Nonlinear response prediction of MDOF system using Window-Recurrent-Fourier Neural Operator

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1. Introduction

Nuclear power plants (NPPs) are critical infrastructure systems with significant safety implications. Among various natural hazards, earthquakes (EQs) pose substantial threats to NPPs, potentially resulting in operational shutdowns or structural damage. Therefore, accurate and rapid prediction of seismic responses is essential for effective structural health monitoring and post-earthquake damage assessment.

Traditionally, the finite element method (FEM) has been employed to analyze NPP behavior under seismic loading. However, FEM-based nonlinear time-history analysis is computationally expensive, often requiring hours to days per EQ scenario, which severely restricts its applicability to real-time post-EQ decision-making.

Recent advances in deep learning (DL) have enabled the development of surrogate models capable of rapidly predicting structural responses under seismic loading. Recurrent architectures such as long short-term memory (LSTM) networks have demonstrated strong performance in capturing sequential, path-dependent structural dynamics [1, 2], while 1D Convolutional Neural Networks (CNNs) offer efficient feature extraction from ground motion (GM) time series, though their accuracy tends to degrade under large plastic deformations [1, 3]. Graph Neural Networks (GNNs) have more recently been applied to leverage the inherent topology of structural systems, enabling generalization across varying building geometries [4, 5]. Transformer-based models further extend these capabilities by capturing long-range temporal dependencies through self-attention mechanisms [6]. Despite these advances, the aforementioned architectures operate in finite-dimensional spaces and remain tied to fixed discretization, limiting their generalizability.

Fourier neural operators (FNOs) [7] have emerged as a promising alternative by learning mappings between infinite-dimensional function spaces, parameterizing the integral kernel directly in the Fourier domain to achieve resolution-invariant and computationally efficient predictions. Recent studies have begun to apply FNOs to structural dynamics: Goswami et al. [8] employed a DeepONet–FNO framework for predicting structural responses under seismic and wind excitations, demonstrating superior accuracy over conventional neural network approaches. Despite their potential, existing FNO-based approaches rely on global Fourier basis functions. While effective in capturing smooth and low-frequency components, such global spectral representations are less capable of describing sharp, localized temporal variations inherent in nonlinear seismic responses. This limitation becomes more evident in nonlinear structural behavior, where path-dependent hysteretic responses depend strongly on loading history and cannot be fully characterized by purely global spectral decomposition.

To address these limitations, we propose the Window-Recurrent Fourier neural operator (WR-FNO). The model integrates FNO for efficient operator learning in the frequency domain, windowed input processing for multi-scale temporal feature extraction, and gated recurrent unit (GRU) connections for capturing sequential dependencies across windows and nonlinear drift behavior. The proposed approach enables rapid prediction of floor-wise nonlinear seismic responses in multi-degree-of-freedom (MDOF) systems, thereby facilitating efficient structural damage assessment under EQ scenarios.

2. Target Structure

2.1 Auxiliary building of nuclear power plants

An auxiliary building houses critical safety systems including emergency power supplies, control systems, and cooling water systems. Its seismic performance is crucial to ensuring overall plant safety during EQ events. The finite element (FE) model of the target auxiliary building is shown in Fig. 1.

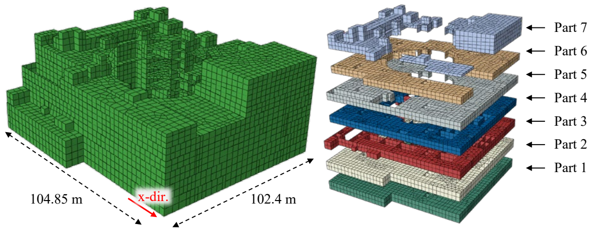

Fig. 1. FE model of the target auxiliary building (left) and its floor-wise visualization divided into Parts 1–7.

The FE model was constructed in ABAQUS using 17,233 S4R shell elements, with reinforcing bars represented using layered shell elements. The structural base was assumed to be fully fixed, and seismic loading was applied along the x-direction via time-history acceleration input. As illustrated in Fig. 1, the considerable size and geometric complexity of NPP structures make direct full-scale simulations computationally intensive. Further details of the FE model configuration are available in Lee et al. [9].

Although this study targets the NPP auxiliary building, the full-scale FE model is converted into a lumped mass model (LMM), as described in Section 2.2, to facilitate efficient training data generation and to test the proposed model's ability to reproduce nonlinear structural behavior.

2.2 Lumped mass model

To enable efficient nonlinear dynamic analysis while preserving the essential dynamic characteristics of the auxiliary building, an LMM was developed using OpenSeesPy [10]. The continuous structure represented by the FEM is transformed into a MDOF system in which floor masses are concentrated at each story level and adjacent floors are connected through nonlinear lateral elements representing inter-story stiffness and inelastic behavior. The equation of motion governing the dynamic response under seismic excitation is:

$$(1)\ \mathbf{M\ddot{u}} + \mathbf{C\dot{u}} + \mathbf{f(u)} = -\mathbf{M1\ddot{u}_g}$$

where $\mathbf{u}$, $\dot{\mathbf{u}}$, and $\ddot{\mathbf{u}}$ denote the displacement, velocity, and acceleration vectors of the MDOF system, respectively. $\mathbf{M}$ and $\mathbf{C}$ represent the mass and damping matrices. $\mathbf{f(u)}$ denotes the nonlinear restoring force vector. $\ddot{\mathbf{u}}_\mathbf{g}$ is the ground acceleration time history, and $\mathbf{1}$ is the influence vector that distributes the ground motion input to all degrees of freedom.

The LMM consists of seven nodes corresponding to Parts 1–7 of the auxiliary building. And this LMM is shown in Fig. 2.

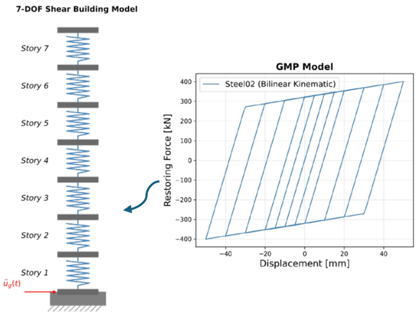

Fig. 2. Representative hysteretic response of the GMP material model assigned to each story of the 7-DOF shear building.

Floor masses are assigned at each node, and inter-story behavior is modeled using nonlinear two-node link elements. A Giuffrè–Menegotto–Pinto (GMP) hysteretic model [11] with a post-yield stiffness ratio of 5% is employed to simulate inelastic behavior, with yield strengths determined from inter-story stiffness and an assumed yield drift representative of reinforced concrete structures. Rayleigh damping is applied based on modal properties from eigenvalue analysis, targeting a damping ratio of 7%. Seismic excitation is introduced as uniform base acceleration, and nonlinear transient responses are computed using the Newmark average acceleration method with adaptive time-stepping to address convergence issues.

To generate training data for the proposed DL model, nonlinear time-history analyses are performed using 300 artificial GM records of 30 s duration, scaled up to 1.75 g to ensure sufficient nonlinear responses, thereby covering a broad range of intensity levels that include both elastic and inelastic structural behaviors, comprising 49% and 51% of the dataset, respectively. Floor-wise displacement and yielding information are recorded for each simulation. The resulting LMM substantially reduces computational cost compared to the full FEM while retaining the essential nonlinear and dynamic characteristics of specific node sets required for DL-based seismic response prediction.

3. Proposed WR-FNO Model

3.1 Model Architecture

The WR-FNO model consists of three main components: windowed input processing, Fourier neural operator layers, and recurrent output refinement, as illustrated in Fig. 3.

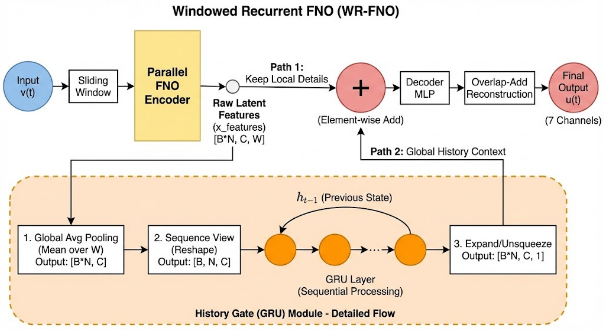

Fig. 3. Architecture of WR-FNO

Ground acceleration time histories are divided into overlapping windows of length $T_w = 2\,s$ (i.e., 200 sample points at 100 Hz) with 25% overlap. Each window is processed through FNO layers that operate in the frequency domain via fast Fourier transform, enabling efficient capture of multi-scale spectral features. This windowing strategy allows the model to represent both short- and long-term features. The extracted features from successive windows are then passed to an GRU-based recurrent module, which maintains hidden and cell states across windows to capture sequential dependencies and path-dependent nonlinear behavior. Floor-wise displacement is predicted at each window step.

3.2 Training Strategy

The WR-FNO model is trained using the Mean Squared Error (MSE) loss function. The dataset is split into 80% for training and 20% for testing. The model is optimized using the Adam optimizer and trained for 5,000 epochs with a step decay schedule that reduces the learning rate by a factor of 0.8 every 1,500 epochs. Detailed hyperparameter settings are summarized in Table I.

Table I. Hyperparameters for training

Hyperparameter	Value
Window length (T_w)	2 s (200 points)
Window overlap	20%
FNO Fourier modes	16
FNO hidden channels	32
FNO layers	4
GRU hidden size	64
GRU layers	1
Batch size	256
Initial learning rate	1.0×10^{-3}
LR decay factor	0.8
LR decay interval	700 epochs
Total epochs	2,000
Optimizer	Adam

4. Experimental Results

The WR-FNO model achieves high accuracy in predicting floor-wise displacement responses of MDOF system. The model attains a mean MAPE of 3.4% across all floors. Floor-wise prediction accuracy, measured by R^2 values, ranges from 0.86 to 0.94 across the seven stories (i.e., floors 1–7: 0.91, 0.86, 0.90, 0.92, 0.94, 0.93, and 0.91, respectively). The highest accuracy is observed at mid-height floors (i.e., floors 5 and 6, with R^2 values of 0.94 and 0.93), while slightly lower performance appears at floor 2 (i.e., R^2 = 0.86), where stronger nonlinear behavior is typically observed.

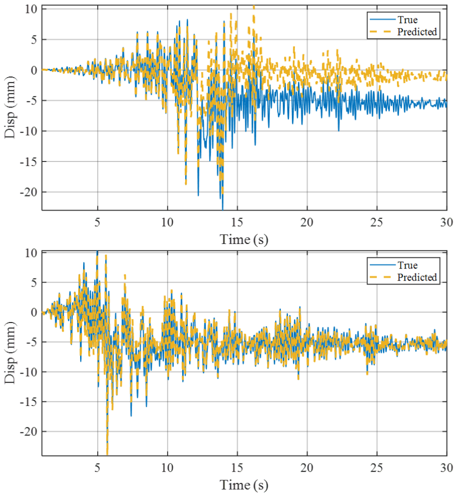

Fig. 4. Comparison of predicted and ground truth displacement responses for nonlinear behavior under different GMs.

Fig. 4 shows representative results with relatively large and small prediction errors for nonlinear responses. As shown in the figure, the model accurately reproduces both transient oscillatory responses and cumulative drift behavior characteristic of inelastic structural responses, although discrepancies remain for certain GMs. While elastic responses and overall nonlinear trends are well captured, still some limitations exist in predicting instantaneous displacement values under strong hysteretic behavior, as illustrated in the top panel of Fig. 4. This limitation is primarily associated with the path-dependent nature of hysteresis, where small differences in loading history can produce locally divergent responses.

Future research will concentrate on methodological refinements to better address the path-dependent characteristics of hysteretic structural behavior, thereby improving prediction stability under highly nonlinear loading conditions. Moreover, validation using real earthquake records and corresponding structural response data will be conducted to evaluate the model's generalizability and practical applicability. These extensions are expected to enhance the robustness of the proposed framework for post-earthquake response assessment of NPPs.

5. Conclusion

This study proposed WR-FNO, a DL surrogate model that combines FNO with windowed input processing and recurrent GRU for nonlinear seismic response prediction of MDOF systems. The model achieves high prediction accuracy (i.e., mMAPE of 3.4%) while providing efficient computational cost.

Key contributions include the introduction of a windowing strategy for temporal feature extraction and the integration of FNO with GRU to capture both frequency-domain characteristics and sequential path-dependent dependencies. The proposed framework successfully predicts nonlinear structural responses without requiring explicit knowledge of hysteretic behavior, relying solely on GM inputs and corresponding nonlinear response data generated from numerical simulations.

Nevertheless, several limitations should be noted. First, the structural model employs the GMP material model, which is typically used for steel structures, to represent the inelastic behavior of an auxiliary building primarily composed of reinforced concrete, thereby introducing modeling simplifications. Second, the training and testing datasets consist entirely of artificial GM records, which may not fully capture the characteristics of real ground motions. Future research will address these limitations by incorporating more representative material models and real earthquake records, as well as by further refining the proposed framework to better capture highly nonlinear structural behavior and improve predictive accuracy.

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