Developing Seismic Fragility Curves Using ANN Based Probabilistic Seismic Demand Models Derived from Structural Design Parameters

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Abstract. Assessing the fragility and damage state of multiple buildings in an urban setting remains a challenging task requiring considerable time and cost. This study proposes deriving seismic fragility curves using an Artificial Neural Network (ANN) based Probabilistic Seismic Demand Model (PSDM) to overcome these challenges. Seismic fragility curves were developed using the ANN based PSDM to derive the regression function of interstory drift and spectral acceleration. The methodology involves conducting nonlinear dynamic analysis for 540 steel moment frames(SMFs) using 240 seismic records to construct a PSDM for each SMF. The ANN-based PSDM was developed using nine design variables (number of stories, number of bays, bay width, first-story height, floor dead load, roof dead load, and first to third natural periods of SMFs) as input and the regression function of interstory drift and spectral acceleration as output. Fragility curves for SMFs were derived using the ANN-based PSDM. ANN-based PSDM exhibited an accuracy of R-value 0.96 for the training database. The developed ANN-based PSDM is validated and compared with the results obtained from the general method using nonlinear dynamic analysis. The results show that the ANN-based PSDM accurately predicts damage states and the fragility curves derived using this method are consistent with those obtained from nonlinear dynamic analysis. The proposed methodology offers a time-efficient and reliable approach for assessing the fragility of SMFs without the need for detailed structural modeling and time-consuming nonlinear analysis.

Keywords: Seismic fragility curves, Artificial neural networks(ANN), Probabilistic seismic demand model(PSDM), Steel moment frame(SMF), Seismic performance evaluation

1 Introduction

Steel moment frames (SMFs) are the most widely used lateral resisting system for resisting seismic loads. With an increase in the height of buildings in urban areas, SMFs have been commonly used to shorten the construction period and reduce CO2 emissions during construction. Studies have been actively conducted to evaluate the seismic performance of SMFs. Most seismic performance evaluation techniques are suitable for individual buildings. However, they are difficult to apply to urban-level seismic performance evaluation that requires seismic performance evaluation for multiple buildings because they require precise simulation models and nonlinear analysis. Hence, assessing the fragility and damage-state of buildings after an urban earthquake is an urgent issue.

It is necessary to derive the engineer demand parameter (EDP)-intensity measure (IM) relationship to assess the fragility and damage-state of a building. Fragility curves provide the probability that a structure or its EDP will reach a certain level of damage for a given IM of ground motion. Studies to derive seismic fragility curves have been conducted since the 1980s, and many studies have been conducted to evaluate the behavior of structures with respect to ground motion. Kircher et al. performed idealization to a single degree of freedom based on the structural type, material, and height of the building applied in HAZUS, and they proposed a seismic vulnerability function [1].

With the development of structural analysis technology, studies on dynamic analysis have been actively conducted. Methods for deriving the fragility curves of structures via nonlinear static analysis and statistical methods have been developed [2-6]. Incremental dynamic analysis (IDA) can predict the dynamic response of a structure at the maximum ground acceleration of an earthquake with a specific return period or at the spectral acceleration in the natural period of the structure by increasing the seismic intensity and observing the response of the structure [7]. Based on this nonlinear dynamic analysis, various methods were derived for the fragility curves of structures. Various fragility curve derivation methods based on nonlinear dynamic analysis have been utilized [8-12]. However, they require dozens or hundreds of nonlinear dynamic analyses, thereby consuming considerable time for analysis. Additionally, there involve complicated considerations, such as material nonlinear models, failure modes, and strength and stiffness reduction, for the modeling of structures. The fragility curves derived using nonlinear dynamic analysis are accurate but difficult to apply to urban-level seismic performance evaluation for multiple buildings because they require considerable time [13].

Machine learning technology and artificial neural network models have been used to predict member-level and system-level behavior in the field of civil engineering [14-17]. Recently, various machine learning-based seismic analysis techniques were developed in order to reduce the time required for earthquake analysis and to process massive data. A new approach to nonlinear modal analysis based on the machine learning method [18]. A novel procedure for identifying the dynamic characteristics of a building and diagnosing whether the building has been damaged by earthquakes, using a back-propagation neural network approach [19]. Machine learning methods were applied in many civil engineering areas such as damage identification [20-24], damage state of steel frame [25], predicting the nonlinear time history response of structure [26]. However, most seismic response prediction models can only predict responses such as top displacement, floor acceleration and so on, for a specific earthquake intensity, and it is difficult to derive a relationship between seismic intensity and response.

This study aimed to develop a seismic fragility analysis method that enables fragility assessment of steel moment frames (SMFs) without the need for detailed structural modeling and time-consuming nonlinear analysis. The proposed methodology involved the use of an Artificial Neural Network (ANN)-based Probabilistic Seismic Demand Model (PSDM) to derive fragility curves for SMFs. (1) For 540 SMFs, nonlinear time history dynamic analysis was conducted via 240 seismic records. Based on the dynamic analysis results, data for a probabilistic seismic demand model (PSDM) were constructed for each SMF. (2) Artificial neural network (ANN)-based PSDM that uses nine design variables of SMFs as input values and the regression function of interstory drift and spectral acceleration as an output value was developed. (3) seismic fragility curves of SMFs were derivated using ANN-based PSDM.

2 Methodology for seismic fragility curves using ANN based PSDM

2.1 Derivation of seismic fragility curve

The conventional fragility curve is calculated as the probability that EDP will exceed limit states at IM. Therefore, EDP of a structure should be predicted at random IM to derive fragility curves. Two methods are mainly available to predict EDP of a structure. The first method involves measuring EDP by conducting the dynamic analysis of the structure while increasing IM of seismic records. This method, which is referred to as incremental dynamic analysis, requires scaling of seismic records to increase their IM. During the scaling process, the unique characteristics of the original seismic record can change. Hence, it is necessary to consider whether the scaled seismic records are reasonable. To address this problem, the cloud method that uses only the data of original seismic records has been commonly used [27].

The cloud method derives PSDM and EDP-IM relationship using the data obtained by conducting a nonlinear dynamic analysis of the structure through original seismic records. PSDM assumes that EDP follows a lognormal probability distribution [28].

$$\ln(EDP) = \ln(a) + b\ln(IM) \qquad (1)$$

Where a and b denote the regression coefficients that can be determined from a regression analysis of the response obtained from dynamic analysis.

Given the seismic demand and capacity, the fragility of the structure at each damage states (DS) can be calculated as follows:

$$P[DS|\mathrm{IM}] = \Phi\left[\frac{\ln(IM)-\lambda}{\xi}\right] \qquad (2)$$

Where Φ[•] is the cumulative distribution function of the standard normal distribution; λ and ξ are the median and standard deviation of the IM, respectively.

$$\lambda = \frac{\ln(S_c) - \ln(a)}{b} \quad (3)$$

$$\xi = \frac{\sqrt{\beta_{D|IM}^2 + \beta_C^2}}{b} \quad (4)$$

where S_c and β_c(=0.3) denote the median estimate and logarithmic standard deviation of the capacity, respectively; $\beta_{D|IM}$ denotes the standard deviation of the demand that can be calculated as follows.

$$\beta_{D|\mathrm{IM}} = \sqrt{\frac{\sum_{i=1}^{N}[\ln(EDP_i) - \ln(aIM^b)]^2}{N-2}} \quad (5)$$

where N denotes the total number of simulation cases. ξ is a parameter that can take into account the uncertainty of the analysis model and the uncertainty of the nonlinear dynamic analysis. β_c is a parameter considering the uncertainty of the numerical model, and $\beta_{D|IM}$ is a parameter considering the uncertainty of the nonlinear analysis results. Uncertainty in the data was reflected through the arithmetic sum of β_c and $\beta_{D|IM}$. The proposed fragility analysis enables derivation of fragility curves by replacing structure modeling, nonlinear dynamic analysis, and regression analysis processes, which consume a significant amount of time in the cloud method involving ANN-based PSDM. Specifically, ANN-based PSDM derives the regression curve of IM (spectral acceleration$_{\text{1st period}}$) and EDP (inter-story drift) as the design parameter of the structure. Based on the derived regression curve, the fragility curve was derived using equations (1) to (5).

2.2 Data generation for ANN based probabilistic seismic demand model

The methodology to develop ANN-based PSDM consists of five steps. (1) A simulation model for SMFs is constructed. In this study, 540 SMFs that satisfy AISC 360-16 were modeled [29]. (2) 240 ground motion records were collected. (3) Nonlinear dynamic analysis was conducted 129,600 times using 540 SMFs and 240 ground motion records. (4) PSDM was derived using the story drift ratio and spectral acceleration obtained via the nonlinear dynamic analysis results of each of 540 SMFs, and a database was constructed for the regression coefficient. (5) ANN-based PSDM was trained by selecting the design parameters of structures, and the first, second, and third natural periods were selected as input data and three regression parameters as output data.

In this study, 540 SMFs were selected as target buildings [29]. The number of stories ranged from 5 to 19, and the ratio of the first-story height to the typical story height was set to 1.0, 1.5, and 2.0. The number of bays was set to 3 and 5. The bay width was set to 6.1, 9.14, and 12.19 m. The database of SMFs was composed of 162 five-story, 162 nine-story, 128 fourteen-story, and 88 nineteen-story. Archetypes of SMRFs were designed with a spectral acceleration of S_s=2.25 g and S_1=0.6 g based on site class D of Los Angeles, California used in the ATC-123 Project [30]. The floor dead load was set to 2.39, 3.83, and 5.27 kN/m^2. The lower values denote the case of using a thin slab of lightweight concrete while the upper value shows the case of using a thicker slab of normal-weight concrete. The roof dead load was set to 0.96, 3.23, and 5.51 kN/m^2. The lower value corresponds to the case in which only steel decks are used while the upper value corresponds to the case in which steel decks with normal-weight concrete are used. Furthermore, a load of 2.39 kN/m^2 was applied as the floor live load based on offices, and a load of 0.96 kN/m^2 was applied as the roof live load. Gravity load (seismic mass) was defined as 1.05DL+0.25LL according to FEMA P695. Furthermore, 2% was selected for the allowable drift ratio according to ASCE 7, and the yield stress of steel was 345 MPa.

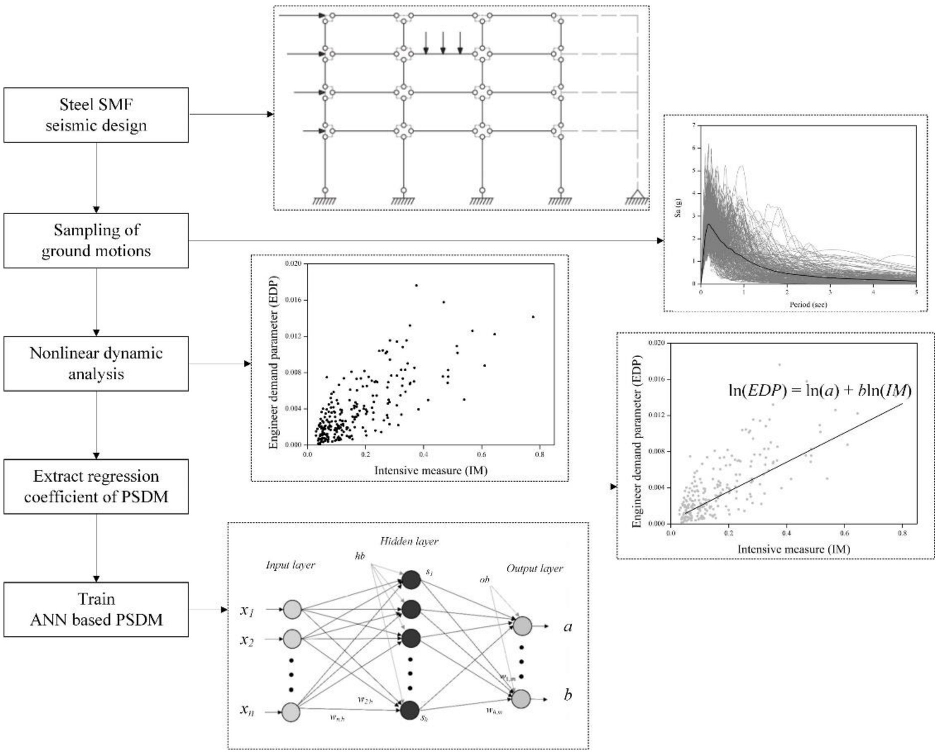

Fig. 1 Overview of the methodology for ANN based PSDM

A total of 240 earthquake acceleration time histories recorded in the state of California for 12 different earthquakes were used in this study. A particularly large number of earth-quake ground motions was selected in order to assess the dispersion of the inelastic displacement ratios.

Some scholars studied the seismic performance of structures by introducing frequent or non-frequent records to consider the randomness of ground motion [31]. The 240 non-frequent ground motion records are acceleration records for 12 seismic records that occurred in California [32]. Furthermore, 240 ground motions are the ground motions in high seismicity zones. All seismic records were measured from rock and firm sites with a mean shear wave velocity of 180 m/s or higher. The soil-structure interaction effect was neglected. Furthermore, the magnitude of seismic records ranged from M 6.0 to M 7.0, and the average was M 6.7. The maximum ground acceleration ranged from 0.03 g to 0.77 g. Fig. 3 shows the individual and average acceleration spectra of 240 seismic records.

2.3 Extracting regression coefficients of PSDM

In this study, IM of PSDM in equation (1) was defined as the spectral acceleration in the 1st period and EDP as the maximum interstory drift ratio. The spectral acceleration is a value derived based on the displacement value according to the change in the natural period of SDOF, and the spectral acceleration of the target structure in the 1st period has a significant impact on its seismic response displacement. Therefore, in this study, the spectral acceleration that considers the influence on the structure was selected as IM as opposed to PGA, which is the unique characteristic of seismic records. As for the seismic response EDP of structures, there are various types, such as interstory drift, maximum interstory drift, and floor acceleration. Among several EDPs, the maximum interstory drift (DR_{max}) has the largest influence on damage to a structure. It has been used as the threshold of the damage state in many studies, such as Hazus ML [33] and FEMA P-58 [34]. Equation (6) is the regression curve of the selected S_a and DR_{max} PSDM as follows:

$$\ln(DR_{max}) = \ln(a) + b\ln(S_a) \qquad (6)$$

Where a and b denote the regression coefficients that can be determined based on a regression analysis of the response obtained from dynamic analysis.

$$\beta_{D|\mathrm{IM}} = \sqrt{\frac{\sum_{i=1}^{N}[\ln(DR_{max_i}) - \ln(a(S_a)^b)]^2}{N-2}} \qquad (7)$$

For each SMF, the regression analysis of S_a and DR_{max} was conducted via the dynamic analysis results of 240 ground motions, and regression coefficients and $\beta_{D|\mathrm{IM}}$ were derived. The regression coefficients (a, $b$and $\beta_{D|\mathrm{IM}}$ of a total of 540 SMFs were converted into a database. Fig. 2 shows the nonlinear dynamic analysis results of 240 ground motions, and the regression analysis results for 5-story 3-bay and 14-story 5-bay SMFs.

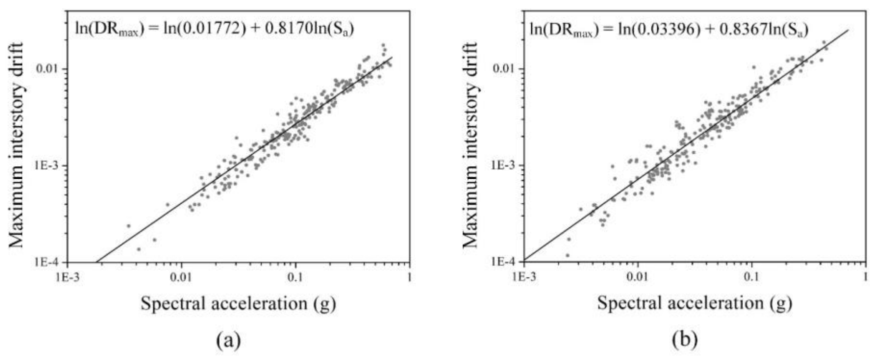

Fig. 2 Structural response of (a) 5-story – 3-bay SMF, (b) 14-story–5-bay SMF

2.4 Determination of input & output data

For the training of the ANN model, it is very important to construct the training sets of input and output data. In this study, a total of nine input variables were defined using six design parameters (the number of stories, ratio of the first-story height to the typical story height, number of bays, bay width, floor dead load, and roof dead load) and three dynamic properties (1^{st}, 2^{nd}, and 3^{rd} natural periods) of SMFs. The two coefficient parameters (a, b) and $\beta_{D|\mathrm{IM}}$, which were converted into a database in section 2.2.4, were defined as output variables. Table 2 summarizes the statistic properties of the 9 input variables and 3 output variables. ANN-based PSDM was trained by constructing a total of 540 training sets.

3 Derivation of seismic fragility curves using ANN based PSDM

3.1 Description of two steel moment resisting frame

In this section, seismic analysis is conducted on two example SMFs using the developed ANN-based PSDM. The two example SMFs were not included in the SMF database constructed in section 2.2, and 8-story 5-bay and 19-story 5-bay SMFs were selected. Both structures were designed as offices and had a first-story height of 7.92 m, floor height of 3.96 m for the other floors, and bay width of 12.94 m.

They had natural periods of 1.887 and 2.58 seconds, respectively, and were designed based on Los Angeles, California, Site D. Their design spectral accelerations were 0.36 g and 0.26 g, and the MCE level spectral accelerations were 0.54 g and 0.39 g, respectively. Tables 4 and 5 summarize the cross-sectional information of the two SMFs.

3.2 Comparison fragility curves between PSDM using ANN model and Cloud method

The design parameters and 1^{st}, 2^{nd}, and 3^{rd} natural periods of the 8-story and 19-story SMFs as well as ANN-based PSDM were used to derive the regression coefficients of the two structures. Fig. 10 shows PSDM derived using the regression coefficients, the 95% confidence interval of PSDM obtained using β, and PSDM derived using the cloud method after conducting nonlinear dynamic analysis using 240 seismic records. ANN-based PSDM was consistent with PSDM derived using the cloud method for the 8-story and 19-story structures. Furthermore, 236 data (98.3%) out of 240 data were included in the range of the regression function calculated with the 95% confidence interval of ANN-based PSDM for the 8-story SMF, thereby confirming the high reliability of ANN-based PSDM. In the case of the 19-story SMF, 228 data (95%) out of 240 data were included in the range of the regression function calculated with the 95% confidence interval of ANN-based PSDM, thereby confirming that the regression function of ANN-based PSDM is highly reliable.

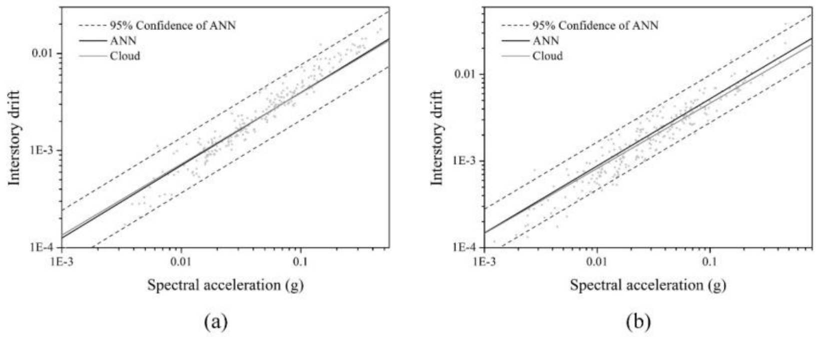

Fig. 4 Probabilistic seismic demand model derived from ANN model and cloud method; (a) 8-story SMF, (b) 19-story SMF

3.3 Seismic fragility curve using ANN-based PSDM

In section 3.3, seismic fragility analysis was conducted using the fragility curves of 8-story and 19-story SMFs derived via ANN-based PSDM. To verify the fragility curves derived via ANN-based PSDM, the fragility curves derived using nonlinear dynamic analysis and cloud method were compared with the seismic fragility analysis results. Based on the regression function and $\beta_{D|IM}$ of ANN-based PSDM for 8-story and 19-story SMFs obtained, fragility curves for the damage state in Table 6 were derived using equations (1) to (5). We evaluated the maximum interstory drift predicted by the regression function through the ANN-based PSDM according to the damage state of steel moment frames in FEMA 356. Collapse of structures was defined as a case where the inter-story displacement ratio exceeded 4%. Fig. 5 shows the fragility curves derived using ANN-based PSDM and those derived using the cloud method via the nonlinear dynamic analysis results. For the design level spectral acceleration (0.36 g) derived via ANN-based PSDM, the probabilities that the 8-story structure exceeds the LS and CP levels were 1.54% and 0.933%, respectively. For the design level spectral acceleration derived via the cloud method, the fragility probabilities at the LS and CP levels were 1.6% and 0.97%, respectively, almost identical to the fragility curves derived through ANN-based PSDM. For the MCE level spectral acceleration (0.54g), the fragility probabilities at the LS and CP levels were 2.04% and 1.24%, respectively, which were similar to the fragility probabilities at the LS and CP levels derived via the cloud method (2.08% and 1.27%). In the case of the design level spectral acceleration (0.26g) of the 19-story structure derived through ANN-based PSDM, the fragility probabilities at the LS and CP levels were 1.49% and 0.84%, respectively, resulting in a slight difference of 0.12% when compared to the fragility probabilities derived via the cloud method (1.32% and 0.72%). For the MCE level spectral acceleration (0.39g), the fragility probabilities at the LS and CP levels were 1.89% and 1.11%, respectively, which were similar to the fragility probabilities derived via the cloud method (1.68% and 0.96%), with a difference of 0.2%. Seismic fragility assessment was very similar to conventional seismic fragility assessment that uses nonlinear dynamic analysis and the cloud method. This indicates that seismic fragility assessment is a reasonable fragility assessment method

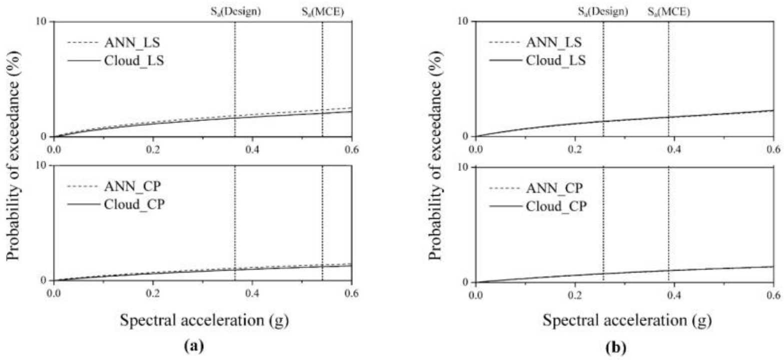

Fig. 5 Fragility curves derived from ANN-based PSDM and cloud methods at LS, CP level; (a) 8-story SMF, (b) 19-story SMF

4 Conclusion

The study began by highlighting the importance of assessing the fragility and damage state of buildings after an urban earthquake. It discussed the challenges of applying existing seismic performance evaluation techniques to multiple buildings in an urban setting due to the requirement of precise simulation models and nonlinear analysis.

ANN-based PSDM derived the spectral acceleration-interstory drift regression function based on the nine parameters of SMFs (number of stories, number of bays, bay width, first-story height ratio, floor dead load, roof dead load, and 1st, 2nd, and 3rd natural periods) and the results showed good prediction. The developed ANN model was trained and validated using a large dataset of SMFs and ground motion records. The performance of the ANN model was evaluated using mean square error (MSE) and regression R-value. The results showed high prediction accuracy with an R-value of 0.9681 or higher and an average MSE of 2.25%.

Fragility curves derived via ANN-based PSDM exhibited similar accuracy when compared to those derived through nonlinear dynamic analysis. For the design level spectral acceleration, the fragility probabilities of the eight-story SMF at the LS level derived using the two methods were very similar, with a difference of 0.16%.

Overall, the proposed methodology using the ANN-based PSDM provided a reliable and efficient approach for assessing the fragility and damage state of SMFs. It eliminated the need for detailed structural modeling and time-consuming nonlinear analysis, making it suitable for urban-level seismic performance evaluation of multiple buildings. The study's findings contribute to the field of earthquake engineering by offering a practical and efficient method for assessing the seismic vulnerability of SMFs.

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