	40.00	0.38	3.00	84.00	1270.00	1205.76	400.00	#N/A
Standard Deviation	0.09	9.51	0.25	0.81	63.52	1034.78	624.26	42.84	19.04
Sample Variance	0.01	90.47	0.06	0.66	4034.40	1070760.09	389699.82	1835.05	362.67
Kurtosis	2.10	0.52	2.36	-0.38	0.89	1.14	0.51	1.00	-0.78
Skewness	1.85	0.82	1.86	-0.13	1.51	1.57	0.83	1.36	0.25
Range	0.30	37.00	0.83	3.00	207.00	3487.00	2322.97	159.00	69.11
Minimum	0.20	25.00	0.17	1.00	34.00	450.00	169.56	391.00	31.30
Maximum	0.50	62.00	1.00	4.00	241.00	3937.00	2492.53	550.00	100.41
Sum	13.17	1695.60	18.27	115.00	4653.00	68739.00	48231.66	19839.00	2854.70
Count	46.00	46.00	46.00	46.00	46.00	46.00	46.00	46.00	46.00

4. Modelings

Previous figures indicated that estimating the confined compressive strength of concrete wrapped with FRP cannot be obtained from single properties. Therefore, to provide the prediction of this significant parameter, it is very essential to employ mathematical and/ or machine learning models by including the compressive strength of concrete and the essential properties of the FRPs. The following sections introducing the employed models.

a. Multivariable Linear Regression (MLR)

Multivariable linear regression models are used to predict fcc' based on the considered properties. These models use addition or subtraction terms to model the relationship between independent variables and the dependent variable (Ali, 2023a). This allows for a more accurate representation of underlying patterns in the data. Multivariable linear regression assumes a linear relationship between independent variables and the dependent variable, but this may not account for non-linear correlations. The mathematical expression of the model is:

$$f'_{cc} = \beta_0 + \beta_1 \frac{d}{h} + \beta_2 f'_c + \beta_3 t_f + \beta_4 n + \beta_5 E_f + \beta_6 f_{fu} + \beta_7 A_s + \beta_8 f_y \qquad (1)$$

b. Multivariable Non- Linear Regression (MNLR)

The multivariable nonlinear regression model is used to predict $fc'c$ of concrete based on properties such as, diameter to length ratio of the sample, unconfined compressive strenght of concrete, the thickness of FRP, number of wrapped layers, modulus of elsticity of FRP, and the ultimate tensile strength of FRP. This model uses power/exponential terms to describe nonlinear relationships between independent and the dependent variables, identifying non-linear correlations that may better reflect data patterns. The multivariable nonlinear regression method seems to be superior to the linear regression method in capturing non-linear correlations (Ali, 2023b). It can be expressed as:

$$f'_{cc} = \beta_0 + \beta_1 \left(\frac{d}{h}\right)^{\beta_2} + \beta_3 {f'_c}^{\beta_4} + \beta_5 {t_f}^{\beta_6} + \beta_7 n^{\beta_8} + \beta_9 {E_f}^{\beta_{10}} + \beta_{11} {f_{fu}}^{\beta_{12}} + \beta_{13} {A_s}^{\beta_{14}} + \beta_{15} {f_y}^{\beta_{16}} \qquad (2)$$

5. Evaluation Criteria

The performance of the proposed models was evaluated using various metrics, including R2 (coefficient of determination), SI (scatter index), a20-index, VAF (variance accounted for), RMSE (root mean squared error), and MAE (mean absolute error). The following formulas can be utilized to calculate these assessment measures:

$$R^2 = \left(\frac{\sum_{P=1}^{P} (yi - yi')(yp - yp')}{\sqrt{[\sum_{P=1}^{P} (yi - yi')^2][\sum_{P=1}^{P} (yp - yp')^2]}} \right)^2 \qquad (3)$$

$$RMSE = \sqrt{\frac{\sum_{P=1}^{P}(yp - yi)^2}{p}} \quad (4)$$

$$MAE = \frac{\sum_{P=1}^{P}|yp - yi|}{p} \quad (5)$$

$$a20 - index = \frac{m20}{N} \quad (6)$$

$$VAF = \left(1 - \frac{var(yi - yp)}{var(yi)}\right) * 100 \quad (7)$$

In the equations that were discussed before, variables such as yp and yi are utilized to represent the expected and actual values of the path pattern, respectively. Furthermore, the variables yp' and yi' are used to indicate the averages of the actual and forecasted values, and the variable n is used to denote the number of patterns that constitute the dataset. A score of zero is intended to be assigned to each of the evaluation factors, with the exception of R2, a20-index, and VAF. Between 0.8 and 1.2 is the range of the m20 measure, which represents the ratio of the values that were seen to those that were anticipated. N denotes the total number of data samples that were collected. Furthermore, the a20-index guarantees that the model accurately forecasts values within a margin of error of ±20% when compared to the actual values. The variance attributable factor (VAF) analysis determines the proportion of the dependent variable's variance that can be attributed to the independent variables. The VAF value is a good indicator of the accuracy of the measurement. The results that were predicted by the models were also visually depicted by employing error margin lines that were either positive or negative. These lines were used to show the percentage of overestimated and underestimated (fcc’) in relation to the actual values that were acquired from the trials.

7. Results and Discussions

In this section, the outcomes for the linear and non-linear models are illustrated. The accuracy of the models was compared with the experimental values of the compressive strength of reinforced concrete wrapped with CFRP. Figure 1 depicts the comparison between predicted and experimental values for the MLR model. It is evident that the R2 value for the data is 0.926, with RMSE values of 5.34 MPa. For an accurate prediction, this model cannot be relied upon. However, it is a very simple model to be applied for rough estimating the value of Since the mathematical form of the model is very simple, Equation 8 represents the outcome of the model.

$$f'_{cc} = 1008.7\frac{d}{h} + 0.99f'_c - 351t_f + 8.1n + 5.93E_f - 0.385f_{fu} + 0.0005A_s + 0.028f_y - 182.5 \quad (8)$$

As far as the results of MNLR are concerned, this model seems to reduce the scattering, as it offered an R2 value of 0.86 with an RMSE of 7.27 MPa. Compared to MLR, it performed better with a higher R2 and a lower RMSE (Figure 2). However, this model can provide predictions with a 20% error. This might be acceptable for an approximate estimation. To obtain an accurate value, advanced mathematical models are required. Nevertheless, this model can still be advantageous for its application in practice, as it has a simple mathematical form, as illustrated in Equation 9.

$$f'_{cc} = 2.24\left(\frac{d}{h}\right)^{0.95} + 12.42{f'_c}^{0.49} + 4.34{t_f}^{-0.1} + 0.0000095n^{10.5} + 0.18{E_f}^{1.32} - 0.13{f_{fu}}^{0.91} - 3.52{A_s}^{-31.9} - 0.445{f_y}^{-3.05} + 2.1 \quad (9)$$

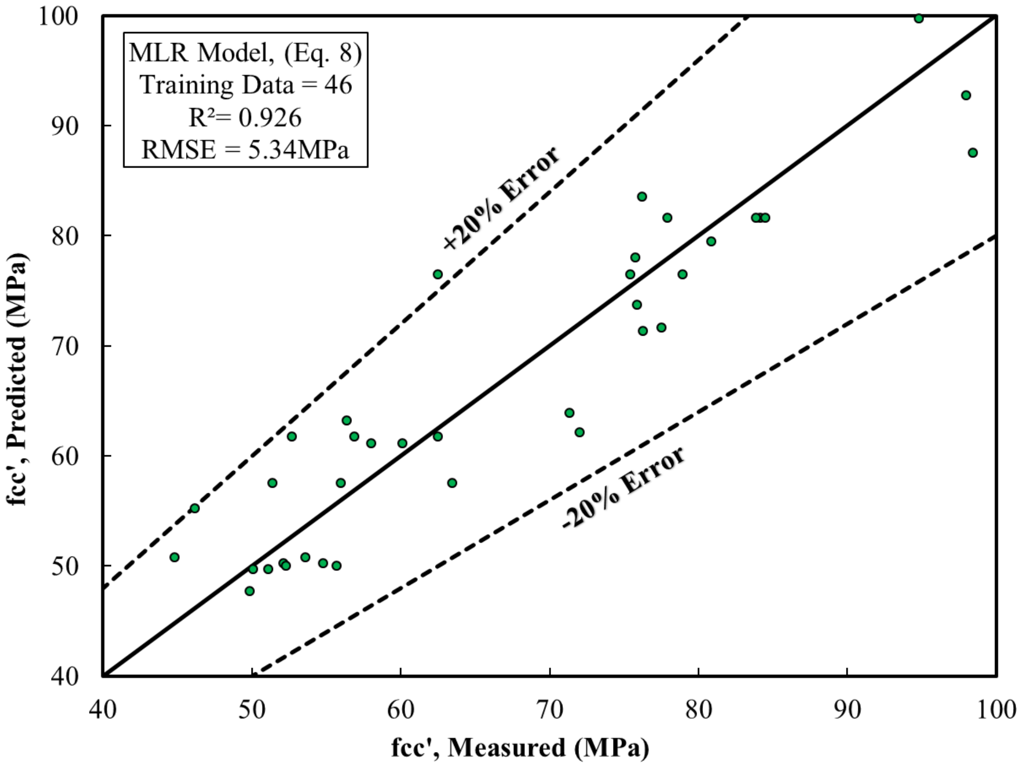

Figure 1: Comparison between measured and predicted values of the confined compressive strength for MLR model

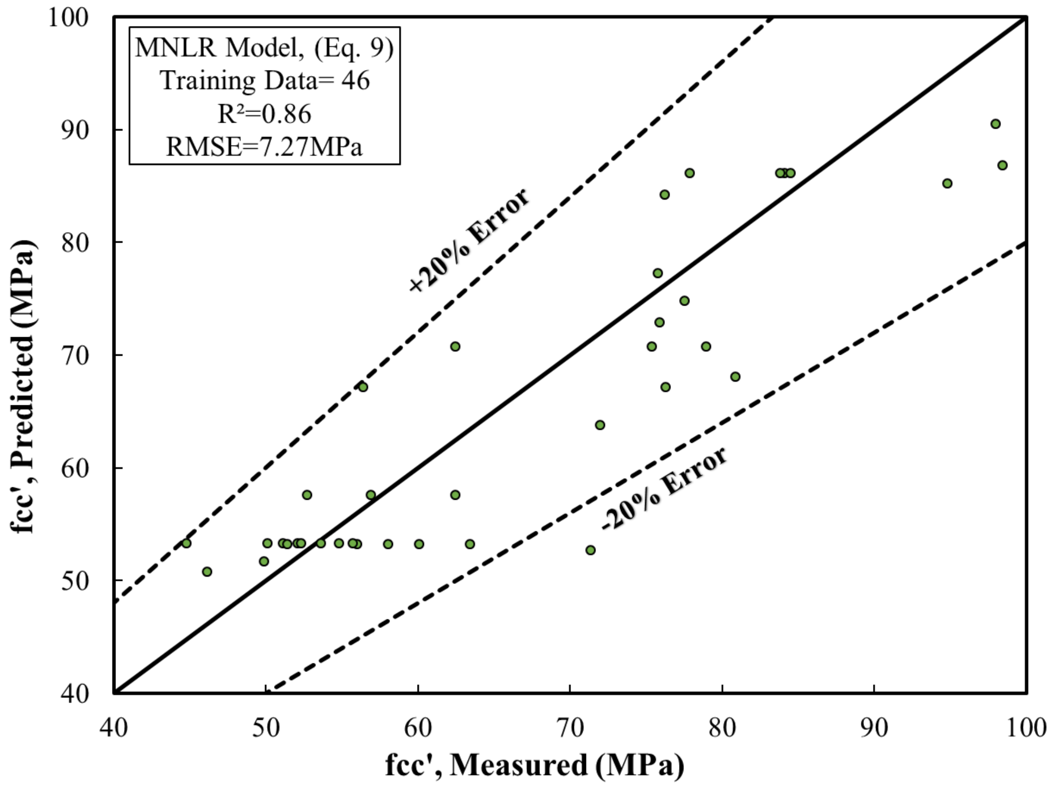

Figure 2: Comparison between measured and predicted values of the confined compressive strength for MNLR model

8. Model Comparison

The performance of the multivariable mathematical models that are utilized to predict the confined compressive strength (fcc') of concrete can be evaluated based on a number of statistical assessment criteria. These criteria include the coefficient of determination (R2), root mean square error (RMSE), mean absolute error (MAE), a20-index (the percentage of errors that are within ±20% of the observed values), and variation accounted for (VAR) values.

R2 values are a measure of the proportion of the variance in the fcc' that can be accounted for by the models. R2 values that are higher imply that the model is performing better. Based on the data presented in Table 3, it is evident that the MLR model has the greatest R2 value (0.926). An R2 score of 0.86 indicates that the MNLR (Multivariable Non-linear Regression) model likewise demonstrates satisfactory performance. MLR.

Root Mean Square Error (RMSE): The RMSE values are the average magnitude of the prediction errors that are made by the models. When the RMSE values are lower, it indicates that the models are more accurate. Based on the data presented in Table 3, the MLR model has the lowest RMSE value, which is 5.34 MPa, and the MNLR has a RMSE value of 7.27 MPa.

The mean absolute error (MAE) values are numbers that indicate the average magnitude of the absolute prediction errors that are produced by the models. When the MAE numbers are lower, it indicates that the models are more accurate. Based on the data presented in Table 3, it is clear that the MLR model has the lowest MAE value, which is 4.23 MPa while MNLR model offered the MAE value of 5.4 MPa.

The values of the a20-index are quantified as the percentage of mistakes that fall within a range of ±20% of the values that have been observed. When the a20-index values are higher, it indicates that the models are more consistent. Based on the data presented in Table 3, it is evident that the MLR model possesses the greatest a20-index value, which is 1.0. The MNLR model has the lowest a20-index value that is 0.96. The variance accounted for (VAR) values are a representation of the percentage of variation that can be attributed to the models. VAR values that are higher suggest that the model is performing better. Based on the data presented in Table 3, it is evident that the MLR model possesses the largest VAR value, which is 91.99%, The MNLR model has the lowest VAF value that is 85.57%. Compared to the other models, the VAR values are smaller, which indicates that they explain less variance.

When it came to estimating the compressive strength of reinforced concrete wrapped by CFRP, the MLR model consistently demonstrated higher performance, as determined by the statistical assessment criteria that were utilized. With higher R2 values, lower RMSE and MAE values, higher a20-index values, and higher VAR values, this model demonstrated improved accuracy, stability, and explanatory power. Based on the performances presented before for both MLR and MNLR it can be considered as an applicable in the real-world and an approximate value of the compressive strength of concrete wrapped with CFRP can be estimated, particularly, MLR model which performed better than MNLR model.

Table 3: Statistical assessment measures.

	R^2	RMSE (MPa)	MAE (Mpa)	a20-index	VAF (%)
MLR	0.93	5.34	4.23	1.00	91.99
MNLR	0.86	7.27	5.40	0.96	85.57

10. Conclusion

Reinforced concrete columns are deteriorating due to corrosion and spalling, affecting aging infrastructure. The most common repair method is the wrapping of columns with fiber reinforced polymer (FRP). FRP offers high strength-to-weight ratio and corrosion resistance. In practice, it is significant to estimate the compressive strength of a column wrapped with FRP. In this work, multivariable linear and nonlinear regression mathematical methods were employed to estimate the confined compressive strength of reinforced concrete wrapped with CFRP. The results indicated that MLR model more accurate than MNLR. Therefore, despite the minor differences in the performance, both MLR and MNLR models can be advantageous to be applied in real-world, particularly, MLR model which performed better than MNLR model.

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