Smart Structures and Systems, *Vol. 26, No. 4 (2020) 403-418*
DOI: https://doi.org/10.12989/sss.2020.26.4.403

Evaluating the bond strength of FRP in concrete samples using machine learning methods

Juncheng Gao[1,2], Mohammadreza Koopialipoor[3], Danial Jahed Armaghani[*4], Aria Ghabussi[5], Shahrizan Baharom[6], Armin Morasaei[7], Ali Shariati[**8,9], Majid Khorami[10] and Jian Zhou[11]

[1]*China Vanke Co., Ltd., Shenzhen, 518000, China*
[2]*State Key Laboratory of Coastal and Offshore Engineering, Dalian University of Technology, Dalian, 116000, China*
[3]*Faculty of Civil and Environmental Engineering, Amirkabir University of Technology, 15914, Tehran, Iran*
[4]*Institute of Research and Development, Duy Tan University, Da Nang 550000, Vietnam*
[5]*Department of Civil Engineering, Central Tehran Branch, Islamic Azad University, Tehran, Iran*
[6]*Department of Civil and Architectural Engineering, Eyvanekey University, Tehran, Iran*
[7]*Department of Civil Engineeing, K.N. Toosi University of Technology, Tehran, Iran*
[8]*Division of Computational Mathematics and Engineering, Institute for Computational Science, Ton Duc Thang University, Ho Chi Minh City 758307, Vietnam*
[9]*Faculty of Civil Engineering, Ton Duc Thang University, Ho Chi Minh City 758307, Vietnam*
[10]*Facultad de Arquitectura y Urbanismo, Universidad UTE, Quito, Ecuador*
[11]*School of Resources and Safety Engineering, Central South University, Changsha 410083, China*

(*Received August 17, 2019, Revised February 17, 2020, Accepted March 5, 2020*)

Abstract. In recent years, the use of Fiber Reinforced Polymers (FRPs) as one of the most common ways to increase the strength of concrete samples, has been introduced. Evaluation of the final strength of these specimens is performed with different experimental methods. In this research, due to the variety of models, the low accuracy and impact of different parameters, the use of new intelligence methods is considered. Therefore, using artificial intelligent-based models, a new solution for evaluating the bond strength of FRP is presented in this paper. 150 experimental samples were collected from previous studies, and then two new hybrid models of Imperialist Competitive Algorithm (ICA)-Artificial Neural Network (ANN) and Artificial Bee Colony (ABC)-ANN were developed. These models were evaluated using different performance indices and then, a comparison was made between the developed models. The results showed that the ICA-ANN model's ability to predict the bond strength of FRP is higher than the ABC-ANN model. Finally, to demonstrate the capabilities of this new model, a comparison was made between the five experimental models and the results were presented for all data. This comparison showed that the new model could offer better performance. It is concluded that the proposed hybrid models can be utilized in the field of this study as a suitable substitute for empirical models.

Keywords: FRP; ICA-ANN; ABC-ANN; prediction; bond strength

1. Introduction

The use of Fiber Reinforced Polymers (FRPs) around Reinforced Concrete (RC) that leads to the increased strength is introduced as a common state in this area (Teng *et al.* 2002, Oehlers *et al.* 2004). Over recent years, FRPs have been used in different forms to strengthen various forms of concert structures and in different sectors of civil engineering. The characteristics such as high corrosion resistance, fatigue loading resistance, high strength and hardness compared to its volume and weight have led to the prosperity of these materials. In addition to these characteristics, compatibility and flexibility of FRP materials in reinforcing different sectors, especially civil infrastructures, have led to their significant advantage over other methods (Wu *et al.* 1999).

The Intermediate Crack (IC) mechanism is one of the common ways to investigate the flexibility and bending strength of RC members which have been strengthened using FRPs bonded around it. Fig. 1 shows the single-lap shear test in a simple way, which can be used in combination with FRP and concrete under tension conditions (Chajes *et al.* 1996). This process is presented for the critical state of IC (Chen *et al.* 2001, Yao *et al.* 2005). Using this test, the strength of bond and interface bond stress–slip relationship can be identified, and through greater recognition of debonding mechanism, one can better analyze and design the numerical and analytical models (Wu *et al.* 2010). The single-lap shear tests have been used in a variety of experimental studies as a solution to determine the bond strength (Takeo *et al.* 1997, Zhao *et al.* 2000, Chen *et al.* 2001, Yao *et al.* 2005, Sharma *et al.* 2006, Woo *et al.* 2010). In addition, several experimental equations have been extracted and developed by researchers

*Corresponding author, Ph.D.,
E-mail: danialjahedarmaghani@duytan.edu.vn

**Co-corresponding author, Ph.D.,
E-mail: alishariati@tdtu.edu.vn

http://www.techno-press.org/?journal=sss&subpage=7
ISSN: 1738-1584 (Print), 1738-1991 (Online)

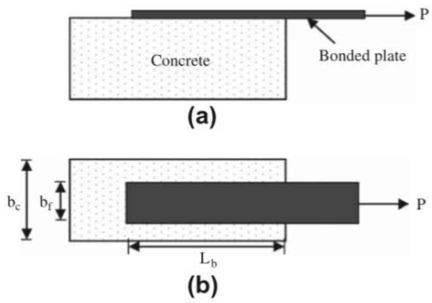

Fig. 1 Two view of single-lap shear test (a) side (b) top

to investigate and assess the bond strength of FRP in different concrete samples and their joints using numerical methods of IC (Brosens 1997, Neubauer *et al*. 1997, Chen *et al*. 2001, Yang *et al*. 2001, Lu *et al*. 2005, Yao *et al*. 2005, Ye *et al*. 2005, Toutanji *et al*. 2007). However, the problems such as the limited prediction of the bond strength of FRP in the conducted tests, the complex and time-consuming experimental relationship and their relatively low accuracy have caused their application to be limited. In some cases, considering the changes made in experiments and developing them, the old experimental models have become obsolete due to their lower flexibility.

Considering the development of the computation using computer models, the methods in this area have widely expanded in the engineering area (Koopialipoor *et al*. 2019h, Zhou *et al*. 2019a, b, Cai *et al*. 2020, Koopialipoor *et al*. 2020a). As the newest computational methods, artificial intelligence methods are used in a variety of sectors and for various data and create a more ideal relationship between the dependent and independent variables. Among the advantages of these methods is that they are not confined to special assumptions, and this has led to the expansion and development of these methods in the previous works (Nehdi *et al*. 2001). By changing these parameters or extending their range, these models create high flexibility for adaptability. Neural networks are composed of neurons that perform different calculations based on mathematical mapping (Jeon 2007, Ghaleini *et al*. 2019, Koopialipoor *et al*. 2020b). These neurons are, in fact, derived from the human brain system, that is why they have high adaptability in learning different components of problems (McCulloch *et al*. 1943, Guo *et al*. 2019, Koopialipoor *et al*. 2019f). Among different applications of neural network methods are classification, clustering, prediction and removal of additional data. Over recent years, some developed models have also been presented given their ability to expand like e.g., hybrid models of Imperialist Competitive Algorithm (ICA)-Artificial Neural Network (ANN), Particle Swarm Optimization (PSO)-ANN, Artificial Bee Colony (ABC)-ANN, and optimization and probabilistic models. A variety of research works have been done in civil engineering, which can be called new models in this area (Toghroli *et al*. 2014, Gordan *et al*. 2019, Koopialipoor *et al*. 2019a, g, Xu *et al*. 2019, Afshar *et al*. 2020, Shariati *et al*. 2020b, Toghroli *et al*. 2020, Zhou *et al*. 2020a). Several of these topics are in structural engineering, the study of structural damage, the liquefaction of foundations and optimal structural design (Mukherjee *et al*. 1996, Feng *et al*. 1998, Rafiq *et al*. 2001, Cladera *et al*. 2004, Abdalla *et al*. 2007, Mohammadhassani *et al*. 2014b, Toghroli *et al*. 2018b, Mansouri *et al*. 2019).

Employing artificial intelligence techniques has been expanded through a variety of applications as data validation and data estimation. Prediction of the structural characteristics, such as compressive strength of concrete or ultimate stress of steel shear connectors, has been studied through these techniques. Besides, the authenticity of the test results could be easily verified by artificial intelligence. The prediction quality of these methods has been confirmed in recent studies, which shows the capability of them to use in various investigations (Shariati *et al*. 2012a, 2016a, 2019a, c, d, f, 2020c, d, e, Khorami *et al*. 2017, Khorramian *et al*. 2017, Shariat *et al*. 2018, Katebi *et al*. 2019, Milovancevic *et al*. 2019, Trung *et al*. 2019a, Armaghani *et al*. 2020, Safa *et al*. 2020).

Several studies have been conducted to investigate the steel-concrete composite floor systems. Also, employing different shear connectors and innovative concrete mix designs has been considered during these studies. However, using FRP as one of the novel ways to enhance flexibility and toughness has not been reviewed yet. FRP could be employed in the concrete slabs to improve the performance of the composite systems. Moreover, the fire-resistivity of these systems could be a challenger for researchers (Shariati *et al*. 2011, 2012b, 2017, Shariati 2013, Mohammadhassani *et al*. 2014a, Khorramian *et al*. 2016, Shahabi *et al*. 2016b, Tahmasbi *et al*. 2016, Hosseinpour *et al*. 2018, Nasrollahi *et al*. 2018, Paknahad *et al*. 2018, Wei *et al*. 2018, Davoodnabi *et al*. 2019).

Steel rack connection is a popular choice in industrial storage and other types of rack system applications. On the other hand, several studies have examined different approaches to strengthen and alleviate the weight of the system. The use of FRP as a new way could be a logical topic for further investigations (Shah *et al*. 2015, 2016, 2018, Chen *et al*. 2019).

FRP strengthening technique has been trustfully proved in case of building retrofit or beam strengthening and other similar cases. Also, FRP is a handy way to repair some damaged parts of a structure. Besides, FRP reinforced beams or floor systems have been evaluated during and after a seismic accident. Hence, the dynamic response of the FRP reinforced structures could be an appealing issue for further studies (Shariati 2008, Arabnejad Khanouki *et al*. 2010, 2011, Daie *et al*. 2011, Jalali *et al*. 2012, Zandi *et al*. 2018, Shariati *et al*. 2020a).

Concrete, as one of the artificial construction materials, has been made up of different parts such as cement, water, aggregate, and other substantial parts. Using new material components is one of the most fashionable ways to enhance the mechanical and fresh properties of the concrete. In other words, employing supplement elements could improve the concrete structural performance during and after applying service loads or different kinds of load on concrete. Reinforcing concrete with FRP is the most appropriate way to enhance the bending moment and flexibility of the concrete in addition to control the crack propagation (Sinaei *et al*. 2011, Toghroli *et al*. 2017, 2018a, Ismail *et al*. 2018, Nosrati *et al*. 2018, Ziaei-Nia *et al*. 2018, Li *et al*. 2019, Luo *et al*. 2019, Sajedi *et al*. 2019, Shariati *et al*. 2019b, e, Trung *et al*. 2019b, Xie *et al*. 2019, Naghipour *et al*. 2020).

Considering recent limitations in the investigation of the bond strength of FRP in concrete structures, the new and developed models were implemented in this study. Given the tests conducted, a dataset including 150 laboratory samples was collected. Two models of ICA-ANN, and ABC-ANN models were designed based on different conditions and the results from each of them were compared with the existing samples.

2. Existing models to predict bond strength of FRP fittings to concrete

Considering the existence of experimental models in the assessment of the bond strength of FRP in concrete samples, a summary of them is presented in this part. The three first models were selected out of the new methods and the two other methods were chosen from the international regulations. These models were obtained and compared based on different laboratory samples which had FRP in their concrete fittings. Different details of these methods can be found in their original sources. In this research, the aim is to use these models to be compared with new smart models. Therefore, attempts were made to provide the same conditions for comparison in all states. In all models, some assumptions have been considered, namely: the concrete bed is well prepared and the quality of the samples is designed under common and identical conditions. In this research, all variables were tried to consider with a constant index.

2.1 Lu et al. (2015)

This model which was presented to determine the bond strength model of FRP in the concrete samples is based on the interfacial fracture energy. In the following, the bond strength is obtained from the below relations.

$$P_u = \beta_1 b_f \sqrt{2E_f t_f G_f} \tag{1}$$

where

$$\begin{aligned}
&\beta_1 = \begin{cases} 1 & if\ \mathrm{L} \geq \mathrm{Le} \\ \dfrac{L}{Le}\left(2-\dfrac{L}{Le}\right) & if\ \mathrm{L} < \mathrm{Le} \end{cases} \\
&Le = a + \frac{1}{2\lambda_1} ln\left[\frac{\lambda_1 + tan(\lambda_2 a)}{\lambda_1 - tan(\lambda_2 a)}\right] \\
&G_f = 0.308\beta_w^2\sqrt{f_t} \\
&\lambda_1 = \sqrt{\frac{\lambda_{max}}{s_0 E_f t_f}} \\
&\lambda w_{t\,max} \\
&\lambda_2 = \sqrt{\frac{\lambda_{max}}{(s_f - s_0)E_f t_f}} \\
&s_0 = 0.0195\beta_w f_t \\
&s_f = \frac{2G_f}{\lambda_{max}} \\
&a = \frac{1}{\lambda_2} arcsin\left[0.99\sqrt{\frac{(s_f - s_0)}{s_f}}\right]
\end{aligned} \tag{1a}$$

and

$$\beta_w = \sqrt{\frac{2.25 - \frac{b_f}{b_c}}{1.25 + \frac{b_f}{b_c}}} \tag{1b}$$

2.2 Dai et al. (2015)

This model was presented based on the interfacial fracture energy and stiffness in FRP samples to obtain the maximum level of bond strength. Here, it is supposed that the length of *L* connection is greater than the length of the effective *Le* in samples. In the following, the relation of this model is presented.

$$P_u = (b_f + \Delta b_f)\sqrt{2E_f t_f G_f} \tag{2}$$

where $G_f = 0.254(f_c')^{0.236}$ where the value of Δb_f =3.7 is obtained based on the assumptions with laboratory basis.

2.3 Wu et al. (2010)

Woo *et al*. (2010) proposed a new model for laminated structures which is similar to Dai *et al*. (2005) model. This model is based on the use of IC theory which is not affected by *Le* parameter.

$$P_u = \beta_w b_f \sqrt{2(1 + \frac{\lambda'}{\sum})E_f t_f G_f} \tag{3}$$

$$\begin{aligned}
&\beta_w = \sqrt{\frac{2 - \frac{b_f}{b_c}}{1 - \frac{b_f}{b_c}}} \\
&\lambda' = \frac{t_d}{t_f} \\
&t_d = 3.5\ \mathrm{mm} \\
&\sum = \frac{E_f}{E_c}
\end{aligned} \tag{3a}$$

where the value of G_f is considered to be 0.17 N/mm.

2.4 FIB model (Du Béton 2001)

Neubauer *et al*. (1997) model was modified by Holzenkämpfer (1994) and was applied as a more adaptable solution to investigate the bond strength of FRP in concrete samples.

$$P_u = \begin{cases} 0.64\alpha k_c \beta_w b_f \sqrt{E_f t_f f_t} & \text{if } L \geq Le \\ 0.64\alpha k_c \beta_w b_f \sqrt{E_f t_f f_t} \dfrac{L}{Le}(2 - \dfrac{L}{Le}) & \text{if } L < Le \end{cases} \quad (4)$$

where

$$\beta_w = 1.06 \sqrt{\frac{2 - \frac{b_f}{b_c}}{1 + \frac{b_f}{400}}} \geq 1$$
$$Le = \sqrt{\frac{E_f t_f}{2 f_t}} \quad (4a)$$
$$\alpha = 1.0 \text{ and } k_c = 1.0$$

2.5 CNR-DT200 (Soudki and Alkhrdaji 2004)

Considering the proposed model CNR-DT200 (Soudki and Alkhrdaji 2004), the following relation can be used to assess the bond strength of FRP

$$P_u = b_f \sqrt{2 E_f t_f k_G \beta_w \beta_1 \sqrt{f_c' f_c}} \quad (5)$$

where

$$k_G = 0.03$$
$$\beta_1 = \begin{cases} 1 & \text{if } L \geq Le \\ \dfrac{L}{Le}(2 - \dfrac{L}{Le}) & \text{if } L < Le \end{cases}$$
$$Le = \sqrt{\frac{E_f t_f}{2 f_f}} \quad (5a)$$
$$\beta_w = \sqrt{\frac{2 - \frac{b_f}{b_c}}{1 + \frac{b_f}{400}}} \geq 1 \text{ if } \frac{b_f}{b_c} < 0.33$$

then the value β_w is calculated using $\frac{b_f}{b_c} < 0.33$.

3. Methodology

3.1 Artificial neural network

Using simple learning patterns, more complex mechanisms were introduced by Hebb (1955) known as neural networks. This new mechanism is inspired by the neurons of the brain. The neurons used examine the connections between input and output data in a big collection for learning the system (Koopialipoor *et al*. 2019c, Liao *et al*. 2019). The functions defined in neural models work like brain systems. They take information from the previous neuron, and by processing it, transfer it to the next neuron. Neural models consist of several layers, each of which can have a number of different neurons. The relationship between the different layers is regulated and controlled using their weights. Activation functions in ANN models are responsible for controlling these weights. (Fig. 2). Among the various algorithms for model training, the Back-propagation algorithm has been recommended as the most common type among various researches. The purpose of this algorithm is to reduce the error calculated by the layers and adjust the weights to reach the defined minimum value. This process is done repeatedly to achieve its goal (Fig. 2) (Koopialipoor *et al*. 2019d, Sun *et al*. 2019, Yang *et al*. 2019).

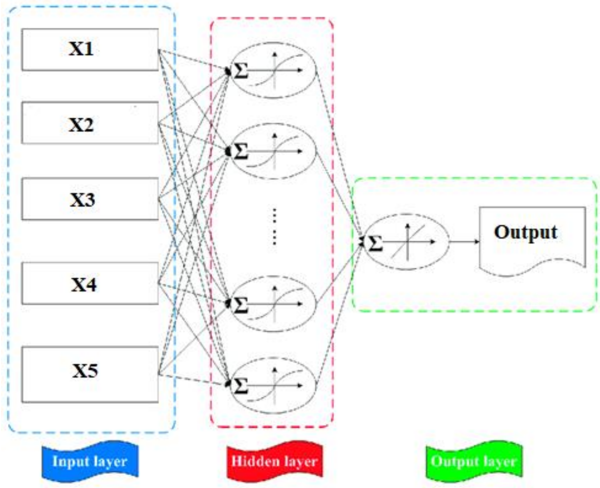

Fig. 2 The structure of ANN model

3.2 Artificial bee colony (ABC)

The ABC algorithm is known as one of the new algorithms that is inspired by the collective life of bees. This algorithm is introduced in various fields as a new optimization solution (Karaboga 2005). In this algorithm, there are three important types of bees, which are: employed, onlookers and scouts bees (Koopialipoor *et al*. 2019d). In the first step of this algorithm, searching for food sources is done by two scouts. During these searches, a large number of bees are assumed as onlookers. A type of movement, called waggle dance, is made by the bees to make connections. In this process, the scouts inform the employed bees of the quality of food sources (answers). In these conditions, various bees can use the achieved information and opt the required sources of the beehives. The quality of the obtained solution is investigated according to the amount nectar available as a food source.

Various parameters affect the performance of the ABC algorithm that by adjusting and optimizing them, the performance of the algorithm can be increased. These parameters are: number of bees dispatched to other food source (N_{sp}), the number of scout bees (N), number of iteration (I_{max}) and amount of food source (M). In the first step, the position of the resources to start the search is provided

$$X_{ij} = X_j^{min} + ran(0,1)(X_j^{max} - X_j^{min}) \quad (6)$$

where X_j indicates the variable number and X_{ij} is the number of the answer or food source, respectively. In the next step,

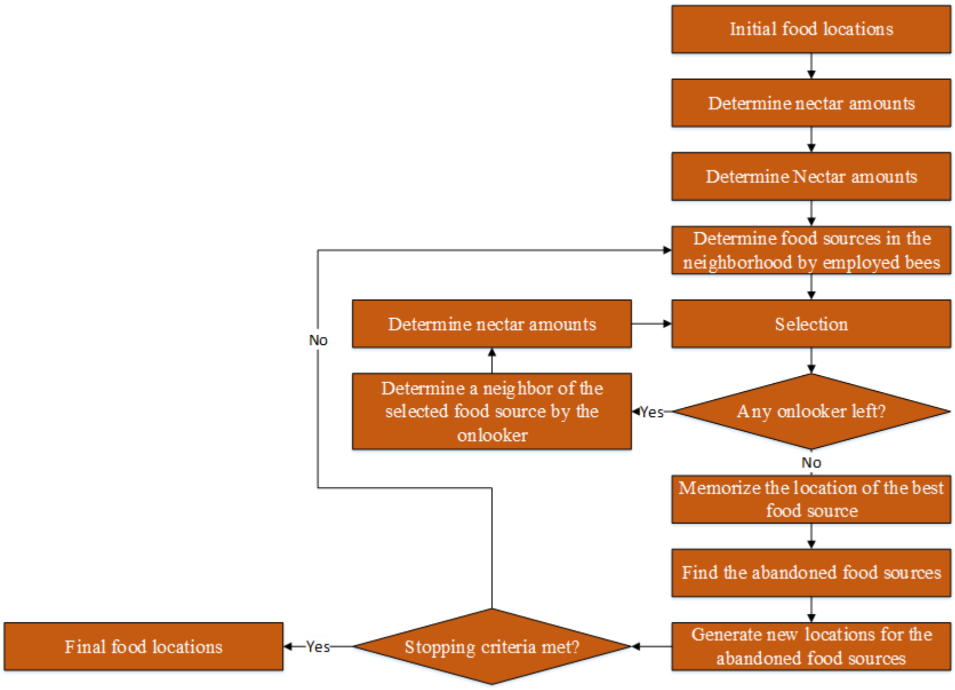

Fig. 3 The presented flowchart for ABC algorithm (Zhao *et al*. 2019)

the new solution (V_{jk}) is presented using the following equation

$$V_{jk}(t+1) = X_{jk}(t) + \emptyset_{jk}(t)(X_{jk}(t) - X_{wk}(t)) \quad (7)$$

$$K = int(rand \times N) + 1 \quad (8)$$

where the X_{jk} and ϕ_{jk} indicate the jth solution from among the solutions set of the kth parameter and the uniform distribution of random numbers and the jth solution from among the solutions set of the kth parameter, respectively. N is number of answer or food source. The parameter K and ϕ_{jk} are randomly defined from ranges [1 and -1] and [1 and N], respectively. Finally, using the defined conditions, whichever solution gets the best answer replaces the previous one. Using Eq. (9), the scout bee examines the available solutions. Depending on the characteristics of each problem, this process is variable and ultimately the best result is extracted from them (Koopialipoor *et al*. 2019e). Fig. 3 presented a general process for ABC algorithm.

$$P_i = \frac{fit(x_i(t))}{\sum_j^N fit(x_i(t))} \quad (9)$$

3.3 Imperialist competitive algorithm

One of the new algorithms, which in recent years has found a good deal in solving problems, is the Imperialist Competitive algorithm (ICA). This algorithm, which is introduced and implemented by Atashpaz-Gargari *et al*. (2007), uses population fundamentals and a global search for problem solving. The implementation of this algorithm is so that countries (as the primary population) or (Ncountry) are produced. In the future, imperialists, i.e., Nimp, are chosen given the lower cost criterion between the countries, and other remaining countries are used as dependent functions of the imperialist between the other empires. Imperialists are introduced as the most powerful attributes among other colonies. Three important attributes including assimilation, revolution, and competition generate custom operations in the ICA algorithm**.** In this algorithm, the colonies are absorbed by the imperialists in the initial conditions, but it is possible that revolution will occur and cause sudden change. Ultimately, the characteristics of the competition between the imperialists will make the colonies given the desirable criteria which they have to get. The same process continues until the desired criteria are completed. In this algorithm, the number of decades is equal to the number of particles and generations in the PSO and GA algorithms. Other information for this algorithm has been investigated in several studies (Armaghani *et al*. 2018, 2019). An original structure of ICA algorithm is presented in Fig. 4.

3.4 Hybrid algorithms

In this research, optimization algorithms were used innovatively to improve the performance of intelligent models. An ANN based model is used first and then, given the unique features of optimization algorithms, they are added to the intelligent model training section, and with the new combination, a new algorithm is proposed for predictions of various engineering problems (Huang *et al*. 2019, Mohamad *et al*. 2019). The reason for using this part of ANN models is the initial weakness of the base model in finding the global minimum. This causes the percentage of error increased in finding the answers. With the introduction

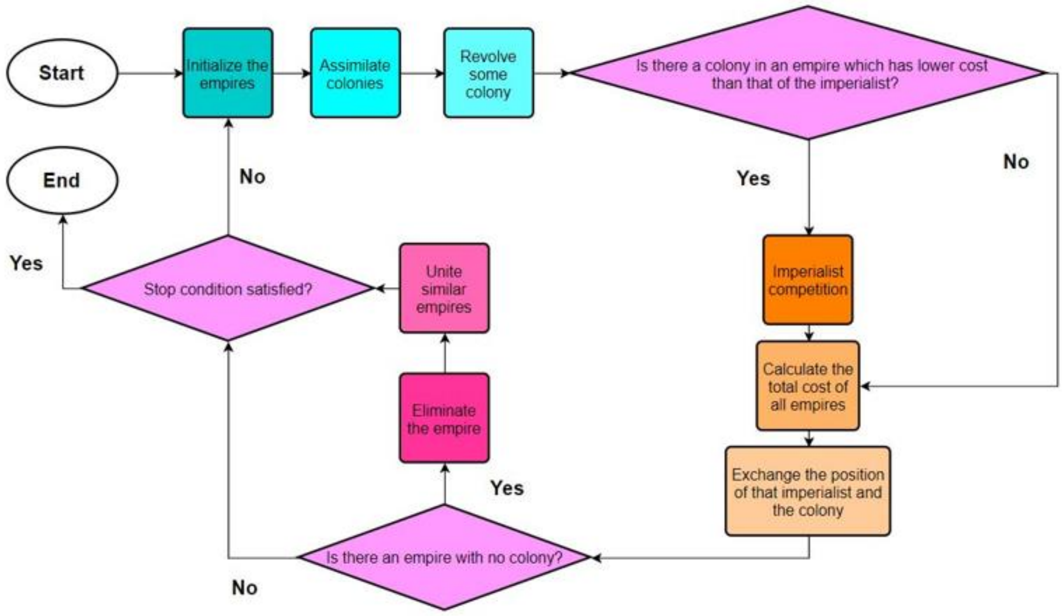

Fig. 4 The main structure of the ICA algorithm

Table 1 Main information of various variables used in the current research

Parameter	Width of prism (b_c)	Concrete cylinder compressive strength (f_c')	Width of FRP (b_f)	Thickness of FRP (t_f)	Modulus of elasticity of FRP (E_f)	Bond length (L)
Min	100.00	16.00	10.00	0.08	83.03	50.00
Max	228.20	50.00	100.00	1.40	300.00	300.00
Average	161.35	33.68	39.89	0.84	178.00	150.59
Std	40.50	9.27	21.47	0.53	58.36	70.68

of optimization models, the power levels of these minima have improved. Optimization algorithms change the performance of the base model using optimal coefficients. In this research ABC-ANN and ICA-ANN models were developed and used to predict the bond strength of FRP in concrete samples. These new models create a new method for evaluating various problems that can be mentioned by their precision and speed in various projects.

4. Modelling

4.1 Data source

In this study, an extracted dataset from laboratory tests contains 150 specimens which carry out for FRP-to-concrete joint test and are provided based on several sources (Neubauer *et al*. 1997, Takeo *et al*. 1997, Zhao *et al*. 2000, Lu *et al*. 2005, Yao *et al*. 2005, Sharma *et al*. 2006, Woo *et al*. 2010). The main information used for different intelligent systems is presented in Table 1. This table contains input and output parameters that represent the intervals of laboratory samples. All specimens were used in accordance with single-lap shear tests (Fig. 1). Also, they failed according to debonding which happened in the concrete samples. Other explanations for each one can be extracted from their main sources.

4.2 ICA-ANN

In this section, the parameters affecting the ICA-ANN model are evaluated. Some of these parameters are obtained according to the recommendations of previous researchers or according to the method of trial and error (Mahdiyar *et al*. 2020, Tang *et al*. 2020, Zhou *et al*. 2020b). Initially, the ANN model, which is assumed to be constant for all models, is selected. After the initial analysis, this basic model was designed as a structure with 11 hidden neurons. In other models, this structure is assumed to be fixed and improved with different performance algorithms. According to the description of the previous section, three parameters N_{country}, N_{decade} and N_{imp} were introduced as the main characteristics of the ICA algorithm. According to past research, for N_{imp}, 10, 20, 30 and 40 values were selected. In these conditions, two parameters N_{country} and N_{decade} with constant values of 300 and 100 were considered respectively. Using the parametric analysis, the appropriate N_{imp} value was obtained 20. This value increases the accuracy in predicting the bond strength of FRP. Then the optimal N_{country} and N_{decade} values are evaluated for the development of prediction models. According to past work, values of 25, 50, 75, 100, 125, 150, 175 and 200 were

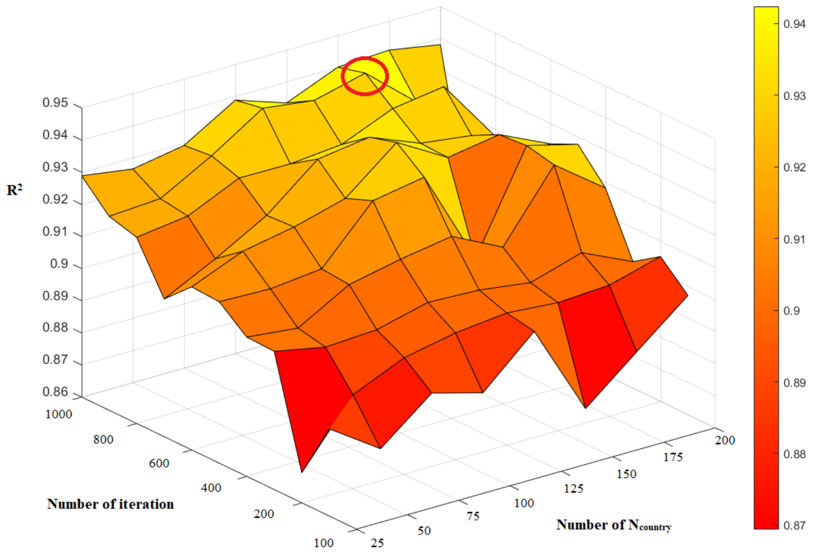

Fig. 5 Effects of number of iteration and $N_{country}$ on ICA-ANN model results

Table 2 Result of 5 models for prediction of the bond strength of FRP using ICA-ANN

Model	No. Model	Train		Test		Train rating		Test rating		Total rank
		R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	
ICA-ANN	1	0.9346	0.1178	0.9158	0.1486	1	1	2	2	6
	2	0.9424	0.1092	0.9269	0.1334	5	5	5	5	20
	3	0.9416	0.1099	0.9178	0.1434	4	4	3	3	14
	4	0.9389	0.1147	0.9244	0.1367	2	2	4	4	12
	5	0.9401	0.1113	0.9099	0.1541	3	3	1	1	8

considered for $N_{country}$. These parameters were run up to the N_{decade} = 1000 intervals so that they could get the RMSE changes. Finally, the results of the models are presented in Fig. 5. The best structure for this new model was $N_{country}$ = 150 and iteration = 900. Then, several models of this structure were designed.

To determine the best models in predicting the bond strength of FRP, two methods developed by previous researchers were used (Zorlu *et al.* 2008, Koopialipoor *et al.* 2019b). These methods are based on scoring and color intensity system. More information can be obtained from previous work. Using these two methods, in this research, the results of the models were compared and the best models were selected. In Table 2, model No. 2 achieved the highest color intensity and the highest possible score. Therefore, this model is presented as an appropriate model of the ICA-ANN method, which predicts the bond strength of FRP.

4.3 ABC-ANN

One of the algorithms used to improve ANN performance was the ABC algorithm. The base ANN model uses the BP algorithm for training and provides various functions on different problems. For this reason, the ABC algorithm was used for training to develop this model. This algorithm helps to improve its performance by finding global errors in the system. It should be noted that one of the main problems of the networks trained by BP is to catch up with the local minimum. This training process continues with finding the best answers in computing space.

In this algorithm, first, the initial coefficients for each solution are generated using Eq. (6), and then a series of new coefficients will be created. Afterward, the predicted values and errors are calculated, and if any progresses, the new coefficients will replace the previous ones, otherwise, they will not be replaced. Coefficients may be appropriate and new ones will be forgotten. After canceling the probability of selecting a coefficient, new items are created around the highest-qualified coefficients. In this case, if a decrease in the error rate occurs, the new coefficients will be replaced, otherwise, they will not be replaced. As in the next few searches, space exploration does not take place, and no more time is spent, and the filing is done (find). Therefore, the speeding speed is improved and the internal ABC system is also optimized. Finally, the new coefficients are generated randomly, if any of the new coefficients are reached by a predetermined value.

11 neurons were used to design the ABC-ANN model. Then the new model was implemented to evaluate the effect of the number of iteration and bees. Other explanations are similar to the previous one. The results are shown in Fig. 6.

As can be seen, the best model has 800 iteration and 30 bees. Finally, five datasets were designed from this model.

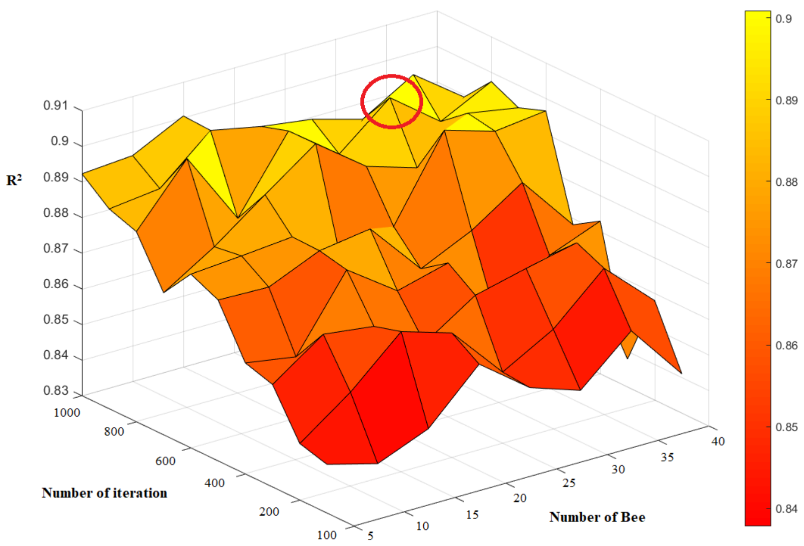

Fig. 6 Effects of number of bee and iteration on ABC-ANN model results

Table 3 Result of 5 models for prediction of the bond strength of FRP using ABC-ANN

Model	No. Model	Train		Test		Train rating		Test rating		Total rank
		R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	
ABC-ANN	1	0.8977	0.1714	0.8851	0.1961	4	4	2	2	12
	2	0.8844	0.1863	0.8763	0.2105	2	2	1	1	6
	3	0.8916	0.1757	0.8993	0.1758	3	3	4	4	14
	4	0.9009	0.1674	0.8999	0.1743	5	5	5	5	20
	5	0.8839	0.1879	0.8951	0.1848	1	1	3	3	8

The results of these models are presented in Table 3 to determine the best model. To evaluate the performance of the models, two scoring systems were used. These scoring systems showed that Model No. 4 is the best model in predicting the bond strength of FRP.

5. Comparison of BPNN prediction with existing models

In this section, the ability of the selected models to assess the bond strength of FRP in the concrete samples was compared with previous models. Here, the results of different models are separately shown for all data. As can be observed from the previous section, the results of ICA-ANN model are better than those of ABC-ANN models. Therefore, this model was selected for comparison with experimental models. Table 4 presents the results of all models to predict the bond strength of FRP. Considering this table, it can be observed that the accuracy of the ICA-ANN, models are higher than experimental models. The R^2 values obtained for ICA-ANN, CNR-DT, FIB model, Wu *et al*. (2010) Dai *et al.* (2015) and Lu *et al*. (2015) models are including 0.9395, 0.8166, 0.8790, 0.7089, 0.8190 and 0.7454 for all data, respectively. This high accuracy in prediction of the bond strength of FRP in concrete samples causes the new model to show high adaptability in different conditions and samples compared to experimental models. That is why the use of these techniques can provide a more appropriate and inclusive solution.

6. Conclusions

In the present paper, in order to assess the bond strength of FRP in concrete samples, new computational methods with high adaptability and accuracy in solving engineering problems were used. These methods actually reduce the error of calculations in civil and structural engineering. Therefore, two different models of artificial intelligence were implemented in this research, including ICA-ANN and ABC-ANN. In order to assess the bond strength of FRP, a dataset from laboratory samples was collected. These samples include the width of prism, concrete cylinder compressive strength, width of FRP, thickness of FRP, modulus of elasticity of FRP and bond length. The intelligent models were designed and implemented, respectively, each of which consists of two parts of training and testing. After that, the effective parameters in these models were identified and the effect of each of them was investigated. Finally, by making a comparison between the predicted values for the bond strength of the FRP, the best model of intelligent models was introduced. ICA-ANN model with accuracies of R^2 = 0.9424 and R^2 = 0.9269 was

Table 4 The final results of various models for assessing the bond strength of FRP

Number	Lu *et al.* (2015)	Dai *et al.* (2015)	Wu *et al.* (2010)	FIB model	CNR-DT	ICA-ANN
	P_M/P_P	P_M/P_P	P_M/P_P	P_M/P_P	P_M/P_P	P_M/P_P
1	0.8846	0.4578	0.7378	1.2055	1.0132	0.9245
2	0.8482	0.6146	0.9905	0.9796	1.1429	1.0704
3	0.9847	0.7134	1.1498	1.0197	1.0197	0.3206
4	1.1079	0.8028	1.2937	1.0625	1.0938	0.8900
5	1.1848	0.8584	1.3835	0.9643	1.0812	0.5207
6	1.1474	0.8313	1.3398	0.9354	1.1467	0.9304
7	1.1855	0.8589	1.3843	1.1098	1.1451	0.9553
8	0.9093	0.6612	0.9657	1.1184	1.0915	1.2798
9	1.0170	0.7396	1.0800	1.0294	1.0690	0.9324
10	1.0768	0.7831	1.1436	0.9167	1.0373	1.1991
11	1.0774	0.7835	1.1442	0.9994	1.0636	0.7938
12	1.1073	0.8052	1.1760	0.9454	1.1098	1.1781
13	1.1007	0.8005	1.1690	1.0715	1.1754	0.7512
14	0.9762	0.7073	0.4611	0.8680	0.8748	1.3870
15	1.0566	0.7656	0.4991	0.8505	0.8573	0.7696
16	1.1901	0.8623	0.5622	0.7983	0.8023	0.7822
17	1.1683	0.8465	0.5519	0.9011	0.9137	1.0721
18	1.1798	0.8549	0.5573	0.9576	0.9910	0.9314
19	0.6610	0.5119	2.2510	1.2621	1.1446	0.9032
20	0.7380	0.5715	2.5130	1.0850	1.0914	0.7147
21	0.7569	0.5862	2.5775	0.9686	1.1249	0.8462
22	0.7670	0.5940	2.6118	0.6463	1.2213	1.0248
23	0.7708	0.5969	2.6247	1.1457	1.3645	0.9406
24	0.8440	0.6536	2.8739	1.0015	1.4263	0.9686
25	0.7326	0.5692	2.5517	0.8879	1.2943	0.8029
26	0.7926	0.6307	2.3494	0.8626	1.2876	0.8925
27	0.7294	0.5512	1.7940	0.9782	1.4993	0.5922
28	0.7846	0.5513	1.5189	0.9434	1.2158	1.1071
29	0.7310	0.5639	2.4228	1.0269	1.4184	1.0466
30	0.7855	0.6066	2.6204	0.9516	0.8211	1.1331
31	0.8403	0.5867	3.0039	0.8642	0.7683	1.0953
32	0.7991	0.6178	2.6892	0.9289	0.8333	0.5752
33	0.8597	0.6808	2.4622	0.9074	0.8336	1.3609
34	0.7374	0.5546	1.7523	1.1041	1.0415	0.8270
35	0.6634	0.4639	1.2409	1.2730	1.2367	0.5614
36	0.8373	0.6494	2.8825	0.8629	0.8639	1.7057
37	0.8623	0.6688	2.9684	1.2446	1.0362	1.0653
38	0.9059	0.7027	3.1188	1.0468	1.1288	1.7216
39	0.8360	0.6485	2.8782	0.9851	1.3745	0.8772
40	0.8079	0.6001	2.3750	0.6936	1.1248	0.8990
41	0.8261	0.6128	2.4022	0.7135	1.0568	0.8441
42	0.8587	0.6379	2.5243	0.9892	1.3978	1.2231
43	0.7935	0.5885	2.3072	1.0706	1.8824	0.9252
44	0.8587	0.6379	2.5243	1.0000	1.2903	1.0426
45	0.7748	0.5747	2.2529	1.1325	1.8072	0.5865
46	0.8288	0.6140	2.3886	0.7365	1.4423	0.6242

Table 4 Continued

Number	Lu *et al.* (2015)	Dai *et al.* (2015)	Wu *et al.* (2010)	FIB model	CNR-DT	ICA-ANN
	P_M/P_P	P_M/P_P	P_M/P_P	P_M/P_P	P_M/P_P	P_M/P_P
47	0.7871	0.5836	2.2828	0.7569	1.5542	1.6412
48	0.7456	0.5520	2.1416	0.8285	1.5843	0.8199
49	0.7706	0.5709	1.5941	1.5376	1.3143	1.5267
50	0.7414	0.5492	1.2459	1.0370	1.2314	0.7351
51	1.0612	0.7857	3.0482	0.9795	1.1131	1.1708
52	0.6764	0.5079	2.1443	0.3604	2.4988	1.0200
53	0.9016	0.6678	3.2301	0.7792	1.4782	0.2583
54	0.8086	0.5995	2.9154	0.7194	1.6866	1.0719
55	0.5067	0.4193	1.4853	1.5527	1.7504	1.4028
56	0.4967	0.4111	1.1615	2.1450	1.5949	1.3623
57	0.6597	0.4103	1.1695	1.6064	0.7861	1.8503
58	0.9672	0.6016	1.7145	1.7323	0.7582	0.6418
59	0.9864	0.6135	1.7485	1.8723	0.9104	0.8866
60	1.0120	0.6295	1.7940	1.5554	1.0246	1.1592
61	0.8006	0.4980	1.4193	1.0705	1.4478	1.4585
62	0.9710	0.6040	1.7213	0.9235	1.3076	0.9291
63	0.6280	0.3928	1.1581	1.8675	0.9535	0.8487
64	0.8435	0.5276	1.5555	2.1390	1.0039	0.7138
65	0.7819	0.4891	1.4420	2.4226	1.3262	0.9901
66	0.8558	0.5353	1.5782	1.6861	1.3990	1.0432
67	0.8373	0.5237	1.5442	0.5378	1.5985	0.6995
68	0.7880	0.4929	1.4533	1.0313	1.8604	0.4926
69	0.5433	0.3413	1.0332	2.3320	1.2322	0.5223
70	0.8478	0.5326	1.6123	2.2445	1.1166	0.3837
71	0.9290	0.5836	1.7667	2.0535	1.2479	0.8679
72	0.9135	0.5739	1.7372	1.4029	1.4653	0.9638
73	0.8120	0.5101	1.5442	0.7353	1.8428	0.9303
74	0.8657	0.5439	1.6464	1.0483	1.8932	1.1875
75	0.4218	0.3447	0.5860	1.1828	1.2888	1.1488
76	0.7370	0.6024	1.0239	1.2923	1.0430	1.2632
77	0.7347	0.6005	1.0207	1.1111	1.2812	0.9625
78	1.0023	0.8192	1.3925	1.4027	1.0844	0.6331
79	0.7075	0.5783	0.9829	1.2532	1.7174	0.9698
80	0.7189	0.5876	0.9987	0.5363	1.1356	0.9528
81	0.3989	0.3279	0.5765	1.5301	1.5736	0.5989
82	0.6496	0.5339	0.9388	1.1409	1.3664	1.0111
83	0.6997	0.5751	1.0113	0.7477	1.4330	0.9288
84	0.7041	0.5787	1.0176	1.4241	1.4861	1.0377
85	0.7023	0.5773	1.0151	0.6633	1.1794	0.9389
86	0.7368	0.6056	1.0648	1.0651	1.3018	1.2488
87	0.3890	0.3211	0.5797	0.7609	1.8042	1.0690
88	0.7526	0.6212	1.1215	1.1798	1.3187	1.0215
89	0.6435	0.5312	0.9590	1.3798	1.8886	1.1469
90	0.7821	0.6457	1.1657	1.2432	1.7940	0.9317
91	0.8033	0.6631	1.1972	0.8421	1.9527	0.9252
92	0.7496	0.6188	1.1171	1.0152	2.2921	1.0426

Table 4 Continued

Number	Lu *et al.* (2015)	Dai *et al.* (2015)	Wu *et al.* (2010)	FIB model	CNR-DT	ICA-ANN
	P_M/P_P	P_M/P_P	P_M/P_P	P_M/P_P	P_M/P_P	P_M/P_P
93	0.3839	0.3212	0.4856	1.2030	1.4812	1.5363
94	0.7505	0.6280	0.9493	0.8462	1.0715	1.4433
95	0.8024	0.6715	1.0150	1.0432	1.2272	0.8537
96	0.7851	0.6570	0.9931	1.0294	1.4482	1.1539
97	0.7170	0.6000	0.9070	1.2757	0.9662	1.2854
98	0.6639	0.5555	0.8398	1.0000	1.1304	0.8636
99	0.2969	0.2498	0.3907	1.3084	2.6168	0.9834
100	0.6797	0.5720	0.8945	0.9388	1.1837	0.9820
101	0.7616	0.6409	1.0023	0.8743	1.1293	0.6053
102	0.5355	0.4506	0.7047	1.2953	1.2435	1.3367
103	0.6076	0.5113	0.7996	0.7910	1.1416	0.7152
104	0.7574	0.6374	0.9968	0.9158	1.1355	0.9874
105	0.2906	0.2456	0.3943	1.0185	1.2037	2.7483
106	0.4305	0.3638	0.5842	1.1875	1.1250	0.8583
107	0.5717	0.4832	0.7759	1.4588	1.1294	0.7107
108	0.6726	0.5685	0.9128	1.0800	1.1600	0.9069
109	0.6700	0.5662	0.9092	0.8835	1.0843	0.9985
110	0.9148	0.7732	1.2414	1.0294	1.1471	0.8557
111	0.6060	0.4912	1.7579	1.4184	1.2241	0.6632
112	0.7182	0.5851	2.1610	1.4423	1.1797	0.5828
113	0.7413	0.6030	2.2067	1.3183	1.0998	0.8319
114	0.7474	0.6010	2.0509	1.1145	0.8110	0.6085
115	0.6898	0.5567	1.9407	0.8565	0.9622	0.8893
116	0.5789	0.4692	1.6810	0.8653	1.0508	5.7973
117	0.9166	0.7430	2.6618	1.3271	0.9384	0.6587
118	0.8816	0.6914	2.4344	1.0892	1.2257	0.9890
119	0.8557	0.6711	2.3629	0.7779	1.4580	1.0378
120	0.7325	0.5095	2.3830	1.0000	1.5035	1.0166
121	0.7492	0.5210	2.4372	1.3333	1.8000	0.7526
122	0.7684	0.5405	2.7080	0.8800	1.9171	1.0090
123	0.7684	0.5405	2.7080	1.0400	1.3600	0.8122
124	0.9139	0.6826	3.8887	1.0327	1.1451	0.6218
125	0.7499	0.5945	2.6341	1.0377	1.5252	0.7982
126	0.9039	0.6715	2.5252	0.9325	1.3743	0.9251
127	0.6840	0.5155	3.0989	0.7712	1.5693	1.0560
128	0.8525	0.6424	3.8619	1.0399	1.5420	1.1092
129	0.6259	0.5006	2.3408	1.4719	1.4522	0.9510
130	0.7328	0.5862	2.7409	0.7647	1.6008	0.9619
131	0.7840	0.6271	2.9323	1.1017	1.8323	1.0287
132	0.6822	0.5113	2.0293	0.8642	1.8677	0.9562
133	0.7656	0.5738	2.2772	1.0341	2.0380	0.9777
134	0.8606	0.6511	4.0091	0.5000	1.3807	0.6169
135	0.8477	0.6413	3.9489	1.0169	1.7165	1.1683
136	0.6358	0.5106	2.4452	0.7190	2.0425	1.1100
137	0.7934	0.6372	3.0515	1.3029	2.0041	1.6072
138	0.6349	0.4778	1.9420	0.7574	2.2215	0.5250

Table 4 Continued

Number	Lu *et al*. (2015)	Dai *et al*. (2015)	Wu *et al*. (2010)	FIB model	CNR-DT	ICA-ANN
	P_M/P_P	P_M/P_P	P_M/P_P	P_M/P_P	P_M/P_P	P_M/P_P
139	0.7567	0.5694	2.3146	1.0174	0.8378	1.2399
140	0.6787	0.5069	2.2737	0.7905	1.2774	1.0903
141	0.5581	0.4425	1.5435	1.0212	1.4970	0.9334
142	0.7522	0.5588	1.6547	0.7970	1.1417	0.8748
143	0.6444	0.4856	2.2986	1.5758	1.4440	1.0183
144	0.5362	0.4041	1.9127	0.3140	1.5184	0.9575
145	0.5796	0.4636	1.7068	1.2635	1.2635	0.9738
146	0.6538	0.4947	2.3981	1.5163	1.0381	1.3588
147	0.6588	0.5290	1.9949	1.3900	1.3127	1.1197
148	0.8505	0.6830	2.5756	0.8373	1.0766	4.0134
149	0.5790	0.4357	1.3945	0.8621	1.1700	1.2415
150	0.8129	0.6117	1.9578	0.9649	1.0965	1.0505
Min	0.2906	0.2456	0.3907	0.3140	0.7582	0.2583
Max	1.1901	0.8623	4.0091	2.4226	2.6168	5.7973
Average	0.7789	0.5852	1.7651	1.0941	1.3181	1.0318
Std	0.1711	0.1186	0.8236	0.3543	0.3485	0.5543
R^2 model	0.7454	0.8190	0.7089	0.8790	0.8166	0.9395

$P_M = P_{Measured}$, $P_P = P_{Predicted}$

selected for two parts of training and testing as a new assessment of the bond strength of FRP. Finally, in order to make a comparison between the selected model and old models, a separate study was conducted. This comparison showed that the ICA-ANN model outperforms other methods and can be used as a new solution to assess the bond strength of FRP in concrete samples.

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