PEER "Research Nuggets"

Title: Towards Deep Learning-Based Structural Response Prediction and Ground Motion Reconstruction

Authors: Khalid M. Mosalam, Issac. K.T. Pang, and Selim Günay, Department of Civil and Environmental Engineering, University of California, Berkeley

Motivation: Structural response prediction is a cornerstone of earthquake engineering. It allows engineers to evaluate how structures perform under seismic loads, enabling safety and reliability. Historically, three primary methods have been used to determine the dynamic structural responses: 1. Field Instrumentation: Installing sensors on real structures provides direct and realistic measurements of their behavior. However, this approach is limited by the relatively small number of instrumented buildings worldwide. 2. Laboratory Testing: Physical models, such as those tested on shaking tables or in quasistatic setups, offer detailed insights into the dynamic response. While valuable, these tests are often constrained by high cost, time requirements, and limited scalability. 3. Numerical Modeling: Computational simulations are widely accessible and flexible, making them the most common approach. However, they rely heavily on assumptions about material behavior, boundary conditions, and loading, which can reduce their accuracy compared to real-world observations. Recent advancements in Artificial Intelligence (AI) and deep learning offer an opportunity to address these limitations. Temporal Convolutional Networks (TCNs) are particularly promising, as they can analyze sequential data to learn temporal patterns, providing a computationally efficient alternative to traditional nonlinear time history analysis. This study builds on these developments, applying TCN to predict structural responses across a variety of scenarios, including both linear and nonlinear behavior.

Objectives: This research aims to bridge the gap between data-driven methodologies and structural engineering principles, improving the accuracy and applicability of AI techniques in earthquake engineering. The specific objectives are: 1. Develop a Methodology: Create a robust framework for predicting the time history of structural responses during seismic events using TCNs. 2. Test Across Diverse Scenarios: Apply the methodology to a wide range of cases, including buildings with higher mode effects and both linear and nonlinear responses, to evaluate the accuracy of TCN predictions. 3. Solve an Inverse Problem: Investigate the potential of TCNs to address the inverse problem of predicting ground motion from structural response data. 4. Integrate Structural Dynamics: Combine AI techniques with fundamental principles of structural dynamics and earthquake engineering to enhance the interpretability and physical validity of predictions. By achieving these objectives, this research seeks to provide a computationally efficient complement –or even alternative– to traditional nonlinear time history analysis.

Methodology: This study introduces a novel approach that combines advanced deep learning techniques with principles of structural dynamics to address these challenges. Specifically, it leverages TCNs, Figure 1, a state-of-the-art deep learning architecture, to predict the time history of structural responses caused by earthquakes. By integrating data-driven methodologies with engineering knowledge, the study aims to enhance predictive accuracy and provide practical tools for seismic performance assessment.

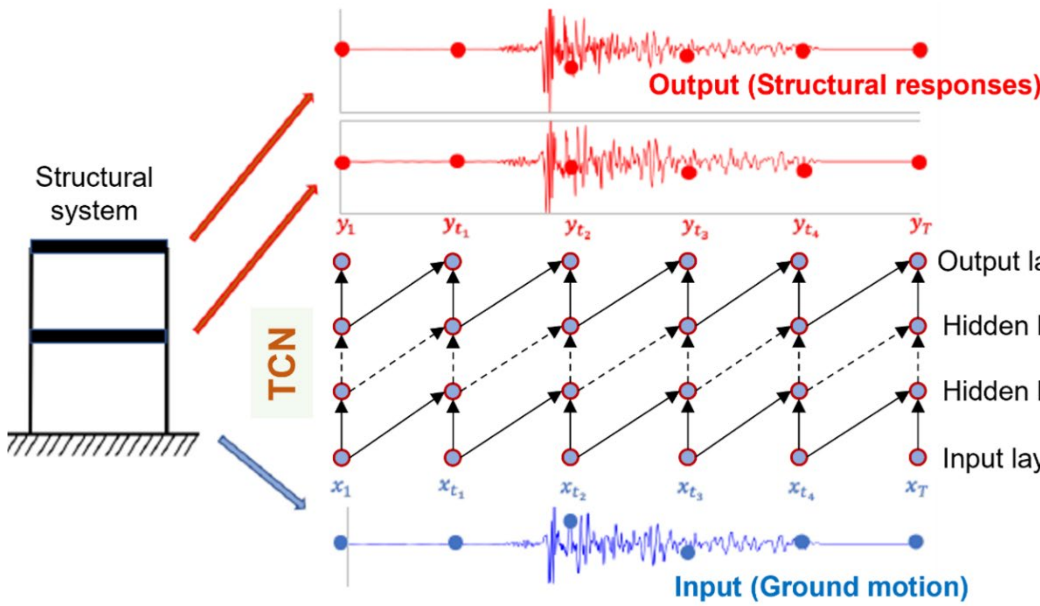

Figure 1. Schematic of TCN architecture applied to a two-story frame.

Results: The main results revolved around these areas: 1. Interpretation of results in earthquake engineering context, and 2. Comparative analysis across case studies.

Conclusions: This study demonstrated the efficacy of TCN in predicting structural responses and ground motions, offering a robust and computationally efficient alternative to traditional modeling techniques. The TCN framework successfully captured both linear elastic and nonlinear inelastic behaviors across a diverse set of case studies, including low-rise, mid-rise, and tall buildings, as well as laboratory-tested frames. Additionally, the model effectively reconstructed ground motions from structural response, addressing key challenges in regions with sparse ground motion recording stations. Key contributions of this work include: 1. A validated methodology for using TCN to predict time-history responses with high accuracy. 2. Demonstration of the model's capability to handle complex phenomena, such as period elongation and higher-mode effects. 3. Expansion of ground motion prediction techniques to under-instrumented areas, leveraging data from structural response. While the results underscore the strengths of TCN, they also highlight limitations such as data constraints and the need for improved interpretability. Addressing these challenges through the integration of Physics-Informed Neural Networks (PINNs) and enhanced training datasets could further advance the model's applicability. In summary, the TCN framework represents a significant step forward in the application of machine learning to earthquake engineering. By combining computational efficiency with predictive accuracy, TCN holds the potential to transform performance-based earthquake engineering and structural health monitoring practices, ultimately contributing to safer and more resilient infrastructure in seismic regions.

Future directions: Future work is based on effective utilization of the PINNs in the context of structural response prediction and ground motion reconstruction.

Keywords: Deep Learning; Ground Motion Reconstruction; Structural Health Monitoring; Structural Response Prediction; Temporal Convolutional Networks.