Bond strength prediction of spliced GFRP bars in concrete beams using soft computing methods

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Abstract. The bond between the concrete and bar is a main factor affecting the performance of the reinforced concrete (RC) members, and since the steel corrosion reduces the bond strength, studying the bond behavior of concrete and GFRP bars is quite necessary. In this research, a database including 112 concrete beam test specimens reinforced with spliced GFRP bars in the splitting failure mode has been collected and used to estimate the concrete-GFRP bar bond strength. This paper aims to accurately estimate the bond strength of spliced GFRP bars in concrete beams by applying three soft computing models including multivariate adaptive regression spline (MARS), Kriging, and M5 model tree. Since the selection of regularization parameters greatly affects the fitting of MARS, Kriging, and M5 models, the regularization parameters have been so optimized as to maximize the training data convergence coefficient. Three hybrid model coupling soft computing methods and genetic algorithm is proposed to automatically perform the trial and error process for finding appropriate modeling regularization parameters. Results have shown that proposed models have significantly increased the prediction accuracy compared to previous models. The proposed MARS, Kriging, and M5 models have improved the convergence coefficient by about 65, 63 and 49%, respectively, compared to the best previous model.

Keywords: bond strength; spliced GFRP bars; concrete beams; soft computing methods; genetic algorithm

1. Introduction

The bond between the bars and concrete is a key factor influencing the mechanical features of the structure (Turk et al. 2005, Ahmad et al. 2018, Golafshani et al. 2014) and an important design parameter that manages the performance of RC sections in both the ultimate and serviceability limit states (Lin et al. 2019). In different offensive environments, corrosion of steel reinforcement is one of the most momentous hazards found in reinforced concrete structures (Maurel et al. 2005, Yao et al. 2015, Moodi et al. 2017, Shirhkhani et al. 2019). Corrosion of steel reinforcement leads to a large reduction of the effective cross-section of the steel rebars. As a result, the bond strength of rebar and concrete undergoes a notable decrease (Wang and Liu 2004). This has caused a growing need for such alternative materials as FRP bars for RC structures. GFRP bars have been more popular for their superior corrosion resistance, high strength-to-weight ratio, and high-cost efficiency (Nanni et al. 1995). For an optimum RC structure design, the load at the concrete and reinforcement interface should be transferred efficiently and reliably through the bond between the two materials (Golafshani et al. 2014). So far, numerous studies have been conducted to estimate the bar-concrete bond strength in spliced concrete beams. Ehsani et al. (1996) proposed a relationship to predict the bond strength of GFRP bars in terms of the bar diameter and concrete compressive strength. The Japanese Design Recommendation (1997) (JSCE) has predicted the bond strength of FRP bars in the splitting failure mode by modifying the steel bars’ bond strength equation. Okelo and Yuan (2005) suggested a relationship similar to that of Ehsani et al. (1996) to estimate the bond strength of FRP bars. Considering the effects of bar diameter, splice length, concrete cover, and confinement provided by the transverse reinforcement, Aly (2005) predicted the bond strength of the GFRP and CFRP bars. Wambeke and Shield (2006) proposed a relationship to calculate the bond strength of GFRP bars through linear regressions on a database including RC beams with GFRP bars; the ACI 440.1R-15 guidelines (2015) has used their relationship. The CAN/CSA S806-12 code (2012) has determined the bond strength of FRP bars considering such parameters as the concrete cover, bar casting position, concrete strength, bar diameter, fiber type and bar surface properties. Choi et al. (2012) presented two relationships to predict the bond strength of the GFRP bars. Esfahani et al. (2013) predicted the bond strength of GFRP bars by the Monte Carlo simulation method considering the effects of such parameters as the transverse reinforcement, bar surface properties, bar diameter, and concrete compressive strength. The CAN/CSA-S6-14 (2014) has predicted the bond strength of FRP bars considering the effects of bar elasticity modulus, confinement, concrete cover, bar casting position, bar diameter, and bar surface properties. Xue et al. (2014) proposed a relationship to calculate the bond strength of the GFRP bars with diameters less than 20 mm and embedment...
lengths less than 20 times the bar diameter. Using the artificial neural network and genetic programming approaches, Golafshani et al. (2015) predicted the bond strength of GFRP bars considering the effects of seven different variables. Ashrafi et al. (2017) proposed an empirical relationship to predict the ultimate tensile stress and the free-end slip of GFRP bars. Bazli et al. (2017) developed some equations to evaluate the influence of various parameters on the bond strength between the different types of concrete and GFRP bars under environmental conditions. Rakhashanimehr et al. (2018) suggested some equations for the local bond strength and displacement modulus of GFRP bars and finally presented a relationship for the bond strength of spliced GFRP bars in RC beams considering the non-uniform distribution of the bond stress along with the splice and effects of the elasticity modulus of the GFRP bars. Koroglu (2018) proposed ANN and regression models to forecast the FRP bar-concrete bond strength.

Although researches that estimate the bond strength of GFRP bars are numerous, studies have shown that the prediction accuracy of their proposed relationships can be improved. To this end, some researchers have suggested that different coefficients of existing relationships can be modified to enhance the prediction accuracy (Zemour et al. 2018). Some others have used machine learning and soft computing methods to achieve higher prediction accuracy (Golafshani et al. 2015). A reliable experimental database, including the 112 spliced concrete beams reinforced with GFRP bars, has been collected from the literature. Most previous models have estimated the bond strength much more or much less than the test values. This paper has made use of the improved MARS, Kriging, and M5 models to forecast the bond strength of GFRP bars in spliced concrete beams with high precision. Since proper selection of regularization parameters would greatly affect the fitting of the models, to enhance the prediction efficiency and accuracy, parameters effective in their fitting have been optimized by the genetic algorithm (GA). To ensure the generalization ability of the proposed models, training and testing data have been considered based on the ten-fold cross-validation technique. The results of the proposed methods have compared with those of other earlier researches and design codes.

2. Effective parameters in calculating the GFRP bar-concrete bond strength

2.1 Bar casting position

It was recognized that air bubbles and water move upward during the concrete casting and get stuck under the rebar. This occurrence reduces the linkage surface between bar and concrete and leads to a significant loss in the bond strength of top-cast bar specimens (Chaallal and Bennmokrane 1993, Ehsani et al. 1993, Tighiouart et al. 1998). So far, several researchers have done some tests to determine the effects of top-cast GFRP bars on the concrete-bar bond strength. Chaallal and Bennmokrane (1993) proposed a top bar factor of 1.23 for normal-strength and 1.18 for high-strength concrete. Ehsani et al. (1996) presented a 1.25 coefficient for the top bar effect. The JSCE (1997) used a 1.3 coefficient for the top-cast bar specimens. After testing the pullout specimens, and to consider the top bar factor of the GFRP bars, Tighiouart et al. (1998) suggested a 1.3 coefficient based on which the ACI 440.1R-03 guidelines (2003) considered the same coefficient for the top bar specimens. Wambeke and Shield (2006) proposed a 1.5 coefficient which was then used by ACI 440.1R-06 (2006) and ACI 440.1R-15 (2015). The CAN/CSA S806-12 (2012) and CAN/CSA S6-14 (2014) design recommendations advised a coefficient of 1.3 for the top-cast specimens. Pay et al. (2014) concluded that specimens with top bars experienced an average 7% loss in bond strength compared to those with bottom bars. Park et al. (2016) considered vertical, horizontal bottom, and horizontal top casting positions for the bar; results showed that the average bond strength of the horizontal top and horizontal top castings were, respectively, 91 and 40% of that of the vertical casting. Saleh et al. (2019) concluded that the bond strength of the specimens with bottom bars was more than that with top bars. To study this effect more precisely, the current paper has collected some similar-characteristic test specimens (Table 1), has found the bond strength ratio of specimens with bottom bars to those with top bars to be 1.12, and has divided the bond strength (estimated through soft computing models) by 1.12 for specimens with top GFRP bars.

2.2 Concrete compressive strength

Studies have revealed that the compressive strength of the concrete nearby the rebar is strictly relevant to the failure type as well as the bond strength. Malvar (1994) showed that for the splitting failure, an increment in the concrete compressive strength would improve the bond strength. Results of the studies of many researchers have shown that the bond strength of FRP bars and concrete has a good relevance with the square root of the concrete compressive strength (Faza and GangaRao 1990, Pleimann 1987, Okelo and Yuan 2005). Achillides and Pilakoutas (2004) found that for the high-strength concrete (>30 MPa), failure would appear on the surface of the FRP reinforcement, and when compressive strength was close to 15 MPa, the concrete damaged in front of the ribs of the FRP reinforcement. Lee et al. (2009) concluded that the bond strength of the steel and helically wrapped GFRP bars was more proportionate to the concrete compressive strength, and that of the sand-coated GFRP bars was determined more by the relative interfacial strengths of interfaces. Baena et al. (2009) showed that the concrete strength influenced the failure mode, and the bond strength of FRP reinforcement did not depend much on the concrete compressive strength for values of more than 30 MPa. Zhou et al. (2012) observed that an increment in the concrete strength would enhance the bond strength of the sand-coated GFRP bars. Hossain et al. (2017) studied the bond characteristics of GFRP bars in the high-strength concrete and ultra-high-strength concrete and concluded that bond
Table 1 Bond strength comparison for specimens with bottom and top-cast GFRP bars

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strength would improve with increasing the concrete compressive strength.

2.3 Bar diameter

For an assumed splice length, the entire bond force generated by the bar increases with increasing the bar diameter. Since the increase rate of bond strength is less than that of the bar cross-sectional area, an increase in the bar diameter will reduce the bond stress. Using the bar with higher diameter leads to the reduction of pullout stress. Thus, as the bar diameter increases, a higher splice length is needed (Nanni et al. 1995, Tighiouart et al. 1998). When the diameter of the bar is larger, more leakage water gets stuck under the rebar which will decrease the bar-concrete linkage surface and the bond strength (Ehsani et al. 1996, Tighiouart et al. 1998, Hao et al. 2006, Baena et al. 2009).

2.4 Concrete cover

The concrete cover encloses the reinforcement and thus increases the bond strength. When the concrete cover is enough, splitting failure will be prevented or delayed (ACI 440.1R-03 2003). Ehsani et al. (1996) observed that the concrete cover extremely affected the bond failure type of FRP bars. Aly (2005) showed that an increase in the concrete cover by up to four times the diameter of FRP bars would increase the bond strength by 27%. Many papers have shown that the concrete cover thickness and bond strength of FRP bars are related (Harajli and Aboumaja 2010, CAN/CSA S806-12 2012, Kotynia et al. 2017). The effect of the concrete cover has been regarded by the ratio of the concrete cover to the bar diameter (C/dh). Where C is the minimum of the side cover, bottom cover, or one-half of the clear spacing between developed bars.

2.5 Splice or embedment length

An increase in the splice length will cause the bond stress distribution to be non-linearized and bond stresses to reduce; the more the splice length becomes, bond stresses will be distributed over a longer length thereby reducing the bar-concrete bond strength. Results of many studies have shown that an increase in the bar splice or embedment lengths will reduce the bond strength of FRP bars (Achillides and Pilakoutas 2004, Okelo and Yuan 2005, CAN/CSA S806-12 2012, Saleh et al. 2019). Embedment length also affects the type of bond failure. Zhou et al. (2012) studied the bond behavior of sand-coated FRP bars and showed that for embedment lengths less than five times the bar diameter, failure is of the pullout type, and for those more than that, it is of the splitting type. The effect of the splice length has been considered by the ratio of the splice length to the bar diameter (L/dh).

2.6 Bar elasticity modulus

Achillides (1998) showed that the splitting bond strength of FRP bars was close to 65 to 75% that of CFRP bars indicating the important role of the bar elasticity modulus in the splitting bond behavior. Mosley et al. (2008) conducted three sets of spliced beam tests with GFRP, AFRP, and steel bars and showed that the bond strength of FRP bars was much less than that of steel bars, and the bar elasticity modulus was a fundamental variable affecting the bond strength. Pay et al. (2014) also have pointed to the effect of the bar elasticity modulus on the bond strength. The effect of the bar elasticity modulus has been considered by the ratio of the elasticity modulus of steel bars to that of FRP bars (E/Eyp).
2.7 Bar surface properties

So far, many researchers have investigated the bond performance of various FRP bars with different surface features and shown that the presence of ribs on the bar surface would improve the bond behavior compared to non-ribbed surfaces. Makitani et al. (1993) concluded that surface features of FRP bars affect the bond strength. Although many researchers have pointed to the role of the bar surface features in the bond strength of FRP bars (Malvar 1994, Achillides and Pilakoutas 2004, Baena et al. 2009, Zhou et al. 2012, Esfahani et al. 2013), some others have believed that such features have had no significant effects on the bond strength (Wambeke and Shield 2006, Pay et al. 2014, Mosley et al. 2008). The parameter \( \alpha \) accounts for the effect of bar surface properties based on the work by Esfahani et al. (2013).

2.8 Transverse reinforcement

So far, few researchers have examined the effects of transverse reinforcement on the bond strength of FRP bars; however, some have shown that its presence along the splice will prevent splitting cracks and will cause the bond force required for failure to increase (Orangun et al. 1977, Tepfers 1982). Achillides (1998) showed that in RC specimens with FRP bars, the transverse reinforcements restrict the crack width after the creation of the splitting cracks and, hence, improve the bond strength. Wambeke and Shield (2006) studied previous papers’ test specimens with transverse reinforcements and concluded that their presence had no notable influence on the bond strength of GFRP bars may be due to their lower relative rib area. Some other researchers have pointed to the effects of transverse reinforcement on the bond strength of FRP bars (Kanakubo et al. 1993, Aly 2005, Esfahani et al. 2013). The effect of the transverse reinforcement has been considered by the ratio of the area of transverse reinforcement to the product of transverse reinforcement spacing, number of developed bars and bar diameter (\( A/snd_b \)).

3. Existing models in predicting bond strength of GFRP bars

The JSCE (1997) revised equations which were used to specify the bond strength for steel bars and proposed the following equation for FRP bars

\[
u_a = \frac{f_{bd}}{1 + \alpha_i}
\]

where \( \nu_a, f_{bd}, \) and \( \alpha_i \) are the bond strength of FRP bars, design bond strength of concrete, and confinement modification factor, respectively. The confinement modification factor can be determined by using the parameter \( k_c \), as follows

\[
k_c = \frac{C'}{d_b} + 15\frac{A_y}{s d_b} \frac{E_s}{E_t}
\]

where \( C' \) is the minimum of bottom clear cover of main reinforcement and half of the clear space between the developed reinforcement (mm), \( d_b \) is the bar diameter (mm), \( A_y \) is the area of transverse reinforcement (mm²), \( s \) is the spacing between the transverse reinforcement (mm), \( E_s \) is the elasticity modulus of transverse reinforcement (MPa), \( E_t \) is the elasticity modulus of steel (MPa), \( f_{bd} \) is the design bond strength between concrete and bar (MPa), \( \alpha_1 \) is the modification factor for bond strength, and \( f_{c} \) is the compressive strength of concrete (MPa).

Okelo and Yuan (2005) performed 151 pullout tests on FRP (AFRP, CFRP, and GFRP) and steel bars to investigate their bond characteristics. They presented the following equation to estimate the bond strength of FRP bars

\[
u_a = \frac{14.7\sqrt{f'}}{d_b}
\]

Aly (2005) tested 33 beam specimens reinforced with spliced carbon or glass FRP bars. He proposed an equation for calculating the bond strength of tensile lap-splice of FRP bars, as follows

\[
u_a = \frac{1}{4490} \left[ \frac{1}{1.5} \frac{f''}{E} + \frac{1}{800} \frac{d_b}{108L_y} \right] + \frac{A_y f_s}{41.5 s d_b}
\]

where \( L_y \) is the splice length (mm), \( E_{f'p} \) is the elasticity modulus of FRP bar (MPa), and \( f_s \) is the yield stress of transverse reinforcement (MPa).

Wambeke and Shield (2006) used a manner similar to that used by Orangun et al. (1977) and presented the following expression for predicting the average bond strength of GFRP bars in the splitting mode of failure

\[
u_a = \frac{1}{0.083 \sqrt{f'}} = \frac{1}{\alpha} \left[ 4 + 0.3 \frac{C''}{d_b} + 100 \frac{L_y}{d_b} \right]
\]

where \( C'' \) is the minimum of the cover to the center of the bar, and one-half of the center-to-center spacing of the developed bars (mm), and \( \alpha \) is the top bar factor which was recommended to be 1.5 and 1 for top and bottom bar specimens, respectively. ACI 440.1R-06 (2006) subscribed to the equation proposed by Wambeke and Shield (2006) for predicting the bond strength of FRP bars. This equation has also been used by ACI Committee 440 for inclusion in the latest version (ACI 440.1R-15 2015).

Based on the CAN/CSA-S806-12 (2012), the bond strength between FRP rebars and concrete can be calculated from Eq. (8).

\[
u_a = \frac{d_s \sqrt{f'}}{1.15(k_i k_j k_i k_e) s d_b}
\]
where \( d_{ct} \) represents minimum of distance from the concrete surface to the center of the developed bars and two-thirds of the center-to-center distance of the developed bars (shall not be taken greater than 2.5 times bar diameter), \( k_1 \) denotes bar location factor (1.0 for bottom cast bars and 1.3 for top cast bars), \( k_2 \) represents concrete density factor (1.0 for normal density concrete, 1.2 for semi-low-density concrete, and 1.3 for low-density concrete), \( k_3 \) corresponds to rebar size factor (1.0 for \( A_b > 300 \text{ mm}^2 \) and 0.8 for \( A_b \leq 300 \text{ mm}^2 \)), \( k_4 \) denotes bar fiber factor (1.25 for AFRP bars and 1.0 for GFRP and CFRP bars), and \( k_5 \) represents bar surface factor (1.0 for surface roughened or sand coated or braided surfaces, 1.05 for spiral pattern surfaces or ribbed surfaces, 1.8 for indented surfaces).

The bond strength of FRP bars as per Canadian Highway Bridge Design Code CAN/CSA-S6-14 (2014) can be obtained from Eq. (9)

\[
u_n = \frac{f_{cr}(d_{ct} + K_c E_{ip} / E_b)}{0.45\pi d_b k_6 k_7}
\]

in which \( f_{cr} \) is the cracking strength of concrete (MPa), and \( K_c \) is the transverse reinforcement index given by \( A_{df}/d_{10.5m} \).

Choi et al. (2012) proposed two following equations to predict the average bond strength of the GFRP bars

\[
\frac{\nu_n}{\sqrt{f_b}} = 0.037 + 0.151 \frac{C}{d_b} + 7.719 \frac{d_b}{L_c}
\]

(10)

\[
\frac{\nu_n}{\sqrt{f_b}} = \left( \frac{0.1 C_0}{C_{min}} + 0.9 \right) \left( 0.026 + 0.149 \frac{C}{d_b} + 7.709 \frac{d_b}{L_c} \right)
\]

(11)

where \( C_{max} \) and \( C_{min} \) are the maximum and minimum of the bottom and side concrete covers, respectively.

Esfahani et al. (2013) suggested the following equation for predicting the bond strength of GFRP bars

\[
\frac{\nu_n}{0.083 \sqrt{f_b}} = \frac{1}{\alpha} \left( 2.36 + 0.177 \frac{C^*}{d_b} + 59 \frac{d_b}{L_c} + f_b \frac{A_{bf}/s_b}{s_b} \right)
\]

(12)

where \( f_b \) is the surface factor of GFRP bar (0.03 for helical wrapped, 0.08 for grooved, 0.17 for sand coated, and 0.21 for ribbed surfaces).

Xue et al. (2014) introduced the following expression for estimating the bond strength of GFRP bars with the diameter less than 20 mm and the embedment length less than 20 times bar diameter

\[
u_n = \alpha' \left( 5.27 f_I \right) \left( 1.477 - 0.028 d_b \right) \left( \frac{L_c}{d_b} \right)^{0.62}
\]

(13)

where \( \alpha' \) represents the coefficient of the outer surface of GFRP bar (1 for sand-coated deformed, 0.64 for sand-coated ribbed, and 0.67 for fabric coated bars), and \( f_I \) denotes the specified tensile strength of concrete (MPa).

Rahkshanimehr et al. (2018) proposed some equations for calculating the local bond strength (Eq. (14)) and the displacement modulus of GFRP bars based on the results of the eccentric and concentric pullout tests. The non-uniform distribution of bond stress (Eq. (15)) and the elasticity modulus of GFRP bars were included in their investigation.

The bond strength of spliced GFRP bars was estimated by using Eq. (16).

\[
u_n = 2.7 \cdot \frac{C}{d_b} + 0.5 \cdot \frac{C}{d_b} + 3.6 \sqrt{f_b}
\]

(14)

\[
M = Cosh(0.0022 L_c \left( \frac{E_f}{E_{ip}} \frac{3}{d_b} \right))
\]

(15)

\[
u_n = \frac{0.24}{\alpha} \left( 1 + \frac{1}{M} \right) \left( 0.85 + 0.15 \frac{C_{med}}{C} \right)
\]

(16)

where \( \nu_n \) denotes the positional bond strength, \( M \) represents the parameter of the non-uniform distribution of bond stress. \( C \) and \( C_{med} \) are the minimum and median of bottom cover, side cover and one-half of the center-to-center spacing of the developed bars, respectively.

4. Data set and modeling methodology

The database of the spliced concrete beams reinforced with GFRP bars in the splitting failure mode contains 112 specimens tested by Achillides (1998), Tighiouart et al. (1999), Aly (2005), Mosley et al. (2008), Harajli and Abouinaj (2010), Choi et al. (2012), Esfahani et al. (2013), Pay et al. (2014), Choi et al. (2014), Rezaei (2017), and Zemour et al. (2018). To avoid over-fitting errors and to ensure the generalization capability of proposed methods, the models are trained and tested according to the ten-fold cross-validation technique. In this technique, the database is randomly broken into ten divisions. Then, one of the divisions is selected to test the model, and the remaining divisions are used to train the model. This manner repeated ten times with different test divisions. To estimate the bond strength of GFRP bars, the effects of seven variables are considered as inputs. Table 2 shows the details of the range of variations of the input and output parameters of the test specimens in the database.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>( f_I ) (MPa)</td>
<td>20</td>
<td>72</td>
<td>35.55</td>
<td>10.18</td>
</tr>
<tr>
<td>( d_b ) (mm)</td>
<td>8.5</td>
<td>25.4</td>
<td>15.06</td>
<td>3.60</td>
</tr>
<tr>
<td>( C/d_b )</td>
<td>1</td>
<td>3</td>
<td>1.73</td>
<td>0.46</td>
</tr>
<tr>
<td>( L/d_b )</td>
<td>15</td>
<td>75</td>
<td>34.94</td>
<td>12.25</td>
</tr>
<tr>
<td>( E_f/E_{ip} )</td>
<td>3.5</td>
<td>5.68</td>
<td>4.76</td>
<td>0.61</td>
</tr>
<tr>
<td>( f_k )</td>
<td>0.03</td>
<td>0.21</td>
<td>0.13</td>
<td>0.07</td>
</tr>
<tr>
<td>( A_{bf}/s_b )</td>
<td>0</td>
<td>0.05</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>( \nu_n ) (MPa)</td>
<td>1.06</td>
<td>6.73</td>
<td>3.04</td>
<td>1.20</td>
</tr>
</tbody>
</table>
model presented by soft computing methods depends on their regularization parameters, the effort has been made in this paper to optimize these parameters by the GA so that the convergence coefficient of the training data for the fitted model may reach its highest possible value. To this end, the following objective function has been minimized by the GA and the optimum effective values of the regularization parameters of the MARS, Kriging, and M5 models have been determined.

\[
\text{min RRSQ} = \frac{1}{R_{\text{train}}^2}
\]

(17)

where \( R_{\text{train}}^2 \) is the determination coefficient of training data.

### 4.1 Multivariate adaptive regression splines (MARS)

Firstly, Friedman (1991) presented the MARS model. It is a regression model commonly used to develop a nonlinear model between a specified dependent variable and the independent variables. As shown in Eq. (18), MARS produces a model from the weighted basis functions in two stages, including the forward stage and backward stage.

\[
\hat{y} = a_0 + \sum_{i=1}^{d} a_i B_i(x)
\]

(18)

in which \( \hat{y} \), \( a_0 \), \( B_i \), \( a_i \), and \( M \) are the output parameter, constant term, \( i \)th basis function, coefficient of the \( i \)th basis function, and number of basis functions, respectively. The model chooses entire feasible basis functions and relevant knot sites in the forward stage, so a complicated model is created which would over-fit the trained data. In the backward stage, the excessive basis functions with the minimum participation to the model are eliminated by using the generalized cross-validation (GCV) criterion (Williams and Gomez 2016, Conoscenti et al. 2016) which is given by

\[
\text{GCV} = \frac{1}{n} + \frac{\sum (y_i - \hat{y}_i)^2}{(1 - C(M)/n)}
\]

(19)

where \( y_i \) represents the \( i \)th target value, \( \hat{y}_i \) denotes the \( i \)th predicted value, \( n \) is the number of data, and \( C(M) \) corresponds to the model complexity penalty factor which increases with increasing the number of basis functions. The MARS model has been implemented using the ARESLab toolbox (Jekabsons 2010a) in the MATLAB. Regularization parameters that affect the MARS model fitting include the Max funcs, C, Cubic, Cubic fast level, Max interactions, Min span, End span, Allow linear, and Self interactions. Where Max funcs denotes the maximum number of basis functions in the forward stage, C represents the Generalized Cross-Validation (GCV) penalty per knot, Cubic is the type of piecewise function (true for piecewise-cubic and false for piecewise-linear functions), Cubic fast level is the level of piecewise-cubic modelling (0 for cubic modelling in both forward and backward stages, 1 for cubic modelling in the backward stage, 2 for cubic modelling of the final model), Max interactions is the maximum degree of interactions between input variables, Min span is a minimum span that takes every Min span-th observation for knot placement (-1 for automatic mode, 0 or 1 for disablement of this feature, and values greater than 1 for tuning the span length), End span denotes a span that do not permit knots locating near to the ends of the data intervals (-1 for automatic mode, 0 for disablement of this feature, and values greater than 1 for tuning the span length), Allow linear represents a factor that permits variables entering basis functions linearly (0 for disagreement with linear variables, 1 for linear variables, and 2 for preference of linear variable), and Self interactions denotes the maximum degree of self interactions for any input variables (Jekabsons 2010a). The regularization parameters are optimized by the GA and are given in Table 3.

The proposed MARS model with the optimal values of the parameters will be as follows

\[
\hat{y} = 3.51 + 639.07BF1 + 75.7BF2 - 25.58BF3 - 1.52BF4 - 1.88BF5 - 3.41BF6 - 0.003BF8 + 3.81BF9 + 460.71BF10 + 34.52BF11 - 33.23BF12 - 1427.27BF13 - 100.73BF14 + 3.27BF15 - 38.54BF16 + 41.01BF17 + 0.05BF18 + 0.26BF19 + 0.05BF20 - 0.05BF21 - 0.15BF22 - 0.24BF23
\]

(20)

where BF's are basis functions which are given in Table 4. The proposed MARS model has yielded convergence coefficients equal to 0.97 and 0.88 for the training and testing data, respectively.

### 4.2 Kriging surrogate model

The main theorem of Kriging was offered by Krige (1951) and later expanded by Matheron (1970) and Sacks et al. (1989). Kriging is a stochastic regression model that employs the spatial covariance matrices to forecast the uncertain variables in new points (Al-Mudhafar 2019). The Kriging method can be defined as (Mallipeddi and Lee 2015, Li and Pan 2019)

\[
\hat{y}(x) = \mu + Z(x)
\]

(21)

in which \( \hat{y} \) is the predicted value, \( \mu \) is a regression parameter representing the average of the samples, and \( Z(x) \) denotes a stochastic procedure with zero mean and covariance function as follows

\[
\text{COV}[Z(x'), Z(x'')] = \sigma^2 \text{R}[R(x', x'', \theta)]
\]

(22)

in Eq. (22), \( R \) defined as correlation matrix, \( \sigma^2 \) corresponds to the process variance, and \( \theta \) is an uncertain correlation parameter to adjust the model. So, the Kriging
model can be presented as

\[ \hat{y}(x) = \hat{\mu} + r^T R^{-1}(y - 1\hat{\mu}) \]  

(23)

here, \( \hat{\mu} \) denotes the approximated regression parameter, \( r \) represents the correlation vector among the forecasted point and the entire known points, \( y \) corresponds to the vector comprising entire the samples. With assuming a value for \( \theta \), the approximated regression parameter \( \hat{\mu} \) and the approximated variance \( \hat{\sigma}_\varepsilon^2 \) are determined using the following equations

\[ \hat{\mu} = \bar{y} R^{-1} y \]  

(24)

\[ \hat{\sigma}_\varepsilon^2 = \frac{(y - 1\hat{\mu})^T R^{-1}(y - 1\hat{\mu})}{n} \]  

(25)

To estimate \( \theta \), the following log-likelihood function should be maximized

\[ \ln(\theta) = - \left[ n \ln(\hat{\sigma}_\varepsilon^2) + \ln|R| \right] / 2 \]  

(26)

The Kriging model, that uses various correlation functions to control the model softness, has been implemented using the DACE toolbox (Lophaven et al. 2002) in the MATLAB Software. As shown in Table 5, the five regularization parameters (including the Lower bound, Upper bound, Regrpply, CorrFunc, and \( \theta_0 \)) effective in the Kriging model fitting have been optimized by the GA. Lower bound, Upper bound, and \( \theta_0 \) respectively determine the minimum and maximum variation range of parameter \( \theta \) and the initial \( \theta \) guess. Regrpply and CorrFunc parameters specify the polynomial order and type of the correlation function (Exponential, Generalized exponential, Gaussian, Linear, Spherical, and Cubic spline), respectively. The model proposed by the Kriging method has yielded convergence coefficients of 0.99 and 0.85 for the training and testing data, respectively.

### 4.3 M5 model tree

Quinlan (1992) was the first researcher who proposed the M5 model tree and then this method expanded by Wang and Witten (1997). M5 is a data-driven model that changes the nonlinear relation of input and output variables into a piecewise linear relation. The M5 model is produced in two steps. First, the parameter space is divided into different subspaces and a linear regression function is built in every subspace. Thus, by employing the splitting criterion of the standard deviation reduction (SDR) factor, the main structure of the tree is built (Behnoood et al. 2015, Mansouri et al. 2016, Nguyen et al. 2019)

\[ SDR = sd(E) - \sum_i \frac{|E_i|}{sd(E)} \]  

(27)

where \( sd \) represents the standard deviation, \( E \) denotes the set of samples achieving the node, and \( E_i \) corresponds to the set of samples resulting from dividing the node. Second, the pruning step is executed to decrease the model complexity (Behnoood et al. 2015, Mansouri et al. 2016). The M5 model has been implemented by the M5PrimeLab toolbox (Jekabsons 2010b) in the MATLAB environment. The seven regularization parameters (Model tree, Min leaf size, Min parent size, Prune, Smoothing-K, Split threshold, and Max depth) effective in the M5 model fitting have been optimized by the GA, as shown in Table 6. Where Model tree determines the type of tree (true for model tree and false for regression tree), Min leaf size is the minimum number of training samples for a leaf node, Min parent size is the minimum number of samples for dividing a node, Prune is the model pruning feature (true for model pruning

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Lower bound</th>
<th>Upper bound</th>
<th>Regrpply</th>
<th>CorrFunc</th>
<th>( \theta_0 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model tree</td>
<td>0.4</td>
<td>2.4</td>
<td>1</td>
<td>Linear</td>
<td>0.4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Lower bound</th>
<th>Upper bound</th>
<th>Regrpply</th>
<th>CorrFunc</th>
<th>( \theta_0 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model tree</td>
<td>true</td>
<td>true</td>
<td>false</td>
<td>true</td>
<td>true</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Min leaf size</th>
<th>Min parent size</th>
<th>Prune</th>
<th>Smoothing-K</th>
<th>Split threshold</th>
<th>Max depth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min leaf size</td>
<td>3</td>
<td>6</td>
<td>false</td>
<td>5</td>
<td>0.3</td>
<td>8</td>
</tr>
</tbody>
</table>

for the training and testing data, respectively.
and false for disabled model pruning). Smoothing-$K$ is the smoothing parameter that softens sharp discontinuities. Split threshold is the minimum threshold for dividing the nodes of the tree, and Max depth is the maximum depth of a tree. The proposed M5 model has yielded convergence coefficients equal to 0.87 and 0.84 for the training and testing data, respectively.

The proposed M5 model tree with the optimal parameter is shown in Fig. 1 and the mathematical equations of each linear model (LM) are given in Table 7.

5. Comparison between proposed models and other existing models on bond strength of GFRP bars

To evaluate the accuracy of different models used in this research, the $R^2$, AAE, RMSE, and MAE statistical indices are employed, as follows

$$ R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_{exp,i} - y_{pred,i})^2}{\sum_{i=1}^{n}(y_{exp,i} - \bar{y}_{exp})^2} \quad (28) $$

$$ AAE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_{exp,i} - y_{pred,i}}{y_{exp,i}} \right| \quad (29) $$

$$ RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_{exp,i} - y_{pred,i})^2}{n}} \quad (30) $$

$$ MAE = \frac{1}{n} \sum_{i=1}^{n} |y_{exp,i} - y_{pred,i}| \quad (31) $$

where $\hat{y}_{exp}$, $y_{exp,i}$ and $y_{pred,i}$ are the mean of the experimental responses, $i$th experimental and predicted responses, respectively. Fig. 2 shows the performance of different prediction models of the bond strength of spliced beams reinforced with GFRP bars. As shown, MARS and Kriging models, with correlation coefficients of respectively 0.94
and 0.93 have had the best performance, and M5 with correlation coefficient of 0.85 has provided better estimates compared to other existing models. Among the previous models, that of Esfahani et al. (2013) has provided a better estimate than other existing models (with a convergence coefficient of 0.57). The proposed MARS, Kriging, and M5 models have been able to nearly improve the convergence coefficient by 65, 63 and 49%, respectively, compared to that of Esfahani et al. (2013). The models provided by CAN/CSA S6-14 (2014) and CAN/CSA S806-12 (2012) have exhibited very low correlation coefficients (0.08 and 0.14, respectively).

Table 8 compares the accuracy and statistical indices of the proposed models with those of the existing ones. All 112 data samples were employed to compare the performance of different models. As shown, the proposed Kriging model has had the best value for the ratio of the predicted to experimental bond strengths and the lowest standard deviation compared to other models. The MARS and M5 models also have yielded a much better mean and standard deviation than other existing models. Among the previous models, the relationships presented by Esfahani et al. (2013) have provided a better estimate than other existing models (with a convergence coefficient of 0.57). The proposed MARS, Kriging, and M5 models have been able to nearly improve the convergence coefficient by 65, 63 and 49%, respectively, compared to that of Esfahani et al. (2013). The models provided by CAN/CSA S6-14 (2014) and CAN/CSA S806-12 (2012) have exhibited very low correlation coefficients (0.08 and 0.14, respectively).

Table 8 Comparison of statistical indices for the proposed and existing models

<table>
<thead>
<tr>
<th>Model</th>
<th>Average of (\frac{(u_m)<em>{\text{pred}}}{(u_m)</em>{\text{exp}}})</th>
<th>Standard deviation of (\frac{(u_m)<em>{\text{pred}}}{(u_m)</em>{\text{exp}}})</th>
<th>AAE</th>
<th>RMSE</th>
<th>MAE</th>
<th>(R^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>JSCE (1997)</td>
<td>0.776</td>
<td>0.258</td>
<td>0.290</td>
<td>1.365</td>
<td>1.002</td>
<td>0.27</td>
</tr>
<tr>
<td>Aly (2005)</td>
<td>0.828</td>
<td>0.526</td>
<td>0.423</td>
<td>1.949</td>
<td>1.351</td>
<td>0.30</td>
</tr>
<tr>
<td>CAN/CSA S806-12 (2012)</td>
<td>1.486</td>
<td>0.591</td>
<td>0.581</td>
<td>1.717</td>
<td>1.447</td>
<td>0.08</td>
</tr>
<tr>
<td>Choi et al. (2012)</td>
<td>1.092</td>
<td>0.294</td>
<td>0.244</td>
<td>1.008</td>
<td>0.720</td>
<td>0.31</td>
</tr>
<tr>
<td>Esfahani et al. (2013)</td>
<td>0.843</td>
<td>0.200</td>
<td>0.209</td>
<td>0.994</td>
<td>0.697</td>
<td>0.57</td>
</tr>
<tr>
<td>CAN/CSA S6-14 (2014)</td>
<td>1.729</td>
<td>0.642</td>
<td>0.766</td>
<td>2.221</td>
<td>1.890</td>
<td>0.14</td>
</tr>
<tr>
<td>ACI 440.1R-15 (2015)</td>
<td>1.297</td>
<td>0.381</td>
<td>0.372</td>
<td>1.143</td>
<td>0.941</td>
<td>0.35</td>
</tr>
<tr>
<td>Rakhshanimehr et al. (2018)</td>
<td>0.916</td>
<td>0.284</td>
<td>0.246</td>
<td>1.121</td>
<td>0.807</td>
<td>0.37</td>
</tr>
<tr>
<td>M5</td>
<td>1.015</td>
<td>0.138</td>
<td>0.111</td>
<td>0.475</td>
<td>0.332</td>
<td>0.85</td>
</tr>
<tr>
<td>MARS</td>
<td>1.016</td>
<td>0.121</td>
<td>0.076</td>
<td>0.286</td>
<td>0.197</td>
<td>0.94</td>
</tr>
<tr>
<td>Kriging</td>
<td>1.009</td>
<td>0.102</td>
<td>0.048</td>
<td>0.318</td>
<td>0.142</td>
<td>0.93</td>
</tr>
</tbody>
</table>

Fig. 2 Comparison of performance of different models for predicting the bond strength of spliced GFRP bars
Saeed Farahi Shahri and Seyed Roohollah Mousavi

Fig. 3 Comparison of error indices for the proposed and existing models

(2013), Choi et al. (2012), and Rakhshanimehr et al. (2018) have presented relatively better statistical indices than other ones. Regarding the RMSE statistical indicator, the MARS and then the Kriging model have had the least error while regarding AAE and MAE statistical indices, the Kriging and then the MARS model have presented a more accurate estimate than other models. The proposed MARS model has had the best convergence coefficient ($R^2=0.94$). It is worth noting that some previous models have been adapted from a smaller database and may be less accurate than the proposed models, which are based on a more extensive database.

The prediction errors of the proposed and previous models are compared in Fig. 3 where a comparison of the statistical indices of different models shows that the models presented by CAN/CSAS6-14 (2014), CAN/CSAS806-12 (2012), and Aly (2005) have had much higher errors than other models. The models proposed in this research have shown the lowest error compared to other available models. The Kriging and MARS models have had the lowest error values. Among the previous models, those of Esfahani et al. (2013), Choi et al. (2012), and Rakhshanimehr et al. (2018) have had a relatively better performance.

Fig. 4 shows box plots of the ratio of the bond strength predicted by different models to that found from experiments. As shown, in all proposed models, the mean of the data is lying next to ratio 1 which means the proposed soft computing models have had precise estimations of the experimental bond strength. The short length of the box plot in the proposed models means greater certainty and high
level of agreement in their predicted results. The Kriging and MARS models have, respectively, had the highest certainty. The length of the box plot in CAN/CSAS6-14 (2014) and CAN/CSA S806-12 (2012) models is higher than others showing great dispersed and scattered data in them. The first quartiles for CAN/CSAS6-14 (2014), CAN/CSAS806-12 (2012), and ACI440.1R-15 (2015) models are located higher than ratio 1, which means their estimations have been much higher than the experimental values. These design recommendations provide an unconservative prediction and considerably overestimate the bond strength of spliced GFRP bars for more than 75% of the specimens. Among previous researchers, Choi et al. (2012) have estimated the bond strength more accurately; however, their estimation has been more than the experimental value. Models presented by the JSCE (1997), Aly (2005), and Esfahani et al. (2013) have been quite conservative because their box plots of predicted to experimental bond strength ratio are below 1; that of Rakhshanimehr et al. (2018) also can be considered as relatively conservative. Although the proposed models are more complicated than previous ones, they have been able to significantly improve the certainty and prediction accuracy of the bond strength between GFRP bars and concrete in spliced concrete beams. This minor disadvantage can easily be defeated using the computer tool. It is worth noting that the bond strength may decrease over a long time (Bazli et al. 2017). The bond degradation of GFRP bars under various environmental conditions can be considered using an environmental reduction factor (ACI 440.1R-15 2015).

6. Conclusions

In this paper, a database of RC beam specimens with spliced GFRP bars in the splitting failure mode has been collected and used to find the GFRP bar-concrete bond strength. The concrete compressive strength, bar diameter, concrete cover, splice length, bar elasticity modulus, transverse reinforcement, and surface properties of GFRP bars have been considered as the main and basic parameters affecting the bond strength. To guarantee the generalization ability of the proposed models, training and testing data have been considered based on the ten-fold cross-validation technique. This paper has used such soft computing models as MARS, Kriging, and M5 to estimate the bond strength. Since regularization parameters highly affect the fitting of the models, these parameters have been so optimized in the proposed models to maximize the convergence coefficient of the training data and improve the accuracy and efficiency of the mentioned models. This optimization has been done with the GA and implemented in the MATLAB Software. The proposed new models intelligently find appropriate regularization parameters for the best model fitting. Results have shown that proposed models have significantly increased the prediction accuracy compared to previous models. The proposed MARS, Kriging, and M5 models have improved the convergence coefficient by approximately 65, 63 and 49%, respectively, compared to the best previous model. Regarding the statistical indices, MARS has had the least error in RMSE; Kriging stands next. Regarding AAE and MAE, Kriging has performed the best followed by the MARS. Most previous models have estimated the bond strength much more or much less than the test values, but the models proposed in this paper have predicted it more accurately with a lower standard deviation. A comparison of the box plot of the ratio of the predicted to experimental bond strengths has shown that Kriging and MARS have had much more accurate estimates than other models. It is worth noting that although the proposed models are more complicated, since they have considerably improved the bond strength predictions and access to computer tools is also easy, using them to find accurate and reliable results is justifiable. For design purposes, an environmental reduction factor can be considered to account for the bond degradation of GFRP bars under various environmental conditions.

References

ACI Committee 440.1R-03 (2003), Guide for the Design and Construction of Concrete Reinforced with FRP Bars, American Concrete Institute, Farmington Hills, Michigan.
ACI Committee 440.1R-06 (2006), Guide for the Design and Construction of Structural Concrete Reinforced with FRP Bars, American Concrete Institute, Farmington Hills, Michigan.
ACI Committee 440.1R-15 (2015), Guide for the Design and Construction of Structural Concrete Reinforced with FRP Bars, American Concrete Institute, Farmington Hills, Michigan.

315
Continuous Fiber Reinforcing Materials, Tokyo, Japan.


Japan Society of Civil Engineers, JSCE (1997), Recommendation for Design and Construction of Concrete Structures Using
Bong strength prediction of spliced GFRP bars in concrete beams using soft computing methods

634-642.

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