STRUCTURAL RESPONSE PREDICTION USING DEEP NEURAL NETWORKS

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Abstract

This paper presents a methodology to obtain the time history of the structural response using the Temporal Convolutional Network, a deep learning method. The presented methodology, in conjunction with sensor data from instrumented buildings, facilitates the prediction of the response in future earthquakes without the need for a structural analysis model. In this way, a computationally effective complement, or even alternative, to standard nonlinear time history analysis is possible. The applications of the developed method for different cases, including available number of records, buildings with higher mode effects, and linear and nonlinear response, are explored using accelerometer data from buildings instrumented by the California Strong Motion Instrumentation Program. Fundamental concepts of structural response and structural dynamics are used to guide the development of the training datasets and to explain the predictions. Furthermore, interpretation of the results is presented using earthquake engineering concepts.

Introduction

There are three fundamental methods used to determine the dynamic response of structures, namely, (a) installing sensors on real structures, (b) testing physical models of the structures in the laboratory, and (c) analyzing the numerical models of structures using computational methods. Among these methods, the first is the most realistic as it is based on the measurements from the real structures. However, there is scarcity of instrumented real structures. Laboratory testing also provides realistic information when the tests are conducted on accurate physical models of the entire structure or its components. Drawbacks of this method are time, cost, and laboratory space constraints. Based on the accuracy of the employed mathematical assumptions, the third method is relatively less realistic compared to the first two. However, it is the most common and convenient approach because of the availability of the many computational platforms to conduct the analysis.

This paper aims at developing a methodology to obtain the time history of the structural response using a deep learning approach, namely the Temporal Convolutional Network (TCN). When the developed methodology is adopted in conjunction with sensor data from instrumented

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buildings, it can facilitate the prediction of the response in future earthquakes without the need for a structural analysis model. In this way, the proposed methodology can complement or even provide a computationally effective alternative to nonlinear time history analysis. The applications of the developed method are presented to assess the minimum number of records for accurate training, and to study buildings with linear and nonlinear response and higher mode effects. In all applications, accelerometer data from buildings instrumented by the California Strong Motion Instrumentation Program (CSMIP) are used.

There has been a limited number of studies in the literature to predict the structural response using deep learning. Some of these studies focused on predicting only the peak response (Zhong et al., 2023). Although the peak response is important in design, assessment, and Performance-Based Earthquake Engineering (PBEE), the entire response history provides a more complete description of the structural behavior. One particular use of the entire response history is detection of the existence, severity, and location of damage in Structural Health Monitoring (SHM), where the peak response is generally insufficient for this purpose (Muin and Mosalam, 2017, 2018; Park and Ang, 1985, Park et al., 1985). Considering the importance of predicting the entire response history, there has been a few studies focused on predicting the entire response using machine learning (e.g., Chen et al., 2023; Zhang et al., 2019; Kundu and Chakraborty, 2020; Li and Spence, 2020). These studies focused on either a structural component or a single instrumented building and have not provided detailed physical explanations of the data-driven predictions. This paper applies the developed methodology to several instrumented buildings with different characteristics and attempts to explain the results using concepts of structural dynamics. Furthermore, interpretation of the results is presented using earthquake engineering concepts.

Following this introduction, the paper provides a brief overview of the adopted TCN, followed by an explanation of the metrics used to assess the accuracy of the predictions. Subsequently, the paper discusses the linear response predictions of instrumented mid-rise buildings governed by the fundamental mode of response and a tall building with higher mode effects. This is followed by investigating the nonlinear response predictions. Finally, conclusions and future studies are discussed.

Temporal Convolutional Network

The TCN was proposed by Lea et al. (2017) and is a powerful and innovative deep learning architecture designed for processing sequential data, particularly for time-series analysis and natural language processing tasks. TCNs are built upon the Convolutional Neural Networks (CNNs) but they can be adapted to model temporal dependencies in sequential data, making them suitable for tasks which require understanding patterns and trends over time. TCNs employ a stack of one-dimensional convolutional layers to efficiently learn dependencies across different time steps. This design allows TCNs to utilize parallel computing, which makes them efficient and fast to train. TCNs have gained popularity due to their ability to capture long-range dependencies in sequential data without suffering from the vanishing gradient problem often encountered by other deep learning methods, like Recurrent Neural Networks (RNNs). They have been successfully applied in various domains, such as natural language processing, speech recognition, and sensor data analysis.

Accuracy Evaluation Metrics

The metrics used for evaluating the accuracy of the predictions of the adopted TCN are: 1) correlation coefficient, 2) probability distribution of the errors, 3) errors in the peak response, 4) frequency contents of the response (obtained from the response spectrum or the Fourier amplitude spectrum), and 5) Cumulative Absolute Velocity (*CAV*). The first two metrics are statistical parameters, where the correlation coefficient and the error at time step *i* are defined with Equations 1 and 2, respectively. As discussed earlier, the peak response is commonly used in design, assessment, and PBEE. Therefore, it needs to be predicted accurately. The third metric focuses on the accuracy of the prediction of the peak response (Equation 3). Comparisons of the frequency contents of the true and predicted responses provide fundamental insights into how the predictions can be improved, e.g., if the dominant frequency in the response is not captured properly, this indicates that the natural frequencies of the building are not "learned" properly by the TCN providing guidance on how to improve the predictions, as discussed later. Finally, *CAV* (Equation 4) is shown to be a reliable indicator of damage (Muin and Mosalam, 2017), which needs to be predicted accurately for any consequent detection of damage from the predicted response using SHM.

$$\rho = \frac{\sum_{i=1}^{i=n}\left(y_i^{real}-\bar{y}^{real}\right)\left(y_i^{predicted}-\bar{y}^{predicted}\right)}{\sqrt{\sum_{i=1}^{i=n}\left(y_i^{real}-\bar{y}^{real}\right)^2\left(y_i^{predicted}-\bar{y}^{predicted}\right)^2}} \tag{1}$$

$$err_i = \frac{y_i^{real}-y_i^{predicted}}{\max\left(y_i^{real}\right)} \tag{2}$$

$$err\_peak_i = \frac{\max\left(y_i^{predicted}\right)-\max\left(y_i^{real}\right)}{\max\left(y_i^{real}\right)} \tag{3}$$

where, y_i^{real} and $y_i^{predicted}$ are respectively the true and predicted responses at time step i, $\bar{y}^{real}$ and $\bar{y}^{predicted}$ are the mean values of the true and predicted responses, respectively, *n* is the number of time steps, and max indicates the peak response.

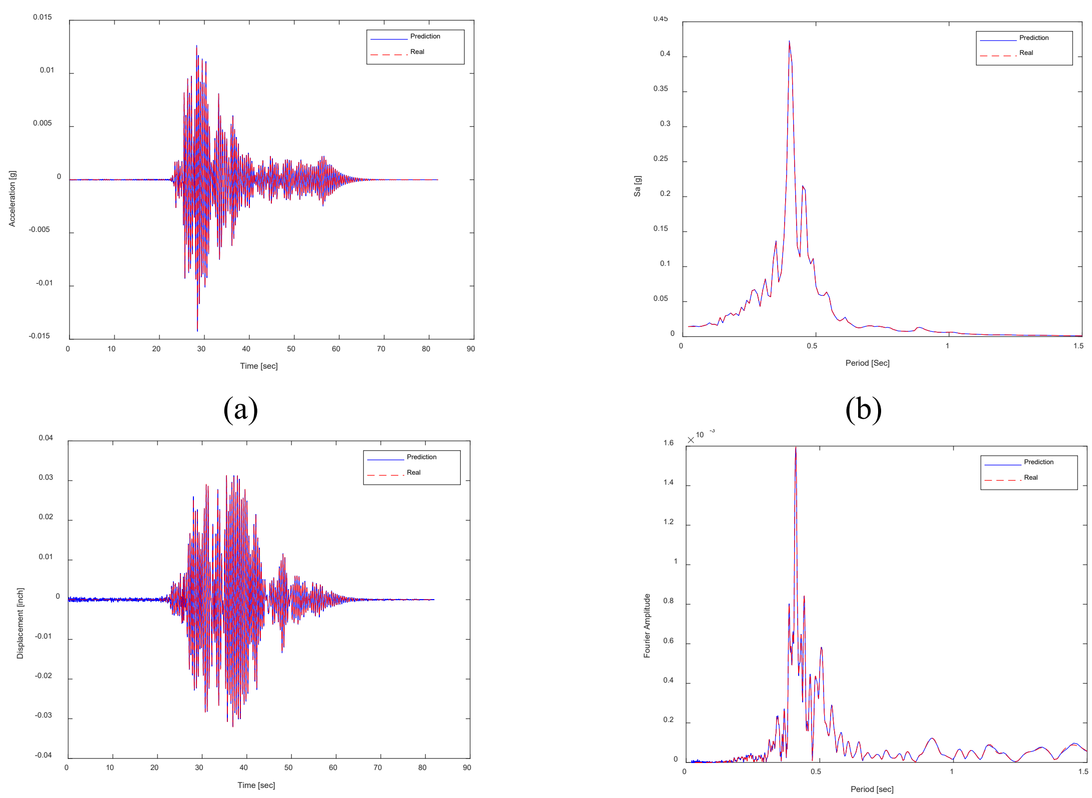
$$CAV(T) = \int_{t=0}^{t=T}|\ddot{u}(t)|dt \tag{4}$$

where *T* is the current time at which *CAV* is computed (typically it is the entire duration of the time series) and $\ddot{u}(t)$ is the response acceleration at a given time *t*.

Linear Elastic Response Prediction of Low and Mid-Rise Buildings

Single Degree of Freedom (SDOF) Numerical Model

For verification of the developed TCN model and its implementation, the displacement and acceleration responses of a linear elastic SDOF system are predicted and compared with the actual computed results. For this purpose, a SDOF system is considered with a period of 0.41 sec and damping ratio of 2.35% and is trained using 11 motions and tested using 7 motions. The chosen period and damping ratio are those identified for the San Bernardino 6-story hotel in the NS direction, which is discussed next. The motions used for training and testing are the recorded ground and response accelerations of the same hotel building. Using the metrics discussed earlier, both displacement and acceleration predictions are very accurate with a correlation coefficient of 99.99% over the 7 tested motions, verifying the implementation of the TCN method. The predicted acceleration and displacement time histories are compared with the computed ones (referred to as real) for one of the test motions (Fontana Earthquake of 25 July 2015) in Figure 1, along with the comparison of the frequency contents, showing a very close match.



(a) (b) (c) (d)

Figure 1. Comparison of predicted and computed (a) acceleration time history, (b) frequency content from acceleration, (c) displacement time history, and (d) frequency content from displacement, for the linear elastic SDOF system in one of the test motions (Fontana Earthquake of 25 July 2015).

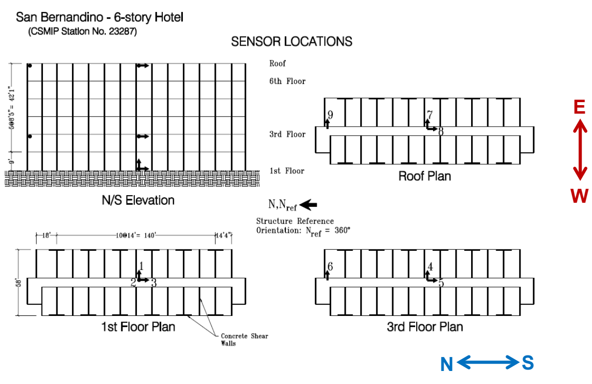
The response of an elastic SDOF system subjected to ground motions depends only on: (a) the natural period of the SDOF system, (b) the damping ratio of the SDOF system, and (c) the applied ground motion, which are considered as the three features to be learned by the TCN for subsequent predictions (Table 1). The highly accurate predictions of the SDOF system indicate that the TCN model is successful in learning the period and the damping ratio (Features 1 and 2, respectively, in Table 1) and the training model has enough variety of the ground motions for the model to learn the response of this system when subjected to different excitations (Feature 3 in Table 1).

Table 1. Features that characterize the earthquake response of different structural systems.

System	Feature 1	Feature 2	Feature 3
Linear Elastic SDOF	Natural period	Damping ratio	Ground motion
Low and Mid-rise Buildings Linear Elastic	First mode period	Varying first mode damping ratios	
Tall Buildings Linear Elastic	Multiple modes periods	Multiple modes damping ratios	
Low and Mid-rise Buildings Nonlinear	First mode period elongation	Varying first mode damping ratios	

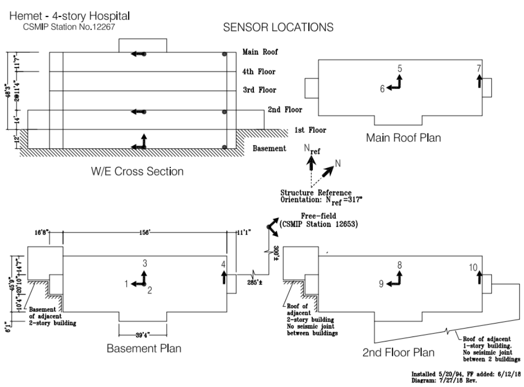
6-Story Reinforced Concrete (RC) Hotel Building in San Bernardino

After this fundamental step of demonstrating that the implemented TCN model is successful in predicting the response history of an elastic SDOF system numerical model, predictions are performed for the linear elastic response of two instrumented CSMIP buildings (Figure 2). The first is a 6-story RC Shear Wall (RCSW) hotel building in San Bernardino, California, designed in 1970. This building is instrumented with 9 accelerometers, three on each of the 1st, 3rd, and 6th (roof) floors, and has recorded multiple seismic events from 1987 to 2018. The EW and NS direction responses of this building are studied in this section for the linear response and in a later section for the nonlinear response. In the EW direction, Channel 1 on the 1st floor is used as input, and Channels 4 and 7, on the 3rd floor and roof, respectively, are used as outputs. It is noted that the 1st floor boundary conditions are fixed. Therefore, Channel 1 directly represents the ground motion input to the structure. There are a total of 26 events recorded by this station, where records 1 to 11 and records 12 to 18 are respectively used for training and testing, Table 2, which lists the Peak Ground Acceleration (PGA) and Peak Floor Acceleration (PFA) for the EW and NS directions. As shown in Figure 3, the motions used in the training set cover the entire range of shaking levels recorded on this building. It is possible to use another Intensity Measure (IM) to define the horizontal axis of this figure, however the PGA is used for simplicity as the objective is not to use the IM for quantitative damage detection or other purposes, but it is rather to characterize the training and testing set motions on a plot with experienced shaking levels. As discussed later, 11 motions were sufficient for predicting accurate results for the linear elastic response in the EW direction, and more motions were utilized for capturing the nonlinear response in the NS direction.



(a)

(b)



(c)

(d)

Figure 2. Sensor locations and photographs of (a, b) 6-story building at San Bernardino and (c, d) 4-story building in Hemet.

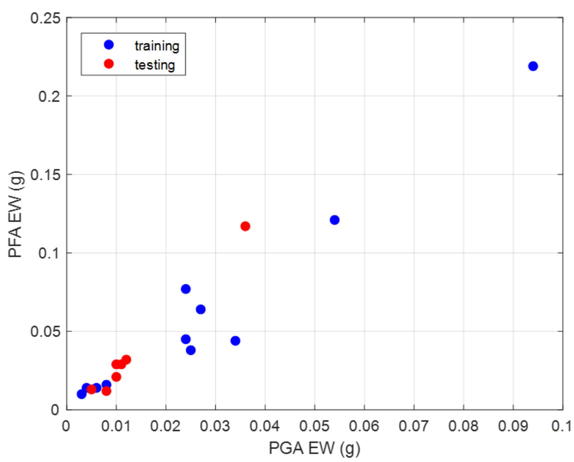


Figure 3. The training and testing sets used for the San Bernardino 6-story building EW direction.

For the input-output pairs, two cases are used: (i) the unprocessed accelerations, and (ii) CSMIP processed accelerations that use bandpass filters and baseline correction. Accuracy of the training and testing sets for both cases, computed using the correlation coefficient (Equation 1), are reported in Table 3. The training accuracy of 0.97 for both the unprocessed and processed data shows that there are no major outliers in the set. From the testing set accuracies, it is observed that training of both unprocessed and processed data result in successful predictions. However, using the unprocessed data results in more accurate predictions, although the difference is small. This observation is not specific to this building and has been observed for the other two studied instrumented buildings. The explanation of this observation is that the processed output is not necessarily the direct result of the processed ground motion input. Therefore, the relationship between the input and output deviates slightly from true physics when processed data is used for input and output. Considering the higher accuracy using the unprocessed data, the rest of the paper reports the results that use unprocessed data.

Table 2. San Bernadino 6-story hotel training and testing records.

#	Earthquake Name	PGA NS (g)	PFA NS (g)	PGA EW (g)	PFA EW (g)
1	Borrego Springs Area Earthquake of 07 Jul 2010	0.053	0.2	0.024	0.045
2	Devore Earthquake of 29 Dec 2015	0.049	0.106	0.054	0.121
3	Fontana Earthquake of 15 Jan 2014	0.04	0.089	0.034	0.044
4	Inglewood Area Earthquake of 17 May 2009	0.008	0.027	0.008	0.016
5	Ocotillo Area Earthquake of 14 Jun 2010	0.006	0.022	0.006	0.014
6	San Bernardino Earthquake of 08 Jan 2009	0.058	0.168	0.094	0.219
7	Beaumont Earthquake of 14 Sep 2011	0.02	0.041	0.027	0.064
8	La Habra Earthquake of 28 Mar 2014	0.021	0.033	0.024	0.077
9	Loma Linda Earthquake of 13 Mar 2017	0.022	0.05	0.025	0.038
10	Ontario Earthquake of 20 Dec 2011	0.004	0.009	0.004	0.014
11	Yorba Linda Earthquake of 07 Aug 2012	0.009	0.016	0.003	0.01
12	Beaumont Area Earthquake of 16 Jan 2010	0.006	0.013	0.005	0.013
13	Big Bear Lake Earthquake of 05 Jul 2014	0.01	0.03	0.011	0.029
14	Fontana Earthquake of 25 Jul 2015	0.011	0.025	0.01	0.021
15	Loma Linda Earthquake of 08 Oct 2016	0.01	0.017	0.008	0.012
16	Devore Earthquake of 28 Apr 2012	0.017	0.043	0.01	0.029
17	Loma Linda Earthquake of 04 Mar 2013	0.007	0.017	0.012	0.032
18	Chino Hills Earthquake of 29 July 2008	0.05	0.113	0.036	0.117

Table 3. Accuracy of the San Bernardino 6-story building acceleration predictions in the E-W direction.

Data	Correlation Coefficient	
	Training Set	Testing Set
Unprocessed	0.97	0.91
Processed	0.97	0.88

The high accuracy indicated by the correlation coefficient is also supported by the narrow probability distribution of the normalized error (Equation 2) with the mean close to zero (Figure 4). The predicted acceleration time histories at the 3rd and 6th (roof) floors are compared with the recorded time histories for one of the test motions (Fontana Earthquake of 25 July 2015) in Figure 5, along with the comparison of the frequency contents, showing a close match at both floors in the time and frequency domains. Comparison of peak values indicated an error of -4.80% and -4.94% according to Equation 3.

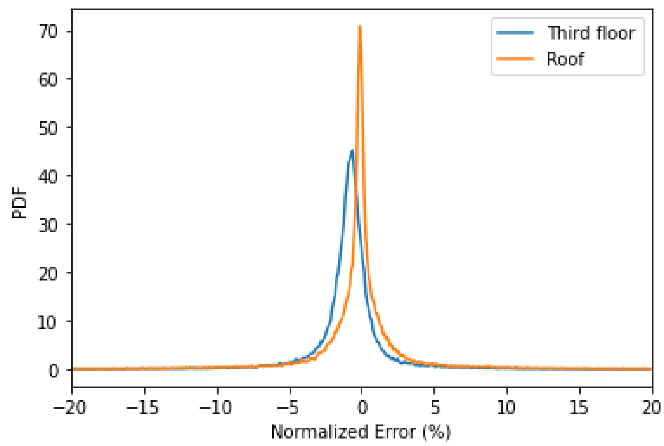


Figure 4. Narrow probability distributions of the normalized prediction errors in the EW direction at the 3rd and 6th (roof) floors of the San Bernardino 6-story building.

It is inevitable in real instrumented buildings to prevent the peak prediction errors completely. Therefore, the errors in the peak predictions can be interpreted from the following two perspectives related to their use in earthquake engineering:

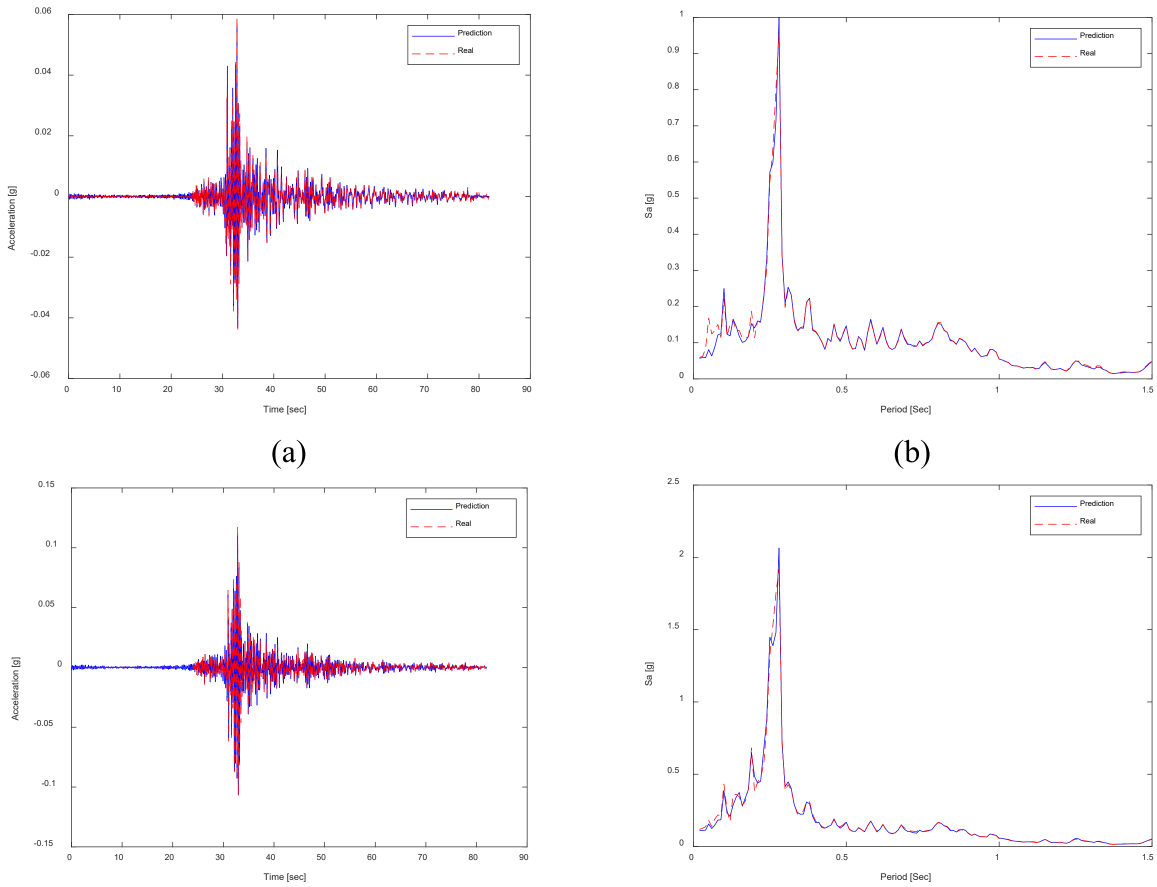
(1) Epistemic uncertainty is due to errors in mathematical modeling, where the error due to the TCN model is an example. Therefore, in design and assessment of buildings, the results of a single ground motion are not used. ASCE7-22 (2022) requires 11 motions for nonlinear dynamic analysis and a varying number of ground motions (e.g., 20) is essential for probabilistic PBEE (Günay and Mosalam, 2013). Accordingly, in addition to the individual motion results, comparison of the probability distributions of the true and predicted responses are helpful for evaluating the accuracy of the predictions. The PFA at the 3rd and 6th floors are assumed to follow a lognormal probability distribution, which are computed using the peak values of all test motions and plotted for the true and predicted accelerations in Figure 6. It is observed that the resulting probability distributions are close to each other at both floors, illustrating the accuracy of the predictions from this perspective.

(2) The relationship between estimated peak response and damage is obtained using fragility functions. Another way of evaluating the peak prediction is the comparison of damage probability corresponding to the predicted and real results. As an example, the fragility function of a cooling tower, assumed to be located at the roof of the San Bernardino 6-story hotel building, is shown in Figure 7. The damage state that this fragility function represents is that the cooling tower and attached piping are damaged. It is defined by a mean of 0.5g and a

dispersion of 0.4 (FEMA-P58, 2018a, b). The probability of exceedance (POE) of this damage state, using the predicted and true 6th floor PFA for the Chino Hills Earthquake of 07 Aug 2012 (Figure 5), are 5.9% and 6.8%, respectively. In addition to the damage prediction for this single event, the POE in the fragility function [($POE(DM|PFA)$, Figure 7] can be integrated with the probability of true and predicted PFA [$p(PFA)$, Figure 6b] using the total probability theorem, resulting in the POE of the damage state considering all the test motions [$POE(DM)$, Equation 5]. It is noted that the probability of the damage state is equal to POE because only one damage state is used herein. Therefore, the resulting probability of damage to a cooling tower located at the roof of the 6-story San Bernardino hotel building, considering all 7 test motions, is 0.33% and 0.30%, respectively, when the true and predicted peaks are used.

$$POE(DM) = \sum_{PFA} POE(DM|PFA)p(PFA) \tag{5}$$

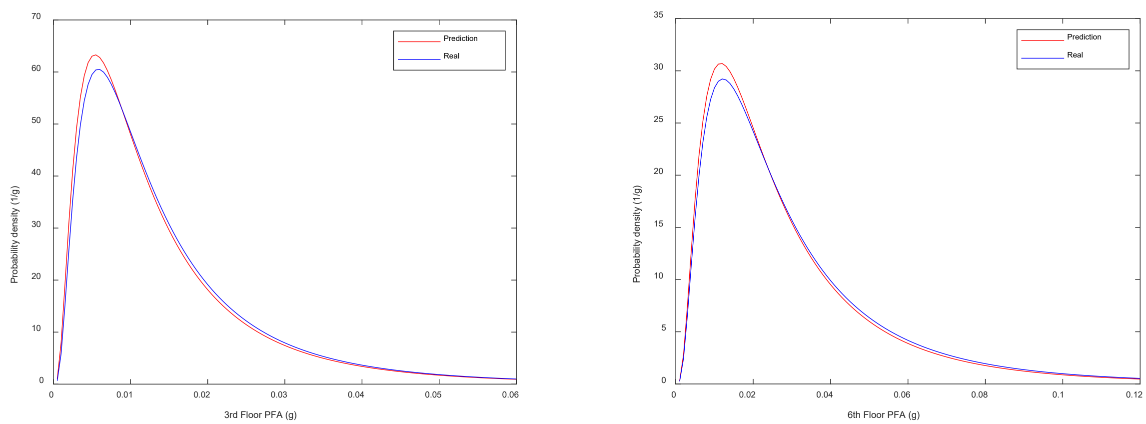
The above discussion presented the results from a probabilistic PBEE perspective based on peak predictions. As discussed earlier, the entire response history is important to characterize the full structural behavior, and in this context the *CAV* (Equation 4) is a parameter that is closely related to damage and is a suitable metric to evaluate the predictions. Figure 8 shows the *CAV* of the predicted and true accelerations for one of the test motions (Chino Hills Earthquake of 07 Aug 2012). From this figure, similar to the acceleration time histories, it is observed that the *CAV* time histories of the predicted and true accelerations are very close to each other, showing that the predicted response can be used reliably to identify damage.



(a) (b)

(c) (d)

Figure 5. Comparison of predicted and recorded acceleration time history and the corresponding frequency contents in the EW direction of the San Bernardino 6-story building at (a, b) 3rd floor, (c, d) 6th floor (Chino Hills Earthquake of 07 Aug 2012).



(a) (b)

Figure 6. Probability distributions of predicted and recorded PFA of the San Bernardino 6-story building at the (a) 3rd and (b) 6th floors.

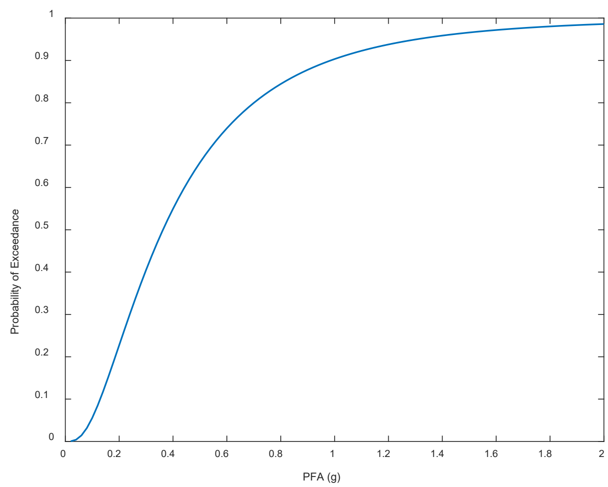
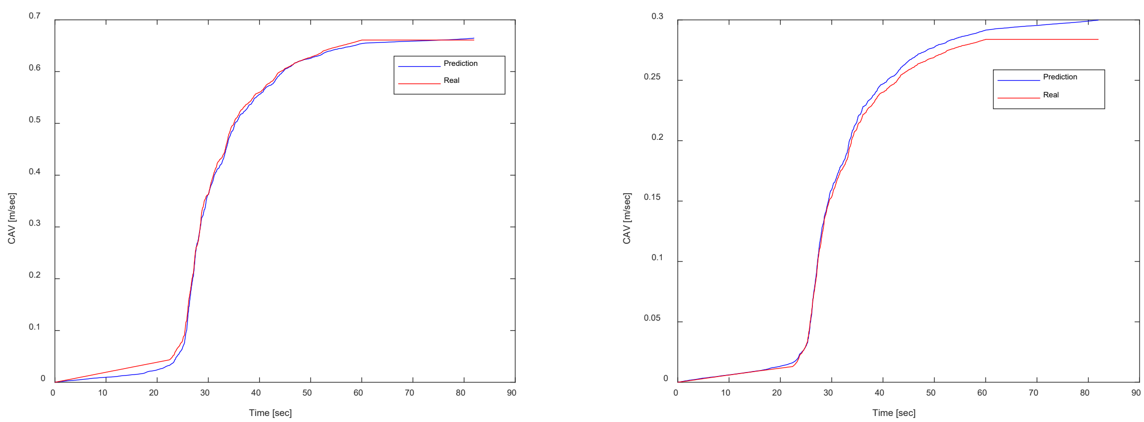


Figure 7. Fragility function for a cooling tower assumed to be located at the 6th floor (roof) of the San Bernardino 6-story building.



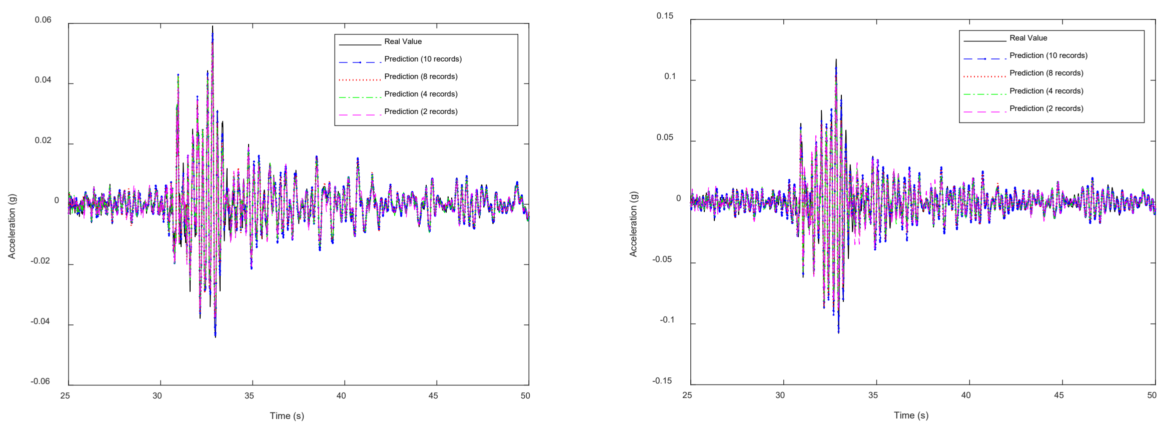
(a) (b)

Figure 8. *CAV* of the true and predicted PFA at the (a) 3rd and (b) 6th floors of the San Bernardino 6-story building (Chino Hills Earthquake of 07 Aug 2012).

Considering these accurate predictions with an 11-motion training set, a parametric study is performed for exploring the minimum number of records needed for acceptable accuracy of the trained model. The number of records used in training is accordingly varied between 1 and 11 and the 3rd and 6th floor accelerations are predicted for each case (Figure 9). Time histories, peak responses, and correlation coefficients are used as parameters for the evaluation of the trained model accuracy. The time history predictions for the Chino Hills Earthquake of 07 Aug 2012 in Figure 9 are similar in general, indicating that the TCN model is capable of accurately learning the entire time history pattern even with 1 or 2 motions. The correct prediction of the time history pattern indicates that the model successfully learns the dominating first mode in this case. This similarity of the predicted time history patterns is also supported by the correlation coefficients in Figure 10(a), which remain unchanged around 0.95 from a training set size of 11 down to 4. However, the error in the peak response, Figure 10(b), increases more dramatically from 5% for a training set size of 11 to 15% for a training set size of 8. This is attributed to lack of the ability of the TCN model to successfully learn the varying damping ratios over the different levels of motions when the number of motions in the training set is reduced.

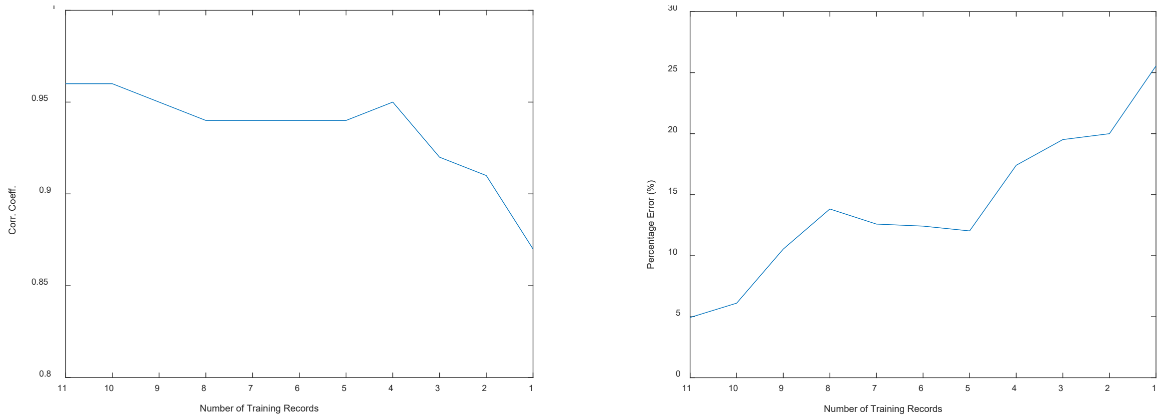
From a structural dynamics perspective, the linear elastic response of a Multi-Degree of Freedom (MDOF) system depends on the natural periods, damping ratios, and mode shapes. The response of low and mid-rise buildings is generally governed by the first mode, which is also the case for the San Bernardino 6-story hotel building. Therefore, similar to the SDOF system previously discussed, the features that define the response are the period and damping ratio of the first mode and the ground motion itself (Table 1). It is noted that the response also depends on the mode shape, however the first mode shape and the modal participation factor can be considered as a constant scale factor for all motions and therefore the mode shape is not listed as a feature in Table 1 for this system.

Although all motions are in the linear elastic range as observed by the identified natural periods, damping ratios vary because of the contribution and complexity of different mechanisms to damping at different intensities (Figure 11). The phenomenon of varying damping levels in linear elastic response is well-known (e.g., Chopra, 2012; Cruz and Miranda, 2017). Even for the same motion in forced vibrations or ambient conditions, the damping ratio varies from segment to segment of the motion (Brownjohn et al., 2018). For proper training, the number of motions in the training set should be sufficient to capture different levels of damping ratios. The selected motions should have different intensities to capture these different damping ratios. Therefore, a few motions are not sufficient for learning the damping ratio feature as opposed to the case for the period feature and more motions are needed in the training set for accuracy in predicting the damping. From the results of this case study, 10 ground motions are clearly sufficient for learning these features (period and damping) and for consequent accurate predictions.



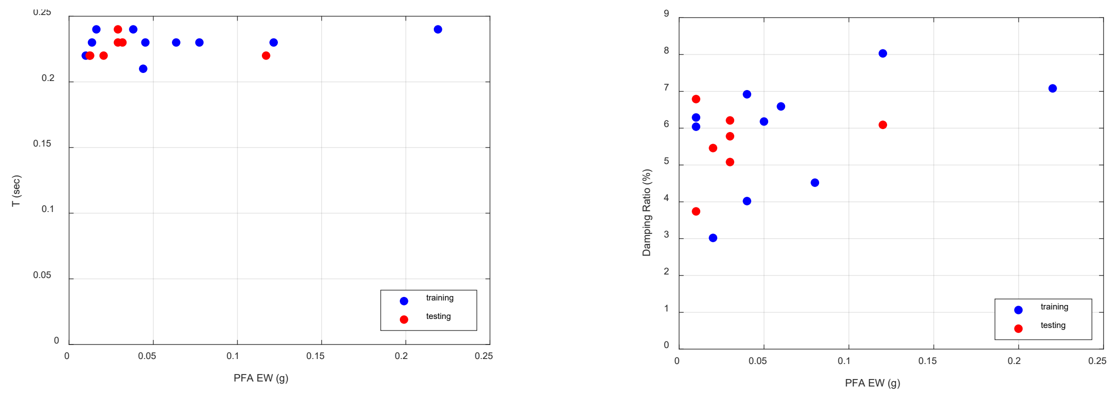
(a) (b)

Figure 9. Comparison of predicted acceleration time histories for the San Bernardino 6-story building using different number of records in training: (a) 3rd floor, and (b) Roof.



(a) (b)

Figure 10. Effect of number of records used in the training set for the San Bernardino 6-story building in terms of (a) correlation coefficient of the predictions, and (b) peak error.

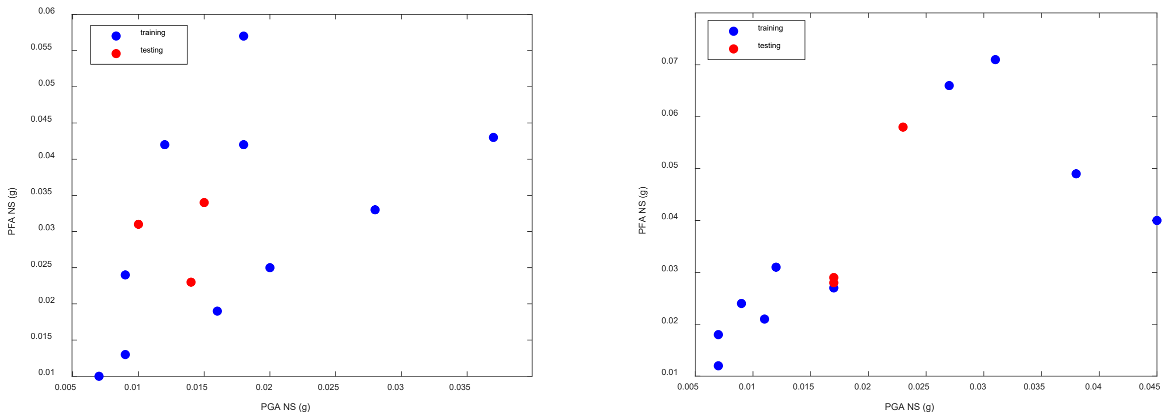


(a) (b)

Figure 11. Identified (a) fundamental mode periods, and (b) damping ratios of the San Bernardino 6-story building.

4-Story RC Hospital Building in Hemet

To demonstrate that accurate predictions are obtained for similar buildings with similar number of records in the training set, a 4-story hospital building with RCSW structural system (similar to San Bernadino Hotel) is tested using the TCN model. This hospital building was designed and constructed in 1965 and instrumented with 10 accelerometers on three levels in 1976 (Figure 2). Channel 1 at the basement and Channels 9 (2nd floor) & 6 (4th floor, i.e., roof) are respectively used as input and output in the EW direction. In the NS direction, Channel 3 at the basement and Channels 8 (2nd floor) & 5 (4th floor, i.e., roof) are respectively used as input and output. All these sensors are at the center of floors. From the recorded 13 events, refer to Figure 12, 10 are used for training (based on the study of the effect of the training set size for the San Bernardino 6-story building linear elastic response) and 3 are used for testing. As observed in Figure 12, the motions used in the training set cover the entire range of shaking levels recorded on this building and the 3 tested motions are those that lie at the middle of this range.



(a) (b)

Figure 12. The training and testing sets used in the Hemet 4-story building (a) EW, and (b) NS directions.

Similar to the San Bernardino building, high correlation coefficients are obtained for the training and testing sets and unprocessed data provided slightly more accurate predictions (Table 4). Sample predictions are shown for one of the motions in Figure 13, showing the accuracy of the predictions in the NS and EW directions. Similar to the San Bernardino building, the TCN model was successful in learning the entire time history of the response of the building, including its natural period and the varying damping ratios, using 10 motions in the training set.

Table 4. Accuracy of the Hemet 4-story building acceleration predictions in the EW and NS directions.

Data	**Correlation Coefficient**			
	Training Set EW	Testing Set EW	Training Set NS	Testing Set NS
Unprocessed	97.0%	91.0%	97.0%	90.0%
Processed	97.5%	90.0%	97.5%	90.0%

Linear Elastic Response Prediction of a Tall Building with Higher Modes

Different from low-rise and mid-rise buildings, a tall building seismic response includes higher mode effects. From a structural dynamics perspective, and the corresponding physics-based explanation of the learning process and the predictions, the features that are required to be learned for a tall building are the periods and the damping ratios of several modes contributing to the response (Table 1). The response also depends on the mode shapes, however, as discussed earlier, the mode shape and the modal participation factor can be considered as a constant scale factor in the linear elastic dynamic response of each mode for each motion and accordingly is not considered as an explicit feature. Considering the increased number of features, the presence of multiple modes in the response may introduce additional challenges to the process of learning and accordingly can impact the accuracy of the predictions. Therefore, a 54-story instrumented building is selected to explore the TCN predictions for a case when there are clearly higher modes present in the response. This 54-story building is a Steel Moment Resisting Frame (SMRF) building with composite slabs of 2.5 inches thick concrete over 3 inches steel deck located at Los Angeles (LA), Figure 14. As shown in this figure, the building is instrumented with 20 accelerometers at the basement (4 levels below ground), ground level, and the 20th, 36th, 46th and penthouse floors. There are Virendeel trusses and 48-inch deep transfer girders at the 36th and 46th floors where vertical setbacks occur. Because there is a sudden change of stiffness at these locations, increased accelerations are expected, and sensors are placed at these floors for monitoring this expected increase of the accelerations.

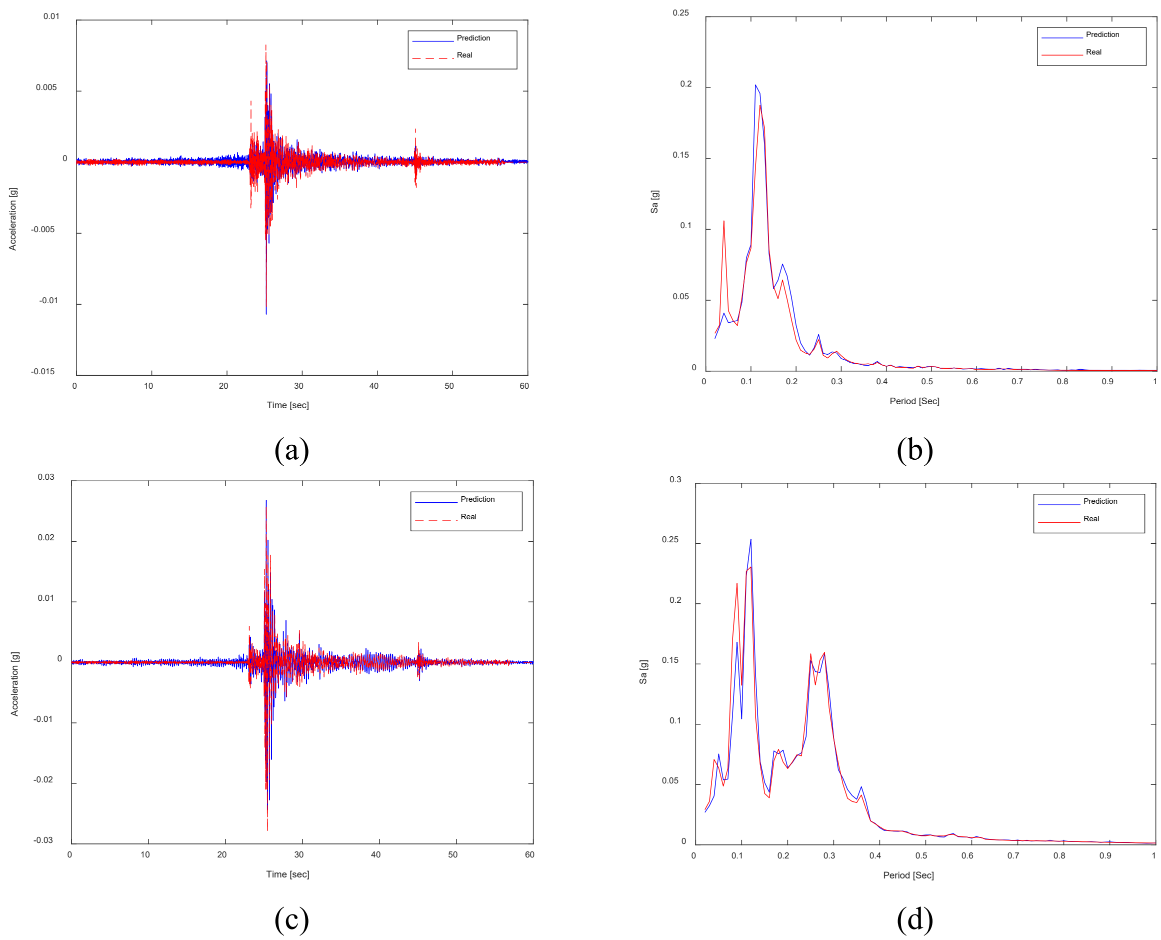
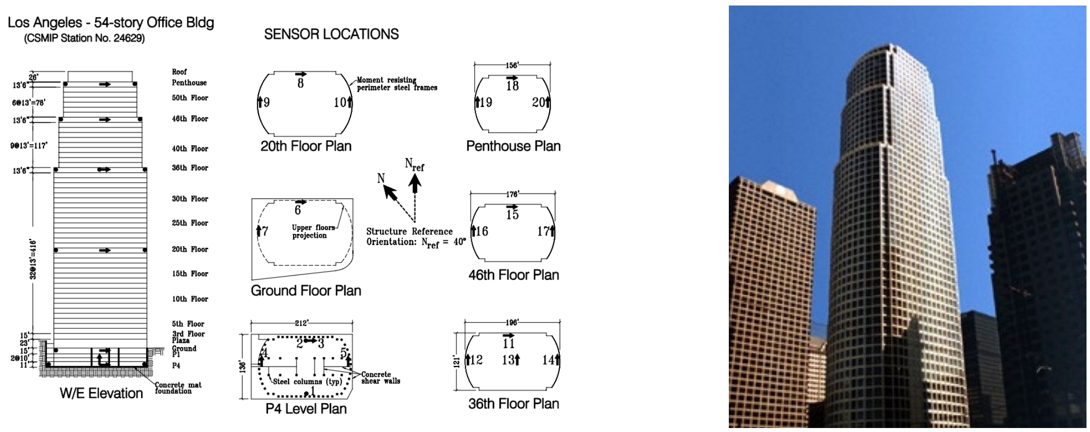


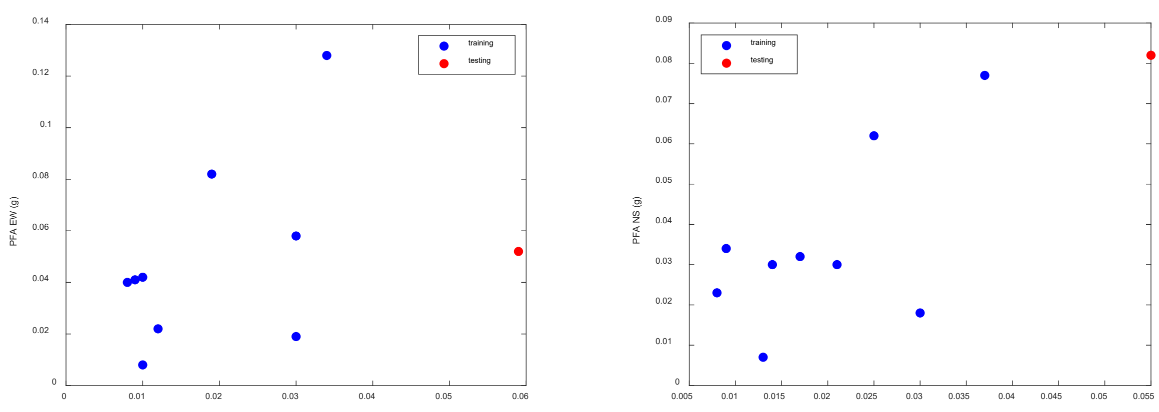
Figure 13. Comparison of predicted and recorded acceleration time history and the corresponding frequency contents in the (a, b) EW and (c, d) NS directions of the Hemet 4-story building (Banning Earthquake of 06 Jan 2016).



(a) (b)

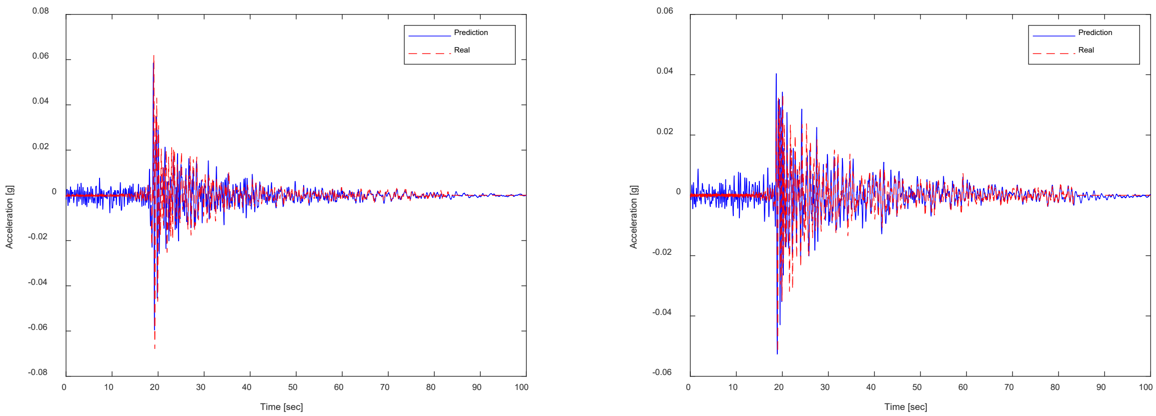
Figure 14. Sensor locations and photograph of the 54-story building at Los Angeles.

In this case study, which has 11 recorded motions, 10 motions, same as the number recommended and used, respectively, for the San Bernardino and Hemet buildings, are used for training and the remaining one motion is used for testing (Figure 15). The testing motion in the EW direction is particularly interesting as the PFA is smaller than the corresponding PGA. This can be due to multiple reasons, including (a) the shape of the response spectrum for this motion, where the response acceleration at the first mode period of the building is smaller than the PGA, and (b) multiple modes counteracting and reducing the accelerations. The successful predictions in the EW and NS directions at the 46th floor for the considered test motion are shown in Figure 16. This figure demonstrates that the trained TCN model is successful in learning more complex responses obtained as a superposition of multiple modes and the 10-motion training set results in accurate responses as in the cases of San Bernardino and Hemet buildings.



(a) (b)

Figure 15. The training and testing sets used for the LA 54 story building (a) EW, and (b) NS directions.



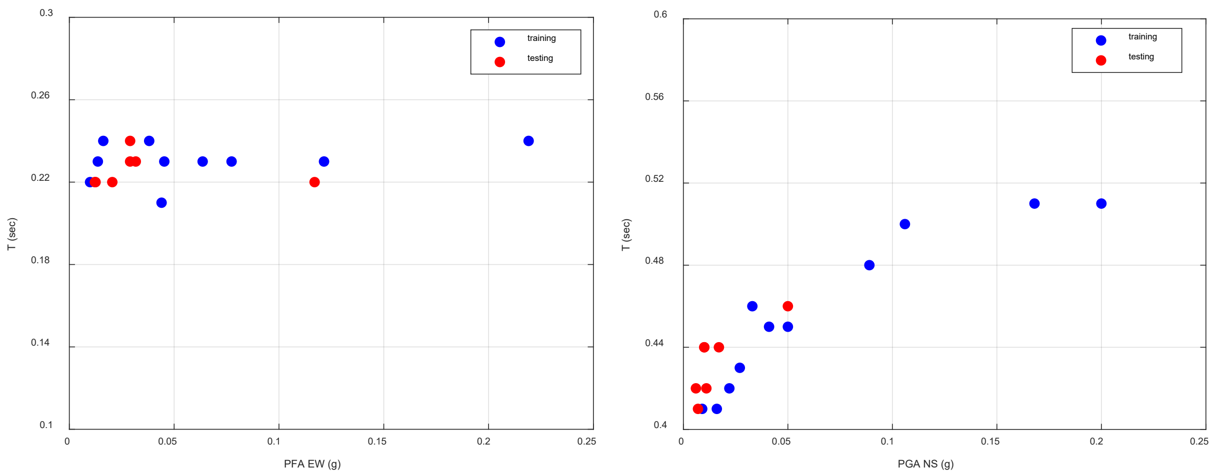
(a) (b)

Figure 16. The 46th story acceleration predictions for the 56-story building in LA: (a) EW, and (b) NS directions (Chino Hills Earthquake of 29 July 2008).

Nonlinear Response Prediction

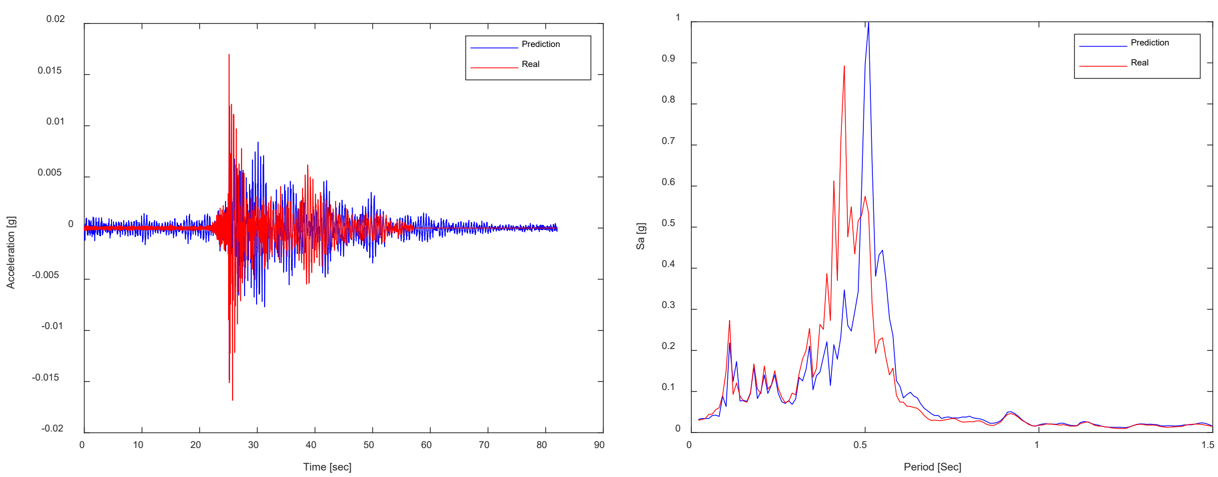
The periods of the San Bernardino 6-story building in the EW and NS directions are identified in Figure 17. The identified periods in the EW direction are almost constant in the tight range of 0.21 to 0.24 sec, independent of the level of shaking, which is indicative of linear elastic response. On the other hand, the periods in the NS direction clearly increase with the level of shaking, indicating nonlinear response. Although it is not entirely clear why this period elongation motion occurs because all ground motions in the training set are relatively low-level motions, potential reasons are minor cracking, foundation rocking, disengagement of partition walls that could provide stiffness, or the loss of contributions from any other nonstructural components.

Although this nonlinear response is not extensive, it presents a more challenging case for prediction compared to the linear elastic response and is therefore discussed here. To predict the response in the NS direction, the first attempt used the same 11 motions that were used in the EW direction. Because of the mentioned nonlinear response, the obtained predictions were not accurate. An example of inaccurate prediction is shown in Figure 18 for the Loma Linda Earthquake of 08 Oct 20126. One clear reason for the mismatch in the prediction is the difference in the dominant frequency of the motion indicating that the TCN model was not able to capture well the period elongation as a function of the ground shaking intensity, which is a relevant feature needed to characterize the nonlinear response (Table 1). As mentioned earlier, the total number of events recorded for this building is 26. To explore if increasing the number of motions used for training facilitates capturing the period elongation and improves the accuracy, 23 of the 26 motions, covering the entire range of shaking levels, are used for training as shown in Figure 19 and three events laying in the middle of the range are used for testing. The results show the increased accuracy of the predictions as demonstrated in Figure 20 for one of the motions in the testing set. Particularly, the time history, the peaks, and the frequency contents are well matched, indicating that increasing the number of motions in the training set from 11 to 23 led to successful learning of the increase of the period elongation with increased shaking intensity.



(a) (b)

Figure 17. Identified periods of the San Bernardino 6-story hotel building in (a) EW, and (b) NS directions in different earthquakes.



(a) (b)

Figure 18. Comparison of inaccurately predicted and true (a) acceleration time history, and (b) the corresponding frequency content, in the NS direction of the 6-story building in San Bernardino (Fontana Earthquake of 25 July 2015).

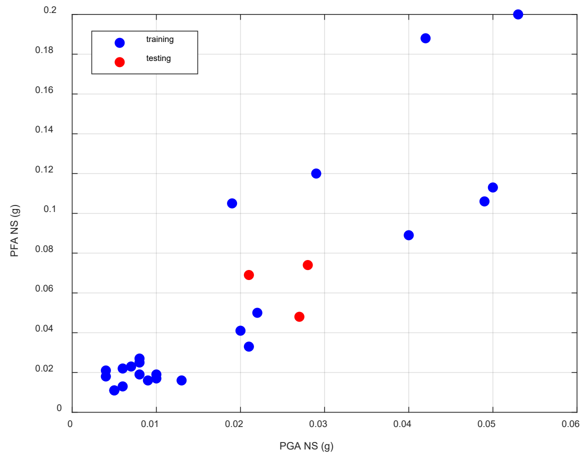
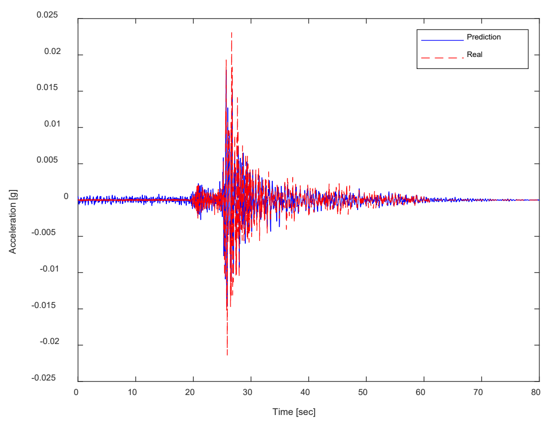
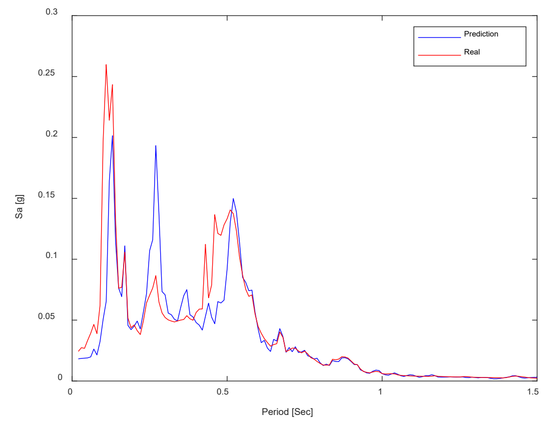


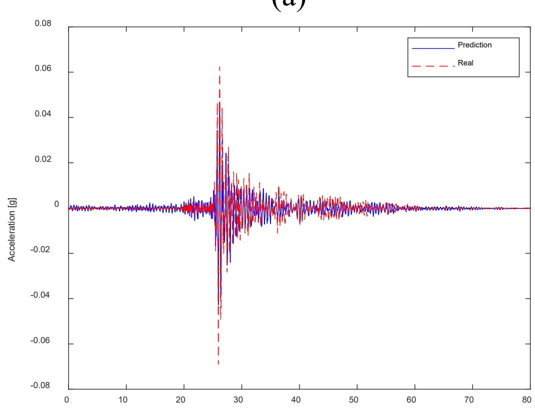
Figure 19. The set used in the San Bernardino 6-story building NS direction to improve accuracy (Testing data includes three moderate events and all others used for Training data).



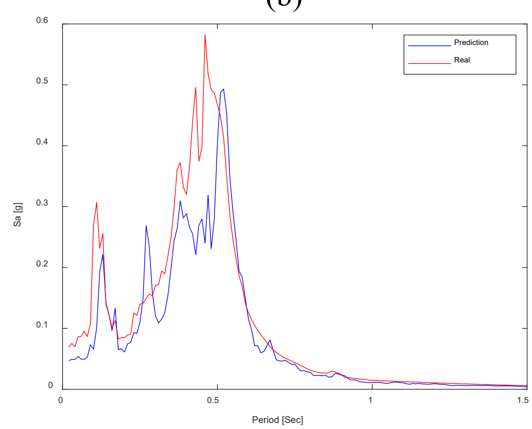
(a)



(b)



(c)



(d)

Figure 20. Comparison of (improved) predicted and recorded acceleration time history and the corresponding frequency contents in the NS direction of the San Bernardino 6-story building at (a, b) 3rd floor, (c, d) 6th floor (Chino Hills Earthquake of 07 Aug 2012).

These successful predictions highlight an important and unique characteristic of obtaining the response using a machine learning approach. As discussed earlier, the potential reasons for the observed period elongation with increased intensity of shaking are concrete cracking, foundation rocking, and disengagement of partition walls or the loss of contributions from any other nonstructural components. None of these aspects are considered explicitly in the common physics-based computational models developed for dynamic analysis. Even if they are modeled, there is a large epistemic uncertainty associated with this type of modeling. Therefore, the obtained data-driven TCN model results show that the adopted machine learning approach fills this gap very well and results in accurate structural response prediction that would not be possible using conventional means. This case study also highlights two important aspects worthy of future investigation, namely, the effect of increased training dataset (justifying need for more instrumented systems) and use of physics-based and data-driven models hand in hand in a digital twin setting of the different structural systems where the digital twin complements and helps interpreting findings from the physical twin.

Conclusions and Future Directions

This paper focused on the use of Temporal Convolutional Network (TCN) models for obtaining the structural response in the form of time histories. Models were trained using the data from several instrumented buildings with different characteristics to predict the response. The results were explained using concepts of structural dynamics and applications in earthquake engineering. The conclusions of the study are summarized as follows:

1. The developed TCN Model was verified by training and testing on a linear elastic Single Degree of Freedom (SDOF) system.
2. The use of raw data results in more accurate predictions as compared to the use of California Strong Motion Instrumentation Program (CSMIP) processed data. This is because the processed output is not necessarily the direct result of the processed ground motion input. Therefore, the relationship between the input and output deviates slightly from true physics when processed data is used for input and output.
3. The TCN model was successful for systems that are characterized by not only relatively simple features, such as a numerical SDOF system characterized by a single natural period and damping ratio, but also those with more complex response such as a tall building with multiple modes of vibration contributing to the overall response.
4. A training set size of 10 motions was sufficient for predicting the response of low-, mid-, and high-rise buildings in the linear elastic range.
5. The correlation coefficient and error in peak response resulted in different conclusions about the minimum number of records needed for accuracy. The error in peak response should be used as the preferred parameter for evaluating the accuracy, as the peak response is commonly used for design, assessment, and Performance-Based Earthquake Engineering (PBEE) and needs to be predicted accurately.
6. The training dataset should include enough motions with varying intensities, frequency contents, and other characteristics for the TCN model to learn the dynamic

characteristics of the buildings (denoted as features) as well as the relationship between the ground motion frequency contents and intensities and these dynamic characteristics.

7. The probability distributions of the predicted and true peak responses were observed to be quite similar. This demonstrated that the TCN model predictions can be confidently used for characterizing the response to multiple ground motions, which is required by building standards and PBEE.
8. The predicted and true responses from multiple test motions, along with relevant fragility functions, were used to compute the probability of damage of a cooling tower assumed to be located at the roof of one of the instrumented buildings. The resulting probability of damage was very close using the true and precited responses. This preliminary exercise provides confidence in the model predicted responses to detect nonstructural (and structural) damage.
9. To demonstrate the importance of predicting the entire time history, Cumulative Absolute Velocity (*CAV*), a parameter closely correlated to damage, was computed using the predicted and true responses and the resulting *CAV* time histories were very close to each other.
10. The slight nonlinear response of the San Bernardino 6-story building in the NS direction, as indicated by the period elongation with increasing shaking intensity, was successfully predicted by the TCN model using a 23-motion training set. As expected, the required number of motions in the training set was larger than that needed for the elastic response, but it was a manageable number, given the available records of this case study. The number of recorded motions required for accurate training is expected to increase with the increased level of the nonlinear response.
11. The successful predictions of the nonlinear response highlighted that a machine learning approach can be a viable solution to predict this response accurately, as the potential sources of the specific nonlinearity observed here are very rarely considered with confidence in conventional physics-based computational models in common engineering practice.

Several planned near-future studies include: (1) application of the TCN models to buildings with (a) irregularities (such as torsion), (b) larger levels of nonlinear response, and (c) potential soil-structure interaction, (2) prediction of displacements, and (3) predicting the responses of selected instrumented buildings in future earthquakes, among others.

Acknowledgements

This research is supported by the California Department of Conservation, California Geological Survey, Strong Motion Instrumentation Program agreement 1022-002.

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