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Preliminary study for CNN-based Damage prediction of SDOF structure

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1. Introduction

Due to the recent earthquakes in Korea and abroad, the safety issue of Nuclear Power Plant is emerging. In particular, not only did the Gyeonju earthquake cause a lot of damages to infrastructure, but also the Wolseong NPP was manually shut down. However, there is a problem with shutting down NPPs under OBE and SSE, such as the Watts bar and North Anna cases. Therefore, in this study, the damage of NPP is predicted by using real-time monitoring system. To predict the damage, a deep learning algorithm was used. Convolution Neural Network (CNN), one of deep learning algorithms, was used to predict damage by considering the Fast Fourier Transform (FFT) of structures as an image for real-time monitoring data. As a basic study to evaluate the state of the structure through CNN, the stiffness of the SDOF system was performed. Several learning cases were considered to compare the results.

2. Methods and Results

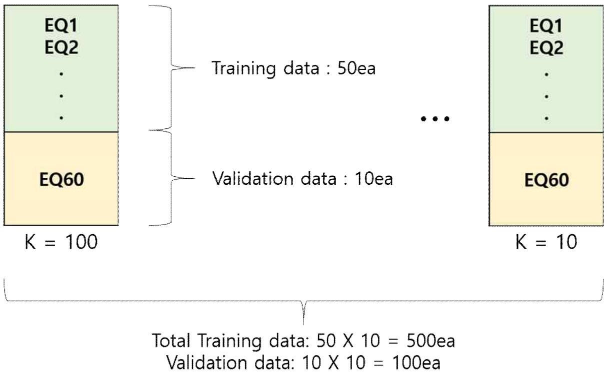
In this section some of the description and techniques used are described. First, brief description of convolution neural network is presented. Then, several case studies performed in this study are described.

2.1 Convolution Neural Network

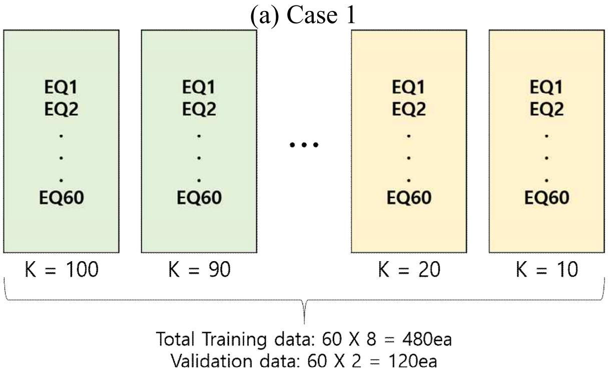
CNN is one of the deep learning structures created by mimicking the human optic nerve. In particular, it is known that the spatial information of the image is maintained by using the convolution operation, the amount of computation is significantly reduced compared to the fully connected neural network, and it shows better performance in image classification. CNN can be divided into two parts, feature extraction and classification. The feature extraction is composed of multiple layers of convolution layers and pooling layers. The convolution layer is an essential element that reflects the activation function after applying a filter to the input data. The pooling layer located after the convolution layer is an optional layer. At the end of the CNN, a fully connected layer for classification is added. A flatten layer is located between the image feature extraction part and the image classification part, which performs image data in an array form.

2.2 CNN model of damage prediction

A total of 6,000 datasets were composed according to the earthquake data (60ea) and the stiffness of the structure (100ea) in this study. In order to predict the damage of the structure, two training cases were considered and the results are shown accordingly. Here, 100 cases of stiffness were given from 1 to 100, but for the convenience of analysis, 10 cases were used in consideration of multiples of 10. Fig. 1 shows the training and validation datasets used for each CNN model.



(a) Case 1



(b) Case 2

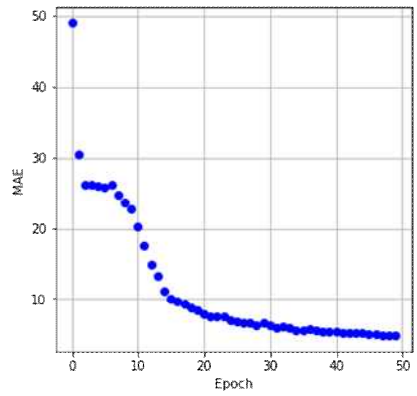
Fig. 1 CNN training and validation model sets

Each input data (training and validation data) represents the response of the structure according to the change of stiffness of SDOF under each seismic load. An example of the FFT image of the structure used in CNN model is shown below.

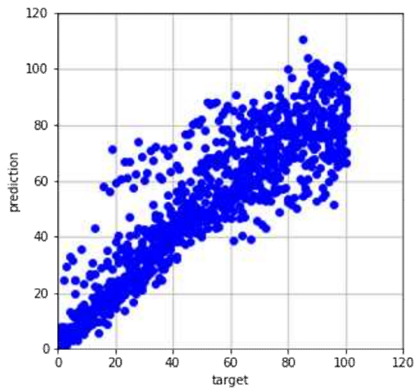
Fig. 2 Image data

3. Test Results

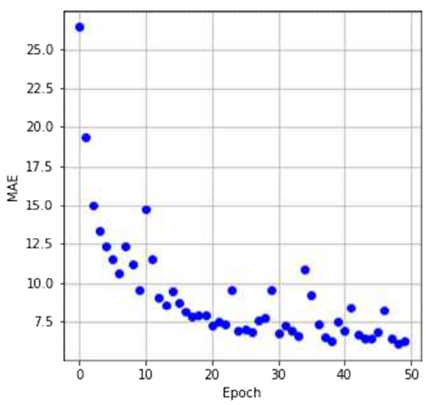
In this study, a CNN model was constructed using pytorch and the results were compared. The figures below show the results according to each case study. As can be seen in Fig. 3, it can be confirmed that a certain level of prediction is possible when predicting with CNN regression model in the validation of un-trained earthquake data. However, in the case of un-learned stiffness case, it is confirmed that the CNN regression model prediction has limitations in the un-trained stiffness test. It is judged that the number of data available for training and validation is insufficient in the Case 2. This is expected to show better results when the training and validation data are sufficient.



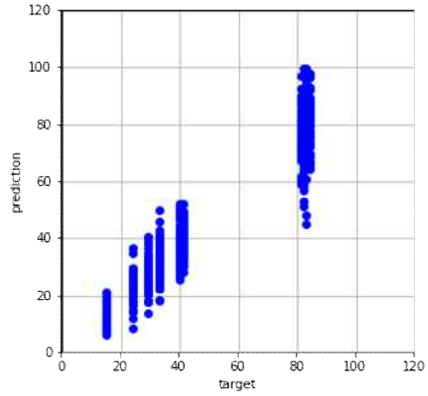
(a) Training Loss (Mean Absolute Error)



(b) CNN model prediction
Fig. 3 Case 1



(a) Training Loss (Mean Absolute Error)



(b) CNN model prediction
Fig. 4 Case 2

4. Conclusions

In this study, a basic research for predicting damage of NPP, CNN model for SDOF was applied and the results were presented. For training and validation data, FFT images of structure according to the various input seismic load and the change of stiffness were considered, and the results were compared through each learning case. As can be seen form the results, it is possible to confirm a certain level of prediction results despite the lack of training and validation data. Through this, it is judged that damage prediction for MDOF can be identified as further study.

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