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STRUCTURAL SEISMIC RESPONSE PREDICTION WITH LSTM-BASED BIDIRECTIONAL URBAN SAFETY NETWORK USING CONDITIONAL VECTOR BASED FREQUENCY DATA

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Abstract. In this study, we present a bidirectional Urban Safety Network for regional safety management. The proposed Urban Safety Network utilizes artificial neural networks to identify relationships among the structural seismic responses of multiple buildings. To construct a network utilizing Long Short-Term Memory (LSTM), which excels in predicting sequence data, we incorporate not only the time-domain seismic responses of buildings but also conditional vectors derived from frequency domain decomposition as input information. This approach enables the prediction of structural seismic responses that account for the inherent characteristics of buildings under dynamic loads. By using frequency domain decomposition information, the inherent properties of buildings are considered, allowing for the prediction of both linear and nonlinear structural seismic responses by taking into account temporal variations in structural characteristics extracted into the conditional vectors. In the proposed LSTM-based response prediction network, the dynamic structural seismic response of a building assumed to have data loss is intentionally excluded, and only the structural seismic responses of the remaining buildings are used as inputs. The intentionally excluded structural seismic response serves as the output of the LSTM-based model. The LSTM model is trained using a dataset constructed in this manner for all buildings within the target urban area. As a result, the proposed LSTM-based Bidirectional Urban Safety Network can predict and recover lost data by utilizing the structural seismic responses of the remaining buildings, even when data from any individual building within the target set is missing..

1 INTRODUCTION

With the occurrence of significant seismic events in South Korea, such as the 2017 Pohang earthquake and the 2016 Gyeongju earthquake, demand for seismic disaster mitigation measures and assurance of seismic performance has increased. Traditionally, nonlinear behavior of individual structures can be assessed and seismic design performed through dynamic analysis techniques; however, these methods have limitations in capturing interaction effects among adjacent buildings. Consequently, interest has grown in AI-based analytical techniques—particularly artificial neural networks—that can learn complex relationships and enable response prediction for sensor-uninstrumented structures by leveraging data from neighboring buildings. Nonlinear behavior reflects structural damage beyond the elastic range, and its precise characterization is one of the key challenges in ensuring structural safety.

Numerous studies have adopted neural networks, which excel at both classification and prediction, to forecast structural responses. Zhang et al. [1] proposed an LSTM-based method for predicting nonlinear seismic responses of structures, exploiting the model's strengths in handling nonlinearity and time-series data; they incorporated K-means clustering on ground acceleration records to enhance inter-story drift predictions. Oh et al. [2] trained a neural network on relationships among sensors attached to a single structural member to predict and recover missing sensor readings—when any sensor's data is unavailable, strain measurements from the remaining sensors are used to reconstruct the missing values—by mapping one-dimensional strain data onto a two-dimensional input map via a convolutional neural network. Oh and Park [3] extended this concept to predicting seismic responses of adjacent buildings by designating the instrumented building as the reference and the building under evaluation as the target, training a CNN with the reference building's seismic responses and earthquake information as inputs and the target building's responses as outputs. However, because this approach relies on unidirectional learning from instrumented to non-instrumented buildings, it loses reliability if reference building sensors fail or become unreliable.

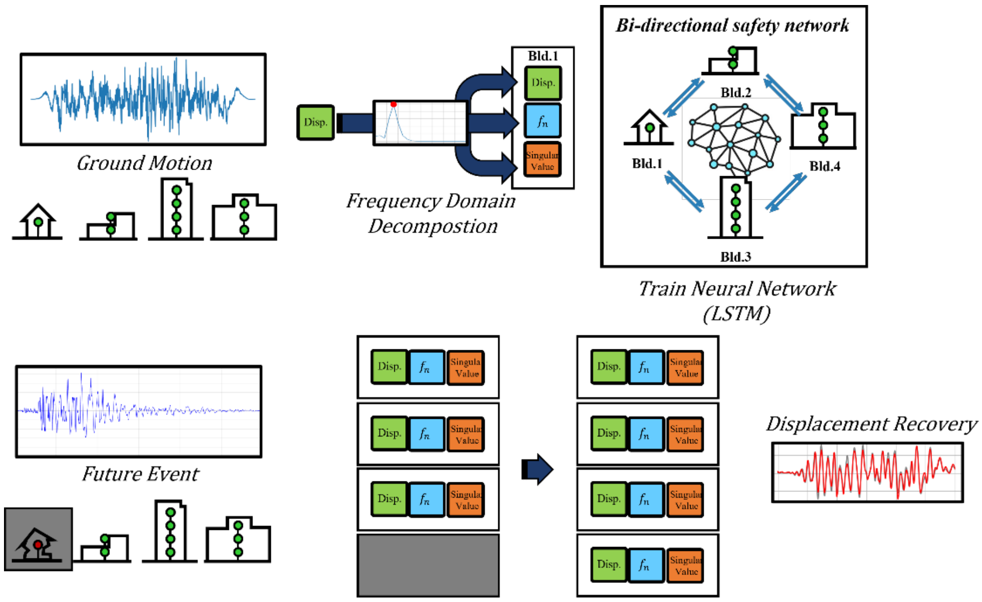

Figure 1: Research scope.

To address these limitations and achieve reliable predictions even in the presence of sensor failures or partial data loss, a bidirectional learning model is required. In this study, we propose a framework that combines a bidirectional structural network with a Long Short-Term Memory (LSTM) model and exploits time-varying natural frequencies and singular values obtained via Frequency Domain Decomposition (FDD) to improve nonlinear behavior prediction. By integrating these modal features, the proposed approach enhances the performance of Structural Health Monitoring (SHM) systems, thereby contributing to more reliable seismic design and strengthened disaster response capabilities.

2 METHODS

The overall workflow of this study is as follows. First, a numerical analysis model is established, and multiple structural models reflecting various parameters are generated. Next, for each model, dynamic analyses are performed using 20 historical earthquake records to obtain the top-story displacement of each building. Of these records, data from 18 earthquakes are used for AI model training, while the remaining two earthquakes are reserved for validation (test set).

2.1 Structural Modeling and Parameter Settings

In this study, reinforced-concrete (RC) moment frames were modeled using OpenSees. The modeling specifications were adopted from Liel et al. [4], and an eigenvalue analysis yielded a first natural period of approximately 1.975 s—very close to the reference value of 1.98 s—thereby validating our model. Thereafter, by varying column width, reinforcement ratio, span length, and number of stories, we generated four additional models whose first natural frequencies span from 0.4 Hz to 0.7 Hz in 0.1 Hz increments

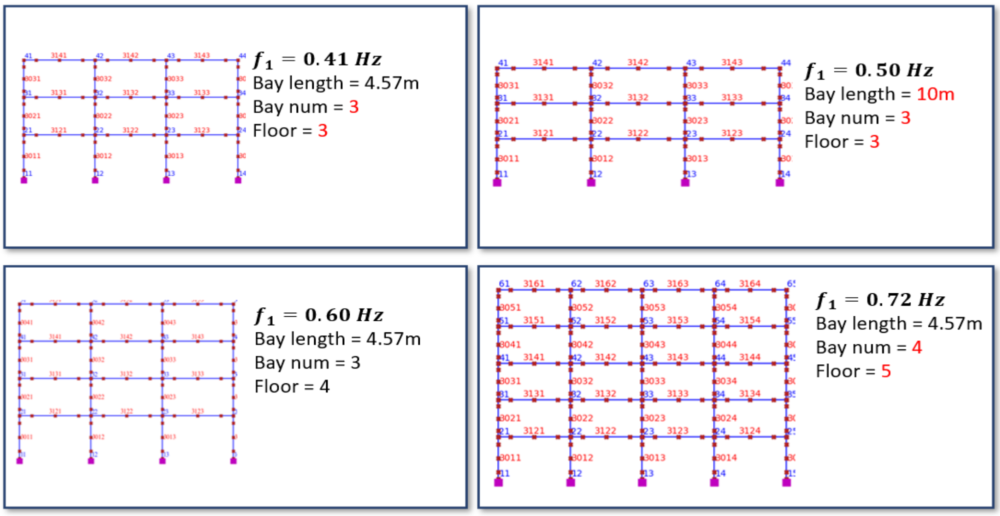

Figure 2: Example structures with diverse structural properties.

Figure 2 illustrates how, starting from the model with a 0.60 Hz first natural frequency, we adjusted the number of stories, number of bays, and bay length to create three-, four-, and fivestory RC moment frames. These four configurations exhibit first natural frequencies of 0.41 Hz, 0.50 Hz, 0.60 Hz, and 0.72 Hz, respectively.

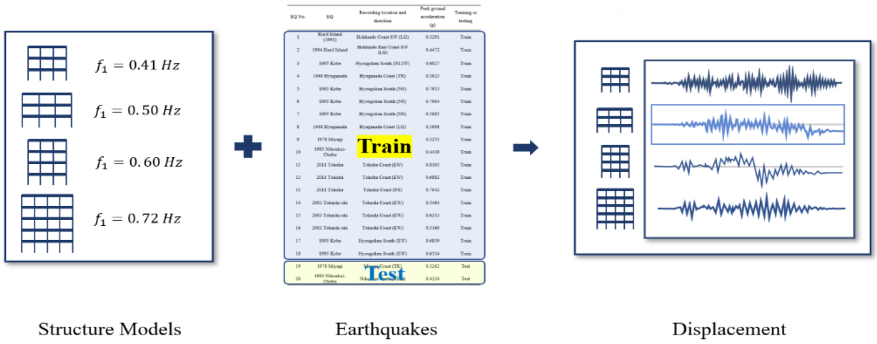

Figure 3: Generating displacement dataset for four example structures under 20 ground motions

Figure 3 depicts the procedure for obtaining top-story displacement time histories: each of the four RC moment-frame models was subjected to 20 historical earthquake records. Of these, 18 records were used for training the AI model, and the remaining two were reserved as the test set. Through this process, nonlinear response datasets were generated for all four structural configurations.

2.2 Frequency Domain Decomposition for Nonlinear Behavior

In nonlinear response, a structure's dynamic properties (stiffness, period, natural frequency, etc.) evolve over time. To capture these changes, Frequency Domain Decomposition (FDD) was applied. We performed FDD over fixed 10 s windows (1 000 data points) using an overlapping sliding-window approach to extract time-varying natural frequencies and singular values. A 10 s window provides a frequency resolution of 0.1 Hz, which balances the trade-off between decreased reliability for very short windows and loss of temporal resolution for overly long windows. Singular values and natural frequencies extracted from the displacement record via short-time FDD.

At each time step, FDD is applied to the 10 s of displacement data commencing at that step; the singular value and natural frequency extracted from that window are then assigned to the current time step. Consequently, the final 10 s of the record cannot be processed by this method. In this study, for the last 10 s interval we carry forward the modal parameters extracted at $t = T_{max} - 10$ s.

The short-time FDD results reveal that, as earthquake exposure continues, the natural period gradually decreases, indicating stiffness degradation. Because the frequency resolution is 0.1 Hz, the natural frequency curve appears in discrete steps, whereas singular values—reflecting PSD intensity—vary continuously at each time step. The final 10 s segment, where FDD cannot be applied, remains constant at the last extracted values.

2.3 Data Augmentation and LSTM Model Training

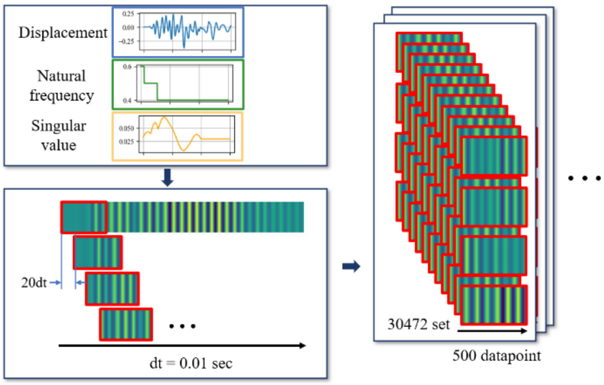

Figure. 4. Data augmentation through overlapping windows

The performance of AI models depends heavily on the quantity and quality of the training data. In this study, the generated displacement, natural frequency, and singular-value time histories were segmented into overlapping windows of length 500 points (5 s) to augment the dataset, yielding 30 742 samples. To simulate sensor loss scenarios, we constructed input sequences in which the displacement series of one arbitrarily selected building were zeroed out, with the original (nonzero) displacement series serving as the target output. During training, the model learns to impute the missing building's response by leveraging the time-series data—displacement, FDD-derived natural frequency, and singular values—from the neighboring structures. The LSTM network was configured with 12 input features and a single-output node, employing an architecture specialized for nonlinear time-series processing.

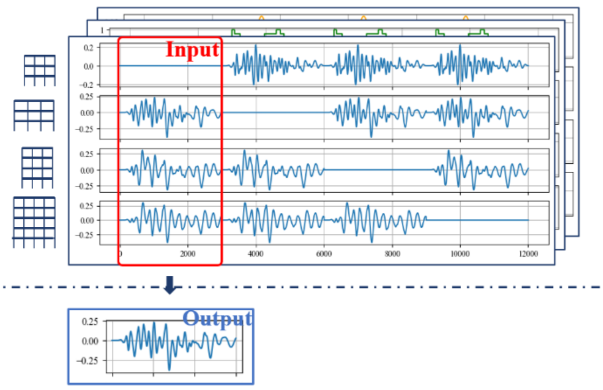

Figure. 5. Data imputation among structural network

Figure. 5 presents the entire Test-set time series concatenated end-to-end. For each sensor-loss scenario, the displacement record of the "sensor-missing" building is replaced with zeros; this zeroed sequence is fed into the network as input, while the original displacement record is used as the ground-truth output.

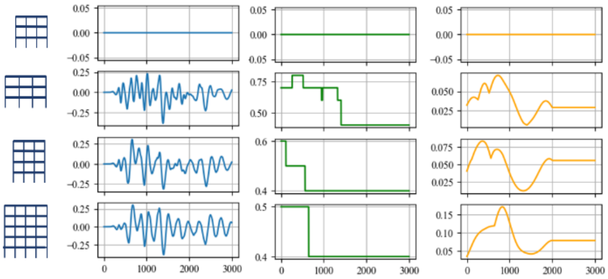

Figure. 6. Input data example for one scenario

Figure. 6 illustrates the input data for a single scenario. Assuming that Building 1's sensor is lost, the inputs consist of the nonlinear displacement time histories and the time-varying natural frequencies and singular values from the remaining three buildings.

2.3 Model Performance Validation

To evaluate whether the inclusion of FDD-derived features leads to more accurate predictions, we built two LSTM models trained on the same displacement dataset: one incorporating FDD inputs and one without.

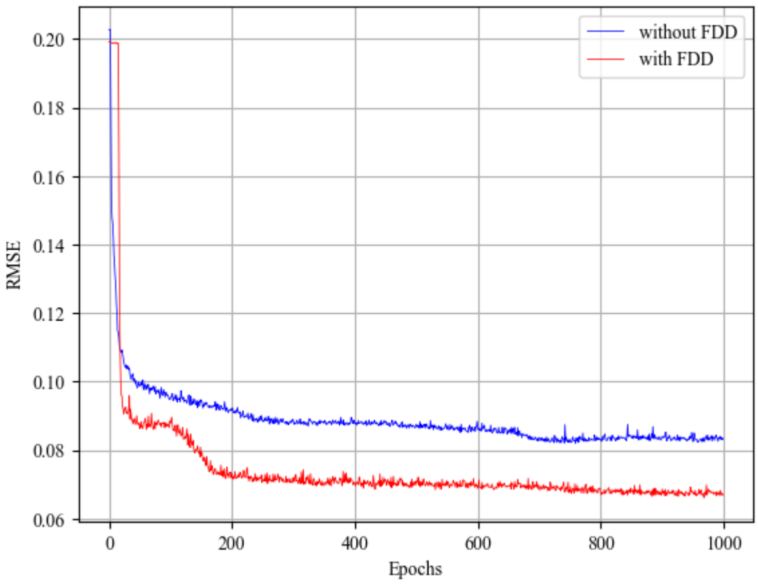

Fig. 7. Loss functions in the training of the LSTM models

After training both models under the same conditions, we compared their prediction errors on the test set. The FDD-based model consistently exhibited lower error, demonstrating that leveraging time-varying natural frequencies and singular values significantly enhances nonlinear response prediction. Moreover, analysis across multiple earthquake scenarios confirmed the bidirectional network with FDD inputs achieves notably accurate forecasts of structural nonlinear behavior.

The results confirm that incorporating frequency-domain characteristics via FDD enables the LSTM-based bidirectional structural network to stably predict responses even when sensors fail. Although the 0.1 Hz frequency resolution produces some step-like behavior in the estimated natural frequency, the continuous variation captured by singular values and other features substantially improves nonlinear-behavior prediction accuracy. This finding suggests real potential for enhancing SHM reliability and improving seismic-design precision.

4 CONCLUSION

This study proposed a method for predicting nonlinear structural responses under sensor-loss conditions by combining a bidirectional structural network with an LSTM model. By leveraging frequency-domain features (time-varying natural frequencies and singular values) extracted via FDD, the proposed approach achieved superior prediction performance compared to a model using only displacement data.

Future work will address:

- Diversifying network configurations and expanding sensor-loss and other disaster scenarios
- Developing methods to improve frequency resolution in short-time FDD windows
- Experimental validation using scaled-model tests beyond numerical simulations

ACKNOWLEDGMENT

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