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DEVELOPMENT OF SURROGATE MODEL FOR NUCLEAR POWER PLANT BUILDING SEISMIC RESPONSE USING DIGITAL TWIN AND PARALLEL FINITE ELEMENT METHOD

Kazumoto Haba[1] Wataru Hotta[2] Minoru Matsubara[3] and Muneo Hori[4]

[1]Manager, Taisei Corporation, Shinjuku, Tokyo, Japan (hb-kzm00@pub.taisei.co.jp)
[2]Manager, Taisei Corporation, Shinjuku, Tokyo, Japan
[3]Manager, Taisei Corporation, Shinjuku, Tokyo, Japan
[4]Principal Scientist, Japan Agency for Marine-Earth Science and Technology, Yokohama, Japan

ABSTRACT

An instantaneous assessment of the integrity of all structural members is required by analysing their seismic responses induced by the earthquake to restart a nuclear power plant when it is shut down due to a major earthquake. A surrogate model based on the plant building can be used for the instantaneous assessment of the integrity of all structural members. We demonstrate the generation of training data and the development of the surrogate model for a virtual nuclear power plant building. We generated training data using the parallel finite element method enhanced to a high-fidelity digital twin of the virtual plant building. We then developed a graph convolutional network as a surrogate model. The proposed surrogate model is outputs seismic responses at predetermined evaluation points of the building when seismic responses at multiple points to which accelerometers are installed are input.

INTRODUCTION

To restart a nuclear power plant after it has been shut down due to a major earthquake, the integrity of the plant building must be assessed through inspection and analysis. If the integrity of nuclear power plants can be assessed Instantaneously, this will lead to a stable supply of electricity in the event of a disaster.

By constructing a high-fidelity numerical analysis model of the ground and structures, that is a high-fidelity digital twin, and then performing seismic response analysis using parallel finite element analysis, it is possible to predict the acceleration response of the entire structure to the input ground motion with a high degree of accuracy. However, there are problems with instantaneous assessments, such as the fact that it takes a certain amount of time to set up and calculate the input ground motion. For this reason, it is effective to use a surrogate model for earthquake response assessment. It is expected that surrogate models trained on the results of seismic response analysis for high-fidelity numerical analysis models can be used to predict the acceleration response at predetermined evaluation points other than the observation point with high accuracy, based on the observed acceleration response at the observation point.

In this paper, as an example, we construct a surrogate model trained on the results of seismic response analysis for a high-fidelity numerical analysis model of a virtual nuclear power plant.

GENERATION OF TRAINING DATA SET FOR SURROGATE MODEL

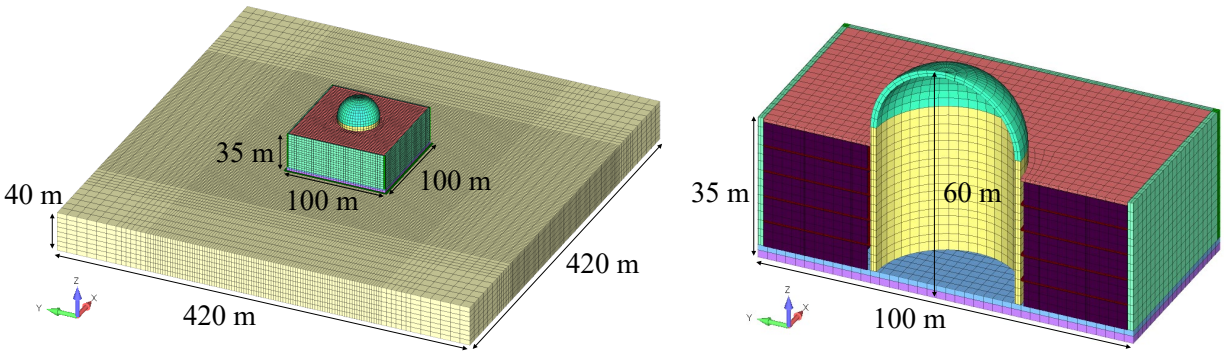
We develop a high-fidelity numerical analytical model of a nuclear power plant building on grounds, which is a high-fidelity digital twin. Then, by conducting a large number of seismic response analyses for the high-fidelity digital twin with varying input ground motions, we generate a set of training data for the surrogate model. In this study, the acceleration responses at both the observation point and other predetermined evaluation points are used as training data. The surrogate model is used to predict the acceleration responses at the evaluation points based on the acceleration response at the observation point.

The target is a standard model of a nuclear power plant of US Department of Energy which consists of a reactor building and the ground. For this plant, a high-fidelity three-dimensional model is constructed with approximately 640,000 degrees of freedom; the number of nodes and elements is 213,517 and 328,572, respectively. The numerical analysis model is shown in Figure 1; a) shows an overview of the model structure, where the reactor building is located on a ground model with dimensions of 420 m × 420 m × 40 m in depth, and b) shows the close-up view of the reactor building. The dimensions of the reactor building are 100 m × 100 m × 60 m in depth, and it consists of an outer shield of a cylinder with a cap, an auxiliary equipment building, and a foundation. The auxiliary equipment building is a five-storey structure with a height of 35 m. The ground consists of a single geological layer of stiff bedrock. The reactor building is a hybrid model using solid and shell elements for concrete and steel reinforcement, respectively. Joint elements are used at the interface between the foundation of the reactor building and the ground, taking into account the soil-structure interaction. In the numerical analysis model of the soil, the absorbing boundary condition is set for the side and bottom surfaces, which are an artificial boundary of the soil.

Maekawa's concrete constitutive relation (Maekawa et al. 2003) is used, which is the stress-strain relation for compression, tension and shear and is widely used in Japan. The soil and the steel reinforcement are elastic bodies. The material properties of the concrete and steel of the reactor building, and the soil of the ground are summarised in Table 1; (a) is for the elastic parameters and density of concrete, steel, and soil, and (b) is for the nonlinear parameters of concrete.

In this study, seismic response analyses were performed using input ground motions in two horizontal directions. The input ground motions were derived by modifying the amplitude of the acceleration waveforms generated by the hazard analysis (Noda et al. 2003) for a specific site in Tokyo to generate creating seismic waves with varying maximum accelerations and amplitude ratios in two directions. Specifically, we generated 1000 and 100 sets of input seismic waves using the Latin hypercube sampling method to ensure uniform distributions of maximum acceleration ranging from about 200 to about 1700 gal in one direction and bidirectional amplitude ratios ranging from 2-1 to 21. However, for this study, the duration of the seismic waves was fixed at 10.24 s. Figure 2 shows an input ground motion with a maximum composite acceleration of 1896 gal.

A series of seismic response analyses of the digital twin were performed using the parallel FEM program E-FrontISTR (Motoyama et al. 2021) by inputting various ground motions. E-FrontISTR was developed by Taisei Corporation, Central Research Institute of Electric Power Industry, The University of Tokyo, Tokyo Electric Power Services CO., National Research Institute for Earth Science and Disaster Resilience, and Ark Information Systems. The analysis was performed in 0.002 second increments. The conjugate gradient method was used to solve a matrix equation with tolerances of 10^{-8}. The seismic response analyses took up to 3.6 hours to compute on a parallel computer with a 120-core AMD EPYC7002 processor (2.6 GHz, 256 M Cache). Figure 3 shows the result of the principal strain distribution in the reactor structure with a ground motion shown in Figure 2.



a) Overview b) Reactor building

Figure 1. Digital twin of nuclear power plant building

Table 1: Material Properties

a) Elastic parameters and density

Material	Young's modulus (MPa)	Poisson's ratio	Density [t/m^3]
Concrete	4.549×10^4	0.30	2.4
Reinforcing steel	2.050×10^5	-	–
Soil (rock)	1.333×10^3	0.33	2.0

b) Nonlinear parameters for concrete

Material	Compressive strength (MPa)	Tensile strength (MPa)	Shear Strength (MPa)	Strain at compressive strength
Concrete	33.00	1.900	12.00	0.002

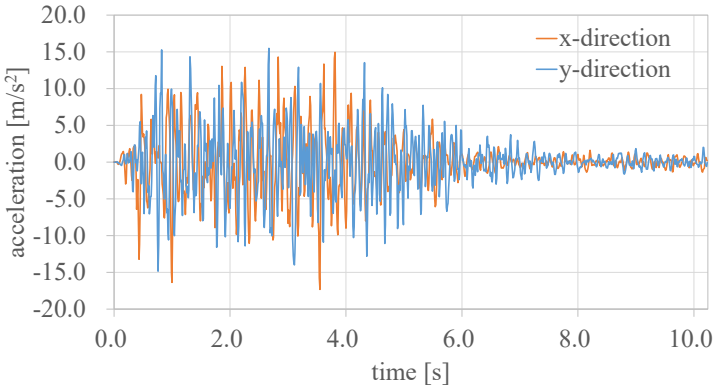
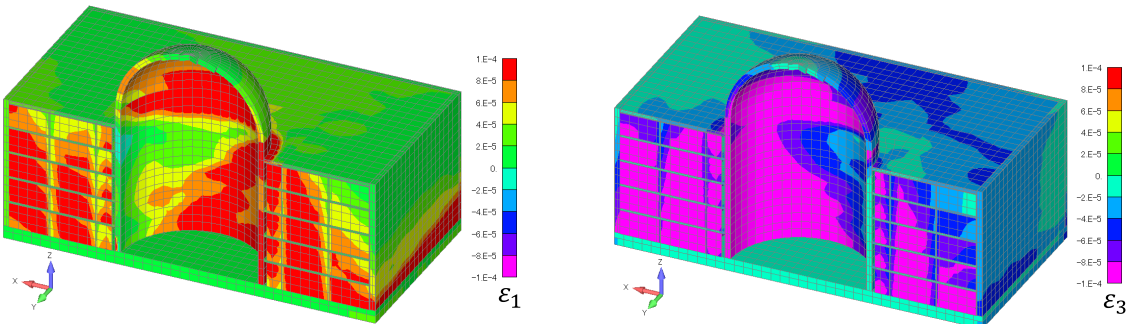


Figure 2. An example of input ground motion.



a) Maximum principal strain b) Minimum principal strain

Figure 3. Contour of a minimum principal strain in the reactor building with input ground motion shown in Figure 2.

BUILDING SURROGATE MODEL

Graph Convolutional Network-based surrogate model

The surrogate model predicts the acceleration Fourier spectrum of the evaluation point from the acceleration Fourier spectrum of the observation points. In this study, the observation points and evaluation points are as shown in Figures 4 and 5; Figure 4 shows 48 observation points on each floor, on the roof of the auxiliary building and in the dome, and Figure 5 shows 70 evaluation points randomly placed on each floor at other locations of the observation points. The irregularly arranged structure of the observation and evaluation points differs from structured objects such as images, where the pixels are arranged in a particular structure. Therefore, in this study, we use a graph convolution network (GCN), where the observation and evaluation points and the connections between them are considered as a graph structure. GCN are good approaches to take the neighbourhood information to make predictions using deep learning models for graph like permutation invariant data structures (Zhou et al. 2020). In the case of predicting the seismic response, the information from neighbouring observation points plays an important role in predicting the response of each evaluation point, and it is believed that the transfer function with foundation contains information about the significant features of the structure. In this study, each evaluation point connects the observation points and evaluation points within a 30 m radius and 20 m height cylinder with the evaluation point at the centre, in addition to the foundation. In particular, the connection structure with the three nearest observation points was always set. Figure 6 shows the graph structure in this model; the black and green dots are the observation points shown in Figure 4, the blue dots are the evaluation points shown in Figure 5, and the red lines are the connections between the observation points and evaluation points.

Figure 7 shows the structure of the graph convolution network of the proposed surrogate model. The nodes in the graph structure of the input and output data are 48 observation points and 70 evaluation points. The feature values for each node are 205 data of acceleration Fourier spectrum data in each horizontal direction from 0 to 20 Hz, in addition to the three-dimensional position of the points, making a total of 413 dimensions. The loss function was the root mean square error (RMSE) between the predicted acceleration Fourier spectrum data and the numerical analysis results for all evaluation points. The proposed model consists of four graph convolutional layers followed by Re-LU activation layers to introduce non-linearity into the GCN. To avoid over-fitting, a dropout regularization with a dropout probability of 1% is introduced. The dimensions of the feature values of each node were varied in each layer with values of 413 in the input layer, 200, 100, 200 in the hidden layers and 413 in the output layer. Such a dimensional structure designed to compress the dimensions and then expand them to the required dimensions, allows global features to be learned.

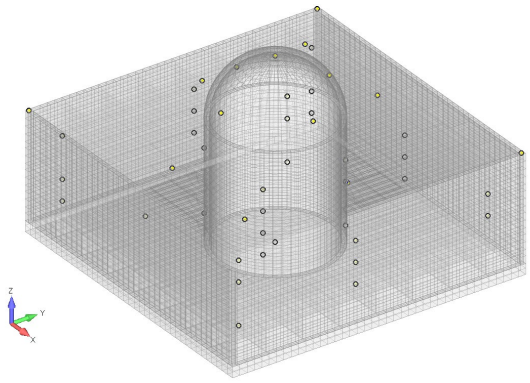


Figure 4. Observation points in reactor building

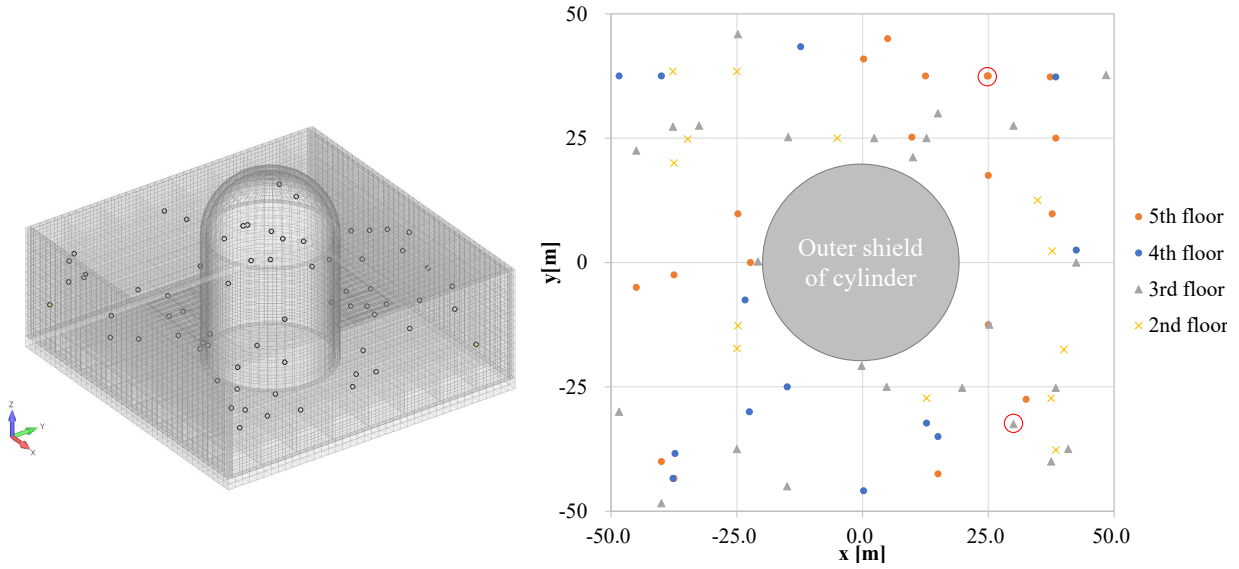


Figure 5. Evaluation points in reactor building.

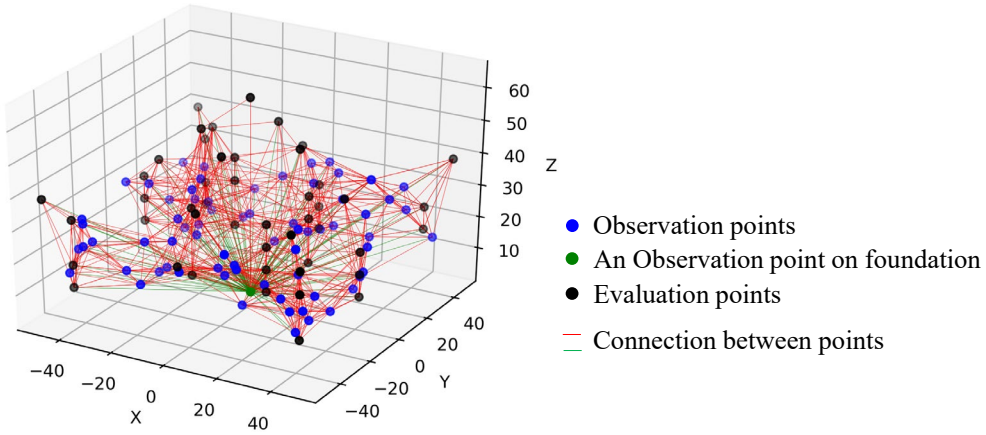


Figure 6. Graph structure

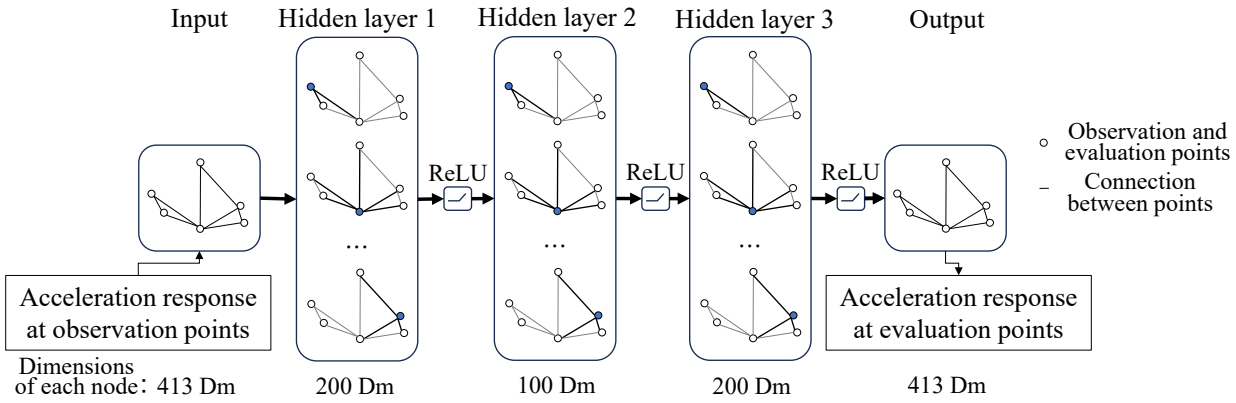


Figure 7. Overview of graph convolution network for seismic response analysis

Training the Surrogate Model

The model architecture was trained using a deep graph library framework based on Pytorch (Wang et al. 2019). The acceleration response obtained from seismic response analyses with 1000 input ground motions was used as the training data, and 100 results generated in the same way were used as the test data. Here, the training data were used after being normalized by the maximum value for each node frequency.

Figure 8 shows the loss curves of the training loss and the test loss. Here, the orange and blue lines in Figure 8 denote the training loss and test loss, respectively. The training loss and the test loss decrease with the number of epochs and converge, indicating that the model is properly trained without any over-fitting.

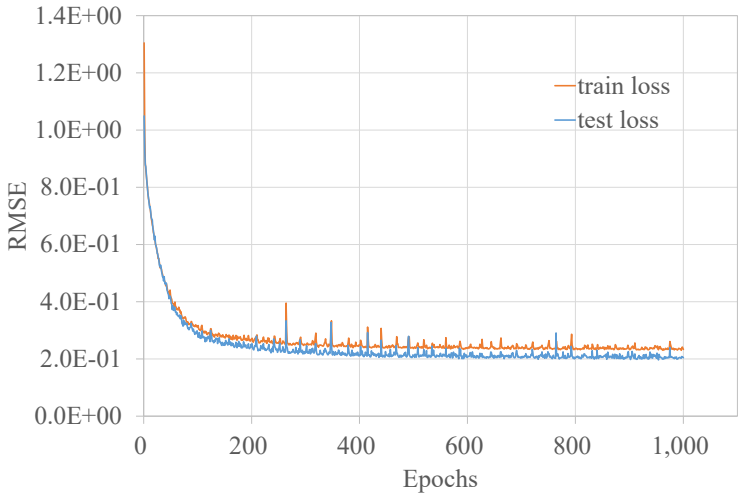
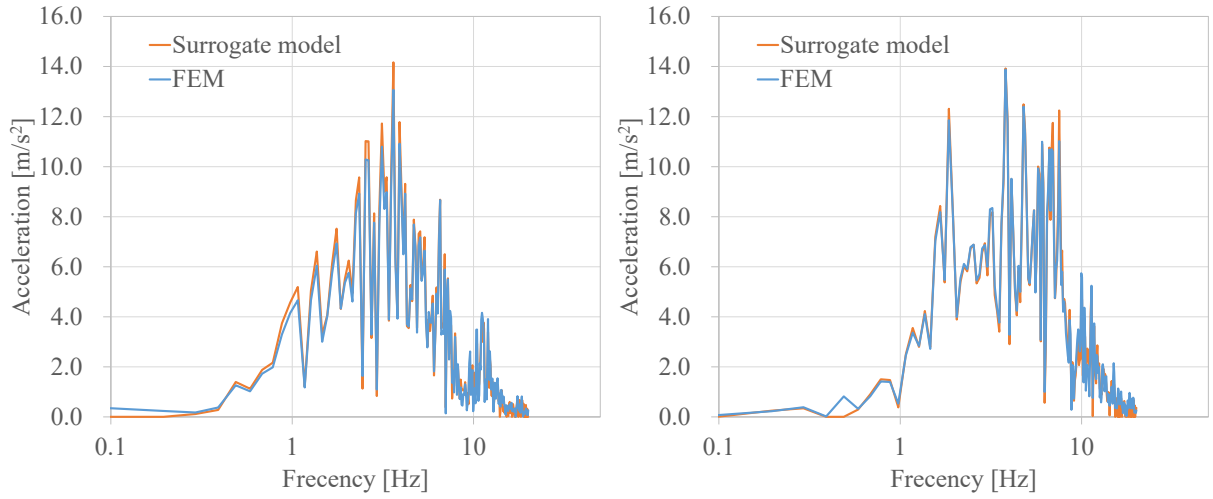


Figure 8. Loss curve. The orange and blue lines denote the training loss and test loss, respectively.

Prediction of Seismic Response with Surrogate Model

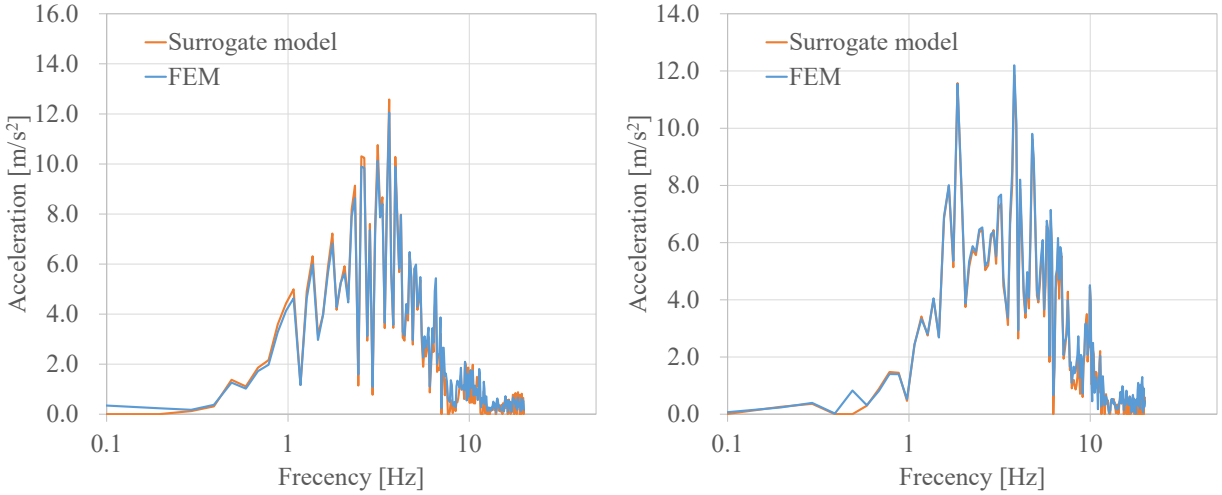
Figures 9 and 10 show the result of the acceleration Fourier spectrum at representative evaluation points on the 5th and 3rd floors respectively, shown as red circles in Figure 5. The orange and blue lines in Figures 9 and 10 are the result of the trained surrogate model and the FEM analysis respectively. This case corresponds to using the input ground motion with the largest average value of acceleration Fourier spectrum in the test data. From these results, it can be seen that the surrogate model effectively reproduces the result of the numerical analysis.

Figure 11 illustrates the relationship between the average values of the acceleration Fourier spectrum at the centre of the foundation and both the RMSE and the relative RMSE. The relative RMSE is defined as the RMSE divided by the average acceleration spectrum at the centre of the foundation. The trained surrogate model has a larger error as the level of input ground motion increases, but the relative RMSE is constant regardless of the level of input ground motion. That suggests that the surrogate model can accurately predict the acceleration response at the evaluation point even as the level of nonlinearity in the concrete increases.



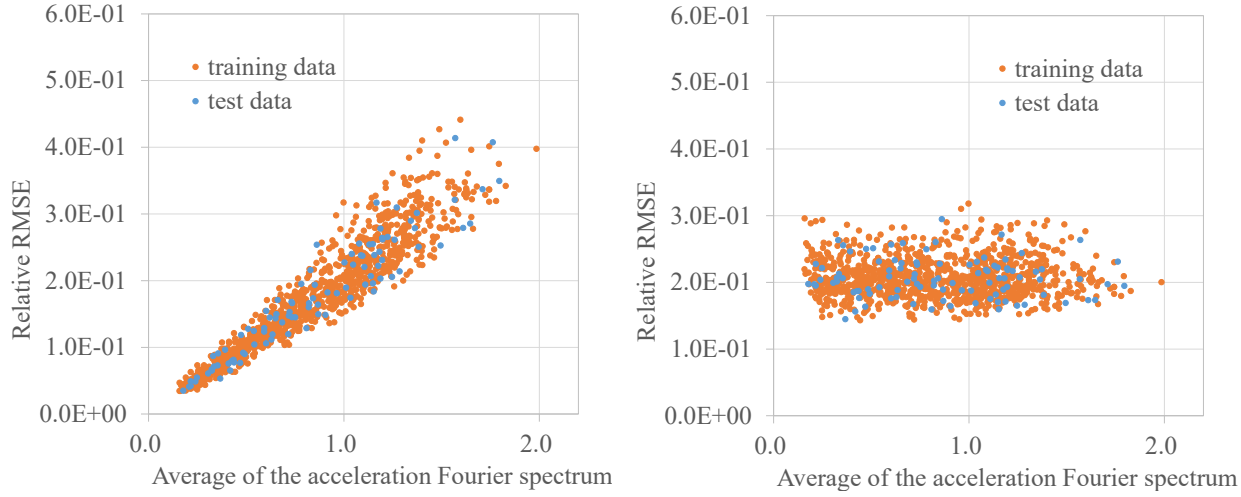
a) x-component b) y-component

Figure 9. Acceleration Fourier spectrum at an evaluation point on 5th floor. The evaluation point is shown as a red circle in Figure 5. The orange and blue lines denote the result with the surrogate model and the FEM analysis, respectively.



a) x-component b) y-component

Figure 10. Acceleration Fourier spectrum at an evaluation point on 3rd floor. The evaluation point is shown as a red circle in Figure 5. The orange and blue lines denote the result with the surrogate model and the FEM analysis, respectively.



a) RMSE b) Relative RMSE

Figure 11. Relationship between RMSE/relative RMSE and average of the acceleration Fourier spectrum at the centre of the foundation.

CONCLUTION

In this study, we have constructed a surrogate model to evaluate the seismic response for a digital twin of a virtual nuclear power plant. The proposed surrogate model predicts the acceleration Fourier spectrum of the pre-determining evaluation point from the acceleration Fourier spectrum of the observation points. The surrogate model is based on GCN, which has a graph structure for observation points, evaluation points, and their connection structure, and it has achieved good prediction results within the range of the input ground motion that was learned. We plan to expand the range of the input ground motion, apply it to more complex structures etc.

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