Deep Learning for Site Response Estimation from Geotechnical Array Data

Kim B. Olsen and D. Roten
San Diego State University, San Diego, CA
Contact: Daniel Roten (droten@sdsu.edu)

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_S, Z_n, Z_s)
• 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).

2. ANN Design
• 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).

3. Performance Test with Theoretical 1D 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 dropout rate did not reduce this overfitting.

4. Results from Observed Mean Amplification Functions
• 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.

5. Summary and Outlook
• Solid green lines show theoretical 1D site amplification functions.

Selected References
1. Hu Z., Olsen K.B. & Roten D., poster #7 at 2019 SCEC annual meeting
4. Withers, K.B., Moschetti, M.P. & Thompson, E.M., GRL 47(6), 2020

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