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Xiamin HU
Assoc. Prof.
Nanjing Arch. & Civil Inst.
Nanjing , China

Chengjian WEI
Assoc. Prof.
Nanjing Arch. & Civil Inst.
Nanjing China

Rongfei ZHAO
Engineer
Nanjing Arch.& Civil Inst
Nanjing China

Xiamin Hu, born 1958, Associate Professor at Nanjing Architectural Civil Engineering Institute. His research interests include composite structures reinforced, concrete structures and neural networks.

Chengjian Wei , born 1957, Associate Professor at Nanjing Architectural Civil Engineering Institute. His interests include neural networks, evolutionary computation, fuzzy system and artificial life

Rongfei Zhao , born 1968, Computer Engineer at Nanjing Architectural Civil Engineering Institute. His interests include neural networks , evolutionary computation, fuzzy system and artificial life

Summary

In this paper, based on the backpropagation model of neural networks, the details of the neural network methodology are presented to predict ultimate shear resistance of stud connectors with profiled steel sheeting. The analysed results show that the neural network predictions have a better agreement with the experimental data of the push-out tests than the predictions using other conventional methods.

1. Introduction

The use of mechanical shear connectors is essential for ensuring composite action in the composite beams. The head stud is the most widely used type of connector in composite construction, especially in composite floors system with profiled steel sheeting. The direct shear strength of connectors may be evaluated by using a representative model test known as the push out test (Fig. 1). In the last two decades years many researchers have conducted the push-out test on studs with profiled steel sheeting and found that specimens that included the profiled steel sheeting reduced both the strength and stiffness of the connection. But since the structural behavior of the stud connectors with profiled steel sheeting is quite complicated and not amenable to simple calculations, until now no accepted calculation model has been developed to predict the shear strength resistance of stud connectors with profiled steel sheeting.

This paper investigates the feasibility of using neural networks to evaluate the ultimate shear strength of stud connectors with profiled steel sheeting. A neural network is an information processing system that essentially mimics the structure and function of the brain. The neural networks are particularly useful for evaluating systems with a multitude of nonlinear variables, but no predefined mathematical relationship between the variables is given. In this paper, based on the backpropagation model of neural networks, details of the neural network methodology are presented to predict ultimate shear resistance of stud connectors with profiled steel sheeting. Where the compressive strength and modulus of the concrete, the tensile strength of the stud material, the size of the stud, the geometry of the profiled sheeting are chosen as the critical factors of the nonlinear variables. The analysed results show that the neural network predictions have a better agreement with the experimental data of the push out tests than the predictions using other conventional methods.

2 Neural Networks

Neural networks are computational models of many nonlinear processing element arranged in patterns similar to biological neuron networks. A typical neural network has an activation value associated with each node and a weight value associated with each connection. An activation function governs the firing of nodes and the propagation of data through network connection in massive parallelism. The network can be learned with examples through connection weight adjustment.

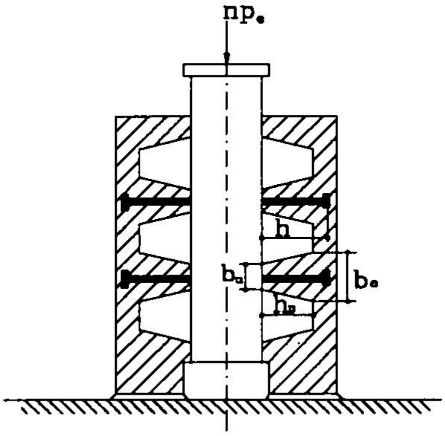

Fig.1 Push-out test

2.1 The computational model of neuron

McCllock and Pitts[1] proposed a binary threshold unit as a computational model for an artificial neuron. This mathematical neuron computes a weighted sum of its n inputs signals, x_j $j=1,2,...n$, and generates an output of 1 if this sum is above a certain threshold u. Otherwise, an output of 0 results. Mathematically

$$y = f\left(\sum_{j=1}^{n} w_j x_j - u\right)$$

where f(.) is a unit step function, and w_j is the synapse weight associated with the jth input

Using sigmoid function replace the Mccllock-Pitts neuron's threshold we get a generalized neuron model. The sigmoid function is a strictly increasing function that exhibits smoothness and has the desired asymptotic properties. The standard sigmoid function is the logistic function, defined by

$$g(x) = 1/(1+\exp(-\beta x)$$

where β is the slope parameter. The computational model of neuron is illustrated in Fig 2.

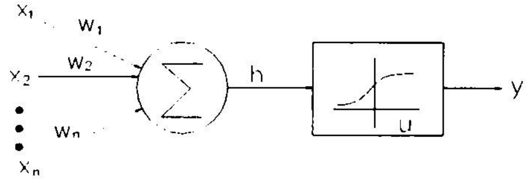

Fig. 2 Model of neuron

2.2 Network Architectures and Learning

Neural networks can be viewed as weighted directed graphs in which artificial neurons are nodes and directed edges are connections between neuron outputs and neuron inputs. Based on the connection pattern, neural networks can be grouped into two categories

- feed -forward network, in which graphs have no loops, and
- recurrent networks, in which loops occur because of feedback connection

A learning process in the neural networks context can be viewed as the problem of updating network architecture and connection weights so that a network can efficiently perform a specific task. The network usually must learn the connection weights from available learning patterns.

2.3 Multilayer feed-forward networks

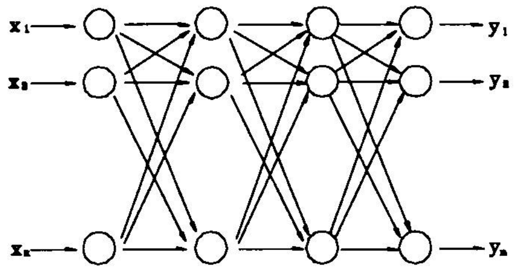

Fig. 3 Typical tree-layer perceptron

Fig. 3 shows a typical three-layer perceptron. In general a standard L_layer feed-forward network consists of an input stage, (L-1) hidden layers, and an output layer of units successively connected fully in a feed-forward fashion with no connections between units in the same layer and no feedback connections between layers.

The most popular class of multilayer feed-forward networks is multiplier perceptions in which each computational unit employs the sigmoid function. The development of the backpropagation learning algorithm for determining weights is a multilayer perceptron has made these networks the most popular among researchers and users of neural networks. The backpropagation learning algorithm is an iterative gradient algorithm designed to minimize the mean square error between the actual output of a multilayer feed-forward perceptron and the desired output. It requires continuous differentiable nonlineararities.

The BackPropagation Learning Algorithm as follows:

step 1 Initialized weights and offsets
set all weights and node offsets to small random values.

step 2 Present Input and Desired outputs
present a continuous valued input vector $x_1, x_2, \cdots x_n$ and specify the desired outputs $d_1, d_2, \cdots, d_m$

step 3 Calculate Actual Outputs
use the sigmoid function to calculate outputs $y_1, y_2, \cdots, y_m$

step 4 Adapt weights
Use a recursive algorithm starting at the output node and working back to the first hidden layer. Adjust weights by

$$w_{ij}(t+1) = w_{ij}(t) + \eta\delta_j x_i^{'} + \alpha(w_{ij}(t) - w_{ij}(t-1))$$

where $0 < \alpha < 1$, w_{ij} is the weight from hidden node *i* or from an input node to node *j* at time *t*, $x_i^{'}$ is either the output of node *i* or is a an input, η is a gain term, and δ_j is and error term from node *j*, if node is an output node then

$$\delta_j = y_j(1-y_j)(d_j - y_j)$$

where d_j is the desired output of node *j* and y_j the actual output.
if node *j* is an internal hidden node, then

$$\delta_j = x_j^{'}(1-x_j^{'})\sum_k \delta_k w_{jk}$$

where *k* is over all nodes in the layers above node *j* , internal node thresholds are adapted in a similar manner by assuming they are connection weights on links from auxiliary constraint-valued inputs.

step 5 Repeat by going to step 2

3. Prediction of the shear resistance

3.1 Learning of the neural network

A total of 65 push-out test specimens reported by Bode and Hu [2] are used here to demonstrate the performance of the backpropagation model in the prediction of the shear resistance of stud connectors with profiled steel sheeting. All these tests were carried out in Gemany and originally reported by Roik and Buehrkner [3,4], Roik and Lungeshausen [5], Bode and Kuenzel [6,7] ,Roik and Hanswille[8].In these tests the holes were cut out in the decking and the stud connectors were welded through the holes to the beam beneath. For a given geometric configuration of a stud with profiled stud sheeting, the ultimate shear strength of the connection P depends on the strength and the size of the stud, on the strength and the stiffness of the concrete, on the geometry of the profiled steel sheeting and on the number of studs per rib. Therefore the following expression is gotten:

$$Mapping\ \ T: f(f_c', E_c, f_u, d, h\text{-}h_p, h_p, b_u, b_o, N_r) \rightarrow P$$

where f_c' and E_c represent the compressive strength and modulus of the concrete, f_u is the tensile strength of the stud material, d is the diameter of the shank of the stud, h is the height of the stud. h_p is the over depth of the profiled sheeting. b_u and b_o represent the bottom width and top width of the profiled sheeting, N_r is the number of studs per rib.

Learning of the neural network is essentially carried out through the presentation of a series of example patterns of associated input and observed output values,and some preprocessing of the data is usually required before presenting the input patterns to the neural network. This usually involves scaling or normalization of the input patterns to values in the range 0-1. In this study, the learning example patterns consisted of 40 typical push-out test specimens collected by Bode and Hu[2] .

The neural network learned is constructed here with nine-nods in input layer, seventeen-nods in first hidden layer, twelve-nods in second hidden layer , fifteen-nods in third hidden layer and one node in output layer. η and α are taken as 0.5 and 0.4. The following expression was used to normalize data

$$Normalized\ value = \frac{Actualvalue - Minimumvalue}{Maximumvalue - Minimumvalue}$$

Learning is carried out iteratively until the average sum squared errors over all learning patterns are minimized based on the above backpropagation model .This occurred after about 1552 cycles of learning.

3.2. Comparison of predicted values with experimental data

On the satisfactory completion of the learning phase, verification of the performance of the neural network is then carried out using patterns that were not included in the learning set. Push-out test specimens that only broadly resemble the data in the learning set were used to verify whether the neural network can generalize correct responses. Details of the testing pattern and the neural network predictions are summarized in table 1. A comparison of the predicted values P_p and experimental values P_e indicate that the neural network is capable of generalization and gave reasonable predictions. Using the ratio of experimental data to neural network predictions as an indicator, the mean and standard deviation of this ratio for the 25 specimens are 1.04 and 0.069, respectively, as shown in table 1.

Prediction using the expressions of Bode and Hu[2] and the expressions of Roik and Lungeshousen[9] were also carried out to compare with the neural network approaches. The average of experimental shear strength to predicted strength ratios given by Bode and Hu's expressions and Roik and Lungeshausen's expressions are 1.06 and 1.07 ,while the corresponding standard deviations are 0.073 and 0.131, respectively. The coefficients of correlation of experimental versus predicted results are 0.976 (neural network approach), 0.975 (Bode and Hu's expressions), and 0.951(Roik and Lungeshausen's expressions). This indicates that the neural network approach is more reliable than the conventional methods.

It is to be noted that EC4 methods were here not compared because the equations in EC4 are not suitable for the predictions of stud connectors with pre-punched decking[2].

4. Conclusions

In this paper, a neural network for prediction of ultimate shear strength of stud connectors with profiled steel sheeting is presented. The study has demonstrated that the neural network can

Table 1 Comparison of Experimental Shear Strength P_e to Predicted Shear Strength P_p

Specimen	P_e,kN	Bode and Hu		Roik and lungeshausen		Neural Network		reference
		P_p,kN	P_e/P_p	P_p,kN	P_e/P_p	P_p,kN	P_e/P_p	
7.1	74.0	75.71	0.99	76.56	0.97	72.28	1.02	3
7.2	78.0	75.71	1.03	76.56	1.02	72.28	1.08	3
2.1	44.5	39.93	1.12	41.22	1.08	41.84	1.08	4
2.2	38.0	39.93	0.95	41.22	0.92	41.84	0.92	4
3.1	82.0	76.89	1.07	68.86	1.19	77.65	1.06	4
3.2	78.5	76.89	1.02	68.86	1.14	77.65	1.01	4
5.1	42.0	39.09	1.07	37.71	1.11	41.30	1.02	4
5.2	49.0	39.09	1.25	37.71	1.30	41.30	1.19	4
8.1	79.0	73.09	1.08	62.66	1.26	75.84	1.04	4
8.2	85	73.09	1.16	62.66	1.36	75.84	1.12	4
11.1	84.5	76.89	1.10	68.86	1.23	76.93	1.06	4
11.2	85.0	76.89	1.11	68.86	1.23	76.93	1.07	4
SH0-1	75.5	78.81	0.96	80.63	0.94	76.32	0.99	6
CS0-1	77.1	78.95	0.98	85.04	0.91	82.60	0.93	6
H1	114.0	111.65	1.02	118.14	0.97	111.35	1.02	7
H2	107.0	111.65	0.96	118.14	0.91	111.35	0.96	7
H3	114.0	111.65	1.02	118.14	0.97	111.32	1.02	7
H4	130.0	111.65	1.16	118.14	1.10	111.32	1.17	7
H5	111.0	111.65	0.99	118.14	0.94	111.35	1.00	7
H6	115.0	111.65	1.03	118.14	0.97	111.35	1.03	7
H7	122.0	111.65	1.09	118.14	1.03	111.31	1.10	7
H8	123.0	111.65	1.10	118.14	1.04	111.31	1.11	7
D1	107.0	96.8	1.11	101.94	1.05	104.47	1.02	8
D2	96.5	96.8	1.00	101.94	0.95	104.47	0.92	8
D3	106.0	96.8	1.10	101.94	1.04	104.47	1.01	8
mean			1.06		1.07		1.04	
Standard deviation			0.073		0.131		0.069	

effectively generalize correct responses that only broadly resemble the data tin the learning sei. The predictions should be reliable, provided the input values are with the range used in the learning set. As new data becomes available, the neural network models can be learned readily with patterns that include these new data. The analyzed results indicate that the neural network has powerful capacity of dealing with inherent noisy or imprecise data. The neural network model was found to be more reliable than other conventional methods.

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