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Prediction of Seismic Damage of NPP cabinet using Deep Neural Network

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1. Introduction

Predicting damage to nuclear power plant (NPP) cabinets is crucial to ensuring the safe and reliable operation of NPP. However, it is difficult to ensure prediction accuracy for cabinets in long-term operating NPPs due to limited information on structural characteristics and seismic performance. To this end, this study develops a Deep Neural Network (DNN) model that can predict the damage of NPP cabinet using only the seismic response measured at the NPP.

2. DNN-based Seismic Damage Prediction Model for NPP Cabinet

In this section, this study develops a deep learning model to predict the damage of NPP cabinet in the event of an earthquake. To this end, this study aims to predict the seismic damage of a specific NPP cabinet using a DNN model that considers both linear and nonlinear seismic responses.

2.1 Simplification of 3D NPP cabinet to SDOF system

For the development of deep learning model that requires a lot of training data, it is necessary to reduce the computational cost by simplifying the NPP cabinet model. Therefore, pushover analysis was performed on the 3D cabinet model to estimate the structural properties, and based on these properties, the 3D model was simplified to a bilinear single-degree-of-freedom (SDOF) model as shown in Fig. 1. Table I shows the properties of the simplified NPP cabinet.

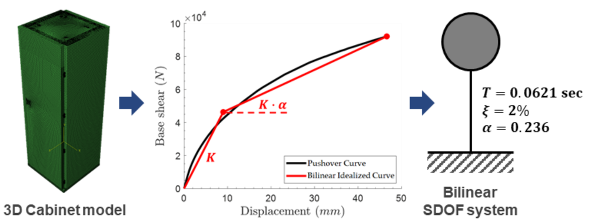


Fig. 1. Simplification procedure based on pushover curve of 3D cabinet model.

Table I: Properties of simplified NPP cabinet

Cabinet Model	Period (T)	Damping (ξ)	Post-yield Stiffness ratio (α)
Bilinear SDOF	0.062 sec	0.02	0.236

2.2 Response spectrum according to damage of cabinet

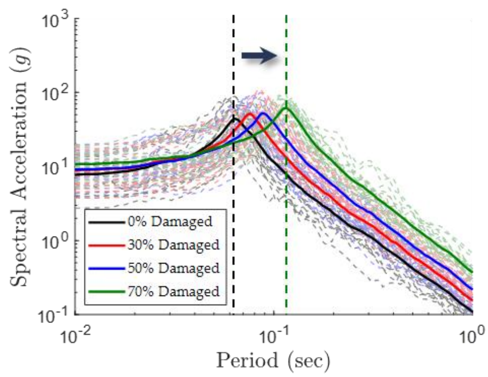
To develop a DNN damage prediction model, seismic responses of damaged NPP cabinet are required as training data. In this study, it is assumed that the occurrence of structural damage leads to a decrease in the stiffness of the structure. When the seismic damage is expressed as a percentage, the lateral stiffness and fundamental period of a structure with D% damage are changed as shown in the following equations.

$$K_D = (100 - D)\% \cdot K \tag{1}$$

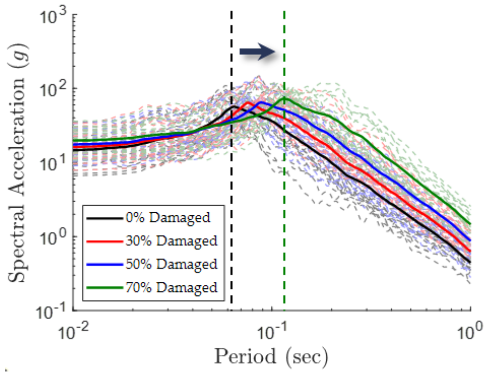
$$T_D = \sqrt{M_D/K_D} \cdot 2\pi \tag{2}$$

where K_D, T_D, and M_D represent the lateral stiffness, fundamental period, and mass of damaged structure, respectively.

In order to estimate the seismic response of the NPP cabinet using various ground motions, a near-field ground motion set in FEMA P695 [1] consisting of 56 (28 pairs of horizontal ground motions in two directions) ground motions is adopted. Since the NPP cabinet exhibits various behaviors from linear to nonlinear during earthquakes, the response spectrums were estimated by scaling the 56 selected ground motions into eight cases (PGA = 0.25 F_y, 0.5 F_y, 0.75 F_y F_y, 1.25 F_y, 1.5 F_y, 1.75 F_y, 2.0 F_y) using OpenSees [2]. Fig. 2 shows the linear and non-linear response spectrum of the cabinet according to the selected ground motion and assumed damage. The mean of response spectrum for each damage is shown by the thick solid line. It can be confirmed that the peak of the response spectrum appearing at a particular period is shifted according to the damage of the cabinet. Using the relationship between the seismic damage and the peak response spectrum, the damage of NPP cabinet can be predicted using the measured seismic response.



(a)



(b)

Fig. 2. Shift of peak spectral acceleration due to damage to NPP cabinet: (a) linear response; and (b) nonlinear response

2.3 Development of DNN damage prediction model

In this section, this study developed a DNN damage prediction model for the NPP cabinet by utilizing Convolutional Neural Network (CNN), which is suitable for dealing large-scaled datasets such as image processing [3-4]. To predict the damage of the NPP cabinet based on the measured seismic response, 110 inputs are required, which are the values of the acceleration response spectrum shown in Fig. 3.

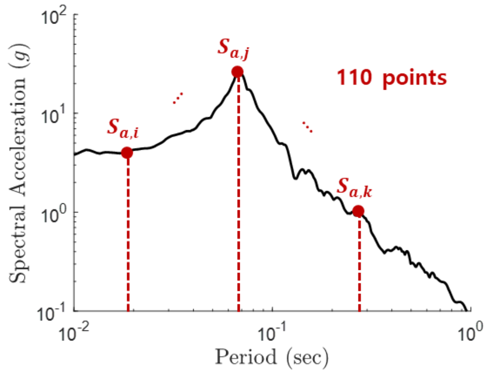


Fig. 3. 110 input parameters of CNN model.

In total, 44,800 acceleration response spectrums of damaged NPP cabinets (56 ground motions × 8 scaled PGA × 100 damage cases) are generated for the development of DNN model. A train set of size 32,256 (72%) and a validation set of size 8,064 (18%) are used to train the DNN models while avoiding over-fitting. The remaining data set of size 4,480 (10%) is employed to test the performance of the trained DNN model.

Based on the generated training data, the CNN employs three different filter sizes (2×1, 4×1, and 8×1) to capture the features within adjacent values of acceleration response spectrum. A sigmoid function is used at the final layer of the DNN model because the correlation coefficient always lies between 0 and 1. The detailed architecture of the DNN model is illustrated in Fig. 4. The values of hyperparameters in the DNN model are determined by a grid search. Note that the development of DNN model was performed using Tensorflow [5].

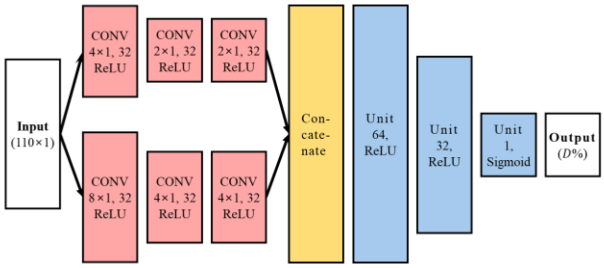


Fig. 4. Architecture of DNN model to predict seismic damage of NPP cabinet.

2.4 Verification of DNN damage prediction model

After training the developed DNN prediction model using the generated 40,320 data, the accuracy of the prediction model was estimated using 4,480 test data which were not used for training. As a result of the verification, the prediction accuracy of the DNN model after 10 iterations of training is presented in terms of Mean Squared Error (MSE) as 1.149×10-4. The prediction results of the DNN model for 10 damage levels at 10% intervals from 5% to 95% are shown in Fig. 5. It can be seen that the results confirm the superior prediction accuracy of the DNN damage prediction model.

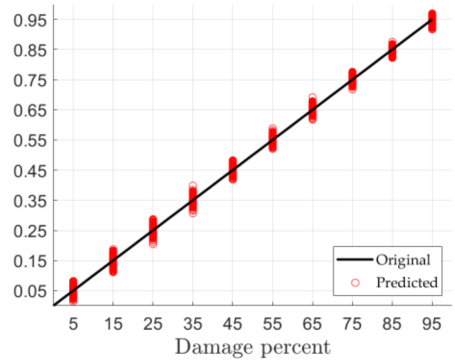


Fig. 5. Prediction accuracy of developed CNN model.

3. Conclusions

A DNN model for predicting seismic damage of NPP cabinet was developed. To train the DNN model, the 3D cabinet model was simplified to a bilinear SDOF system to estimate the seismic damage for various ground motions. The developed model can predict the damage of NPP cabinet with superior accuracy for 110 inputs based on the acceleration response spectrum. The accuracy of the DNN model was tested and demonstrated by comparing the predictions with the seismic damage of NPP cabinet not used for training.

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