Failure Mode Recognition of Columns Using Artificial Neural Network

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Abstract. Columns are one of the most vital segments in bridges since its post-seismic behaviour is of much importance. The retrofitting methods and rehabilitation strategies of bridges mainly rely on the identification of the failure mode of columns. It has been witnessed in various studies on columns that the mode of failure highly depends on section and material properties and there is no specific boundary between the modes, which makes their identification more sophisticated. This paper uses an artificial neural network to predict the modes of failure by analysing the effects of such soft computing methods. In this study, machine-learning models were generated from the experimental data of 253 columns of rectangular cross-section and its accuracy of failure mode prediction was evaluated by considering failure modes mainly flexure, flexure-shear, and shear. The optimal input parameters have also been evaluated for the machine-learning algorithm that enhances the efficiency of failure mode prediction.

1. Introduction

Bridge columns are the most vital part regarding the load-carrying capacities and its post-seismic behaviour. Rectangular columns are more preferred considering its ease of construction and better strength capabilities. Different failure patterns can be exhibited by the columns depending upon their geometric and design details. The column behaviour is highly influenced by the failure modes; a brittle failure is observed in shear failure mode, flexural failure mode indicates a gradual failure by exhibiting large deformation capacity, whereas the flexure-shear columns undergo a ductile shear failure. Various researches have been carried out to explore the post-earthquake performance of RC columns. The identification of flexure and shear failure modes was done by analysing geometric and reinforcement details, as well as empirical models, developed based on shear strength of the columns [1][2][3]. However, the flexure-shear interaction makes the study of flexural-shear failure difficult. Thus, identifying the failure modes, especially the flexure-shear failure mode is of greater importance since the rehabilitation approach and the retrofitting methods to be adopted in the bridges are highly dependent on the column failure modes [4].

2. Experimental database

The study used an experimental database of 253 columns with rectangular cross-sections provided with lateral ties around the perimeter. Among this, 199 columns exhibit flexural failure, 18 columns undergo shear failure and 36 columns have a flexural-shear failure. The identification of these failure modes was from various experimental observations. The various parameters evaluated include the following, and they are falling within the given ranges.

- Compressive strength of concrete: $16 \text{ MPa} \leq f_c \leq 118 \text{ MPa}$
• Yield strength of longitudinal reinforcement: $318 \text{ MPa} \leq f_y \leq 586.1 \text{ MPa}$
• Yield strength of transverse reinforcement: $249 \text{ MPa} \leq f_{yh} \leq 1424 \text{ MPa}$
• Transverse reinforcement ratio: $0.002 \leq \rho_s \leq 0.067$
• Axial load ratio: $0.027 \leq P/(f_cA_g) \leq 0.9$
• Shear span to depth ratio: $1 \leq l/d \leq 7.64$
• Longitudinal reinforcement ratio: $0.0068 \leq \rho_l \leq 0.067$

where $P$ is the axial load on the column. The different properties of columns including breadth, length, depth, splice length, hoop diameter, longitudinal bar diameter, the total number of bars, number of hoop sets, etc., were examined in detail for the current study. The input parameters used for the prediction are shown in Table 1.

| Input parameter                  | Notation |
|----------------------------------|----------|
| Shear span to depth ratio        | $l/d$    |
| Axial load ratio                 | $P/f_cA_g$ |
| Main steel index                 | $\rho_l f_y/f_c$ |
| Lateral ties index               | $\rho_s f_{yh}/f_t$ |

These input parameters were particularly chosen after thorough investigations on the column database [5]. Column failure modes can be predicted as a function of these four variables, even though they cannot be specifically correlated. In this study, the tensile strength ($f_t$) is calculated as $0.625\sqrt{f_c}$ based on recommendations as per ACI. To analyse the relations between different input parameters in failure mode prediction, data visualisation was carried out and presented in figure 1, where two variables are considered for each mode, noticed the following.

- Columns with low values of $l/d$ exhibit shear failure whereas higher values show flexural failure. For an $l/d$ ratio around 2, columns exhibit all the three failure modes varying with other parameters. Thus, $l/d$ ratio alone cannot be relied on for the identification of column failure modes.
- With the increase in $l/d$ ratio, mode switches from shear to flexure-shear and shear.
- The boundaries which differentiate the three modes are irregular and nonlinear.
- The design variables cannot be specifically correlated as seen in figure 1.

3. Overview of Artificial neural network

An artificial neural network (ANN) is a computational network developed based on the system of biological neurons [6]. ANN consists of an input layer, several hidden layers, and an output layer, as shown in figure 2. The input layer corresponds to the input parameters which can be fed into ANN to generate a predictive model. This layer does not take part in actual output modification but transports the data to the hidden layer. The hidden layer has an arbitrary number of layers with an arbitrary number of neurons in it. The nodes in the hidden layer are known as active since they take part in actual output modification. The number of neurons can be varied for improving the classification accuracy in identifying column failure modes. The output values for the neural network are obtained in the output layer. The nodes in this layer are active ones. ANN works through optimised weight values.
Figure 1. Plots of parameters for rectangular columns:

(a) \( \frac{l}{d} \) Vs \( \frac{P}{f_{cA}} \);  
(b) \( \frac{l}{d} \) Vs \( \rho l \frac{f_y}{f_c} \);  
(c) \( \frac{l}{d} \) Vs \( \rho_s \frac{f_{yh}}{f_{ft}} \);  
(d) \( \frac{P}{f_{cA}} \) Vs \( \rho l \frac{f_y}{f_c} \);  
(e) \( \frac{P}{f_{cA}} \) Vs \( \rho_s \frac{f_{yh}}{f_{ft}} \);  
(f) \( \rho_s \frac{f_{yh}}{f_{ft}} \) Vs \( \rho l \frac{f_y}{f_c} \).

For the prediction or classification of three failure modes such as shear, flexure, and flexure-shear, machine learning algorithm such as Artificial Neural Network (ANN) is particularly used in this study. In this study, \( Y = (Y_1 = \frac{l}{d}, Y_2 = \frac{P}{f_{cA}}, Y_3 = \rho l \frac{f_y}{f_c}, Y_4 = \rho_s \frac{f_{yh}}{f_{ft}}) \) are used as input variables [7][8]. The network is trained many times with the training data to minimise the error in predicting the model by varying the weights allotted to the neurons and the efficiency is checked with the test data set, which remains separate from the dataset used for training purposes.

Figure 2. Artificial Neural Network
3.1. Performance of ANN in failure mode identification
To identify the failure modes, the whole data set was divided into two; one for the training purpose while the other is for testing purposes. The predictive model was generated using the training dataset and its efficiency was analyzed with the test dataset. The network is trained several times by changing the number of neurons to improve the efficiency of the prediction model [9]. The entire dataset was divided into 70% and 30% for training and test respectively and these values were randomly assigned. The regression plots obtained after training the entire dataset are shown in figure 3.

![Figure 3. Regression plot](image)

4. Predicted outputs and error variation
It is noted that the classification accuracy in identifying the failure mode increases with the increase in the number of neurons until an optimal value of 15 neurons. With an increase in the neurons beyond 15, the accuracy of the test set and the entire set decreases. The percentage error value has decreased from 21.35% to 19.73% while training the entire dataset by changing the number of neurons from 10 to 15. Out of 61 total specimens, 52 specimens are correctly predicted regarding their failure modes. The prediction accuracy is above 85%, which is far better than any other existing classification methods. Out of 51 specimens, which exhibits flexural failure mode, 48 have been predicted accurately. 3 out of 6 specimens and 1 out of 4 specimens had exact predictions in flexural-shear and shear failure mode respectively. Flexural-shear failure mode which remains as a grey area in most of the existing methods, has more than 50% prediction accuracy using ANN. Since most of the data fed for training involves specimens exhibiting flexural failure mode, it has a high percentage of accurate predictions. Finding out and training more database of columns exhibiting shear and flexural-shear failure modes may improve the prediction efficiency above 90% regarding these failure modes as well as for the whole dataset.

5. Conclusion
The identification of the failure mode of columns is important as it influences the methods being adopted for repairs. Existing methods of classification are based on the aspect ratio [10], displacement ductility, empirical models developed based on the shear strength of columns [11] etc. An artificial neural network was used here. A dataset of 253 test results on rectangular columns including the failure modes, various geometric properties, material properties, reinforcement ratios, and axial load ratios was assembled by carrying out a thorough study of existing literature. It was clear from the preliminary data study that the
column failure modes depend on the sectional and reinforcement details, and the boundaries which
differentiate the three failure modes are complex and irregular. Also, the design variables cannot be
specifically correlated. The regression plots obtained after training of the dataset shows satisfactory
results. The error histogram also showed satisfactory results, since the error function was minimised by
training the dataset many times by changing the number of neurons. The ANN-based model showed
greater efficiency compared to all the other theoretical and experimental methods. ANN has improved
prediction accuracy over the flexural-shear failure mode identification than all other methods.

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