SEISMIC BEHAVIOR OF STEEL MOMENT FRAMES WITH DATA INTENSIVE DAMAGE MODEL USING THE NEURAL NETWORK

H.J. Chang[1], J.H. Kim[2], I.S. Choi[3]

[1] *Ph.D Candidate, Department of Architecture and Architectural Engineering, Yonsei University, Seoul 03722, Republic of Korea, hakjong@yonsei.ac.kr*
[2] *Associate Professor, Department of Architecture and Architectural Engineering, Yonsei University, Seoul 03722, Republic of Korea, junhkim@yonsei.ac.kr*
[3] *Ph.D Candidate, Department of Architecture and Architectural Engineering, Yonsei University, Seoul 03722, Republic of Korea, insub@yonsei.ac.kr*

Abstract

Damage to steel structure is caused not only by earthquake events or heavy impacts, but also by dead and live loads as the structure gets older. Joint damage may include fatigue cracks between bolt holes, bolt failure, and plastic deformation of a joint component. These damages to joints degrade the performance of the joint, affects the performance of the structure and changes dynamic characteristic of the structures. The purpose of this study is to develop the data-intensive damage model by the neural networks using the changed dynamic characteristic data of the damaged structure and to evaluate seismic behaviors of the steel moment frame with data-intensive damage model. First, the dynamic characteristic data of the building trial model was extracted according to damage scenario of the joints. Damage parameters according to damage scenario types were selected as training data of neural network systems. Second, through the neural networks the relationship between dynamic characteristics of structure and damage parameter of the joint such as degrading of stiffness, strength and pinching effects was trained. 90 percent of the data was classified as training data and 10 percent as verification data, and neural network training was conducted. Last, the damage parameters of the joint model were derived from dynamic characteristic data measured from the target structure using trained neural network system. Data-intensive damage model of beam-column joints was developed using damage parameters. The seismic behavior of steel moment frames applying the data-intensive damage models to the beam-column joints was evaluated. As a result of verifying the accuracy of the trained data-intensive model through random input values (dynamic characteristic data), the error of output data (damage parameter) was under 1%. There is no significant different between seismic performance assessment results of real structure model (reference model) and structure model using data-intensive damage model. If this study is continued, it is expected that the structural performance of the damaged building by the mainshock can be easily identified using dynamic characteristic data measured with measuring equipment such as acceleration sensors. In addition, by determining the structural performance of structural members in real time, it will be used as a decision-making tool for aftershock events or additional damage.

Keywords: Data-intensive joint model; the neural networks; Seismic behaviors; steel moment frame;

1. Introduction

Structural elements inside bridges and building structures provide withstanding forces to external loads like earthquakes, typhoons, traffic and gravity throughout the whole building lifecycle. These elements' performances may be damaged and decay over time. Such damage might result in building collapse including casualties and property loss In case of natural disasters like earthquakes, old and deteriorated structures might be damaged much more than expected. To accurately measure building's structural performance and to collect data necessary for maintenance operations, regular safety inspection is required. For a frame structured building's characteristic action, the importance of joint is greater that it is highly important to reasonably assess the condition of joints. Evaluating the health of joint is also important within seismic evaluation and calculation of numerical analysis model. There are preceding research on how to specify the location of damaged joints by detecting notches and damages[1], research about substituting joint's contribution factor to equivalent beam elements[2], and using semi-rigid connected beam elements to assume joint stiffness plus experimental evaluation to predict rotational stiffness[3]. However, existing research does not accurately deal with joint's rotational stiffness which can vary from 0 on pins to infinite on rigid links, making it difficult to apply on real world. Other research on real-time health monitoring using wired/wireless measurement system is also on the way. [4, 5]

Measurement system include deformation sensors to monitor major structural element's safety as well as acceleration sensors to acknowledge building's serviceability. Structure's reaction magnitude varies from different conditions of load time and space, which means safety and damage evaluation based on peak values without analyzing observation data is insufficient. Therefore, dynamic characteristics like natural frequency and mode shape are widely used to predict a structure's damage. [6,7,8,9] Such dynamic characteristics are natural characteristics, which do not change regardless of external load's time and spatial property but only depend on structure's stiffness and mass showing no difference if undamaged, but changes when damaged Normally damage occur when exceeding external loads like earthquake situation, or because of natural aging deterioration over a long time. Structural damage is defined as reduction of resisting performance to external forces, which can also be defined as degradation of stiffness of structural elements. When stiffness degradation occurs, deformation and natural period of building increase. Therefore, by using acceleration response data to analyze dynamic characteristic, it is possible to determine a structure's damage. Accelerometer is a convenient and reliable sensor that can be used to collect building acceleration response data Installing these accelerometers to several stories to collect acceleration response data to acquire natural frequency and mode shape. While these data are useful in representation of system level characteristics, determination of individual element's current status is limited. In order to overcome such limitations, various new techniques are introduced using index changes such as curvature mode-shape and flexibility to predict the location and size of damage inside a structure. [10,11,12,13]

The more sensors installed, the more channel of data acquired to increase the accuracy and reliability of damage evaluation. However, more sensors mean more cost and difficulties of maintenance and operation, limiting the number of sensors installed. [14, 15] To acquire indexes such as modal flexibility and MSE(Modal Stain Energy), plentiful data from different channels of sensors are necessary. But previous buildings with no sensors or less sensors are difficult to analyze. In case of mode-shape and natural frequency, less number sensors are sufficient to operate FFT(Fast Fourier Transform) and modal analysis compared to calculation of Modal flexibility and MSE.[16,17]

In this research, easily acquirable natural frequency and modal data are introduced to ANN(Artificial Neural Network) data-intensive damage model of a steel moment frame joint. Then analyze the effect and correlation of rotational stiffness to dynamic characteristics(natural frequency, mode-shape). Structure's dynamic characteristics are input layers of data, while beam-column joint rotational stiffness is result layer data. Damage index represents the degree of structural damage. Numerical analysis of 3 stories 4bay steel moment frame example is performed to train ANN and verify the result data. Validification of example will be presented to compare ANN method's damage location and grade prediction accuracy.

2. Artificial Neural Network

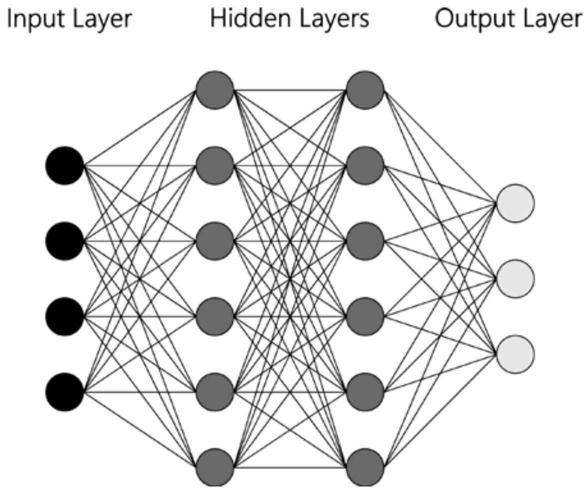


Figure 1 Organization of Artificial Neural Network(ANN)

As shown in Fig. 1, the artificial neural network is composed of input layer, hidden layer and output layer. In the input layer, values are input as many as the number of nodes constituting the input layer. For notice, there are four nodes which make up the input layer shown in Fig. 1. Each input value is changed through linear combination by using weights, and delivered to each node forming the hidden layer. This delivered value is the input to the active function located in the hidden layer. There are various kinds of active functions such as step function, sigmoid function, and ReLU function. The output value of the active function is multiplied again by the weights and summed with the output values of the other nodes in the hidden layer and delivered to the nodes of the output layer. The value of each node in the output layer means the output value. The data collected in advance (input and output) are used as learning data to determine the weight value in the artificial neural network.

The data collected in advance (input and output) means a kind of (input and correct answer) relationship, and when the same data is input to the artificial neural network, the weight value is determined. The neural network generated through this learning process can be used for predict the correct value by passing the input value to the neural network in a situation where knows the input value but the correct value is not known. Artificial neural networks are widely used for various purposes such as design, system identification, damage assessment and earthquake prediction in various engineering fields such as architecture, civil engineering, etc. [18, 19, 20, 21]

3. Data-intensive damage model of steel moment frames

The joint of the steel moment frame is modeled as a rigid connection and a pin connection in the structural analysis, but the actual joint behavior is semi-rigid connection. The deformation of the joint can be classified into three types: bending deformation, shear deformation, and axial deformation. Among these three deformations, particularly, bending deformation can have a big influence in the analysis and design of steel structures. Damage to the steel structure occurs frequently at the joints and the damage can be defined as a deterioration in rotational stiffness of the joints. For this purpose, a plastic hinge model including the rotational stiffness of the joint is presented, and a damage model considering the damaged rotational stiffness is presented.

3.1 Plastic hinge model for connections (FEMA 356)

Plastic hinges for steel members are defined in FEMA 356. Fig. 2 shows the plastic hinge characteristics of the steel member. It is usually modeled as four straight lines, defining the absolute value of the deformation. The stiffness of the strain hardening section is 3% of the elastic section, but if it is proved by the experiment, a larger value can be used. The parameter Q in Fig. 1 is the load and expected strength of each generalized component. Yield strength for each member can be estimated using the average material strength. QCE is yield strength for each member and it can be calculated using the average material strength. For beams and columns, θ is the total angle of rotation and θ_y is the angle of rotation at the yield point. In the yield rotation angle equation, 6EI / l (E modulus of elasticity, I cross-sectional moment, length of l member) means the stiffness of the rotating spring. Therefore, the yield rotation angle of the joint is defined as the yield moment divided by the rotational stiffness of the member.

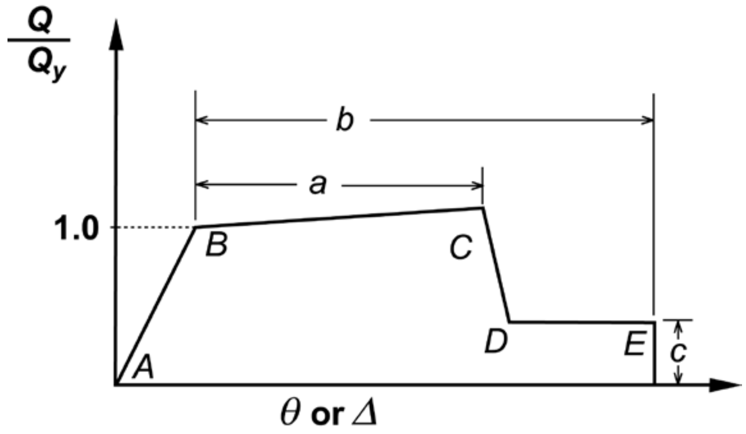


Figure 2 Plastic hinge model in FEMA 356

Beam : $Q_{CE} = M_{CE} = Z \times F_{ye}$ (1)

Column : $Q_{CE} = M_{CE} = 1.18 \times Z \times F_{ye} \times (1-P/P_{ye}) \leq Z \times F_{ye}$ (2)

Beam hinge : $\theta_y = Z \times F_{ye} \times (L_b/6 \times E \times I_b) = Z \times F_{ye}/K_{br}$ (3)

Column hinge : $\theta_y = Z \times F_{ye} \times (1-P/P_{ye}) * (L_c/6 \times E \times I_c) = Z \times F_{ye} * (1-P/P_{ye})/K_{cr}$ (4)

d_c = Column depth, E = Modulus of elasticity, f_{ye} = Expected yield strength of the material
I = Moment of inertia, L_b = Beam length, L_c = Column length, M_{CE} = Expected flexural strength
P = Axial force in the member at the target displacement for nonlinear static analyses, or at the instant of computation for nonlinear dynamic analyses. For linear analyses, P shall be taken as Q_{UF}
Q_{UF} = Force-controlled design action due to gravity loads in combination with earthquake loads
P_{ye} = Expected axial yield force of the member = $A_g \times F_{ye}$
Q = Generalized component load, Q_{CE} = Generalized component expected strength, θ = Chord rotation
θ_y = Yield rotation, Z = Plastic section modulus
Modeling parameters of plastic hinge for each member are calculated by referring to FEMA356 Table 5-6, and the stiffness of the deformation hardening section is determined to be 3% of the elastic section stiffness. Thereby, the maximum strength of the member can be calculated. The plastic hinge can be defined using the yield rotation angle, the yield strength, the maximum strength, and the modeling parameters calculated according to the section and member force for each member.

3.2 Connection damage model using artificial neural networks

In this study, we propose a data-intensive damage model that can estimate the degree of damage of rotational stiffness using Backpropagation Algorithm (BP). The data-intensive damage model proposed in this study selected steel structures as target buildings. The collapse mechanism of the steel structure is assumed to be the beam-hinge collapse mechanism in which hinges occur at points and beams. Through this collapse mechanism, we modeled the hinge model of the boundary and beam joints. The natural frequency and mode vector of the structure were used as input data, and the damage degree of the joint was used as output data. In order to propose a data-intensive damage model, dynamic data is needed according to the stiffness deterioration of the structure. The methodology for extracting these training data is shown in Fig.3. In order to extract the dynamic data, a stiffness deterioration scenario of each joint was created. Stiffness deterioration of the joint was defined as Damage Factor (DF) as shown in Eq. (5). DF of 1.0 means no damage to the joints, and DF of 0.8 means a 20% reduction in the rigidity of the rotating springs. The deteriorated rotational stiffness values are substituted for K_{br} and K_{cr} in equations (3) and (4) and applied to the plastic hinge model. After applying the joint plastic hinge constructed according to the damage scenario, the natural frequency and mode shape of the structure were extracted by eigenvalue analysis. Since the damage of the structure is assumed to be the damage of the joints, the columns and beam members use elastic members, and the stiffness and strength effects of the panel zone are not considered. Rotational stiffness deterioration (DF) and dynamic characteristics data (natural frequency, mode shape) according to the damage scenario of each joint are organized as data for training the artificial neural network. The hidden layer activity function of the artificial neural network uses the sigmoid function. 90% of the damage scenarios are used to train and validate the neural network, and the rest of 10% are used to assess the accuracy of the damage prediction.

$$\text{Damage rotational stiffness} = \text{Damage Factor(DF)} \times \text{Pre-Damage rotation stiffness} \tag{4}$$

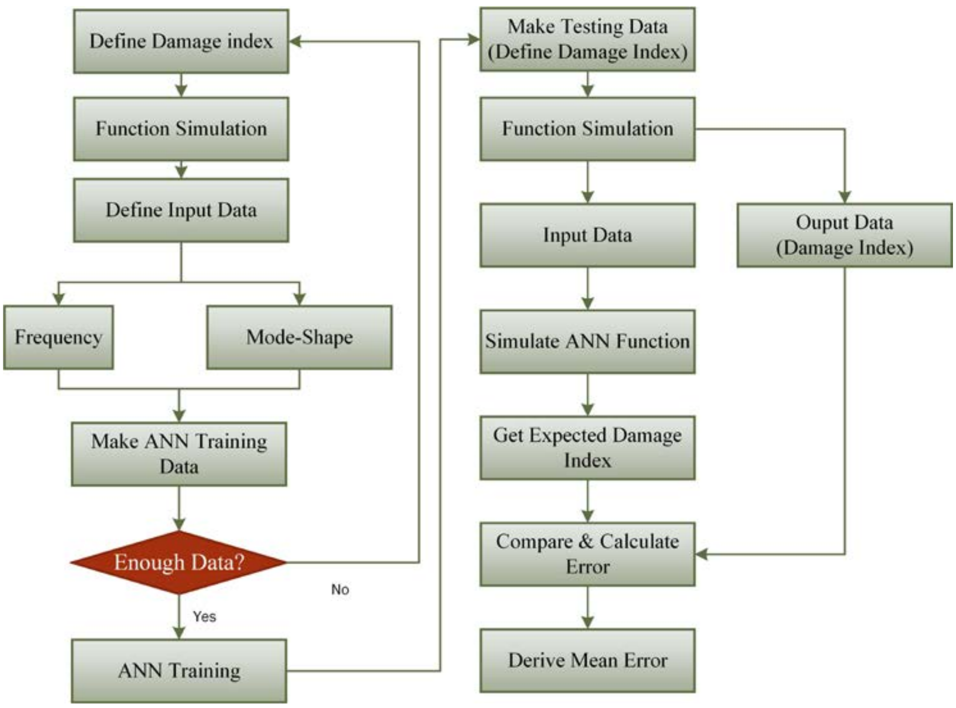


Figure 3 Methodlogy of data-intensive damage model

4. Application of data-intensive damage model in steel moment frame

4.1 Example description

In order to prove the proposed technique, the 3 stories 4bay steel moment frame structure in Fig. 4 is analyzed in the same methodology. And the target building is Pre-Northridge Seattle 3-story model.[22] This research has selected a 3 stories 4bay 2dimension model to consider the effect of stiffness degradation. Fig. 4 is a elevation of selected 2D-model. Table 1 is the material properties of structure and Table 2 provides each beam and column section properties. Columns and beams are made of same material. In this research, damage is only assumed to occur at joints and nonlinear behavior of elements are modeled using FEMA plastic-hinge and linear material. According to the details written in [A. Gupta, H. Krawinkler, Seismic Demands for Performance Evaluation of Steel Moment Resisting Frame Structure, (1999)], floor load generated from earthquake has effective roof mass 70.9 kips-sec2/ft while 2nd and 3rd story's effective mass is 65.53 kips-sec2/ft each. This is the 3D model's effective mass, therefore needs to convert masses suitable for research's 2D structure model. Considering the 3D model's number of nodes, left and right edge side nodes of roof are assigned to be 1.48 kips-sec2/ft each, while other nodes are double the size of end nodes by 2.96 kips-sec2/ft. In the same manner, edge side nodes of 2nd and 3rd story are assigned 1.37 kips-sec2/ft, while other nodes are 2.74 kips-sec2/ft. 1st mode natural period of structure was calculated 1.67 seconds in OpenSees modeling, 1.63 in ZEUS-NL.

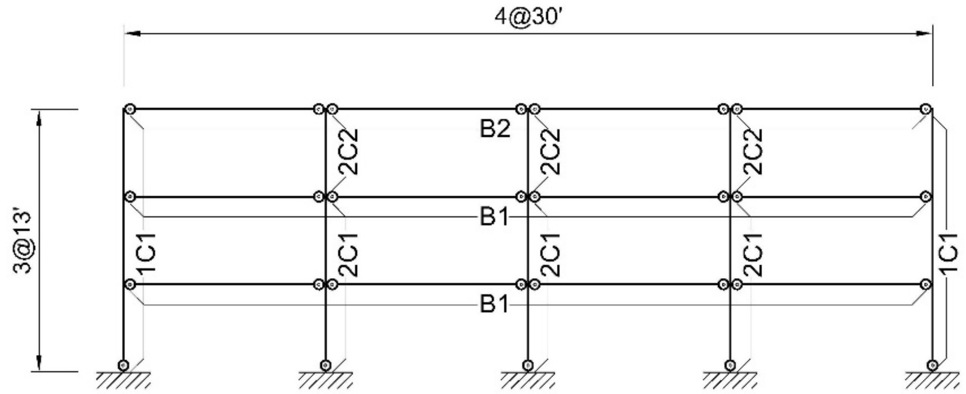


Figure 4 Pre-northridge Seattle 2-dementional model

Table 1 Material properties

Code	Grade	Modulus of Elasticity (ksi)	Poisson's Ratio (%)	Hardening Ratio (%)	Tensile Strength (ksi)	Yield Strength (ksi)
ASTM	A572-50	29000	0.3	0.05	65	50

Table 2 Section properties

Section	1C1	2C1	2C2	B1	B2
Shape	W14X159	W10X77	W10X60	W16X26	W14X22

Pushover analysis is processed to extract pre-damage plastic hinge model of structure According to FEMA356, each element nonlinear modeling is required to perform pushover analysis because it gradually increases earthquake load while considering element level yield and load distribution of nonlinear behavior. However, element's nonlinear behavior varies not only from boundary conditions, but also shear force and axial force. The purpose of pushover analysis is to check the status of element at performance point so that plastic hinge model of joints are modeled for axial & shear force at the performance point. Fig. 5 is the plastic hinge behavior graph according to the considered damage scenario. In this structure model, total 17 damage factors are used. Torsion spring hinges on the same story and same bay are linked with same damage factor. Roof joints are rarely damaged by earthquake loads so it is excluded, considering ground level, 1st story, 2nd story damage scenarios, while output layer is set with 13 nodes to plot each damage factors. In order to train ANN and to evaluate the accuracy of damage prediction, total 3^{13} damage scenarios are considered. All torsion spring hinges may have damage factor of 1.0, 0.8, 0.6 and 3^{13} analysis were taken. Then the result is sorted to be input layer data and output layer data.

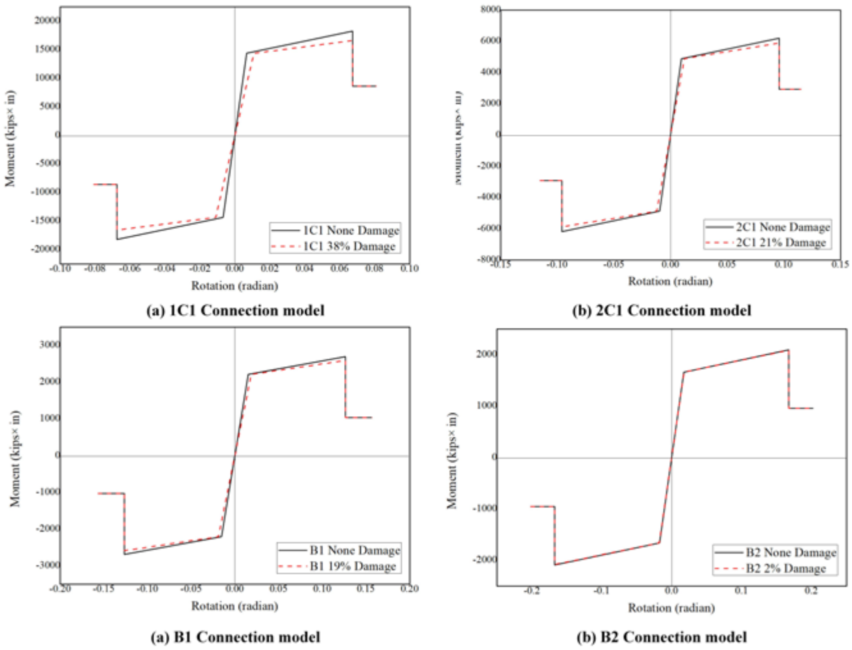


Figure 5 Pre-damage and damage plastic hinge model of connection

4.2 Verification of data-intensive damage model

The artificial neural network is trained using the simulation data of the example structure shown in Fig. 4 and the joint damage prediction is shown in Fig. 6 which is the joint number. Joint 0-1 0-5 means column hinges, joint 1-1 1-4 are the hinges of 1st story. And joint 2-1 ~ 2-4 means the hinge of the 2nd story. In order to verify the trained data-intensive model, the natural frequencies and mode shapes for arbitrary damage scenarios were defined as input values, and the output values from the neural network model were derived. The Estimate DF of Fig. 6 is the degree of damage derived from the data-intensive model, and the Reference DF is the correct answer for the derived degree of damage. From the results of Fig. 6, it was found that the damage degree was well understood in all parts except the joint number 1-1. In the joint number 1-1, the DF was found to have about 10% error.

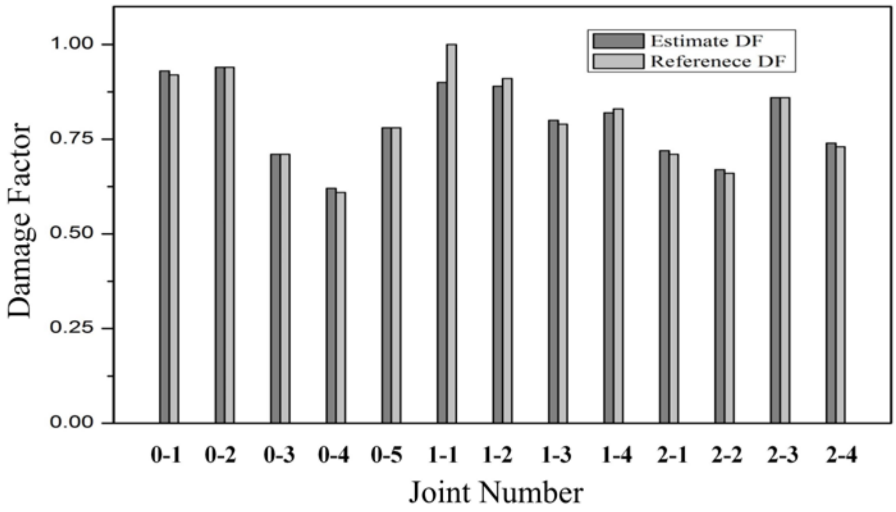


Figure 6 Comparison damage factor between reference & estimated value

4.3 Seismic behavior of steel moment frame with data-intensive damage model

In this section, the behavior of steel moment frame with data-intensive damage model and steel moment frame with pre-damage model was reviewed. Earthquake data were taken from the Northridge earthquake recorded at Beverley Hills. Fig. 7 (a) shows the inner story drift ratio graph of two frames. In both frames, the maximum story drift ratio was recorded on the second story. In the case of the frame with the data-intensive model, the story drift ratio was higher than the frame with the pre-damage model. Figs. 7 (b), (c) and (d) show the joint behavior at positions 1-1, 2-1 and 3-1. In the case of the example building, the data-intensive damage model shows that the larger displacement moves when the joint behavior data of each story is checked. In Fig. 7 (b), the pre-damage model shows nearly linear behavior. On the other hand, the data-intensive model can identify the nonlinear interval more clearly than the pre-damage model. Fig. 7 (c) and (d) also show that the nonlinear behavior is larger for the data-intensive model. This reduction in rotational stiffness has a great effect on the behavior of the structure.

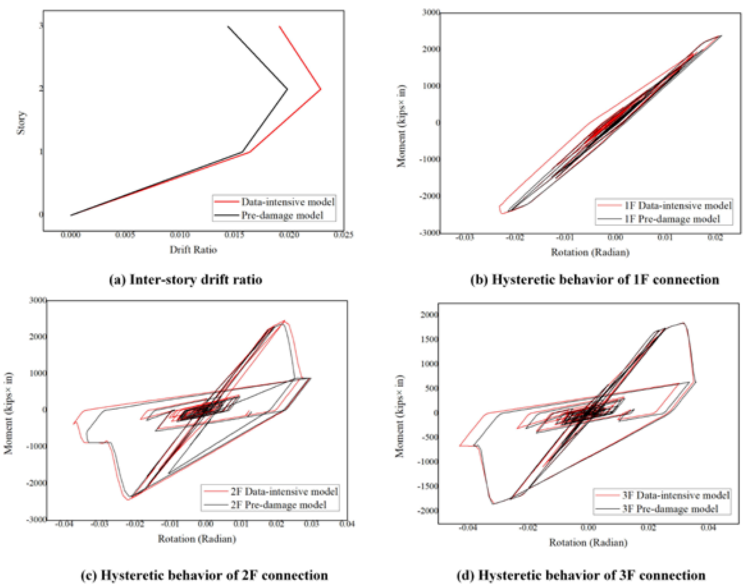
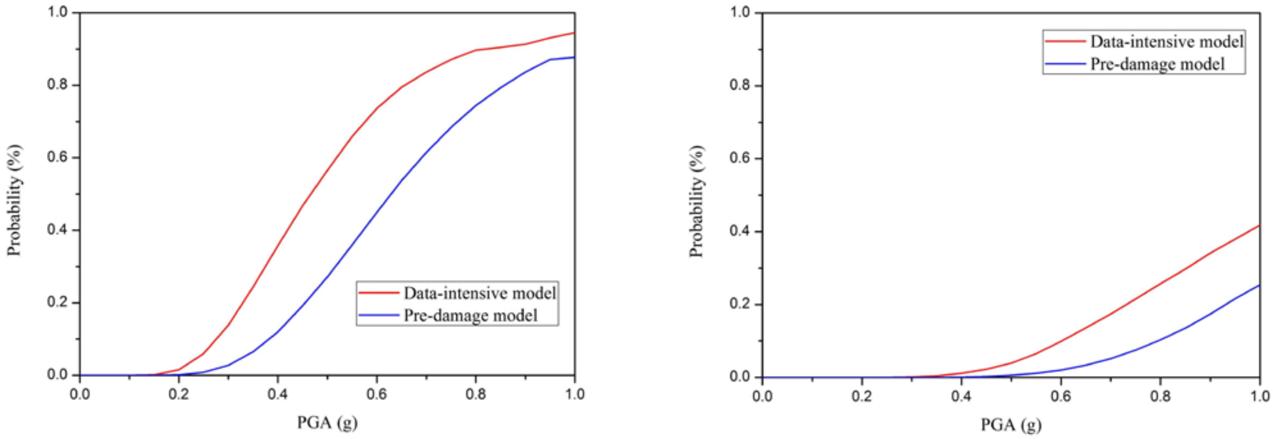


Figure 7 Inter-story drift & Hysteretic behaviors of connections

Fig. 8 is a graph evaluating the seismic performance of the steel moment frame to which the data-intensive damage model is applied and the steel moment frame to which the pre-damage model is applied. Fig. 8 (a) is the probability that the inter-story displacement ratio exceeds 2.5% (LS level), and (b) is the probability that the inter-story displacement ratio exceeds 5% (CP level). About exceeding inter-story ratio 2.5%(LS level), in 0.8g PGA(Peak Ground Acceleration) from kobe 1995, the probability of data-intensive model and predamage model exceeding LS level is 86.5%, and 66.4%.Seismic performance of data-intensive model in 0.8g PGA is more accurate than that of predamage model about 20% of exceeding LS level. About exceeding inter-story ratio 5%(CP level), in 0.8g PGA(Peak Ground Acceleration) from kobe 1995, the probability of data-intensive model and predamage model exceeding CP level is 26.1% and 8.6%. Seismic performance of of data-intensive model in 0.8g PGA is more accurate than that of predamage model about 16% of exceeding CP level



(a) Result of seismic perfermance assessment on LS level

(b) Result of seismic performance assessment on CP level

Figure 8 Results of seismic performance assessment

5. Conclusion

This study proposes a technique to predict the joint damage of steel moment frames using artificial neural networks. We trained the artificial neural network and to determine the accuracy of the damage prediction, 317 damage scenarios were considered. The natural period and mode shape information of the structure are used for the input layer of the artificial neural network, and the rotational stiffness damage index of the structure joint is used for the output layer. The plastic hinge model of the joint of FEMA 356 was used, and a data-intensive damage model with rotational stiffness reduction was proposed. As a result of verifying the example of the three-story 4-span steel moment frame, the damage of each location can be predicted with a reliable level. The seismic behavior and seismic performance of structures with data-intensive damage model and pre-damage model were evaluated. Structures using the data-intensive damage model recorded larger inter-story drift ratio for the same earthquake (Northridge N-S record), with larger strains at the joint of all layers.The seismic performance of the data-intensive damage model can be obtained more accurately about 20% on LS damage level and 16% on CP damage level compared with the case where the connection model is assumed to be pre-damage model. Adjusting data-intensive damage model has a great effect on the behavior of the structure. Therefore, it is need to be considered when evaluating the seismic performance of existing buildings or identifying structural performance.

6. Acknowledgements

Science Research Program through a National Research Foundation of Korea(NRF) funded by the Ministry of Education, Science and Technology(2018R1A2B6006958)

7. Copyrights

8. References

[1] Lam HF, Ko JM, Wong CW (1998): Localization of damaged structural connections based on experimental modal and sensitivity analysis. *Journal of Sound and Vibration,* **210**, 91–115.

[2] Morassi A, Rovere N, (1997): Localizing a notch in a steel frame from frequency measurements. *Journal of Engineering Mechanics*, **123**, 422–432.

[3] Wong CW, Mak WH (1993): System identification of semi-rigid connection in steel frame structures. *Proceedings of the 11th International Modal Analysis Conference*, Florida, USA

[4] Park HS, Shin Y, Choi SW, Kim Y (2013): An integrative structural health monitoring system for the local/global responses of a large-scale irregular building under construction. *Sensors (Basel)*, **13**, 9085-9103.

[5] Choi SW, Kim Y, Kim JM, Park HS (2013): Field monitoring of column shortenings in a high-rise building during construction. *Sensors (Switzerland)*, **13**, 14321–14338.

[6] Yu EJ, Chung L (2012): Seismic damage detection of a reinforced concrete structure by finite element model updating. *Smart Structures and Systems*, **9** (3), 253-271.

[7] Peeters B, Maeck J, De Roeck G (2001): Vibration-Based damage detection in civil engineering: excitation sources and temperature effects. *Smart Materials and Structures*, **10** (3), 518-527.

[8] Doebling SW, Farrar CR, Prime MB (1998): A summary review of vibration-based damage identification methods. *Shock and Vibration Digest*, **30**, 91-105.

[9] Fan W, Qiao P (2011): Vibration-based damage identification methods: A review and comparative study. *Structural Health Monitoring*, **10**, 83–111.

[10] Pandey AK, Biswas M, Samman MM (1991): Damage detection from mode changes in curvature. *Journal of Sound and Vibration*, **145** (2), 321-332.

[11] Shi ZY, Law SS, Zhang LM (2000): Structural damage detection from modal strain energy change. *Journal of Engineering Mechanics*, **126** (12), 1216-1223.

[12] Pandey AK, Biswas M (1994): Damage detection in structures using changes in flexibility. *Journal of Sound and Vibration*, **169 (**1), 3-17.

[13] Yan WJ, Huang TL Ren WX (2010): Damage detection method based on element modal strain energy sensitivity. *Advances in Structural Engineering*, **13** (6), 1075-1088.

[14] Li H, Wang J, Hu J (2008): Using incomplete modal data for damage detection in offshore jacket structures. *Ocean Engineering*, **35 (**17-18), 1793-1799.

[15] Law SS, Shi ZY, Zhang LM (1998): structural damage detection from incomplete and noisy modal test data. *Journal of Sound and Vibration*, **124 (**11), 1280-1288.

[16] James GH, Thomas G, James PL (1995): The natural excitation technique (NExT) for modal parameter extraction from operating structures. *Modal Analysis-the International Journal of Analytical and Experimental Modal Analysis*, **10** (4), 260-277.

[17] He XH, Hau XG, Chen ZQ, Huang FL (2011): EMD-based random decrement technique for modal parameter identification of an existing railway bridge. *Engineering Structures*, **33** (4), 1348-1356.

[18] Rafiq MY, Bugmann G, Easterbrook DJ (2001): Neural network design for engineering applications. *Computers and Structures*, **79** (17), 1541-1552.

[19] Flood I, Kartam N (1994): Neural networks in civil engineering. I: principles and understanding. *Journal of Computing in Civil Engineering*, **8** (2), 131-148.

[20] Wu X, Garrett JH (1992): Use of neural networks in detection of structural damage. *Computers & Structures*, **42** (17), 649-659.

[21] Adeli H (2001): Neural networks in civil engineering: 1989–2000. *Computer-Aided Civil and Infrastructure Engineering*, **16**, 126-142.

