Soft Computing-based Approach on Capacity Prediction of FRP-Strengthened RC Joints

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Abstract. Shear failure of the RC beam-column joints is a brittle failure which has no prior warning and can induce tremendous damages because of collapse of column and joint before the connected beam. This paper is focused on one particular method of strengthening the RC joints, that is, the use of FRP composites as confining element. The results of previous studies have shown that strengthening the RC beam-column joints with FRP composites can improve their shear capacity. In this study, the data collected from the existing standards and studies regarding the FRP strengthened RC joints were used to develop an artificial neural network model for predicting the shear strength contribution of FRP jacket. The developed model was then used to evaluate the role of different parameters on this contribution, and finally derive a formula for contribution of FRP jacket to the shear strength of the RC beam-column joints.

Keywords: RC Joint, FRP, Capacity, ANN

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1. Introduction

The idea of using fiber reinforced polymer (FRP) composites as confining component was first introduced in 1982 by Fardis and Khalili [1]. Later, this idea was developed by laboratory and analytic works of other researchers, such as Lee et al, who used FRP jacket for shear and flexural strengthening of joints [2], Antonopoulos and Thanasis, who studied the use of fiber reinforced polymer (CFRP) composites for strengthening of beam-column joints with focus on fiber debonding [3], and Parvin and Granata [4, 5], who studied the effect of FRP on RC joints through computer modeling as well as laboratory work. These studies have been generally focused on augmenting the shear strength.

The effectiveness of FRP for shear strengthening of RC joints is associated with multiple factors including dimensions of joint, modulus of elasticity of composite material, etc. Considering the complexity of shear failure mechanism and the multitude of parameters affecting the shear capacity of FRP jacket, the use of artificial neural networks (ANN) could be a good solution for finding the relationships between these parameters and their effect on shear strength contribution of FRP component. In this study, an ANN model is developed to predict the shear strength contribution of FRP jacket to shear-strengthened RC joints.

2. Artificial Neural Network

Artificial Neural Network (ANN) is an intelligent system which has had extensive applications in science and engineering since the late 1980s. ANNs can be described as extremely simple electronic model of the human brain. Learning mechanisms of the brain are based primarily on experience, and the extraordinary power of the brain to absorb these experiences originates from the presence of a tremendous number of neurons and their natural connections. The core principles
of ANN models are based on a similar logic [6-11]. A schematic representation of neurons in a network is shown in Fig. 1. Application of ANNs in predicting the response of structural elements has been considered by some researchers [12-19].

2.1. ANNs input parameters
This study was performed using a set of empirical data regarding the FRP-strengthened RC joints. In all collected data, shear strength contribution of FRP was obtained through the following procedure. First, in each experiment, at least one control specimen was used to determine the baseline shear strength of the joint. This baseline shear strength is the sum of shear strength contribution of concrete and that of steel stirrups (when present). Next, the shear strengths of the FRP-strengthened specimens identical to the control specimens were obtained. Finally, the shear strength contribution of FRP was obtained by subtracting the baseline shear strength from the shear strength of the corresponding FRP-strengthened specimen.

Initially, data pertaining to 155 FRP-strengthened joint specimens was collected [20-51]. Of these 155 specimens, 34 specimens had shown debonding during the test and could not be used. Also, 55 specimens had an undesirable mechanism of failure (failure in beam before FRP reaching its capacity in the joint), and were therefore removed from the data. The use of such data instances in the network training will lead to error, because the joint specimen fails before reaching its maximum shear capacity, which means it would have sustained a greater shear force if the beam had a greater shear capacity. Also, 8 specimens were also strengthened with other types of reinforcement, and were therefore removed from the data to ensure the uniformity of inputs. So ultimately, 58 specimens remained for analysis.

After collecting the suitable data for the network, we needed to choose the parameters that would
affect the output values. After reviewing the literature [52, 53], it was concluded that shear strength contribution of FRP is influenced by the six following parameters:

- Effective depth of the FRP on the joint and the angle between the axis of the column and fiber orientation, D (mm)
- Cross-sectional area of the column, $A_c$ (mm$^2$);
- Compressive strength of the concrete, $f'_c$ (MPa),
- Modulus of elasticity of the FRP, $E$ (GPa);
- Thickness FRP, $t_f$ (mm);
- Tensile strength of the FRP, $F_{fu}$ (MPa).

In this study, shear strength contribution of FRP ($V_f$) was considered as the output.

Table 1 shows the statistical characteristics of the laboratory specimens used in the networks.

3. **Modeling of the artificial neural network**

In total, 9 networks with different number of hidden neurons (2 to 10) were trained. The next step after the training was to identify the best network, and then to compare its results with the experimental data. The mean squared error (MSE) and regression value of the developed ANNs are shown, respectively, in Fig. 2 and 3.

All ANNs were trained using the Levenberg-Maequardt algorithm with back propagation method [54]. The back propagation-based ANNs often use the transfer functions Log sigmoid and Tan sigmoid. These functions can also be used for the output function, but that means limiting the
output to a small value. The better option for the output function is the Purlin function which allows
the output to take any value. The stop condition for training algorithm is the minimization of MSE,
that is, the mean squared difference between the output and the target value.

One of the criteria based on which the best ANN can be determined is the regression value. The
regression value (R) measures the correlation between the ANN outputs and the target values; R=1
represents a perfect correlation between the output and the target value, while R=0 means any
relationship between the output and the target value would be random. In this study, MSE and
regression value were used as the criteria for selecting the ideal network.

As it can be seen, all ANNs were properly trained and the obtained errors were very small. The
highest errors (MSE) were 0.35 and 0.44, which belonged to ANNs with 10 and 7 hidden neurons,
and the lowest errors were 0.18 and 0.16, which were observed in ANNs with 5 and 6 hidden
neurons. In the most accurate ANNs (those with 5 and 6 hidden neurons), the regression values for
the entire data were 94% and 98%. As can be seen, the ANN with 6 hidden neurons had a very
good MSE (0.16) and a very high correlation coefficient. The regression values of this ANN for
training, verification, and test data and the entire data were respectively 0.999, 0.939, 0.970 and
0.982. Considering these four criteria, the ANN with 6 hidden neurons was chosen as the best
network and the one to be used for the remainder of work.

MSE graph of the ANN with 6 hidden neurons (Fig. 4) shows a decreasing trend, which represent
the network’s learning process. This graph has three curves, representing the MSE for training
data, validation data, and test data. At the beginning of the learning, this ANN has an error of about
8%, but as the learning process continues, network weights get adjusted and errors decrease until
reaching down, at the twentieth step, to the values of 0.008, 0.2 and 0.1 for training, validation and test data.

The graphs illustrating the process of learning and regressions values of input data are plotted respectively in Fig. 5 and 6. Decreasing trend of gradient graph depicted in Fig. 5 represents the trend of learning. This gradient reduction continues until MSE reaches down to its minimum value. At this point learning stops and from this point onwards gradient is constant. The regression values shown in Fig. 6 imply the proper training of the network and demonstrate the close proximity between its outputs and the target vector.

In view of the described results, it was concluded that the ANN modeled with six hidden neurons has been properly trained for input and output data and is suitable for the remainder of work.

3.1. Comparison of the ANN results with experimental data

To validate the developed ANN, its results were compared with the experimental data. Fig. 7 and table 2 show the relationship between experimentally obtained shear strength contribution of FRP jacket and the value obtained from the developed network. In this figure, the points on 45-degree line represent zero difference between the experimental data and the results of the proposed formulas; and each point’s distance from the 45-degree line represents the magnitude of error in calculated value.

4. The proposed formula for prediction of shear strength contribution of FRP component

The above comparisons show the good agreement of the ANN results with the experimental data. But the direct use of ANN is not a common practice in engineering design; so instead, this paper provides a nonlinear relationship capable of predicting the FRP shear strength contribution.

To derive this formula, first, each parameter needed to be initialized with a value (within its
variation range). Here, values close to the average values of the parameters were chosen for this purpose. The base values assumed for different variables are shown in Table 3. After determining the base values, one of the six input parameters was considered as variable, and the range of its variation was divided into several parts. This division needed to be such as to include the upper and lower bound of the variation range as well as the base value.

The relationship between the ANN output and the parameter (D) was examined. This parameter was chosen because of the low sensitivity it showed during the weight analysis. To determine the relationship between the ANN output and the parameter (D), the other 5 parameters were initialized with their base values, and (D) was gradually changed from its minimum value to its maximum. The effects of these changes on the ANN output are shown in Fig. 8. After determining the relationship of (D) with the ANN output, the same procedure was used to determine the relationship of the output with other 5 parameters.

The algorithm structure was derived from the algorithm of Leung et al. (2006) for calculation of final strain of FRP in flexural-strengthened beams [55, 56]. The resulting model is in the form of equations 1 to 6.

\[
V_{equation} = ( C_{f_c}, C_E, C_{F_{fu}}, C_T, C_D, C_A_c )
\]  \hspace{1cm} (1)

\[
C_{f_c} = C_{f_c} \cdot ( E, F_{fu}, T_f, A_c )
\]  \hspace{1cm} (2)

\[
C_E = C_E ( f'_c, F_{fu}, T_f, A_c )
\]  \hspace{1cm} (3)

\[
C_{F_{fu}} = C_{F_{fu}} ( E, f'_c, T_f, A_c )
\]  \hspace{1cm} (4)
To obtain $V_f$ from equation 1, six correction factors should be calculated and then multiplied by each other. According to Fig. 8, $C_D$ can be obtained from equation 7.

$$C_D = -58.4 \left(\frac{D}{350}\right)^3 + 172.2 \left(\frac{D}{350}\right)^2 - 117.9 \left(\frac{D}{350}\right)^2 + 31.3$$

Fig. 8 to Fig. 28 show the graphs of correction factors of other 5 parameters.

After averaging the values obtained for each parameter, the correction factors were determined as follows.

$$C_{f_c} = 0.535 \left(\frac{f_c}{30}\right) + 0.25$$

$$C_E = 1.995 \left(\frac{E}{180}\right)^3 - 3.65 \left(\frac{E}{180}\right)^2 + 2 \left(\frac{E}{180}\right) + 0.54$$

$$C_{F_{fu}} = 0.64 \left(\frac{F_{fu}}{2800}\right)^3 - 1.99 \left(\frac{F_{fu}}{2800}\right)^2 + 2.07 \left(\frac{F_{fu}}{2800}\right) + 0.355$$

$$C_{T_f} = 0.1 \left(\frac{T_f}{0.75}\right) + 0.82$$

$$C_{A_c} = 0.515 \left(\frac{A_c}{63000}\right)^3 - 2.3 \left(\frac{A_c}{63000}\right)^2 + 3.2 \left(\frac{A_c}{63000}\right) - 0.45$$

The errors in FRP shear strength contribution obtained by the proposed formulas are shown in
Table 4. Fig. 29 shows the relationship between the experimental data and those obtained by the proposed formulas. In this figure, the points on 45-degree line represent zero difference between the experimental data and the results of the proposed formulas; and each point’s distance from the 45-degree line represents the magnitude of error in calculated value.

As the graph of Fig. 29 shows, most points obtained by the proposed formula are positioned near the bisector line, which indicates the good ability of this formula to predict the shear strength contribution of FRP component.

5. **Statistical results of the proposed formula**

In this section, a number of statistical criteria for the error of proposed formula in prediction of FRP shear strength contribution are examined.

**5.1. Average Error (e_{Avg})**

The average error of the proposed formula was calculated using equation 15, and the value of this criterion for 58 available data instances was calculated to 33.3%.

\[
e = \frac{1}{N} \sum_{i=1}^{N} (v_i - v_{\mu})
\]

(13)

**5.2. Standard deviation**

This criterion can express the dispersion of results compared to the mean values. Equation 16 gives the variance for the proposed formula, and the root of this parameter is the standard deviation. The standard deviation of the proposed formula is 8.02%, which indicates the low dispersion of its
results.

\[
\text{var} = \frac{\sum_{i=1}^{N} (v_i - \bar{v})^2}{N}
\]

(14)

5.3. Root mean square error (RMSE)

The other criterion used to measure the error of the proposed formula is the root mean square error (RMSE); the smaller the values of RMSE, the lower are the error of theoretical results compared to experimental data. Using equation 17, the value of this criterion for the proposed formula was calculated to 14.88%, which indicates the good accuracy of the proposed formula.

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{N} (v_i - v_0)^2}{N}}
\]

(15)

6. Conclusion

In this paper, first the previous studies on the shear capacity of the FRP-strengthened RC joints were reviewed. The shear strength contribution of FRP to the RC joints can be influenced by many factors, and given the complex mechanism and danger of shear failure, estimating this contribution is of significant importance for preventing early shear failure of the column before the beam. It was concluded that shear strength contribution of FRP is influenced by the six following parameters including effective depth of the FRP on the joint and the angle between the axis of the column and fiber orientation, cross-sectional area of the column, compressive strength of the concrete, modulus of elasticity of the FRP, thickness FRP, and tensile strength of the FRP. Furthermore, shear strength contribution of FRP was considered as the output. Also, the authors tried to provide a formula for estimating the shear strength contribution of FRP jacket. Artificial neural networks provide a general practical method for real-valued, discrete-valued, and
vector-valued functions from examples and so they have been widely used in the various applications of engineering fields.

Finally, the artificial neural network architecture was used to develop a model for predicting the FRP shear strength contribution, and the developed model was then used to derive a formula for estimating the shear force sustained solely by the FRP jacket in the RC joint. In the end, the results of the proposed formula were compared with the experimental data. The precision of the proposed equation was verified by existing experimental data and good level of agreement was obtained.

REFERENCES


Fig. 1. Typical computational models of artificial neural networks (p = input vector, w = input variables weight, n = internal processing function, f = activation function, a = output vector)

Fig. 2. Mean squared error (MSE) versus number of hidden-layer neurons.

Fig. 3. Correlation coefficient versus number of hidden-layer neuron.

Fig. 4. Performance Trained network with 6 neurons in the hidden layer.

Fig. 5. Learning curve networks trained with 6 neurons in the hidden layer.

Fig. 6. Regression data for training and testing the accuracy of the network with 6 neurons in the hidden layer.

Fig. 7. Error compared to the values obtained by neural networks and relationships.

Fig. 8. Network output changes in relation to changes in effective (D) with constant five other parameters.

Fig. 9. Correction coefficient $C_{f,c}$ Ratio change $E$.

Fig. 10. Correction coefficient $C_{f,c}$ Ratio change $f_{cu}$.

Fig. 11. Correction coefficient $C_{f,c}$ Ratio change $T_f$.

Fig. 12. Correction coefficient $C_{f,c}$ Ratio change $A_c$.

Fig. 13. Correction coefficient $C_{f,c}$ Ratio change $f'_c$.

Fig. 14. Correction coefficient $C_{f,c}$ Ratio change $F_{fu}$.

Fig. 15. Correction coefficient $C_{f,c}$ Ratio change $T_f$.

Fig. 16. Correction coefficient $C_{f,c}$ Ratio change $A_c$.

Fig. 17. Correction coefficient $C_{f,c}$ Ratio change $f'_c$.

Fig. 18. Correction coefficient $C_{f,c}$ Ratio change $E$. 

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Fig. 19. Correction coefficient $C_{f_{fu}}$ Ratio change $T_f$.
Fig. 20. Correction coefficient $C_{f_{fu}}$ Ratio change $A_e$.
Fig. 21. Correction coefficient $C_{f_{fu}}$ Ratio change $f'_{e}$.
Fig. 22. Correction coefficient $C_{T_f}$ Ratio change $E$.
Fig. 23. Correction coefficient $C_{T_f}$ Ratio change $F_{fu}$.
Fig. 24. Correction coefficient $C_{T_f}$ Ratio change $A_e$.
Fig. 25. Correction coefficient $C_{A_e}$ Ratio change $f'_{e}$.
Fig. 26. Correction coefficient $C_{A_e}$ Ratio change $E$.
Fig. 27. Correction coefficient $C_{A_e}$ Ratio change $F_{fu}$.
Fig. 28. Correction coefficient $C_{A_e}$ Ratio change $T_f$.

Fig 29. Comparison of experimental results with predicted values by proposed equation.

Table 1. Statistical criteria of experimental data.
Table 2. Comparison between errors of the values obtained by neural networks and experimental data.
Table 3. Range of input parameters and base values for each parameter.
Table 4. Error values obtained by the proposed equations.
Fig. 1.

\[ a = f(W_p + b) \]

Fig. 2.
Fig. 3.

Fig. 4.
Fig. 5.

- Gradient = 0.0020121, at epoch 20
- Mu = 0.0001, at epoch 20
- Validation Checks = 6, at epoch 20
Fig. 6.
Fig. 7.
Fig. 16.

Fig. 17.

Fig. 18.
Fig. 28.

Fig. 29.
Table 1.

<table>
<thead>
<tr>
<th>Input nodes</th>
<th>$f’$, (MPa)</th>
<th>$E$ (GPa)</th>
<th>$F_{pu}$ (MPa)</th>
<th>$t_f$ (mm)</th>
<th>$D$ (mm)</th>
<th>$Ac$ (mm$^2$)</th>
<th>$V_f$ (kN)</th>
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<td>Average</td>
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<td>2832.6</td>
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Table 2.

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Table 3.

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<th>$F_{pu}$ (MPa)</th>
<th>$t_f$ (mm)</th>
<th>$D$ (mm)</th>
<th>$Ac$ (mm$^2$)</th>
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<td>63000/Ac</td>
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Table 4.

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Ali Kheyroddin received his Ph.D. degree in Structural Engineering in 1996 from McGill University, Canada. He then joined Semnan University where he is presently Professor of Structural Engineering. His major research interests include: analysis and design of tall buildings and HPFRCC technologies.