An Artificial Neural Network Model for Preliminary Design of Reinforced Concrete Beam-Column

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Abstract

The dimensions of a beam-column cross-section and the area of reinforcing steel required to support a specific combination of axial load and moment can be established by using the column design interaction curves, where an interaction curve represents all possible combinations of axial load and moment that produce failure of the cross-section. The bending resistance of an axially loaded column about a particular skewed axis due to biaxial moments can be determined through iterations and lengthy calculations. These extensive calculations are multiplied when optimization of the reinforcing steel or column cross-section is required. This paper investigated the suitability of an Artificial Neural Network (ANN) for modeling a preliminary design of reinforced concrete beam-column. Neural computing is a relatively new field of artificial intelligence (AI), which tries to mimic the structure and operation of biological neural systems, such as the human brain, by creating an ANN on a computer. An ANN back-propagation multi-layered model was developed to design a beam-column, which predicted column cross-section for a given set of inputs, which were concrete compressive strength, column types (Tied and Spiral), reinforcing steel ratio (0.01 – 0.08), factored axial load, P_u , and moment, M_u . In the present research, several different ANN back-propagation trial models with different layers/slabs connections, weights and activation functions were trained. The presented back-propagation multi-layered neural net with logistic activation function, "Rotation" for pattern selection, and "TurboProp" for weight updates was the best one among all other trials, which converged very rapidly to reach an excellent statistical performance. The trained ANN back-propagation model was tested with several actual design data, and a comparative evaluation between the ANN model predictions and the actual designs was presented.

Introduction

Artificial neural network (ANN) is one of the artificial intelligence algorithms that relates to the class of machine learning. It mimics a human brain process of acquiring and retrieving knowledge. It models the biological neuron, which consists of nodes (cells) and links (axon). It is defined as "A computing system made up of a number of simple, highly interconnected processing elements, which processes information by its dynamic state response to external input¹. These ANNs are modeling techniques that are especially useful to address problems where solutions are not clearly formulated² or where the relationships between inputs and outputs are not sufficiently known. ANNs have the ability to learn by example. Patterns in a

series of input and output values of example cases are recognized. This acquired “knowledge” can then be used by the ANN to predict unknown output values for a given set of input values.

ANNs are composed of simple interconnected elements called processing elements (PEs) or artificial neurons that act as microprocessors. Each PE has an input and an output side. The connections on the input side correspond to the dendrites of the biological original and provide the input from other PEs while the connections on the output side correspond to the axon and transmit the output. Figure 1 illustrates a simple PE of an ANN with the analogy of the human brain. The activation of the PE results from the sum of the weighted inputs and can be negative, zero, or positive. This is due to the synaptic weights, which represent excitatory synapses when positive ($w_i > 0$) or inhibitory ones when negative ($w_i < 0$). The PE's output is computed by applying the transfer function to the activation. The type of transfer function to be used depends on the type of ANN to be designed.

Figure 1. Artificial Neural Networks: The Analogy to the Brain

Currently, back-propagation is the most popular, effective, and easy to learn model for complex networks^{3,4}. For the last few years, the first author has been using various ANN back-propagation Multi-layer Perceptron (MLP) modeling techniques in materials science and engineering³⁻⁶. To develop a back-propagation neural network, a developer inputs known information, assigns weight to the connections within the network architecture, and runs in the networks repeatedly until the output is satisfactorily accurate. The weighted matrix of interconnections allows the neural networks to learn and remember⁷. In essence, back propagation training adapts a gradient-descent approach of adjusting the ANN weights. During training, an ANN is presented with the data thousands of times (called cycles). After each cycle, the error between the ANN outputs and the actual outputs are propagated backward to adjust the weights in a manner that is mathematically guaranteed to converge⁸.

This paper describes an ANN back-propagation Multi-layer Perceptron (MLP) model to design a beam-column, which predicts column cross-section for a given set of inputs: concrete

compressive strength, column types (square tied and circular spiral), reinforcing steel ratio (0.01 – 0.08), factored axial load, P_u , and moment, M_u . The trained ANN back-propagation model has been tested with several actual design data, and a comparative evaluation between the ANN model predictions and the actual design has been presented.

ANN Backpropagation Model

The neural network used for the proposed models was developed with NeuroShell 2 software by Ward Systems Group, Inc., using a back-propagation architecture with multi- layers jump connection, where every layer (slab) is linked to every previous layer. Two ANN models were developed. The model-1 network was trained for column size. The inputs were type of column (Type = 1 for square tied column, and type = 2 for circular spiral column), factored load, P_u , Moment, M_u , and steel ratio, ρ_g . In this model concrete ultimate compressive strength, f_c' was 4,000 PSI, and reinforcing steel yield strength, f_y was 60,000 PSI. The model-2 network was trained for determining the values of P_o , P_{nx} , and P_{ny} , which determined the axial load capacity of a biaxial bending column using Bresler equation⁹:

$$1/P_n = 1/P_{nx} + 1/P_{ny} - 1/P_o; \text{ for } P_n \geq 0.1P_o$$

Where P_n = nominal axial load capacity of a column under biaxial bending.

P_{nx} = nominal axial load capacity of a column when the load is placed at an eccentricity e_x .

P_{ny} = nominal axial load capacity of a column when the load is placed at an eccentricity e_y .

P_o = nominal axial load capacity of a column when the load is placed with a zero eccentricity.

The input for model-2 was h , ρ_g , e/h , and γ . The value of γ was estimated using the equation: $\gamma = 1 - (5/h)$, where the column size, h was in inches. Figure 2 shows the column dimensions.

Figure 2. (a) Square tied column dimensions; (b) Circular spiral column dimensions.

The number of hidden neurons, for which the logistic activation function, $f(x) = 1 / \{1 + \exp(-x)\}$ was used, was determined according to the following formula¹⁰:

$$\text{Number of hidden neurons} = 0.5(\text{Inputs} + \text{Outputs}) + \tilde{0}(\text{Number of training patterns})$$

Given the properties of the training data used: 4 inputs, 1 output, and 340 training patterns – the number of processing elements was determined to be 21. The training data was obtained from a series of column design Interaction Diagrams with $g = 0.45, 0.60, 0.75$ and 0.9 for the column sizes in inches as determined by the equation: $h = 5/(1-g)$. A set of data was randomly separated from the training set, and was not used in the training model. These data were used to evaluate the trained model.

ANN Model Training

Network training is an act of continuously adjusting their connection weights until they reach unique values that allow the network to produce outputs that are close enough to the desired outputs. This can be compared with the human brain, which basically learns from experience. The strength of connection between the neurons is stored as a weight-value for the specific connection. The system learns new knowledge by adjusting these connection weights. The learning ability of a neural network is determined by its architecture and by the algorithmic method chosen for training.

Several different ANN back-propagation trial models with different layers/slabs connections, weights and activation functions (including linear, Logistic, Gaussian, etc.) were trained with pattern selections including “Rotation” and “Random”, and weight updates using Vanilla, Momentum and TurboProp. The presented ANN back-propagation Multi-layer Perceptron (MLP) model with logistic activation function, "Rotation" for pattern selection, and "TurboProp" for weight updates was the best one among all other trials, which converges very rapidly to reach the excellent statistical performance (as illustrated in System Performance). Figures 3 - 4 demonstrate the graphical comparisons between the actual column sizes and the network predicted column sizes during training phase of the ANN model. They clearly demonstrate very good agreement between the actual and predicted performance. Table 1 shows a good agreement between the column sizes and the ANN predicted column sizes during the evaluation phase.

Figure 3. Square Tied Column Sizes for the ANN Training Patterns Processed

Figure 4. Circular Spiral Column Diameters for the ANN Training Patterns Processed

Table 1 Column size prediction during ANN model evaluation

Square tied column with $\rho_g = 0.04$ ($f'_c = 4$ ksi; $f_y = 60$ ksi)				Circular spiral column with $\rho_g = 0.04$ ($f'_c = 4$ ksi; $f_y = 60$ ksi)			
P_u (Kips)	M_u (ft-kip)	h (in)	ANN-h ^(a) (in)	P_u (Kips)	M_u (ft-kip)	h (in)	ANN-h ^(a) (in)
37.19	28.17	9.09	9.09	25.96	19.67	9.09	9.26
56.20	29.80	9.09	9.09	51.93	19.67	9.09	9.39
74.38	28.17	9.09	9.09	64.91	19.67	9.09	9.46
90.91	27.55	9.09	9.09	82.11	18.66	9.09	9.52
117.36	26.67	9.09	9.09	117.81	17.85	9.09	9.69
165.29	25.04	9.09	9.27	186.94	14.16	9.09	9.98
234.71	17.78	9.09	9.47	59.52	62.00	12.50	10.65
90.63	94.40	12.50	10.98	122.72	63.92	12.50	11.07
171.88	89.52	12.50	11.26	147.26	61.36	12.50	11.14
218.75	91.15	12.50	11.57	189.60	59.25	12.50	11.33
265.63	83.01	12.50	11.60	260.16	54.20	12.50	11.61
343.75	71.61	12.50	11.76	376.13	39.18	12.50	11.91
468.75	48.83	12.50	11.95	188.50	314.16	20.00	20.31
280.00	466.67	20.00	20.28	376.99	251.33	20.00	18.57
540.00	450.00	20.00	20.08	376.99	314.16	20.00	20.49
640.00	426.67	20.00	19.98	565.49	282.74	20.00	20.07
760.00	380.00	20.00	19.74	736.70	245.57	20.00	19.86
960.00	320.00	20.00	19.81	1005.31	167.55	20.00	19.65
1240.00	206.67	20.00	19.85	1374.45	5726.86	50.00	50.00
2000.00	8333.33	50.00	49.97	2748.89	5726.86	50.00	50.00
3750.00	7812.50	50.00	50.00	3141.59	5235.99	50.00	49.84
4425.00	7375.00	50.00	50.00	3926.99	4908.74	50.00	49.86
5250.00	6562.50	50.00	50.00	4908.74	4090.62	50.00	49.95
6375.00	5312.50	50.00	50.00	6450.08	2687.53	50.00	50.00

^(a) ANN-h = ANN predicted value of h

System Performance

The neural network used for the presented model demonstrated an excellent statistical performance as indicated by the R^2 and r -values as shown in Table 2. During network training, R^2 was obtained as 0.9980 and 0.9984 during network evaluation, which were very close to 1.0 indicating a very good fit between the actual and the network prediction. R^2 is a statistical indicator usually applied to multiple regression analysis, and can be calculated using the following formulae¹⁰:

$$R^2 = 1 - (SSE/SS_{yy})$$

Where $SSE = \sum (y - \hat{y})^2$, $SS_{yy} = \sum (y - \bar{y})^2$, y is the actual value, $\hat{y}$ is the predicted value of y , and $\bar{y}$ is the mean of the y values.

The correlation coefficient, r is a statistical measure of the strength of the relationship between the actual vs. predicted outputs. During network training, r -values were obtained as 0.9991, and 0.9993 during network evaluation, which were very close to +1.0 indicating a very good fit between the actual and the network prediction. The formula for r :

$$r = SS_{xy} / \sqrt{SS_{xx} SS_{yy}}$$

Where $SS_{xy} = \sum xy - (1/n)(\sum x)(\sum y)$; $SS_{xx} = \sum x^2 - (1/n)(\sum x)^2$; $SS_{yy} = \sum y^2 - (1/n)(\sum y)^2$; Where n equals the number of patterns, x refers to the set of actual outputs, and y refers to the predicted outputs. Table 2 shows the overall statistical performance of the trained ANN model.

Table 2 Statistical performance of the ANN trained model

Items	ANN – training phase	ANN – evaluation phase
Pattern processed	340	48
R Squared	0.9980	0.9984
Correlation Coefficient, r	0.9991	0.9993
Mean Squared Error	0.529	0.425
Mean Absolute Error	0.466	0.418
Minimum Absolute Error	0.0	0.0
Maximum Absolute Error	4.479	1.854
Percent within 5%	70.882	72.917
Percent within 5% to 10%	18.529	18.750
Percent within 10% to 20%	10.294	8.333
Percent within 20% to 30%	0.294	0
Percent > 30%	0	0

Examples

Several reinforced concrete short columns with uniaxial and biaxial bending moments were designed using the ANN models; a few of the results are shown in Tables 3 and 4. For predicting the required column sizes, the inputs for the ANN model-1 were type of column (Type

= 1 for square tied column, and type = 2 for circular spiral column), factored load, P_u , Moment, M_u , and steel ratio, ρ_g (selected within 0.01 to 0.08). For a circular spiral column with biaxial moments, the resultant moment, M_u was calculated by taking the square root of the sum of the squares of the moments from two perpendicular directions, M_{ux} and M_{uy} . For a square tied column with biaxial moments, M_u for the ANN model-1 was calculated using the equation¹¹:

$$fM_{nx}' = M_{ux} + M_{uy} \{(1 - b)/b\}, \text{ where } b \text{ varies from 0.55 to 0.65}$$

In the example problems, the load-contour curvature with the parameter, $b = 0.65$ was used. Once the size of the square tied column with biaxial bending was predicted through the ANN model-1, a reasonable size was selected, and the capacity of the column, fP_n was calculated using the Bresler equation as stated earlier from the values of P_{nx} , P_{ny} , and P_o . The values of P_{nx} , P_{ny} , and P_o were obtained from the ANN model-2. In general, all the cases, the ANN models produced pretty good results in determining column sizes with varying steel ratio.

Table 3 Column size prediction using ANN Model-1

Column Type	P_u (Kips)	M_{ux} (ft-kips)	M_{uy} (ft-kips)	ρ_g	h (in)	Selected h (in)
1	640	330	0	0.03	19.55	20
1	600	140	0	0.03	15.60	16
2	408	204	0	0.015	18.36	20
2	424	127	0	0.041	15.64	16
1 ^(a)	378	189	158	0.02	19.04	22
1 ^(b)	432	108	144	0.03	16.23	18
2	378	189	158	0.02	21.09	22
2	432	108	144	0.03	17.61	18

Note:

^{(a), (b)} See Table 4 for Column Load Capacity by Bresler Equation using ANN Model-2

Table 4 Column Load Capacity by Bresler Equation using ANN Model-2

P_o (Kips)	P_{nx} (Kips)	P_{ny} (Kips)	P_n (Kips)	Check $P_n \geq 0.1P_o$	ϕP_n (Kips)	Check $\phi P_n \geq P_u$
^{1(a)} 1817.25	824.12	945.75	581.23	OK	406.86	OK
^{1(b)} 1633.52	1068.44	934.89	717.66	OK	502.36	OK

Note:

^{1(a), 1(b)} See Table 3 for the tied column size

Educational Significance

It is increasingly important to go beyond traditional departmental course curriculum boundaries for some areas of science and engineering education. ANN is one such field, because although electrical/computer engineers developed it largely, its applications are very extensive and

interdisciplinary. Especially the graduate students should be encouraged to learn various applications of contemporary computing techniques including artificial neural network, genetic algorithm, etc. This paper is an example of ANN's interdisciplinary application in the fields of structural engineering.

Conclusions

This paper investigated the suitability of an Artificial Neural Network (ANN) for modeling a preliminary design of reinforced concrete beam-column. It was established in this paper that an ANN back-propagation model with Multi-layer Perceptron (MLP) network could be applied to design reinforced concrete beam-columns. The neural networks demonstrated an excellent statistical performance in the network training as well as in the evaluation of the trained networks. Several reinforced concrete short columns with uniaxial and biaxial bending moments were studied and found that the ANN models produced pretty good results in determining column sizes with varying steel ratio. The application of an ANN model certainly minimized the extensive calculations, especially required for column with biaxial bending during the optimization of the reinforcing steel or the column cross-section.

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