SEISMIC DAMAGE ASSESSMENT OF RC BUILDINGS USING ARTIFICIAL NEURAL NETWORK

Saitama University Student Member ○Sanjeev Bhatta
Saitama University Regular Member Ji Dang

1. INTRODUCTION

The problem of assessing the seismic vulnerability of existing r/c buildings is a key structural engineering issue that has become a global study topic. The quick (in real time) and accurate assessment of seismic damage will limit casualties, reduce financial losses, and allow for speedy functional recovery. On-site structural damage investigations are the conventional method utilized for calculating post-event seismic damage. These investigations necessitate well-trained professionals to assess the building damage. Furthermore, they are time-consuming and labor-intensive, and as a result, they often become the bottleneck in emergency response and post-event recovery efforts. Seismic vulnerability assessment of a building can be accomplished using nonlinear finite element model; however, they can't be adopted for numerous buildings as it requires high time and cost. Machine learning methods have advanced quickly in recent years, allowing for rapid and reliable prediction of buildings seismic damage. In this study, Artificial Neural Networks (ANNs) model is developed considering both the seismic parameters and structural parameters as inputs and the degree of damage as outputs as shown in Figure 1. The model accuracy is evaluated based on the prediction of damage state of buildings in testing dataset which were not used during training.

2. PREPARATION OF INPUT PARAMETERS

2.1 Structural parameters

In this study,15 structural parameters such as number of stories, story height, total height, length of buildings in x and y direction, fundamental period, stiffness, beam section, column section, percentage of reinforcement in beam and column, grade of steel, footing type, construction year and damping ratio are considered as listed in Figure 1. 35 Reinforced Concrete (RC) Buildings ranging from 3 to 7 stories and having story height of 3 meters are considered. The reinforced concrete structure is designed based on the Indian Standard code (IS 456: 2000, IS 13920: 2016).

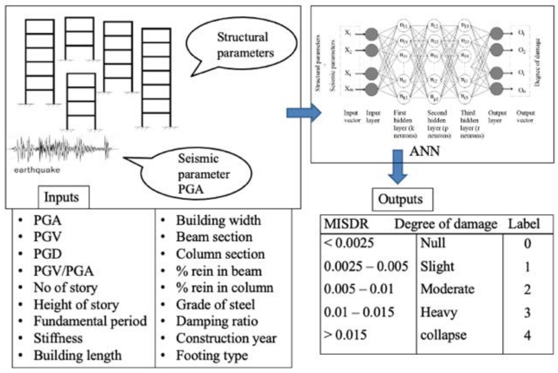


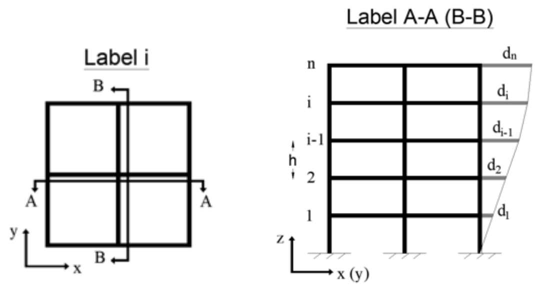
Fig. 1. Flowchart for quick seismic damage assessment using ANNs

2.1 Seismic parameters

The evaluation of the influence of seismic motions on structures, and especially on RC buildings, is an extremely complex and multi-parametric problem. As a result, a large number of seismic parameters have been introduced for evaluating earthquake effects on structures (Kia et al. 2014). In this study four seismic parameters such as peak ground acceleration (PGA), peak ground velocity (PGV), peak ground displacement (PGD) and ratio of (PGV/PGA) are considered.

3. PARAMETER FOR ASSESSING RC BUILDINGS' DAMAGES

Maximum Inter-Story Drift Ratio (MISDR) is used as a damage index to predict the seismic damage of the buildings. The MISDR data required to train the model is calculated using nonlinear analysis of each RC buildings with damping ratio of 3%, 3.5%, 4%, 4.5% and 5% under earthquake waves with different seismic characteristics as shown in Figure 2. The output of the model is classified into 5 categories based on the MISDR values as shown in Figure 1.



Story displacement = d_1, d_2, d_{i-1}, d_i, d_n ; with respect to ground
Inter story drift: $u_1 = d_1$; $u_2 = d_2$ - d_1 and so on
Inter story drift ratio = Inter story drift / corresponding story height

Maximum Inter Story Drift Ratio = Max (Inter story drift ratio)

Fig. 2. Determination of MISDR of n-story building

Keywords: seismic vulnerability assessment, damage evaluation, ANNs, machine learning
Contact address: 255 Shimo-Okubo, Sakura-Ku, Saitama University, 338-8570, Japan, Tel: +81-070-8518-7147

4. ARTIFICIAL NEURAL NETWORK

The artificial neural networks (ANNs), also called neural networks (NNs) are, biologically inspired computational networks. An ANN consists of interconnected processing units or nodes called artificial neurons. An artificial neuron transforms the input signals (X_1, X_2, … X_m) to the output signals (O_1, O_2, … O_n) utilizing activation functions. Figure 1 shows the ANNs architecture adopted in this study where three hidden layers are considered. Relu activation function is used in the input layer and three hidden layers whereas softmax function is used in the output layer.

5. PREPARATION OF DATASET

The database includes a total of 1925 dataset. The number of label data for five damage class is shown in Figure 3. The whole dataset is separated into a training and a test set in such a way that the information of the test data does not include in the training set. The purpose of splitting the data set is to predict the unknown characteristics from the dataset that has not been seen before. The data are randomly split into 70% and 30% for training and testing, respectively.

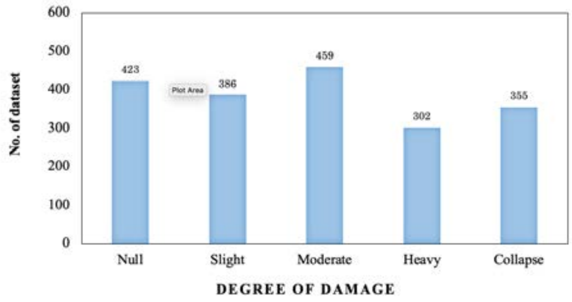


Fig. 3. Number of label data of five damage class

6. RESULTS AND DISCUSSION

The ANNs model is trained using the training dataset. The model training accuracy curve and training loss curve is shown in Figure 4. This figure illustrates that the model accuracy is increasing, and the model loss is decreasing with increase in epochs. It is seen that the model can predict the test dataset with an accuracy of 85.29%. This suggest that the model is capable of successfully predicting the degree of damage of RC buildings. The confusion matrix shown in Figure 5 illustrates that many of the prediction errors are due to confusion between four classes 0, 1, 2 and 3. Furthermore, the performance of the model based on the model metrics such as precision, recall and f1-score is high as shown in Table 1.

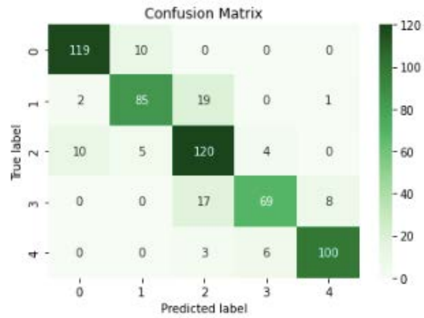
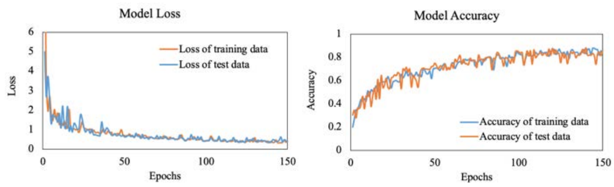


Fig. 5. Confusion matrix of ANN model



(a) (b)

Fig. 4. Loss and accuracy of ANN model

Table 1: Precision, Recall and f1-score of ANN model

	Precision	Recall	f1-score	No.
0	0.922	0.908	0.915	129
1	0.794	0.850	0.821	107
2	0.863	0.755	0.805	139
3	0.734	0.873	0.798	94
4	0.917	0.917	0.917	109
avg/total	0.846	0.861	0.851	578

7. CONCLUSION

In this study, nonlinear analysis of numerous RC buildings subjected to different ground motions is carried out to calculate the building seismic response in the form of maximum inter-story drift ratio. Then the ANNs model is trained considering both the structural parameters and seismic parameters. The prediction accuracy on testing dataset suggests that this model can be used for quick and reliable prediction of the seismic damages of RC structures. However, the dataset can be increased considering more seismic waves with low to high magnitudes which can further increase the model accuracy. More seismic parameters can be introduced in the model for near-real prediction of seismic damage on RC structures. Furthermore, this study can be extended to train ANNs model considering the response of existing RC buildings subjected to real earthquake data for region or city scale level seismic vulnerability assessment.

REFERENCES

Kia, A. and Sensoy, S.: Assessment the effective ground motion parameters on seismic performance of R/C buildings using artificial neural network. Indian Journal of Science and Technology, 7(12), 2014, pp. 2076–82.

IS 456: 2000. Indian Standard: Plain and Reinforced Concrete - Code of Practice, Bureau of Indian Standards, New Delhi, 2000.

IS 13920: 2016. Ductility Design and Detailing of Reinforced Concrete Structures Subjected to Seismic Forces - Code of Practice, Bureau of Indian Standards, New Delhi, 2016.