Hybrid artificial intelligence-based bond strength model of CFRP-lightweight concrete composite

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Abstract. Different retrofitting techniques are commonly used to sustain the design life of heavy damage and deteriorated concrete structures, whilst epoxy-bonded carbon fiber reinforced polymer (CFRP) has emerged as a widely known retrofitting method. Consequently, a sound understanding of the bond strength between structural lightweight concrete (LWC) and CFRP based on influential factors is essential in safety and economic requirements. In this study, a hybrid bond strength model using the artificial neural network (ANN) and genetic algorithm (GA) was developed to furtherly understand the bond of a CFRP strengthened LWC structure. ANN was able to establish under satisfactory performance the relationship between the maximum bond load and the following influential parameters: width of CFRP (b_{frp}), total CFRP bond length (L_{frp}), CFRP thickness (t_{frp}), and CFRP angle of orientation (θ_{frp}). Furthermore, GA was able to derive the optimal configuration of the influential parameters resulted in high bond performance. Moreover, the optimization results also validated the sensitivity of each parameter on the interfacial bond behavior between LWC and CFRP.

1 Introduction

Rapid deterioration, excessive seismic damage, and outdated design codes and provisions of concrete infrastructure become the principal challenges of all nations worldwide. In response to these challenges, repair and strengthening of existing concrete structures became the solutions in order to still meet the required ultimate load carrying capacity and serviceability. Consequently, carbon fiber reinforced polymer (CFRP) has emerged as one of the notable accepted retrofitting materials of the civil engineering community in recent years [1]. Several studies account the success of CFRP as reinforcement in a wide variety of applications for different materials such as aluminum [2, 3], steel [4, 5], and concrete [6-8]. The utilization of CFRP as retrofitting material provides technically sound and cost-efficient due to its lightweight, resistance to corrosion, and ease of handling and installation [9-11]. CFRP can be in the form of laminates, sheets, or strips as shown in Fig. 1. Furthermore, CFRP has very advantageous mechanical properties of high specific strength and high specific stiffness compare to other strengthening materials [12].

On the other hand, interfacial debonding is concluded to be the most common mode of failure of CFRP strengthened concrete structures. According to Pellegrino et al. [13], the bond mechanism for effective stress transfer is vital in the performance of the CFRP-concrete composite. Sayed-Ahmed et al. [14] conducts an extensive investigation to review the different analytical models of bond strength between CFRP and concrete considering

different parameters and assumptions. Furthermore, several studies have developed different prediction models on the bond strength of CFRP and concrete under different considerations [15-20]. Different modeling techniques are also utilized in developing the maximum bond load and bond strength prediction models [21-24].

However, previous studies focus only on the performance of CFRP on normal weight concrete even there is an apparent growing demand for the use of lightweight concrete (LWC) in construction projects over the past decades. Still, less attention is given in the investigation of bond performance between LWC and CFRP [9]. Thus, this present study aimed to model the underlying behavior of the bond strength performance between LWC and CFRP using a hybrid artificial intelligence (AI) model wherein recent studies [25-28] show its promising application in the field of civil engineering and construction materials. The study specifically aimed to develop a prediction model of the bond strength between LWC and CFRP using the artificial neural network (ANN); and to utilize genetic algorithm (GA) optimization in producing high bond strength performance between LWC and CFRP.

2 Materials and Methods

2.1 Double Lap Shear (DLS) Test Datasets

In this study, a total of fifty-five datasets from the double lap shear (DLS) test were retrieved from the paper published by Al-Allaf et al. [9] (Refer to table 1). These

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datasets were summarized and utilized as the primary input in the development of the hybrid model. The following factors considered by Al-Allaf et al. [9] in the DLS test such as the width of CFRP (b_{frp}), total CFRP bond length (L_{frp}), CFRP thickness (t_f), and CFRP angle of orientation (θ_{frp}) were also used in this study as the influential parameters for the prediction of bond strength between LWC and CFRP.

2.2 Hybrid Neural Network-Genetic Algorithm

The development of hybrid bond strength model was composed of two stages namely the ANN modeling and the GA optimization. Generally, ANN was utilized to develop a prediction model that established the relationship between the maximum bond load (P_{max}) and the influential parameters. The neural network for the maximum bond load between LWC and CFRP was developed using the simplest and widely used ANN model known as the feedforward multilayered supervised neural network with error back-propagation algorithm. The network was structured based on the following internal parameters such as the training algorithm, transfer function, number of hidden layers, and number of neurons per hidden layer. The Levenberg-Marquardt (LM) algorithm and hyperbolic tangent sigmoid function or *tansig* function were utilized as training algorithm and transfer function respectively. The number of the hidden layer was set at one and the number of neurons per hidden layer was based on the value proposed by Asteris et al. [29]. Moreover, the predicting performance of the neural network was assessed based on Pearson correlation coefficient (R) and mean square error (MSE) while the topology of the bond strength neural network model was constructed and run using MatLab® R2015a software.

The GA was deployed for the purpose of optimizing the independent variables in Equation 1 that will yield a

high bond load performance. The objective function and the corresponding constraints for the GA optimization are expressed as follows:

$$\text{Maximize: } P_{max} = f(b_{frp}, L_{frp}, t_f, \theta_{frp}) \quad (1)$$

$$50 \leq b_{frp} \leq 150 \quad (2)$$

$$100 \leq L_{frp} \leq 200 \quad (3)$$

$$0.1178 \leq t_f \leq 0.2356 \quad (4)$$

$$0 \leq \theta_{frp} \leq 90 \quad (5)$$

The P_{max} is the prediction model developed during the first stage of the hybrid model. Equations 2 to 5 were used as constraints for the algorithm intended to search for the global and realistic solution of the optimization problem. Furthermore, the genetic algorithm was formed based on the procedure originally proposed by Goldberg [30]. This algorithm is generally composed of three genetic operators namely the selection, mutation, and crossover. In this study, the stochastic uniform method was used as the selection operator while the adaptive feasible model was utilized as mutation operator. Moreover, scattered and one-point models were explored as crossover operators.

3 Results and Discussions

After several simulations, the final topology of the bond strength prediction model of the LWC-CFRP composite was structured. The final model was composed of three neurons with one hidden layer. The biases and weights for the input layer of the final ANN architecture are given by Equations 6 to 7 respectively, while for the hidden layer, Equations 8 and 9 represent the biases and weights respectively.

Fig. 1. Forms of CFRP ©2017 Google Image: (a) sheets, (b) strips, and (c) laminates

Table 1. Summary of ANN input and output parameters. Retrieved from Al-Allaf [9]

Variable	Details of Variable			
	Minimum	Maximum	Range	Mean
Input				
CFRP width, b_{fr} (mm)	50	150	100	100
Total CFRP bond length, L_{frp} (mm)	100	200	100	130
CFRP thickness, t_f (mm)	0.1178	0.2356	0.1178	0.1392
CFRP angle of orientation, θ_{frp} (°)	0	90	90	22.91
Output				
Test failure load, P_{test} (kN)	0.47	29.69	29.22	18.87

Fig. 2. Pearson correlation coefficient performance of the bond strength neural network

$$b_I = \begin{bmatrix} 3.31225 \\ 1.96781 \\ -3.86852 \end{bmatrix} \quad (6)$$

$$W_I = \begin{bmatrix} 2.75362 & 3.78588 & -0.034438 & -1.92568 \\ -1.84853 & 1.472366 & 2.019534 & -0.55476 \\ -6.91359 & 0.52008 & 0.58746 & -4.14345 \end{bmatrix} \quad (7)$$

$$b_H = [-0.42735] \quad (8)$$

$$W_H = [0.72335 \quad 0.63921 \quad -0.83450] \quad (9)$$

The performance of the final ANN bond strength prediction model was remarkably high at 0.95 correlation coefficient. This was also evident based on the correlation coefficients of the training, validation and testing stages with values greater than 0.95 as shown in Fig. 2. Additionally, LM Algorithm and *Tansig* Function were still proven to be high performing training algorithm and transfer function respectively in the present study.

For GA optimization, the optimal combination of the influential parameters (i.e. $b_{frp} = 91.5$ mm, $L_{frp} = 200$ mm, $t_f = 0.2356$, and $\theta_{frp} = 90^\circ$) for high bond load performance was determined for over 200 generations as shown in Fig. 3. Based on this combination, the optimization procedure was able to yield a maximum bond load of $P_{max} = 40$ kN. Furthermore, it is observed that larger values of the CFRP's total bond length, thickness, and angle of orientation increase the bond load while increasing the width of the CFRP sheet provides limited benefit on the bond load capacity.

4 Conclusion

Further investigation of the interfacial bond behavior of LWC with externally bonded CFRP using previously proposed hybrid model was studied in this research. At this point, the hybrid neural network-genetic algorithm was able to provide satisfactory results in terms of developing the bond strength prediction model and optimization of the considered influential parameters. Satisfactory establishment of the relationship between the influential parameters and the bond load was completely achieved based on justifiable Pearson correlation coefficient. Moreover, the optimization results showed that each influential parameter has a different effect on the bond quality between LWC and CFRP, wherein the orientation

of the CFRP sheet (θ_{frp}) greatly affects the shear distribution of load to the fiber of CFRP sheet.

Fig. 3. Results of genetic algorithm optimization

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