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Prediction of seismic responses of structural systems having degradation and pinching using deep learning

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1. Introduction

The seismic design and assessment of structural systems involves predicting the responses under a set of ground motions. Structural systems are, in general, designed to behave in nonlinear ranges, requiring nonlinear static or nonlinear dynamic analysis procedures for reliable estimation of structural responses. While the nonlinear dynamic analysis procedure produces the most accurate results by solving dynamic equilibrium equations at every time step, it requires significant computational effort. On the other hand, the nonlinear static analysis procedure relies on relatively simple equations, but due to the randomness in seismic excitation, this method often results in a significant level of uncertainty in prediction. Therefore, this study presents a novel method proposed by the authors that uses deep learning to predict seismic responses of structural systems exhibiting degradation and pinching effects. The numerical investigation shows that the proposed method is computationally efficient and provides accurate assessment for engineering practices [1].

2. Seismic demand database

2.1 Modified Bouc-Wen-Baber-Noori model

A seismic demand database is required to train the deep neural network (DNN) model. To generate seismic responses of various types of hysteretic behaviors, we propose a modified Bouc-Wen-Baber-Noori (m-BWBN) model. This model introduces a parameter controlling the yield strength of the structure to a Bouc-Wen class model developed by Baber and Noori [2]. Note that the Bouc-Wen-Baber-Noori (BWBN) model can describe stiffness and strength degradations, as well as pinching phenomena in hysteresis. A total of 14 parameters are employed to describe the hysteretic behaviors by an m-BWBN model.

The feasible parameter domain of the m-BWBN model is identified by examining the results of quasi-static cyclic analysis of reinforced concrete (RC) columns [3]. The sensitivity analysis is also performed to figure out relatively insensitive parameters. By fixing the insensitive parameters to a representative value, we can significantly reduce the computational costs of constructing the seismic demand database.

2.2 Development of the database

A total of 129,600 different hysteretic behaviors are generated by discretizing the feasible domain of the m-BWBN model parameters identified in the previous subsection. In the meantime, by introducing 1,499 ground motions from NGA-West database [4], a total of 194,270,400 (=129,600×1,499) time history analyses are carried out to construct the database.

3. Deep neural network model

3.1 Architecture of the deep neural network model

Fig. 1 illustrates the architecture of the DNN model which is inspired by the authors' previous work [5, 6]. The DNN model predicts the peak seismic responses of structures based on earthquake and structure information. The earthquake ground motion is characterized by three types of features, including earthquake characteristics, ground acceleration characteristics, and response spectrum. On the other hand, a convolutional neural network is employed to extract distinct features of the force and displacement relationship, which is commonly known as a hysteresis loop. The hysteresis loop is characterized by performing quasi-static cyclic analysis using a predefined displacement step. By introducing a hysteresis loop as an input of the DNN model, the model can consider the impact of complex hysteretic behaviors, such as stiffness and strength degradations, pinching effects, and smooth transitions from the elastic to inelastic range, which are challenging to characterize using a single scalar value.

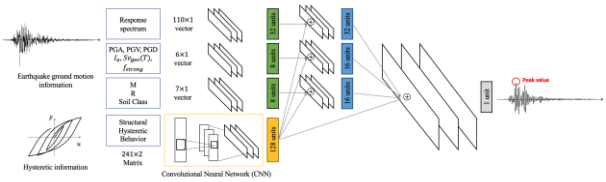

Fig. 1. Architecture of the DNN model.

3.2 Training methodologies and prediction accuracy

A pretraining scheme that only uses a subset of the dataset is employed to accelerate the training convergence of the DNN model. Moreover, a natural logarithm is applied to the inputs and outputs to mitigate the skewness. The DNN model is trained using 80% of the dataset, while the remaining 20% is used to check whether the model falls into a local minimum. Table 1 presents the mean squared error (MSE) and mean absolute error (MAE) for both the train and test datasets. The results indicate that the DNN model does not overfit to the train dataset.

Table 1. Prediction accuracy of the DNN model

Dataset	MSE	MAE
Train	0.0391	0.1406
Test	0.0434	0.1497

4. Numerical investigation

We introduce three single-degree-of-freedom (SDOF) reinforced concrete (RC) columns exhibiting stiffness and strength degradations to demonstrate the applicability and effectiveness of the DNN model. We use the 'Concrete02' and 'Steel02' material commands in OpenSees [8] and vary the mass of the RC columns to obtain hysteresis loops with different normalized yield strength and stiffness, as shown in Fig. 2.

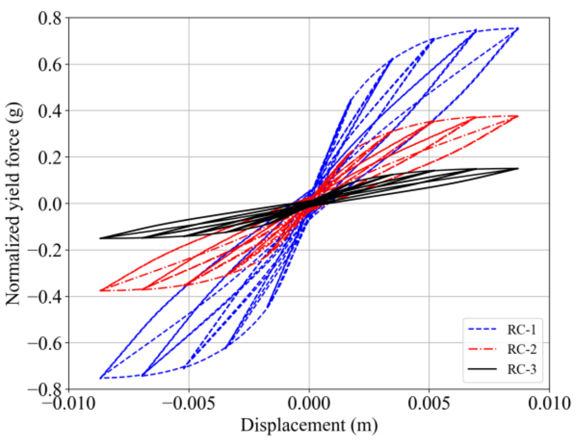

Fig. 2. Hysteresis of the RC columns.

Table 2 presents the MSE of the seismic responses obtained from the DNN model and those from the dynamic analysis in a log scale. 135 ground motions are introduced for the numerical investigation. To test the performance, the DNN model is compared with the coefficient method, which is a nonlinear static analysis procedure widely used in practice [7]. Results show that the DNN model outperforms the coefficient method for all three cases. However, the error increases as the hysteresis exhibits more significant degradation and pinching effects, despite the use of the m-BWBN model. To mitigate this issue, it is necessary to supplement the response showing significant nonlinearities by incorporating a ground motion scale factor.

Table 2. Prediction error of the coefficient method and the DNN model

Method	RC-1 T=0.115	RC-2 T=0.162	RC-3 T=0.257
Coefficient method	0.277	0.476	0.856
DNN model	0.068	0.172	0.257

5. Conclusions

This study developed a deep neural network (DNN) model to predict seismic responses of structures with complex hysteretic behavior. In this regard, three contributions have been made. First, a modified Bouc-Wen-Baber-Noori (m-BWBN) model was proposed to generate various hysteretic behaviors. Second, a seismic demand database was constructed by performing a huge number of dynamic analyses using the m-BWBN model. Third, a new DNN architecture was proposed to consider the effect of the complex hysteretic characteristics on the peak seismic responses. The developed database, DNN model, and source codes are available for download at http://ERD2.snu.ac.kr. The proposed approach showed promising results and the DNN model outperformed the conventional coefficient method.

Future study is planned to improve the prediction accuracy of the DNN model in the domain where the accuracy is currently insufficient. Moreover, we extend the approach to multi-degree-of-freedom systems. The proposed approaches have the potential to significantly improve the accuracy and efficiency of seismic response prediction, which can have important implications for structural design and earthquake engineering.

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