Asian Journal of Civil Engineering
https://doi.org/10.1007/s42107-023-00695-1

RESEARCH

Improving axial load-carrying capacity prediction of concrete columns reinforced with longitudinal FRP bars using hybrid GA-ANN model

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Received: 26 April 2023 / Accepted: 29 April 2023

Abstract

This study aims to develop a hybrid machine learning model, so-called Genetic algorithm–Artificial neural network (GA-ANN), for efficiently predicting the axial load-carrying capacity (ALC) of concrete columns reinforced with fiber reinforced polymer (FRP) bars. For that, a set of 280 experimental test data is collected to develop the GA-ANN model. Seven code-based and empirical-based formulas, which were proposed by various design codes and published studies, are also included in comparison with the developed machine learning model. The performance results of GA-ANN are compared with those of seven previous equations. Statistical properties including goodness of fit (R^2), root mean squared error (*RMSE*), and $a20-index$ are calculated to evaluate the accuracy of those predictive models. The comparisons demonstrate that GA-ANN outperforms other models with very high R^2 and $a20-index$ values (i.e., 0.993 and 0.89, respectively), and a small *RMSE* (148 kN). Moreover, the influence of input parameters on the predicted ALC is assessed. Finally, an efficient graphical user interface tool is developed to simplify the practical design process of FRP-concrete columns.

Keywords Concrete column reinforced with FRP bars · Axial load-carrying capacity · Genetic Algorithm-Artificial neural network · Graphical user interface

Introduction

Reinforced concrete (RC) structures have been degraded their structural capacity due to the reinforcement corrosion. Therefore, it is necessary to prevent the corrosion of reinforcing bars by finding a non-corroded material for reinforcement. Some studies pointed out that fiber reinforced polymer (FRP) bars can be a feasible solution (Nanni & Dolan, 1993; Tighiouart et al., 1998). Previous study showed that flexure and axial theories of RC beams are also valid to concrete beams reinforced with FRP bars (Shehata et al., 2000). However, the design of FRP-concrete beams is not just using the conventional formulas since its mechanical properties differ to the normal reinforcement.

The use of FRP bars for concrete columns is not recommended in ACI 440.1R (2015). Meanwhile, CSA (2012) suggests employing FRP bars in concrete columns under centric axials, however, ignoring the presence of FRP bars in the calculation process. In the last decades, numerous studies have focused on the concrete columns reinforced with FRP longitudinal bars and stirrup (Afifi et al., 2014; AlAjarmeh et al., 2019; De Luca et al., 2010; Mohamed et al., 2014; Tobbi et al., 2012). Based on those experimental studies, it was pointed out that the ignorance of FRP bars underestimated the axial load-bearing capacity (ALC) of columns (Choo et al., 2006; Tobbi et al., 2012). Tobbi et al. (2012) concluded that the FRP bars contribute a significant role in increasing the axial compression capacity of concrete columns. Elmessalami et al. (2019) emphasized that FRP bars can provide from 3%-14% of axial load bearing capacity of columns.

A guideline for designing FRP-concrete columns under eccentric loads is not specified in current design codes such as CSA (2012) or ACI 440.1R-15 (2015). However, consideration of the eccentricity in the design process is critical.

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Published online: 08 May 2023

Thus, it is required to evaluate the column subjected to both axial force and moment. Hadhood et al. (2017) tested circular FRP-concrete columns under eccentric loads. They pointed out that glass FRP bars can reach to 0.4% strain at the maximum axial load. Khorramian and Sadeghian (2017) concluded that FRP bars were not failured at the maximum compressive loading. Hadi et al. (2016) conducted experiments for evaluating the performance of glass FRP-concrete circular columns under centric and eccentric loads. They found that the ALC of columns were reduced when replacing normal reinforcements by FRP bars. A similar observation was also stated in Karim et al. (2016). Moreover, various studies proposed the formuas for calculating ALC of FRP-concrete columns (Afifi et al., 2014; CSA, 2012; Maranan et al., 2016; Mohamed et al., 2014; Tobbi et al., 2012; Xue et al., 2018). However, the effects of eccentricity have not considered in the previous formulas.

Recently, machine learning (ML) models has been applying popularly in structural engineering (Kaveh & Bondarabady, 2004; Kaveh & Servati, 2001; Kaveh et al., 2008; Nguyen et al., 2022; Tran & Nguyen, 2022). Among that, artificial neural network (ANN) is one of the most preferable ML models applying for RC structures (Ahmed et al., 2019; Kaveh & Iranmanesh, 1998; Kaveh & Khalegi, 1998; Kaveh & Khavaninzadeh, 2023; Mai et al., 2022; Nguyen et al., 2021a, b, c; Rönnholm et al., 2005; Selvan et al., 2018; Tran & Kim, 2020; Tran et al., 2022; Vakhshouri & Nejadi, 2018; Yang et al., 1992; Zorlu et al., 2008). Moreover, Genetic algorithm (GA), a type of optimization algorithm, is commonly employed to optimize the weights and biases of the ANN model and then to improve the prediction accuracy (Bülbül et al., 2022; Chaabene & Nehdi, 2020; Congro et al., 2021; Vijayakumar & Pannirselvam, 2022). So far, several studies have developed ML models for predicting ALC of FRP-concrete columns. Karimipour et al. (2021) developed three ANN models for estimating ALC of concrete columns reinforced with glass FRP bars. They showed that developed ML models outperformed others predictive models with the goodness of fit value (R^2) larger than 0.90. Bakouregui et al. (2021) presented an extreme gradient boosting model (XGBoost) for predicting ALC of FRP-concrete columns. The performance result of XGBoost algorithm was efficient with R^2 value up to 0.98. Recently, Tarawneh et al. (2022) proposed an ANN model for calculating ALC, slenderness ratio as well as developing the interaction diagram of FRC-concrete columns. Cakiroglu et al. (2022) developed different ML models to predict the ALC value of concrete columns reinforced with FRP bars. A set of predictive equations was proposed for calculating ALC of the columns. However, it is also required to evaluate the GA-ANN model for ALC prediction of FRP-concrete columns. Additionally, an efficient tool for simplifying the design process of FRP-concrete columns should be developed.

This study develops a hybrid ML model, namely GA-ANN, for improving the ALC prediction of FRP-concrete columns. For that, a total of 280 tested specimens of FRP-concrete columns are gathered and employed to develop the GA-ANN model. The performance of GA-ANN is compared with that of seven empirical formulas. Typical statistical properties including R^2, RMSE, and a20-index are calculated to evaluate the accuracy of those models. Moreover, the effects of input parameters on the predicted axial strength are quantified. Finally, a practical graphical user interface (GUI) tool is built for simplifying the design process of the FRP-concrete column.

Data collection

We collected a set of 280 data sets from published experiments of FRP-RC columns in the literature (Bakouregui et al., 2021). It should be noted that this database considers both rectangular and circular cross-section columns as well as centric and eccentric axial loads. Table 1 summarizes the used the data samples. Input parameters include the area of the FRP bars (A_{FRP}), column slenderness (λ), gross section area of column (A_g), compressive strength of concrete ($f_c^{'}$), elastic modulus of FRP (E_{FRP}), ultimate tensile strength of FRP bars (f_{FRPu}), and the eccentricity (e_r). Whereas P_{max}, the axial load capacity of columns, is the output parameter. The histogram of the datasets is shown in Fig. 1.

Table 1 Statistical indicators of the used database

	A_{FRP} (mm2)	λ	A_g (mm2)	f_c' (MPa)	E_{FRP} (GPa)	f_{FRPu} (MPa)	e_r = e/D (%)	P_{max} (kN)
Min	19.63	10.00	14,400.00	25.60	39.00	574.00	0.00	90.00
Max	2411.52	62.00	372,100.00	90.00	151.00	2000.00	100.00	15,235.00
Mean	369.74	21.62	75,532.26	44.68	70.64	1248.18	20.42	2019.01
Std	453.16	7.61	50,424.29	14.45	35.62	390.87	25.29	1867.34
COV	1.23	0.35	0.67	0.32	0.50	0.31	1.24	0.92

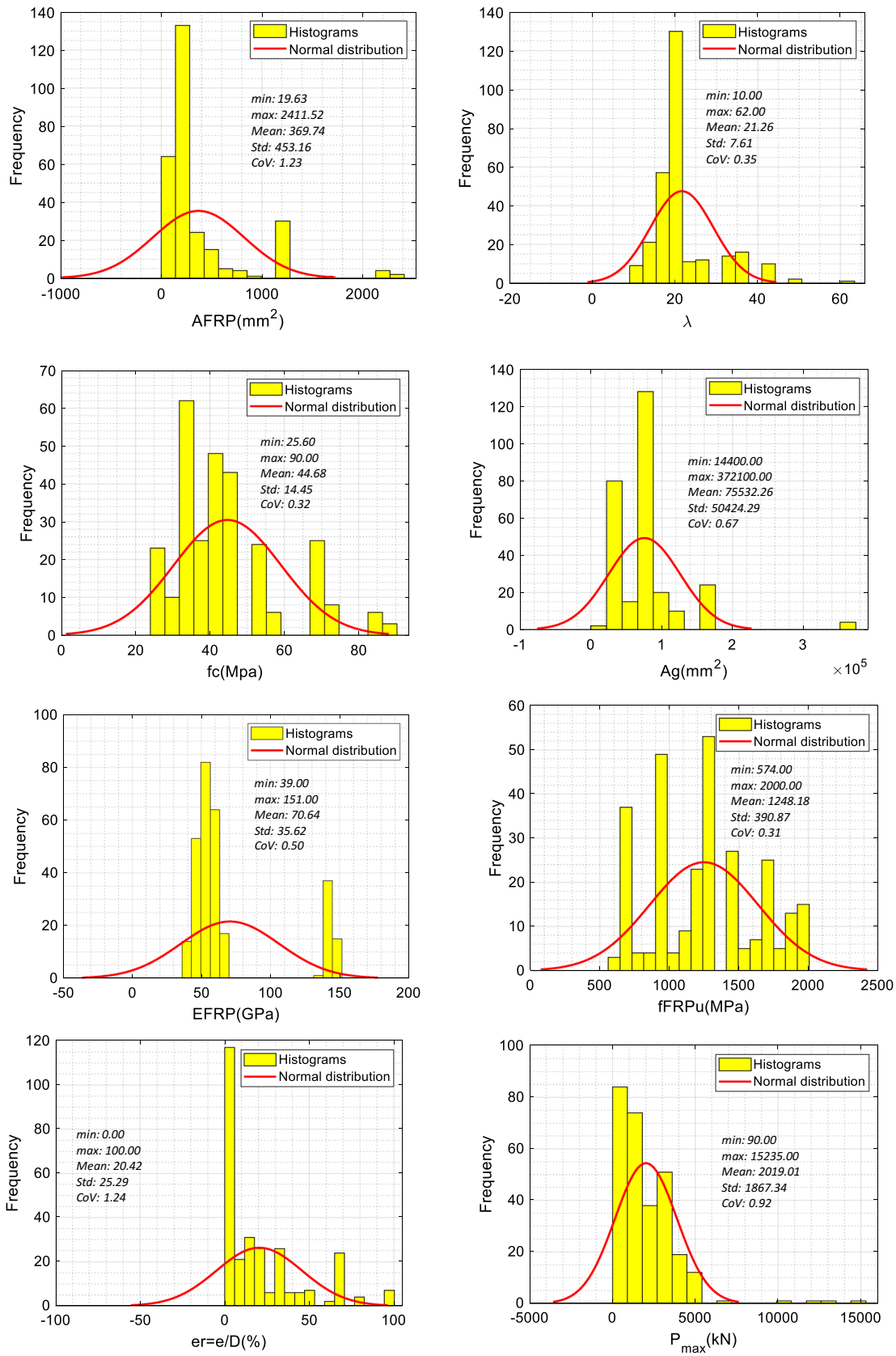


Fig. 1 Histograms of the datasets

Existing formulas for calculating ALC of FRP-concrete columns

So far, there are numerous studies that proposed equations for calculating the shear strength of FRP-concrete columns. In this study, seven typical formulas are evaluated, including CSA S806-12 (2012), Tobbi et al. (2012), Affifi et al. (2014), Mohamed et al. (2014), Maranan et al. (2016), Xueet al. (2018), and Cakiroglu et al. (2022) Table 2.

Development of machine learning models

Normalized training data

To improve the accurate performance of GA-ANN model, training data is normalized within the range of -1 and 1 prior to developing the ML model, according to the suggestion of Golafshani and Ashour (2016). The normalization is expressed as follows.

$$X_n = 2 \times \frac{(X - X_{min})}{(X_{max} - X_{min})} - 1 \tag{8}$$

where X_n is the normalized sample, X is the original sample, X_{max} and X_{min} are the maximum and minimum value of each variable, respectively. The normalized values have been put into the GA-ANN model and conducted by the MATLAB tool.

Genetic algorithm – artificial neural network (GA-ANN) model

Among ML models, ANN has been commonly employed to solve various engineering problems (Naser et al., 2021; Nguyen et al., 2021a, b, c; Patel & Mehta, 2018; Patil & Subbareddy, 2002; Tran et al. 2019, 2021; Zorlu et al., 2008). An ANN is a type of ML that is inspired by the structure and function of the biological neural networks in the human brain. ANNs consist of interconnected processing nodes or "neurons" that can receive, transform, and transmit information in parallel, using weighted connections and activation functions. In this study, the back propagation neural network combined with the Levenberg–Marquardt algorithm was chosen, in which a three-layers structure was adopted. The model structure includes input, hidden, and output layers. The connection between three layers is adjusted by the weights and biases of neurons. The mathematical expressions are shown as follows.

$$f : X \in R^D \rightarrow Y \in R^1 f(X) = f_0\left(b_2 + W_2\left(f_h\left(b_1 + W_1 X\right)\right)\right) \tag{9}$$

where b_1, W_1, and f_h are the biases vectors, the weight matrix, and the activation function of the hidden layer, respectively. Meanwhile, b_2, W_2, and f_0 are the biases vector, the weight matric and the activation function of the hidden layer output layer, respectively.

The used activation function for the hidden layer was a nonlinear function, namely tansig function. And linear function, so-called *purelin* function, was selected for the output layer (Nikbin et al., 2017). The equations representing the activation functions tansig and *purelin* are expressed in Eq. (10) and Eq. (11), respectively.

$$\text{tansig}(x) = \frac{2}{(1 + \text{epx}(-2\text{x}))} - 1 \tag{10}$$

$$purelin(x) = x \tag{11}$$

The training of the ANN model was performed in terms of continuous feedback loops. To obtain the optimal model

Table 2 Considered existing formulas for calculating ALC of FRP-concrete columns

Reference	Formula	
CSA S806-12 (2012)	$P = \alpha_1 f_c^{'}\left(A_g - A_{FRP}\right); \alpha_1 = 0.85$ A_g is the cross-section area of column; A_{FRP} is the area of FRP bars; $f_c^{'}$ is the compressive strength of concrete.	(1)
Tobbi et al. (2012)	$P = \alpha_1 f_c^{'}\left(A_g - A_{FRP}\right) + \alpha_{FRP} f_{FRP} A_{FRP}$; $\alpha_1 = 0.85$; $\alpha_{FRP} = 0.35$	(2)
Affifi et al. (2014)	$P = \alpha_1 f_c^{'}\left(A_g - A_{FRP}\right) + \alpha_{FRP} f_{FRP} A_{FRP}$; $\alpha_1 = 0.85$; $\alpha_{FRP} = 0.25$	(3)
Mohamed et al. (2014)	$P = \alpha_1 f_c^{'}\left(A_g - A_{FRP}\right) + 0.002 E_{FRP} A_{FRP}$; $\alpha_1 = 0.85$	(4)
Maranan et al. (2016)	$P = \alpha_1 f_c^{'}\left(A_g - A_{FRP}\right) + 0.002 E_{FRP} A_{FRP}$; $\alpha_1 = 0.9$	(5)
Xue et al. (2018)	$P = \alpha_1 f_c^{'}\left(A_g\right) + 0.002 E_{FRP} A_{FRP}$; $\alpha_1 = 0.85$	(6)
Cakiroglu et al. (2022)	$P = 0.00123 A_g^{0.9946} f_c^{0.9266} \lambda^{-0.1474} \rho_{FRP}^{-0.1474} f_{FRPu}^{0.0589}$ ρ_{FRP} is the longitudinal FRP bar ratio	(7)

during training, the mean square error (MSE) was employed, in which MSE is represented by the following expression.

$$MSE = \min_{b_1,b_2,W_1,W_2} \frac{1}{N}\sum_{i=1}^{N} e_i^2 \tag{12}$$

where e_i is the difference between the predicted output and the experimental data; N is number of samples of the ML model.

Overall, the training for obtaining the optimal ANN structure can be performed by using various training data ratios and different numbers of hidden layer neurons. In this study, we used 6 training ratios including 0.6, 0.65, 0.70, 0.75, 0.8, and 0.85, meanwhile, the number of neurons in the hidden layer was changed from 1 to 20. As a result, 120 ANN structures were investigated. Finally, we obtained the optimal ANN model with the training ratio of 0.70 and 20 neurons in the hidden layer.

To improve the efficiency of the ANN model, some optimization algorithms can be used such as Particle swarm optimization (PSO) (Eberhart & Kennedy, 1995), GA (Holland, 1992) or other metaheuristic algorithms (Kaveh, 2014). Since GA is known as one of the most practical techniques in solving optimization problems (Chou & Ghaboussi, 2001; Feng et al., 1997; Marasco et al., 2022), thus, it was employed to optimize the developed ANN model in this study. This technique has been inspired by the natural selection mechanism and biological species evolution (Holland, 1992). GA uses an objective function to find an optimal solution for a problem. In this algorithm, a cost function (i.e., fitness function) that should be minimized or maximized is described, then, in the available space of the problem, a population of solutions is created. Individuals of this population are represented as strings of chromosomes for each of which the cost function can be calculated. The algorithm contains numerous optional solutions that each individually proposes their optimum solution. Based on the value of each individual, a percentage of the best individuals is selected as parents to reproduce a new generation. There are three genetic operators for fulfillment the generation task contained reproduction, crossover, and mutation. Figure 2 depicts the flowchart of the GA-ANN model.

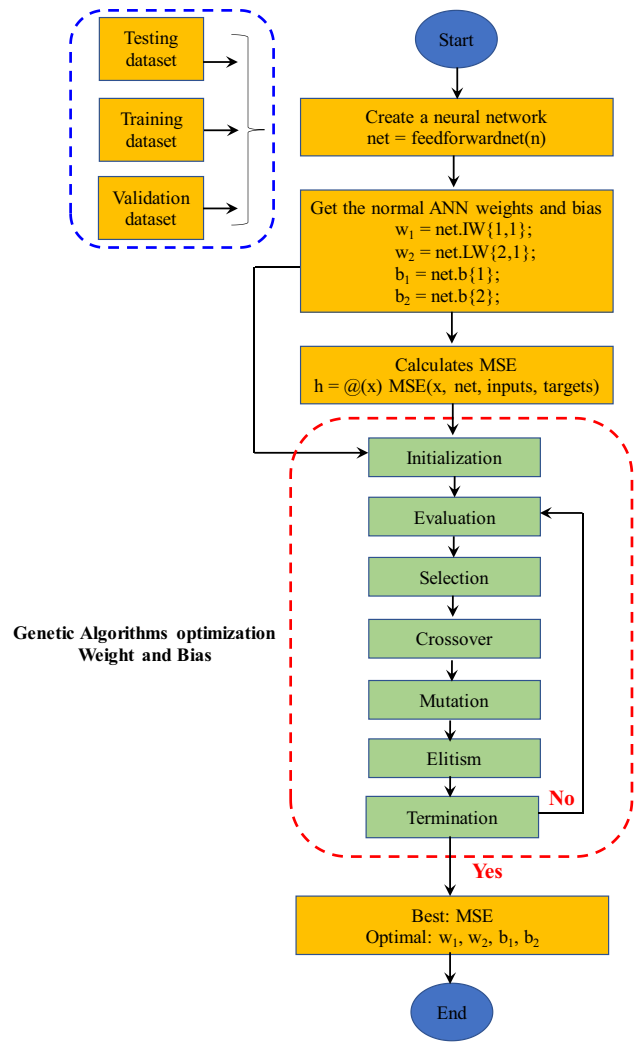


Fig. 2 Flowchart for GA-ANN model

Performance metric

To evaluate the optimal model, three statistical indicators, which include goodness of fit (R^2), root mean squared error ($RMSE$), and $a20-index$ are employed to measure the accuracy of the predictive models, as suggested by Zorlu et al. (2008). The best performing GA-ANN model is the model with the highest R^2 and $a20-index$, and smallest $RMSE$. They are expressed as follows.

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N}\left(t_i - o_i\right)^2}{\sum_{i=1}^{N}\left(t_i - \overline{o}\right)^2}\right) \tag{13}$$

$$RMSE = \sqrt{\left(\frac{1}{n}\right)\sum_{i=1}^{n}\left(t_i - o_i\right)^2} \tag{14}$$

$$a20 - index = \frac{n20}{n} \tag{15}$$

where t_i and o_i represent the target and output of ith data point, respectively; $\overline{o}$ is the mean of output data samples; n is the number of samples; $n20$ is the number of samples with the ratio of the experimental value to the predicted value between 0.8 and 1.0.

Results and discussions

Performance of GA-ANN model

The convergence of GA-ANN model was obtained after 13 epochs and the mean square error (MSE) was very small (almost zero), as shown in Fig. 3. Moreover, performance results of the GA-ANN model are shown in Fig. 4. It can be observed that R^2 values obtained for training, testing, validation, and all data are 0.994, 0.989, 0.992, and 0.993. Furthermore, the regression lines are mostly identical with the 1:1 line. These performance results indicate that the hybrid GA-ANN model significantly improved the ACC prediction of FRP-concrete columns.

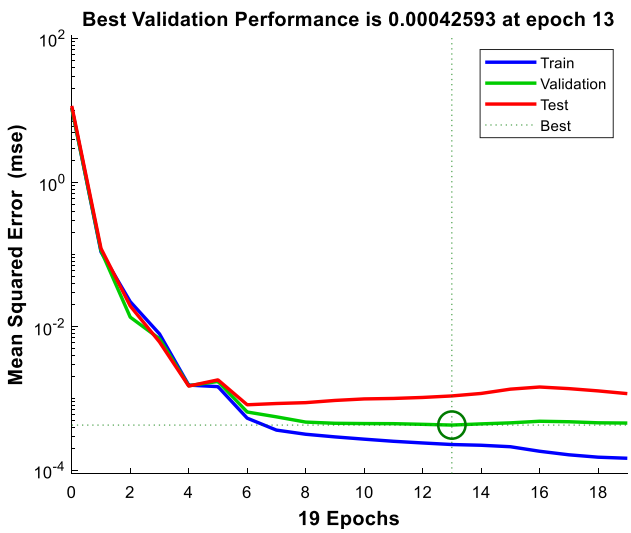
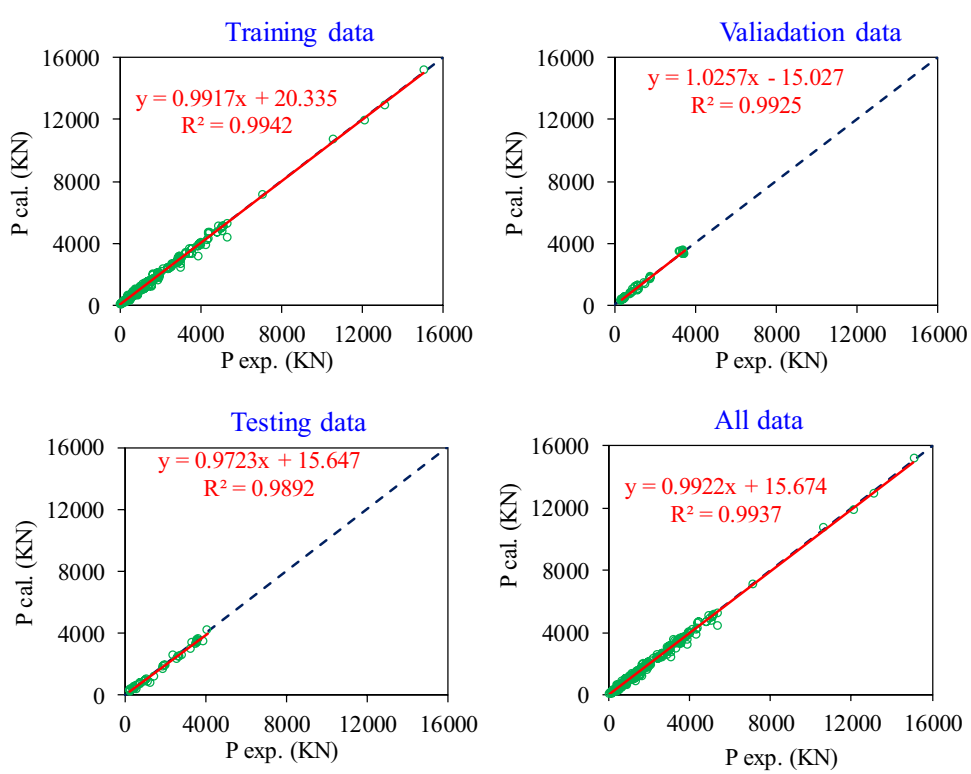


Fig. 3 Convergence of GA-ANN

Comparison between the predictive models

Figure 5 shows the comparisons of the ALC of FRP-concrete columns between the predictive models and experimental results. It can be found that six empirical-based equations estimate the axial capacity significantly lower compared to that of experiments. In other words, the existing formulas predict the ALC of FRP-concrete columns more conservatively. Moreover, the results obtained from six previous formulas have a large scattering with a relatively small value of R^2, approximately 0.45. Even though the equation of Cakiroglu et al. (2022) included the effects of the slenderness and FRP properties, however the calculated results still had a large difference with the experiments. This discrepancy is likely due to the effects of eccentricity and elastic modulus of FRP were not considered in the published equations. On the contrary, the predicted results of GA-ANN model are very close to those of experimental ones, in which a small scattering and a very high value of R^2 (0.993) are obtained.

Fig. 4 Performance of GA-ANN model



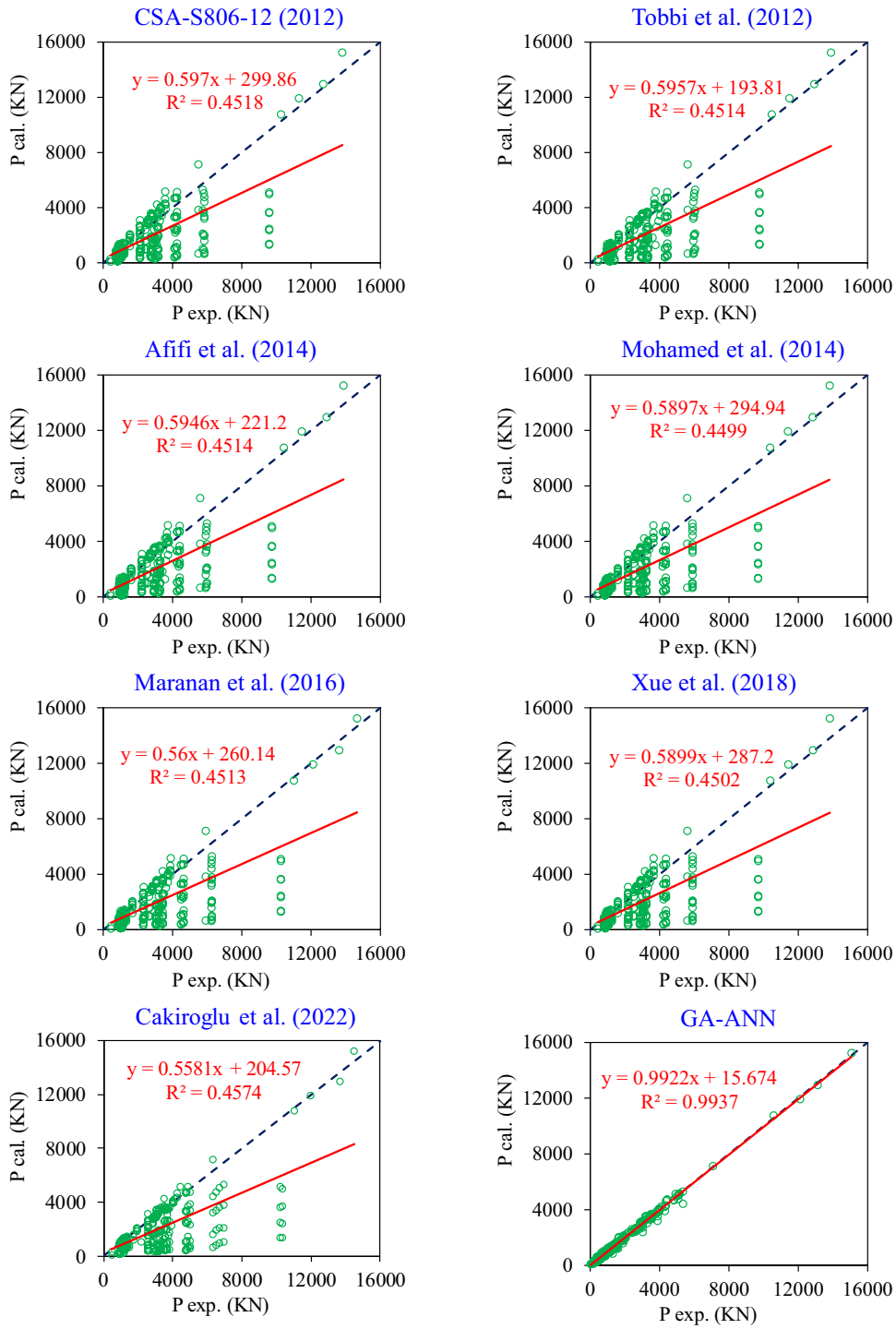


Fig. 5 Comparison between the results of considered predicted models

Table 3 summarizes the statistical parameters (R^2, $RMSE$, and $a20-index$) and the characteristics of the ratio P_{cal}/P_{exp}. Once again, the GA-ANN model shows a superior performance than the other models. In addition to a higher R^2 value, the value of $RMSE$ is also significantly smaller (148.48 kN) compared to those of previous studies. Moreover, the ratio P_{cal}/P_{exp} is equal to 0.999, very close to unity, emphasizing that the developed ML model predicts the axial strength of FRP-RC columns accurately.

Table 3 Statistical parameters for evaluating performance of different models in calculating ALC of FRP-concrete columns

	R^2	RMSE (kN)	a20-index	P_{cal}/P_{exp}				
				Min	Max	Mean	StD	CoV
CSA S806-12 (2012)	0.451	1833.34	0.388	0.682	10.800	2.270	2.149	0.947
Tobbi et al. (2012)	0.451	1928.79	0.381	0.715	11.258	2.496	2.365	0.947
Affifi et al. (2014)	0.451	1909.19	0.409	0.710	11.189	2.441	2.306	0.944
Mohamed et al. (2014)	0.449	1867.12	0.395	0.697	11.017	2.304	2.182	0.947
Maranan et al. (2016)	0.451	2033.26	0.424	0.744	11.780	2.507	2.374	0.946
Xue et al. (2018)	0.450	1872.76	0.399	0.698	11.041	2.318	2.194	0.946
Cakiroglu et al. (2022)	0.457	2097.44	0.412	0.822	12.330	2.576	2.383	0.941
GA-ANN	0.993	148.48	0.890	0.114	1.544	0.999	0.140	0.140

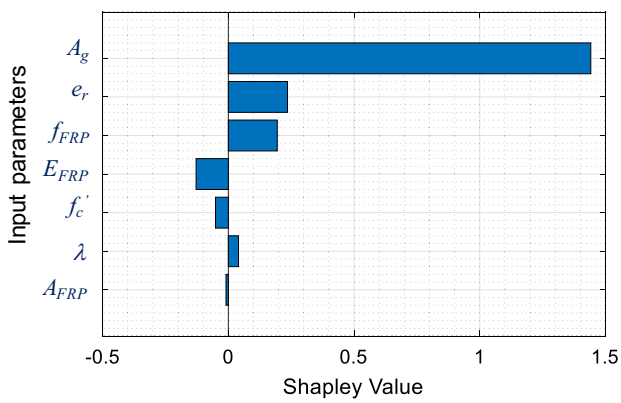


Fig. 6 Effects of input parameters on the output using Shapley value

Effects of input parameters on the output

To assess the effects of input parameters on ALC of FRP-concrete columns, a series of sensitivity analyses are performed. In this study, the Shapley value (Roth, 1988) is used to identify the influence of input features on the output. Basically, the Shapley value can help us understand how much each feature or input variable contributed to the final prediction, and how much credit or blame we should assign to each feature for a given prediction. All parameters in Table 1 are considered in calculating Shapley values. The Shapley value result is shown in Fig. 6. It can be found that the gross section area of column (A_g) is the most influential parameter on the axial capacity of FRP-concrete columns, followed by the eccentrically (e_r) and is the ultimate tensile strength of FRP bars (f_{FRPu}).

Practical GUI tool

To simplify the design process, a practical tool should be developed for rapidly calculating the ALC of FRP-concrete columns. In this study, a graphical user interface (GUI) tool is constructed, in which designers only need to provide input values, then they can immediately obtain the output (i.e., the ACC value). Figure 7 shows the developed GUI tool using MATLAB. It should be noted that the hybrid GA-ANN model can predict the ALC output within the range of input data samples in Table 1. To expand the boundary of the ML model, additional data samples should be considered.

Conclusions

This study develops a hybrid GA-ANN model for improving the ALC prediction of FRP-concrete columns. A set of 280 experimental data sets of FRP-concrete columns is gathered to construct the GA-ANN model. The performance results of GA-ANN are compared with those of empirical formulas. Statistical parameters including R^2, RMSE, and a20-index are calculated to evaluate the accuracy of predictive models. The following conclusions are obtained.

The GA-ANN model accurately predicts the ALC of FRP-concrete columns with a very high R^2 value (0.993) and small RMSE (148 kN).

An efficient GUI tool is developed to simplify the design process of FRP-concrete columns.

The gross section area of column (A_g) is the most influential parameter on the axial capacity of FRP-concrete columns, followed by the eccentrically (e_r) and is the ultimate tensile strength of FRP bars (f_{FRPu}).

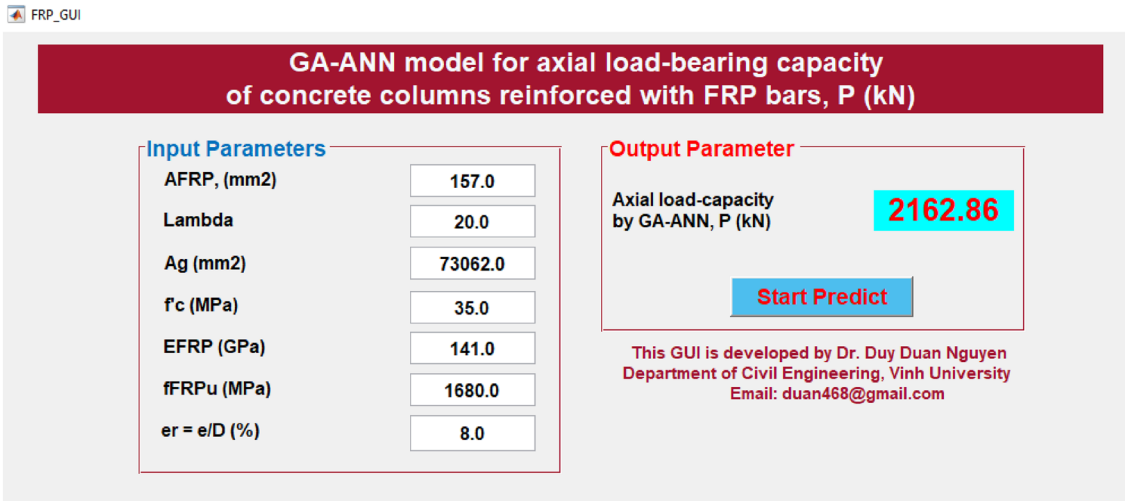


Fig. 7 Practical GUI tool

Author contributions T-HN Conceptualization, Software, Writing-Original Draft, Writing-Review & Editing; N-LT, V-TP Visualization, Validation, D-DN Methodology, Formal analysis, Writing–Original Draft, Writing–Review & Editing, Supervision.

Funding No funding was used in this study.

Data availability The data used to support the findings of this study are included in the article.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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