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Design of 1D CNN Kernels for Predicting Seismic Response of Nuclear Power Plants

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ABSTRACT

Nuclear power plants (NPPs) play a critical role in energy generation; however, their structural integrity is vulnerable to seismic events, necessitating precise seismic response predictions to ensure operational safety. Recent advancements in artificial intelligence have enabled the development of highly effective models for this purpose, with one-dimensional convolutional neural networks (1D CNNs) demonstrating notable success in modeling the complex relationships between seismic excitations and structural behavior. As seismic responses are fundamentally governed by the frequency characteristics of ground motions, it is essential for prediction models to effectively extract relevant frequency-domain features. 1D CNNs, which apply localized convolution operations analogous to finite impulse response (FIR) filters, are influenced by the kernel size when determining which frequency components are captured. To improve the ability of the model to extract meaningful features across a broad range of frequencies inherent in seismic signals, this study proposes a hierarchical 1D CNN architecture that systematically decreases the kernel sizes across the network layers. By combining multiple kernel scales within a single framework, the hierarchical design improves the ability of the model to extract diverse frequency components and enhances the overall prediction accuracy. The proposed model is validated using a case study of NPP structures, where the experimental results demonstrate its ability to achieve significantly lower prediction errors compared with fixed-kernel CNNs, accurately capturing both long-term structural behavior and short-duration seismic events.

INTRODUCTION

Rising energy consumption, driven by population growth and economic expansion, highlights the critical importance of stable and secure nuclear power generation (IAEA, 2020). However, nuclear facilities are inherently vulnerable to seismic events, necessitating the accurate evaluation of seismic responses to ensure safe and continuous operation (U.S. NRC, 2019). Although conventional physics-based methods, such as finite element analysis (FEA), provide detailed and reliable predictions, their computational complexity and extensive processing time limit their utility in real-time assessments and rapid decision-making during seismic events (Zienkiewicz et al., 2014). Consequently, there is a growing demand for efficient surrogate models capable of providing rapid and accurate seismic response predictions to support real-time decision-making and emergency response measures (Sun et al., 2020).

Recently, deep learning-based surrogate models have demonstrated strong potential as computationally efficient alternatives to traditional numerical simulations (Xie et al., 2021). Among the various neural network architectures, one-dimensional convolutional neural networks (1D CNNs) have emerged as particularly advantageous for processing sequential seismic signals because of their capacity to effectively capture local temporal dependencies and directly extract informative features from raw time-series data (Kiranyaz et al., 2021). Compared with traditional machine learning approaches, 1D CNNs exhibit enhanced robustness to noise, require minimal data preprocessing, and offer superior computational efficiency, making them highly suitable for real-time applications (Abdeljaber et al., 2018; Mousavi et al., 2019). Several studies have validated the effectiveness of 1D CNNs in seismic applications. Mousavi et al. (2019) employed 1D CNNs for real-time seismic phase detection, achieving significantly improved accuracy and computational efficiency compared with conventional methods. Abdeljaber et al. (2018)

effectively utilized 1D CNNs for structural vibration feature extraction, thereby facilitating rapid and accurate structural damage detection. Furthermore, Wang et al. (2019) demonstrated the superior performance of 1D CNNs in seismic waveform classification, emphasizing their capability to accurately distinguish earthquake signals from background noise, thereby confirming their reliability in seismic analyses.

Despite these advances, limited research has addressed the impact of critical model parameters such as kernel size on seismic response prediction accuracy. In 1D CNNs, the kernel size plays a crucial role in determining the frequency extraction capabilities, similar to the window size in short-time Fourier transforms (STFT) (Farag et al., 2022). Larger kernels have broader receptive fields, effectively capturing the low-frequency content that is crucial for global seismic responses, whereas smaller kernels are adept at detecting transient high-frequency oscillations. Therefore, this study systematically investigates how varying kernel sizes influence prediction accuracy across different frequency ranges, specifically focusing on the seismic responses in nuclear power plant (NPP) auxiliary structures. Various 1D CNN architectures, including temporal convolutional networks (TCNs) and fully convolutional networks (FCNs), have demonstrated their effectiveness in analyzing sequential and temporal data. However, these methods typically employ fixed or limited kernel configurations, which restrict their capability to capture diverse frequency components comprehensively and simultaneously. Although omni-scale CNNs concurrently utilize multiple kernel sizes, their parallel structure often results in increased model complexity and computational demands. To address these limitations, this study proposes a hierarchical residual 1D CNN architecture explicitly designed to efficiently extract frequency-specific features from seismic signals by progressively decreasing the kernel sizes across the network layers.

Experimental comparisons of smaller (kernel size 10) and larger (kernel size 100) kernel models have revealed distinct advantages. The model employing a larger kernel size (100) demonstrated superior accuracy within lower frequency ranges, effectively capturing the broad, long-term structural behavior characteristics of seismic responses. Conversely, a smaller kernel (size 10) provided better performance in capturing rapid fluctuations and transient oscillations within higher frequency ranges. These observations highlight the inherent trade-off between the kernel size and frequency capture capability. Building upon these insights, the proposed hierarchical CNN employs a systematic approach, starting with large kernel sizes to effectively capture low-frequency seismic responses and progressively transitioning toward smaller kernel sizes to detect high-frequency transient details.

The proposed innovative hierarchical residual 1D CNN framework provides several distinct advantages:

1. Improved accuracy across frequency ranges: Unlike fixed kernel models that are restricted to narrow frequency bands, the proposed model reduces prediction errors across both low- and high-frequency spectra, enabling balanced and comprehensive seismic response modeling.
2. Enhanced computational efficiency: By reducing the trainable parameters while maintaining prediction accuracy, the hierarchical structure significantly enhances the training efficiency and real-time deployment feasibility, which are crucial for emergency response scenarios.

Integrating these advancements, this study significantly progresses seismic response prediction methodologies, delivering a highly accurate and computationally efficient framework ideal for the real-time structural assessment of NPP auxiliary structures. The proposed model notably improves the predictive performance in critical frequency bands, thereby enhancing the reliability of detecting rapid structural changes that are essential for seismic early-warning systems and structural health monitoring.

PROPOSED PREDICTION MODEL

1D CNN

Convolutional neural networks (CNNs) have become widely used in image processing owing to their ability to effectively capture spatial patterns by applying convolution kernels across two-dimensional (2D) data.

Although traditionally associated with 2D data, CNNs have also been successfully adapted for analyzing one-dimensional (1D) sequential data, such as time series and signals (Kiranyaz et al., 2021; Abdeljaber et al., 2018). 1D CNNs utilize convolution kernels along a single dimension, enabling the extraction of local temporal dependencies and intrinsic patterns from sequential data. As the convolution kernels traverse the input sequence, they identify the relationships between neighboring data points. Increasing the network depth allows the convolutional layers to capture progressively abstract and complex sequential features, whereas the pooling layers efficiently reduce the feature map dimensionality by preserving essential information.

Residual connections, which are frequently incorporated into deep CNN architectures, improve network performance by addressing issues such as vanishing gradients. These skip connections facilitate direct information flow between non-adjacent layers, enhancing convergence and accurately capturing hierarchical temporal features. The architecture of the residual 1D CNN used in this study is depicted in Figure 1, with further technical details available in He et al. (2021).

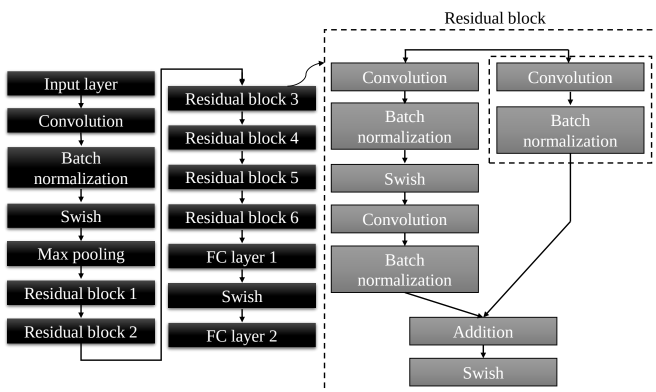


Figure 1. Deep residual 1D CNN architecture.

Relationship between 1D CNN kernels and finite impulse response (FIR) filters

The kernel operation of a 1D CNN functions identically to a FIR filter, playing a role in extracting frequency information from ground motions. The operation equations of the 1D CNN kernel and FIR filter are shown in Equations (1) and (2), respectively.

$$y[n] = \sum_{k=0}^{M-1} h[k] \cdot x[n-k], \tag{1}$$

where $y[n]$ is the output signal, $x[n]$ is the input signal, $h[k]$ is the coefficient of the FIR filter, and M is the length of the FIR filter.

$$y[i] = \sum_{k=0}^{K-1} w[k] \cdot x[i+k] + b[k], \tag{2}$$

where $y[i]$ is the CNN output, $x[i]$ is the input signal, $w[k]$ is the weight of the kernel (a trainable parameter), $b[k]$ is the bias term, and K is the kernel length.

Equations (1) and (2) show that the FIR filter operation is equivalent to a fixed-weight, time-reversed version of the 1D CNN kernel for the bias term. Consequently, the output of the 1D CNN convolutional kernel, known as a feature map, represents the presence of specific frequency components at specific times within the signal. Therefore, applying a Fourier transform to the feature map explicitly reveals the frequency content extracted from the input signal.

Furthermore, the kernel size of a 1D CNN significantly affects its frequency resolution and frequency-capturing capabilities. Small kernels tend to capture high-frequency components effectively because of their limited receptive fields, making them sensitive to transient oscillations and rapid signal changes. In contrast, larger kernels provide broader receptive fields, enhancing their ability to capture low-frequency components related to the overall structural behaviors and slowly varying signal patterns. This relationship between the kernel size and frequency resolution is conceptually analogous to adjusting window sizes in short-time Fourier transform (STFT) analysis. While STFT explicitly computes frequency-domain representations by varying the window sizes, 1D CNN kernels implicitly capture frequency information through learned temporal patterns, enabling comprehensive and adaptive frequency characterization of signals.

Model architecture: Hierarchical 1D CNN

Various 1D CNN architectures have been explored in previous studies, demonstrating their effectiveness in analyzing sequential and temporal data. Notable examples include omni-scale CNNs (Tang et al., 2020), TCNs (Bai et al., 2018), and FCNs (Wang et al., 2017). Omni-scale CNNs use multiple kernel sizes in parallel to simultaneously capture diverse temporal features, whereas TCNs employ dilated and causal convolutions to effectively model long-range temporal dependencies. FCNs rely solely on convolutional layers, enabling the hierarchical extraction of temporal features without explicit frequency optimization.

In contrast, this study proposes a hierarchical 1D CNN architecture explicitly designed for the efficient extraction of frequency-specific features from seismic signals. Seismic responses are inherently dependent on seismic input signals and the natural frequencies of structures. As discussed in Section 2.2, the kernel operation of a 1D CNN closely resembles a FIR filter that extracts specific frequency components from time-series signals, particularly in the case of seismic data. The ability to capture relevant frequency information is crucial for accurately modeling the structural behavior under seismic loads.

Unlike the previously mentioned architectures, the proposed hierarchical CNN systematically employs kernels with sizes that progressively decrease from the initial large kernels to smaller kernels in deeper layers. This strategy allows the model to effectively capture low-frequency seismic responses with larger kernels in the initial layers and subsequently identify high-frequency transient details with smaller kernels in deeper layers. Specifically, large initial kernels are adept at extracting slowly varying global pattern characteristics of structural behaviors, whereas progressively smaller kernels focus on rapid fluctuations and localized transient oscillations. The proposed hierarchical 1D CNN architecture is illustrated in Figure 2. The first set of residual blocks uses a kernel size of 100, corresponding to a period of 1 s, to capture low-frequency features. The second set employs a kernel size of 50 (0.5 s) to extract mid-frequency components. Finally, the third set uses a kernel size of 10 (0.1 s) to capture high-frequency features.

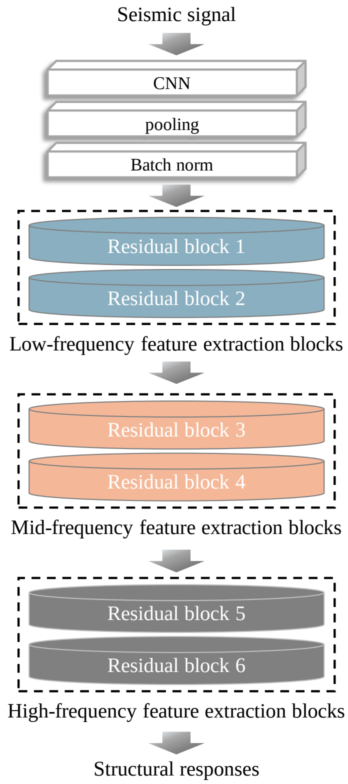


Figure 2. Architecture of the proposed hierarchical 1D CNN model.

The proposed hierarchical structure offers clear and distinct advantages:

1. Adaptability to different frequency components: The systematic reduction in kernel size across the network layers enables the model to effectively capture a wide range of frequency components, from low-frequency structural dynamics to high-frequency transient details, although the coverage remains constrained by kernel configurations and data characteristics.

2. Enhanced computational efficiency: As the network depth increases, progressively decreasing kernel sizes lead to a reduction in trainable parameters, improving the computational efficiency while preserving the prediction accuracy. Therefore, the proposed architecture is suitable for real-time applications.

3. Balanced and interpretable feature extraction: The explicit separation of frequency components across layers facilitates robust and accurate predictions and enhances the interpretability of learned features, allowing a clearer identification of frequency contributions to seismic responses.

By strategically combining kernels of decreasing size, the proposed hierarchical architecture substantially improves the capability of the model for comprehensive and accurate seismic response analysis, enabling precise and frequency-aware predictions crucial for effective structural assessment.

APPLICATION EXAMPLE

Target structure

This study used the auxiliary building of the APR 1400 NPP as an application example. The auxiliary building, consisting of six floors, was modeled using ABAQUS software with 17,233 shell elements (S4R). The reinforcing bars were represented by layered shell elements. In the finite element model (FEM), the building base was fixed and seismic forces were applied horizontally in the x-y plane. Figure 3 shows the detailed FEM configuration. A time-acceleration approach was utilized to replicate the earthquake effects accurately. Specifically, seismic forces were introduced using the ABAQUS base-motion option, enabling the dynamic analysis of the seismic responses. A linear elastic material model was selected to maintain the computational efficiency while ensuring a realistic representation of the seismic response of the building. The detailed material properties, including the Young's modulus, density, and Poisson's ratio for both the concrete and reinforcing steel, are listed in Table 1. Additionally, the dynamic response of the building was analyzed using the modal superposition method (MSM). MSM breaks down complex dynamic responses into simpler independent modal contributions, allowing for a comprehensive and systematic evaluation. This approach provided deeper insights into the role of each mode in the building's overall seismic performance, thereby enhancing the simulation accuracy and reliability.

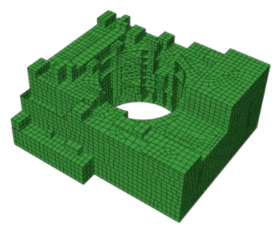


Figure 3. FEM of the auxiliary building of the APR 1400 NPP.

Table 1. Material properties of the auxiliary building of the APR 1400 NPP.

	Concrete	Reinforcing bar	Steel
Elastic modulus (psi)	4,031,000	29,000,000	29,008,000
Density ($lbf s^2/in^4$)	0.000225	0.0007346	0.0007346
Poisson ratio	0.17	0.30	0.30

Model training

The proposed model was trained using artificially generated earthquake signals. In total, 300 synthetic earthquakes were generated, of which 260 were used for training. The earthquake signals were 100 Hz with a length of 30 s. The remaining 40 earthquakes were used for validation and testing. The training process used a batch size of 400 and an Adam optimizer. The model was trained for 1000 epochs, with a learning rate decay applied every 300 epochs by a factor of 0.1 to enhance convergence. To prevent overfitting, global L2 norm-based gradient thresholding was applied, and the L2 regularization was set to 1e-5. The mean squared error (MSE) was used as the loss function to optimize model performance. The training was conducted using a high-performance computing system equipped with an NVIDIA RTX 4090 GPU and an Intel Core i9-14900K processor.

Prediction results

To assess its generalization capability, the trained model was evaluated using 40 earthquake signals that were not included in the training phase. The performance of the model was quantified using the maximum mean absolute percentage error (mMAPE) metric (Shin et al., 2018). The proposed model achieved an mMAPE of 0.45% on the test dataset, demonstrating significantly lower prediction errors and highlighting its high predictive accuracy.

To further validate the model performance, the predicted seismic response at the top floor of the auxiliary building of the NPP was directly compared with the reference response obtained from FEA. Figure

4 illustrates this comparison, with the left plot presenting the full time-series response, and the right plot (within the dotted box) providing an enlarged view of the first 5 s. The model accurately captured both the overall trend and peak responses, confirming that the proposed model was effectively trained and generalized, enabling reliable predictions of seismic responses to previously unseen earthquake data.

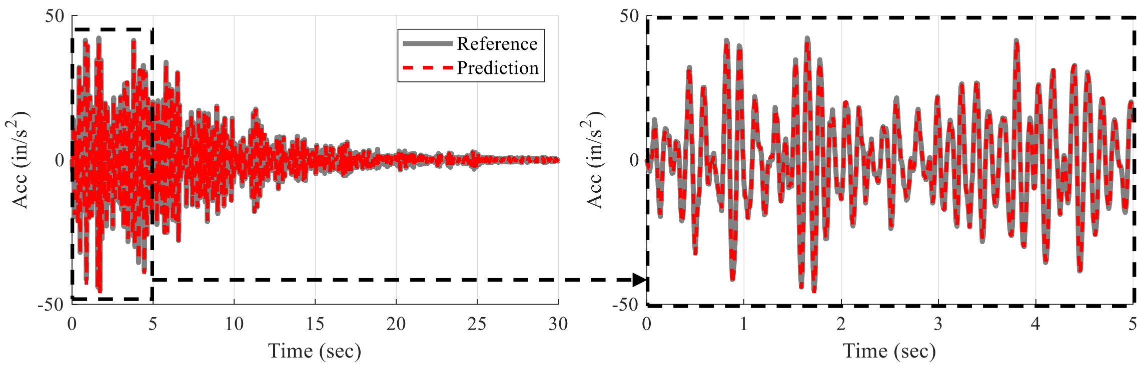


Figure 4. Seismic response prediction of the proposed model for unseen earthquakes (Top floor of the auxiliary building of the NPP).

To further analyze the effectiveness of the model, the predictions were compared across different kernel configurations, including fixed kernel sizes of 5 and 100, as well as the proposed hierarchical kernel structure. Comparisons were performed in both the time and frequency domains to comprehensively assess the capability of the model to capture seismic response characteristics. Figures 5 and 6 illustrate these comparative analyses, highlighting the advantages of the hierarchical approach in effectively preserving the critical frequency components and minimizing prediction errors.

Figure 5 presents a comparison of the root mean squared error (RMSE) values calculated from the fast Fourier transform (FFT) of the time-series predictions of the fixed-kernel models (kernel sizes 5 and 100) and the proposed hierarchical CNN model. The model with kernel size 5 exhibited the highest RMSE and demonstrated a mMAPE > 3% in time-series predictions, indicating inadequate capability in extracting relevant seismic information. Conversely, increasing the kernel size to 100 significantly improved the capability of the model to capture low-frequency components. However, this significantly increased the number of trainable parameters to approximately 6.2 million, negatively affecting computational efficiency and increasing training costs. Additionally, the larger kernel model exhibited diminished accuracy in capturing high-frequency signals.

In contrast, the proposed hierarchical CNN model substantially reduced the number of parameters to approximately 1.7 million, representing only 27% of the parameters of the kernel size 100 model. Despite this reduction, the hierarchical CNN achieved superior predictive accuracy across the entire frequency range, demonstrating lower overall RMSE values than fixed-kernel models.

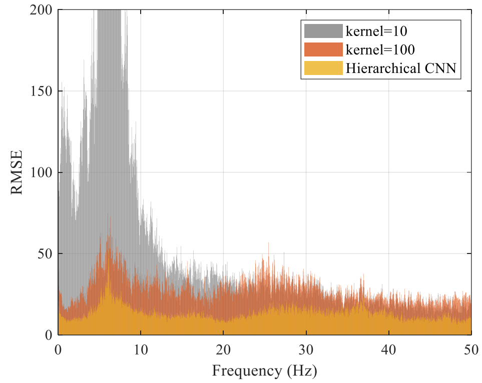
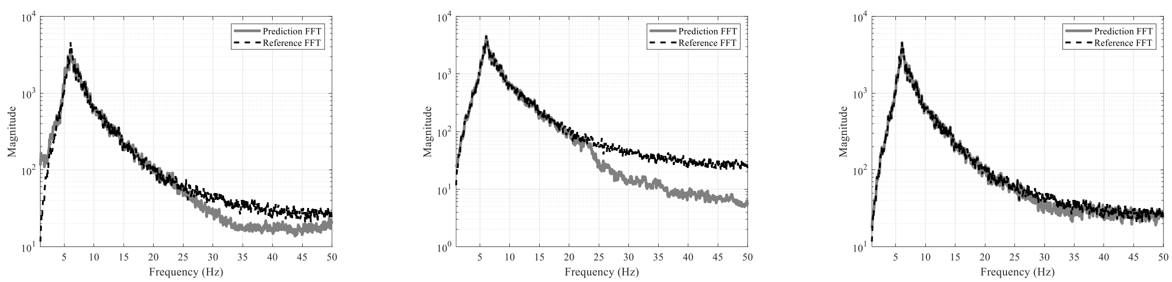


Figure 5. Comparison of RMSE values for the frequency contents of the fixed-kernel CNNs and the proposed hierarchical CNN.

Figure 6 shows the FFT results for three models: (a) kernel size 10, (b) kernel size 100, and (c) hierarchical. In Figure 6 (a), the kernel size 10 model shows an acceptable error in the high-frequency period, whereas in Figure 6 (b), the kernel size 100 model shows a high error in the high-frequency period. However, in Figure 6 (c), the hierarchical model shows a much lower error compared to the other models, which means that it has both low- and high-frequency content extraction capacities. From the perspective of the structural response of an auxiliary building, it is important to capture the dominant low-frequency content in the structural response. Therefore, the mMAPEs for the models with kernel sizes 10 and 100 were 3.12% and 0.92%, respectively, which is an effect of the frequency target difference between the models. However, in the hierarchical CNN model, the mMAPE was 0.45%, which was significantly lower than that of other models. As shown in Figure 6, the frequency content capture ability of the hierarchical CNN model was higher in all frequency periods compared with the other two models.



(a) (b) ©

Figure 6. FFT comparison for models in the frequency range > 20 Hz; (a) kernel size 10, (b) kernel size 100, (c): hierarchical.

CONCLUSION

In this study, a novel hierarchical 1D CNN architecture was proposed to accurately predict seismic responses by capturing the complex frequency characteristics inherent in seismic signals. Traditional CNN methods, such as TCNs and FCNs, typically employ fixed or limited kernel configurations which constrain their ability to comprehensively capture diverse frequency components simultaneously. Although omni-scale CNNs utilize multiple kernel sizes simultaneously, their parallel structure can increase the model complexity and computational demands. In contrast, the proposed hierarchical model overcomes these limitations by systematically decreasing the kernel sizes across the network layers, thereby facilitating the effective extraction of frequency-specific features. Larger kernels in the initial layers are optimized to capture global, low-frequency structural responses, whereas progressively smaller kernels in deeper layers target transient, high-frequency details. This strategic kernel size reduction significantly enhances the adaptability of the model across varying frequency bands, achieving balanced and interpretable feature extraction.

Experimental results demonstrated the superior predictive performance of the model, achieving a notably low mMAPE of 0.45% on previously unseen seismic datasets. Comparative evaluations against fixed-kernel CNN models further highlighted the enhanced accuracy of the hierarchical CNN, particularly in capturing critical low-frequency structural behaviors and high-frequency transient dynamics, which are both crucial for structural safety assessments. Additionally, the hierarchical kernel approach substantially improves the computational efficiency by reducing the total number of trainable parameters as the network depth increases, thereby enhancing its suitability for real-time seismic response prediction and emergency management applications. Future research will focus on refining the high-frequency feature extraction capabilities, exploring alternative training methodologies to further improve model generalization, and validating the hierarchical CNN architecture using real-world seismic data to ensure practical applicability and reliability.

ACKNOWLEDGEMENTS

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