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Araştırma Makalesi / Research Article

Reliability Prediction of SMRF Based on the Combination of Neural Network And Incremental Dynamic Analysis

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Abstract

This paper conducts a comprehensive vulnerability analysis of steel structures, taking into account the stringent HAZUS restrictions. The demand distribution for each mode of failure takes the form of a normal logarithm after extracting the fragility chart. Thus, the two parameters of mean and standard deviation can be used to construct the fragility chart. A total of five modes of failure were used in this paper. Therefore, 10 unknown values were used to derive the fragility curves. Afterward, Incremental Dynamic Analysis (IDA) was used under 40 natural records to obtain the fragility curve. To save time in the analysis and prediction of structural responses, a neural network method was used to select records more efficiently. It was observed that this method is better than the analytical method in considering random uncertainty in steel structures when several acceleration values are used.

Keywords: *MLP algorithm, Monte Carlo method, Aleatory uncertainty, Fragility curve, IDA.*

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SMRF'nin Sinir Ağı ve Artımlı Dinamik Analizin Birleşimine Dayanan Güvenilirlik Tahmini

Öz

Bu makale, sıkı HAZUS kısıtlamalarını dikkate alarak çelik yapıların kapsamlı bir güvenlik açığı analizini yürütmektedir. Her başarısızlık türü için talep dağılımı, kırılganlık tablosunun çıkarılmasından sonra normal bir logaritma şeklini alır. Böylece, kırılganlık tablosunu oluşturmak için ortalama ve standart sapma olmak üzere iki parametre kullanılabilir. Bu yazıda toplam beş başarısızlık modu kullanıldı. Bu nedenle kırılganlık eğrilerini türetmek için 10 bilinmeyen değer kullanılmıştır. Daha sonra kırılganlık eğrisini elde etmek için 40 doğal kayıt altında Artımlı Dinamik Analiz (IDA) kullanılmıştır. Yapısal yanıtların analizinde ve tahmininde zaman kazanmak amacıyla, kayıtları daha verimli bir şekilde seçmek için bir sinir ağı yöntemi kullanılmıştır. Çeşitli ivme değerleri kullanıldığında çelik yapılarda rastgele belirsizliğin dikkate alınmasında bu yöntemin analitik yönteme göre daha iyi olduğu görülmüştür.

Anahtar kelimeler: *MLP algoritması, Monte Carlo yöntemi, Rastgele belirsizlik, Kırılganlık eğrisi, IDA.*

1. Introduction

Structural collapse is a major cause of economic losses and human casualties in earthquakes (Wyllie et al., 1989). Furthermore, keeping structures away from this limit state through earthquakes has been a key factor in performance and force-based evaluation, including innovative performance-based seismic evaluation procedures (Foutch, 2000; Celarec & Dolšek, 2013). Using more accurate prediction methods for evaluating the collapse capacity of structures, considering different sources of uncertainties, leads to more reliable seismic evaluation of structures, earthquake risk analysis, and earthquake consequence management (Karimi ghale jough et al., 2021).

To reduce the computational effort in the program, the Monte Carlo method for surface response was adopted (Jough & Şensoy, 2016). The response surface method used in Monte Carlo simulations has a certain limitation. It assumes a fixed functional form when calculating the standard deviation and mean of the collapse fragility curve. This means that the higher the order of the applied function, the more data is needed to accurately adjust the factors.

Artificial neural networks can be used to approximate any type of function. Li (1996) stated that the radial basis function of an Artificial Neural Network (ANN) has the remarkable ability to promptly estimate all available derivatives. It is noteworthy to mention that all these assumptions on each function are relatively mild, which proves the fact of multivariate functions. Only a few studies were used the ANN algorithm to create fragility curves.

Lagaros and Fragiadakis (2007), as well as Papadrakakis et al. (2008) studied the chance of surpassing the limit state in concrete dams. In addition, they thoroughly analyzed the susceptibility of these dams and took into account the inclusion of randomized material properties within the fragility curves. In previous studies, randomness was considered the main source of uncertainty. In the present study, a total of five modes of failure were used in nonlinear analysis. Therefore, 10 unknown values were used to derive the fragility curves. The fragility curve was then obtained by applying Incremental Dynamic Analysis (IDA) to a set of 40 natural records. Given that such analyses are time-consuming, a neural-network-based method was used to reduce the time of analysis for the prediction of structural responses. It was observed that this method is better than the analytical method at considering random uncertainty in steel structures when several acceleration values are used.

2. Fragility Curves in Steel Moment Building

The intensity measure (IM) of strong ground motion is defined as an IM-based collapse limit state in which the excited structure undergoes a damage limit state. On the other hand, the damage limit state is defined as the measure of the intensity of HAZUS restrictions (Kircher et al., 2006). As a result, the collapse fragility curve formulation can be written using following Eq. (1). Figure 1 depicts the methodology considered in this study.

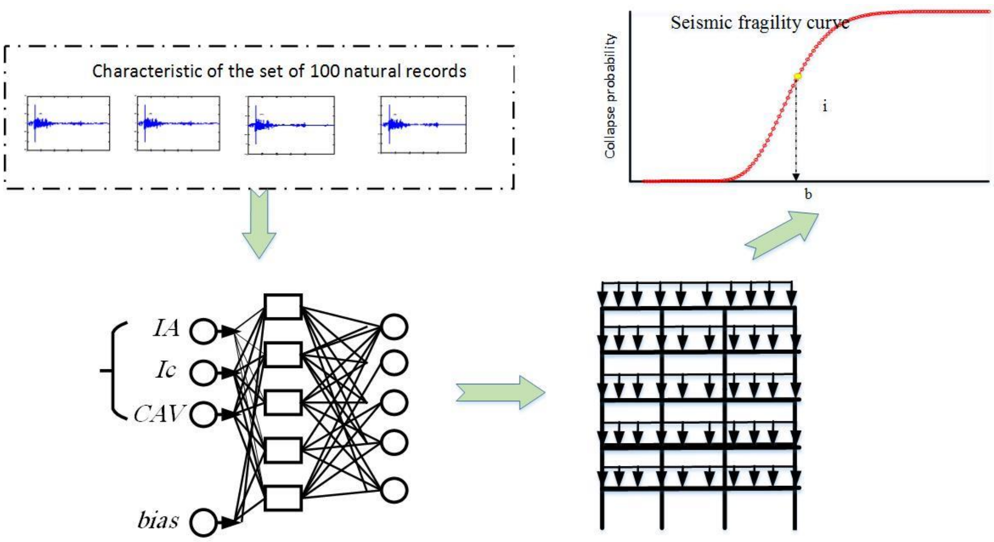

Figure 1. Proposed approach flowchart for considering aleatory uncertainty.

$$P(Collapse|IM = im_i) = P\left(im_i > IM_{collapse}\right) = F_{IM_{collapse}(im_i)} \quad (1)$$

The best probability distribution for representing the fragility curve's collapse of any structure is a log-normal probability distribution function (Karimi & Şensoy, 2020). As a result, the log-normal probability distribution is going to apply as the cumulative probability distribution of Eq. (1), results in Eq. (2).

$$\boldsymbol{P(Collpase|IM = im_i)} = \left(\frac{\boldsymbol{LN(im_i) - IN(\mu_k)}}{\boldsymbol{\beta_k}}\right) \quad (2)$$

The Gaussian distribution function, represented by Eq. (2), is the dispersion and mean of the collapse probability function.

3. Artificial Neural Network (ANN)

The procedure for the proposed method is defined in Figure 2. The input layer of the network consists of modeling parameters for structure. The output layer consists of the standard deviation and mean of the collapse fragility curves. The hidden layer consists of a number of artificial neurons (Karimi Ghaleh Jough & Beheshti Aval, 2018). The number of neurons in the hidden layer is referred to as the hidden layer size. Input weights, bias factors, and transfer functions define the connections between the components of the input layer and the artificial neurons in the hidden layer. If I is an R-length input, Vector, S is hidden layer size, transfer functions and bios vectors of neurons in hidden layer are f and b, then output of hidden layer will be presented as Eq. (3).

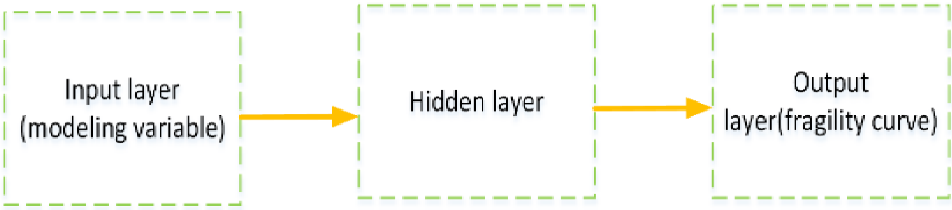

Figure 2. Architecture of proposed method.

$$a = f\ (W_1 I + b_1) \quad (3)$$

Output layer and w1 is an input weight matrix of hidden layer. Vector of output is calculated by Eq. (4), in which W_2 and b_2 are weight matrix and bios vector of output layer neuron.

$$O = g\ (W_2 I + b_2) \quad (4)$$

To minimize prediction error, training data is used to evaluate weight matrices and bias vectors. The aim of this study is to evaluate training data using a limited simulation of modeling parameters. Collapse fragility analysis of the structure is performed using incremental dynamic analysis. The modeling parameters of the structure are assigned as the simulated input vector. To predict the mean and standard deviation of collapse fragility curves, two distinct neural networks were trained (Karimi ghale jough & Ghasemzadeh, 2023).

In order to accurately estimate outcome variables, it is crucial to minimize errors rather than maximize them. This prevents the network from generating inaccurate variables for outcomes that were not included in the initial data.

When training an artificial neural network (ANN), the following steps are involved: selecting shift parameters, defining the network architecture, and optimizing weight values. Typically, a portion of the reliable data is allocated for training purposes, for example, 80%.

The remaining data is then used to validate the accuracy of the neural network predictions. To reduce dispersion in estimating mean and standard deviation, the number of neurons in hidden layers needs to be determined. The number should not be maximized because it can make the network produce inaccurate results for data that was not in the validation dataset.

As a result, bios vectors and weight matrices are adjusted to achieve the lowest possible error in the estimated outcome variables. Also, the MSE value, which is an indicator of neural network error, is obtainable in Eq. (5).

$$E = \sum_{m} \frac{1}{2} \left(Y\left(x^m; (w, A)\right) - t^m\right)^2 \quad (5)$$

In which, a is S-length vector, and supposed to be as input to Eq. (5), the training pair (x, t) number is m, respectively, and m-th are the target data and input. Y is the neural network predicted value whose architecture is A, and weight matrix is W. The evaluation of network optimum weight, which minimizes the error of the network, is achieved by solving the minimization problem. T the propagation algorithm which is a common minimization algorithm is applied in this research to update the weight by several iterations. The network weights in iteration t+1 are calculated by Eq. (6).

$$w^{(t+1)} = w^t + \Delta\, w^t \quad (6)$$

The value of Δw^t is calculated by Eq. (7), and w is the matrix's weight in iteration with t.

$$\boldsymbol{\Delta\, w^t = \alpha . \Delta\, w^{t-1} + \eta . d^t} \quad (7)$$

in which dt contains partial derivatives of the error function and shows weighted search directions, the corresponding size of step is α and momentum term which has been defined in [0,1] is η.

The Resilient back propagation learning algorithm, summarized as Rprop (Riedmiller & Braun, 1993), is adopted in this paper. Rprop is an effective local algorithm. It uses an adaptive version of the Manhattan-learning rule, which has been proven to work well in previous studies when combined with the sigmoid activation function (Riedmiller & Braun, 1993).

4. Records Selection

The key characteristics of amplitude intensity measures obtained from ground motion are PGA (high frequency parameter), PGV (intermediate frequency parameter), and PGD (low frequency parameter). These measures represent the maximum velocity, displacement, and effective acceleration. Amplitude IMs are used in the empirical relationship derivation applied in the probabilistic hazard approach. The variables are set based on the dependence of IMs on the magnitude of site-specific distance and ground motion. Multiple spectral sources and the amplitude distribution of a record amongst multiple frequencies have been used to explain the frequency content of IMs.

The main properties of ground motion are Arias intensity (I_A), which measures amplitude, characteristic intensity (I_C), which indicates frequency content, and cumulative absolute velocity (CAV), which estimates the potential for building damage based on the record duration.

Arias intensity (I_A) is expressed as the time-integral of the square of the time series of ground motion and is defined by:

$$I_A = \frac{\pi}{2g} \int_0^{\infty} [a(t)^2] dt \quad (8)$$

Cumulative Absolute Velocity (CAV) is expressed as the time-integral of the square of the time series of ground motion and is defined by:

$$\boldsymbol{CAV} = \int_{\boldsymbol{0}}^{\boldsymbol{T_d}} |\boldsymbol{a(t)}|\boldsymbol{dt}| \qquad (\boldsymbol{9})$$

in which |a(t)| is the absolute value of acceleration in t. Characteristic intensity (IC) is given as:

$$\boldsymbol{I_C} = \boldsymbol{\alpha_{rms}^{1.5} T_d^{0.5}},$$

$$\propto_{\boldsymbol{rms}} = \frac{\boldsymbol{1}}{\boldsymbol{t_d}} \int_{\boldsymbol{0}}^{\boldsymbol{t_d}} [\boldsymbol{a(t)^2}]\, \boldsymbol{dt} \qquad (10)$$

where α_{rms} is given by root mean square of acceleration.

5. Research Methodology

The primary goal of incremental dynamic analysis (IDA) is to determine a curve by the intensity measure (IM) function that is defined by the maximum drift and the spectral acceleration ratio of the building defined by an EDP. The purpose of the proposed methodology is to apply an artificial neural network (ANN) with the intention of estimating the EDP, which is represented in terms of the first mode pseudo acceleration (Sa (T1, 5%)) for a given value of the limit state, which is also presented by obtaining the maximum drift ratio, which is the EDP employed in this manuscript. Therefore, the ANN could be capable of correctly estimate Sa (T1, 5%) from a triad specified properties of the ground motion record that considered I_A, I_C and *CAV* in this paper. The IM must be set accordingly based on the seismic demand in consideration for a given intensity; therefore, it could be applied in defining the properties of the record as input to the ANN. In this study, a proposed method of seismic response is applied by a properly set ANN in the SMRF (Steel Moment Resistant Frame) of structural fragility analysis.

In order to describe the input of the ANN at the beginning of the proposed method, 40 vectors of intensity measure are selected randomly, while the EDP in the Hazsus (FEMA, 2003) limit states (slight damage, moderate damage, extensive damage, complete damage, and collapse damage) are considered over the 100 sets of records, according to Jough & Şensoy (2016). The variation of these 100 records for the characteristic intensity measure is shown in Figure 3. The 40 realizations are assessed by means of the IDA analysis with reference to their structural performance. The training input from ANN is applied in the next step of the proposed methodology. This step includes the selection of a suitable ANN set and the validation of the ANN. Therefore, the training and testing procedures are done successfully, and the testing set is then capable of estimating whether the new design vectors are suitable in terms of structural constraint checks without computing any computational IDA analyses. Finally, it can be decided how many records are suitable for the prediction of the fragility curve.

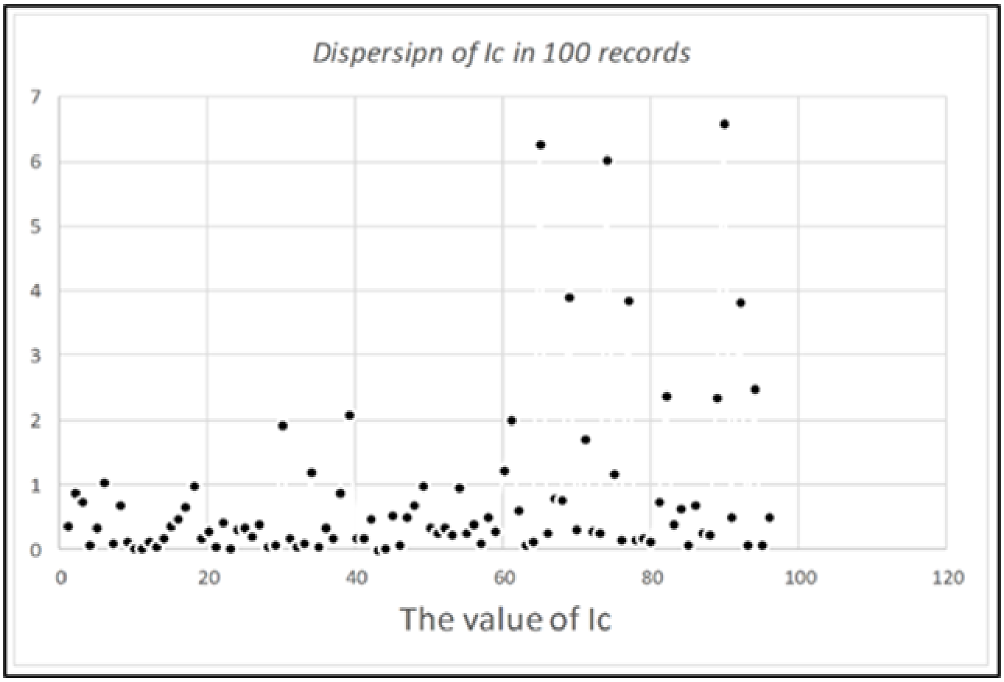

Figure 3. Scatter plot of characteristic intensity for 100 selected records.

6. Structural Models and Numerical Simulation

To evaluate the performance in curves of collapse fragility, the proposed method is applied and illustrated in a 5-storey moment resisting steel frame in Figure 4. The designed member sections are shown in Table 1. The plan and elevation of the assumed structure is symmetric, and that allows two dimensional analyses of structure.

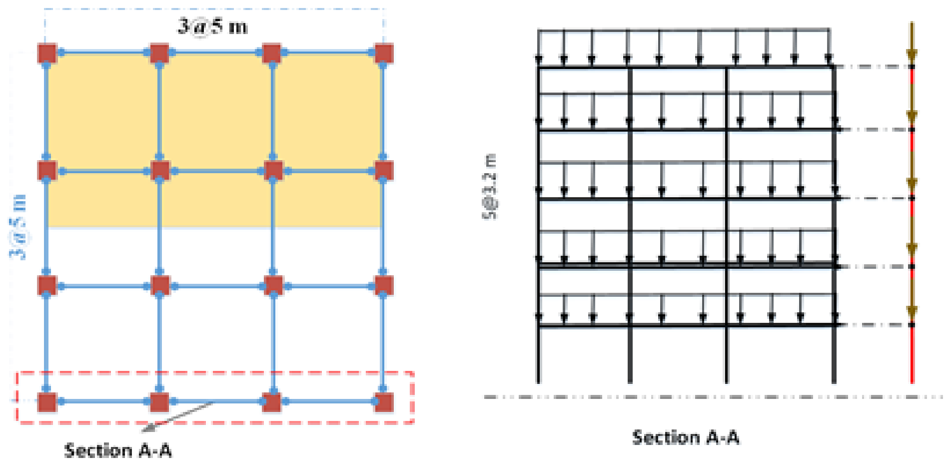

Figure 4. The analytical model of five-story, three-bay moment-resisting frame

Table 1. Considered sections of designed structure

story	C1	C2	B1	B2
1	BOX 180x180x2.0	BOX 300x300x2.0	IPE 400	IPE 400
2	BOX 180x180x2.0	BOX 300x300x2.0	IPE 400	IPE 400
3	BOX 180x180x2.0	BOX 300x300x2.0	IPE 400	IPE 400
4	BOX 160x160x1.6	BOX 200x200x1.6	IPE 330	IPE 330
5	BOX 160x160x1.6	BOX 200x200x1.6	IPE 330	IPE 330

Spectral acceleration at the first-mode period of the structural system (Sa (T1)) is considered an intensity measure. This IM is applied in various research studies (Baker & Allin, 2005) and is shown to fulfill sufficiency and efficiency criteria in the prediction of structural damage, which is the main goal of this study. Maximum Inter-Storey Drift Ratio (IDR) is selected as an engineering demand parameter since it represents the global behavior of the building, which has a good correlation with global collapse. The construction of these buildings is supposed to be on soil type B. The plan of the building is shown in Figure 4. A rigid diaphragm is supposed to be based on the roof system in most buildings.

Gravity loads are considered and assumed for the usual structures in Iran. There are a total of 7 modification factors (i.e., R), and each one is used by Iranian Seismic Code 2800 (2007). The finite element program OpenSees has been used to be able to apply analysis and modeling to the building samples. IDA analysis and nonlinear statics are done for a 2D external sample frame. In order to be able to model the steel structure element, a bilinear kinematic stress-strain curve is used to model the steel behavior by accessing the library of OpenSees (McKenna, 2011). At the intersection point of the first and second tangents (i.e., tangent moduli) of this material, a transition curve has been provided. The main goal of this curve is to avoid any unusual change in local stiffness matrices because these matrices are used to ensure an effortless and smooth transition between plastic and elastic regions formed by elements. On the other hand, to be able to model the cross sections for beams and columns with the highest accuracy rate, the displacement-based design of beams and columns in accordance with fiber sections needs to be applied. It is noteworthy to mention that displacement-based elements are more stable than force-based ones. Furthermore, the leaning column is going to provide the P-delta effects. Also, all connections that have been faced with moment-resisting are going to be evaluated according to their behaviors based on the modified model of Ibarra-Krawinkler and considered as rotational springs. As stated in Figure 5, the model of the M2-WO panel zone has been selected due to the well-representation of columns, beams, and panel zones yielding (2007). The static pushover and time history approach is done on the sample model to assess the lateral strength and drift ratio of the sample structure. The capacity curve and drift ratio for the sample structure are shown in Figures 6 and 7.

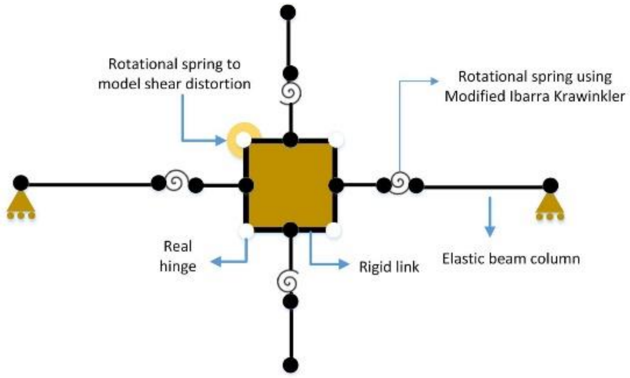

Figure 5. Detail of OpenSees model

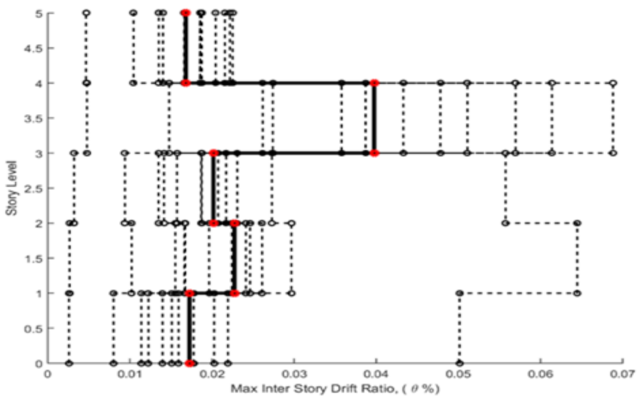

Figure 6. Drift ratio based on the nonlinear time history analysis

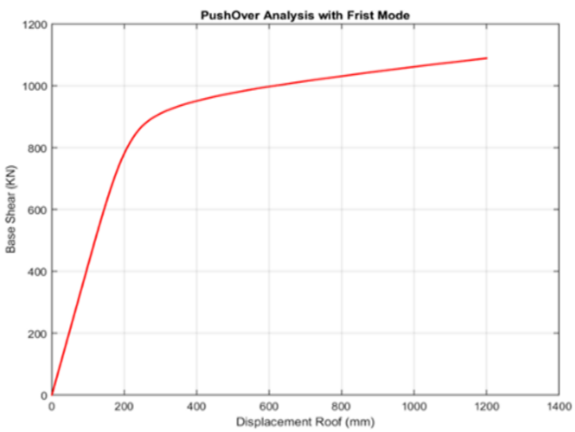

Figure 7. Drift ratio based on the nonlinear time history analysis

7. Using Artificial Neural Network (ANN) to Predict Seismic Demand

The key purpose of this paper is to study the behavior of SMRF structures by applying computationally efficient fragility analysis. For this target, the two values of Eq. (4) have to be performed under consideration of each limit state. These two parameters are affected by natural ground motion size sets, and the prediction of those leads to an analysis of fragility in different limit states. In this study, an ANN is applied to achieve the seismic level of demand according to EDP, expressed in terms of the structural first-mode period (Sa (T1, 5%)). The ground motions that express the uncertainty of demands have been defined with the help of the IMs vector and in accordance with the ANN itself. In more detail, IMs can state delegate values for each single ground motion seismic; therefore, IMs can be considered an input of ANN. The estimation abilities of the proposed ANN are represented for the considered examples as the first step of the suggested method.

The target of the ANN estimation method is to estimate and predict the different sets and combinations of the three IMs in accordance with the limit state value, which is given by the proposed demand, to assume that they are more suitable for the record definition. Therefore, in this case study, the total number of input nodes for the ANN is considered to be 3, but there will be two hidden layers with a total of 42 nodes in each. It is noteworthy to mention that this study has been done using a trial-and-error approach, and each of these hidden nodes is capable of providing a compromise between efficient calculations and accurate estimation. The damage that has been stated previously can be obtained by the total of 5 nodes in the output layer that correspond to the Sa (T1, 5%). Therefore, the 3–42–42–5 ANN configuration is applied for the case study. Figure 8 and the IDA curve of the sample structure are shown in Figure 9 in accordance with the ANN performance, where the obtained results of full IDA are compared with the estimated values of ANN. In Figure 10, the direct IDA evaluated value is represented on the horizontal axis, and the vertical axis refers to the estimated value by regressed analytical functions. The position of IDA-based values is equal to the approximated values, which have been indicated by the solid blue line. Also, the achieved data has been shown with dots, and the bounds are represented with dashed lines, which include 68.7% of the dots. The data deviation from the solid blue line (estimated error) is presented by the average of the ratio represented by equation (11). It is noteworthy to mention that the three training sets with the ground motion sizes of 40, 30, and 20 have been tested and simulated, and as a result, the 40-sample size has been taken as an equally well-sized sample compared to the other two ground motion training sets.

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{n_i}(y_i - \widehat{y_i})^2}{\sum_{i=1}^{n_i}(\widehat{y_i})^2}\right] \qquad (11)$$

Where y and $\hat{y}$ are predicted and definite values, respectively, and n_i is consider as total number of samples.

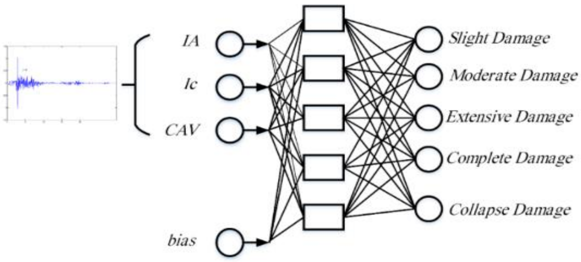

Figure 8. The structure of the MLP network implemented.

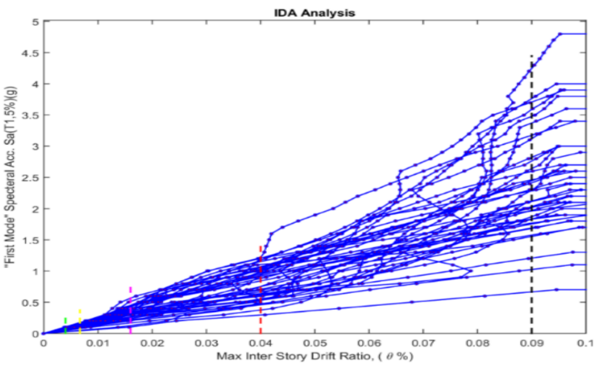

Figure 9. IDA curve of 40 suit records in SMRF sample

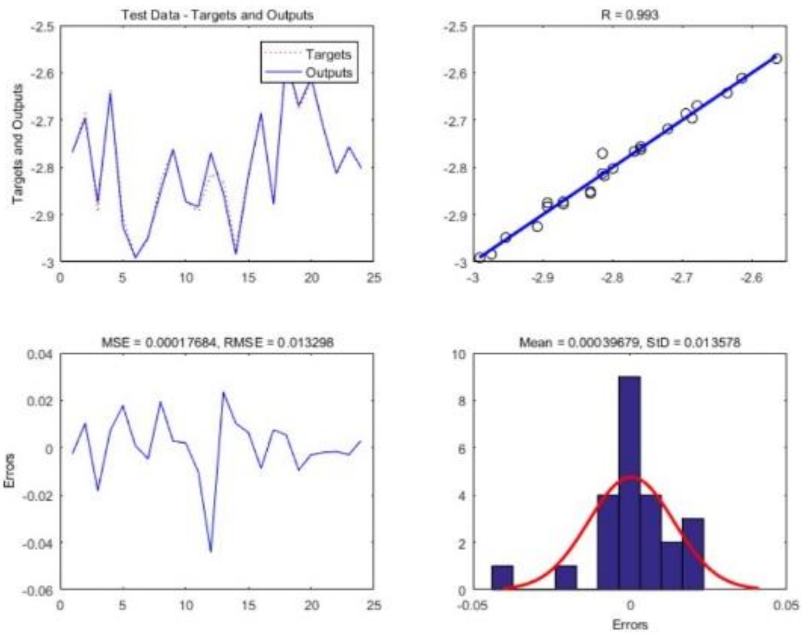

Figure 10. ANN analysis graph for 40 earthquake (a) Train data (b) Test data

8. Fragility Curve

In the second part of this proposed method, five damage are applied to the states of fragility curves for sample buildings. The considered damage-states has been defined by the values of maximum means drift and structural damage range from availability and usability to life cycle safety of structure in accordance with the sideway collapse. The following θ_{max} values has been selected, based on HAZUS (FEMA, 2003) research study with respect of each one of the five damage-states: 0.4% (slight damage), 0.67% (moderate damage), 1.6% (extensive damage), 4% (complete damage) and 4.8% (collapse damage) or last-converged point on an IDA curve any one reaches early for the SMRF building with five symmetric story. For each single of damage state, the IM-based and IDA has been applied to compute the two factors of μ and β from Eq. [4] by using "log fit" function of Mat-lab. IM-based has been defined and calculated for all five states of damage. In accordance to the target of proposed method, five cases have been applied to calculate the two factors of ($\boldsymbol{\mu_k}$, $\boldsymbol{\beta_k}$, k = 1 . . . 5): IDA-20, IDA-40, IDA-60, IDA-80 and IDA-100, where 10–100 records are implemented.

Figure 11 represents the fragility curves in different damage state that cover the entire damage range of sample structure. For the test case, the fragility curves deriving based on the IDA-100 are considered as the ''perfect'' ones. Initially, it can be observed that the IDA-20 damage states are overestimated the structure capacity. On the other hand, the capacity of the structure is underestimated for both damage states of IDA-40 and IDA 60. So, it can be noted that 80 records offer a good prediction of the two Based on $\boldsymbol{\mu_k}$and $\boldsymbol{\beta_k}$, the fragility curves of IDA-80 approximately coincide with case of IDA-100 which is our acceptance criteria. So, it can be resulted that IDA-80 is the best case among others according robustness and efficiency. Therefore, it can be noted that more natural ground motions are required for an efficient and reliable computation of $\boldsymbol{\mu_k}$ and $\boldsymbol{\beta_k}$ factors and accordingly for the deriving the fragility curves in various damage state.

9. Conclusion

A neural network-based approach is applied for achieving a suitable prediction of the Sa (T1, 5%) given the building capacity, which is subsequently applied for the fragility evaluation of steel moment-resistant frames. Especially, ANN is applied as the proposed approach when incorporated into the IDA analysis, which indicates that it is suitable. The main target is to suggest a procedure capable of preparing accurate Sa (T1, 5%) of the structural frame at a suitable analytical time that is then incorporated into the computational fragility curve. ANN are trained to apply a fixed number of IM, which can be simply derived from natural records. For the purpose of efficiency and representing the proposed method, a five-story symmetric steel moment building has been discussed.

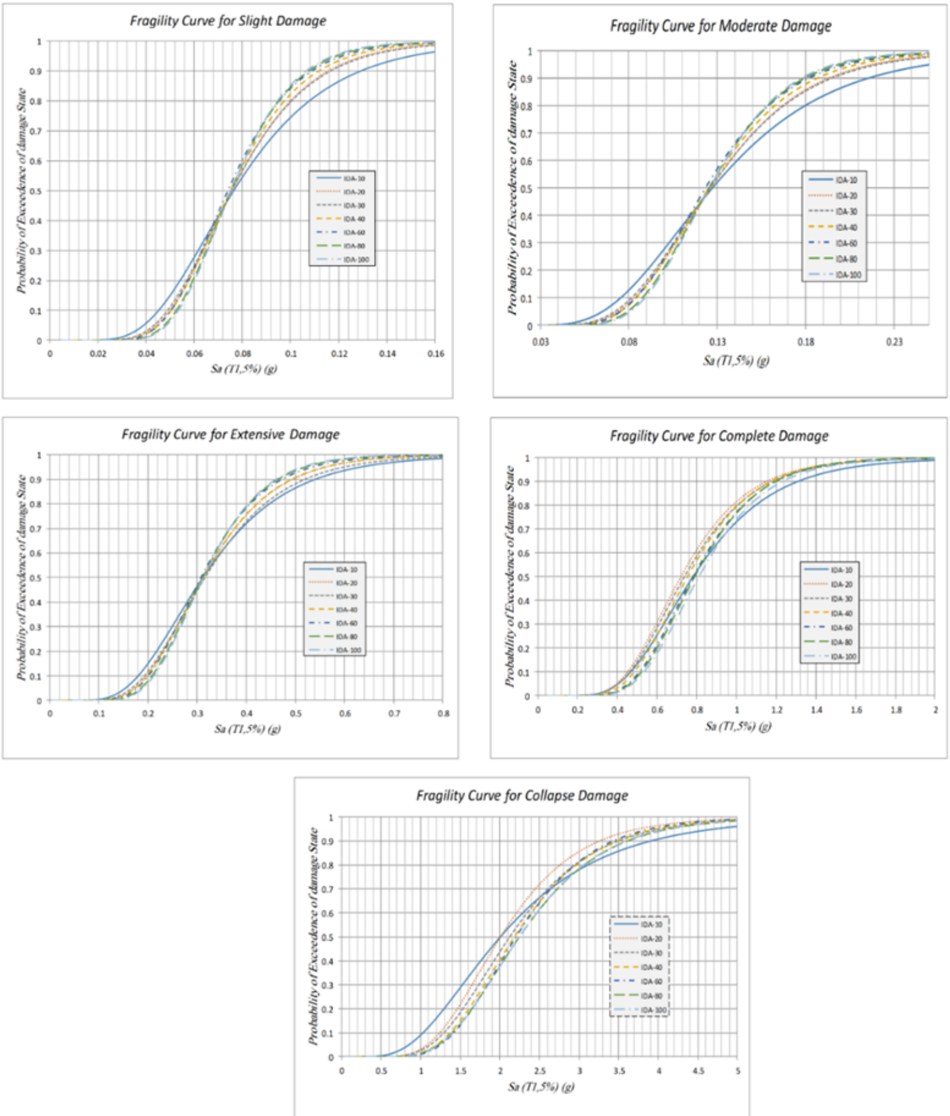

Figure 11. Fragility curves for five damage-states applying alternative number of records.

There are three parts to numerical attention. Firstly, the capability of predicting by the ANN is tested. As was shown, 40 training and testing samples (IM) are enough for efficient training, testing, and validation of the ANN to estimate the seismic demand presented by the Sa (T1) for the five damage states. Second Based on the trained ANN's estimation, we have successfully derived a set of five damage state fragility curves. On the other hand, the analytical cost of the proposed ANN is tested. It was represented that the analytical cost applied by the predicted ANN would be reduced by comparing various fragility curves in different limit states.

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