Using Machine Learning Models To Represent Isolated Nonlinearities Within Structural Systems

D. Dane Quinn[1*], David Najera-Flores[2,3], Anthony Garland[4], Vlachas Konstantinos[5], Eleni Chatzi[5], and Michael Todd [3]

[1]*The University of Akron, Akron, OH USA;* [2]*ATA Engineering, San Diego, CA USA;* [3]*University of California San Diego, La Jolla, CA USA;* [4]*Sandia National Laboratories*[†]*, Albuquerque, NM, USA;* [5]*ETH Zürich, Zürich, Switzerland*

Abstract. In a structural system with an isolated nonlinear region, a neural network is trained to predict the effect of the nonlinearities within the region on the remaining structure. Based on a novel order-reduction formulation developed previously, these predicted forces are incorporated within an associated ideal system to predict the response of the overall structural system, thus replacing the detailed description of the isolated region and providing a computationally efficient model of the nonlinear system.

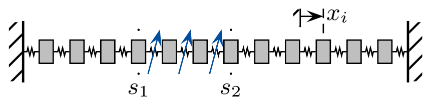
Introduction

Techniques in machine learning, including neural networks, open the possibility of describing the response of engineering systems where the underlying physics is either unknown or too complicated to accurately resolve in a computationally efficient simulation. The present work seeks to employ predictions from a neural network to represent the nonlinearities in an isolated region of a larger structural system, so that the neural network essentially serves as a constitutive model for the nonlinearities. A novel order-reduction approach developed previously by Quinn and Brink [1] is used to introduce the effect of the nonlinearities on the underlying ideal linear system, which are then captured by the application of the neural network. This approach is illustrated with a example structural system where the nonlinearities are assumed to arise from cubic stiffness and damping, as well as state-dependent damping so that the isolated region contains internal hysteretic variables.

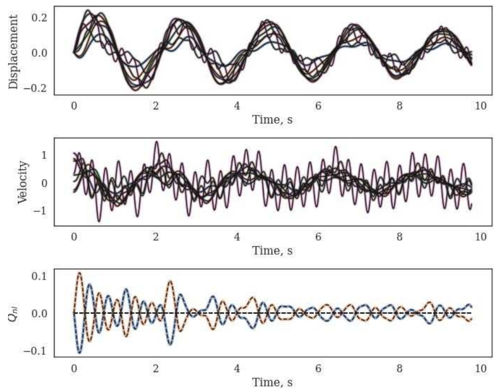
Results and Discussion

The system is assumed to be decomposed into a region $\mathcal{C}_1$ that is linear, coupled to a region $\mathcal{C}_2$ containing the nonlinearities in the structure. In the order-reduction method the effects of the nonlinearities are captured by an internal force vector $\underset{\sim}{\boldsymbol{Q}}$ that only reflects the influence of the nonlinearities within the isolated region $\mathcal{C}_2$ on the external linear region $\mathcal{C}_1$. This force is then determined from a model capturing the nonlinear response, but localized to the isolated region. As a result, the response of the linear region is determined only by the internal force vector.

This approach is illustrated on a chain of oscillators, representing the discretization of a rod undergoing longitudinal deformations, as illustrated in Figure 1a. The nonlinearities are localized within the region $s \in (s_1, s_2)$, while the remainder of the rod is linear. A Multilayer Perceptron is used to identify the internal force $\underset{\sim}{\boldsymbol{Q}}$ that acts at the boundaries of the isolated region, arising from the nonlinearities. After training, this predicted internal force is used within an ODE solver to determine the response subject to initial conditions and external forcing. The training takes place with a single specific realization of initial conditions and excitation. However, this is sufficient to provide accurate predictions when the system is subject to a variety of initial conditions and excitations, as illustrated in Figure 1b.



(a) Example system



(b) System response with an excitation distinct from the training excitation.

Figure 1: Isolated Nonlinearities

References

[1] Quinn D.D., Brink A.R. (2021) Global system reduction order modeling for localized feature inclusion. *Journal of Vibration and Acoustics*, 143:041006, 2021.

*quinn@uakron.edu

†Sandia National Laboratories is a multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International, Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE–NA0003525. This paper describes objective technical results and analysis. Any subjective views or opinions that might be expressed in the paper do not necessarily represent the views of the U.S. Department of Energy or the United States Government.