A knowledge transfer LSTM model to estimate the seismic response of existing structures

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Abstract. A novel deep learning framework is proposed to rapidly and accurately predict the seismic response of a structure. By transferring the most relevant knowledge determined via an unsupervised learning technique, only two temporal ground motion records and the corresponding structural displacements are required to train and test the deep learning model. The proposed framework consists of four parts: 1) the seismic information history database; 2) the Structural Seismic Response network (SSR net); 3) an unsupervised nearest neighbor algorithm to identify the most relevant previous earthquake when a new earthquake occurs; and, 4) a knowledge transfer strategy incorporating information from the most relevant previous earthquake. To validate the novel framework, ground motion data and field structural response data measured from a building are utilized. The results show that the proposed framework can reliably predict seismic structural responses without excessive training procedures and offer significant potential in advancing seismic fragility analyses and reliability assessments.

1. Introduction

Long-term records from the National Earthquake Information Center, since about 1900, reveal that there are on the order of 20,000 earthquakes all over the world in any given year. Moreover, sixteen significant earthquakes of magnitude seven or greater are statistically expected annually. In most catastrophic earthquakes, many buildings and infrastructure experience structural damage due to the strong ground motion. Entire cities have been completely destroyed, and there have been countless casualties as a result of such catastrophic earthquakes. Much research has focused on the development of advanced design methods (Whittaker et al., 1999, Sezen and Moehle, 2004), mitigation strategies (Dyke et al., 1998, Buckle et al., 2002), and retrofitting methods (Thermou and Elnashai, 2006, Hueste and Bai, 2007). The previous approaches can mostly be divided into experimental- and numerical- or analytical-based approaches. Because of the direct measurement of unidentified phenomena, experiments have been treated as the most reliable approach in structural engineering (second to real-world measurements). However, additional experiments are required to justify this conclusion for any modifications to existing structural designs or for new loading conditions. Additional experiments are not always feasible considering the large scale of infrastructure and the expensive nature of such tests. Nonlinear dynamic analyses built upon various theoretical backgrounds are available for a wide range of structures with thousands of degrees of freedom. Extensive research based on numerical approaches has been conducted to simulate the time history of the nonlinear structural behavior and determine the seismic fragility curves for various types of infrastructure (Papantonopoulos et al., 2002, Lim et al., 2018). These nonlinear dynamic analysis methods have been extended to account for stochastic uncertainties of earthquakes and structural systems. Although such numerical methods have significantly improved the understanding of the seismic performance of buildings and infrastructure, there are still a few challenges. Assumptions made in numerical approaches may have an adverse effect on the results if they are in fact different from reality. Moreover, thousands of simulations varying the structural properties and loading conditions should be implemented to adopt stochastic uncertainties in seismic hazard analysis. A complex numerical model typically requires significant computational cost and time. In the worst case, the stability of nonlinear solutions may not be guaranteed due to the intrinsic convergence issue in the iteration procedure. An alternative way to address such drawbacks is machine learning (ML)- or deep learning (DL)-based approaches. Earlier ML studies have used support vector machines or artificial neural networks (ANNs) to estimate structural system nonlinear behaviors under quasi-static or dynamic loading conditions (Huang et al., 2003, Dong et al., 2008). However, using an ANN for estimating highly complex nonlinear dynamic behavior is often impractical because of the fixed length of the input vector and highly-complicated model architecture. The convolutional neural network (CNN) and recurrent neural network (RNN), which are more recent advancements in ML, may be more useful in this domain.

2. Literature Review

Deep neural networks have demonstrated unprecedented performance in many engineering problems. In particular, CNNs and RNNs have been gaining attention in the earthquake engineering realm. Several studies have utilized a CNN or RNN to estimate the structural response under dynamic loading conditions. There have been a few studies based on CNNs for predicting the dynamic behavior of a structure (Kim et al., 2019, Oh et al., 2020, Wen et al., 2022) and classifying seismic vibration versus ambient vibration (Liao et al., 2021). These studies have shown their proposed CNN-based models can deal with a large volume of signal data and automatically extract valuable spatial information. As can be expected, many prior studies regarding seismic responses or damage assessments have focused on RNNs or long short-term memory (LSTM) models (Huang and Chen, 2021, Xu et al., 2021) since those model architectures are specifically designed to capture sequential dependencies between input and output variables. Ahmed et al. (2022) used the overlapped data sequence to train their LSTM model. Some variations of RNN or LSTM architecture also have been reported in several studies (Li et al., 2022, Xu et al., 2022). Yu et al. (2020) and Zhang et al. (2020) embedded physics principles into DL-based approaches. Notably, Xu and Noh (2021) adopted a physics-informed DL and domain adversarial network to diagnose building damages induced by earthquakes based on the data from different buildings.

Although promising results have been reported with complicated models, additional studies should be further investigated to bridge the following research gaps. First, Generally, a large amount of data is necessary to train a complex DL-based model since it intrinsically has thousands of parameters to be trained. Secondly, low-fidelity data generated by numerical models is not helpful for accurately predicting real-world situations, and high-fidelity data from more detailed numerical models is difficult to calibrate and computationally expensive. Lastly, existing methods do not explain how to effectively deal with a new earthquake which is not represented in the utilized dataset. Based on long-term records, earthquakes have a wide variability of intensity, duration, and general appearance. Consequently, the existing DL-based approaches may not be able to provide reliable response prediction for a new earthquake outside of the established data. To address the aforementioned issues in the existing DL-based approaches in structural engineering, this study proposes a novel framework based on LSTM networks that can rapidly and precisely predict the structural response under unknown seismic loading, by integrating transfer learning (TL) and unsupervised learning. Transfer learning (TL) aims to manipulate a model trained on one domain (source domain) to provide accurate predictions in another related domain (target domain). Thus, a robust prediction model can be achieved without excessive training data and computing resources, thanks to the knowledge transferred from a pre-trained model. Although TL has shown great potential in the field of structural engineering (Pak and Paal, 2022, Pak et al., 2023), it is still most common in the CNN model architecture to share spatial features (e.g., VGG-16 or ResNet50). A few studies have applied TL to LSTM models (Tariq et al., 2020, Fong et al., 2020). When transferring knowledge from the source domain to the target domain, the performance of TL approaches depends on how similar the two domains are. Therefore, choosing an appropriate source domain closer to the target domain can maximize the performance of TL approaches. However, it can be challenging to determine the similarity between the domains, since there is no label information. In such cases, unsupervised learning, a class of ML algorithms that can learn and analyze patterns from unlabeled datasets, can intelligently provide an appropriate source domain to improve the performance of TL.

The purposes of this study are summarized as follows: (1) to propose a deep transfer learning framework for predicting the structural dynamic response without a massive volume of ground motion data; (2) to intelligently handle the correlation between recorded ground motions and a new one; and, (3) to provide a pre-trained model as a practical tool for engineers and researchers, similar to how VGG-16 or ResNet50 is heavily used in spatial feature extraction for image datasets. These three main goals can be achieved by the proposed framework consisting of four parts, and a detailed explanation of the proposed framework will be presented in Section 3.

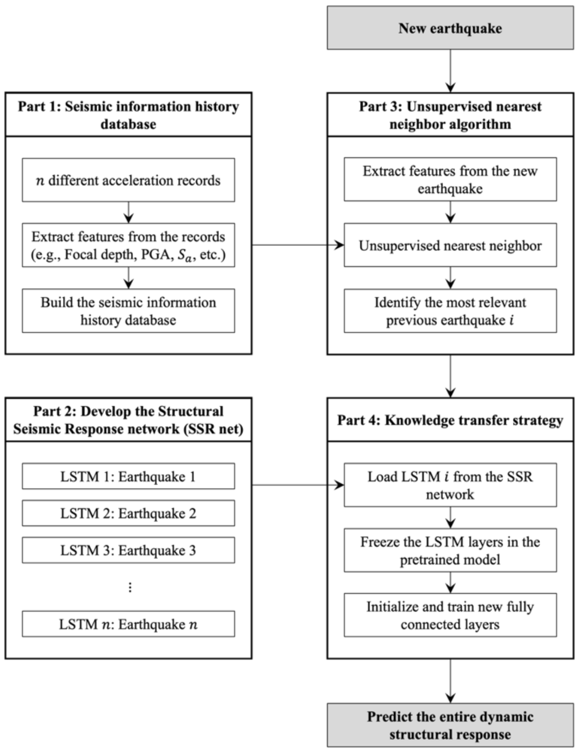


Figure 1 The overview of the proposed framework for leveraging knowledge from previous earthquakes

3. A Novel Knowledge Transfer LSTM model

In a general sense, the seismic response of a structure is affected by many factors, for example, the spatial information for the earthquake epicenter, earthquake intensity, structural characteristics, etc. Thus, most existing approaches for predicting the nonlinear structural response induced by an earthquake require a large dataset to maintain prediction performance even in an unseen earthquake. The dataset typically includes a variety of ground motions, structural responses, and material properties. However, the generalization capability of a trained model, which is its ability to appropriately handle new data, is not always ensured. In such situations, a trained model that consumed a significant amount of computational cost and time for training would be useless. By adopting transfer learning and unsupervised learning, this study proposes a novel deep learning framework to rapidly and accurately predict the seismic response of a structure in only a few seconds (from data processing to prediction). Figure 1 shows the schematic procedure of the four parts of the proposed generalized framework.

3.1 Seismic Information History Database

The aim of the first component of this framework is to build a seismic information database for a specific structure, consisting of several important values extracted from ground motions that have been previously recorded. As can be seen in Figure 1, important values are extracted from the previously recorded n different ground motions, where n is the number of ground motions that have been recorded. The extracted values are representative of each earthquake (e.g., focal depth, epicentral distance, peak ground acceleration (PGA), etc.). The database established with the extracted values in this part will be used as the input to identify the most relevant previous earthquake for a new earthquake in Part 3.

3.2 Structural Seismic Response Network (SSR net)

In the second component, a group of LSTM networks, referred to as the Structural Seismic Response Network (SSR net), is established based on the previously recorded ground motions and displacements. Instead of training the entire n different ground motions on a single LSTM network, the SSR net is composed of n different LSTM networks, each of which is trained on a ground motion during a specific earthquake and the corresponding displacements. Each LSTM network is expected to understand how to predict the time history of the structural displacement based on a single earthquake ground motion. Therefore, this approach results in much simpler and less resource-intensive LSTM networks than the models developed in previous studies. Even though an individual LSTM network in the SSR net is only trained on a specific ground motion, the ability of this framework to accurately predict the structural responses caused by arbitrary earthquakes will be explained in Parts 3 and 4. The n different LSTM networks established in this part provide a stable and reliable foundation for leveraging common knowledge to predict the structural seismic response caused by an unseen earthquake.

Data Preprocessing

The dataset fed into the i-th LSTM network in the SSR net contains the time histories of the ground motion for the i-th previous earthquake, $\mathbf{x}_i = [x_1, x_2, \cdots, x_t]^\mathrm{T} \in \mathbb{R}^{t\times 1}$, and the corresponding displacement vector, $\mathbf{y}_i = [y_1, y_2, \cdots, y_t]^\mathrm{T} \in \mathbb{R}^{t\times 1}$, where t is the number of time steps. Note that only one ground motion and the corresponding structural displacement record are needed to train and test an individual LSTM network in the SSR net. Generally, the initial format of the data acquired from sensors may not be adequate for training and testing an LSTM network, so a few steps are necessary before training or testing the model. First, to minimize adverse effects caused by scale and to easily learn the problem task, scaling the dataset is common before training or testing a model. Subsequently, the original dimension of the input and output variables, $\mathbb{R}^{t\times 1}$, should be converted to the proper format, $\mathbb{R}^{t'\times w}$, where w is the length of the input sequence. Finally, the format of the input data should be reshaped to a 3-dimensional array for the LSTM layers used in the proposed framework.

Individual LSTM Networks in SSR net

As can be seen in Figure 1, the SSR net consists of n different LSTM networks trained on n different historically recorded earthquakes. Each model is randomly initialized and trained on a single earthquake event, rather than all previous earthquakes. In every LSTM network in the SSR net, the recorded ground motion is used as the input variable, and the corresponding structural displacement record is defined as the response variable. The first 50% of the recorded ground motion is used for training, and the test set is set to be the remaining 50% of the data. Three metrics, mean square error (MSE), root mean square error (RMSE), and the coefficient of determination (R^2) are monitored during the training procedure and evaluated on the test set after training the model. Each individual LSTM model consists of an input layer, two LSTM layers, one fully connected layer, and an output layer, which were selected after conducting preliminary tests. To effectively find the optimal hyperparameters, the Bayesian optimizer (Bergstra et al., 2013) has been implemented. According to the hyperparameter tuning results, the number of neurons in each layer and the length of the input sequence, w, can be determined. The model architecture determined by the hyperparameter tuning process is consistently maintained for the n LSTM networks in the SSR net. The model architecture may appear oversimplified to provide accurate predictions on an unseen earthquake. Each individual LSTM network, however, is only expected to learn about a single earthquake event. The generalized prediction ability to unknown earthquakes will be achieved by transferring the acquired knowledge across the individual earthquakes. Thus, such a simple model architecture with a few layers is enough.

3.3 Unsupervised Nearest Neighbor Algorithm

To ensure the generalization capabilities of the proposed framework, the aim of Part 3 is to identify the most relevant previous earthquake when a new earthquake occurs. Once the most relevant previous earthquake i, is selected, knowledge acquired from earthquake i will be transferred to predict the structural displacement caused by the new earthquake. Thus, the previous earthquake i , should be appropriately chosen from all n previously recorded earthquakes. First, similar to the procedures introduced in Part 1, several important values are extracted from the new earthquake that are representative of the new earthquake ((e.g., focal depth, epicentral distance, peak ground acceleration (PGA), etc.). Subsequently, an ML model trained on the seismic information history database established in Part 1 is employed to decide the most relevant previous earthquake to the new one. Because there is no response variable quantifying how similar or dissimilar earthquakes are, the unsupervised nearest neighbor (UNN) algorithm in the proposed framework identifies the most relevant previous earthquake in the high-dimensional Euclidean space. The UNN algorithm can be mathematically represented as:

$$unn(\mathbf{x}) = \arg \min_{i=1,\cdots,n} \|\mathbf{x} - \mathbf{x}_i\|_p \tag{1}$$

where $\mathbf{x}_i$ is the input vector, $\mathbf{x}$ is the test instance, and $\|\cdot\|_p$ is the p-norm of a vector.

Based on Equation (1), the Euclidean distance ($p = 2$) is computed between the new earthquake and every other earthquake in the seismic information database. The algorithm appropriately selects the most relevant previous earthquake i, and the LSTM network trained on the earthquake i will be used as a source LSTM network in Part 4.

3.4 Knowledge Transfer Strategy

The generalized prediction ability is the most critical component of the trained LSTM network in earthquake engineering because it should maintain good performance when a new earthquake occurs. One problem is that the new earthquake will produce new ground motions and corresponding structural displacements that have never been experienced before. So far, the individual LSTM network in the SSR net ensures the ability to predict the structural displacement induced by a single ground motion. However, due to the intrinsic variability of tectonic activity and the lack of training data, it is still challenging for a prediction model to learn everything associated with the earthquake ground motion and the corresponding structural displacements. Thus, an individual LSTM network in the SSR net may not work well when a new earthquake occurs. Such a drawback can be resolved by adopting the knowledge transfer strategy developed in this work. The purpose of Part 4 is to maintain or increase the performance of the proposed framework for an unseen earthquake event. Although no individual LSTM model in the SSR net will be trained on the unseen earthquake, the proposed framework is expected to accurately predict the structural displacement record by transferring knowledge from the most relevant previous earthquake identified in Part 3. In this part, the model parameter-based transfer strategy has been utilized when transferring knowledge gained from the most relevant earthquake. Such a procedure assumes that a new earthquake and the most relevant earthquake have a great deal in common, or at least to some extent. Therefore, the underlying relationship between the most relevant previous earthquake and the corresponding displacement record can be a reliable foundation for predicting the structural displacement when a new earthquake occurs. The knowledge information in the i-th LSTM network, which is trained on the most relevant earthquake event, i, is utilized to predict the structural displacements induced by a new earthquake. Thanks to the knowledge transfer strategy in the proposed framework, an LSTM model for a new earthquake can easily build a generalized prediction from the LSTM network trained on the most relevant previous earthquake. The transferred LSTM layers are frozen during the remaining procedures of the proposed framework since the long-term dependencies of two earthquakes are assumed to be sufficiently correlated with one another. On the other hand, a fully connected layer is randomly initialized and placed after the transferred LSTM layers. By virtue of those transferred layers, a substantial portion of the parameters in the network does not need to be trained from scratch. Therefore, the proposed framework can significantly improve computational efficiency and reduce the number of training samples needed to obtain an accurate predictive model.

4. Case Study

The proposed framework's robustness was verified by real-world earthquake records provided by the Center for Engineering Strong Motion Data (CESMD) (Haddadi et al., 2008). An existing five-story building in San Bernadino, California was chosen to evaluate the performance of the proposed framework. The acceleration time history recorded at the ground level is fed into an LSTM network, and the trained LSTM network is expected to precisely estimate the dynamic displacements caused by an unseen ground motion. To monitor the structural seismic response, ten accelerometers are located on the basement, third, and roof floors in different directions. A more detailed description of the structural configuration, sensor locations, and their orientations is shown in Figure 2. This RC building has been exposed to several strong ground motions, and the measured accelerations with the corresponding structural displacement records are available through the CESMD website. In this study, the earthquake on June 10, 2016, was assumed as the new earthquake (the target earthquake), and the proposed framework is implemented by following the procedures introduced in Section 3.

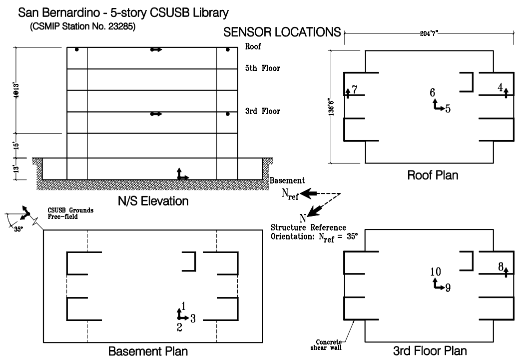


Figure 2 Structural configuration and sensor locations in the five stories building

The first step is to establish the seismic information history database for this building. The statistics of the seismic information history database for the five-story RC building are listed in Table 1. The second step is to establish the SSR net introduced in Section 3.2. Each LSTM network in the SSR net is specialized for an individual earthquake that has been experienced before. Based on the hyperparameter tuning results, the most stable and highest prediction can be found when the length of the input sequence, w is 5, the number of units in the first LSTM layer is 100, the number of units in the second LSTM layer is 50, and the number of units in a fully connected layer is 10. Ten LSTM networks are developed for each earthquake since ten sensors are located throughout the building. Thus, each network is expected to accurately predict the structural displacements measured from an individual sensor. The UNN algorithm introduced in Section 3.3 has confirmed that the earthquake on Jul 07, 2010 (the source earthquake) is the most relevant and similar earthquake to the target earthquake. Thus, in Part 4, knowledge acquired from the source earthquake is transferred into a new LSTM network to predict the seismic response caused by the target earthquake. By virtue of the transferred knowledge, the number of parameters that should be trained can be remarkably reduced from 71,521 to 521. Furthermore, notably, only 5% of the acceleration time history was used to fine-tune the LSTM network with transferred knowledge, which would be impossible if a conventional LSTM network was used. The remaining 95% of the time history sequence was used to evaluate the performance of the proposed framework.

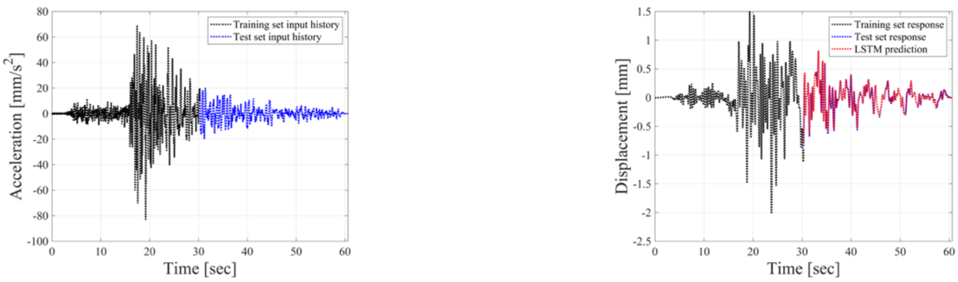
Table 1 Statistics of the seismic information history database for the five stories RC building

Parameter	Unit	Average	Standard deviation	1st quartile	3rd quartile
Magnitude		5.225	1.091	4.400	6.025
Focal depth	km	9.582	4.517	6.975	13.075
Epicentral distance	km	79.543	69.404	28.050	112.800
Ground PGA	g	0.023	0.027	0.008	0.022
Acceleration Peak	g	0.015	0.015	0.007	0.015
Velocity Peak	mm/s	0.921	1.071	0.283	0.950
Displacement Peak	mm	0.400	1.222	0.000	0.100
S_a at 0.3 sec	g	0.027	0.026	0.009	0.033
S_a at 1 sec	g	0.008	0.010	0.002	0.012
S_a at 3 sec	g	0.001	0.001	0.000	0.001
Structure PGA	g	0.076	0.091	0.024	0.093

To more comprehensively evaluate the performance of the proposed framework, peak values in each vibration cycle were extracted from the entire displacement time history and compared with those values precited via the proposed framework. When comparing the measured and predicted peak values, the symmetric mean absolute percent error (SMAPE) is additionally considered. The performance of the LSTM network designed for the source earthquake is summarized in Table 2. Since the results showed accurate predictive performance, the knowledge from this network will be a valuable resource to predict the displacements caused by the target earthquake. This hypothesis is well demonstrated based on the results listed in Table 2, which show the performance of the LSTM network designed for the target earthquake. According to the comparison of time histories at Sensor 5, which is depicted in Figure 3 and Figure 4, the proposed methodology has shown outstanding performance. It should be noted that Sensor 5 has the lowest R^2 value. Interestingly, such a remarkable performance can be achieved with only 5% of the acceleration history along with the transferred knowledge from the LSTM network trained on the most relevant earthquake. Because of the transferred knowledge, the computational cost can be drastically reduced, and the time history of the displacement can be predicted in just a few seconds.

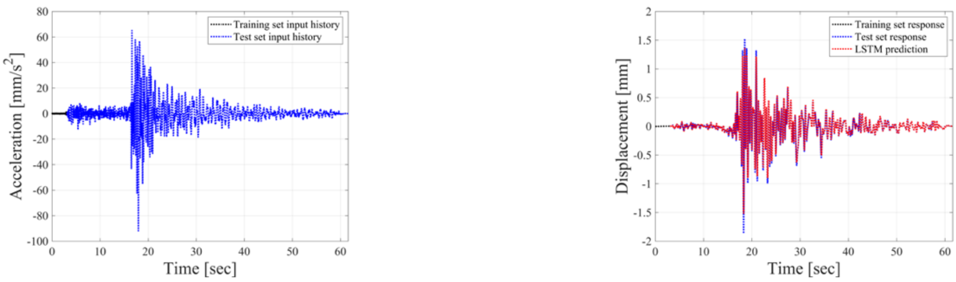
Table 2 Prediction results for the source and target earthquakes

Domain	Input sensor	Output sensor	Entire history		Peak values		
			RMSE [mm]	**R^2**	**RMSE [mm]**	**Pred/True**	**SMAPE [%]**
Source earthquake	1	1	0.005	0.999	0.007	0.979	2.297
		4	0.012	0.998	0.013	1.007	2.493
		6	0.013	0.997	0.014	0.970	3.767
		7	0.008	0.998	0.007	0.995	2.608
		8	0.006	0.999	0.006	0.995	1.756
		10	0.009	0.998	0.013	1.007	3.307
	2	2	0.004	0.997	0.008	0.960	4.123
	3	3	0.004	0.999	0.005	0.999	2.029
		5	0.009	0.998	0.013	0.983	3.638
		9	0.010	0.996	0.014	0.965	4.600
Target earthquake	1	1	0.012	0.987	0.023	0.960	7.308
		4	0.071	0.979	0.061	1.077	7.469
		6	0.054	0.976	0.055	1.024	6.381
		7	0.039	0.976	0.038	0.993	2.842
		8	0.021	0.990	0.016	1.040	4.289
		10	0.022	0.984	0.029	1.072	7.139
	2	2	0.005	0.995	0.012	1.025	5.408
	3	3	0.011	0.991	0.017	0.973	3.721
		5	0.037	0.975	0.050	0.981	3.928
		9	0.020	0.980	0.026	0.990	1.992



(a) Time history of acceleration (b) Time history of displacement

Figure 3 Comparison of the measured and predicted time history at Sensor 5 during the source earthquake



(a) Time history of acceleration (b) Time history of displacement

Figure 4 Comparison of the measured and predicted time history at Sensor 5 during the target earthquake

5. Conclusions

The proposed framework provides reliable and efficient predictions for the displacement time history caused by unknown earthquakes. It takes only a few seconds to conduct the entire procedure, including training. Furthermore, the proposed methodology is flexible to integrate as many available earthquake records as possible, enabling straightforward integration of the most helpful knowledge for a new earthquake. Therefore, it can be very practically implemented without rigorous training of a model from scratch in each instance. As more earthquake records are included in the seismic information history database, the performance of the proposed framework will be enhanced. This study has significant potential in seismic fragility or reliability assessments for any type of structure. Without performing nonlinear time history analyses, engineers will be able to effectively estimate the dynamic response of a structure caused by ground motions.

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