**Physics-based Transformer Models for Predicting Nonlinear Hysteresis in Structures**

[Abstract]

Disasters such as earthquakes and typhoons induce random excitations that may degrade structural stiffness, potentially leading to failures. Therefore, understanding the hysteretic behavior of structures under such excitations is essential for accurate risk assessment. However, conventional approaches face limitations as they attempt to fit a prediction model to complex real-world data through a small set of parameters, often resulting in errors due to reliance on predefined mathematical models.

To address these challenges, deep learning models have been developed to effectively learn the complex interactions governing structural hysteresis by directly training on force-displacement relationships. Especially, time-series forecasting models such as recurrent neural networks and long short-term memory models have been recently introduced for unified hysteresis modeling of various Equation-Parametrized Hysteresis (EPH) models. However, these sequential models struggle to capture long-term dependencies and fail to adapt to certain hysteresis models due to limitations in processing time history data.

In this study, we propose a transformer-based deep learning model to predict the nonlinear hysteresis of single-degree-of-freedom structures under random excitations. The model encodes displacement and its variation in the encoder, while using reaction force as input in the decoder. Using the multi-head attention mechanism, the model captures long-term dependencies in the time history, enabling it to effectively identify basic nonlinearity, strength degradation, and pinching effects.

However, using a conventional transformer model alone may lead to poor generalization or physically unrealistic results due to the complexity of multidimensional data and data scarcity. To overcome this issue, we incorporate physical and mathematical phenomena of hysteresis directly into the deep learning model. By enforcing such domain knowledge, the model enables efficient training and logical inference on unseen data, thereby going beyond black-box learning.

The proposed unified hysteresis modeling approach is tested for EPH models such as Bouc-Wen class models, Ramberg-Osgood model, and Ibarra-Medina-Krawinkler model. Through comparisons with existing studies and parametric analyses, we show that the proposed physics-encoded transformer model can accurately predict the force-displacement relationships in real-world structures, demonstrating high robustness to unseen loading conditions.

To address these challenges, Deep learning models such as recurrent neural networks and long short-term memory models have been recently introduced to effectively learn the complex interactions governing structural hysteresis by directly training on force-displacement relationships, which result in unified hysteresis modeling of various traditional form-constrained hysteresis model.