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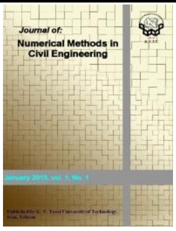

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Providing Models of the Compressive Strength of Square and Rectangular (S/R) Concrete Confined Using Genetic Programming

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Abstract:

The accurate prediction of the compressive strength of FRP (Fiber-Reinforced Polymer)-confined is essential for structural engineers and designers. Several experimental studies have been conducted on concrete confined with FRP sheets. Different models to determine the compressive strength of FRP-confined concrete are provided in the previous research. This study develops a practical model using genetic programming (GP) to reliably predict the compressive strength of FRP-confined concrete across various FRP types, enhancing its applicability for engineers. Firstly, a wide range of experimental data for square and rectangular (S/R) columns confined with a variety of FRP sheets has been collected (Including 463 specimens). 324 specimens (70 %) were used for modeling. For proposing models by using GP, the input and output variables were considered dimensionless. So input variables including b/h, r/b, r/h, r/t_f, t_f/h, F_f/f_{co}, and E_f/f_{co}, and output is considered as f_{cc}/f_{co}. To present the model using GP, the three-transfer function set was selected. Finally, the results are compared with the existing models. The predictions of GP show satisfactory estimations, so GP has an averagely increased R^2 approximately 9.91% rather than other models.

1. Introduction

In civil engineering, Fiber-Reinforced Polymer (FRP) is widely used due to its high strength-to-weight ratio. One of the usages of FRP is confining concrete with FRP sheets to increase the compressive strength of concrete. Due to the lateral expansion of concrete, confining concrete with FRP sheets in the hoop direction has received much attention, and the effect of various parameters such as the shape and dimensions of the cross-section, compressive strength of concrete, type of FRP, etc. on confined-FRP concrete has been experimentally investigated, in past studies. The first experimental studies on FRP-confined concrete were presented by [1]. Three kinds of FRP were used for confining concrete with ordinary strength under uniaxial compressive loading. Results of their study showed that compressive strength and ductility are raised by using FRP confinement. In the initial research, an attempt was made to use FRP confinement analytical models based on the models previously used for steel plates [2, 3]. Later researchers realized that the results of these models were incorrect and non-conservative [4]. After that, different models were presented to determine the compressive strength of concrete confined with FRP [5–10]. Most of these models are empirical and calibrated based on limited experimental databases.

Recently, artificial intelligence methods have been widely used in various fields of civil engineering due to their ability to simulate complex processes [11–16]. Genetic programming (GP), which was presented for the first time by [17], is one of the evolutionary algorithm methods and can optimize the structure of the model and its components. GP provides an explicit relationship based on variables and parameters of the process. While other evolutionary computing methods use string chromosomes, [17] used computer programs in the form of a tree representation in the LISP language and showed that the genetic algorithm can be applied in this way to a wide range of problems. GP is a method that automatically solves problems without needing the user to specify the form of the solution [18].

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The GP method has been extensively applied in civil engineering [19–23]. This method was used to estimate the inertia of hybrid FRP-steel reinforced concrete by Kheyroddin and Maleki.[24] Torabi et al. [25] used the gene expression programming (GEP) model as a powerful machine-learning method for predicting the Hydraulic permeability of soil. GP was used by Lim et al. [26] to propose a new model for the ultimate conditions of FRP-confined concrete columns with circular sections.

In addition to genetic programming (GP), various metaheuristic algorithms, such as the Improved Vibrating Particle System (IVPS) and other evolutionary techniques, have been successfully applied to optimization problems within civil engineering. These methods, including Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), excel in finding near-optimal solutions for complex, large-scale problems. However, they cannot often generate explicit relationships, a key advantage of GP. For example, Kaveh and Rad [27] employed metaheuristics for optimal truss design, demonstrating significant time reduction, while Alavi et al. [28] optimized gas pipeline routing by integrating seismic risk assessment with a metaheuristic algorithm. In contrast, GP not only optimizes the solution but also provides an interpretable, symbolic formula, which is beneficial for practical engineering applications.

In this study, experimental data from square and rectangular (S/R) concrete specimens confined with FRP were utilized, which had been previously used in the study conducted by [29]. It is noted that a wider range of statistical populations leads to more reliable results for modeling purposes. The used statistical population in this study is wider than in the previous research. The database consisted of 463 specimens, of which 324 were used for modeling and 139 for model evaluation. A key contribution of this study is the development of an accurate model for estimating the compressive strength of S/R concrete confined with various types of FRP, including normal-strength concrete (NSC) and high-strength concrete (HSC). This model is applicable across different FRP types, offering practical value for design engineers in various structural applications. The research utilized genetic programming (GP) methods for the first time to model the compressive strength of FRP-confined S/R concrete. The GP method, unlike some estimation techniques, provides an explicit formula that allows engineers to estimate compressive strength without the need for computer software, making it more practical for real-world applications. For this purpose, the input and output parameters were dimensionless. The GP model significantly improved the prediction accuracy, increasing R^2 by approximately 10.67% for modeling specimens and 8.13% for evaluation specimens compared to other established models.

In this context, the benchmark problem is defined as the need for a comprehensive database that encompasses various concrete types and confinement systems. This allows for the formulation of a reliable relationship that can estimate the compressive strength of FRP-confined concrete across different applications, thereby enhancing the applicability of the proposed model for engineers.

2. Past study models for prediction

In previous studies, different methods have been proposed to estimate the compressive strength of R/S FRP-confined concrete. To compare the methods of this study with previous study methods, some of those are summarized in Table 2 of [29] the study was used.

3. Experimental data

Many studies have been conducted on confined concrete with FRP [30–34]. The database of this study contains specimens from the mentioned studies, and their characteristics were presented in the study of Moodi et al. [29]. The range of variables of this database is presented in Table 1. 70% of the specimens were randomly selected for the modeling process (instructor specimens) and the remaining specimens were used in the evaluation stage.

FRP composites consist of two main components: reinforcing fibers (usually made of high-strength materials like carbon or glass) and a polymer matrix that binds the fibers together. This structure provides FRP with its exceptional strength and durability, making it ideal for structural reinforcement applications (see Figure 1)

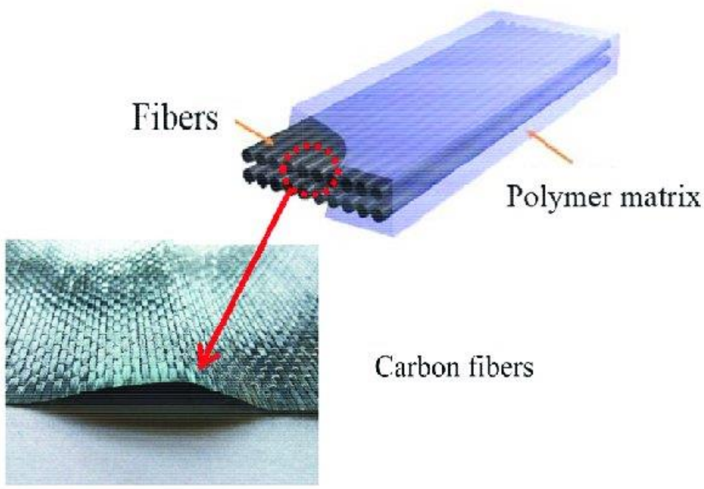


Fig. 1: Components of FRP composite

Table 1: The range of variables

Variable	Range
Width (b)	70-450 mm
Length (h)	70-600 mm
Corner radius (r)	0-60 mm
Compressive strength (f_{co})	10-110.8 MPa
Types of FRPs	CFRP, AFRP, and GFRP
Modulus of elasticity of FRP (E_f)	10.3—257 GPa
FRP thickness (t_f)	0.072-9.6 mm
Tensile strength of FRP (F_f)	154—4830 GPa

4. Genetic Programming (GP)

The GP method is one of the artificial intelligence techniques developed by Koza [17] and is now considered in various sciences, including engineering. This method compares and approaches the ideal state during the learning process. For this purpose, there are functions that measure the extent of this tendency (penalty function).

The step-by-step process of genetic programming can be summarized as follows [35]:

a. Randomly generate an initial population of composite functions representing predictive patterns (Generation of chromosomes)

b. Introducing the primary population to the program and evaluating each individual (gene) of the said population using fitting functions (identifying the most effective individuals like the phenomenon).

c. Selection of effective genes for reproduction, mutation, mating, and reproduction of new individuals with modified traits (children).

d. Applying iterative development processes to the children in each production to a specified number or until the best response is achieved

Figure 2 is a flowchart for the genetic programming paradigm. The index i guides an individual in the population of size M. The variable GEN is the number of the current generation [17].

In this study, to present the model using GP, input and output variables were considered non-dimensional. To this aim, seven non-dimensional parameters are considered as input variables including b/h, r/b, r/h, r/t_f, t_f/h, F_f/f_{co}, and E_f/f_{co}, and output is considered as f_{cc}/f_{co}. To present the model using GP, the three transfer function sets are considered. The first set (GP1) of transfer functions includes ($\times$, +, $-$, /, $\sqrt{x}, x^2, x^3$), the second set (GP2) of transfer functions includes ($\times$, +, $-$, /, sin, cos, tan, cotan) and the third set (GP3) of transfer functions includes ($\times$, +, $-$, /, log, exp). The GP model characteristics that are used in the present study are shown in Table 2. The Population Size indicates the number of candidate solutions evaluated in each generation. The Number of Generations refers to the total iterations the GP undergoes for optimization, where each generation refines the solutions to improve accuracy. Tournament Size represents the number of individuals chosen for selection in each tournament, and the Tournament Type specifies the method used for selecting individuals during reproduction. Termination Condition defines the criteria for stopping the GP process, which in this case is achieving an error below a certain threshold. The Termination Value indicates the error threshold, where the process halts once the RMSE (Root Mean Square Error) reaches below 0.001.

In this study, MATLAB software was utilized for implementing the genetic programming (GP) model, including generating random populations, applying genetic operators such as crossover and mutation, and evaluating the fitness of the models."

Table 2: The GP parameters

Parameter name	Parameter specification
Number of gens	5
Population size	1000
Number of generations	150
Tournament size	30
Tournament type	Pareto (probability = 0.7)
Termination Condition	True
Termination Threshold	0.001

The applications of Genetic Programming (GP) in civil engineering are vast and impactful. Several studies illustrate its effectiveness in various contexts. For instance, Moradi et al. [36] demonstrated GP's capability in modeling the behavior of steel fiber-reinforced concrete, achieving precise equations grounded in fundamental material properties. Similarly, Jeong et al. [23] employed GP to enhance the bond-slip model for reinforced concrete beams, significantly improving prediction accuracy over conventional models. Moreover, Kalfat et al. [20] showcased GP's potential in developing models to enhance bond performance in patch-anchored FRP joints, outpacing traditional methodologies. Lim et al. [19] also leveraged GP to formulate better predictions for the ultimate conditions of FRP-confined concrete with circular sections. Cevik et al. [22] utilized GP to accurately predict the torsional strength of RC beams, surpassing the predictions made by standard building codes. Additionally, Gandomi et al. [21] introduced a GP-based model that effectively balances accuracy and complexity in creep predictions for concrete.

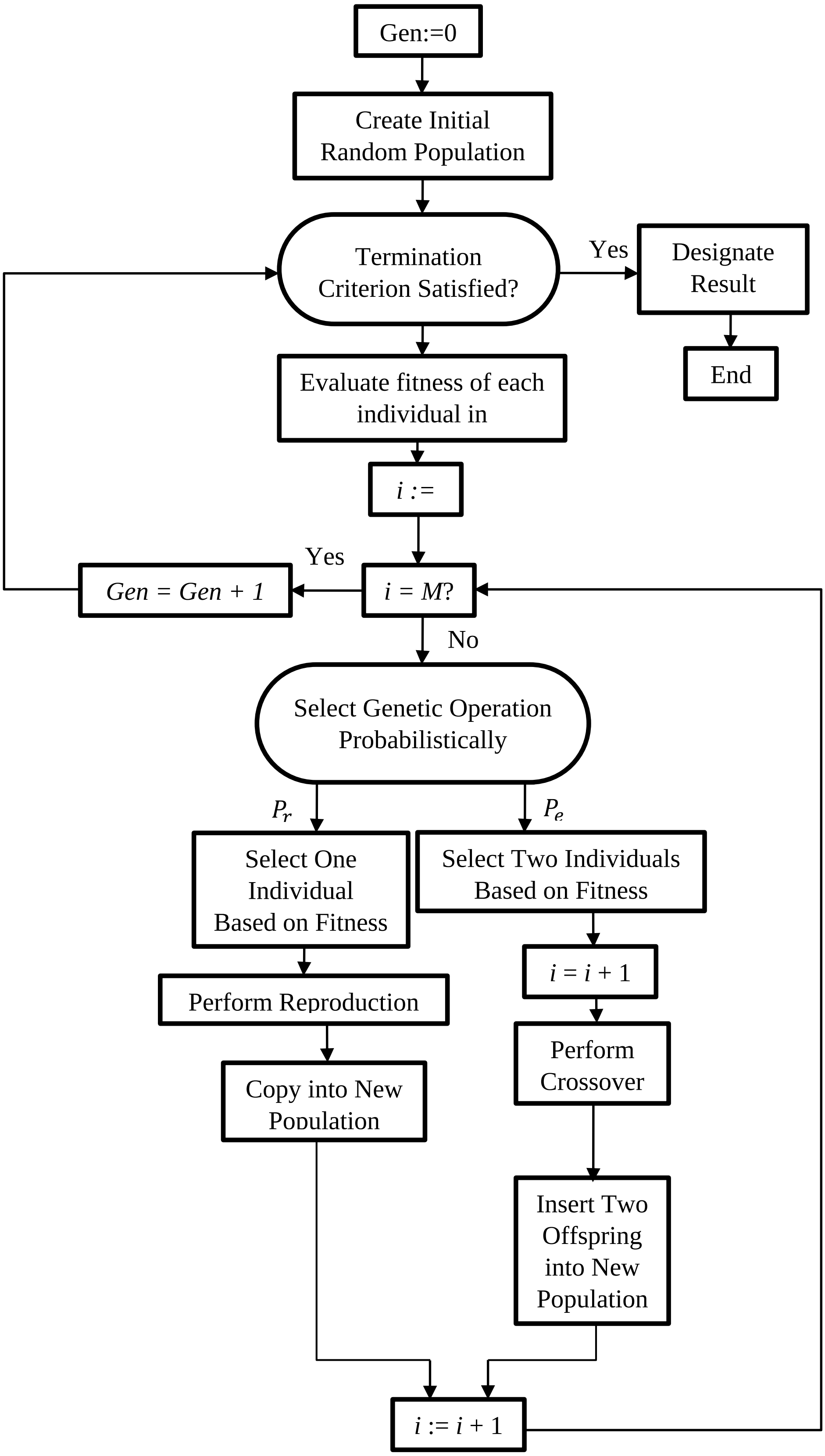


Fig. 2: Flowchart of the genetic programming paradigm [17]

5. Discussion and evaluation of proposed models

To dimensionless the input and output variables, the general state of the obtained relationships for estimating confined compressive strength in all three sets of transfer functions will be as follows:

$$f'_{cc} = f'_{co} \cdot f\left(\frac{b}{h}, \frac{r}{b}, \frac{r}{h}, \frac{t_f}{h}, \frac{r}{t_f}, \frac{F_f}{f'_{co}}, \frac{E_f}{f'_{co}}\right) \quad (1)$$

Analysis was performed on 324 randomly selected specimens which were chosen as modeling specimens. Eqs. (2-4) for predicting the compressive strength of confined S/R concrete with FRP for three transfer functions mentioned in the previous section, respectively, were presented.

GP1:

$$f'_{cc} = f'_{co}\begin{bmatrix} 1.248\times10^{-6}\dfrac{t_f}{h}\left(\dfrac{E_f}{f'_{co}}\right)^2 \\ +0.08708\dfrac{r}{h}\dfrac{t_f}{h}\left(\dfrac{F_f}{f'_{co}}\right)^2 \\ +0.9461\dfrac{t_f}{h}\dfrac{E_f}{f'_{co}}\left(\dfrac{r}{h}\right)^2 \\ -0.01589\dfrac{r}{h}\left(\dfrac{F_f}{f'_{co}}\right)\left(\dfrac{r}{h}+\dfrac{b}{h}\right) \\ -1.896\dfrac{r^2}{bh}\left(\dfrac{F_f}{f'_{co}}\right)\left(\dfrac{E_f}{f'_{co}}\right)\left(\dfrac{t_f}{h}\right)^2 \end{bmatrix} \quad (2)$$

GP2:

$$f'_{cc} = f'_{co}\begin{bmatrix} 1.024+1.49\times10^{-6}\dfrac{t_f}{h}\left(\dfrac{E_f}{f'_{co}}\right)^2 \\ +8.875\times10^{-4}\tan\left(2\dfrac{E_f}{f'_{co}}-\sqrt{\dfrac{r}{t_f}}\right)+ \\ 0.03026\tan\left(\dfrac{r}{h}\dfrac{t_f}{h}\right)\left(\dfrac{b}{h}-\dfrac{t_f}{h}\right)\left(\dfrac{F_f}{f'_{co}}\right)^2+ \\ 0.3374\dfrac{E_f}{f'_{co}}\tan\left(\dfrac{t_f}{h}\right)\left(\dfrac{r}{h}\right)^2\dfrac{r}{h}\dfrac{t_f}{h}\left(\dfrac{F_f}{f'_{co}}\right)^2 \\ -1.072\times10^{-6}\dfrac{r}{h}\dfrac{t_f}{h}\tan\left(\dfrac{r}{h}\dfrac{F_f}{f'_{co}}\right)\left(\dfrac{F_f}{f'_{co}}\right)^2 \end{bmatrix} \quad (3)$$

GP3:

$$f'_{cc} = f'_{co}\begin{bmatrix} 3.176\times10^{-5}\dfrac{t_f}{h}\left(\dfrac{F_f}{f'_{co}}\right)^3 \\ +9.191\times10^{-8}\dfrac{E_f}{f'_{co}}\left(\dfrac{F_f}{f'_{co}}\right) \\ -3.88\times10^{-5}\exp\left(\dfrac{t_f}{h}\dfrac{E_f}{f'_{co}}\dfrac{r}{h}\right) \\ +1.246\times10^{-6}\dfrac{t_f}{h}\left(\dfrac{E_f}{f'_{co}}\right)^2 \\ +0.459\dfrac{b}{h}\dfrac{t_f}{h}\dfrac{E_f}{f'_{co}}\left(\dfrac{r}{h}\right)^2+1.063 \end{bmatrix} \quad (4)$$

Among the input variables, two variables *r/b* and r/t_f are less used in the presented relationships, which indicates that these two variables have less effect on the strength of confined concrete.

To compare the performance of models proposed by the GP method with the existing models, statistical parameters are introduced. These parameters are mean square error (MSE), average absolute magnitude error (AAE), standard deviation (SD), and the total error that are given by Eq. (5) to Eq. (8):

$$\text{MSE} = \frac{\sum_{i=1}^{N}\left(\dfrac{\text{Theo}_i-\text{Expe}_i}{\text{Expe}_i}\right)^2}{N} \quad (5)$$

$$\text{AAE} = \frac{\sum_{i=1}^{N}\left|\dfrac{\text{Theo}_i-\text{Expe}_i}{\text{Expe}_i}\right|}{N} \quad (6)$$

$$\text{SD} = \sqrt{\frac{\sum_{i=1}^{N}\left(\dfrac{\text{Theo}_i}{\text{Expe}_i}-\dfrac{\text{Theo}_{avg}}{\text{Expe}_{avg}}\right)^2}{N-1}} \quad (7)$$

$$e_{tot} = 100\times\frac{\sum_{i=1}^{N}|\text{Expe}_i-\text{Theo}_i|}{\sum_{i=1}^{N}|\text{Expe}_i|} \quad (8)$$

where $Expe_i$ and $Theo_i$ are the compressive strength from experimental data and the compressive strength predicted by the theoretical model, respectively. *N* is the total specimens.

The statistical parameters to evaluate the accuracy of the models proposed by GP are shown in Table 3 for all specimens. Pham and Hadi's [37] model is impractical for specimens in which the corner radius is zero. Hence, statistical parameters have been calculated for 449 specimens for this model.

As shown in Table 3, models proposed by GP are more accurate rather other models. Models GP1, GP2, and GP3 have averagely reduced the total error for all the specimens (463) by 48.29, 48.47 and 45.87%, respectively, compared to the average error of models proposed by Moodi et al. [38], Lam and Teng[39], Pham and Hadi [37], Harajli et al. [40], Ilki and Kumbasar [41], Wei and Wu [42] and Toutanji et al. [43].

To illustrate the efficiency of models proposed by genetic programming, experimental compressive strength against compressive strength resulting from the proposed models is shown in Figures 3 and 4. This figure shows that models proposed by genetic programming are in good agreement with experimental data. Correlation coefficients (R^2) are also illustrated for them. As it is seen, the best correlation coefficient is related to GP2, which has used trigonometric transfer functions.

In Figure 5, it can be seen that the error values obtained from the GP method are accepted and could estimate the values of the strength of the S/R columns confined by FRP.

For more comparisons, the parameter of Z, which involves the effects of the total error and correlation coefficient, was calculated by Eq. (9) and was provided in Table 4 for all the models studied in this research (463 specimens).

$$Z = 1 - R^2 + e_{tot} \tag{9}$$

To investigate the effects of the proposed models, percent reductions created by all three models compared to the other mentioned models are given in Table 4. In Table 4, a negative sign indicates a decrease in the value of Z compared to other mentioned models. Results in Table 4 show that model GP2 performs better, but it should be noted that their accuracies do not differ much. According to this table, models GP1, GP2, and GP3 averagely reduce the value of the Z by 42.94, 42.94, and 42.22%, respectively, compared to other models mentioned in this study.

6. Sensitivity analysis

In this section, the importance of each input parameter, including b/h, r/b, r/h, r/t_f, t_f/h, t_f/b, F_f/f_{co}, and E_f/f_{co}, on the output parameter (f_{cc}/f_{co}) is investigated. Equation 10 is employed to show the contribution of each parameter. The provided equation suggests that as the value of "S" increases for each parameter, the corresponding parameter has a greater impact on the model output. This implies that variations or changes in the input parameters, particularly those with higher "S" values, have a more pronounced effect on the overall output of the model.

$$S\left(X_i, Y\right) = \frac{\sum_{i=1}^{n}\left(X_i - \bar{X}\right)\left(Y_i - \bar{Y}\right)}{\sqrt{\sum_{i=1}^{n}\left(X_i - \bar{X}\right)^2 \sum_{i=1}^{n}\left(Y_i - \bar{Y}\right)^2}} \tag{10}$$

Table 3: Statistical parameters

Model	MSE	AAE	SD	e_{tot}
Train specimens				
Moodi et al. [38]	2.45	12.14	15.63	15.73
Wei and Wu [42]	3.76	14.70	18.77	19.54
Toutanji et al. [43]	6.59	18.32	23.56	24.65
Pham and Hadi [37]	11.57	23.51	32.28	30.43
Harajli et al. [40]	9.70	25.51	23.48	32.49
Ilki and Kumbasar [41]	7.30	18.71	26.71	24.46
Lam and Teng [39]	5.73	16.36	23.61	20.46
GP1	1.68	9.96	12.90	12.50
GP2	1.50	9.86	12.20	12.36
GP3	1.70	10.18	12.96	12.82
Test specimens				
Model	**MSE**	**AAE**	**SD**	e_{tot}
Moodi et al. [38]	2.40	12.18	15.55	13.34
Wei and Wu [42]	3.67	15.36	18.73	18.16
Toutanji et al. [43]	6.08	19.25	22.54	22.37
Pham and Hadi [37]	10.85	25.12	31.66	27.36
Harajli et al. [40]	10.12	27.20	23.50	29.24
Ilki and Kumbasar [41]	5.98	18.42	24.34	21.31
Lam and Teng [39]	4.20	15.51	20.26	17.59
GP1	1.95	10.28	14.02	10.84
GP2	1.98	10.48	14.14	10.97
GP3	2.50	11.14	15.87	11.83
Total specimens				
Model	**MSE**	**AAE**	**SD**	e_{tot}

Moodi et al. [38]	2.43	12.15	15.59	12.91
Wei and Wu [42]	3.73	14.90	18.74	16.51
Toutanji et al. [43]	6.44	18.60	23.23	20.67
Pham and Hadi [37]	11.35	23.99	32.05	25.44
Harajli et al. [40]	9.82	26.02	23.47	27.17
Ilki and Kumbasar [41]	6.90	18.62	25.99	20.24
Lam and Teng [39]	5.27	16.11	22.63	16.86
GP1	1.76	10.05	13.27	10.33
GP2	1.64	10.05	12.81	10.29
GP3	1.94	10.47	13.89	10.81

In the above equation, X_i and Y_i represent the input parameter and the output for the given input parameter X_i, respectively. $\bar{X}$ and $\bar{Y}$ denote the mean of the input parameters and the output values, respectively. *n* represents the amount of data. The sensitivity analysis results, according to Equation 10, are presented in Table 5.

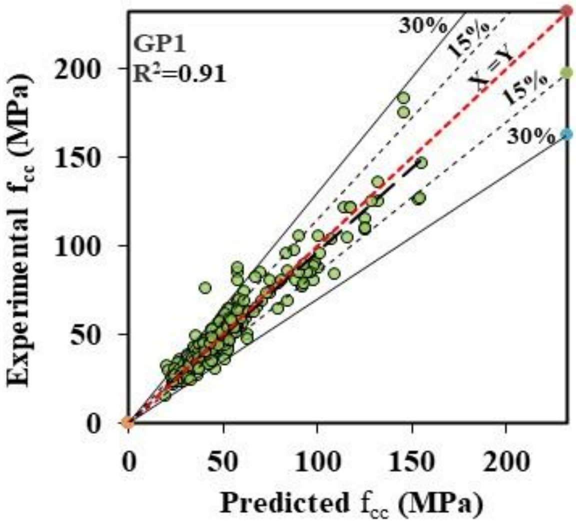
Table 4: Comparison of Z for models.

	Proposed Model	**GP1**	**GP2**	**GP3**
	Z	0.21	0.20	0.21
Previous Model	**Z**	**Percent decrease**	**Percent decrease**	**Percent decrease**
Moodi et al. [38]	0.26	21.06	21.06	20.07
Wei and Wu [42]	0.30	30.85	30.85	29.99
Toutanji et al. [43]	0.39	46.34	46.34	45.67
Pham and Hadi [37]	0.51	59.08	59.08	58.56
Harajli et al. [40]	0.46	54.65	54.65	54.08
Ilki and Kumbasar [41]	0.41	49.03	49.03	48.39
Lam and Teng [39]	0.34	39.55	39.55	38.79
GP1	0.21	-	-	-
GP2	0.20	-	-	-
GP3	0.21	-	-	-

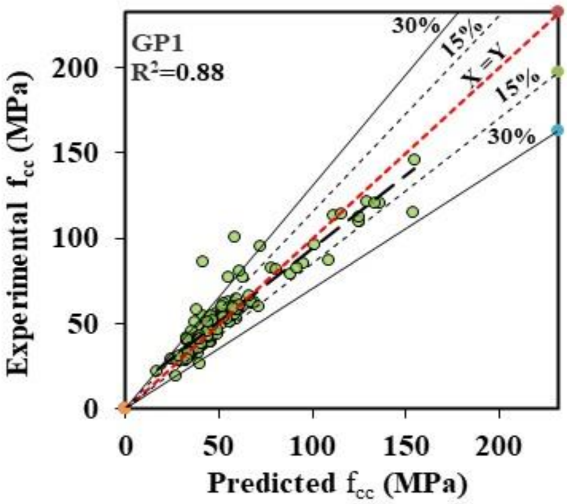
Table 5: Results of sensitivity analysis

	b/h	**r/h**	**r/b**	**r/t_f**	**t_f/b**	**t_f/h**	**F_f/f_{co}**	**E_f/f_{co}**
S	0.22	0.43	0.32	0.11	-0.14	-0.10	0.46	0.43

A positive or negative "*S*" value in the input variables indicates a direct or inverse effect of the input variable on the output variable, respectively. Among the eight investigated parameters, t_f/b and t_f/h parameters have an inverse effect on the output parameter. Also, E_f/f_{co}, F_f/f_{co}, and *r/h* parameters having the highest *S* value, have the highest effect on the compressive strength of confined concrete pressure resistance, and r/t_f, and t_f/h variables have the least effect on the output variable.



(a)



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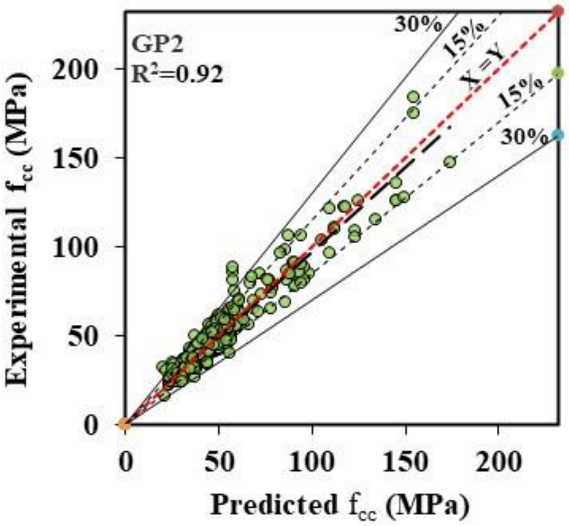

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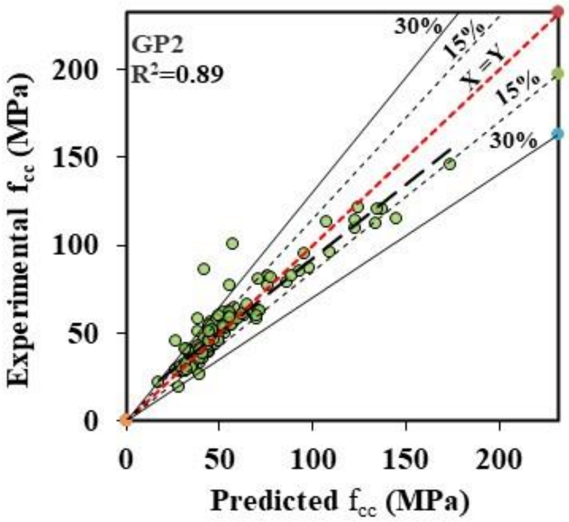

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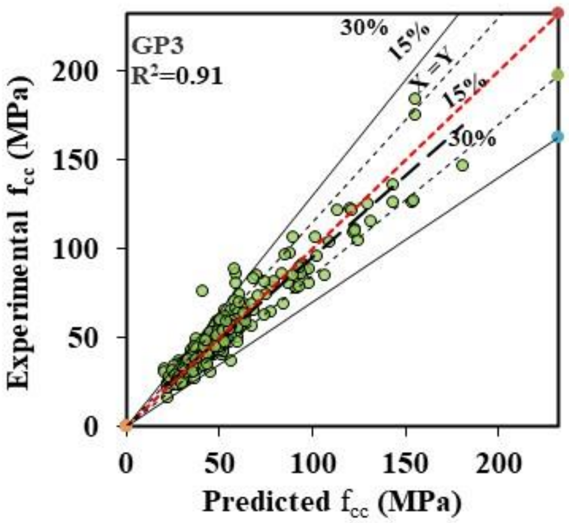

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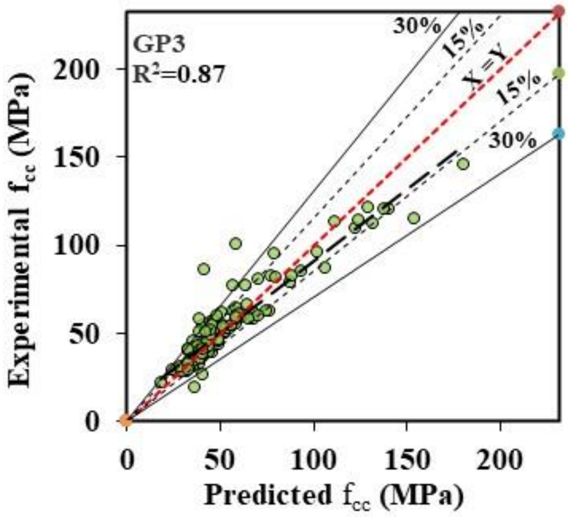


(f)

Fig. 3: Performance of models presented with GP: (a), (b): refer to the training and test specimens of GP1; (c), (d): refer to the training and test specimens of GP2; (e), (f): refer to the training and test specimens of GP3

7. Conclusion

In this paper, genetic programming is used to predict the compressive strength of the confined S/R concrete columns with FRP. To this aim, the dimensionless form of the variables obtained from the experimental data was used to create the model. The three-transfer function sets are used to estimate models for this column. Hereby, the results are summarized as follows:

1- GP predicts the compressive strength of the confined concrete columns with FRP, accurately. The models GP1, GP2, and GP3 proposed by GP averagely reduce the total error by 48.29 %, 48.47 %, and 45.87 % compared to the models mentioned in this study.

2- Two input variables t_f/h and r/t_f have less effect on the compressive strength of the confined S/R concrete columns with FRP and E_f/f_{co}, F_f/f_{co}, and r/h parameters have the highest on this compressive strength.

3- Changing transfer functions does not have much effect on the accuracy of the models provided by GP, so using trigonometric functions causes a total error of 0.352% compared to when not in use.

The GP model may offer higher accuracy compared to traditional methods, but achieving even greater precision may require longer and more complex relationships. Such complexity could limit practical use, particularly for engineers who need to estimate compressive strength without computer assistance. Our primary goal was to develop a practical and applicable model, which may account for the slight increase in error observed.

The proposed future works could include developing a compressive strength model for columns confined with

LRS-FRP, applying estimation methods for rubberized or recycled concrete confined with FRP, and extending experimental studies to encompass a wider range of concrete types and FRP configurations.

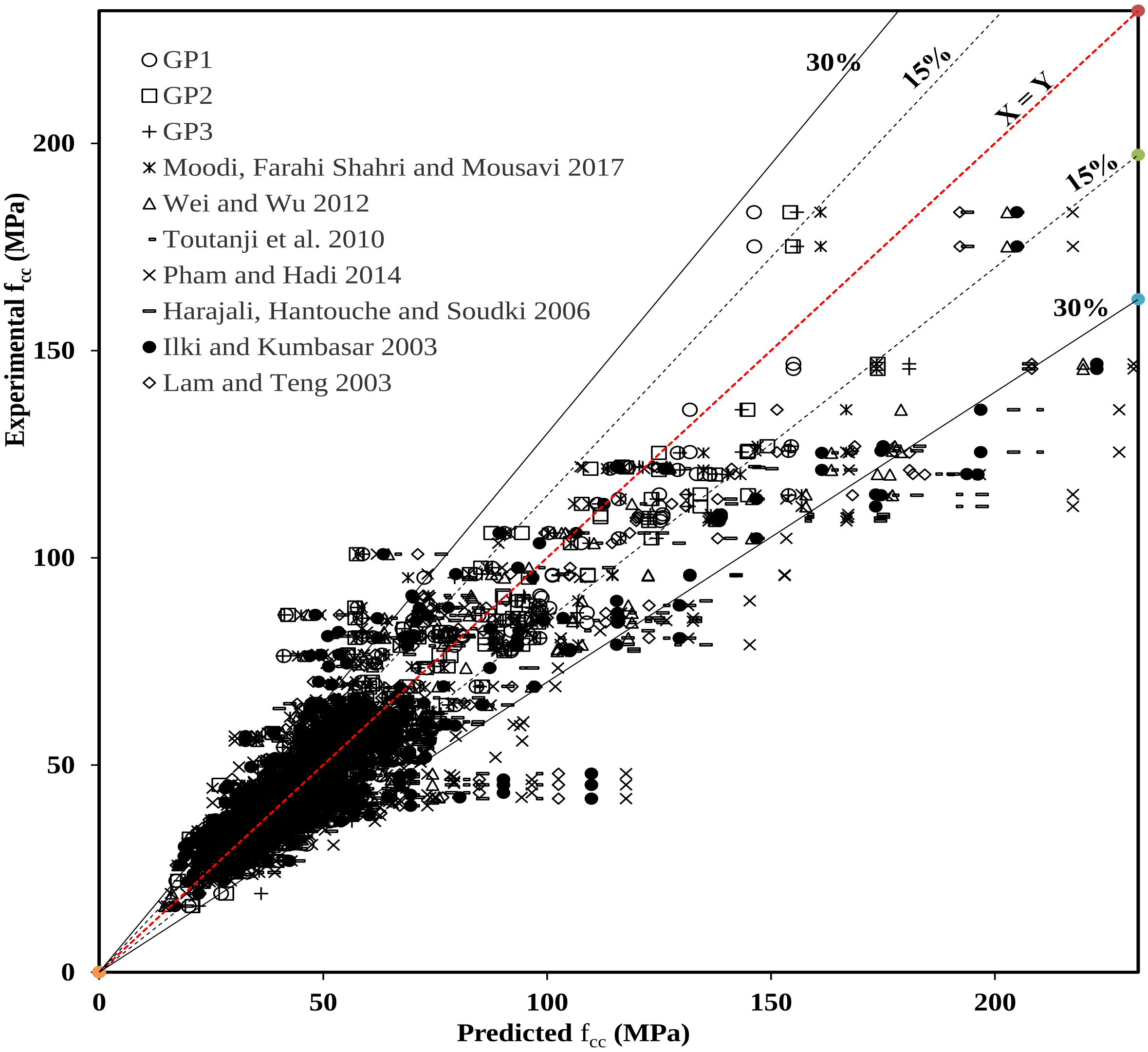
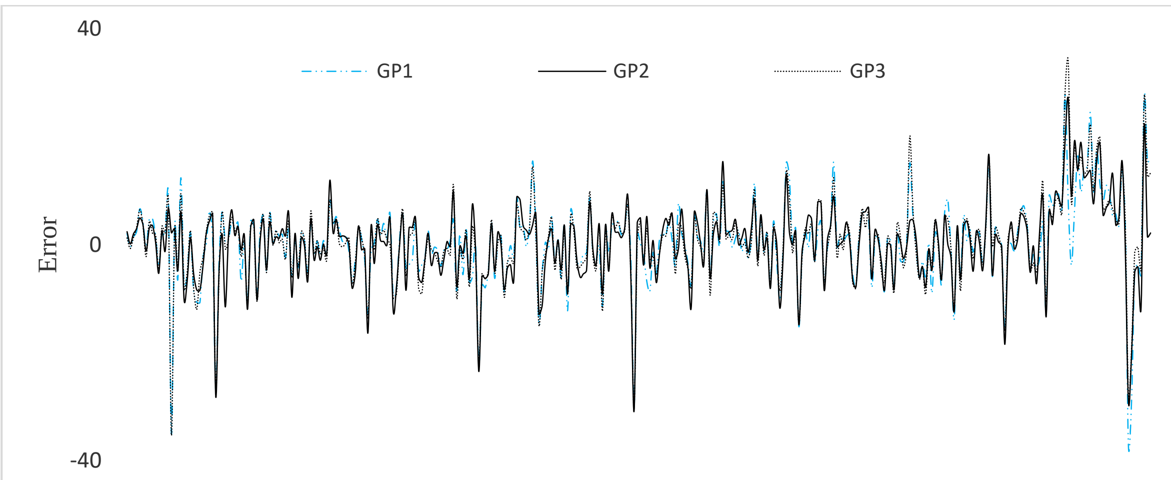
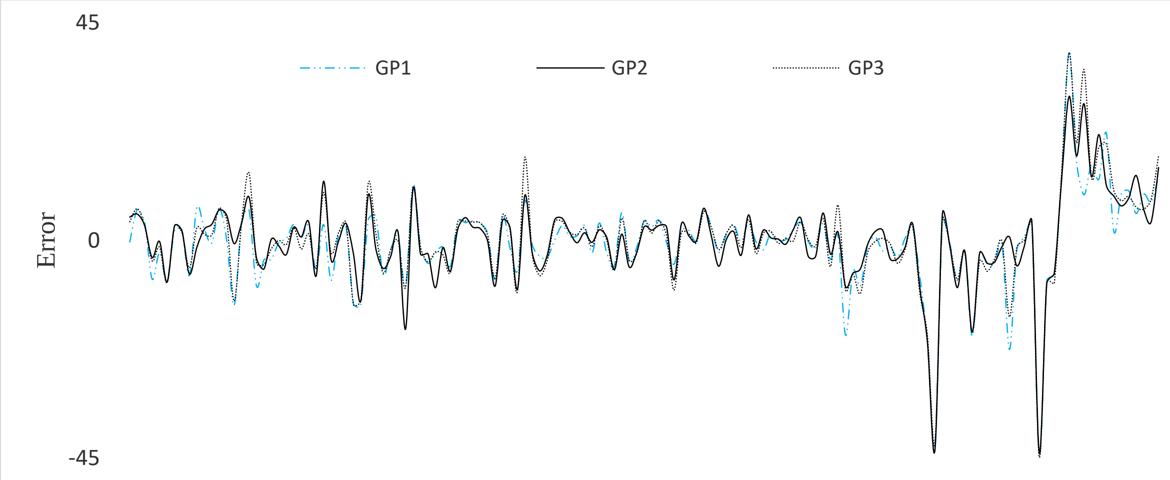


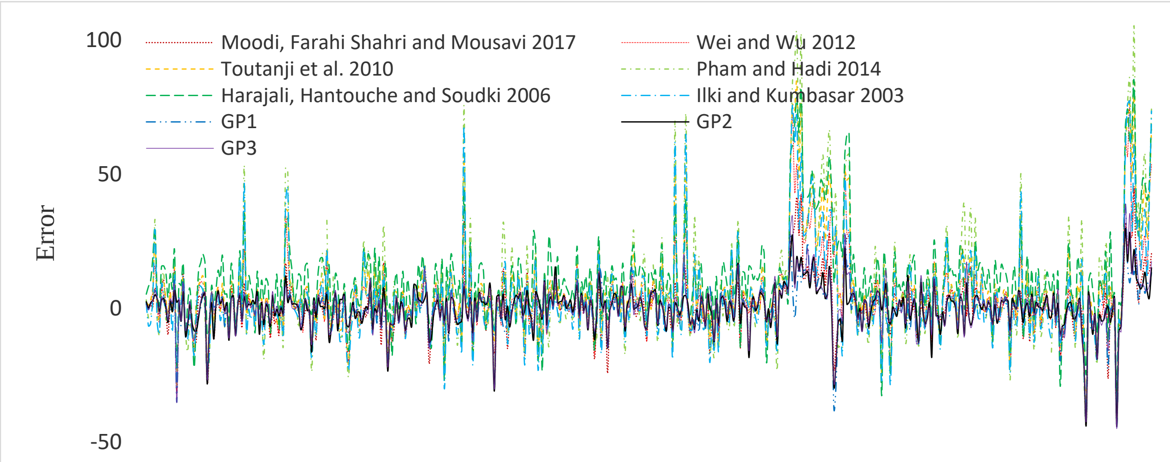
Fig. 4: Performance of all models



(a) Train data



(b) Test data



(c) All data

Fig. 5: Comparison of performance for experimental data

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