Application of an interpretable artificial neural network to predict the interface strength of a near-surface mounted fiber-reinforced polymer to concrete joint

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Objective

Accurately estimating the interfacial bond capacity of the near-surface-mounted (NSM) carbon fiber-reinforced polymer (CFRP) to concrete joint (see Fig. 1) is a fundamental task in the strengthening and retrofit of existing reinforced concrete structures.

The objective of this study is seeking to develop an interpretable artificial neural network (ANN) model with quantized input variables importance based on the collected extensive experimental database to accurately and directly predict the bond strength of NSM CFRP to concrete joint.

Existing semi-analytical model

$$P_u = \begin{cases} \sqrt{2G_f E_f A_f C_{failure}} & when\ L_b \geq L_e \\ \beta_L \sqrt{2G_f E_f A_f C_{failure}} & when\ L_b < L_e \end{cases} \quad (1)$$

$$G_f = 0.4\gamma^{0.422} f_c^{0.619} \quad (2)$$

$$\beta_L^{99\%} = \frac{L_b}{L_e}(2.08 - 1.08\frac{L_b}{L_e}) \quad (3)$$

$$L_e = \frac{1.66}{\eta} \quad (4)$$

$$\eta^2 = \frac{\tau_{max}^2 C_{failure}}{2G_f E_f A_f} \quad (5)$$

$$\tau_{max} = 1.15\gamma^{0.138} f_c^{0.613} \quad (6)$$

It is the existing best model for predicting bond strength.

Many parameters in Eqs. (1)-(6) are obtained through a regression analysis of numerical results from a finite-element model.

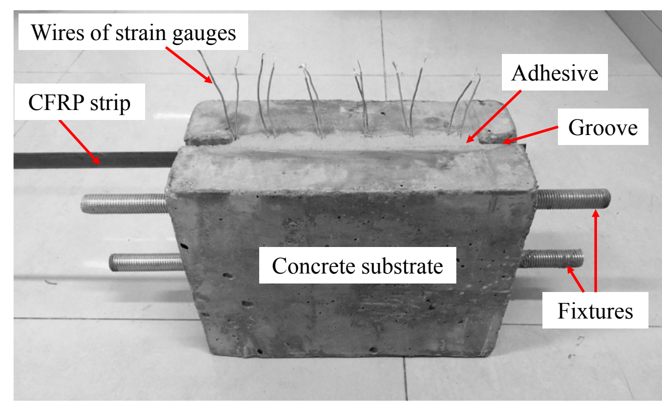

Fig. 1. Pull-out test of NSM CFRP to concrete joint

Experimental data collection

- **The database used to establish the ANN includes 163 testing samples, where 112 was conducted by the author's research group in the recent years, and 51 are collected from the published literature. The statistical characteristics of the variables in the database are outlined in Table 1 .**
- **The database is divided into two sets: (1) the training dataset (80%), and (2) the testing dataset (20%).**

Table 1. Statistical characteristics of the variables

Variables	Symbols	Unit	Min	Max	Mean	Standard deviation
Bond length	L_b	mm	30	450	257.1	72.7
FRP thickness	t_f	mm	1.2	20.6	3.4	2.1
Height of FRP	h_f	mm	10	40	15.7	3.4
Elastic modulus of FRP	E_f	MPa	129837	173000	137925.2	12711.1
Cylinder compressive strength of concrete	f_c	MPa	11.85	71.1	34.2	9.4
Height of concrete block	h_c	mm	150	220	179.9	29.7
Groove width	w_g	mm	3	35	11.1	5.9
Groove height	h_g	mm	11	51	26.7	6.9
Edge distance	a_e	mm	20	226	90.9	41.6
Bond strength	P_u	kN	14.8	205.1	65.7	27.8

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Research methodology

❑ Neural interpretation diagram (NID)

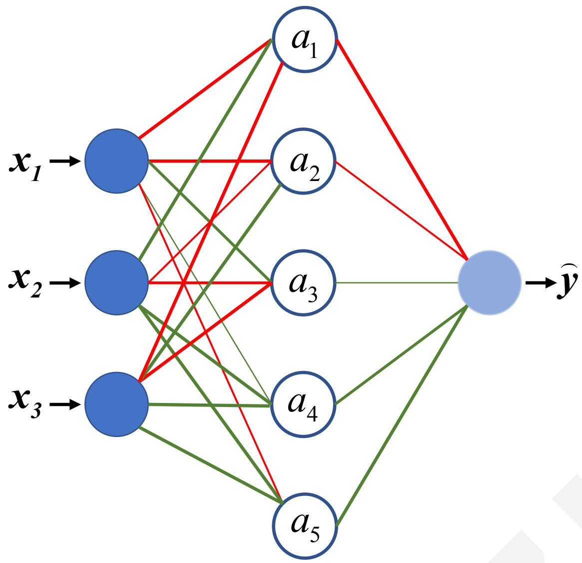

Fig. 2. Single-hidden-layer NID

- Providing a visual interpretation of the connection weights among neurons.
- The red line represents a positive weight and the green line represents a negative weight.
- The line thickness is proportional to the absolute magnitude of each weight.
- The final effect of each input variable that has on the output is depended on the multiplication of the two connection weight directions.

❑ Interpretation of connection weights for single layer NID

- **Garson's algorithm:** It uses the absolute values of the connection weights when calculating variable contributions, and therefore does not provide the direction of the relationship between the input and output variables.
- **Connection weights approach:** Calculates the product of the raw input-hidden and hidden-output connection weights between each input neuron and output neuron and sums the products across all hidden neurons.

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Research methodology

- A three-hidden-layer back propagation neural network (BPNN) with a neuron architecture of (15, 31, 22) is chosen as the machine learning used in this work, as shown in Fig. 3.
- NID is employed in the model to show the contribution of each input feature on the output. The red line represents a positive weight, and the green line represents a negative weight. In addition, the thicker the line, the greater the weight.

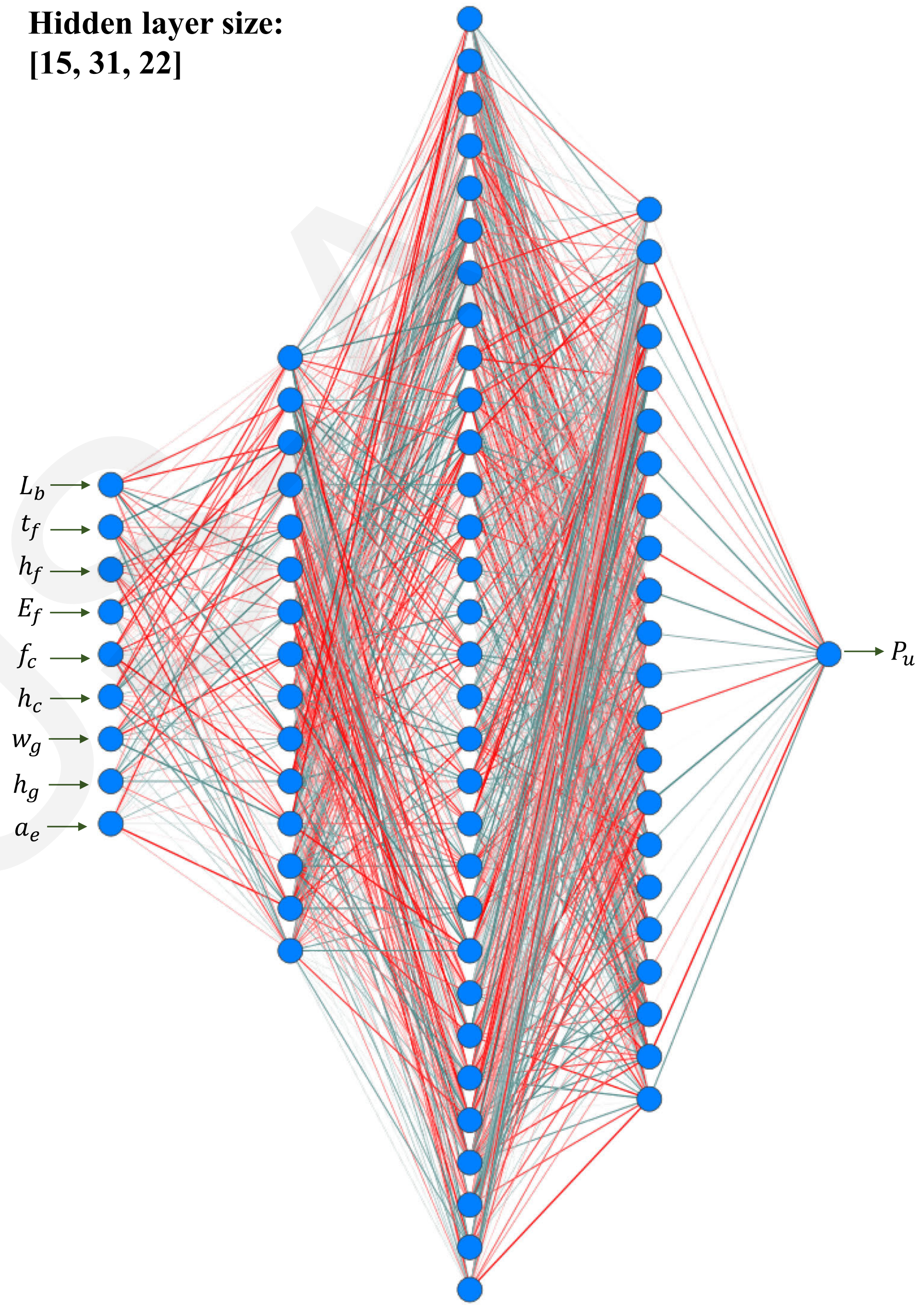


Fig. 3. Architecture of optimal NID-BPNN model

Results and discussion

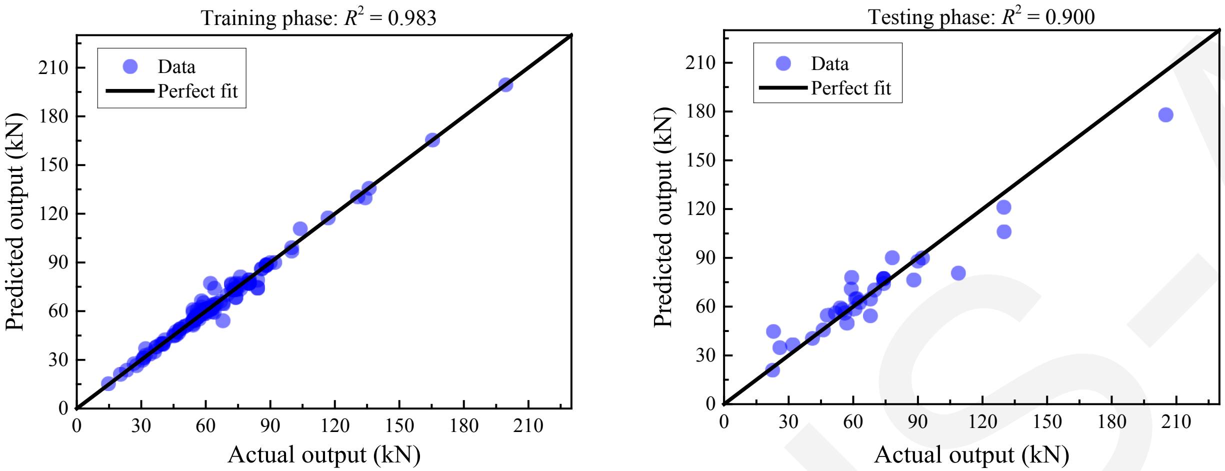


Fig. 4. Prediction results using default input variables.

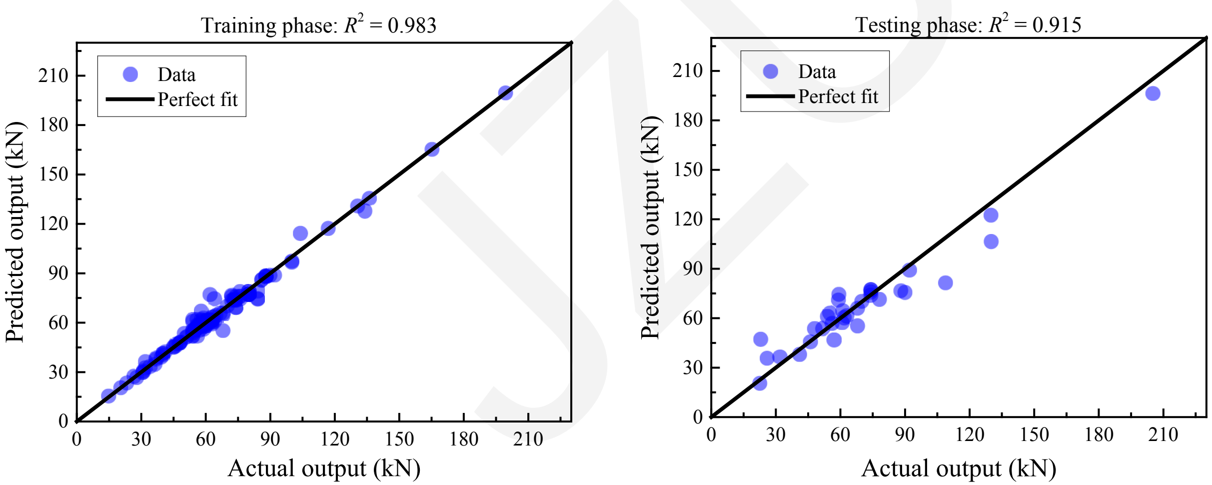
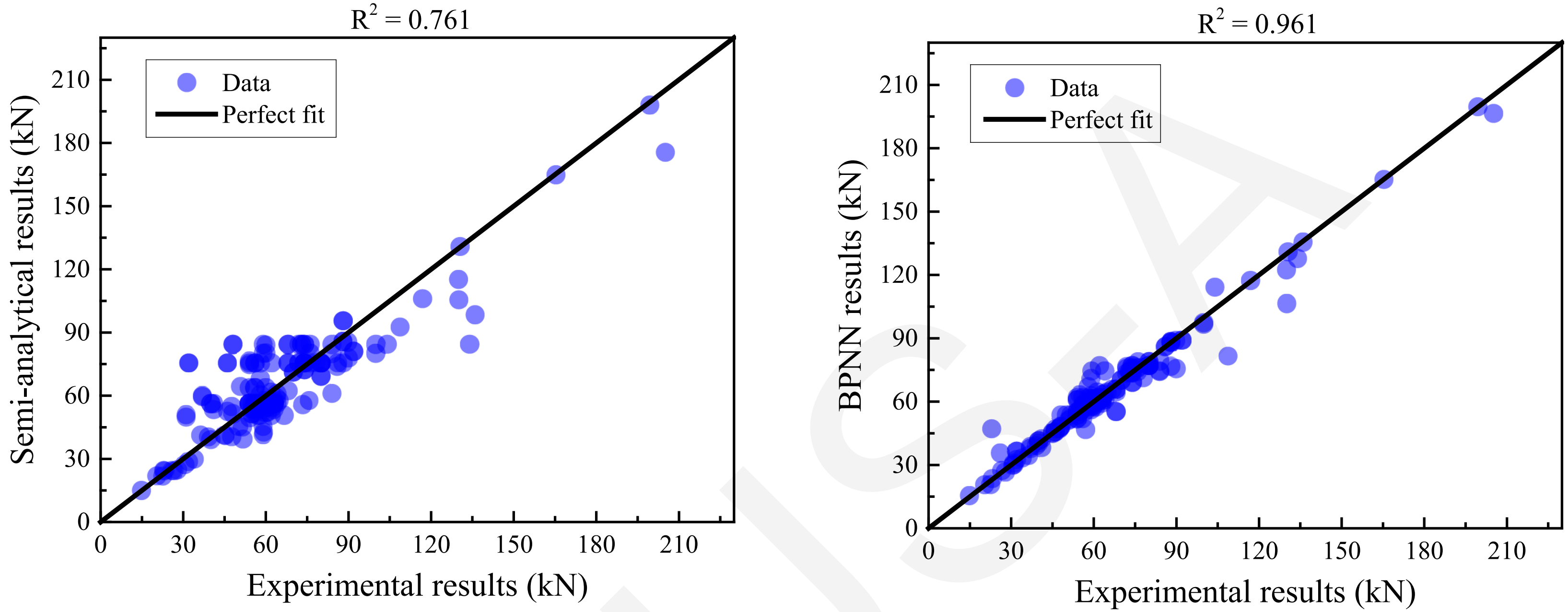


Fig. 5. Prediction results using selected input variables.

- **Figures 4-5 clearly observed that the predictions agree well with the ground truth.**
- **Moreover, removing the redundant parameters by incorporating feature importance analysis into the NID-BPNN model can improve its computation efficiency without decreasing its prediction accuracy.**

Results and discussion



(a) Semi-analytical model

(b) BPNN model

Fig. 6. Prediction results comparison between semi-analytical model and BPNN model.

As shown in Fig. 6, the semi-analytical model and the BPNN yield R^2 values of 0.761 and 0.961, respectively. In the light of other indicators, the BPNN model also demonstrates a more accurate prediction (RMSE = 5.45 kN, MAE = 3.11 kN, MAPE = 5.23 %) than does the semi-analytical model (RMSE = 13.52 kN, MAE = 9.68 kN, MAPE = 16.73 %). It is worth noting that the proposed ANN model need not use any theoretical assumptions but maps the relationship between the input variables and the output based on the experimental database. Therefore, it is more direct, simple, and efficient.

Conclusions

- **In this study, we have developed an ANN-based model, i.e. the BPNN model, for predicting the bond strength of a NSM CFRP to concrete joint. The proposed BPNN model relies on a large experimental database to capture the complex pattern between a set of nine material and geometric input variables and one output value. The prediction error analysis proves that the BPNN can give accurate predictions on the bond strength of the NSM CFRP to concrete joint.**
- **In particular, the NID technique employing Garson's algorithm and the connection weight approach is successfully used to quantify the relative importance of the input features, which makes the BPNN model interpretable. The results show that the connection weight approach is more reasonable in determining the feature contribution.**
- **Furthermore, the performance of the BPNN model (R^2 = 0.961) is superior than the existed semi-analytical model (R^2 = 0.761).**
- **A significant advantage of the proposed machine learning approach is that it need not use any theoretical assumptions and, therefore, it is more direct, simple, and efficient than the traditional semi-empirical or semi-analytical methods.**

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