Prediction of Allowable Debonding Strain of FRP-Strengthened RC Beam Based on GA-BP Neural Network

Tianyu Hu, Jiahe Wang, Guibing Li and Binbin Zheng

Collage of Management Science and Engineering, Shandong Technology and Business University, Yantai, China
Email: zhengbin@sdtbu.edu.cn

Abstract. In order to avoid the debonding failure of FRP-strengthened RC beams, most codes have proposed models of the allowable debonding strain of FRP. However, experimental studies have shown that the incomplete consideration of parameters suggested by the codes leads to low accuracy and greater variability, and it is impossible to guarantee that the strengthened members will not be peeled off. In order to accurately calculate the allowable debonding strain of FRP-strengthened RC beams, a neural network model for predicting allowable debonding strain of FRP-strengthened RC beams was established, and genetic algorithm were introduced to optimize the weights and thresholds of the network. The established model was trained and simulated through experiment data. The results show that the established model has a coefficient of variation of 17%, and compared with the traditional BP neural network and codes, the built model has better accuracy and stronger robustness.

Keywords. FRP-strengthened, RC beams, genetic algorithm, BP neural network.

1. Introduction
The debonding failure caused by the intermediate crack is one of the most common failure modes of FRP-strengthened RC (reinforced concrete, RC) beams. In response to this problem, the codes and researchers have proposed different models of allowable debonding strain for prevention of debonding failure: ACI440.2R-17 [1] corrected the model of Teng [2] based on the maximum tensile strain of the FRP-strengthened beams with debonding failure caused by the intermediate crack, and proposed a calculation model for the allowable debonding strain of FRP. Kim and Harries [3] proposed a statistically oriented model of FRP effective strain based on the Monte Carlo method. Oller et al [4] established the model of FRP-concrete interface ultimate tensile based on nonlinear fracture mechanics and the bilinear constitutive relationship of the FRP-concrete interface. Lu et al [5] proposed a model of FRP ultimate tensile strain based on the shear test and finite element analysis. Bilotta et al [6] established the standard value and design value calculation model of the maximum tensile strain of FRP when the intermediate crack caused the debonding failure based on the bending test of FRP-strengthened beams. These models enrich the basic theory of FRP-strengthened RC beams and provide a basis for engineering. However, experimental research and statistical evaluation [3, 7, 8] show that the above models have problems such as incomplete considerations of parameters and large coefficient of variation.

BP (Back Propagation, BP) neural network has been applied to various fields of civil engineering since the 1980s. However, there are few studies on the allowable debonding strain of...
FRP-strengthened RC beams. Since there are many factors that affect the debonding failure of FRP, such as the mechanical properties of various materials, the geometric dimensions of components, the deformation and cracks of the specimen, and the complex nonlinear relationship between allowable debonding strain and various parameters. Calculation equations established based on theories and experimental results tend to have low accuracy and greater variability, and it cannot guarantee that the strengthened member will not be peeled off. The characteristic of nonlinear mapping of BP neural network can theoretically simulate complex nonlinear relationships well. However, the BP neural network uses the gradient descent to determine the weights and thresholds, it is easy to cause the model to fall into a local optimum, it needs to be improved by algorithm [9-11], so this paper introduces genetic algorithm (GA) to optimize the weights and thresholds of the network [12, 13], collecting experimental data through literature reading, establishing the non-linear mapping relationship between each parameter and the allowable debonding strain of FRP-strengthened RC beams. By comparing with codes and traditional BP neural network, the GA-BP neural network established in this paper can better predict the allowable debonding strain of FRP-strengthened RC beams.

2. Determination of Parameters and Design of the Network

2.1. Determination of Parameters
FRP-strengthened RC beams are mainly composed of FRP sheets, concrete and steel bars. According to codes and related experimental studies[1, 4, 6, 14], the parameters that affect the allowable debonding strain are determined as: concrete strength ($f'c$), FRP stiffness ($Ef\times t_f$), the ratio of FRP to the length of the strengthened beam ($L_f/L$), the ratio of FRP to the width of the strengthened beam ($b_f/b$), the ratio of shear span to depth of the strengthened beam ($\lambda$), longitudinal reinforcement ratio ($\rho_s$), stirrup reinforcement ratio ($\rho_v$), yield strength of steel bars ($\epsilon_{sy}$).

2.2. BP Neural Network
BP neural network is a multi-layer forward neural network trained according to the error back propagation algorithm. The gradient descent is used to adjust the weights and thresholds of neurons in each layer to reduce the error of the network until the error reaches the preset error. BP neural network can realize arbitrary non-linear mapping of inputs and outputs, and can realize self-learning and have simple structure. However, BP neural network has the shortcomings of being easy to fall into local optimum [12].

2.3. Design of GA-BP
Considering the parameters of FRP-strengthened RC beams and the characteristics of neural network, the design of the model of allowable debonding strain of FRP-strengthened RC beams is as follows:

First, selecting the concrete strength ($f'c$), FRP stiffness ($Ef\times t_f$), the ratio of FRP to the length of the strengthened beam ($L_f/L$), the ratio of FRP to the width of the strengthened beam ($b_f/b$), ratio of shear span to depth of the strengthened beam ($\lambda$), longitudinal reinforcement ratio ($\rho_s$), stirrup reinforcement ratio ($\rho_v$), yield strength of steel bars ($\epsilon_{sy}$) as the input layer of the neural network, and then the hidden layer is selected as one layer. The number of neurons in the hidden layer is determined according to the empirical equation and through trials. The empirical equation is shown in equation (1):

$$L = \left( m + n \right)^{1/2} + a$$

In the equation: $L$ is the number of neurons in the hidden layer, $m$ is the number of neurons in the input layer, $n$ is the number of neurons in the output layer, $a$ is a constant, take $(1, 10)$, $m=8$, $n=1$ in this paper, after repeated debugging, take $L=10$.

Finally, the allowable debonding strain is taken as the output layer, the topology of the model is shown in figure 1.
In addition, in order to solve the possibility of BP neural network being easy to fall into local optimum, GA is used to optimize the weights and thresholds of the network, and the error back propagation neural network model optimized by genetic algorithm is established. The calculation idea of the network is shown in figure 2. GA mainly includes coding, calculating of fitness function, selection, crossover, and mutation.

3. Training of Neural Network and Analysis of the Result

3.1. Collection of Experimental Data
In order to study the allowable debonding strain of FRP-strengthened RC beams and to train the neural network better, this article refers to the experimental data collected in [3].

3.2. Training and Simulating of the Model
The number of samples is sixty. The distribution of training, validation, and test is freely controlled by neural network. The results of training and simulation of BP neural network and GA-BP neural network are shown in figures 3 and 4.

It can be seen from figures 3 and 4, in terms of overall regression, the correlation coefficient between the overall predicted value of GA-BP and the true value of the sample is 0.91733, which is greater than 0.89254 of BP, indicating that GA-BP is slightly improved compared to BP in terms of fit. Also, the regression coefficient of the test set of BP is only 0.24, and there is a phenomenon of over-fitting. To further compare the performance of GA-BP and BP, the two models were simulated twenty times and the comparison of error is shown in figure 5.
It can be seen from figure 5 that the coefficient of variation of GA-BP is between 15% and 30%, and the coefficient of variation of BP is between 15% and 55%, which indicates that GA-BP neural networks has a better performance than traditional BP neural networks in accuracy and robustness.

4. Evaluation of the Model
In order to further reflect the effectiveness of GA-BP, this section compares the regression value of GA-BP with the calculated values of several current international codes. The result is shown in figures 6~8.
It can be seen from figures 6~8, GA-BP is significantly better than JSCE and ACI in terms of fit. In addition, table 1 further quantitatively analyzes the accuracy and robustness of each codes and GA-BP.

|               | JSCE | ACI | GA-BP |
|---------------|------|-----|-------|
| Min           | 0.22 | 0.50| 0.72  |
| Max           | 1.63 | 4.24| 1.74  |
| AV            | 0.52 | 1.39| 1.01  |
| STD           | 0.29 | 0.75| 0.17  |
| CV            | 55%  | 54% | 17%   |
| C             | 92%  | 32% | 52%   |
| N-C           | 8%   | 68% | 48%   |

From table 1, the values of JSCE, ACI and GA-BP are respectively 0.22~1.63, 0.50~4.24, 0.72~1.174 times of the experimental value. The coefficient of variation(CV): GA-BP <ACI<JSCE, and the coefficient of variation of codes are all greater than 45%, while the coefficient of variation of GA-BP is only 17%. Compared with codes, GA-BP has higher accuracy. In addition, 92% of the value of JSCE is lower than the experimental value, 68% of the value of ACI is higher than the experimental value, while the conservative(C) and non-conservative(N-C) values of GA-BP are roughly equal, it indicates that GA-BP is more stable than codes.

5. Conclusion
After being simulated twenty times, the established model is better than the traditional BP neural network in terms of accuracy and robustness.

The established model for predicting allowable debonding strain of FRP-reinforced RC beams based on GA-BP neural network has a coefficient of variation of 17%. Compared with JSCE, ACI, it
has higher accuracy.

Model established in this paper still has shortcomings in data collection and robustness. In the future, these two aspects need to be improved to establish a better prediction model.

Acknowledgments
The authors are grateful for the financial supports from the Shandong Provincial Natural Science Foundation (Project No.: ZR2017ME019) and the National Natural Science Foundation of China (Project No.: 51804178)

References
[1] ACI-440.2R 2017 Guide for the Design and Construction ofExternally Bonded FRP Systems forStrengthening Concrete Structures ACI: Farmington Hills. Mich. p 110.
[2] Teng J G, et al. 2003 Intermediate crack-induced debonding in RC beams and slabsConstruction and Building Materials 17 447-462.
[3] Kim Y and Harries K 2013 Statistical characterization of reinforced concrete beamsstrengthened with FRP sheetsJournal of Composites for Construction 17 357-370.
[4] Oller E D and Mari A R 2011 Laminate debonding process of frp-strengthened beams Structure and Infrastructure Engineering 7 131-146.
[5] Lu X Z, et al. 2007 Intermediate Crack Debonding in FRP-Strengthened RC Beams: FEAnalysis and Strength ModelJournal of Composites for Construction 11 161-174.
[6] Bilotta A, et al. 2013 Design by testing procedure for intermediate debonding in EBR FRPstrengthened RC beamsEngineering Structures 46 147-154.
[7] Rusinowski P and Täljsten B 2009 Intermediate crack induced debonding in concrete beamsAdvances in Structural Engineering 12 793-806.
[8] Xu J Y, et al. 2018 Research on allowable debonding strain of CFRP-reinforced reinforcedconcrete beamsChinese Safety Science Journal 28 70-75.
[9] Jiang J T, et al. 2005 Prediction of ultimate bearing capacity of normal section of reinforcedconcrete columns under compression and bending-Based on BP neural network technologyJournal of South China University of Technology 33 80-82+94.
[10] Liu B, et al. 2020 Constraint recovery stress output characteristics and constitutive model ofNiTi shape memory alloy wireMaterials Review 34 10082-10087.
[11] Sun L Z, Wang T C and Zhang H B 2006 Shear Strength and Intelligent Analysis of SeawaterCorroded Beams Journal of Tianjin University 39 284-288.
[12] Xie J H, et al. 2014 Prediction model for flexural debonding capacity of damaged RC beamsstrengthened by FRPChina Journal of Highway and Transport 27 73-79.
[13] Wang Y L, et al. 2020 GA_BP neural network short-term photovoltaic power generationforecast based on MIV analysisActa Solar Energy 8 236-242.
[14] Garden H N, et al. 1998 An experimental study of the anchorage length of carbon fibercomposite plates used to strengthen reinforced concrete beamsConstruction and BuildingMaterials 12 203-219.