Bond strength prediction of the composite rebars in concrete using innovative bio-inspired models

Fatemeh Alizadeh | Hosein Naderpour | Masoomeh Mirrashid

Faculty of Civil Engineering, Semnan University, Semnan, Iran

Correspondence
Masoomeh Mirrashid, Faculty of Civil Engineering, Semnan University, Semnan, Iran.
Email: m.mirrashid@semnan.ac.ir

Abstract
The bond strength among the concrete and reinforced bars is one of the most important factors in designing the reinforced concrete structures. One of the serious problems encountered by utilization of steel-reinforcement bars is corrosion when exposed to different environments. Glass fiber-reinforced polymers (GFRPs) are known as a solution to prevent the destruction of the civil infrastructure. The present study attempts to predict the bond strength between the GFRP bars and concrete based on the neuro-fuzzy inference system and artificial neural networks using 159 beam specimens including notched, splice, hinged, and inverted hinged. The neuro-fuzzy inference system consists of five input series. The output, which is the bond strength, is compared with those presented in the various code relations such as ACI 440.1R-15 and CSA S806-12. It was concluded that the outputs are more compatible with the experimental results in comparison with the amounts obtained from the codes equations.

KEYWORDS
bond strength, composite rebar, concrete, neural network, neuro-fuzzy inference system

1 | INTRODUCTION

The functionality of the concrete or steel, and creating an integrated reinforced concrete member would stand on the total bond among the concrete and reinforced bars. Despite all the valuable features of steel in reinforced concrete constructions such as the high resistance and flexibility, it bears the feature of being rusty and aging because of the natural forces during the time. Nowadays, fiber-reinforced polymers are used as suitable materials for reinforcing concrete. Some researchers have investigated the properties and application of such materials. The glass fiber-reinforced polymer (GFRP) bars are considered important alternatives. The most important reasons to choose it can be: (a) the high chemical strength of these bars, (b) the high ratio of strength to the weight of GFRP bars, (c) the high economic efficiency, and (d) the high resistance to rust. Ehsani et al. worked on GFRP bar bond relations in concrete with normal strength relying on 78 lab samples and a theoretical basis. These samples were examined according to the variables such as the mode of failure (ie, splitting or pullout), the concrete compressive strength, cover thickness, bar effects, and the GFRP bar diameter. In their study, in addition to the stated issues, the impact of the radius of bend on these hooks and extension on them were also investigated. The results indicated that the impacts for upper steel bars in concrete surface also exist for GFRP bars.
It was also found that increasing the radius of the curve in hooked bars significantly increases the rupture load of bars. Benmokrane et al. studied the load distribution of the GFRP reinforced and combined bars in the concrete, which deals with the exact estimation of the relations. In their study, 20 concrete specimens having GFRP bars, which were built with four types of diameters ranging from 12.7 to 25.4, were investigated. The test results showed that the impact of the diameter of GFRP reinforcing bars and steel bars diameter on the bond are the same. They also found that bond strength of GFRP bars is about 60% to 90% lower than steel bars. In addition, bond strength in beam samples is about 55% to 95% lower than pullout samples. In their study, the results showed that the distribution of bond tension along the development length of GFRP reinforcing bars is nonlinear. Ehsani et al. examined the basics of the design for the GFRP bar bond in the concrete, and they suggested proposals for the design. Altogether, 102 samples were built and experimented under the stable static force. This study includes 48 bar samples, 18 tension samples, and 36 samples with hook bars. In their research, the loaded tension was gradually imposed on the bars, and it continued till the concrete was cracked, and the bar under tension released or broke. The effective variables in this research were the concrete compressive strength, the development length, the concrete cover, the bar diameter, the concrete, effective depth, the curve radius, and the sequence length. In their study, new criteria were introduced for acceptable performance of GFRP bars in concrete which was used in order to estimate experimental results. Some instructions were also obtained for calculating development length of straight and hooked GFRP bars in concrete. In addition, factors were calculated in order to reflect the impact of concrete coating and bar location.

Taighiourt et al. worked on the GFRP bond bars, which were imposed under the static load. They examined the lab specimens. The key factors are the GFRP bar diameter and the development length. Sixteen lab samples of the concrete bar are undergone tension. In this study, the bond development length for the concrete steel bars is gained by the ACI construction regulation. The result of the experiment shows that it is necessary to apply the total coefficient of 1.3 multiplied by the development length of the GFRP bond bars to achieve the sufficient tension and cover of the patch length. Aly and Benmokrane worked on the cracking and cover patch of the bond strength in the GFRP bars. Golafshani et al. worked on the bond strength among the concrete and GFRP bars by applying the artificial neuron network and programming based on the genetic algorithm (GA). About 159 lab samples of the bar types such as cavity type, articular, reverse patch are studied, which are adopted from other studies, and they are applied for the model making of artificial neuron network and genetic programming. There are seven effective factors applied as the inputs, and the only output gained is the GFRP bar bond strength in the concrete. The gained amount of Mean Absolute Error (MAE) in test data is less than 1.06 and 0.76 mg p, which is conservative for the artificial neuron networks and genetic programming. This indicates the accuracy of their method in determining the bond strength of GFRP bars in comparison with other designing regulations. In 2016, Yan et al. considering high importance of GFRP bar bond strength in construction, conducted a comprehensive review, focusing on rupture states and bond strength of these bars in concrete. In 2017, Yan et al. presented an optimal modeling strategy that represents the ability of powerful nonlinear mapping of the neural network along with the searching ability of GA in predicting GFRP bar bond strength in concrete. They used the parameters affecting bond strength of GFRP bars, which include bar conditions, concrete, and confinement from transverse reinforcements, and they achieved very good performance and prediction of bond strength of GFRP bars in this modeling compared to other design regulations. In 2020, Zhou et al. built an Artificial Neural Network (ANN) model that assessed the effects of various variables on the bond strength based on a large database from an extensive survey of existing single-lap shear bond tests on FRP-concrete specimens. Neuro-fuzzy and Group Method of Data Handling (GMDH) modeling have been applied in many literature works referred to several fields like engineering geology, mechanical engineering, electrical engineering, science and industrial ergonomics. The results of researches reported that soft computing methods in predicting are accurate and reliable. Thus, according to the importance of the bond strength of the GFRP bars, this research aimed to predict it based on the neuro-fuzzy inference system, artificial neural network and GMDH which operate based on the results of the experimental data collected from various descripts and is expressed based on the terms of bar condition, concrete, and confinement from transverse reinforcements.

2 THEORETICAL BASIS OF BOND STRENGTH

It is only possible for the steel bar to operate as the tension element and compensate for the weakness of the concrete strength under tension. If there is a total bond between concrete and steel, there is the possibility of tension transition between the subsequent cracks from concrete to steel. Steel can only tolerate a part of tension at the tension zone (eg, in
The bond strength between the concrete and bar if it constantly operates with the concrete. The exterior bars rarely enter the bars directly, and the bars get their share of the exterior bars from the surrounding concrete. The bond is defined as the amount of tension created between steel and concrete. When the bond tension is created between the concrete and steel, it causes the steel and concrete to be a combined constructional part and operate untidily. The bond strength is explained in Equation (1):

\[ u = \frac{d_b f_s}{4L_d} \]  

In this equation, \( d_b \) is the bar diameter, \( L_d \) is the development length, \( f_s \) is the steel tension, and \( u \) is the bond tension. Because of the unique complications of bond and the lack of normal theoretical solution, the structural engineers have tried to apply the experimental methods to gain the bond strength value, development length, or splice. The experiments have continued for 10 years, and the scientists have been close to the goal. For these purposes (bond strength, bond length, and bond splice), the technical committees and other committees have modified and updated the ACI regulation and the regulations of different countries according to these innovations to achieve the special formulas of bond strength and the development length. The experimental results have revealed that the bond strength is created out of three following actions based on Figure 1. Shear strength (\( v_a \)) is created out of the cement combination adhesion on the side surface of the bars. Besides, the bars are pressed because of the concrete condensation, the friction between concrete and bar increases. Shear stress (\( v_c \)) which operates on a cylinder surface of concrete between the adjacent edges. Figure 1 shows \( f_b \), which is called the touch strength.

3 | THEORETICAL BASIS OF GFRP BAR

Many factors are influencing the bond strength between the bar and the concrete. These factors are divided into three main groups. They can be mentioned as constructional features, bar features, and concrete features. The constructions whose parts are constructed with the combination of two or various materials containing different features bear special features and complexities. The concrete constructions, which are the combination of concrete and steel, bring about a lot of fundamental issues for the designers despite their numerous benefits. This kind of construction is only confirmed economically (as well as from the security and expiration point of view) if all the necessary technical points are considered. The critical designing of the patch must be considered specifically. At this point, the bond strength and flexibility are highly important to be examined. The factors such as the salt in the sea, the factories’ sewage, the salt used for the antifreeze of the streets, and roads, especially in the cold areas, in addition, the carbon gas, and other pollutants in the air cause the steel bars in the concrete to deteriorate slowly. Especially if the cracks increase beyond the normal limit, the pollutants penetrate the concrete more, and the bars decay faster. Thus the concrete constructions lose their resistance, and they get closer to their expiration date, so they need to be repaired and fixed after a while, which imposes high costs. Sometimes they need to be destroyed and replaced with the new constructions.

Economically speaking, it brings about an unfortunate problem for human society. Most of the reinforced concrete constructions, especially the bridges built in the 20th century, even those not more than 40 years old, must be repaired and destroyed. These kinds of bars are so resistant to the pollutants because of their special chemical combinations, and they do not decay during the time the expiration date increases. The FRP bars are created with a combination of two materials, including fibers and the background substance. The used fibers include glass, carbon, and steel types.
The bond strength of these bars is more than the steel bars; furthermore, the FRP bars do not have the problem of the steel bars becoming rusty. One of the disadvantages of the FRP bars is their vulnerability to the temperatures more than 100°C. As the temperature increases, the background substance becomes mild little by little, and the strength between the resistance fibers and the background substance diminishes. In addition, because of the FRP bars’ low elasticity modules, their hardness reduces.41-45 As a result, manipulating the control of the permitted places of the armed concrete constructions into FRP bars should be highly considered.46 On the other hand, studies show that the strength bond of the FRP bars is less than the steel bars because of their low elasticity modules.47,48 The GFRP bars show a different bond behavior from other steel bars, which is caused by the difference in the material and the surface tissue. These features lead to the creation of a difference in the hardness of the surface and the force transition mechanism between the reinforcing bar and concrete. The GFRP bars operates elastic linear till it is released while the steel reinforcing bars show clearly a level of elasticity with much transformation after being surrendered. The factors affecting on the adhesion behavior, the release forms and the bond strength of the GFRP in the concrete are detected and drawn so that the engineers can find out the damage completely. It should be especially mentioned that there is a linear relation between the bond strength and the critical factors such as (a) pressure strength of concrete, (b) concrete cover, and (c) the bar size. Also, there is a nonlinear relation between the bond strength and the development length. In addition, the released resin and the width restrictions are accepted as the effective factor on the increase of the bond strength of the GFRP bars of the concrete.19,48-53

4 TYPES OF TESTS PERFORMED FOR DETERMINING THE BOND STRENGTH

There are usually two general categories for bond tests: Reinforced beam sample test and also the test of direct drawing out of the bar. The concrete adjoining the bar is put under pressure in the test of direct drawing out of the bar that this is contrary to the practical state. At the opposite point, the concrete adjoining the bar is stretched in beam tests that this is exactly the same as the practical state. The data used for modeling bond strength are only collected from the results of tests of the beam sample. However, in order to study the general conditions in comparison to a particular scenario, most rupture states have indicated that when collecting the data, the current samples should also be considered. Information from 687 samples has been collected in order to estimate the main rupture states.18,50-52 As can be seen in Figure 2, the majority of these rupture states comprise rupture of the types of drawing out the bar and fraction that are 38/70% and 42/16%, respectively.

Therefore, the data obtained from these two types of rupture are enough as a complete basis and without loss of any generality. In order to complete the above contents, the data have been collected from beam samples, taking into account the ruptures of the types of drawing out and fraction.

![Figure 2: Bond rupture states](image_url)
TABLE 1  Statistical data of effective factors on bond strength

| Parameter | Mean | Maximum | Minimum | SD  |
|-----------|------|---------|---------|-----|
| Pos       | 1.26 | 2.00    | 1.00    | 0.44|
| Surf      | 2.30 | 3.00    | 1.00    | 0.92|
| \(d_b\) (mm) | 18.67 | 28.58 | 9.53 | 5.03|
| \(f'_c\) (Mpa) | 34.97 | 48.86 | 23.43 | 7.11|
| \(C/d_b\) | 2.66 | 6.20 | 1.00 | 1.15|
| \(l_d/d_b\) | 18.16 | 97.24 | 3.56 | 15.81|
| \(A_{tr}/snd_b\) (mm) | 0.02 | 0.08 | 0.00 | 0.02|
| \(\tau_b\) (Mpa) | 7.83 | 22.34 | 1.64 | 5.04|

5 | COLLECTED DATA FOR BOND STRENGTH

The bond among the concrete and GFRP bars is one of the most important issues in reinforced concrete structures, which is influenced by various factors. In this study, the results of 159 samples of experimental concrete beams from articulated, lap-spliced and dentate types, which were collected from different sources, have been used. The statistical data of these cases, which has been collected based on the results of 159 beam samples, has been briefly shown in Table 1.

Among these parameters, the bar surface profile is stated by numbers 1, 2, and 3, which show surface states as helical lugged, spiral-wrapped, and sand coated, respectively. In this paper has been shown also indicate bar location in the bottom and top of the surface by the numbers 1 and 2, respectively. It should be noted that the latitudinal reinforcing cross-section ratio (\(\rho\)) is the ratio of reinforcing latitudinal bars surface to the distance between these reinforcing and the number and diameter of longitudinal bars \(A_{tr}/snd_b\). It is clear that other factors have also been partially effective in bond strength, which has been neglected.

6 | SOFT COMPUTING

In the following, the three soft computing methods, which are famous were reviewed. They are GMDH, ANN, and also ANFIS that will be used.

6.1 | GMDH

GMDH type neural networks build a model based on the relationships between input and output data for a complex system using multi-layer networks’ structure that this network is similar to Feed-Forward neural networks. GMDH, which is a self-organized method that can be used for complex modeling, was firstly proposed by Ivakhnenko. Each element in a neural network is, in fact, a nonlinear equation between two inputs and one output, and its coefficients are determined based on regression methods. Non-useful elements are automatically eliminated during the network construction process due to their inability to determine the correct output, and useful connections in each hidden layer, which lead to increased network performance and are involved in predicting the correct output, remain. By repeating these steps, eventually, a GMDH type neural network is achieved, which has the least error, and its predictive power in determining correct answers close to the output is high. With the help of the GMDH algorithm, a model is created, which is a set of neurons in different layers; in other words, this neural network is a self-organized and unidirectional network, consisting of several layers, and each layer consists of several neurons.

6.2 | ANN

Artificial neural networks take a series of observations as input and judge, and after training, they would be used operationally, mainly in predicting time series. Artificial neural networks are usually composed of several layers, each
containing some processor elements known as neurons. Each neuron receives signals that contain general information or external stimuli from other neurons as input and processes them and hands over the output signal. Neurons in neural networks perform information processing, using activation functions, and post-processing information are transmitted as an output signal to other neurons. The number of neurons and hidden layers and the position of these neurons in different layers and method of neurons connecting each other in each layer determines the architecture of the neural network. Determining the importance of each of the inputs and its relation to the output is determined by their weights. By using the conversion or activation function, the output neurons would be processed. A general structure of the neural network model, which can be explained as a mathematical model, is shown in Figure 3.

Mathematical description of the neural process shown above is presented using Equation (2) as follows:

$$y_k = \phi \left( \sum w_{km} x_m + b_k \right)$$  \hspace{1cm} (2)

where $w_{km}$ = binding weight of the source of neuron $m$ to the target neuron $k$; $b_k$ = bias; $y_k$ = output; and $\phi$ = transfer function.

### 6.3 ANFIS

ANFIS is an abbreviation that is built from the first letters of the Adaptive Neuro-Fuzzy Inference System (Figure 4). ANFIS, with the help of a set of input/output data, creates a Fuzzy Inference System (FIS). The parameters of membership functions of this system are regulated through the backpropagation algorithm or its combination with the least-squares method. This regulation operation allows fuzzy systems to learn its structure from the data set. The ANFIS structure is composed of five layers. The output of each node in the $L$-layer is indicated by the term $o_{l,n}$ that $l$ is the number of layers, and $n$ is the number of the next layer’s neuron. Figure 4A,B show the network structure of an ANFIS system and fuzzy-reasoning mechanism. In this figure, the structure of ANFIS with two inputs $x$ and $y$ and with an output $f$ has been
indicated, which was first introduced by Jang. In this system, the rules base includes two fuzzy if-then rules similar to the rules described by Takagi and Sugeno:

Rule 1: IF \( x \) is \( A_1 \) and \( y \) is \( B_1 \), THEN \( f_1 = p_1x + q_1y + r_1 \)

Rule 2: IF \( x \) is \( A_2 \) and \( y \) is \( B_2 \), THEN \( f_1 = p_2x + q_2y + r_2 \)

which, \( p_i, q_i \) and \( r_i (i = 1, 2) \) are the second linear parameters of first grade fuzzy Takagi and Sugeno’s model.

7 | MODELING

In this study, it has been tried five parameters effective in all existing design regulations and enters them into modeling. By doing a lot of modeling and affecting all parameters and their combination and ratio to each other, ultimately, some parameters were chosen as inputs that had the closest response to experimental results. The selected inputs for modeling all the systems are considered as: The diameter of the bar \( (d_b) \) in millimeters, the compressive strength of concrete \( f'_c \) in MPa, the ratio of the lowest concrete coating to the bar diameter \( (c/d_b) \), the ratio of development length of the bar to the diameter of the bar \( (l_d/d_b) \), the ratio of the surface of latitudinal bars which are reinforcing, to the distance between these reinforcing and the number and diameter of longitudinal bars \( (A_{tr}/\pi d_b) \) in millimeters, and also bond strength \( (\tau_b) \) in Mega-Pascal is considered as the output.

Considering the heterogeneity and diversity of data, the ability to train and generalize in modeling is increased in modeling through ANFIS, ANN, and GMDH methods. Therefore, the similarity and homology of the selected data for modeling should be reduced. Therefore, both types of input and output data in the range of \([0 1]\) have been normalized. The normalizing formula is based on Equation (3):

\[
x_N = \frac{x - x_{\min}}{x_{\max} - x_{\min}}
\]

where \( x_N \) is the normalized value of the variable \( x \); furthermore, \( x_{\max} \) and \( x_{\min} \) are the highest and the lowest values of the variable \( x \), respectively.

7.1 | GMDH model

The structure of GMDH in this article is depicted in Figure 5. There are ten polynomials in the predicted model middle layer. The equations of these polynomials are defined as below (Equation (4)). Based on previous polynomials, the final output of the model is obtained (Table 2).
### TABLE 2  The proposed formula parameters

| Polynomials | C1 | C2 | C3 | C4 | C5 | C6 |
|-------------|----|----|----|----|----|----|
| Y1          | 0.4767 | 0.1947 | -2.2337 | 0.2295 | 2.17833873 | -1.1212173 |
| Y2          | 0.7947 | -0.6743 | -2.8601 | 0.3313 | 2.27230495 | 0.66443722 |
| Y3          | 0.5743 | -1.2244 | 0.0055 | 0.9546 | 0.63885691 | -0.5609408 |
| Y4          | 0.6057 | -2.8341 | 0.1271 | 1.8976 | -0.4104794 | 1.02082031 |
| Y5          | 0.0885 | 1.1276 | -1.2989 | -2.5358 | -0.220193 | 4.89082352 |
| Y6          | 0.0002 | 0.2741 | 0.5368 | 0.1612 | -1.1000626 | 1.43116811 |
| Y7          | 0.0601 | 1.3253 | -1.1913 | -0.4729 | 1.95394776 | 0.01551702 |
| Y8          | 0.0117 | 0.2167 | 0.5922 | 3.6605 | 2.88122421 | -6.3439904 |
| Y9          | 0.0261 | 0.6180 | 0.1639 | -0.8281 | -1.4466611 | 2.59423963 |
| τ_b = Y10   | -0.0027 | 0.4247 | 0.5594 | 4.1485 | 4.46076572 | -8.6315663 |

\[ Y_i = C_1 + C_2X_i + C_3X_j + C_4(X_2^2) + C_5(X_1^2) + C_6X \]  (4)

### 7.2  ANN-model

The final structure of the proposed neural network is shown in Figure 6. Bond strength, which is the output of the model is shown with \( \tau_b \) and \( l_b/d_b, \alpha_{cb}/\pi d_b, \) and \( c/d_b, f'_c, \) and \( d_b \) are the normalized values of inputs of the model. As can be seen in the figure, there are eight neurons in the hidden layer. These nodes transfer their values to the final layer through the Tangent-Sigmoid function. For the final layer, the Tangent-Sigmoid function has been used too. Details of the layers are shown in Tables 3 and 4. In these tables, \( b_1 \) and \( b_2 \) are biases of the hidden and the final layers, respectively.

![Figure 6](image-url)  
*The proposed structure of ANN*
TABLE 3 Bias and input weights of the hidden layer

| Neuron | Input 1 | Input 2 | Input 3 | Input 4 | Input 5 | $b_1$ |
|--------|---------|---------|---------|---------|---------|-------|
| $N_1$  | 0.19164 | 1.4622  | -0.048011 | -0.48435 | -1.5865 | -0.69059 |
| $N_2$  | -0.093518 | -0.13936 | 0.09432 | -0.044597 | 0.18428 | -0.12134 |
| $N_3$  | 0.14737 | 1.9652 | -0.19515 | 2.4427 | -1.926 | 1.8363 |
| $N_4$  | -0.27077 | 0.093951 | 0.37209 | 0.56294 | -0.22401 | -0.3252 |
| $N_5$  | -0.063095 | -0.16736 | -0.11717 | -0.39483 | 0.23262 | 0.084866 |
| $N_6$  | -0.14826 | -0.16137 | 0.12826 | -0.23724 | 0.20282 | -0.09422 |
| $N_7$  | -0.032015 | -0.22259 | 0.24231 | -0.13176 | 0.23419 | -0.17815 |
| $N_8$  | -0.0032215 | -0.00071 | 0.0032706 | -0.00052 | 0.000646 | -0.00183 |
| $N_9$  | -0.70501 | 0.012051 | 0.36142 | 0.31821 | 0.76941 | -0.31811 |
| $N_{10}$ | 1.1778 | -0.031861 | -0.52892 | 0.47341 | -0.13007 | 0.68244 |

TABLE 4 Bias and layer weights of the final layer

| $N_1$ | $N_2$ | $N_3$ | $N_4$ | $N_5$ | $N_6$ | $N_7$ | $N_8$ | $N_9$ | $N_{10}$ | $b_2$ |
|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| 2.3138 | 0.3174 | -2.057 | -0.576 | 0.41662 | 0.43304 | 0.4764 | 0.004 | -0.7083 | -0.912 | -0.7217 |

Note: N, neuron.

7.3 ANFIS model specifications

Modeling is done based on the ANFIS method. After normalizing all data, 135 data are selected completely randomly out of 159 raw data for modeling with the help of the training process. In order to evaluate the correctness of the model results, the test data, which are 24 ones, are used. It should be noted that these test data are completely distinct from training data and are only used in order to evaluate the constructed model. Before starting the FIS training process, the initial structure of FIS should be determined. In this research, the initial structure of the model is created by the fuzzy C-means algorithm. Also, the hybrid method as the optimization method, which is a combination of least squares method and backpropagation gradient descent method is selected. The structure of the adaptive neural fuzzy inference system of the final model, which has the most stable and the closest outputs to experimental results, is showed by Figure 7. Other details of the model are presented in Tables 5-7.

FIGURE 7 The final structure of the considered adaptive neural fuzzy inference system
### Table 5 ANFIS rules

| Number | Rule |
|--------|------|
| Rule 1 | If X1 is C1, X2 is C1, X3 is C1, X4 is C1, and X5 is C1, then \( \tau \) is CL1. |
| Rule 2 | If X1 is C2, X2 is C2, X3 is C2, X4 is C2, and X5 is C2, then \( \tau \) is CL2. |
| Rule 3 | If X1 is C3, X2 is C3, X3 is C3, X4 is C3, and X5 is C3, then \( \tau \) is CL3. |
| Rule 4 | If X1 is C4, X2 is C4, X3 is C4, X4 is C4, and X5 is C4, then \( \tau \) is CL4. |
| Rule 5 | If X1 is C5, X2 is C5, X3 is C5, X4 is C5, and X5 is C5, then \( \tau \) is CL5. |
| Rule 6 | If X1 is C6, X2 is C6, X3 is C6, X4 is C6, and X5 is C6, then \( \tau \) is CL6. |
| Rule 7 | If X1 is C7, X2 is C7, X3 is C7, X4 is C7, and X5 is C7, then \( \tau \) is CL7. |
| Rule 8 | If X1 is C8, X2 is C8, X3 is C8, X4 is C8, and X5 is C8, then \( \tau \) is CL8. |

### Table 6 Gaussian membership function’s parameters

| Membership function | Parameter | Inputs |
|---------------------|-----------|--------|
|                     | \( \sigma \) | In1, In2, In3, In4, In5 |
| C1                  | \( \sigma \) | 0.2714, 0.2501, 0.3731, 0.0641, 0.2424 |
|                     | C         | 0.3117, 0.1879, 0.7014, 0.0486, 0.1948 |
| C2                  | \( \sigma \) | 0.1769, 0.2503, 0.3207, 0.0596, 0.0482 |
|                     | C         | 0.9629, 0.7606, 0.3404, 0.1913, 0.0005963 |
| C3                  | \( \sigma \) | 0.1207, 0.2249, 0.1103, 0.127, 0.1915 |
|                     | C         | 0.3695, 0.5067, 0.2373, 0.292, 0.3114 |
| C4                  | \( \sigma \) | 0.2525, 0.194, 0.2752, 0.0698, 0.0668 |
|                     | C         | 0.9118, 0.2049, 0.1195, 0.0250, 0.0129 |
| C5                  | \( \sigma \) | 0.1997, 0.1027, 0.116, 0.0403, 0.0559 |
|                     | C         | 0.3383, 0.1967, 0.1792, 0.0082, 0.0035 |
| C6                  | \( \sigma \) | 0.4795, 0.2971, 0.3435, 0.1569, 0.0765 |
|                     | C         | 0.4394, 0.7737, 0.3634, 0.1654, 0.0047 |
| C7                  | \( \sigma \) | 0.1409, 0.2016, 0.1517, 0.1793, 0.2901 |
|                     | C         | 0.819, 0.2609, 0.0681, 0.1088, 0.5172 |
| C8                  | \( \sigma \) | 0.1515, 0.0636, 0.1299, 0.2965, 0.2501 |
|                     | C         | 0.3152, 0.3031, 0.2934, 0.1904, 0.8363 |

### Table 7 Weights of the rules

| Number | Weight’s relationship |
|--------|-----------------------|
| \( W_{\text{Rule}1} \) | \((C1x1) \times (C1x2) \times (C1x3) \times (C1x4) \times (C1x5)\) |
| \( W_{\text{Rule}2} \) | \((C2x1) \times (C2x2) \times (C2x3) \times (C2x4) \times (C2x5)\) |
| \( W_{\text{Rule}3} \) | \((C3x1) \times (C3x2) \times (C3x3) \times (C3x4) \times (C3x5)\) |
| \( W_{\text{Rule}4} \) | \((C4x1) \times (C4x2) \times (C4x3) \times (C4x4) \times (C4x5)\) |
| \( W_{\text{Rule}5} \) | \((C5x1) \times (C5x2) \times (C5x3) \times (C5x4) \times (C5x5)\) |
| \( W_{\text{Rule}6} \) | \((C6x1) \times (C6x2) \times (C6x3) \times (C6x4) \times (C6x5)\) |
| \( W_{\text{Rule}7} \) | \((C7x1) \times (C7x2) \times (C7x3) \times (C7x4) \times (C7x5)\) |
| \( W_{\text{Rule}8} \) | \((C8x1) \times (C8x2) \times (C8x3) \times (C8x4) \times (C8x5)\) |
In the structure of the selected model, eight membership functions of Gaussian type (gaussmf) for each of the five input parameters have been created; and in its fuzzy rules base also eight fuzzy rules have been constructed during the training process. Membership functions of all the inputs of the model are shown in Figure 8.

7.3.1  The impact of model inputs on bond strength predicted by ANFIS

In this section, the impact of each of the parameters influencing the output value, which is bond strength, are determined. The diagrams related to the effect of the two inputs on one output are extracted while other inputs remain in their median values. Here, the effects of all five inputs that have entered the system as normalized and have participated in modeling have presented. As can be seen in Figures 9 and 10, the horizontal axes of these shapes represent the normalized values.
The highest value of bond strength in all normalized data based on the numbers shown on the vertical axis in the pictures, which is the maximum value of the vertical axis, is 3. The input parameters in this picture are \( \frac{c}{db} \) and \( db \). It can be seen that the inputs of \( \frac{c}{db} \) and \( db \) have the greatest effect on bond strength compared to other parameters; however, with care in the pictures, it can be seen that the effect of the \( db \) parameter is greater, and the larger its value is, the bond strength of GFRP bars in the concrete will be more. So, in the end, it can be said that the diameter of the bar, \( db \), and...
then the ratio of concrete coating to the diameter of the bar c/db, are the parameters having the highest impact on bond strength of GFRP bars in concrete. It should be noted that, as stated in the preceding chapters, always the diameter of the GFRP bar and the concrete coating of this bar has been one of the most important issues in the proposed relationships and experiments of researchers, which itself is a testimony showing accuracy and correctness of the model recommended by ANFIS.

8 | COMPARISON OF THE VALUES PREDICTED BY THE MODELS WITH THE VALUES OBTAINED FROM THE RECOMMENDED RELATIONSHIPS OF VALID REGULATIONS

In recent decades, the main factors influencing bond strength and adhesion behavior of GFRP bars have been determined based on tests of beam samples as well as direct drawing out and finally have entered the design regulations of the United States, Canada, and Japan; these are summarized in Table 8.

These effective factors include the following independent variables: diameter of the bar (d_b), concrete strength (f'_c), bar location, development length of bar (l_d), concrete cover (c), bar surface profile, latitudinal reinforcing cross-section ratio

| Table 8 | Variables outlined in the existing design codes influencing bond strength^{20} |
|---------|-------------------------------------------------|
|          | design standards | Surface | l_d | Position | c | f'_c | d_b | ρ |
| ACI 440.1R-15 | ✘ | ✓ | ✓ | ✓ | ✓ | ✓ | ✘ |
| CSA S806-12 | ✓ | ✘ | ✓ | ✓ | ✓ | ✓ | ✘ |
| CSA S6-14 | ✓ | ✘ | ✓ | ✓ | ✓ | ✓ | ✓ |
| JSCE | ✘ | ✘ | ✓ | ✓ | ✓ | ✓ | ✓ |
Also, it should be mentioned that the bond strength, predicted by ACI 440.1R, is closer to the experimental data, and there are trivial differences among the regulations about the other predictions of the bond strength by JSCE and CSAS6, CSA S806.17,63 Comparison of the different designing regulations about the prediction of the bond strength manifests the four key elements, such as the concrete strength, bar diameter, cover, and the position of the bar. Development length is applied in ACI 440 regulation to calculate the bond strength. However, more information is neglected in the regulation of Canada and Japan, such as the bar surface, the type of applied resin as the reinforcing, and the restriction caused by the width reinforcing.

The equations related to the bond strength which are gained by ACI 440 is linked with the cracking release and afterward. The formulas related to the pulled out release for more important purposes needs to be investigated.40,64,65 In addition to these cases, it is seen that the predicted bond strength by regulations’ relationships is more conservative in comparison with experimental results. In this section, in order to examine the accuracy and efficiency of the models constructed by ANFIS, ANN, and GMDH for prediction of bond strength, the results obtained from the models with the results obtained from the relationships of credible design regulations of ACI 440.1R-15 and CSA S806-12 has been compared. In order to evaluate the efficiency and carefully examine the models results and the relationships in regulations, the same three functions of statistical error measurement absolute error mean percentage (MAPE), root mean of squared error (RMSE), and $R^2$ correlation coefficient are used. Final results were shown in Table 9 and Figures 11-20. It was concluded that ANFIS had fewer errors and higher correlation factor than GMDH and ANN.

As can be seen, the correlation coefficient ($R^2$) for all data in the predicted values by ACI and CSA 806 regulations are equal to 0.82374 and 0.29555, respectively that compared to the correlation coefficient of 0.97684 for all data in ANFIS model, has a higher error rate, that this will be much more intense for CSA 806 regulation, because the closer this parameter is to one, shows lower error rate in the predicted value. Also, the statistical functions of MAPE and RMSE for all the data predicted by ACI and CSA 806 regulations are MAPE $= 2.0871698$, RMSE $= 3.2929$, MAPE $= 4.215786$, and RMSE $= 5.7033$ respectively. These values show a high error compared to the ANFIS model, which is as MAPE $= 0.741317$,

| Model       | TRAIN-135 data | TEST-24 data | ALL-159 data |
|-------------|----------------|--------------|--------------|
|             | RMSE | MAE | $R^2$ | RMSE | MAE | $R^2$ | RMSE | MAE | $R^2$ |
| ANFIS       | 1.0731 | 0.721 | 0.9233 | 1.089 | 0.851 | 0.9785 | 1.0755 | 0.741 | 0.9768 |
| ANN         | 1.3028 | 0.940 | 0.9229 | 1.304 | 1.046 | 0.9682 | 1.3030 | 0.956 | 0.9662 |
| GMDH        | 1.7683 | 1.285 | 0.8911 | 1.379 | 1.166 | 0.9408 | 1.7153 | 1.267 | 0.9403 |
| ACI 440.1R  | 3.5235 | 2.286 | 0.8687 | 11.072 | 0.965 | 0.8162 | 3.2929 | 2.087 | 0.8237 |
| CSA S806    | 6.0284 | 4.503 | -0.0955 | 3.327 | 2.596 | 0.3063 | 5.7033 | 4.215 | 0.2955 |

**TABLE 9** Concise results

**FIGURE 11** The error between models output, regulations predictions and experimental results for all data
FIGURE 12  The error between models output, regulations predictions and experimental results for train data

FIGURE 13  The error between models output, regulations predictions and experimental results for test data

FIGURE 14  The error histogram between models output, regulations predictions and experimental results for train data
**Figure 15** The error between models output, regulations predictions and experimental results for test data

(A) ANFIS  
(B) ANN  
(C) GMDH  
(D) ACI440.1R  
(E) CSA S806

**Figure 16** Scatter plots of ACI and CSA regulations and models predictions and targets for all data
FIGURE 17  Predicted value vs experimental value of bond strength of GFRP in concrete for train data

FIGURE 18  Comparison of performance for experimental data, proposed models and codes
**FIGURE 19** The error histogram between models output, regulations predictions and experimental results for all data.

**FIGURE 20** Predicted value vs experimental value of bond strength of GFRP in concrete for all data.
and RMSE = 1.0755; because the best value for these functions is the lowest of them, and the ANFIS model, compared to regulations, shows a much lower amount. The diagrams plotted based on the results of regulations that show their performance for prediction of bond strength compared to the better models is shown in the following.

9 | CONCLUSIONS

The adhesion behavior of GFRP bars in concrete has a leading role in concrete structures. The factors affecting the bond strength of these bars in concrete based on the information collected from 159 beam specimens existing in reliable scientific articles include three categories of bar characteristics (diameter, cross-section, location, and development length), concrete characteristics (thickness and compressive strength) and latitudinal reinforcement. In this study, three well-known soft computing methods, including neural networks, ANFIS, and GMDH, were examined for predicting the bond strength of these bars in concrete. In all models, 135 data were utilized as training data, and the remaining 24 data were used for test (all these data have been selected randomly). In addition, in GMDH model, a definite equation for predicting the bond strength was obtained; and in ANFIS, the impact of the individual parameters on bond strength among the concrete and GFRP bars was investigated leading to conclude that not only bar diameter but also concrete cover parameters have the greatest impact on bond strength. The soft computing methods used in this research have an acceptable convenience. The comparison between the results predicted by ANFIS, neural networks, and GMDH and the laboratory results show high accuracy and very low dispersion of the data in the comparative fuzzy-neural inference model. Also, according to the examinations, it was found that the predicted values of bond strength by credible regulations are conservative and have a significant difference with actual values and laboratory results; and this issue is higher in Canadian regulations. Finally, considering all of these, it can be concluded that the better results in predicting the bond strength among the concrete and GFRP bars could be achieved by ANFIS. Therefore, it could be stated that ANFIS can be used to obtain the exact amount of bond strength instead of using regulation formulas. Replacing these methods in engineering fields makes progress more conservative in the industry and resource. For future works, more investigations such as parametric studies considering the proposed model may be useful as sensitivity analyses.

PEER REVIEW INFORMATION

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CONFLICT OF INTEREST

The authors declare no potential conflict of interest.

ORCID

Masoomeh Mirrashid https://orcid.org/0000-0002-2751-8585

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