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A Comparative Study on AI-based Surrogate Models for Predicting Seismic Response of Nuclear Power Plants

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1. Introduction

The seismic safety of Nuclear Power Plants (NPPs) is a paramount concern, directly impacting public safety and environmental protection. Traditionally, the seismic response of NPP structures has been evaluated using high-fidelity numerical analysis methods, such as STRATA-SASSI, which incorporate complex soil-structure interaction (SSI) [1, 2]. While these methods provide precise results, they are computationally intensive and time-consuming, posing significant challenges for real-time safety monitoring or large-scale probabilistic seismic hazard analysis. Consequently, there is an urgent need for advanced technological solutions that can maintain high accuracy while drastically reducing computational costs.

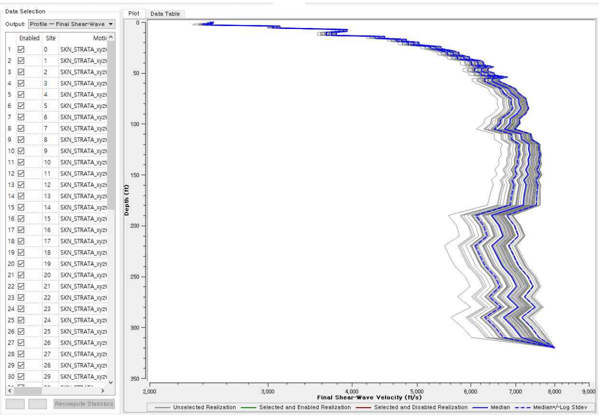
In response to these challenges, this study focuses on developing AI-based surrogate models to rapidly predict structural responses. Following global trends in nuclear digital transformation and the Korean government's AI-centered nuclear R&D policies, utilizing artificial intelligence is becoming essential for enhancing the social acceptance and technical reliability of nuclear power. This research aims to construct a comprehensive dataset comprising 1,226 SSI analysis scenarios generated from two representative NPP sites, multiple earthquake input motions, three directional components, and varied non-linear soil conditions, and to evaluate the performance of diverse deep learning architectures, including convolutional neural network (CNN), long short-term memory (LSTM), multi-input multi-output (MIMO), and Transformer. By comparing their efficacy in predicting both acceleration and floor response spectrum (FRS), this study provides a robust technical foundation for establishing a real-time seismic safety evaluation framework for nuclear facilities.

2. Methods and Results

This section describes the systematic approach for developing AI-based surrogate models to predict the seismic response of NPPs. The research follows a structured workflow: generating a high-fidelity dataset through SSI analysis, designing diverse deep learning architectures including CNN and Transformer to capture both time and frequency domain characteristics, and rigorously evaluating their predictive accuracy. By comparing the performance of these models, this study identifies the most effective AI framework for rapid and reliable seismic safety assessment.

2.1. Dataset Generation and Preprocessing

To construct a robust dataset for AI training, this study performed SSI analyses for the Site1 and Site2 nuclear power plant sites. The simulation framework was established by integrating the STRATA and SASSI programs [3, 4]. First, equivalent-linear analyses were conducted using STRATA to account for the nonlinear behavior of the soil. By utilizing input seismic waves, soil profile data, and nonlinear curves (G/G_{max} and damping ratio), the equivalent shear wave velocity (V_s) and damping ratios for each soil layer were calculated. These results were subsequently utilized as input parameters for the SASSI program to perform repetitive SSI simulations, generating high-fidelity ground truth data for surrogate modeling.



Output: Profile — Final Shear-Wave

	Enabled	Site	Moti
1	☑	0	SKN_STRATA_xyz
2	☑	1	SKN_STRATA_xyz
3	☑	2	SKN_STRATA_xyz
4	☑	3	SKN_STRATA_xyz
5	☑	4	SKN_STRATA_xyz
6	☑	5	SKN_STRATA_xyz
7	☑	6	SKN_STRATA_xyz
8	☑	7	SKN_STRATA_xyz
9	☑	8	SKN_STRATA_xyz
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15	☑	14	SKN_STRATA_xyz
16	☑	15	SKN_STRATA_xyz
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25	☑	24	SKN_STRATA_xyz
26	☑	25	SKN_STRATA_xyz
27	☑	26	SKN_STRATA_xyz
28	☑	27	SKN_STRATA_xyz
29	☑	28	SKN_STRATA_xyz
30	☑	29	SKN_STRATA_xyz

Figure 1. Equivalent-linear analysis results from STRATA, reflecting the site-specific non-linear soil characteristics.

The input dataset consists of seismic wave sets corresponding to various earthquake events and three-directional motions (H_1, H_2, and V). These acceleration records in the time domain were processed through

STRATA to reflect site-specific damping and stiffness characteristics. The output data, serving as the ground truth, were categorized into two domains: time-history acceleration at major structural nodes and FRS in the frequency domain. This dual-domain approach allows the surrogate models to learn both the peak dynamic responses and the spectral characteristics essential for seismic safety evaluation.

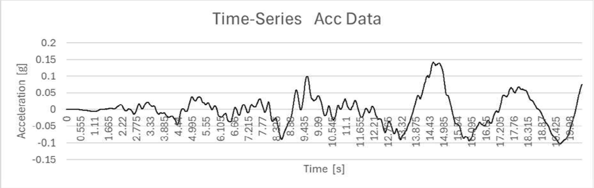


Figure 2. Time-Series acceleration used for the analysis.

To enhance the stability of the deep learning training process, a rigorous preprocessing procedure was implemented. Raw output files from STRATA and SASSI were integrated into a standardized CSV format, structured with site names, earthquake IDs, soil properties, and response information. Missing values (NaN) and abnormal amplitudes resulting from numerical instabilities were identified and removed. To ensure data quality, extreme peak values were treated using a clipping method. Finally, the total dataset was partitioned into training, validation, and testing sets using random sampling to ensure an even distribution of earthquake types and soil conditions.

The total dataset comprised 1,226 SSI analysis scenarios, which were generated by systematically combining two NPP sites (Site1 and Site2), multiple earthquake input records, three directional components (H1, H2, and V), and non-linear soil-property conditions used in the STRATA equivalent-linear analysis. For each scenario, the input ground motion and site-specific soil profile were first processed in STRATA to obtain equivalent shear wave velocity and damping ratio, and the resulting parameters were then transferred to SASSI to compute the structural seismic response. Through this repetitive workflow, 509 scenarios were generated for Site1 and 717 scenarios for Site2, yielding a total of 1,226 high-fidelity SSI response cases for AI training and validation.

Table 1. Input and Output Variables for AI-based Seismic Response Prediction Model

Variables	items
Input	Non-linear soil curves
	Shear wave velocity by layer
	Damping ratio
	Input earthquake motion
Output	Time-series acceleration
	Floor Response Spectrum

2.2. AI Model Architecture and Training Strategy

This study develops a deep learning-based surrogate modeling framework to approximate the complex input-output relationships of STRATA-SASSI simulations. To identify the optimal architecture for predicting structural responses, we implemented and compared multiple deep learning models: CNN, LSTM, MIMO, and Transformer for time-series acceleration, and Transformer, LSTM, and MIMO for FRS prediction. The input features, comprising normalized seismic ground motions and soil property conditions, are processed through the network, while the outputs are restored to physical quantities via de-normalization to ensure consistency with actual structural behavior. The dataset, consisting of 1,226 scenarios, was partitioned into training (80%), validation (10%), and testing (10%) sets using random sampling to maintain a balanced distribution of earthquake events and soil profiles. Training was conducted using the Adam Optimizer with an initial learning rate of 1e-4, incorporating an early stopping mechanism to prevent overfitting. The final model selection was based on a comprehensive evaluation of three statistical metrics (MAE, RMSE, and R^2) to ensure both numerical precision and physical validity of the predicted responses.

2.2.1. Long Short-Term Memory (LSTM)

The LSTM model is designed to capture the temporal dependencies and dynamic behavior of structural vibrations. It consists of an LSTM encoder with two layers and 128 hidden units, processing sequential data such as time-history acceleration. To handle varying signal lengths, input data are padded and fed into the core RNN block, where the model learns the continuous decay and phase shifts of seismic responses. For FRS prediction, a joint-prediction structure is applied, utilizing the last hidden state (h_n) as a summarized temporal feature to map structural responses across multiple depths and frequencies.

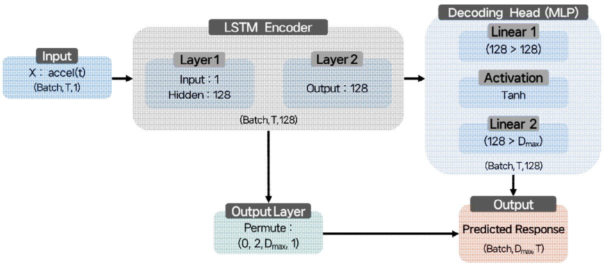


Figure 3. LSTM model architecture.

2.2.2. Multi-Input Multi-Output (MIMO)

The MIMO architecture integrates multimodal inputs, including seismic ground motions and static soil property data (shear wave velocity, modulus, and damping), to simultaneously predict time-history acceleration and FRS. The time-series inputs are processed via LSTM or 1D-CNN encoders, while static geotechnical parameters are embedded through Multi-Layer Perceptrons (MLP). These features are fused—for instance, tiling a 64-dimensional site embedding with a 128-dimensional temporal feature—to form a comprehensive vector that represents the coupled interaction between soil properties and seismic excitation.

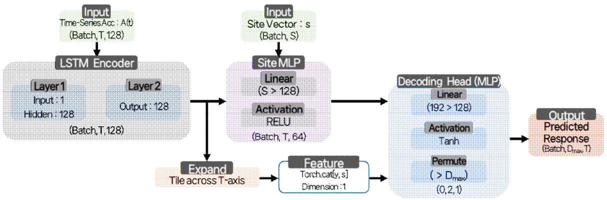


Figure 4. MIMO model architecture.

2.2.3. Convolutional Neural Network (CNN)

The CNN model focuses on extracting local hierarchical features from seismic signals and soil profiles. It comprises a CNN branch for processing fixed-length (4,096 points) time-series data and an MLP branch for soil property vectors consisting of unit weight, shear wave velocity, and damping ratios. By concatenating the 80-dimensional combined feature vector, the model effectively maps input excitations to output response histories. The training protocol includes an automated learning rate scheduler and early stopping to ensure optimal convergence.

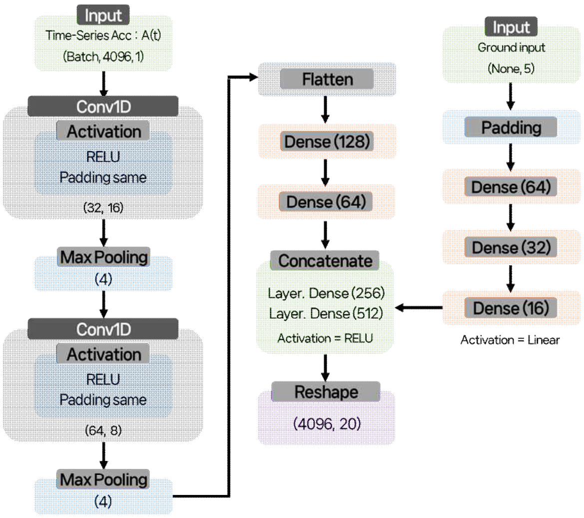


Figure 5. CNN model architecture.

2.2.4. Transformer

The Transformer model leverages a Multi-modal Encoder structure to learn global dependencies through Self-Attention mechanisms. Four independent encoders—for acceleration, soil profile, and nonlinear material curves—project various physical features into 128-dimensional latent vectors. The acceleration encoder identifies long-term correlations across 4,096 time steps, while the soil profile encoder utilizes time-average pooling to summarize stiffness distributions. These integrated features are passed to specialized decoding heads for simultaneous prediction of time-domain acceleration and frequency-domain FRS.

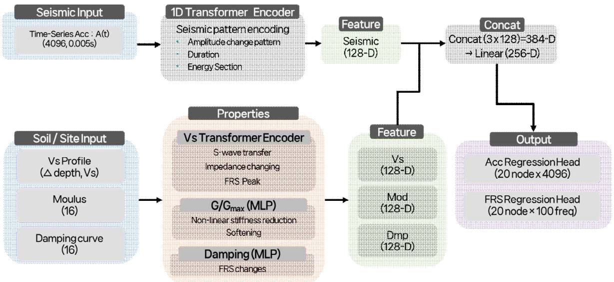


Figure 6. Transformer model architecture.

2.3. Performance Evaluation and Results

To evaluate the performance of the proposed surrogate models, we selected four key nodes (No. 139, 145, 151, and 158) out of 20 structural points as representative evaluation targets. The predictive accuracy and consistency of time-history acceleration and FRS were verified using three statistical metrics: MAE, RMSE, and R^2. These metrics allow for a comprehensive assessment of overall error magnitude, sensitivity to peak responses, and the model's ability to reproduce dynamic trends.

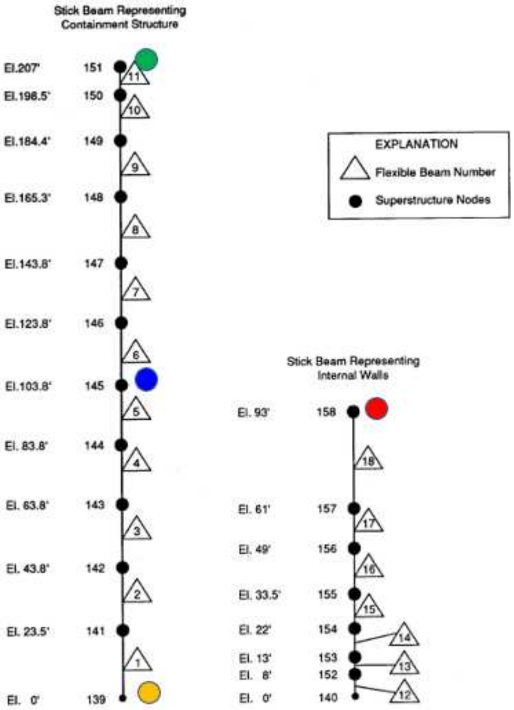
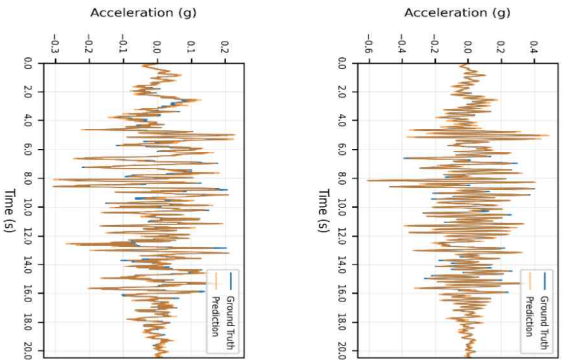


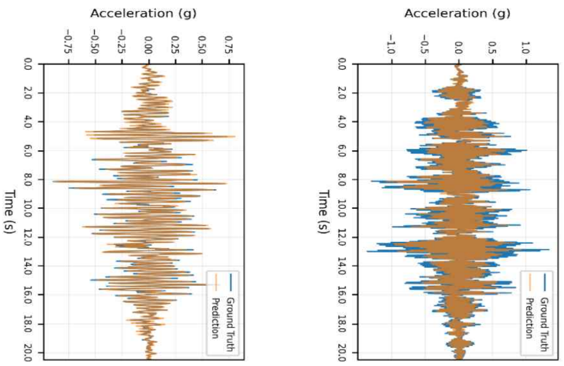
Figure 7. Finite Element Stick Models Representing Containment and Internal Structures.

2.3.1. Performance Analysis for Time-History Acceleration

The predictive results in the time domain were compared with the SASSI ground truth. Quantitative analysis showed that while the LSTM model achieved the lowest average MAE (0.2046 g), demonstrating stable error performance in basic response estimation, the CNN model exhibited the most superior performance across other critical metrics. The CNN model recorded the lowest RMSE (0.3625 g) and the highest R^2 score (0.6417), effectively capturing peak amplitudes and the overall hierarchical patterns of structural vibrations. In contrast, the MIMO model showed higher errors (MAE: 0.2392 g, R^2: 0.2634), likely due to limitations in global pattern reproduction. Consequently, the CNN model is identified as the most suitable architecture for time-domain seismic response prediction.



a) No. 139 b) No. 145



c) No. 151 d) No.158

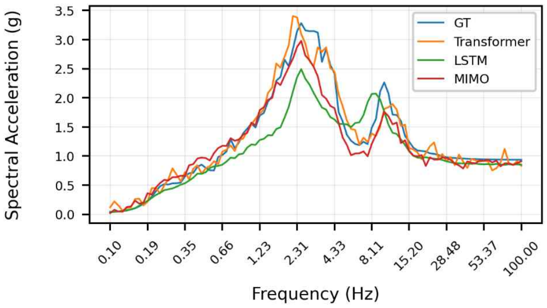
Figure 8. CNN Model Predicted Acceleration Graph

Table 2. Validation Performance Comparison by Model

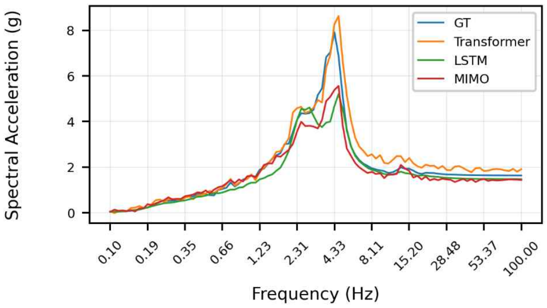
Evaluation Metrics	LSTM	MIMO	CNN	Transformer
MAE	0.2046	0.2392	0.2196	0.2207
RMSE	0.4010	0.4182	0.3625	0.3892
R^2	0.3227	0.2634	0.6417	0.3619

2.3.2. Performance Analysis for Floor Response Spectrum (FRS)

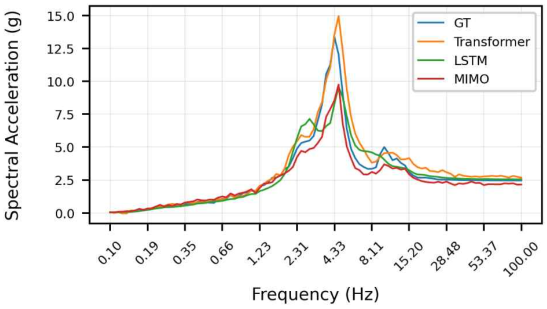
For frequency-domain prediction, the Transformer model significantly outperformed other architectures across all evaluation metrics. It achieved the lowest MAE (0.3218 g) and RMSE (0.5884 g), along with the highest R^2 score (0.7213), proving its capability to accurately reconstruct frequency distribution and peak spectral responses. This superiority stems from the Self-Attention mechanism, which effectively learns global correlations across the entire frequency range. While the MIMO model showed moderate performance (R^2: 0.6001), the LSTM model struggled in the frequency domain (MAE: 0.7531 g, R^2: 0.4496), as its architecture is inherently specialized for sequential time-series modeling rather than spectral mapping. Thus, the Transformer is the optimal choice for rapid and precise FRS prediction.



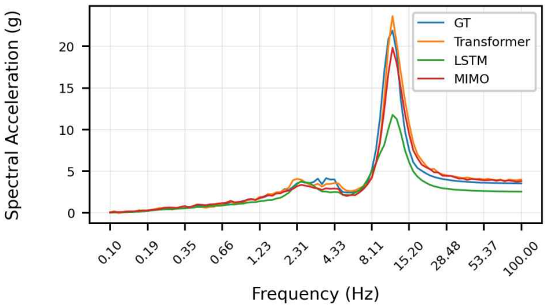
a) No. 139



b) No.145



c) No. 151



d) No. 158

Figure 9. Comparison Results by Model

Table 3. Validation Performance Comparison by Model

Evaluation Metrics	Transformer	LSTM	MIMO
MAE	0.3218	0.7531	0.5589
RMSE	0.5884	1.3992	1.0782
R^2	0.7213	0.4496	0.6001

3. Summary and Conclusion

This study developed and evaluated AI-based surrogate models to overcome the computational limitations of traditional seismic response analysis for nuclear power plants. By constructing a high-fidelity dataset based on STRATA-SASSI simulations and comparing diverse deep learning architectures, we identified optimal models for different response domains. The experimental results demonstrated that the CNN model is most effective for predicting time-history acceleration, showing superior performance in capturing peak responses and overall vibration patterns (R^2: 0.6417). In contrast, the Transformer model proved to be the most suitable architecture for frequency-domain FRS prediction, achieving high precision through its Self-Attention mechanism (R^2: 0.7213). These findings suggest that implementing specialized AI architectures according to the target response domain is crucial for ensuring the reliability of seismic safety assessments. The proposed AI surrogate models enable near-real-time seismic response prediction, which can significantly enhance the efficiency of probabilistic safety assessments and emergency monitoring systems in nuclear facilities. Future research will focus on expanding the dataset to include diverse site conditions and integrating physics-informed neural networks (PINN) to further improve the physical consistency and generalization performance of the models.

Acknowledgement

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