**Predicting Nonlinear Hysteresis Behavior of Structures Using Physics-Encoded Transformer Models**

[Abstract]

Disasters like earthquakes and typhoons generate repetitive and irregular excitations that degrade structural stiffness and can ultimately lead to failure. Understanding the exact hysteretic behavior of structures under such excitations is crucial for risk assessment. However, conventional approaches face limitations as they attempt to fit complex real-world data into a small set of parameters, often resulting in errors due to reliance on predefined mathematical models.

To address these challenges, deep learning frameworks have been proposed to capture hysteretic behavior. These models can effectively learn the complex interactions underlying structural hysteresis by directly training on force-displacement relationships. Recently, time series forecasting models such as RNNs and LSTMs have been introduced to predict various Equation-Parametrized Hysteresis(EPH) models in an integrated manner. However, these sequential models struggle to capture long-term dependencies and fail to adapt to certain hysteresis models due to their inherent limitations in processing time history data.

In this study, we propose a Transformer-based deep learning model to forecast the nonlinear hysteresis of single-degree-of-freedom (SDOF) structures under random excitations. The model embeds displacement and its variation in the encoder and reaction force in the decoder as input. Using the Multihead Attention mechanism, the model captures long-term dependencies in the time history, enabling it to effectively identify basic nonlinearity, strength degradation, and pinching effects.

Nevertheless, 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 domain knowledge, the model goes beyond merely learning representations as a black-box system, enabling more efficient training and logical inference on unseen data.

The proposed model's performance is validated using EPH models such as the BW Class model, Ramberg-Osgood model, and IMK model. Through comparisons with existing studies and parametric analyses, we demonstrate that the physics-encoded Transformer model can accurately replicate the displacement-reaction relationships of actual structures and maintain high robustness under previously unseen loading conditions.