Prediction of site amplification of shallow bedrock sites using deep neural network model

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Abstract. Site amplification models are widely used with ground prediction equations to estimate ground motion intensity measures. The time-averaged shear wave velocity of top 30 m (V_{S30}) is the primary site proxy in site amplification models. A large number of models have been developed for a range of site conditions. However, the simplified nature of all models produce large residuals compared with the computed responses. The prediction accuracy of the models can be greatly enhanced through use of machine learning technique. In this study, the outputs of nonlinear one-dimensional site response analyses are used to train the deep neural network (DNN) model. The linear and nonlinear components are separately trained. The comparisons highlight that the DNN model successfully captures the amplification characteristics of the shallow bedrock sites and produces significantly lower residual compared with the available simulation based model.

Keywords: Site amplification, Shallow bedrock, Deep neural network.

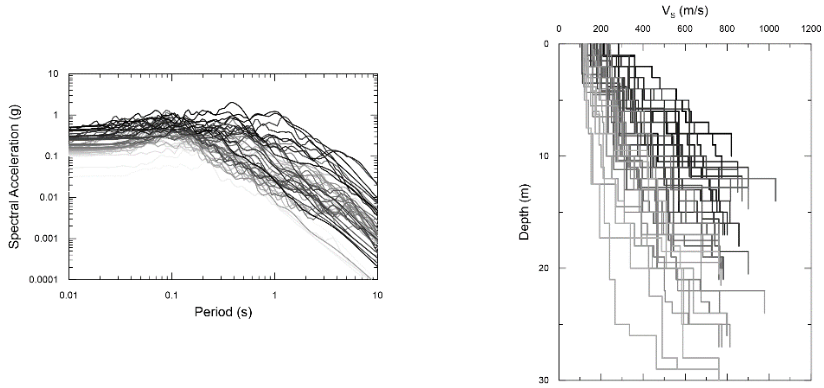
1 Introduction

In geotechnical earthquake problems, one-dimensional (1D) site response analysis is widely used to estimate the local site amplification effects [1]. The site amplification factors are the important parameters for the design of the geotechnical structures. Most of researches are based on the simulation-based data and utilized the Monte Carlo (MC) simulations for the surface response spectra [2]. In this study, we performed the linear 1D site response analyses and trained all the simulation results using the deep neural network (DNN) model.

2 Site amplification prediction models

2.1 Site response analysis

Linear analyses were performed in frequency domain using 1D site response analysis software DEEPSOIL v7 [3]. The number of analyses was 42,840 using 840 shear wave velocity (V_S) profiles and 51 motions (Fig. 1). The simulation results are used to train the proposed DNN model.



(a) Acceleration response spectra of ground motions

(b) Shear wave velocity profiles

Fig. 1. Input ground motions and shear wave velocity profiles

2.2 Proposed deep neural network model

Fig.2 shows the architecture of the proposed DNN model. The input features consist of three groups for representing the input ground motions as well as soil properties. The first part of hidden layers for each feature is created to learn and understand the input features. After processing three groups of features, all layers are merged and connected to the fully-connected hidden layers. We labeled the output as the surface spectral acceleration of a 113×1 vector. In all hidden layers, the rectified linear unit, ReLU [4], was applied as an activation function. Before the training, the weights and biases of the DNN model were initialized by Glorot uniform initializer [5] and zero, respectively. The optimization algorithm used in this study is the Adam optimizer [6] and the mean squared error (MSE) was selected as the loss function. The batch size is 128 and the training has been stopped after 1,000 epochs. The whole dataset was split into 80% of dataset as training set and 20% dataset as test set.

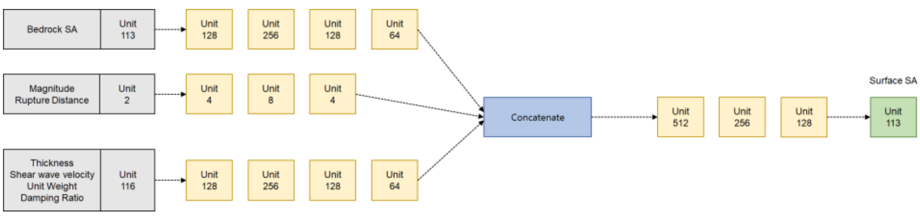


Fig. 2. An architecture of proposed DNN model.

3 Results

The results of the trained network are presented in Table 1 and Fig. 3. The MSE and MAE show that the DNN model does not overfit and the train and test show almost identical values. The DNN model can capture the simulation results of the surface response through the spectral periods. However, the results of conventional method [7] using regression analysis only can predict the median trend of the site amplifications. The DNN model shows the exceptional performance for predicting the linear site amplification.

Table 1. Comparison of MSE and MAE between train and test dataset

Analysis	Dataset	MSE	MAE
Linear	Training	0.0011	0.0226
	Test	0.0012	0.0235

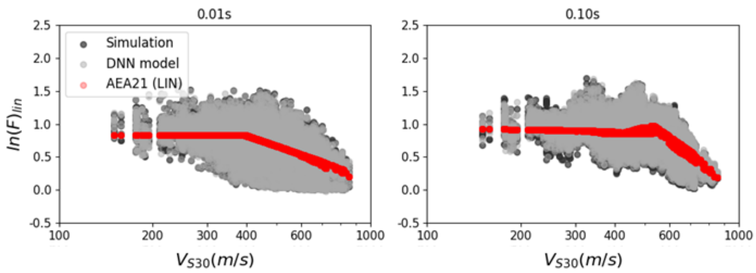


Fig. 3. Comparison of linear amplification components for the spectral periods of 0.01s (left) and 0.1s (right).

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