

# Modeling the shear capacity of externally bonded fiber reinforced polymer strengthened beams by artificial neural network

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## ABSTRACT


The current guidelines, namely ACI 440.2R and fib TG-9.3, quantify the nominal shear strength of strengthened reinforced concrete (RC) beams by simply summing up the shear strength contribution of the three components: concrete ( $V_c$ ), steel stirrups ( $V_s$ ), and externally bonded fiber reinforced polymer (EB-FRP) ( $V_f$ ). However, as reported in the literature, this assumption is inaccurate due to an adverse interaction between EB-FRP and steel stirrups. This research study adopts a machine learning method called Artificial Neural Network (ANN) to model EB-FRP shear strength contribution. The model is built by considering the possible interaction mentioned above. Considering the collective response of these three components is crucial in accurately predicting the shear behavior because the performance potential of EB-FRP strengthening depends on the material properties of existing members. To implement the ANN modeling method, a database of 191 test specimens reported by a total of 40 individual studies is gathered. For the assessment of the proposed ANN model, a sensitivity analysis is conducted. The proposed model prediction is then compared statistically with experimental results and with the predictions of the existing guidelines such as ACI 440.2R and fib TG-9.3. The results showed that the developed ANN model could predict the EB-FRP shear strength contribution with higher accuracy than the current guidelines. Moreover, a user-modified executable program is also developed in this study to readily execute the proposed ANN model by inputting the properties of the existing beam and EB-FRP.

**Keywords:** Shear Strengthening, Interaction, ANN, Machine learning, Database.

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## 1. INTRODUCTION

Strengthening the structures using Externally Bonded Fiber Reinforced Polymer (EB-FRP) is becoming an attractive choice for repair and/or seismic rehabilitation in the construction industry. EB-FRP strengthening technique has a wide range of applications, especially flexural and shear strengthening of beams. Since the 1990s, the EB-FRP strengthening technique has been studied and exhibited rapid growth in its application. However, among other applications, shear strengthening is a complex phenomenon and is still a matter of further research (Bousselham and Chaallal, 2006; Perera et al., 2014; Altoubat et al., 2020). When studying the shear behavior, it is widely accepted that the shear mechanism of concrete structures is a complex matter. The matter gets even more complicated by adding a new component ( $V_f$ ) to the existing shear expression.

Several studies (experimental and analytical) have investigated the shear behavior of EB-FRP strengthened beams in the past two decades (Triantafillou and Costas, 2000; Chen and Teng, 2003; Ekenel and Myers, 2007; Bukhari et al., 2010; Mofidi and Chaallal, 2011; Chen et al., 2016; Karzad et al., 2017; Altoubat et al., 2018; Pujol and Marí, 2019;

Hazem et al., 2020).

Some of these studies resulted in various empirical models to predict the contribution of EB-FRP to the shear strength of the strengthened member. Some of these models are adopted by well-known organizations such as ACI and fib. The existing guidelines consider the EB-FRP contribution to the shear strength as a simple summation to their current shear expression from concrete and steel. For example, the ACI 440.2R adds  $V_f$  to their existing shear expression ( $V_n = V_c + V_s$ ) from ACI 318 code, and fib TG 9.3 follow a similar approach by adding  $V_f$  to the current expression of shear strength from Eurocode 2 (FIB, 2001; ACI 440.2R 2017).

As widely reported in the literature, there exists an interaction between internal shear reinforcement (steel stirrups) and EB-FRP reinforcement. This indicates that the current assumption of simply adding the contribution from three components: concrete, steel, and EB-FRP to the shear strength is inaccurate. Therefore, some researchers explored this interaction and proposed new models for  $V_f$  to account for this interaction (Pellegrino and Modena, 2006; Chen et al., 2010; Mofidi and Chaallal, 2014; Ebead and Saeed, 2017; Li et al., 2018). Those prediction models are developed empirically and are based on conventional regression analysis (El-maaddawy and Chekfeh, 2012; Baggio et al., 2014; Al-Rousan and Issa, 2016; Karzad et al., 2019). As mentioned previously, shear behavior is a complex matter which may not be accurately solved using simple regression techniques. For this reason, machine learning techniques nowadays are getting more popular and can be used to tackle the modeling problem in this field.

One of the machine learning techniques called Artificial neural network (ANN) has been used in many fields and can also be used to improve the predictive capacity of the current guidelines for shear strengthening (Perera et al., 2010; Perera et al., 2014). ANNs can be implemented to solve complicated issues that conventional analytical approaches cannot handle. ANNs comprise some neurons (nodes) that interact with each other through connections with assigned weights to constitute a network. These nodes can be arranged into different layers of input, output, and hidden. Characterization of ANNs is based on an architecture and its learning mechanism (Yao, 1999). Further details about ANN are presented in section 4.1 of this paper.

The existing literature on the application of the ANNs technique in shear strength prediction of RC beams strengthened using EB-FRP (Tanarslan et al., 2012; Bashir and Ashour, 2012; Hosseini, 2017; Jumaa and Yousif, 2018) is not adequate to fully address the interaction-related concerns. The existing literature about ANN modeling of EB-FRP shear strength is focused on the beams without any shear reinforcement (which is not recommended by the current standard codes for design and construction), or they combined the two different configurations of EB-FRP strengthening (U shape and full wrapping) in the modeling

process. The latter combination will not give the full picture of the matter as the full wrapping does not primarily fail due to debonding while it is the dominant and the concerning mode of failure in U shape configuration.

The objective of the current research study is to propose an ANN model for predicting the shear capacity of EB-FRP strengthened RC beams. The beams included in the study contain at least a minimum amount of conventional shear reinforcement (steel stirrups) and are strengthened either by a U-shape or side bonded EB-FRP. To that end, an experimental database consisting of 191 RC beams test results was compiled from existing literature. Using the collected database, an ANN model was built by considering the materials-related and geometry-related parameters. In developing the ANN network, a total of 16 parameters were considered as input nodes.

## 2. METHODOLOGY FRAMEWORK

The methodology framework consists of four stages (see Fig. 1). At stage one, the data about tested beams, including their characteristics and performance, was collected from literature to use in the ANN modeling process. More than 40 articles were reviewed, and the data was retrieved and stored. The criteria for retrieving the data included RC beams with EB-FRP, the existence of the shear reinforcement, and the load configuration (i.e., simply supported three or four points loading). In stage two, the model development and testing were executed. Given the widespread use of the ANN technique and its proven performance over many other methods, it was adopted for modeling purposes. Several ANN model architectures were attempted to best fine-tune the model to favor our prediction purposes.

Furthermore, the best ANN model was compared with other conventional models for predicting  $V_f$ , including ACI 440.2R and fib TG9.3. At stage three, a sensitivity analysis was conducted using the ANN model to reveal the interrelation between the dependent variable (the  $V_f$ ) and the other independent variable. This stage was essential to give the reader further in-depth dimension about the relationship between the variables in real life. Finally, a standalone application was developed to integrate the best ANN model to ease the process of  $V_f$  prediction to other interested researchers and practitioners.

## 3. DATABASE COLLECTION

A literature review was conducted extensively to collect enough data points. Also, previously published databases have been reviewed (Sas, 2011; Barakat et al., 2019), and as a result, a database of 191 strengthened RC beams test results was retrieved from the literature (see the appendix for details). The database contains RC beams with internal steel stirrups strengthened in shear with EB-FRP. Since the beams without steel stirrups are not recommended by the

standard codes in practice (e.g., ACI 318), only beams with conventional shear reinforcement (steel stirrups) are considered in the current database. The collected data were about simply supported conventionally reinforced beams tested under three points loading or four points loading. The samples collected present a high diversity containing slender beams, short or deep beams, T beams, Rectangular beams, and beams with different concrete compressive strength but higher than 20 MPa. Based on the codes and the literature, concrete compressive strength lower than 20 MPa is not advised as structural concrete.

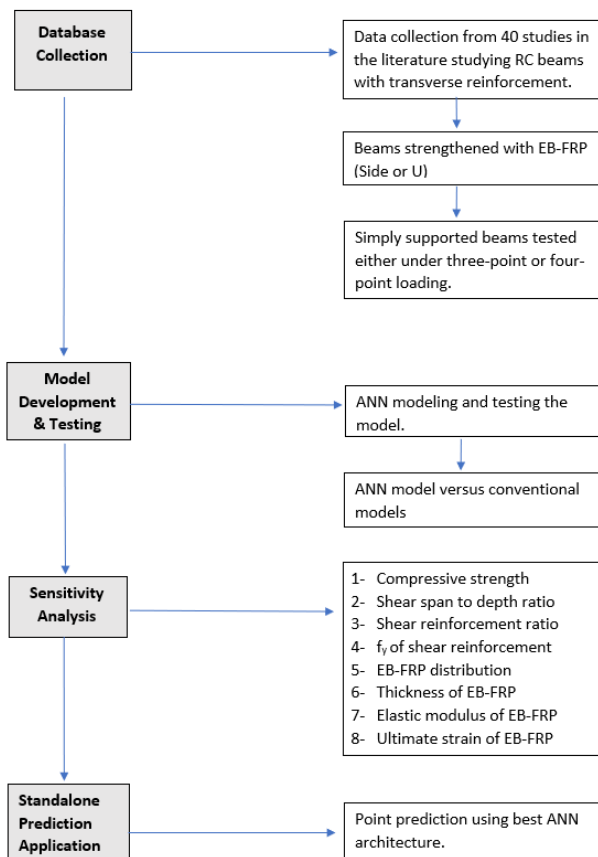
longitudinal and transverse reinforcement properties, and finally, the contribution of EB-FRP to the shear strength ( $V_f$ ).

The reported specimens in the database were made of concrete with a compressive strength of 20 to 60 MPa. 33% of the beams have  $20 \text{ MPa} < f'_c < 25 \text{ MPa}$ , 57% of beams have  $25 \text{ MPa} < f'_c < 45 \text{ MPa}$  and 10% of beams have  $45 \text{ MPa} < f'_c < 60 \text{ MPa}$ . This wide range of concrete strength covers the old concrete  $f'_c < 25 \text{ MPa}$ , which is the case in rehabilitation application, conventionally used concrete  $25 \text{ MPa} < f'_c < 45 \text{ MPa}$  and relatively high strength concrete  $f'_c > 45 \text{ MPa}$ , which can be the case for strengthening application. 40% of the beams have a T-section, and the remaining 60% have a rectangular cross-section. Both slender and short beams are included in the database, with 23% of short beams and 77% of slender beams.

The beam specimens included in the database are strengthened with either CFRP (C) sheets or GFRP (G) sheets. Only 8% of the beams are strengthened with GFRP sheets, and the rest are strengthened with CFRP sheets. The continuous (Ct) and discrete (Dt) distributions of EB-FRP strengthening reported in the database comprise 43% and 57%, respectively. The majority of the specimens included in the database are strengthened with a vertical inclination ( $90^\circ$ ), and 4% of reported specimens have an inclined configuration strengthening application. The debonding failure mode (DB) was prevalent among the specimens reported in the database. The beams that exhibited rupture failure (RT) of the EB-FRP sheets are 18% of the total specimens. One-fourth of the samples with EB-FRP showed a strength increase of around 50%.

It was evident from the literature that conducted experimental studies followed procedures more representing strengthening with very few studies on the repair. Almost all the studies did not involve sustained loading or pre-loading condition to cause noticeable damage that results in loss of original capacity. While in reality, the member in need of repair or strengthening will be subjected to some extent of sustained loading and the presence of some level of damage which can be a highlight for further investigations.

Fig. 2 presents a visualization of the data distribution in the collected database. The distribution histograms plotted in the Figure are only for the parameters used as input variables for ANN modeling. However, the number of variables reported in the database is 31 consisting of all the geometric and mechanical properties of the components of the beams (concrete, steel, and EB-FRP). The histograms illustrate the number of papers in the database that reported the same value of a specific parameter. For instance, there are 50 papers (Frequency 50) in the database that reported beams with  $f'_c$  of 25 MPa as shown in the first histogram of Fig. 2.



**Fig. 1.** Methodology framework

All the samples collected in the database are strengthened either with carbon fiber reinforced polymer (CFRP) or glass fiber reinforced polymer (GFRP) sheets. Only two types of EB-FRP strengthening configuration are included in this research: side bonding and U jacketing (with and without anchorage). Because side bonding and U jacketing strengthened beams exhibit similar failure modes where debonding is the dominant failure mode. The collected database reports all the properties, including the geometry of the beams, materials properties, reinforcement details, and test results of the samples. The variables gathered in the database are the compressive strength of concrete, cross-sectional properties of the beams, shear span-to-depth ratio, mechanical and geometric properties of EB-FRP materials,

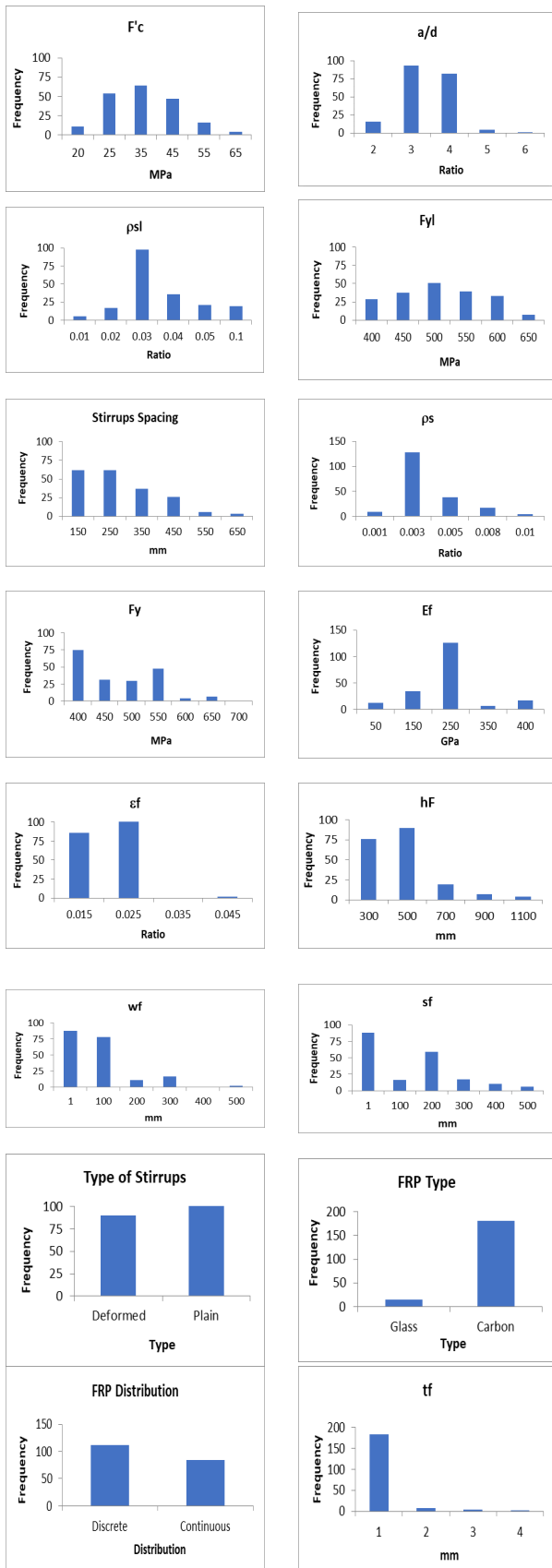


Fig. 2. Histogram of variables used for modeling

## 4. MODEL DEVELOPMENT

### 4.1 ANN Background

ANNs have been used in various fields (i.e., engineering, military, medical, biological, business, finance, manufacturing, etc.) to solve complicated problems by performing complex functions (Berrais, 1999; Jumaa and Yousif, 2018). ANNs perform simulated complex modeling and conduct calculations via training similar to the human brain. ANNs can be classified into two types according to their connectivity: feedforward and recurrent. Unlike the conventional numerical methods, ANNs feedforward do not provide closed-form solutions; however, it offers an accurate solution to a complex issue based on learning from a set of historical data called the training stage. In ANNs, the learning is obtained by adjusting the weights assigned to the connection iteratively to perform specific tasks. ANNs Learning is classified into three types: supervised, unsupervised, and reinforcement learning (Yao, 1999).

ANN is a group of small individually interconnected neurons (units) used to pass the information along interconnections. Each connection has an input value and a weight assigned to it, and the output will be a function of the summed value. ANNs can learn, respond, create the answer, and adjust their solution by learning from experience to meet the changing conditions. To enable that, the ANN needs to be trained first. ANNs learning, also called training, is performed by presenting a group of input units with a known output (target). In the learning process, the weights of the internal connections are adjusted by ANNs to minimize errors between the output provided by the network and the target output. This optimization algorithm is called backpropagation (Perera et al., 2014).

Data or input units used for learning can be empirical, theoretical, or a combination of both. Once the neural network training is completed, new patterns may be given to the network for prediction (testing stage). The training of ANNs neither requires complex mathematical equations nor computer models or impractical physical models. Indeed, the analysis by ANNs can be regarded as a background processing approach that the user does not need to know sophisticated mathematics (Perera et al., 2010).

Generally, the ANNs system consists of a fully interconnected input, an output layer, and many hidden layers (see Fig. 3). The values for the input layer come from the outside world then the output layer provides the predictions required. However, the hidden layer performs the main task that connects the input to the output layer and provides the network outcome by extracting and memorizing the main structures of the input trends. The ANNs are differentiated based on the activation function utilized by the hidden layers. The networks use two common activation functions: the sigmoid transfer function and the Gaussian radial basis function (Perera et al., 2010).

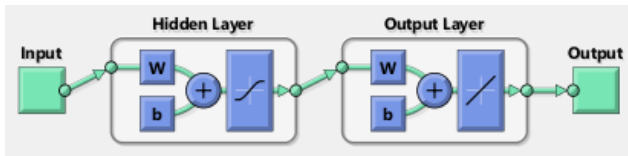


Fig. 3. ANN structure

### 4.2 ANN Modeling of EB-FRP Shear Strength ( $V_f$ )

This research study uses the feedforward two-layer network with sigmoid hidden neurons and linear output neurons for modeling. The training algorithm used to train the network is the most commonly used algorithm based on backpropagation Levenberg–Marquardt. MATLAB coding software was used to create, train, and implement the ANN modeling. The training of the network was performed iteratively to minimize the error between the network outputs and the target by considering the outcome of the mean square error (MSE) function, mean absolute error (MAE) function, and coefficient of determination ( $R^2$ ). The neural network used in this study consisted of 16 inputs, one hidden layer, and one output layer. The number of neurons (nodes) in each layer depends on the number of variables in those nodes.

In the neural network configuration, the beam shear capacity was the target node (output) for the presented data set. Choosing the suitable input nodes from the list of parameters is critical in successfully implementing the system to optimize the ANN. On the other hand, there should be sufficient parameters and data points to represent the system properly. One should also remember that the higher number of input nodes in the neural network can also result in a less efficient training process. Considering the shear behavior of FRP strengthened beams, there are several critical parameters, some of which are also considered by existing design guidelines and are as follow: FRP configuration, FRP effective strain ( $\epsilon_e$ ), FRP elastic modulus ( $E_f$ ), FRP reinforcement ratio (considering thickness, width, and spacing), inclination angles of the FRP layers, beam geometry, compressive strength of concrete ( $f'_c$ ), shear span to depth ratio ( $a/d$ ), transverse shear reinforcement properties (i.e., ratio, modulus, and yield strength), the ratio of longitudinal reinforcement, and its yield strength.

In the present study, it was decided to build the network considering 16 parameters. The sensitivity analysis of the model was performed only for the most influential parameters. As reported in the literature, the major parameters that significantly affect the shear behavior are: the FRP effective strain, FRP elastic modulus, FRP reinforcement ratio ( $\rho_f$ ), FRP configuration (continuous or discrete), shear span to depth ratio ( $a/d$ ), compressive strength of concrete ( $f'_c$ ), the ratio of transverse shear ( $\rho_s$ ) and its yield strength.

The 196 collected data points were randomly arranged into a training set (70%), a validating set (15%), and a testing set (15%). After conducting some trial runs, the number of hidden neurons chosen for training the networks

was fixed at 15 neurons. The results of modeling using the commercial software called MATLAB is presented in Fig. 4.

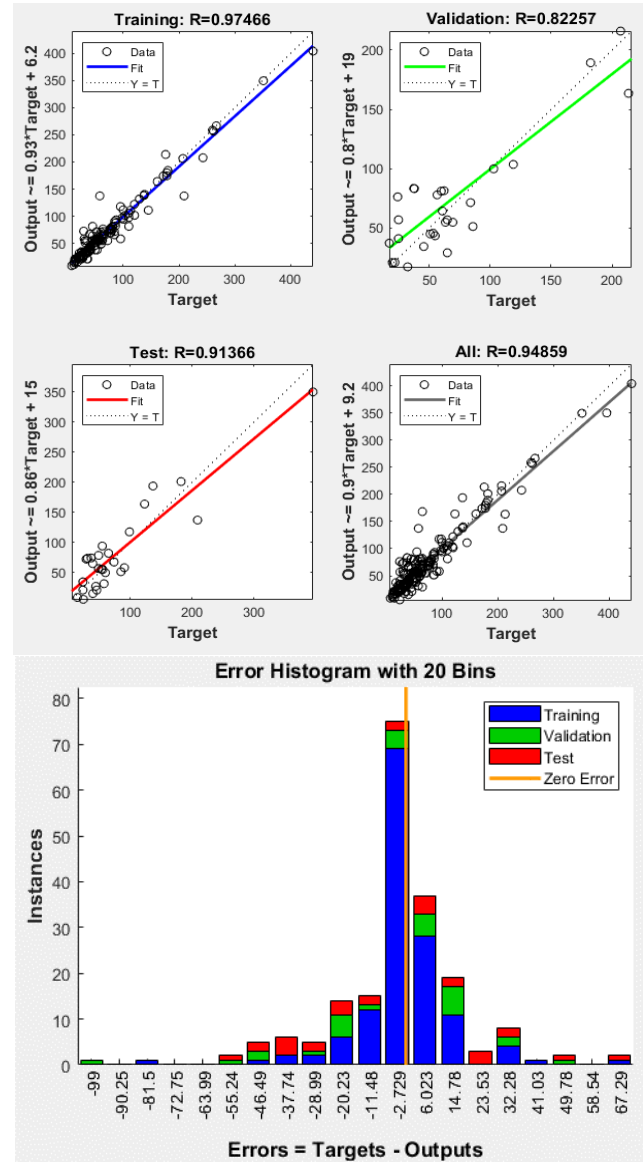


Fig. 4. Modeling error estimations from MATLAB

### 4.3 ANN Model versus Existing Conventional Models

The performance of the shear strength ANN prediction model is assessed by comparing the outputs with the actual experimental results (target) or the prediction of some existing design guidelines. The assessment was done based on the values of  $R^2$ , MSE, and MAE defined as follow:

$$\text{Correlation Coefficient (R)} = \frac{\sum [(X - X_m) \times (Y - Y_m)]}{\sqrt{[\sum (X - X_m)^2 \times \sum (Y - Y_m)^2]}} \quad (1)$$

$$R^2 = (\text{Correlation Coefficient})^2 \quad (2)$$

Where

X – Data points in Data set X, Y – Data points in Data set Y,  
 Xm – Mean of Data set X, Ym – Mean of Data set Y

$$MSE = \frac{1}{n} \sum_{i=1}^n (exp - pred)^2 \quad (3)$$

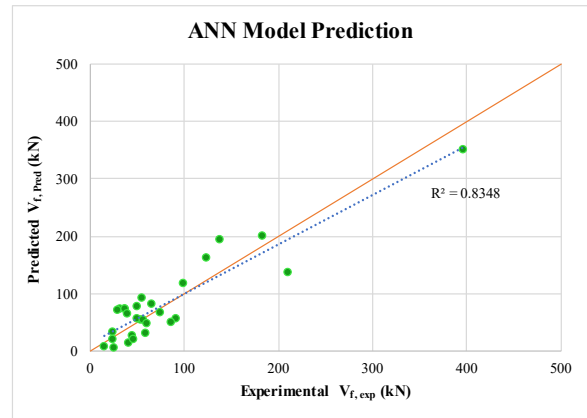
$$MAE = \frac{1}{n} \sum_{i=1}^n |exp - pred| \quad (4)$$

The shear strength predictions by the ANN model for the testing data set (see Fig. 5a) and the set of all data points (see Fig. 5b) are plotted against the experimental results shown in Fig. 5. As can be inferred from the Fig., most data points fall near the diagonal line, also called the equality line. This indicates that the scatter is low around the equality line, suggesting how reasonable the shear strength prediction is by the ANN model presented in this paper.

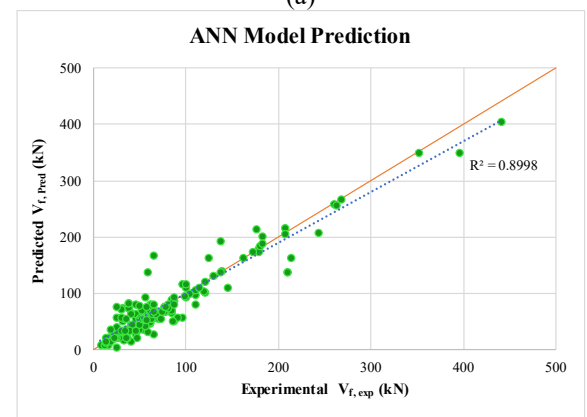
The prediction comparison of the proposed ANN model to the predictions by the mostly used guidelines (namely ACI 440.2R and fib TG9.3) is plotted in Fig. 6. For a better comparison, statistical analysis is also conducted. The values in terms of MSE, MAE, R<sup>2</sup>, the ratio between the experimental and predicted values ( $V_{f,Pre} / V_{f,exp}$ ), and the relative standard deviation also called coefficient of variation (CoV) are shown in Table 1. By comparing the values reported in Table 1 and observing Fig. 6, the more accurate predictions were obtained using the proposed ANN model.

### 5. SENSITIVITY ANALYSIS

Performing sensitivity analysis of the proposed model would be beneficial to determine the most critical parameters in modeling. Therefore, further analysis is conducted to assess the sensitivity of the network against different parameters. The sensitivity analysis is performed by varying one parameter at a time and keeping the rest of the parameters constant. Even though there exist a wide variety of parameters affecting the shear behavior of FRP strengthened beams, the sensitivity analysis in this study is focused only on eight major parameters: concrete compressive strength ( $f'_c$ ), shear span to depth ratio (a/d), transverse shear reinforcement ratio ( $\rho_s$ ), yield strength of shear reinforcement, distribution of EB-FRP layers (continuous or discrete), EB-FRP thickness (number of layers), and elastic modulus & ultimate strain of EB-FRP sheet.



(a)



(b)

Fig. 5. ANN model prediction versus experimental result; a) testing data, b) all data

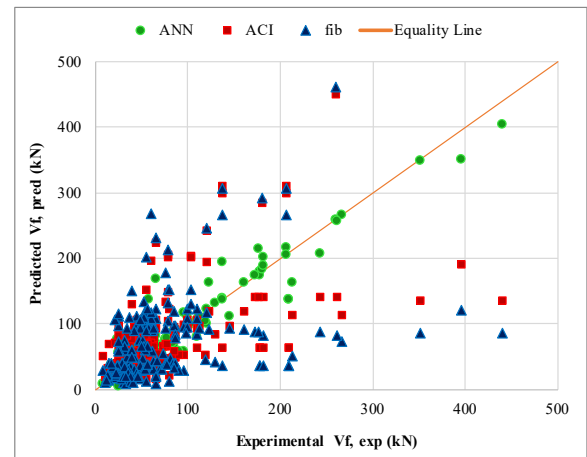


Fig. 6. Comparison of models prediction for  $V_f$  contribution to the shear strength

Table 1. Statistical comparison

Model	MSE		MAE		R <sup>2</sup>		Vpre / Vexp		CoV	
	Test	All	Test	All	Test	All	Test	All	Test	All
ANN	960	430	26	13	0.83	0.90	1.14	1.11	0.38	0.52
ACI 440.2R	6617	5275	52	48	0.1	0.14	1.38	1.27	0.72	0.73
fib TG 9.3	4540	3670	44	40	0.29	0.31	1.47	1.35	0.66	0.63

The result of the sensitivity analysis is presented in Fig. 7. As can be seen in Fig. 7(a), by increasing the  $f'_c$ , the  $V_f$  increases. This trend was expected since the higher compressive strength results in higher tensile strength and thus improves the bond between the interface of EB-FRP and concrete. Fig. 7(b) presents the  $a/d$  relationship with  $V_f$ . Given that if only slender beams are to be considered, the higher the  $a/d$  ratio is, the higher  $V_f$  capacity would be.

In Fig. 7(c), it can be observed that the shear strength predicted by the model decreases with the increase in “ $\rho_s$ ”. This behavior agrees with the previous research findings in the literature on the so-called adverse interaction between EB-FRP and steel stirrups (Chen et al., 2010; Mofidi and Chaallal, 2014; Ebead and Saeed, 2017; Li et al., 2018). The explanation can be that the higher the amount of shear reinforcement, the more distributed will be the cracking pattern which can trigger the premature debonding of EB-FRP. This results in a less effective contribution by EB-FRP. Furthermore, it is reported in the literature that the presence of EB-FRP disturbs the role of steel stirrups and may not reach yielding.

As illustrated in Fig. 7(d), the increase in “ $f_y$ ” decreases the “ $V_f$ ”. A possible reason behind such observation is that in the presence of EB-FRP, if the steel is stronger (higher  $f_y$ ) which will better arrest the cracks propagation thus will not trigger the full involvement of EB-FRP (Siddika et al., 2019). Because the EB-FRP gets fully activated once the steel is on the verge of yielding, this is another aspect of the adverse interaction which leads to a lower shear strength than expected.

Fig. 7(e) illustrates that the model predicts higher strength contribution when the EB-FRP sheet is applied in a continuous configuration compared to discrete strips. This is in agreement with the existing guidelines; however, this is controversial because some papers in the literature suggest that discrete configuration is superior to continuous. The model sensitivity is also investigated against the thickness of the EB-FRP layer (number of layers). It is clear from Fig. 7(f) that the strength gain is not proportional to the number of layers applied. This means that increasing the thickness (number of layers) does not increase the shear strength by the same ratio and, at some point, will become almost constant. In addition, providing a very thick layer of EB-FRP for shear strengthening will cause a brittle failure (Barakat et al., 2019), which can also be the interpretation of the sensitivity analysis showing a declining trend with an increase in EB-FRP thickness.

Fig. 7(g) shows that increase in moduli of EB-FRP results in less contribution to shear capacity. The possible explanation could be the brittleness of the system because higher modulus means more stiff behavior that can trigger a sudden debonding failure hence less effectiveness of EB-FRP strengthening. To some extent, a similar observation was made in a previous study (Bashir and Ashour, 2012) that higher  $E_f$  does not result in higher  $V_f$  values and remains constant at a certain degree. Referring to Fig. 7(h),

it can be noticed that the prediction of  $V_f$  reduces with the increase in ultimate strain. This trend is attributed to the fact that GFRP sheets provide less shear strength despite having higher ultimate strain compared to CFRP sheets.

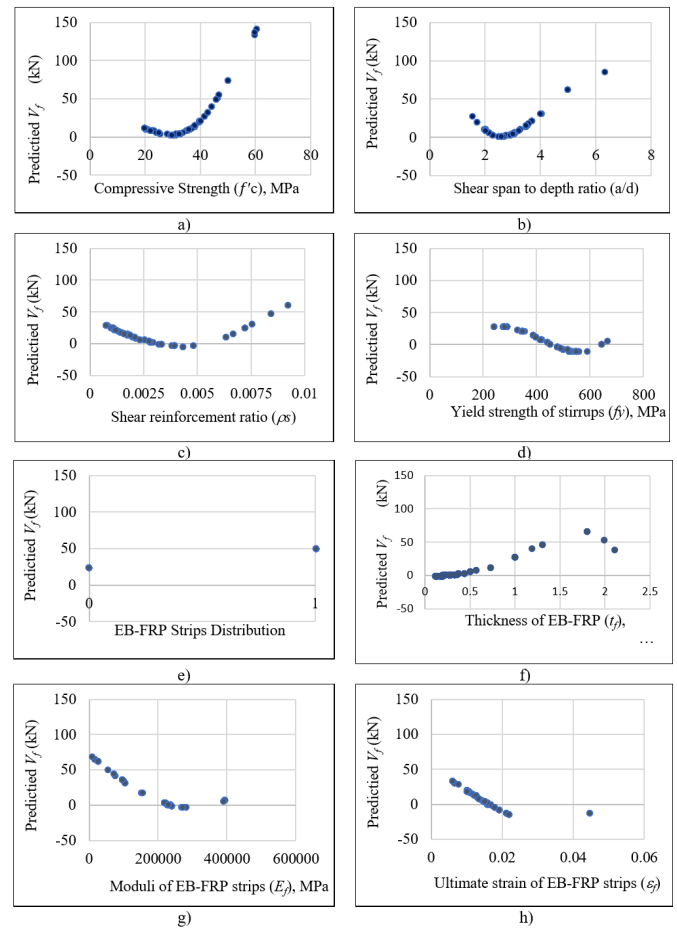


Fig. 7. Sensitivity analysis of ANN model

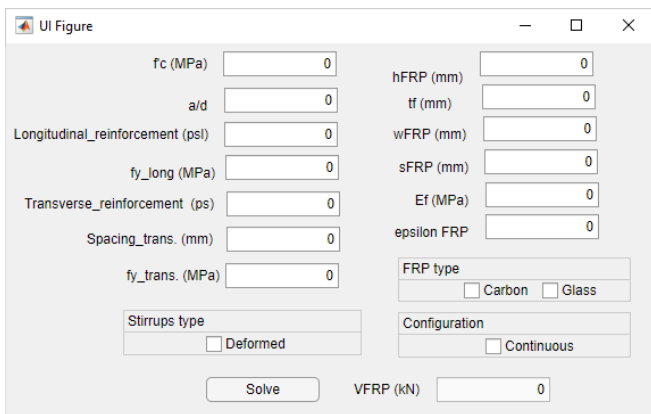
## 6. STANDALONE SOFTWARE APPLICATION

For ease in implementing the proposed ANN model, an executable program (app) is also developed in this study. The EXE program is made using an app design tool in MATLAB software, and its layout is shown in Fig. 8. To use the app the user just needs to input the material and member properties, and by clicking the solve button, the program will provide the shear strength contribution by EB-FRP ( $V_f$ ). It is worth mentioning that the app works only for the beams with applied EB-FRP strengthening scheme.

## 7. SUMMARY AND CONCLUSIONS

This paper focused on developing a machine-learning (ML) model to predict the shear strength contribution ( $V_f$ ) provided by externally bonded fiber-reinforced polymer (EB-FRP) to the shear capacity of strengthened RC beams. The study main objective is to model the contribution of EB-

FRP to the shear strength by considering the interaction between the steel stirrups and EB-FRP. In addition, the findings of this research will further contribute to the existing literature by illustrating the feasibility and capabilities of advanced machine learning models to solve complex behaviors as compared to conventional modeling techniques (linear and non-linear regression). A comprehensive database was built from existing literature (a total of 191 large-scale beams). The reported experimental database contains studies that performed experimental procedures representative of strengthening and rehabilitation/repair of beams having steel stirrups.



**Fig. 8.** App layout, built using MATLAB App design tool

ANN model was chosen as the primary ML model to be utilized in this research. The best-performed ANN model (i.e., one-hidden layer with 15 neurons in the hidden layer) was compared with other conventional EB-FRP strengthening models from the literature. The statistical results and graphical observation (data-scatter) indicate that the proposed ANN model is more accurate in its predictions. The MAE, MSE, and  $R^2$  for the ANN model considering all the data points were found to be 13 kN, 430, and 0.9 respectively. While for the ACI & fib models the mentioned values were 48 kN & 40 kN, 5275 & 3670, and 0.14 & 0.31 respectively. The ANN model outperformed the conventional models, therefore suggesting the need to reconsider the current prediction practice of EB-FRP by simply adding the contribution of each component based on simple summation. The proposed model accounts for the interaction between steel stirrups and EB-FRP when predicting  $V_f$  without modifying the strength provided by the existing component of the member (Concrete and steel) as per the standard practice codes. A sensitivity analysis was conducted between some of the considered variables and the output ( $V_f$ ). Overall, the effect of the considered parameters was analyzed and discussed. Finally, a standalone software application was built to host the best ANN model to facilitate the application of our proposed ANN model by other researchers and practitioners.

## DATA AVAILABILITY

The database of the test specimens and the Matlab file along with the executable program can be shared upon request.

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