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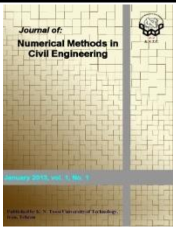

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A swift neural network-based algorithm for demand estimation in concrete moment-resisting buildings

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Abstract:

Rapid evaluation of demand parameters of different types of buildings is crucial for social restoration after damaging earthquakes. Previous studies proposed numerous methodologies to measure the performance of buildings for assessing the potential risk under the seismic hazard. However, time-consuming Nonlinear Response History Analysis (NRHA) barricaded implementing a prompt loss estimation for emergency confronting actions. The present study proposes a swift framework for demand estimation in concrete moment-resisting buildings using artificial neural networks. For this purpose, a simplified model is developed based on the HAZUS method. To eliminate the required time-consuming NRHA from the post-earthquake actions, Artificial Neural Networks (ANNs) are used. Before the event, ANNs are studied to estimate the demand parameters using a set of time-history analyses. This study applies to a suite of 111 earthquake events, originally developed in the SAC project and uniformly scaled from 0.1 g to 1.5 g , to achieve a generalized prediction model. Bayesian Optimization (BO) algorithm is carried out to tune the architecture of the NNs. Results reveal that the presented approach is reliable for predicting the structural response, and is cost-effective compared to the conventional NRHA. This framework can be implemented in the body of a risk assessment platform to expedite the postearthquake actions required for crisis management.

1. Introduction

Previous seismic events reveal that post-earthquake damage assessment is imperative for community resilience [1]. In recent years, important lessons have been gained from damaging earthquakes, such as the 2008 Wenchuan earthquake, the 2015 Nepal earthquake, and the 2011 Tohoku earthquake [2–5]. Each of these events caused more than 10,000 causalities and a huge loss to the structures and facilities. Experiences gained from these ground motions reveal the importance of seismic damage simulation to manage the post-earthquake crisis [6–8]. Several methodologies are developed to estimate the seismic damage subjected to urban areas. Probability matrix-based approaches are widely used in the past three decades to evaluate the seismic damage of an affected urban area. These methods estimate the extent of damage using the modified Mercalli intensity measure.

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Moreover, reconnaissance data obtained from past events are used at the foundation of these approaches to calculate the vulnerability properties of buildings [9]. *HAZUS-97* proposed an alternative methodology in terms of loss estimation software [10]. This approach is used the response spectra characteristics of the scenario-based earthquakes to estimate the corresponding loss. The method presented by Advanced Engineering Building Module (AEBM) is a generalized extension of the *HAZUS* approach. The framework was proposed to develop the building's damage and loss functions by engineering experts by using the intersection of the building capacity curve and the demand spectrum to categorize the structural damage [11]. In general, the capacity curve of the structure is based on first-mode nonlinear static analysis. Therefore, it is difficult to consider the effect of higher vibrating modes of the structure in calculating the severity of damage. In addition, this method did not encounter the effect of different properties of earthquake motions, e.g. duration and velocity pulses related to the near-fault ground motions. Finite or discrete element models, known as the refined models, provide a more resolution of the damage prediction taking into account the dynamic characteristics of structures.

Moreover, Nonlinear Time History Analysis (NTHA) is used to include all the properties of the ground motions (e.g. frequency content, duration and intensity) [12]. Simultaneous application of the refined models and NTHA provides a robust method for analysing the individual buildings. However, this method is not appropriate for estimating the demand parameters related to buildings in the scale of a metropolis because of the time-consuming analyses required for a large number of buildings. In other words, several numbers of powerful computer systems are required to conduct the rapid assessment of the city, which impose high maintenance cost [8,13]. Performance-based seismic assessment methods prove the importance of estimating the seismic demands under various seismic hazards. It is well-understood that the maximum inter-story drift ratio (IDR_{max}) is highly correlated to the damage states defined for structural and some of non-structural elements. Moreover, the peak floor acceleration and also peak floor velocity have a direct relation to the damage of different types of non-structural elements [14–18]. Therefore, estimating these parameters can be significantly efficient in determining the extent of damage in different building types [19].

Machine Learning (ML) is a scientific discipline that investigates the study and development of mathematical algorithms that can construct functional relationship between quantities in terms of known information and rules [20,21]. ML algorithms are widely used for estimating the behavior as well as structural damage of a system under different types of excitations [22]. A regression problem maps the output of the system unto the corresponding input features through optimizing objective functions [23] Neural networks from the most commonly used algorithms are used for performing the nonlinear statistical modeling to estimate the outcome of a structure by feeding corresponding input [24]. These regressive algorithms are an alternative approach for time-consuming response estimation methods. Karami et al. proposed a cost-effective neural network-based algorithm to identify the structural damage of cylindrical equipment [20]. Weinstein et al. investigated the application of ANNs using the operational response data as input features to develop a probabilistic model of bridge behavior. The concept of the proposed method was based on measuring the strain data during the traffic load and comparing the value of maximum strain in each location with other measured locations. A numerical model was developed to calibrate the effect of damage on the structural response. Results depicted that the location and extent of damage could be successfully identified, even though the ANN is trained under an unsupervised learning method [25]. Gu et al. proposed a two-stage damage identification method using a multi-layer NN and novelty detection to differentiate the changes in natural frequencies due to damage from those induced by temperature variations. A numerical simply supported beam from an experimental grid structure, which simulates different levels of stiffness reductions under varying temperature conditions, were used to validate the efficiency of the proposed method in detecting the structural damage [26]. Oh et al. introduced a response prediction method using the Convolutional Neural Networks (CNNs). They utilized the acceleration response of the structure under the seismic excitation as the damage attribute to the network for predicting the displacement response history [27].

According to the previous studies, there is a research gap in expanding a swift algorithm for demand estimation concrete moment-resisting buildings under the seismic motions. A swift framework in this regard can be applied at the body of the risk estimation platforms to assess the response of a city to the ground motion in a short time after the event.

This paper presents a simplified model which was adopted to perform as the concrete moment-resisting buildings. A Neural Network-based framework is introduced in the present study to remove the necessary time-consuming analyses from the post-earthquake confronting actions. The logic of the simplified model is based on the structural properties presented in the HAZUS [11] for different lateral resisting systems. A case study building type is used to evaluate the effectiveness of the proposed method, including low-, medium-, and high-rise concrete moment frame buildings (labeled as C1L, C1M, and C1H, respectively). Eventually, Neural Networks (ANNs) are implemented to introduce a swift algorithm that can be employed for rapid regional risk assessment. Generally, Neural networks are used to predict the demand parameters of buildings without conducting NTHA. Bayesian Optimization algorithm is applied to tune the hyperparameters related to the architecture of the neural networks.

2. Simplified model

The present study employs the simplified model introduced by *SimCenter* hazard simulation platform [8]. As shown in figure 1, this model is a Multi-Degree of Freedom (MDOF) system with nonlinear properties at each story. The following assumptions are laid at the foundation of this model:

- All the floors have a similar mass *m*, height *h*, and initial stiffness k_0
- The structural properties of the building are similar for both horizontal directions
- The mass *m* is obtained by considering the area and the functionality of building
- Stiffness and damping factors are considered as the random variables with a mean value of 1.0 and a dispersion of 0.1

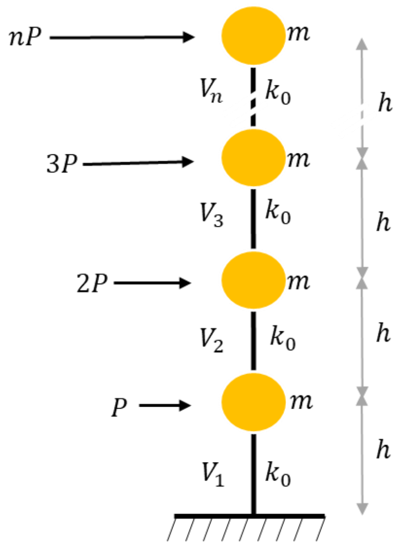


Fig. 1: Simplified model

Considering the above mentioned assumptions, the mass and stiffness matrices of the system can be written as below:

$$K=\begin{pmatrix} 2 & -1 & & & \\ -1 & 2 & -1 & & \\ & -1 & O & O & \\ & & O & 2 & -1 \\ & & & -1 & 1 \end{pmatrix} k_0=[A]k_0 \qquad (1)$$

$$M=\begin{pmatrix} 1 & & & \\ & 1 & & \\ & & O & \\ & & & 1 \end{pmatrix} m=[I]m$$

Thus, the fundamental period of the system can be obtained as:

$$\omega_1=\sqrt{\frac{K}{M}}=\sqrt{\frac{[\varphi_1]^T[K][\varphi_1]}{[\varphi_1]^T[M][\varphi_1]}}=\sqrt{\frac{k_0}{m}}\sqrt{\frac{[\varphi_1]^T[A][\varphi_1]}{[\varphi_1]^T[I][\varphi_1]}} \qquad (2)$$

where K_1^* and M_1^* are the stiffness and mass matrices of the first vibrating mode, respectively, and ϕ_1 is the first mode shape of the system. The fundamental mode shape of the system can easily be determined by implementing an eigenvector analysis knowing the mass and stiffness matrices. In this paper, as the mass and stiffness values are identical for different stories of the building (according to the basic assumptions), the first vibrating mode shape of the system was independent of changes in k_0 and m. Hence, the fundamental mode-shape of the system was obtained by assuming a value for k_0 and m so that [8]:

$$\frac{[\varphi_1]^T[I][\varphi_1]}{[\varphi_1]^T[A][\varphi_1]};\ 0.4053N^2+0.405N+0.1869 \qquad (3)$$

where N is the number of stories. Therefore, the stiffness of the stories is determined as:

$$k_0=\frac{4\pi^2 m}{T_1^2}\left(0.4053N^2+0.405N+0.1869\right) \qquad (4)$$

where $T_1 = 2\pi/\omega_1$, and can be calculated as follow:

$$T_1=\frac{N}{N_0}T_0 \qquad (5)$$

where T_0 is the first vibrating period of the reference building introduced in Table 5.5 of HAZUS-MH [28], N_0 is the number of stories of the particular reference building. Moreover, the yield capacity of i_{th} floor was calculated as follow:

$$V_i=SA_y.\alpha_1.W.\Gamma_i \qquad (6)$$

where Sa_y is the yield spectral acceleration of the structure, α is nonlinear static mode response factor calculated from table 5.5 of HAZUS-MH [28], $W = mgN$, and $\Gamma_i = V_i/V_1$. As a common assumption, the design seismic load is linearly increased by increasing the height of the structure. The story shear strength is then calculated by the following formula [8]:

$$\Gamma_i=\frac{\sum_{j=i}^{N}W_jH_j}{\sum_{k=1}^{N}W_kH_k}=1-\left(\frac{i(i-1)}{(N+1)N}\right) \qquad (7)$$

Figure 2 illustrates the backbone curve adopted to define the nonlinear behavior of different stories according to the trilinear curve introduced in *HAZUS-MH* [28]. In this figure, η, β, and δ_c variables were the strain-hardening ratio, the ratio of ultimate strength to the yield strength, and the ultimate drift ratio at the collapse state of the building, respectively. These parameters can be calculated using the following equations:

$$\eta_i=\frac{SA_u-SA_y}{SD_u-SD_y}\cdot\frac{SD_y}{SA_y}$$
$$\beta_i=\frac{SA_u}{SA_y} \qquad (8)$$
$$\Delta_{c,i}=\delta_{C0}\cdot h$$

where SA_y and SD_y are yield spectral acceleration and the yield spectral displacement capacity, respectively. Besides, SA_u and SD_u are respectively the ultimate spectral acceleration and ultimate spectral displacement capacity of the building. Also h is the story height which is constant for all stories as mentioned in the basic assumptions.

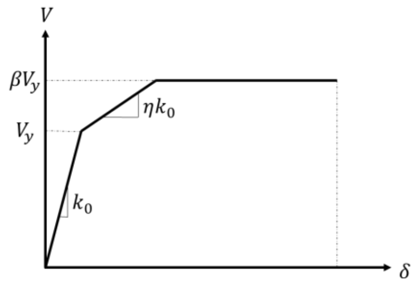


Fig. 2: triangle backbone curve

2. Modelling

As mentioned in the previous section, the multi-story concentrated-mass model developed by Lu et al. [8] was considered in the present study to simulate the nonlinear behavior of generic buildings. The nonlinear behavior of each story was modeled by the inter-story hysteretic force-deformation function. Lu et al. [8] proposed Modified-Clough, bilinear elasto-plastic, and pinching model simulating the behavior of systems with different lateral behavior. Among these constitutive models, the Modified-Clough model was proposed for modelling the hysteretic behavior of reinforced concrete moment-resisting frames. Figure 3 illustrates this constitutive model. The HAZUS-MH [28] capacity curve divided into three parts on the yield and ultimate capacity boundaries. The parameters related to the inter-story backbone curve are the initial lateral stiffness, shear yield strength, hardening ratio and ductility factor. In this paper, to expedite the time of analysis, all the numerical models are simulated by the *Python* programming software using the *Openseespy* library [29]. Nonlinear behavior between the stories of the buildings are modeled by *Hysteretic* uniaxial material model [30]. In fact, these functions are used to calibrate the above-mentioned hysteretic behaviors for different building types. To simulate the effect of natural damping on the structural response, the Rayleigh damping model was employed.

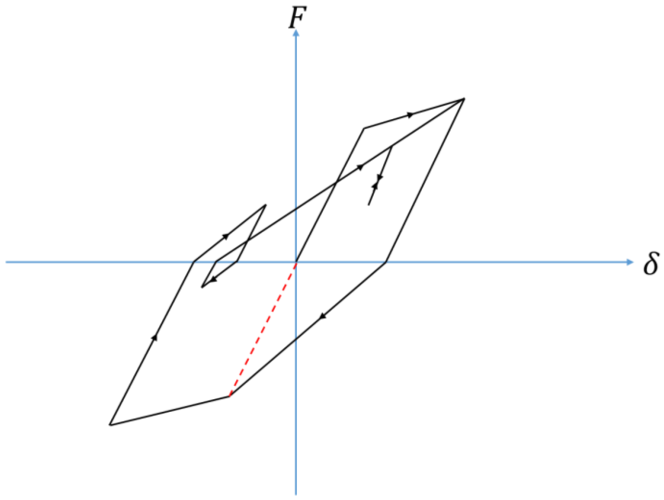


Fig. 3: Modified-Clough Model

3. Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are among the most commonly used ML techniques for application in different engineering aspects. Particularly, ANNs can be implemented to solve both classification and regression problems. The high speed in solving complex relationships is one of the main advantages of the NNs. The ANNs also have great capacity in predicting the behavior of intricate systems (e.g. predicting the nonlinear response of a structure). ANNs are a family of mathematical algorithms adopted from the structure of biological neural networks, such as those existing in the central nervous system of humans. A basic NN typically includes an input layer, a hidden layer, and an output layer, where each layer contains some neurons. Each neuron of a layer is connected to every neuron in the next layer. At the start, n input values are weighted and summed to produce the activation signal as below:

$$a = \sum_{i=1}^{n} w_i x_i + b \tag{9}$$

where *n* is the number of neurons in each layer, x_i is the input value, and *b* is the bias. Then, an activation function will act on the activation signal to relate the input values with corresponding target values. The activation function is either a linear or nonlinear function such as hyperbolic tangent, sigmoid, rectified linear unit, etc. During the training phase, the input data are crossed over the entire network for their labels to be predicted. After each forward propagation, a loss function will be used to assess the workability of supposed weights. This loss-function can be the mean squared error written as below:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2 \tag{10}$$

where n is the total number of input values, xi is the i_{th} input value, and $\hat{x}_i$ is the predicted input value corresponding to the i_{th} input. This function estimates the error by evaluating how good the predictions are as compared to the correct label. As shown in figure 4, connection between the neurons presents a multi-layer neural network. The neural network algorithms are generally based on the supervised learning which preserves the computed outputs close to the corresponding target values defined for training, testing, and validating sets. The weight and bias of each neuron is updated by a learning algorithm (e.g. Levenberg-Marquardt, Quasi-Newton, Gradient Descent, and Back-Propagation) to prevent the NN outputs from deviating from the defined target values. The Levenberg-Marquardt learning method is the most widely used optimization algorithm in the body of NNs [31,32].

In this study, the sigmoid and linear functions were used as the activation functions for the hidden layers and output layer, respectively. Moreover, the objective function of the neural networks was optimized using Levenberg-Marquardt algorithm. Besides, Bayesian optimization algorithm was conducted to tune architecture of the neural networks. In fact, the number of layers (ζ) along with the number of neurons in each layer (η_i) were obtained by Bayesian optimization algorithm.

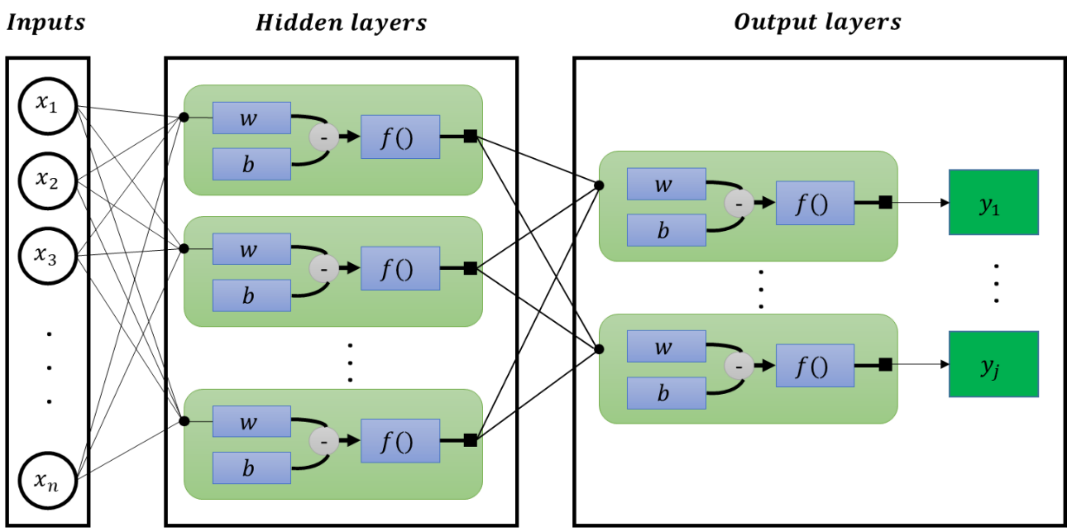


Fig. 4: Structure of the multi-layer feed-forward neural network

As mentioned before, it can be concluded that the selection of hyperparameters (including the layers (ζ) and the number of neuron in each layer (η) has significant effects on the performance of the neural networks. To achieve a generalized predictive model, simple hold-out method was used. For this purpose, the dataset is divided into three random splits, including train set (70% of the dataset), validation set (15% of samples), and test set (15% of dataset). Notably, the validation error was selected as the objective function that can be obtained using a Gaussian process as follow:

$$V_{loss} \sim GP(M, \sum + \sigma^2 I) \quad (11)$$

where $\sum$ is the covariance matrix that can take many types of kernel functions such as squared exponential kernel, exponential kernel, etc.[33]. M represents the mean value of the Gaussian process. It should be mentioned that the initial mean is considered as 0. Moreover, it is assumed that the observations contain Gaussian noise with variance of σ^2. Also, I is the identity matrix which has a compatible dimension. To assess the next sampling point, Bayesian optimization maximizes an acquisition function written as below:

$$EI(x) = E[max(0, \mu(x_{best}) - CV_{loss})] \quad (12)$$

where x_{best} is the location of lowest posterior mean, and $\mu(x_{best})$ is the lowest value of the posterior mean. The Bayesian algorithm stops after, (1) a pre-defined number of iterations, (2) a pre-defined deal of time, and (3) a stopping criterion that is defined for the algorithm. In the present study, the stopping criterion is defined as the maximum number of iterations which was considered depending on the complexity of the intended regression algorithm. Readers are encouraged to review Rasmussen [33] and Snoek et al. [34], for detailed information on conducting the Bayesian optimization algorithm for hyperparameter selection. Figure 5 summarizes the overall view of the proposed method in terms of a flowchart.

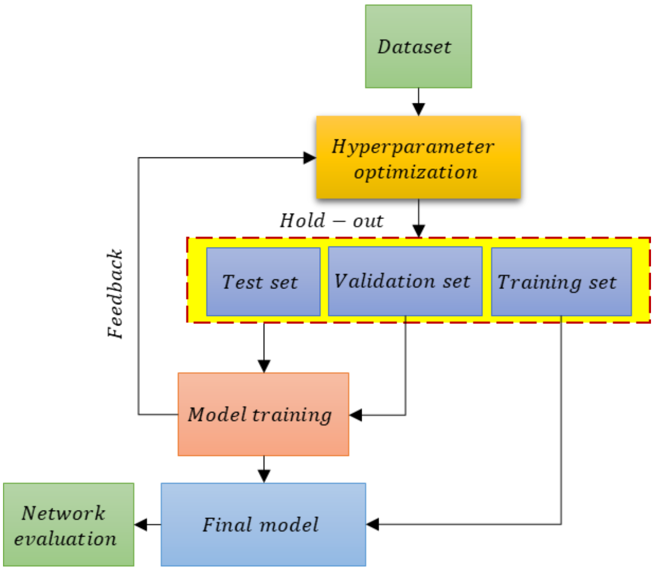


Fig. 5: Overall view of the proposed algorithm

4. Implementation

The theoretical backgrounds required to implement the proposed framework are explained in the previous sections. Different steps for implementing the framework are discussed below.

According to HAZUS-MH[11] three different buildings in terms of their height ranges (i.e. low-rise, medium-rise, and high-rise) are considered to conduct the proposed framework. A suite of 111 earthquake motions, originally developed in the SAC project, is considered to generate a generalized dataset. Each of the events are scaled to 14 different scales ranging from 0.05g to 1.5g to produce a wide range of intensities for the input excitations. On the other hand, these motions include a series of near-field and far-field earthquakes to provide a generalized frequency content for the selected events.

Next, appropriate features are proposed for training the neural networks. For this purpose, four different damage indicators containing the spectral acceleration at *0.2s* period, the spectral acceleration at *1.0s* period, the spectral acceleration at the first vibrating period of the structure (fundamental period), and the peak ground acceleration (PGA) of the ground motion are defined as the neural network inputs. Generally, these attributes were fed to the neural networks as follow:

$$A_i = [Sa_{0.2}^i, Sa_1^i, Sa_{T1}^i, PGA^i] \qquad (13)$$

where i represents the number of the observation vector. Three different neural networks were trained to estimate the acceleration, velocity, and drift response of the structure. As mentioned in the previous section, artificial neural networks are used to map the features' space onto the structural response captured from the buildings.

The simple hold-out approach was implemented to prevent the overfitting issue. In addition, Bayesian optimization algorithm was conducted to tune the hyperparameters of the networks. The following section presents the results derived from the proposed framework.

5. Results

This section presents the results of demand estimation for the case study models. These results are the performance curve of the training process for the learning algorithm, regression plots of the neural network for the train, test and validation set, and some comparative examples for evaluating the efficiency of the proposed method. Figure 6 illustrates an example performance curve for the 12-story building when the prediction model is set to estimate the drift response of the building.

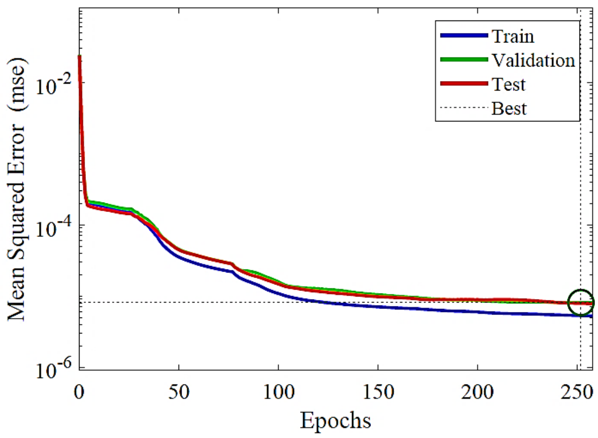
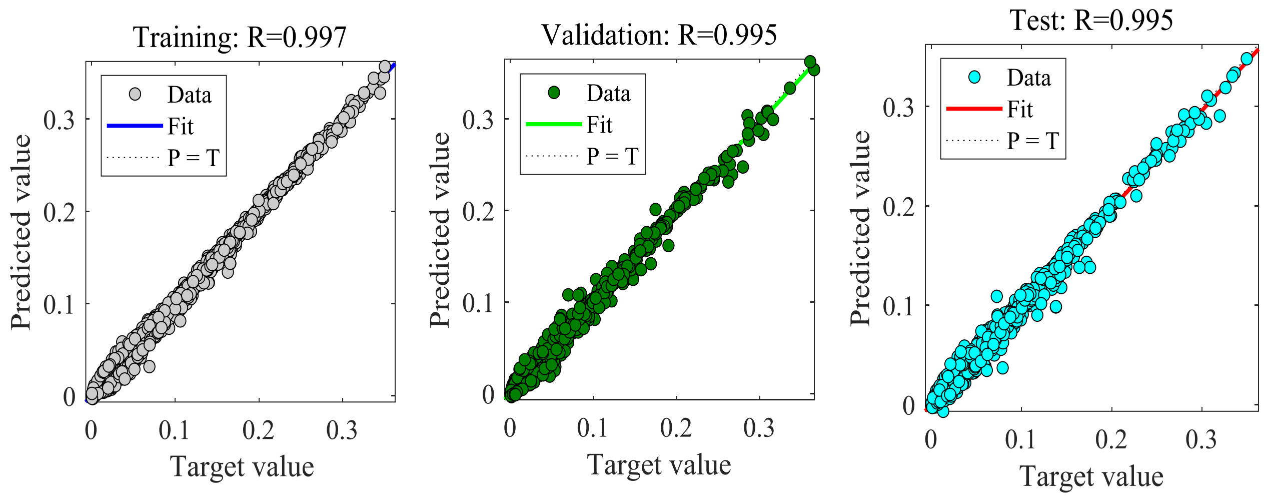
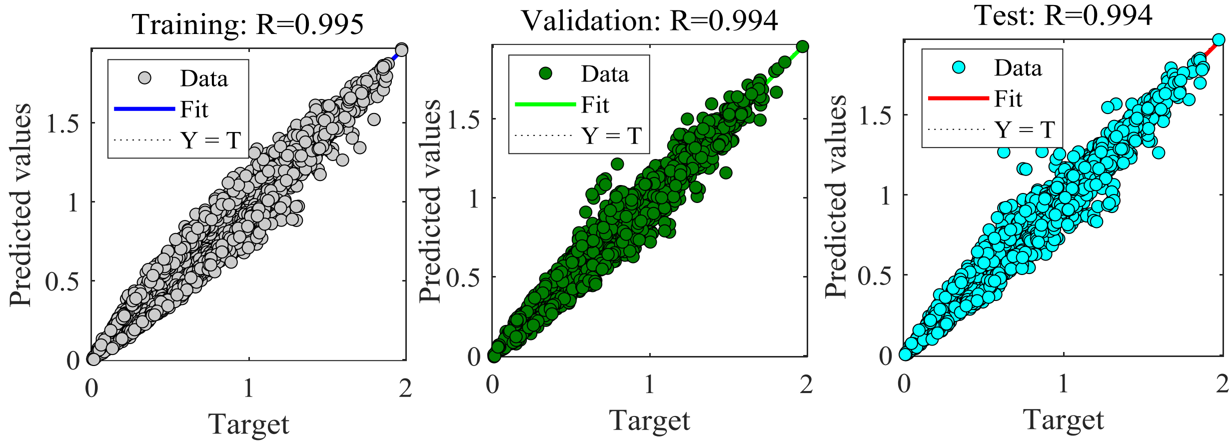


Fig. 6: performance curves for 12-story building

According to this figure, since the MSE of the train, test, and validation sets are close to each other, it can be concluded that the neural network is well-trained, and the over-fitting problem did not occur in the model. For better understanding the quality of the training process, figure 7 shows an example of the regression plot for these models. According to this figure, it is obvious that all of the regression correlation values are close to 1.0, which indicates the efficiency of the proposed method in predicting the acceleration and drift response of the 12-story building. Table 1 summarizes the performance of different predictive models in estimating the drift, velocity, and acceleration response of the concrete moment-resisting frame buildings in terms of MSE value for the train, test, and validation set. A close look at this table reveals that all the prediction models are trained well, and the overfitting problem did not affect the results because of closeness between the train, test and validation MSE values.



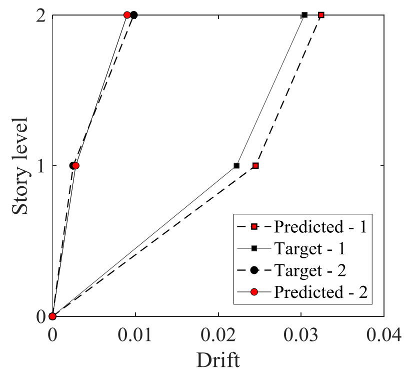
(a) Drift parameter



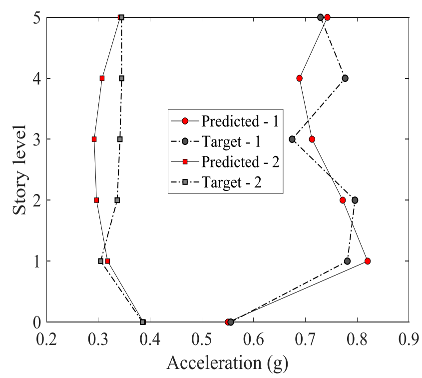
(b) Acceleration parameter

Fig. 7: Regression plots for the train, validation and test set of the 12-story prediction model

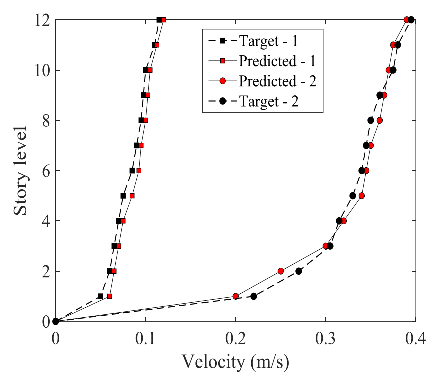
To show the robustness of the proposed method in a perceptible manner, figure 8 illustrates the correlation between the demand parameters obtained by the prediction models and those calculated through nonlinear response history analysis. It should be mentioned that the samples presented in these figures are randomly selected from the test set of the prediction models. According to these figures, the proposed framework presents promising accuracy in estimating the demand parameters related to damage occurred at the structural and nonstructural components of 2-, 5-, and 12-story concrete moment-resisting buildings.



(a) Drift response for 2-story building



(b) Acceleration response for 5-story building



(c) Velocity response for 12-story building

Fig. 8: performance of the trained model

Table. 1: performance metrics for the trained models

Number of stories	Demand parameter	Train MSE	Validation MSE	Test MSE
2	Acceleration	2.25×10^{-3}	2.45×10^{-3}	2.41×10^{-3}
	Velocity	1.15×10^{-3}	1.36×10^{-3}	1.42×10^{-3}
	Drift	3.14×10^{-6}	3.22×10^{-6}	4.35×10^{-6}
5	Acceleration	3.45×10^{-3}	3.66×10^{-3}	3.51×10^{-3}
	Velocity	4.05×10^{-3}	4.26×10^{-3}	4.11×10^{-3}
	Drift	3.61×10^{-6}	3.91×10^{-6}	4.01×10^{-6}
12	Acceleration	3.56×10^{-3}	3.75×10^{-3}	3.71×10^{-3}
	Velocity	4.25×10^{-3}	4.91×10^{-3}	4.61×10^{-3}
	Drift	4.71×10^{-6}	6.21×10^{-6}	7.91×10^{-6}

6. Conclusion

This paper presented a demand estimation framework for concrete moment-resisting buildings, especially concrete-moment resisting frames. This framework applies the neural network algorithms to remove the time-consuming nonlinear time history analyses from the post-earthquake actions. Bayesian optimization algorithm was used to tune the hyperparameters of the neural networks. The following results can be mentioned as the main conclusions of the present study.

- The proposed features are well-correlated to the demand parameters of the concrete moment-resisting buildings.
- Bayesian optimization algorithm aimed at the neural network-based method to perform in its optimum form and eliminate errors related to unsuitable architecture of the model.
- Despite the lower resolution of the simplified model in estimating the response of the buildings under the earthquake motions, this model aimed to implement a swift framework for response identification of the buildings in the scale of a city.
- It is clear that the proposed method is not over-fit on the dataset because of obtaining comparable train, validation, and test performance for different buildings.
- The proposed method can directly be used in the body of a risk assessment platform as the rapid demand estimation module.
- The presented algorithm can be implemented for all generic buildings to achieve a general framework for estimating the demand parameters related to building performance during strong ground motions.

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