Deep Learning for Site Response Estimation from Geotechnical Array Data

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1. Motivation and Scope

- Theoretical methods for prediction of site effects often fail due to modeling simplifications [e.g., 1]
- Data-informed site response models (site terms in GMPEs, empirical frequency-dependent site amplification functions, shallow neural networks) [2-4] typically approximate the soil profile using proxies (e.g. V_{S30}, $Z_{1.0}$, $Z_{2.5}$)
- These proxies can be considered *engineered features* in traditional machine learning methods, which may not be needed in deep learning models.
- Our goal is to train a deep neural network that predicts site response directly from the full soil profile, without relying on proxies or simplifications.
- We use a fully connected artificial neural network (ANN) with 7 hidden layers, where the input layer consists of a discretized soil profile and frequency of amplification, while the output layer provides the surface-to-borehole amplification of two-component Fourier velocity spectra (Fig. 2).
- We work with theoretical and observed mean amplifications functions from vertical arrays in Japan (KiK-net) and California (CSMIP).
- 90% of sites were assigned to the training set and 10% to the test set (Fig. 1).

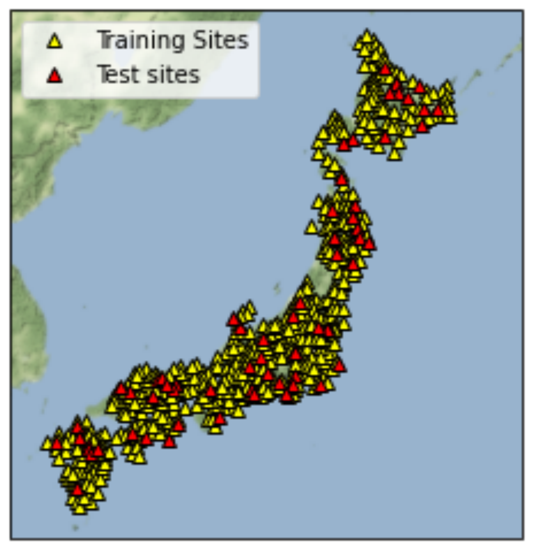

Figure 1. Location of KiK-net sites assigned to training and test sets.

2. ANN Design

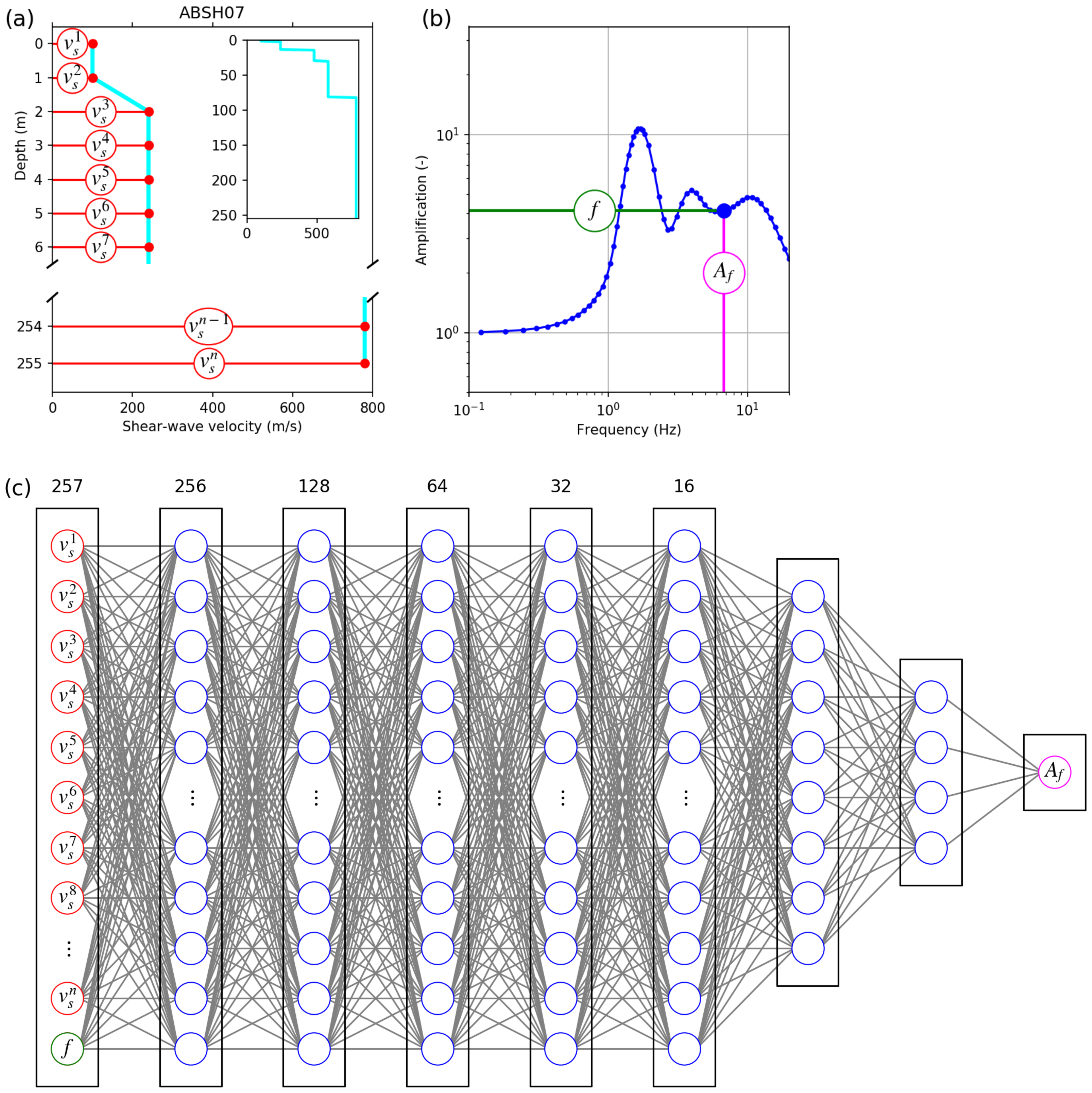

Figure 2. Design of ANN for prediction of site amplification functions. Shear-wave velocities (v_s, red nodes) are fed into the input layer at n discrete depths (a,c), along with the frequency f (green node). Hidden layers in (c) are shown by blue neurons. Where not all nodes are shown, the true number of nodes are given at the top of the layer. The output node contains the amplification A_f at the specified frequency (b,c). For results shown on the right, the v_s profile was sampled at n=104 irregularly spaced depths to a maximum depth of 1,500 m.

3. Performance Test with Theoretical 1D Amplification Functions

- Minibatch gradient descent was carried out using the Adam optimizer [5] to minimize the mean square logarithmic error between observed and predicted theoretical amplification functions (Fig. 3)
- Dropout regularization was used to reduce overfitting to the training data. The dropout rate was adjusted to a value of 0.05 by trial and error.
- The mean absolute error (MAE) is 0.31 on the training and 1.07 on the test data.
- Theoretical 1D amplification functions for both training and test sites are reproduced by the ANN (Fig. 4)

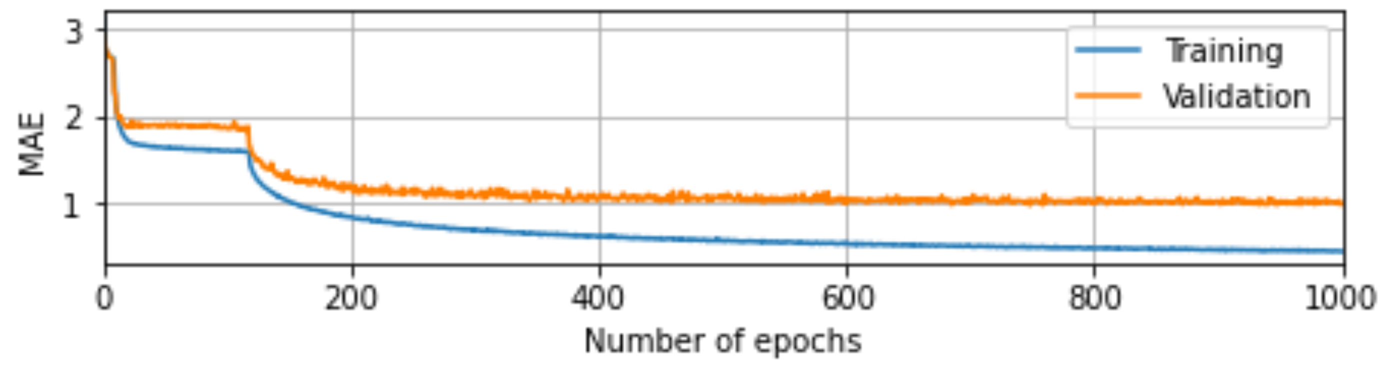

Figure 3. Mean absolute error (MAE) during training on theoretical amplification functions.

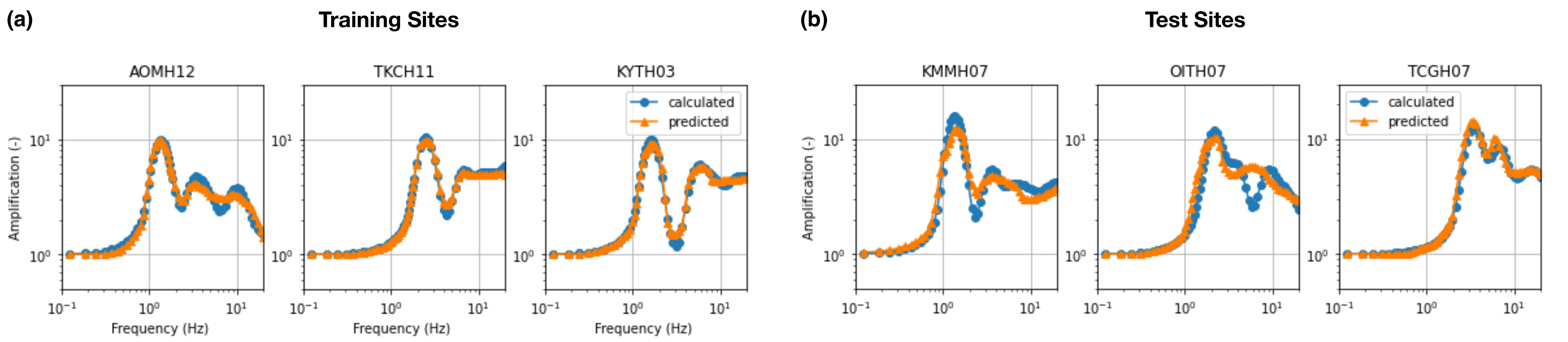

Figure 4. Comparison between theoretical amplification functions (blue) and amplification functions predicted by the ANN (orange) for three randomly selected sites in (a) the training set and (b) the test set.

4. Results from Observed Mean Amplification Functions

- Mean site amplifications were computed from records with 0.05 g < PGA < 0.2 g (excluding nonlinear effects).
- A MAE of 0.5 is obtained on training data derived from observed mean spectra (Fig. 5). Validation and test errors are closer to 1.5.
- Amplifications of training sites are reproduced well (Fig. 6 a), but the quality of the prediction at test sites varies (Fig. 6 b).
- Increasing the drop-out rate did not reduce this overfitting.

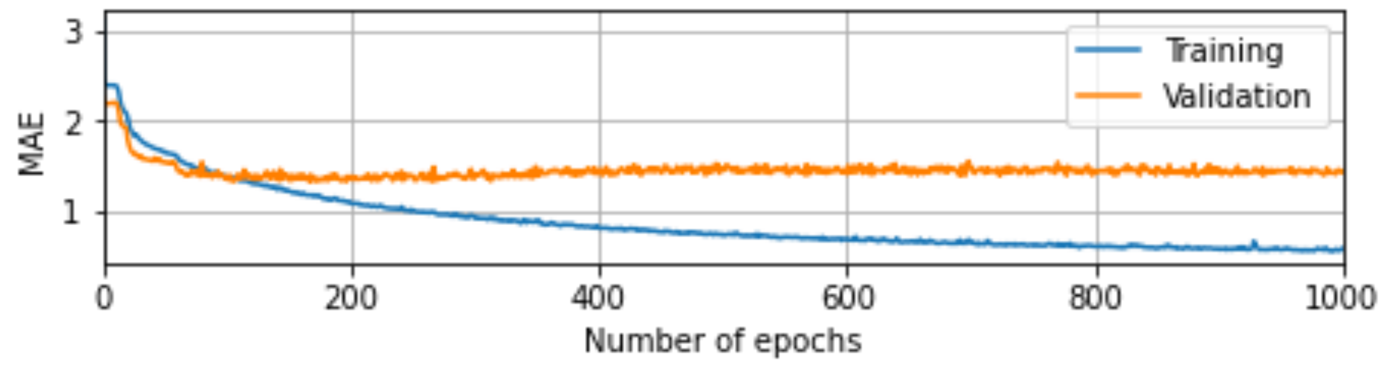

Figure 5. Mean absolute error (MAE) during training on observed amplification functions.

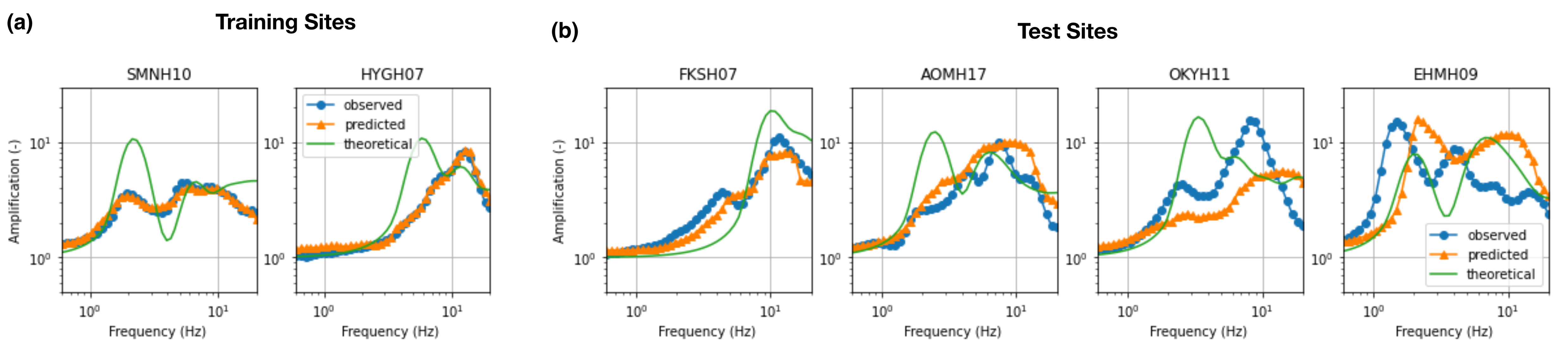

Figure 6. Comparison between observed mean amplification functions (blue) and amplification functions predicted by the ANN (orange) for randomly selected sites in (a) the training set and (b) the test set. Solid green lines show theoretical 1D site amplification functions.

5. Summary and Outlook

- A properly regularized ANN with multiple hidden layers can be trained to predict theoretical amplification functions for sites not included in the training set.
- Application of the method to observed amplification functions may produce predictions which are more reliable than theoretical amplification functions.
- However, more work is needed to reduce overfitting and improve the ANN's performance for the prediction of observed amplification functions.

Selected References

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