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An Intelligent Model for the Prediction of Bond Strength of FRP Bars in Concrete: A Soft Computing Approach

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Abstract: Accurate prediction of bond behavior of fiber reinforcement polymer (FRP) concrete has a pivotal role in the construction industry. This paper presents a soft computing method called multi-gene genetic programming (MGGP) to develop an intelligent prediction model for the bond strength of FRP bars in concrete. The main advantage of the MGGP method over other similar methods is that it can formulate the bond strength by combining the capabilities of both standard genetic programming and classical regression. A number of parameters affecting the bond strength of FRP bars were identified and fed into the MGGP algorithm. The algorithm was trained using an experimental database including 223 test results collected from the literature. The proposed MGGP model accurately predicts the bond strength of FRP bars in concrete. The newly defined predictor variables were found to be efficient in characterizing the bond strength. The derived equation has better performance than the widely-used American Concrete Institute (ACI) model.

Keywords: data mining; bond strength; FRP-bar; multi-gene genetic programming

1. Introduction

Corrosive environments for reinforcing steel bars in concrete structures may lead to severe deterioration. Controlling the corrosion of steel reinforcement has been a major concern for researchers and engineers. To deal with this issue, a number of studies have been focused on replacing steel rebars with fiber reinforcement polymer (FRP) bars [1–3]. The FRP bars offer several advantages including a non-corrosive nature, high tensile strength, light weight, fatigue resistance, nonmagnetic electrical insulation, and small creep deformation [4]. The bond strength between the FRP bars and concrete is one of the crucial factors in reinforced concrete structures. Accurate prediction of the bond strength between FRP bars and concrete is important to design reliable concrete structures. Over the past few decades, numerous studies have been conducted to determine the primary factors that affect the FRP bond behavior via either beam tests or direct pullout tests [5–10]. These studies have presented practical models for estimating the bond strength of FRP bars in concrete. Some of the key parameters in these models are concrete compressive strength, concrete cover, bar diameter, bar position, bar surface, and embedment length. Reports have shown that the bond strength predicted by the standard design equations such as the American Concrete Institute (ACI) model is a conservative estimation of the real values [11].

Over the last two decades, various soft computing techniques such as Artificial Neural Networks (ANNs), Decision Trees, Fuzzy Logic (FL), Adaptive Neuro Fuzzy Inference Systems (ANFIS), and Support Vector Machines (SVM) have been increasingly implemented to tackle civil engineering problems [12–18]. Some of these techniques have also been utilized for the prediction of the bond strength and shear capacity of the FRP bars in concrete. Coelho et al. [19] presented the effectiveness of two soft computing algorithms (ANN and SVM) in analyzing the bond behavior of FRP systems inserted in the cover of concrete elements, which is commonly known as the near-surface mounted (NSM) technique. The ANN and SVM models were found to be robust and more accurate than the guideline models. Koroglu [20] developed an ANN and the regression analysis model to predict the bond strength of FRP bars in concrete. The ANN model made accurate estimations of the bond strength of FRP bars in concrete and gave better result than the ACI and the Canadian Standards Association (CSA) models. Bashir and Ashour [21] deployed ANNs to estimate the shear capacity of concrete members. These members were reinforced longitudinally with FRP bars without any shear reinforcement. It was found that the ANN model can predict the shear capacity of FRP reinforced concrete members with acceptable accuracy [21]. However, one of the major disadvantages of the previously published soft computing methods is that they are not capable of providing practical prediction equations. Genetic Programming (GP) is an alternative approach that can overcome this limitation [22,23]. GP generates simplified prediction equations without assuming a prior form of the relationship [24–29]. This method has been successfully applied to the behavioral modeling of FRP concrete. For instance, Kara [30] proposed a GP model to predict the concrete shear strength of FRP-reinforced concrete slender beams without stirrups. The GP model outperformed nearly all of the shear strength equations provided by current standard codes [30].

Multi-Gene Genetic Programming (MGGP) is a fairly new branch of the classical GP [31]. Unlike standard regression methods, MGGP does not require simplifying assumptions in developing the models. Despite the remarkable prediction capabilities of the MGGP approach [31], there is only limited research focusing on the application of MGGP to civil engineering tasks. The main goal of this study is to explore the potential of the MGGP method for predicting the bond strength of FRP bars in concrete. A number of predictor variables were identified to formulate the bond strength [32–37]. The proposed MGGP model was compared with the widely-used ACI model. Based on the results, the MGGP model can reliably be employed for pre-design purposes.

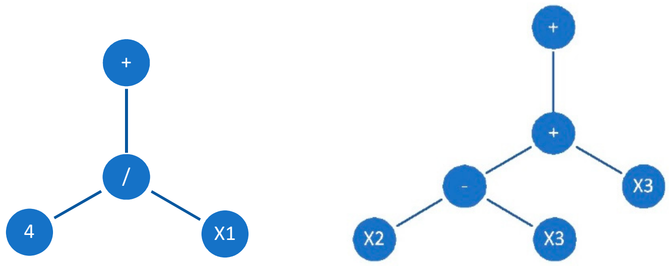
2. Genetic Programming

GP is a soft computing method capable of creating computer programs to solve a problem by simulating the biological evolution of living organisms. GP uses genetic operators similar to those of Genetic Algorithms (GA). The difference is that a GA would give an optimized solution as a string of numbers, while the solution generated by GP is a computer program representing a model of the system behavior [22,23].

Multi-Gene Genetic Programming

While the traditional GP representation is based on evaluating a single tree expression (the model), an individual in MGGP is derived from several expression trees [38]. Each model evolved by MGGP is a weighted linear combination of the outputs of several GP trees. The trees are called "genes." Figure 1 shows a typical program evolved by MGGP. The input variables of the model are x_1, x_2, and x_3 and the function set is arithmetic operations such as plus, minus, multiplication and protected division. The model is linear in the parameters with respect to coefficients d_0, d_1, and d_2, despite using nonlinear terms. In practice, the maximum allowable number of genes (Gmax) for a model and the maximum tree depth (Dmax) of any gene can be specified by the user. Therefore, very good control over the maximum complexity of an evolved model can be exerted. Enforcing rigid tree depth restrictions (i.e., maximum depths of 4 or 5 nodes) usually results in the evolution of relatively compact models.

The evolved models are linear combinations of low-order nonlinear transformations of the predictor variables [31]. Figure 2 depicts the block diagram of MGGP.



$$y = d_0 + d_1(4/x_1) + d_2(x_2 - x_3) + x_3$$

Figure 1. A typical multi-gene GP model.

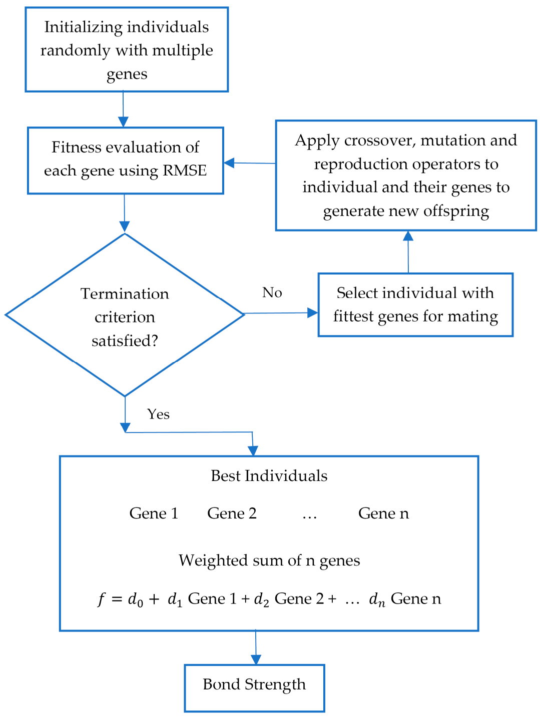


Figure 2. The MGGP block diagram.

An ordinary least squares analysis is performed on the training data in order to obtain the linear coefficients. However, it is possible to embed a multi-gene approach within a partial least squares method [38].

The initial population generated by MGGP contains GP trees with different randomly generated genes. In addition to traditional GP recombination operators, MGGP uses a tree crossover operator, called two-point high level crossover, which is used to acquire and delete genes [31].

As an example, assume that two parent programs evolved by MGGP contain three (Gene 1, Gene 2, and Gene 3) and four genes (Gene 4, Gene 5, Gene 6, and Gene 7). The genes enclosed by the crossover points are denoted by { } as follows: (Gene 1 {Gene 2 Gene 3}) and (Gene 4 {Gene 5 Gene 6 Gene 7}). Thus, during crossover, the genes are exchanged to create two new programs: (Gene 1, Gene 5, Gene 6, Gene 7) and (Gene 4, Gene 2, Gene 3). In MGGP, standard GP subtree crossover is referred to as low level crossover. In this case, a gene is chosen randomly from each parent individual. Then, the standard subtree crossover is applied, and the created trees replace the parent trees in the unaltered individual in the next generation. There are also different types of mutation in MGGP such as subtree mutation, mutation of constants using additive Gaussian perturbations, or setting a randomly selected constant to zero [31].

3. Data Acquisition

An experimental database of 223 test results for bond strength of the FRP concrete was collected from the literature and was utilized to develop the MGGP model [39–54]. The database is provided in Appendix A. The parameters involved in the model development were the cover the bar surface (Surf), bar position (Pos), bar diameter (d_b), concrete cover to bar diameter ratio (c/d_b), bar embedment length to bar diameter ratio (l_d/d_b), and concrete compressive strength ($f'c$), and the bond strength (τ_b) as the single output parameter. The maximum, minimum, mean, median, and standard deviation of these variables are shown in Table 1. Numbers 1 and 2 for the bar position variable indicate top and bottom location of the FRP bars in the beam bond test, respectively. Additionally, numbers 1, 2, and 3 for the bar surface variable show helical lugged surfaces, which are spiral wrapped and sand coated for FRP bars, respectively.

Table 1. Parameters involved in the model development.

Variables	Min	Max	Mean	Median	STD
Surf	1	3	1.16	1	0.44
Pos	1	2	1.25	1	0.43
d_b (mm)	6.35	21	10.54	8.5	2.88
c/d_b	1.68	9.34	3.58	3	1.82
l_d/d_b	3.56	115.79	30.14	20.16	23.01
$f'c$ (Mpa)	23.43	55.06	40.04	40.2	6.72
τ_b (Mpa)	0.76	21	6.79	5.3	4.15

According to Banzhaf et al. [22], an efficient approach to prevent overfitting is to test other individuals from the run on a validation set to find a better generalizer. This technique was used in this study to improve the generalization of the models. For this purpose, the available data sets were randomly divided into training, testing, and validation subsets. The training data were used for learning (genetic evolution). The validation data were used to specify the generalization capability of the evolved programs on data they did not train on (model selection). In other words, the training and validation data sets were used to select the best evolved programs. This technique provides decent results as long as the models perform well on the training data sets [22]. The validation data were finally used to measure the performance of the models obtained by MGGP on data that played no role in building the models. The selection was such that the maximum, minimum, mean, and standard deviation of parameters were consistent in training, testing, and validation data sets. Out of 223 available data points, 157, 33, and 33 records were used for the training, testing, and validation of the models, respectively.

4. Model Development

The MGGP optimal parameter settings are shown in Table 2. As seen in this table, various parameters are involved in the MGGP predictive algorithm. The parameter selection affects the model generalization capability of MGGP. These parameters were selected based on some previously suggested values [32,33] after an extensive trial-and-error approach. The right population size and number of generations often depend on the problem complexity and on the number of possible solutions. A fairly large population size and number of generations were tested in this study to find models with minimal errors. Programs were run until automatically terminated. The maximum allowable number of genes in an individual and the maximum tree depth directly determine the complexity of solutions. After performing a number of simulations, these parameters were set to best trade-off values between the running time and the complexity of the evolved solutions.

Table 2. Parameter setting for the MGGP algorithm.

Parameter	Setting
Function set	+, −, /, √, ln, square, cubic power
Population size	1000
Number of generations	500
Max number of genes	8
Max tree depth	6
Tournament size	12
Elitism	0.01% of population
Crossover events	0.85
Mutation events	0.1
Probability of pareto to tournament	0.2

The GPTIPS toolbox [31] in conjunction with subroutines coded in MATLAB, was used to implement MGGP. The fitness function evaluates expressions to find the best encoded expressions [38]. The default GPTIPS multi-gene symbolic regression fitness function, which includes the root mean squared error, was used to minimize the loss function. The best MGGP models were selected based on their fitness value on the training and testing data and on the simplicity of the models [55]. The correlation coefficient (R), Mean Absolute Error (MAE), and Root-Mean-Squared Error (RMSE) were used to evaluate the performance of models. R, MAE, and RMSE were calculated using the following equations.

$$\mathrm{R} = \frac{\sum_{i=1}^{n}\left(h_i - \overline{h_i}\right)\left(t_i - \overline{t_i}\right)}{\sqrt{\sum_{i=1}^{n}\left(h_i - \overline{h_i}\right)\sum_{i=1}^{n}\left(t_i - \overline{t_i}\right)^2}} \tag{1}$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n}|h_i - t_i|}{n} \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(h_i - t_i)^2}{n}} \tag{3}$$

where h_i and t_i are the measured and calculated output values for the i-th output, respectively. $\overline{h_i}$ and $\overline{t_i}$ are the average of the measured and calculated outputs, respectively, and n is the number of samples.

5. Results and Discussions

5.1. The MGGP-Based Formulation for Bond Strength

Table 3 shows the individual genes of the model evolved by MGGP. These genes are automatically summed and then simplified by the GPTIPS code to generate the following optimal MGGP prediction model for the bond strength of FRP bars in concrete.

$$\begin{gathered}\tau\ (\mathrm{Mpa}) = 0.0665\, f'c - 0.189\, d_b + 0.0406\, l_d/d_b + 2.26\, \mathrm{In}(c\, d_b/l_d\, d_b) - \\ 0.0665\sqrt{(c/d_b)^3} - 4.16\, \mathrm{In}(2\mathrm{surf} + l_d/d_b + (f'c \times l_d/d_b) + 0.00558\, \mathrm{In}(l_d/d_b) + \\ 0.0175(\mathrm{pos}\, l_d/d_b) - 0.00108\, (f'c)^2 + 39.8\end{gathered} \tag{4}$$

A comparison of the MGGP-predicted versus the experimental bond strength is shown in Figure 3. As seen, the MGGP model can predict the target values with a high degree of accuracy. It can be observed from these figures that the prediction performance has improved on the testing data.

Table 3. Individual genes in the MGGP model.

Term	Value
Bias	4.67
Gene 1	$0.00558\ \ln(l_d/d_b) + 0.0174\ \text{pos}\ l_d/d_b$
Gene 2	$-0.00108\ (f'c)^2$
Gene 3	$0.0665\ f'c - 0.133\ l_d/d_b - 0.0665\ \sqrt{(c/d_b)^3} + 0.249$
Gene 4	$-4.16\ln(2\text{surf} + l_d/d_b + (f'c \times l_d/d_b))$
Gene 5	$0.174 l_d/d_b$
Gene 6	$2.26\ln(c\ d_b/l_d\ d_b)$
Gene 7	$-0.189\ d_b$
Gene 8	34.9

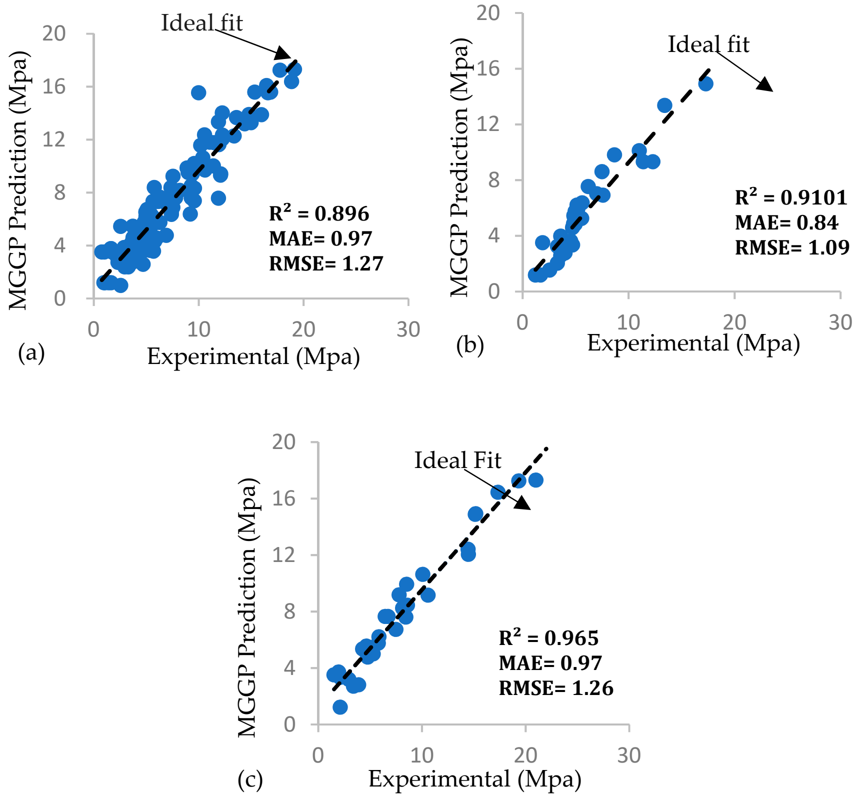


Figure 3. MGGP Prediction versus experimental bonding strength of (**a**) training data (**b**) testing data, and (**c**) validation data.

The statistical significance of each of the eight genes of the derived model is visualized in Figure 4. According to Figure 4a, the weight (coefficient) of the bias term is higher than that of other genes. This indicates a high contribution of the bias term in the proposed model. Figure 4b depicts the degree of significance for each gene evaluated when using p-values. As seen, the contribution of genes to an explanation of variations in bond strength is quite high, since their relevant p-values are very low and close to 0. The statistical significance of the first and forth gene (Gene 1 and Gene 4) is higher than that of the other genes.

Figure 5 presents the population of the evolved models in terms of their complexity (number of nodes) as well as their fitness. The generated models that perform relatively well and are much less complex than the best model in the population, can be identified in this figure. The best model in the population is highlighted with a red circle. Each green circle represents a model that is not strongly dominated by other models in the population in terms of fitness and model complexity.

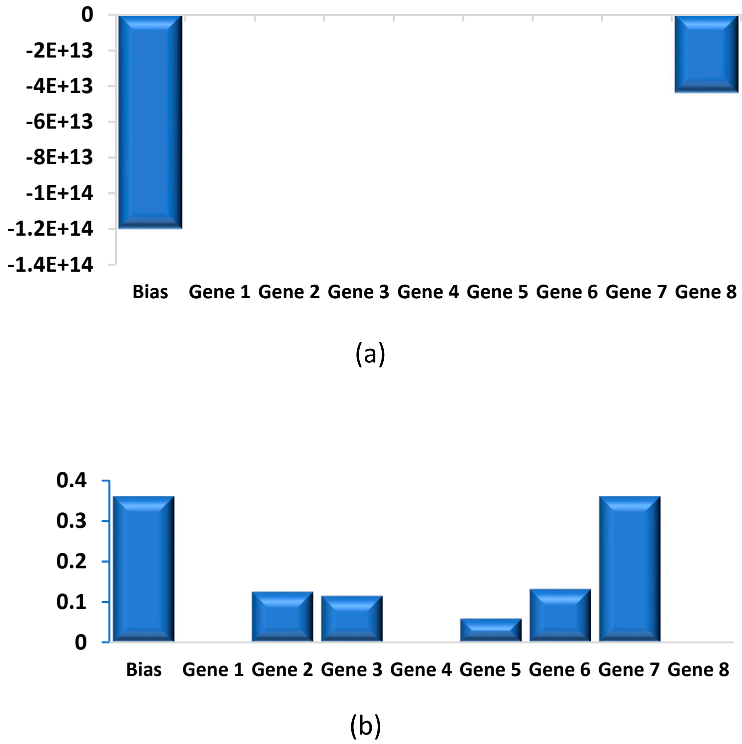


Figure 4. Statistical properties of the evolved MGGP model on the training data (**a**) Gene Weights (**b**) P-Value (low = significant).

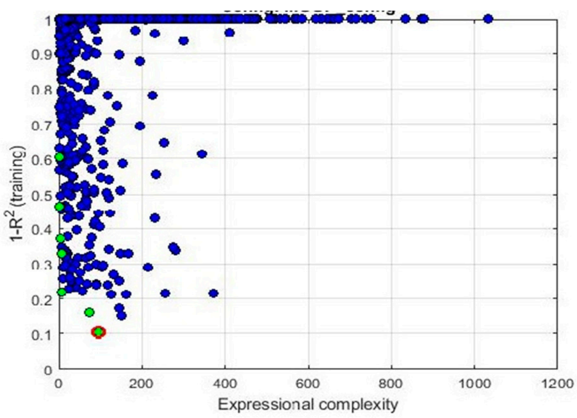


Figure 5. Population of the evolved models in terms of their complexity and fitness.

5.2. Comparative Study

In order to have an idea about the predictive power of the MGGP model, a comparative study was performed in this study. Accordingly, the performance of the MGPP model was benchmarked against the following equation proposed by the ACI [56].

$$\tau_b = (\sqrt{f'c}\,(0.332 \;+\; 0.025\, c/d_b \;+\; 8.3\, d_b/l_d) \qquad (5)$$

where, c/d_b is the concrete cover to bar diameter ratio, d_b/l_d is the bar diameter to bar embedment length ratio, $f'c$ is the concrete compressive strength, and τ_b is the bond strength of FRP bars in concrete. As seen, some of the parameters of the ACI formula ($f'c$, c/d_b, and d_b/l_d) have been included in the

MGGP model. Figure 6a,b shows the performance indices of the MGGP and ACI models in terms of MAE and RMSE. The MGGP model has notably lower error values than the ACI equation.

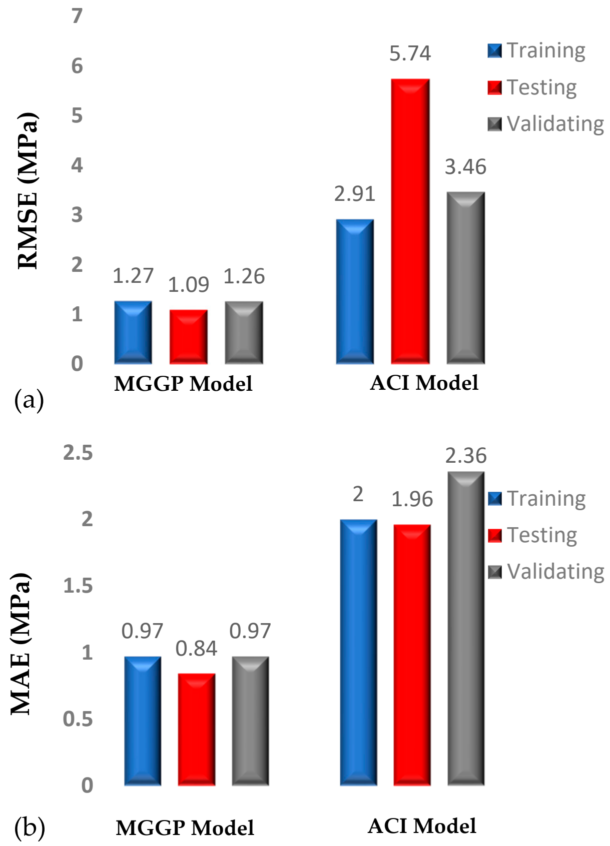


Figure 6. (**a**) RMSE of the MGGP and ACI models. (**b**) MAE of the MGGP and ACI models.

A comparison of the measured and predicted bond strength by the MGGP and ACI models is shown in Figure 7. As can be seen, the proposed MGGP accurately predicts the bond strength. The ACI equation estimations are more conservative values. Figures 8 and 9 illustrate a comparison of the experimental/ predicted bond strength by the MGGP and ACI models, respectively. The predictions lie above or below the target line (experimental/ predicted = 1). As can be observed, the MGGP predictions are closer to the target line when compared to the ACI code equation. The averages of the experimental/predicted bond strength are equal to 1.02 and 1.19 for the MGGP and ACI models, respectively.

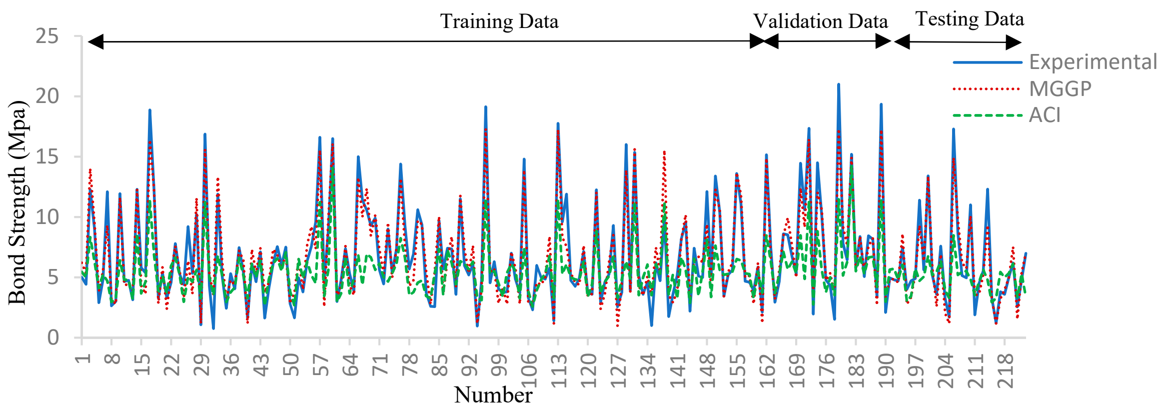


Figure 7. Bond strength predictions using the MGGP and ACI models.

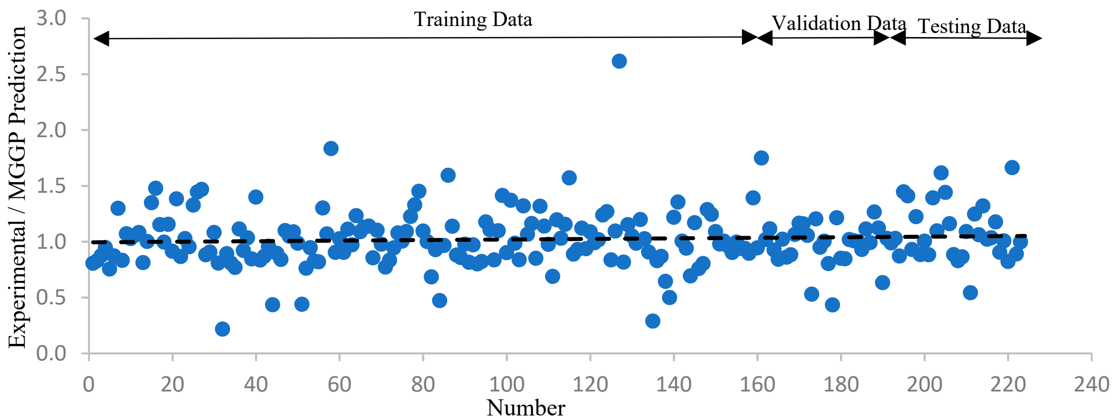


Figure 8. Experimental to MGGP-predicted bond strength rations.

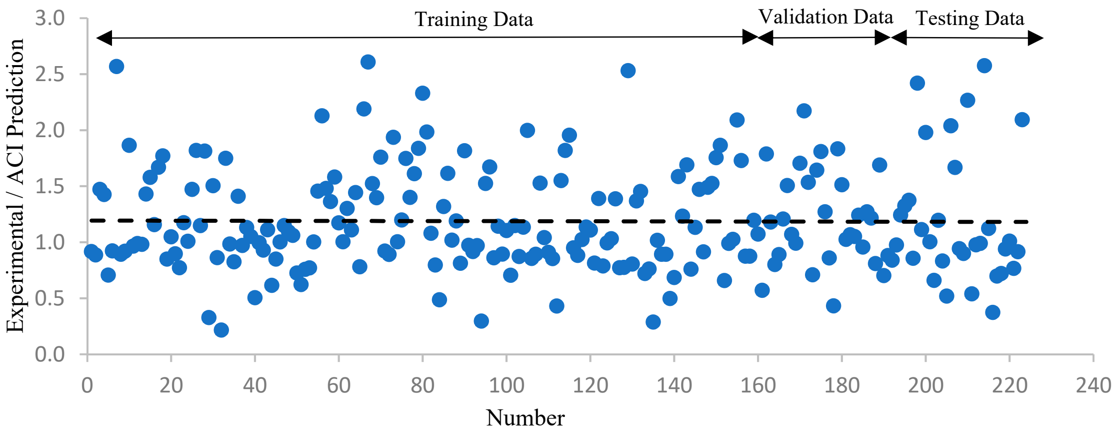


Figure 9. Experimental to ACI-predicted bond strength rations.

6. Conclusion and Future Directions

In this study, a promising extension of the classical GP called MGGP was employed to predict the bond strength of FRP bars in concrete. A design equation was developed for the prediction of FRP bond strength using a database of 223 experimental bond beam tests. The MGGP model provides accurate predictions of the bond strength and notably outperforms the ACI model. Using the MGGP approach, the bond strength of FRP bars in concrete can be estimated without carrying out a sophisticated and time-consuming laboratory test. The proposed model can be easily retrained and improved to make more accurate predictions for a wider range of parameters by including data of other test conditions. In this context, future research can be focused on developing new models for the bond strength of Aramid fiber reinforced polymer (AFRP), carbon fiber reinforced polymer (CFRP), and glass fiber reinforced polymer (GFRP) reinforcing bars. MGGP is very robust in nonlinear relationships modeling. However, the underlying assumption that the input parameters are reliable is not always the case. Since fuzzy logic can provide a systematic method to deal with imprecise and incomplete information, the process of developing hybrid fuzzy and MGGP models can be a suitable topic for further studies. Hybridizing MGGP with optimization algorithms such as Tabu Search can also be investigated to improve the proficiency of MGGP.

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Appendix A

Table A1. The database used for the model development [39–54].

Test No.	*Pos*	*Surf*	d_b (mm)	$f'c$ (Mpa)	c/d_b	l_d/d_b	τ_b (Mpa)
1	2	2	18.44	39.06	6	24.79	5.26
2	2	1	9.53	29.81	2	10.67	11.5
3	2	1	28.58	47.33	4	23.11	3.8
4	2	3	19.1	43.03	1.68	36.65	3.28
5	2	2	10	29.05	4	10	11.89
6	2	1	12.7	39.94	9.3	20	7.36
7	2	3	19.1	39.94	2.09	36.65	3.28
8	2	1	19.05	28.94	3.7	5	15.35
9	2	1	15.75	44.36	3	24.19	4.29
10	2	3	15.9	39.94	2.52	44.03	2.95
11	1	1	9.53	49	4	16	8.2
12	2	1	15.75	44.36	2	24.19	4.1
13	2	3	12.7	43.03	2.52	62.99	4.71
14	2	2	15.88	28.94	4.4	7.5	12.26
15	1	1	9.53	49	6	21.33	7
16	2	1	15.75	44.36	2	24.19	3.74
17	2	3	15.9	49	2.01	31.45	4.04
18	2	1	12.7	49.98	5.41	30	4.6
19	2	2	10	29.38	4	40	5.1
20	2	2	19.3	38.69	2	13.16	6.11
21	2	2	19.66	43.56	2	19.38	5.02
22	2	2	19.66	43.56	3	25.84	4.92
23	2	3	19.1	39.94	2.09	36.65	3.3
24	2	1	12.7	51.98	9.34	20	7.5
25	2	2	9.68	34.93	4	15.75	9.58
26	2	1	10.6	35.05	1.89	75.47	2.2
27	2	2	9.68	29.81	2	10.5	11.07
28	2	2	19.3	38.69	2	13.16	6.74
29	1	2	18.44	47.61	6	24.79	4.96
30	1	3	10	49.14	2.5	15	9.3
31	1	1	15.88	44.36	2	47	2.12
32	2	2	18.44	47.61	6	24.79	5.58
33	2	2	19.66	43.56	3	19.38	4.81
34	2	3	9.5	39.94	3.37	84.21	5.16
35	2	1	9.53	49	6	21.33	6.2
36	2	1	12.7	31.02	2.36	97.24	1.65
37	2	2	12.7	28.94	5.5	5	17.76
38	2	2	6.35	46.51	3.12	78	1.52
39	2	1	12.7	51.98	5.41	20	7.5
40	2	1	12.7	37.95	9.34	10	12.29
41	1	1	19.05	47.75	6	24	4.8
42	2	1	12.7	36.97	9.3	10	14.45
43	2	2	10	25.1	4	10	16
44	2	2	10	30.14	4	20	9
45	2	2	10	26.63	4	20	11.4
46	2	1	15.75	44.36	3	20.16	5
47	2	1	10.6	40.2	1.89	61.32	3
48	2	2	10	31.81	4	20	12.3
49	2	2	19.66	43.56	2	25.84	4.61
50	2	1	12.7	30.91	3.4	10	10.56
51	2	3	9.5	40.96	3.37	52.63	5.8
52	2	2	10	31.25	3.8	20	12.09
53	2	1	15.75	44.36	3	24.19	4.74
54	2	1	15.75	44.36	3	24.19	4.64
55	2	1	10.6	40.2	1.89	61.32	2.6

Table A1. *Cont.*

Test No.	*Pos*	*Surf*	d_b (mm)	$f'c$ (Mpa)	c/d_b	l_d/d_b	τ_b (Mpa)
56	2	2	12.7	28.94	5.5	7.5	15.15
57	2	2	19.66	43.56	3	19.38	6.3
58	2	2	27.41	44.62	6	27.8	3.43
59	1	2	27.41	44.62	6	27.8	3.57
60	2	1	10.6	35.05	1.89	70.75	3.3
61	2	1	15.75	44.36	2	75.81	1.7
62	1	1	19.05	43.56	3	15	7.58
63	2	3	9.5	43.03	3.37	68.42	5.69
64	2	1	15.75	44.36	2	20.16	4.84
65	2	1	15.75	44.36	3	20.16	5.14
66	2	1	15.75	44.36	2	24.19	4.26
67	2	1	15.9	31.02	1.89	97.17	2.31
68	2	3	19.1	39.94	2.09	36.65	2.8
69	1	1	9.53	35.05	4	16	8.9
70	2	2	19.66	43.56	3	19.38	5.79
71	2	1	10.6	38.32	1.89	76.42	4
72	2	2	9.68	48.86	4	15.75	9.3
73	2	1	12.7	31.02	2.36	78.74	1.96
74	2	2	6.35	46.51	3.12	78	1.01
75	2	3	9.5	40.96	3.37	52.63	5.3
76	2	2	18.44	39.06	4	22.04	5.62
77	2	1	15.9	31.02	1.89	54.72	2.64
78	2	2	15.88	28.94	4.4	5	18.87
79	2	1	9.53	49	4	16	9.3
80	2	2	19.66	43.56	3	19.38	6.02
81	2	1	12.7	55.06	9.34	20	7.41
82	2	1	15.75	44.36	3	20.16	4.98
83	2	2	10	26.63	4	10	13.61
84	2	3	19.05	23.43	3.7	7.5	14.8
85	2	1	15.75	44.36	2	20.16	5.06
86	2	1	12.7	28.94	5.5	5	19.14
87	2	1	15.75	44.36	2	20.16	4.72
88	2	3	9.5	39.94	4.21	52.63	6.91
89	2	3	9.5	43.03	3.37	84.21	3.74
90	2	3	9.5	39.94	4.21	68.42	5.69
91	2	1	15.9	31.02	1.89	42.45	3.14
92	2	1	12.7	39.94	9.3	10	12.25
93	2	2	19.66	43.56	2	25.84	4.53
94	2	1	15.75	44.36	2	75.81	1.65
95	2	2	19.66	43.56	3	25.84	4.64
96	2	2	19.05	28.94	3.7	5	10
97	2	2	6.35	46.51	3.12	78	0.76
98	2	3	15.9	39.94	2.52	31.45	4.04
99	2	2	6.35	46.51	3.12	78	1.9
100	2	1	10.6	35.05	1.89	66.04	2.1
101	2	2	19.66	43.56	2	25.84	5.37
102	1	2	9.68	48.86	4	15.75	8.15
103	2	2	16	31.25	2.38	20	9.59
104	2	1	15.88	28.94	4.4	5	17.35
105	2	1	12.7	39.94	9.34	10	14.49
106	2	2	10	36.84	3.8	10	13.39
107	2	1	15.75	44.36	3	24.19	4.45
108	1	3	8	49.14	3.13	15	5.77
109	2	1	12.7	28.94	5.5	5	21
110	2	2	19.66	43.56	2	25.84	5.33
111	2	1	28.58	27.56	2	3.56	15.19
112	2	1	19.05	39.19	6	24	5.1
113	2	3	12.7	39.94	3.15	62.99	4.71
114	2	2	6.35	46.51	3.12	78	1.75
115	1	3	10	49.14	2.5	15	7.8

Table A1. *Cont.*

Test No.	*Pos*	*Surf*	d_b (mm)	$f'c$ (Mpa)	c/d_b	l_d/d_b	τ_b (Mpa)
116	2	1	15.75	44.36	2	20.16	4.55
117	2	2	10	28.84	4	10	13.41
118	2	1	19.05	28.94	3.7	5	16.87
119	2	2	10	32.38	3.8	15	10.09
120	2	1	12.7	28.94	5.5	7.5	17.29
121	2	2	10	27.25	4	40	6.99
122	2	1	9.53	35.05	6	21.33	7.8
123	2	1	12.7	39.94	9.34	5	16.49
124	2	1	15.75	44.36	3	16.13	5.97
125	2	2	10	39.31	3.8	20	9.6
126	2	1	12.7	30.91	3.4	16	8.67
127	2	1	15.75	44.36	2	24.19	4.71
128	2	2	19.66	43.56	2	19.38	4.86
129	2	2	9.68	34.93	6	21	7.55
130	1	3	10	49.14	2.5	15	8.45
131	2	2	10	32.38	3.8	15	10.4
132	2	2	12.7	30.91	3.4	10	12.27
133	2	1	8	31.02	5	20	11.01
134	2	2	19.3	38.69	2	13.16	7.15
135	2	1	15.75	43.56	2	20.16	4.83
136	2	1	9.53	35.05	4	16	9.9
137	2	1	19.05	39.19	4	21.33	5.4
138	2	2	19.66	43.56	3	19.38	4.96
139	2	2	10	29.48	4	10	15
140	2	2	12.7	28.94	5.5	5	19.35
141	1	3	11	49.14	2.27	15	7.47
142	1	1	15.88	44.36	3	12.5	8.61
143	2	3	9.5	39.94	4.21	52.63	5.3
144	2	3	12.7	39.94	3.15	39.37	6
145	2	3	19.1	39.94	2.09	41.88	3.3
146	2	1	10.6	40.2	1.89	61.32	3.7
147	2	3	9.5	39.94	4.21	52.63	4.78
148	2	2	13.46	38.69	2	10.38	9.69
149	2	3	9.5	40.96	3.37	52.63	4.78
150	2	1	15.9	31.02	1.89	54.72	2.44
151	2	1	10.6	35.05	1.89	66.04	4.4
152	2	2	27.41	39.69	6	27.8	3.79
153	2	1	15.75	44.36	3	20.16	5.59
154	1	1	28.58	47.33	6	26.67	3.6
155	2	1	9.53	49	2	10.67	12.1
156	2	1	10.6	40.2	1.89	61.32	3.9
157	2	2	19.66	43.56	2	32.3	3.41
158	2	2	19.66	43.56	2	19.38	4.68
159	2	1	15.75	44.36	3	16.13	6.15
160	2	1	15.75	44.36	3	24.19	4.31
161	2	2	19.3	38.69	2	13.16	6.31
162	2	2	10	31.25	4	20	9.39
163	2	1	15.75	44.36	3	16.13	6.11
164	2	1	19.05	47.75	4	21.33	5.2
165	2	1	28.58	39.69	6	26.67	3.6
166	2	1	19.05	28.94	3.7	7.5	14.39
167	1	2	9.68	34.93	4	15.75	8.53
168	1	2	27.41	39.69	6	27.8	3.84
169	2	2	19.3	38.69	2	13.16	6.46
170	2	3	15.9	43.03	2.01	44.03	2.95
171	2	1	19.05	47.75	6	24	4.9
172	1	1	19.05	39.19	6	24	5.2
173	2	1	12.7	31.02	2.36	36.22	3.73

Table A1. *Cont.*

Test No.	*Pos*	*Surf*	d_b (mm)	$f'c$ (Mpa)	c/d_b	l_d/d_b	τ_b (Mpa)
174	2	1	12.7	51.84	9.3	30	4.61
175	2	2	10	41.47	3.8	15	9
176	2	1	12.7	37.95	9.3	20	7.5
177	2	3	9.5	39.94	4.21	84.21	3.74
178	2	2	19.66	43.56	3	25.84	5
179	2	1	8	31.02	5	15	10.2
180	2	1	15.75	44.36	2	75.81	1.07
181	2	3	19.1	39.94	2.09	26.18	3.6
182	2	3	9.5	40.96	3.37	115.79	4.76
183	1	3	8	49.14	3.13	15	8.38
184	1	1	15.88	44.36	3	15	7.11
185	2	2	10	31.25	3.8	20	11.39
186	2	1	15.75	44.36	2	75.81	1.41
187	1	3	13	49.14	1.92	15	4.96
188	2	2	10	33.18	4	20	10.6
189	2	2	16	41.47	2.38	15	11.89
190	2	1	15.75	44.36	3	24.19	4.43
191	2	1	15.75	43.56	2	20.16	5.28
192	2	2	19.05	28.94	3.7	5	16.6
193	2	1	15.75	44.36	3	16.13	5.65
194	2	1	12.7	55.06	5.41	20	7.41
195	2	2	19.66	43.56	2	19.38	5.3
196	2	2	10	28.94	4	20	10.61
197	1	1	28.58	39.69	6	26.67	3.6
198	2	3	19.1	39.94	2.09	57.59	2.56
199	2	3	9.5	39.94	4.21	84.21	5.16
200	2	1	12.7	31.02	2.36	97.24	1.63
201	1	3	10	49.14	2.5	15	7.37
202	2	1	15.75	44.36	2	20.16	5.23
203	2	1	12.7	49.98	9.34	30	4.6
204	2	2	9.68	48.86	6	21	6.19
205	2	2	19.66	43.56	2	19.38	5.37
206	2	3	19.1	40.96	1.68	26.18	3.6
207	2	1	15.75	44.36	2	75.81	0.97
208	2	1	15.75	43.56	2	20.16	4.66
209	1	2	27.41	39.69	4	24.1	3.94
210	2	2	16	39.31	2.38	20	9.2
211	1	3	12	49.14	2.08	15	7.54
212	2	3	19.1	39.94	3.66	36.65	2.9
213	2	1	15.75	44.36	2	75.81	1.22
214	1	2	18.44	39.06	6	24.79	5.35
215	2	2	19.66	43.56	3	25.84	4.75
216	2	1	15.75	44.36	3	16.13	7.35
217	1	1	28.58	44.76	2	19.56	3.8
218	2	3	9.5	39.94	4.21	68.42	5.13
219	2	1	15.75	44.36	2	20.16	2.57
220	2	1	10.6	35.05	1.89	66.04	3
221	1	2	9.68	29.81	2	10.5	11.94
222	2	1	15.75	44.36	3	20.16	5.85
223	2	3	19.1	40.96	1.68	57.59	2.56

References

1. Cosenza, E.; Manfredi, G.; Realfonzo, R. Behavior and modeling of bond of FRP rebar to concrete. *J. Compos. Constr.* **1987**, *1*, 40–45. [CrossRef]
2. Edwards, A.D.; Yannopoulos, P.J. Local bond stress to slip relationship for hot rolled deformed bars and mild steel plain bars. *ACI J.* **1979**, *7*, 405–419.

3. Galati, N.; Nanni, A.; Dharani, L.R.; Focacci, F.; Aiello, M.A. Thermal effects on bond between FRP rebars and concrete. *Compos. Manuf. A* **2006**, *37*, 1223–1230. [CrossRef]
4. Hao, Q.D.; Wang, B.; Ou, J.P. Fiber reinforced polymer rebar's application to civil engineering. *Concrete* **2006**, *9*, 38–40.
5. Benmokrane, B.; Tighiouart, B. Bond strength and load concrete. *ACI Mater. J.* **1996**, *93*, 254–259.
6. Makitani, E.; Irisawa, I.; Nishiura, N. Investigation of bond in concrete member with fiber reinforced plastic bars. *Fiber-Reinf.-Plast. Reinf. Concr. Struct.-Int. Symp.* **1993**, *138*, 315–331.
7. Mazaheripour, H.; Barros, J.A.; Sena-Cruz, J.M.; Pepe, M.; Martinelli, E. Experimental study on bond performance of GFRP bars in self-compacting steel fiber reinforced concrete. *Compos. Struct.* **2013**, *95*, 202–212. [CrossRef]
8. Okelo, R.; Yuan, R.L. Bond strength of fiber reinforced polymer rebars in normal strength concrete. *J. Compos. Constr.* **2005**, *9*, 203–213. [CrossRef]
9. Yan, F.; Lin, Z.; Zhang, D.; Gao, Z.; Li, M. Experimental study on bond durability of glass fiber reinforced polymer bars in concrete exposed to harsh environmental agents: Freeze-thaw cycles and alkaline-saline solution. *Compos. Part B Eng.* **2017**, *116*, 206–421. [CrossRef]
10. Yan, F.; Lin, Z.B. Bond durability assessment and long-term degradation prediction for GFRP bars to fiber-einforced concrete under saline solutions. *Compos. Struct.* **2017**, *161*, 393–406. [CrossRef]
11. Ametrano, D. Bond Characteristics of Glass Fiber Reinforced Polymer Bars Embedded in High Performance and Ultra-High-Performance Concrete. Master's Thesis, Ryerson University, Toronto, ON, Canada, 2011; pp. 1–132.
12. Dahou, Z.; Sbartai, Z.M.; Castel, A.; Ghomari, F. Artificial neural network model for steel-concrete bond prediction. *Eng. Struct.* **2009**, *31*, 1724–1733. [CrossRef]
13. Golafshani, E.M.; Rahai, A.; Sebt, M.H.; Akbarpour, H. Prediction of bond strength of spliced steel bars in concrete using artificial neural network and fuzzy logic. *Constr. Build. Mater.* **2012**, *36*, 411–418. [CrossRef]
14. Nehdi, M.; EI Chabib, H.; EI Naggar, M.H. Predicting performance of self-compacting concrete mixtures using artificial neural networks. *ACI Mater. J.* **2001**, *98*, 394–401.
15. Parsaie, A.; Azamathulla, H.M.; Haghiabi, A.H. Prediction of discharge coefficient of cylindrical weir–gate using GMDH-PSO. *ISH J. Hydraul. Eng.* **2018**, *24*, 116–123. [CrossRef]
16. Azamathulla, H.M.; Haghiabi, A.H.; Parsaie, A. Prediction of side weir discharge coefficient by support vector machine technique. *Water Sci. Technol. Water Supply* **2016**, *16*, 1002–1016. [CrossRef]
17. D'Angelo, G.; Laracca, M.; Rampone, S. Automated eddy current non-destructive testing through low definition Lissajous figures. In Proceedings of the 2016 IEEE Metrology for Aerospace (MetroAeroSpace), Florence, Italy, 22–23 June 2016; pp. 280–285.
18. D'Angelo, G.; Laracca, M.; Rampone, S.; Betta, G. Fast eddy current testing defect classification using lissajous figures. *IEEE Trans. Instrum. Meas.* **2018**, *67*, 821–830. [CrossRef]
19. Coelho, M.R.F.; Sena-Cruz, J.M.; Neves, L.A.C.; Pereira, M.; Cortez, P.; Miranda, T. Using data mining algorithms to predict the bond strength of NSM FRP systems in concrete. *Constr. Build. Mater.* **2016**, *126*, 484–495. [CrossRef]
20. Köroğlu, M.A. Artificial neural network for predicting the flexural bond strength of FRP bars in concrete. *Sci. Eng. Compos. Mater.* **2018**, *26*, 12–29. [CrossRef]
21. Bashir, R.; Ashour, A. Neural network modelling for bars. *J. Compos. B* **2012**, *43*, 3198–3207. [CrossRef]
22. Banzhaf, W.; Nordin, P.; Keller, R.; Francone, F. *Genetic Programming—An Introduction*; Morgan Kaufmann: San Francisco, CA, USA, 1998.
23. Koza, J.R. *Genetic Programming-on the Programming of Computers by Means of Natural Selection*; MIT Press: Cambridge, MA, USA, 1993.
24. Alavi, A.H.; Gandomi, A.H. A robust data mining approach for formulation of geotechnical engineering systems. *Eng. Comput.* **2011**, *28*, 242–274. [CrossRef]
25. Alavi, A.H.; Gandomi, A.H.; Modaresnezhad, M.; Mousavi, M. New ground-motion prediction equations using multi expression programing. *J. Earthq. Eng.* **2011**, *15*, 511–536. [CrossRef]
26. Gandomi, A.H.; Alavi, A.H. Expression programming techniques for formulation of structural engineering systems. In *Metaheuristic Applications in Structures and Infrastructures*; Newnes: Burlington, MA, USA, 2013; pp. 439–455.

27. Gandomi, A.H.; Alavi, A.H.; Sahab, M.G. New formulation for compressive strength of CFRP confined concrete cylinders using linear genetic programming. *Mater. Struct.* **2010**, *43*, 963–983. [CrossRef]
28. Mohammadi Bayazidi, A.; Wang, G.G.; Bolandi, H.; Alavi, A.H.; Gandomi, A.H. Multigene genetic programming for estimation of elastic modulus of concrete. *Math. Probl. Eng.* **2014**. [CrossRef]
29. Sarveghadi, M.; Gandomi, A.H.; Bolandi, H.; Alavi, A.H. Development of prediction models for shear strength of SFRCB using a machine learning approach. *Neural Comput. Appl.* **2015**. [CrossRef]
30. Kara, I.F. Prediction of shear strength of FRP-reinforced concrete beams without stirrups based on genetic programming. *Adv. Eng. Softw.* **2011**, *42*, 295–304. [CrossRef]
31. Searson, D.P. *GPTIPS: Genetic Programming and Symbolic Regression for MATLAB*; Newcastle University Library: Newcastle upon Tyne, UK, 2009.
32. Gandomi, A.H.; Alavi, A.H. A new multi-gene genetic programming approach to nonlinear system modeling—Part I: Materials and structural engineering problems. *Neural Comput. Appl.* **2012**, *21*, 171–187. [CrossRef]
33. Gandomi, A.H.; Alavi, A.H. A new multi-gene genetic programming approach to non-linear system modeling—Part II: Geotechnical and earthquake engineering problems. *Neural Comput. Appl.* **2012**, *21*, 189–201. [CrossRef]
34. Muduli, P.K.; Das, S.K. CPT-based seismic liquefaction potential evaluation using multi-gene genetic programming approach. *Indian Geotech. J.* **2014**, *44*, 86–93. [CrossRef]
35. Rezaei, M.; Eftekhari, M.; Mahin, S.; Ranjbar, M. A CO_2-oil minimum miscibility pressure model based on multi-gene genetic programming. *Energy Explor. Exploit.* **2013**, *31*, 607–622. [CrossRef]
36. Mousavi, S.M.; Aminian, P.; Gandomi, A.H.; Alavi, A.H.; Bolandi, H. A new predictive model for compressive strength of HPC using gene expression programming. *Adv. Eng. Softw.* **2012**, *45*, 105–114. [CrossRef]
37. Golafshani, E.M.; Rahai, A.; Sebt, M.H. Artificial neural network and genetic programming for predicting the bond strength of GFRP bars in concrete. *Mater. Struct.* **2015**, *48*, 1581–1602. [CrossRef]
38. Searson, D.P.; Leahy, D.E.; Willis, M.J. GPTIPS: An open source genetic programming toolbox for multigene symbolic regression. In Proceedings of the International Multi-Conference of Engineers and Computer Scientists (IMECS '10), Hong Kong, China, 17–19 March 2010; pp. 77–80.
39. Aly, R.; Benmokrane, B. Bond splitting strength of lap splicing of GFRP bars in concrete. In Proceedings of the 33rd Annual General Conference of the Canadian Society for Civil Engineering, Toronto, ON, Canada, 2–4 June 2010.
40. Aly, R.; Benmokrane, B.; Ebead, U. Tensile lap splicing of fibre-reinforced polymer reinforcing bars in concrete. *ACI Struct. J.* **2006**, *103*, 857–864.
41. Cosenza, E.; Manfredi, G.; Pecce, M.; Realfonzo, R. Bond between glass fiber reinforced plastic reinforcing bars and concrete-experimental analysis. *ACI SP Int. Symp. FRP Reinf. Concr.* **1999**, *188*, 347–358.
42. DeFreese, J.M.; Wollmann, R.C.L. *Glass Fiber Reinforced Polymer Bars as Top Mat Reinforcement for Bridge Decks*; Contract Report for Virginia Transportation Research Council: Charlottesville, VA, USA, 2002.
43. Ehsani, M.R.; Saadatmanesh, H.; Tao, S. Bond of GFRP rebars to ordinary-strength concrete. *ACI IntSympon Non-Met. Contin. Reinf.* **1993**, *138*, 333–346.
44. Ehsani, M.R.; Saadatmanesh, H.; Tao, S. Design recommendations for bond of GFRP rebars to concrete. *J. Struct. Eng.* **1996**, *122*, 247–254. [CrossRef]
45. Kanakubo, T.; Yonemaru, K.; Fukuyama, H.; Fujisawa, M.; Sonobe, Y. Bond performance of concrete members reinforced with FRP bars. *Fiber-Reinf.-Plast. Reinf. Concr. Struct.-Int. Symp.* **1993**, *138*, 767–788.
46. Maji, A.; Orozco, A.L. Prediction of bond failure and deflection of carbon fiber reinforced plastic reinforced concrete beams. *Exp. Mech.* **2005**, *45*, 35–41. [CrossRef]
47. Okelo, R. Realistic bond strength of FRP rebars in NSC from beam specimens. *J. Aerosp. Eng.* **2007**, *20*, 133–140. [CrossRef]
48. Pecce, M.; Manfredi, G.; Realfonzo, R.; Cosenza, E. Experimental and analytical evaluation of bond properties of GFRP bars. *J. Mater. Civ. Eng.* **2001**, *13*, 282–290. [CrossRef]
49. Shield, C.K.; French, C.W.; Retika, A. Thermal and mechanical fatigue effects on GFRP rebar-concrete bond. In Proceedings of the Third International Symposium on Non-Metallic Reinforcement for Concrete Structures, Sapporo, Japan, 14–16 October 1997; pp. 381–388.
50. Shield, C.K.; French, C.W.; Hanus, J.P. Bond of glass fiber reinforced plastic reinforcing bar for consideration in bridge decks. *ACI SP Int. Symp. FRP Reinf. Concr.* **1999**, *188*, 393–406.

51. Thamrin, R.; Kaku, T. Bond behaviour of CFRP bars in simply supported reinforced concrete beam with hanging region. *J. Compos. Constr.* **2007**, *11*, 129–137. [CrossRef]
52. Tughiouart, B.; Benmokrane, B.; Geo, D. Investigation of bond in concrete member with fiber reinforced polymer (FRP) bars. *Constr. Build. Mater.* **1998**, *12*, 453–462. [CrossRef]
53. Tughiouart, B.; Benmokrane, B.; Mukhopadhyaya, P. Bond strength of glass FRP rebar splices in beams under static loading. *Constr. Build. Mater.* **1999**, *13*, 383–392. [CrossRef]
54. Won, J.P.; Park, G.G.; Kim, H.H.; Lee, S.W.; Jang, C.I. Effect of fibers on the bonds between FRP reinforcing bars and high-strength concrete. *Compos. Part B Eng.* **2008**, *39*, 747–755. [CrossRef]
55. Gandomi, A.H.; Alavi, A.H.; Sahab, M.G.; Arjmandi, P. Formulation of elastic modulus of concrete using linear genetic programming. *J. Mech. Sci. Technol.* **2010**, *24*, 1273–1278. [CrossRef]
56. American Concrete Institute. *ACI Committee 440.1R-06 (2006) Guide for the Design and Construction of Structural Concrete Reinforced with FRP Bars*; American Concrete Institute: Farmington Hills, MI, USA, 2006.