Artificial Neural Network Based Approach for Design of RCC Columns

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Recent developments in artificial neural network have opened up new possibilities in the field of structural engineering. The paper demonstrates the usefulness of artificial neural network (ANN) for design of RCC columns subjected to combined axial load and biaxial moments. The design of column is affected by many factors such as the initial crookedness, eccentricity of loading, shape and size of the column cross section, grade of steel, and grade of concrete. Therefore, design code adopts formulae, which requires a number of scalar constants and ends up with trial and error design. Hence, an attempt has been made to capture the mapping between the design variables using ANN. A feed forward network and backpropagation training algorithm has been used. Training data are generated from a 'C' program that designs RCC column by conventional design method. For training, about 500 data sets have been generated for each type of column cross-section.

Keywords: Neural network; RCC column design; '+' Cross section column

NOTATION

\[ A_{si} \] : area of reinforcement bar \( i \)

\[ B_D \] : breadth and depth, respectively, of cross section measured in the plane of cantilever

\[ B_i \] : width of strip

\[ D_\text{c} \] : distance of centroid of reinforcement to concrete extreme fibre distance

\[ f_{ci} \] : stress at centre of strip \( i \)

\[ f_{ck} \] : characteristic compressive strength of concrete

\[ f_{si} \] : stress in reinforcement bar \( i \)

\[ f_y \] : characteristic yield strength of steel

\[ M_{x_{max}}, M_{y_{max}} \] : factored biaxial moment acting on the column about \( X-X \) and \( Y-Y \) axes, respectively

\[ M_{x_{max}}, M_{y_{max}} \] : uniaxial moment carrying capacity of the column along \( x \) and \( y \)-axes, respectively

\[ p \] : percentage of reinforcement required

\[ P_u \] : factored axial load acting on the column

\[ t_i \] : thickness of centre line of strip \( i \)

\[ x_{ci}, y_{ci} \] : distance of mid-point of centre line of strip \( i \) from \( Y-Y \) and \( X-X \) axes, respectively

\[ X_u \] : depth of neutral axial measured for the compression fibre

\[ \varepsilon_c \] : maximum strain in the high compressed concrete extreme fibre

\[ \varepsilon_s \] : maximum strain in reinforcement

INTRODUCTION

The neural network exploits the massively local processing and distributed representation properties that are believed to exist in the brain. The main benefit in using a neural network approach is that the network can be trained to learn the relationship between input and output parameters. The neural network architectures can provide improved computational efficiency relative to existing methods when an algorithmic description of functional relationships, is either totally unavailable or is very complex in nature. Such a modelling strategy has important implication for designing highly non-linear complex design problem especially that of RCC columns subjected to biaxial moments. Here, ANN models are developed for the design of RCC columns subjected to biaxial moments.

The normal design of structural components by computer is highly iterative, as it requires fulfilling the equilibrium and compatibility requirements of the member. In the present method, the sensitivity of the reinforcement in column to depth to cover ratio, arrangement of reinforced bars, grade of concrete and grade of steel are captured in the ANN. Now, with proper training, the neural network can respond to the query about the design variables instantaneously (the fastest way possible) and can even extrapolate the results. This process of using the ANN for design is similar to the designer using the tables and charts for manual design. The relative advantage of the present method...
in overall design process over the conventional algorithmic method has been substantiated.

ARTIFICIAL NEURAL NETWORK
The artificial neural network (ANN) is an appropriate attempt to simulate the biological neural network, which is present in human brain. Similar to the functioning of a biological neural network, an artificial neural network is simulated using a simple artificial neuron, which is an appropriate mathematical model of its biological counterpart. In the present work, a feed forward network has been used. The backpropagation (BP) algorithm has been used for the training of the network. A good performance of the network has been assured by providing sufficient information as input to the network. This facilitated correct mapping of the desired relationship between the selected input/output vectors.

Feed Forward and Backpropagation Architecture
Recent research has shown that artificial neural network-based modelling is a promising method. An artificial neural network consists of a number of processing elements that are arranged logically into two or more layers and interact with each other through weighted connections to constitute a network. The computational characteristics of neural networks are remarkable in their ability to learn functional relationships from training examples and to discover patterns and regularities in data through self-organization. Most neural network applications are based on the error backpropagation algorithm. The backpropagation algorithm consists of forward propagation of a set of patterns presented as input to the network and, then, backward error propagation beginning at the output layer where errors are propagated back through the intermediate layers toward the input layer. Figure 1 shows the typical architecture of backpropagation neural networks with an input layer, and output layer, and one hidden layer.

The input layer neurons just pass the input pattern values to the hidden layer with no calculations taking place. Each of the hidden layer neurons computes a weighted sum of its input, passes the sum through its activation function and presents the activation value to the output layer. The process of forward and backward propagation continues until the error is reduced to an acceptable level. The learning process primarily involves the determination of connection weight matrices and the pattern of the connections. In addition, the choice of an activation function may significantly influence the applicability of a training algorithm since it defines how the net input received by a unit combines with its current levels of activation to compute a new level of activation. When the activation function is continuous and bounded it is common to use a sigmoid function, the derivative of which is easy to form so that little extra calculation is needed. A detailed explanation of back-propagation networks is beyond the scope of this paper. However, the basic algorithm for back-propagation neural network is described in the literature.

COLUMN SUBJECTED TO BIAXIAL BENDING
The load carrying capacity of a biaxial eccentrically loaded column depends upon the size of the column, the disposition of reinforcement, the stress-strain curves of the materials used, the yield limits of the materials and above all, the eccentricity of load.

The analysis of eccentrically loaded columns is generally cumbersome and may require several hours of computational effort. Thus, the design of the member subjected to combined axial load and biaxial bending will involve lengthy calculation by trial and error. The resistance of a member subjected to axial force and biaxial bending shall be obtained on the basis of assumptions given in clauses 39.1 and 39.2 of IS: 456-2000 with neutral axis chosen so as to satisfy the equilibrium of force and moment about two axes. Exact design of members subject to axial load and biaxial bending is extremely difficult. In order to overcome these difficulties interaction diagrams can be used. These have been prepared and published by BIS. In this study rectangular, circular and ‘+’ cross sections have been considered. Since the interaction diagram for ‘+’ cross section is not available in IS code, a C program has been developed to capture the design points, i.e., the axial and moment resisting capacity of the column for various cover to depth ratio, $f_y$ and area of reinforcement. The ‘+’ section is geometrically symmetrical about the axes of bending as shown in the Figure 2. These columns may have a large variation in geometry defined by depth ($D$) to width ($B$) ratio of the section. It may have many possible ways of reinforcement detailing. For the present study,
the type of reinforcement detailing considered for '+' section is shown in Figure 2. Reinforcement equally distributed along all the sides has been considered for rectangular and circular cross section columns.

If the eccentricity of the load exceeds 0.05 times the lateral dimension of the column, the calculation of axial load and moments can be made by assuming the position of neutral axis. The assumed position of neutral axis should satisfy the requirement of resultant internal force acting at the eccentricity of external load. If it is not satisfied, then the assumed position of neutral axis is altered and the method is repeated till the resultant internal force coincides with the point of application of the external load within the acceptable limit of accuracy.

For assumed position of neutral axis, a numerical approach is used for calculating axial force and moments where compression zone of concrete is split into a number of strips of equal thickness as shown in Figure 3. The strain at centroid of each strip is determined by interpolation from known values. The stress-strain at the centroid of each strip is determined from the stress-strain relation of concrete. Then, the compressive force in each strip and moments due to compressive force in each strip are calculated as:

Axial force in strip \( i \),
\[
P_{ci} = t_i B_i f_{ci}
\]

Moment due to axial force \( P_{ci} \) in strip \( i \) about \( X-X \) axis,
\[
M_{xci} = P_{ci} y_i
\]

Forces and moments due to reinforcement bars in the section are calculated by determining strain in the reinforcement bars and then stress from the stress-strain curve as:

Axial force in reinforcement bar \( i \),
\[
P_{si} = A_{si} f_{si}
\]

Moments due to axial force \( P_{si} \) in reinforcement bar \( i \) about \( X-X \) axis
\[
M_{xsi} = P_{si} y_i
\]

In the same way \( M_{xci} \) and \( M_{xsi} \) are determined by taking strips parallel to \( Y-Y \) axis. The total axial force and moments are obtained by summing axial force and moments due to concrete strips and reinforcements bars as:

Total axial force,
\[
P_u = \sum P_{ci} + \sum P_{si}
\]

Total moment about \( X-X \) axis,
\[
M_{ux} = \sum M_{xci} + \sum M_{xsi}
\]

Total moment about \( Y-Y \) axis,
\[
M_{uy} = \sum M_{yci} + \sum M_{ysi}
\]

The section is safe if the design ultimate load is within the ultimate load capacity otherwise it is unsafe. Accordingly, the assumed section and the reinforcement area are successively corrected until the strength of the section approaches the required value.

For values of \( \frac{P_u}{P_{uz}} = 0.2 \) to 0.8, the values of \( \alpha_u \) vary linearly from 1.0 to 2.0. For values less than 0.2, \( \alpha_u \) is 1.0; for values greater than 0.8, \( \alpha_u \) is 2.0. \( M_{ux} \) and \( M_{uy} \) are the uniaxial moment carrying capacity of the column along \( x \)-axis and \( y \)-axis respectively.

For the design of long column, ‘Additional Moment Method’ suggested in IS: 456-2000\(^2\) has been used. According to this method every slender column should be designed for biaxial eccentricity, which include the \( P-D \) moment components, ie,

\[
M_k = P_u (e_x + e_{ax}) = M_{ux} + M_{ax}
\]

\[
M_y = P_u (e_y + e_{ay}) = M_{uy} + M_{ay}
\]

Here, \( M_k \) and \( M_y \) denote the total design moments, \( M_{ax} \) and \( M_{ay} \) denote the primary factored moments obtained from first order structural analysis; and \( M_{ax} \) and \( M_{ay} \) denote the additional moments with reference to bending about the major and minor axes, respectively.

**CONFIGURATION OF THE NETWORK**

A dilemma arises when determining the number of hidden-layer nodes. A large number of hidden-layer nodes will lead to

[Figure 3 Stress-strain variation along cross-sections]
an over-fit at intermediate points, which can slow down the operation of the neural network, both during training and in use. On the other hand, an accurate output may not be achieved if too few hidden-layer nodes are included in the neural network. Flood suggested that the number of nodes in the hidden layer be between the sum and the average of the number of nodes in the input and output layers.

For a particular number of epochs of about 5000 epochs, a number of networks having different hidden layer and different nodes in each hidden layer have been studied for its performance and convergence. After a number of trials, the values of the network parameters considered by this study are:

- Number of hidden layers = 2;
- Number of hidden neurons in layer 1 = 128;
- Number of hidden neurons in layer 2 = 32;
- Number of training examples = 500;
- Number of testing examples = 10;
- Training cycles = 30,000;
- Learning rate = 0.90.

**NETWORK TRAINING AND TESTING**

A ‘C’ program has been developed for the design of column subjected to biaxial moments. This program uses the design procedure specified by SP: 163. About 500 design data has been generated from the program to use it for training the network. Separate network has been considered for the rectangular, circular and ‘+’ cross section column design. The input variables and its range of values are given in Table 1.

In neural network, learning process is achieved by estimating the connection weights by minimising the error. Training means to present the network with the experimental data and have it learn, or modify its weights. However, training the network successfully requires many choices and training experiences. In this study, the network configuration was arrived after watching the performance of different configurations for a fixed number of cycles. Then, learning parameters were changed and learning processes were repeated. In addition, to avoid over-training the convergence criterion adopted in this study depends on whether the RMS error of the testing data has reached its minimum or not.

The neural network shown in Figure 4 has \( L_{\text{eff}}, B, D, d'/D, f_{ck}, f_y, P_u, M_{ux}, M_{uy} \) as input and \( p/f_{ck} \) as output. The output is normalized to 1. This is because sigmoid function is used as activation function in the network.

The convergence is shown in Figure 5. The error was of the order of \( 4.5 \times 10^{-9} \) from the network considered for rectangular section. After training, the network was tested with 10 data sets to check its performance. The results from the ANN model are quite promising and the output from the network is shown in Tables 2-4 for rectangular, circular and ‘+’ cross-section columns, respectively. A comparison between the actual design

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Rectangular section range</th>
<th>Circular section range</th>
<th>‘+’ Section range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effective length of column, mm</td>
<td>3000-8000</td>
<td>3000-8000</td>
<td>3000-8000</td>
</tr>
<tr>
<td>Breadth of column, mm</td>
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<td>—</td>
<td>200-400</td>
</tr>
<tr>
<td>Depth of column, mm</td>
<td>300-600</td>
<td>300-600</td>
<td>800-1200</td>
</tr>
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<td>0.05-0.20</td>
<td>0.02-0.08</td>
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<td>20-40</td>
<td>20-40</td>
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<tr>
<td>Grade of steel, N/mm²</td>
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<td>415</td>
<td>415</td>
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<td>500-4000</td>
<td>500-6000</td>
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<td>Moment about ( x )-axis, kNm</td>
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<td>25-500</td>
<td>50-3000</td>
</tr>
<tr>
<td>Moment about ( y )-axis, kNm</td>
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<td>25-500</td>
<td>50-3000</td>
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Table 2  Design results for rectangular column

<table>
<thead>
<tr>
<th>L_{eff}, m m</th>
<th>Type of column</th>
<th>Breadth, m m</th>
<th>Depth, m m</th>
<th>d'/D</th>
<th>P_{u}, kN</th>
<th>M_{ux}, kNm</th>
<th>M_{uy}, kNm</th>
<th>p/f_{ck}</th>
<th>Error, %</th>
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<td>500</td>
<td>100</td>
<td>80</td>
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<td>0.1000</td>
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<td>200</td>
<td>125</td>
<td>0.16</td>
<td>0.1510</td>
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<td>100</td>
<td>250</td>
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<td>0.2350</td>
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Average Error 2.10

Table 3  Design results for circular column

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<th>Diameter, m m</th>
<th>d'/D</th>
<th>P_{u}, kN</th>
<th>M_{ux}, kNm</th>
<th>M_{uy}, kNm</th>
<th>p/f_{ck}</th>
<th>Error, %</th>
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<tbody>
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Average Error 3.18

Table 4  Design results for ‘+’ cross-section column

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<tr>
<th>L_{eff}, m m</th>
<th>Type of column</th>
<th>Breadth, m m</th>
<th>Depth, m m</th>
<th>d'/D</th>
<th>P_{u}, kN</th>
<th>M_{ux}, kNm</th>
<th>M_{uy}, kNm</th>
<th>p/f_{ck}</th>
<th>Error, %</th>
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</thead>
<tbody>
<tr>
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<td>800</td>
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</table>

Average Error 4.31

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and ANN design has also been made and shown in Figure 6 keeping all parameters: \( L_{eff} = 2500 \) mm; breadth = 450 mm; depth = 450 mm; cover ratio = 0.10; \( f_{ck} = 25 \) N/mm\(^2\); \( f_y = 415 \) N/mm\(^2\); \( P_u = 2000 \) kN; \( M_{ux} = 150 \) kNm constant and \( M_{uy} \) varying from 25 kNm to 500 kNm.

**CONCLUSION**

Neural networks have been applied to structural engineering in recent years. This study is multidisciplinary in nature, which attempts to use soft computing technique for structural engineering problems. The paper demonstrates the application of ANN in the design of concrete short and long column. It has been observed that the performance of the network with two hidden layers gives very satisfactory results with quick convergence. The technique has been applied for the design of rectangular, circular and ‘+’ shaped cross section. The results presented here are encouraging for adopting the concept of using ANN to develop a single network for the design of column subjected to biaxial moments.

Since, the design of column of rectangular, circular and ‘+’ section are similar, same network configuration have been used for all the three cross sections. The convergence pattern and training time is also found to be similar. Compared to the conventional trial and error procedure the method is very fast and the error % in the \( p/f_{ck} \) value vary from 0.0 to 5.63 for rectangular, 0.0 to 7.17 for circular and 0.14 to 8.64 for ‘+’ shaped column sections. The developed methodology is working well for all values of variables within the range specified. The methodology can be extended to different types of cross sections, such as, \( T \) and \( L \), column sections.

**REFERENCES**