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Enhancing Seismic Fragility Analysis of Structural System

– Developing Intensity Measure and Ground Motion Selection Algorithm –

구조물의 지진 취약도 해석 고도화

– 지진강도척도 및 지진동 선택 알고리즘 개발 –

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이 논문을 공학석사 학위논문으로 제출함
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Abstract

Structural collapse is the dominant cause of deaths and injuries under seismic excitation. Thus, collapse prevention of building during strong earthquake is the most important design objective of modern seismic design provisions to promote life-safety and to prevent socio-economic losses. In order to ensure an acceptably small likelihood of structural collapse under the earthquake load, nonlinear dynamic analysis coupled with probabilistic seismic hazard analysis is needed. However, nonlinear structural responses under seismic excitation vary greatly even if ground motions are scaled to get the same level of intensity measure (e.g., ground motions are scaled to get the same spectral acceleration at first mode period of structure). Furthermore, a large set of ground motions are needed for comprehensive reflection of hazard characteristics at a given site, which incurs high computational cost during dynamic analyses. To reduce the variability of structural responses as well as the number of ground motion time series used in nonlinear stochastic analyses, the study aims to develop a new seismic intensity measure by combining a cumulative IM, e.g. Arias intensity (Arias 1970) and a peak IM, e.g. spectral acceleration, and a new algorithm about selecting ground motion time series for IDA. To this end, various techniques of statistical methods such as linear regression, clustering analysis, and best subset selection method are employed. In order to demonstrate the proposed intensity measure (IM) and algorithm, nonlinear dynamic analyses are performed using a validated computational model of ductile steel frame structure and one of the reinforced concrete (RC) structural frames modeled by Haselton *et al.* (2011). It is found that using a developed IM and ground motion selection algorithm, one can obtain a reliable estimation on the collapse potential of structure using far less number of ground motion time histories with uncertainty reduced.

Keywords: Intensity measure, ground motion selection, fragility analysis, incremental dynamic analysis (IDA), energy balance ratio, critical features.

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Chapter 1. Introduction

1.1. Study Background

A strong earthquake event has the potential to cause severe damage to structural system which may result in considerable economic losses and threaten life safety. In order to minimize the ultimate socio−economic outcomes, an acceptably small likelihood of structural collapse under seismic excitation should be ensured. To meet such demand, it is necessary to evaluate collapse likelihood of the building during strong earthquake appropriately. Estimating collapse capacity of structures, however, is evasiveness task due to both significant uncertainties in ground motions and chaotic responses of a structure. Therefore, current seismic analysis approach, especially for the collapse risk assessment of the structural system, adopt probabilistic assessment frameworks which can deal with not only randomness of seismic demand but also variability of structural capacity. The framework intertwines earthquake intensity (e.g., peak ground acceleration, spectral acceleration) and corresponding engineering demand parameter or structural responses (e.g., inter−story drift, equivalent velocity ratio) through series of nonlinear dynamic analyses such as incremental dynamic analysis (IDA) so that one can figure out level of structural damage in a probabilistic manner (Vamvatsikos and Cornell 2002).

IDA is a widely used method to evaluate structural collapse capacity under seismic excitation which is based on so called "IDA curve" that tracking the relationship between an "intensity measure" (IM) and a corresponding "damage measure" (DM) (Vamvatsikos and Cornell 2002, FEMA−350 2000, Maison *et al.* 2008, ATC−63 2009, Gunay and Mosalam 2013). The main idea of the IDA is that nonlinear dynamic analyses are carried out as the intensity level is increased incrementally until the structure shows dynamic instability (i.e., the loss of ability to sustain gravity loads).

Collapse risk assessment based on IDA, however, have several limitations. First, a significant level of variabilities in terms of intensity levels of ground motions as well as structural responses is often observed. Second, the approach entails high computational costs due to the fact that even a single IDA curve requires a large number of dynamic analyses. While numerous research efforts are reported in the literature to address these issues, collapse risk assessment based on IDA have not yet been investigated thoroughly by stochastic analyses of computational simulation and statistical methods. Therefore, this study develops (1) a new measure of seismic intensity to evaluate the structural collapse with reduced uncertainty when predicting structural collapse and (2) a ground motion selection algorithm to address the high computational cost of dynamic seismic response analysis.

1.2. Objectives, Framework and Importance of the Research

The objectives of the study are summarized as follows:

- Propose a new seismic intensity measure by considering cumulative IM, peak IM, strong earthquake duration and the effects of softening nonlinearities on the structures to predict the collapse of a structural system with less uncertainty.
- Investigate the impact of the energy balance ratio (i.e., ratio of seismic input energy given dissipated hysteretic energy) on collapse risk assessment.
- Provide a method to identify the characteristics of ground motions which are well correlated with the behavior of IDA-curve.
- Develop a new clustering based ground motion selection algorithm coupled with a Euclidian metric distance (Chun *et al.* 2000) which can reduce the number of time series required for IDA.

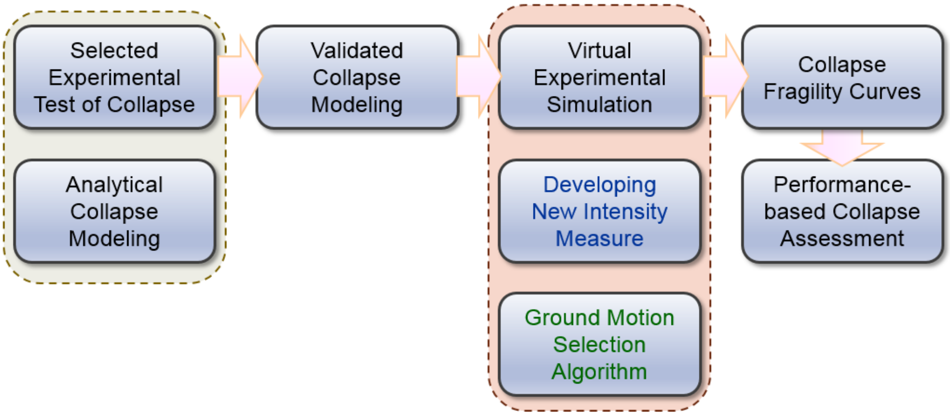

Figure 1.1 Framework for probabilistic assessment of structural collapse.

Figure 1.1 illustrates the integration between main components of the study: analytical models for the selected experimental case studies of structural collapse, computational simulations of collapse behavior using analytical model, and proposal of new IM as well as ground motion selection algorithm. First, an analytical model is needed to predict the collapse behavior and validated near-collapse experiments reported in the literature (Lignos *et al.* 2008). Recently, Deniz (2014) developed an analytical model of steel frame structure, this study employs the computational model developed by Deniz (2014) for simulating nonlinear time history analysis. Second, using the analytical model validated by the test results, IDA are performed for a total of 155 ground motions from 22 earthquake events (see Appendix A for details). The ground motion set was selected from NGA-West2 database (Ancheta *et al.* 2013) based on the criteria by Haselton and Deierlein (2007). Third, a new IM is developed by combining cumulative and peak indices based on structural dynamics, i.e., adopting the inverse form of equivalent velocity ratio which will be discussed later. Finally, this paper presents a new ground motion selection algorithm based on clustering analysis in terms of the behavior of "IDA-curve."

The study described here aims to advance understanding of structural responses regarding different kinds of ground motion time histories for accurate evaluation of collapse capacity, to evaluate the adequacy of current collapse assessment methods, and to provide suggestions to enhance existing methods. This paper, thus, may have a potential impact across several structural engineering experts to improve the evaluation of structural collapse capacity to prevent disproportionate collapse. The foremost goal of this study is to enhance the life safety by avoiding structural collapse because of comprehensive understanding between seismic demand and structural capacity.

1.3. Organization of the Study

The chapters in this study are outlined below:

- Chapter 2 provides a comprehensive review of IDA which is one of the most widely-used approaches to evaluate the collapse capacity of structure under earthquake. Then, statistical procedure for fitting fragility functions to structural analysis data will be discussed.
- Chapter 3 develops a new intensity measure which involves the cumulative IM, peak IM, strong earthquake duration, and the effects of softening nonlinearities on the structure. To this end, energy-based collapse criterion and descriptor with ductile steel frame computational model whose near-collapse behavior is validated is employed. Furthermore, in order to highlight the effects of energy parameters when evaluating collapse risk assessment, collapse capacity of structure will be demonstrated with different set of ground motions in terms of earthquake energy balance ratio. Throughout numerical examples, applicability and effectiveness of new IM will be tested and demonstrated.
- Chapter 4 introduces the main framework of a new ground motion selection algorithm using clustering based adaptive sampling procedure. To this end, subset selection method is used to identify critical features which is employed in the algorithm. Moreover, Euclidian metric distance (MD) which

measures the "distance" between the previous and current fragility curves is introduced as stabilized parameter of fragility curve. The algorithm is also tested in terms of the applicability and effectiveness through various numerical examples

- Finally, Chapter 5 provides a summary of the study and main findings.

Chapter 2. Incremental Dynamic Analysis and Collapse Fragilities

Assessment of collapse capacity of structures under seismic excitation requires: (1) performing nonlinear dynamic analyses to simulate the structural behavior up to collapse, and (2) prediction of structural collapse with integration of uncertainties in ground motions and analytical models (Zareian and Krawinkler 2007). Therefore, this chapter first describes IDA, a nonlinear dynamic method to evaluate the collapse capacity of structural system, then presents several statistical procedures for estimating fragility functions using dynamic structural analysis results with integration of existing uncertainties.

2.1. Incremental Dynamic Analysis

Incremental Dynamic Analysis (IDA) (Vamvatsikos and Cornell 2002) is a parametric analysis method that estimates structural performance under seismic load by performing a series of nonlinear dynamic analyses of structural model for several ground motion records. This concept has been first mentioned by Bertero (1977) and has been modified and improved by many experts and researchers. Recently, the U.S. Federal Emergency Management Agency (FEMA) guidelines adopted incremental dynamic analysis as a method to determine the global collapse capacity of structural system under earthquake (FEMA-350 2000, FEMA-351 2000). This approach usually takes the following steps to evaluate the performance of structure (Vamvatsikos and Cornell 2002):

1. A proper computational structural model needs to be developed with a suite of ground motion time histories.
2. Intensity measure (IM, e.g., peak ground acceleration) and damage measure (DM, e.g., drift ratio) should be selected.
3. For each record, perform nonlinear dynamic analysis as incrementally increase the intensity level and track the

relationship between IM and calculated DM

4. One can obtain IDA curves of the structural responses for all ground motions
5. Collapse or limit state is defined on each IDA curve based on selected criteria of structural collapse
6. Fragility curve is obtained based on both IDA results and statistical procedure

As an example, IDA curves using 5 story steel braced frame under 30 ground motion time series are shown in Figure 2.1 (Vamvatsikos and Cornell 2002).

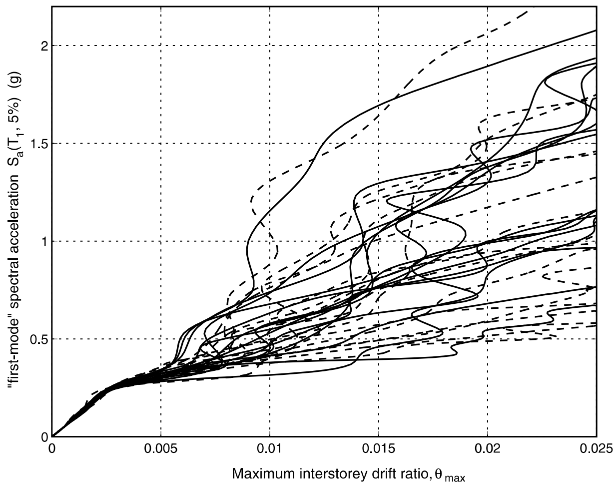

Figure 2.1 IDA curves for 30 records on a 5 story steel braced frame by Vamvatsikos and Cornell (2002).

The main premise of IDA is that the occurrence of "collapse" is usually indicated by a large increase of DM or EDP caused by a small increase in the IM (i.e., a flat plateau of "IDA curve" as an indication of collapse). However, sometimes IDA curves may show erratic behavior instead of monotonical increase of DM as IM increases. This chaotic structural behavior makes collapse prediction ambiguous and uncertain. Therefore, subjective threshold value based collapse criteria in conjunction with "IDA curve" is widely used to identify structural collapse capacity: IM−based criteria (e.g., lower than 20% of the initial IDA slope) and DM−based criteria (e.g., exceedance of 10% maximum drift)

(Vamvatsikos and Cornell 2002). However, collapse assessment based on the existing collapse criteria may be sensitive to the assumed threshold value, which may not estimate the likelihood of structural collapse appropriately (Deniz *et al.* under review). To address such issues, Deniz *et al.* (under review) proposed an energy–based collapse limit–state using dynamic instability. Since energy parameters are aggregated quantities considering redistribution and variation of each individual component–damage within the structural system, this approach can identify and quantify the global collapse behavior of structure. The energy–based collapse criteria will be introduced in Chapter 3.

2.2. Statistical Procedure for Fitting Fragility Functions to Structural Analysis Data

Structural collapse fragility is defined as the conditional probability of collapse given a ground motion intensity. Although structural fragilities are derived using various approaches such as static structural analyses or field observation of damage (Kennedy and Ravindra 1984, Kim and Shinozuka 2004, Calvi *et al.* 2006, Porter *et al.* 2007, Villaverde 2007, Shafei *et al.* 2011), statistical procedures for fitting fragility curve based on nonlinear analyses are herein presented (Baker 2015). Using IDA and collapse criteria, each ground motion has a single IM value associated with its onset of collapse. Using the lognormal cumulative distribution to provide a continuous estimation of the probability of collapse, the likelihood of structural collapse at a given IM level, x, can be computed as follows (Ang and Tang 2007):

$$P(C \mid IM = x) = \Phi\left(\frac{\ln x - \lambda}{\xi}\right) \tag{2.1}$$

where $\Phi(\ )$ indicates the cumulative density function of the standard normal distribution, λ and ξ represent the mean and standard deviation of $\ln IM$, respectively. The mean and standard deviation of the $\ln IM$ can be calculated using the results of IDA using following mathematical form (Baker 2015):

$$\hat{\lambda} = \frac{1}{N}\sum_{i=1}^{N} \ln IM_k \tag{2.2}$$

$$\hat{\xi} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(\ln IM_k - \hat{\lambda}\right)^2} \tag{2.3}$$

where N is the number of ground motions which is used in IDA, and IM_k is the IM value associated with its onset of collapse for the k^{th} ground motion. This method is denoted "Method A" by Porter *et al.* (2007), which can calculate fragility curve by computing the moments from a set of data.

2.2.1. Maximum Likelihood Estimate (MLE) Formulation

When performing IDA, several issues are raised due to the fact that some ground motions need to be scaled to large IM values to produce structural collapse (Baker and Cornell 2005). One strategy to address these issues is to limit the scale of ground motions up to certain level, $IM_{\max}$. Since IDA carried out only up to some level may result in insufficient data of collapse, one cannot use the "Method A" to estimate the parameters of fragility function. Rather than using method of moments, one can use the MLE formulation to compute the parameters of lognormal distribution, $\hat{\lambda}$ and $\hat{\xi}$.

When the total n ground motions are performed IDA only up to certain level, generally m ground motions may cause structural collapse i.e., n is always greater and equal to m. After performing IDA, IM values of m ground motions at collapse are known value. Then, the likelihood of a ground motion causing structural collapse at IM_i is mathematically denoted as

$$l_{1,i}(\lambda,\xi) = \phi\left(\frac{\ln IM_i - \lambda}{\xi}\right) \tag{2.4}$$

where $\phi(\ )$ represents the PDF of the standard normal distribution and IM_i is the seismic intensity of i^{th} ground motion at collapse point among m ground motions. The likelihood of the ground motion that did not produce structural collapse is also computed in the same manner as following

$$l_2(\lambda,\xi) = 1 - \Phi\left(\frac{\ln IM_{\max} - \lambda}{\xi}\right) \tag{2.5}$$

where $IM_{\max}$ is some upper bound limit level when performing IDA. Assuming the effect of ground motion to structural system is statistically independent, the likelihood function that ground motions were observed to cause collapse can be calculated as product of the individual likelihoods.

$$L(\lambda,\xi) = \left(\prod_{i=1}^{m} l_{1,i}(\lambda,\xi)\right)\cdot\left(l_2(\lambda,\xi)\right)^{n-m} \tag{2.6}$$

The estimated parameters of fragility curve can be obtained by maximizing the likelihood function. It is, however, difficult to find the parameters which can maximize likelihood function. Therefore, many researchers find the value that maximizes the natural logarithm of the likelihood function, $\ln\left(L(\lambda,\xi)\right)$ as follows:

$$(\hat{\lambda},\hat{\xi}) = \arg\max_{\lambda,\xi}\sum_{i=1}^{m}\ln l_{1,i}(\lambda,\xi) + (n-m)\cdot\ln\left(l_2(\lambda,\xi)\right) \tag{2.7}$$

2.2.2. Fragility Function based on Probabilistic Seismic Demand Model

For effective and reliable collapse risk assessment, some researchers use fragility function developed based on the probabilistic seismic demand model, which represents the relationship between seismic demand and structural capacity (Cornell *et al.* 2002, Baker and Cornell 2006, Deniz 2014). In particular, if a ground motion set selected from seismic hazard analysis may not capture the earthquake demand at a given site sufficiently, structural collapse assessment with probabilistic model evaluates structural collapse capacity more effectively compared to other methodologies such as MLE formulation. Since structural fragility rests on both the specific IM-DM equation and results of dynamic analyses, the bias which comes from record set can be alleviated by probabilistic equation. Different fragility curves can be obtained with respect to statistical method. It is, however, noted that one cannot determine whether they are correct or not. Moreover, this is the topic that requires a thorough investigation in the earthquake engineering community.

The relationship between demand and capacity can be demonstrated using linear/nonlinear regression model based on IDA-based data points. The difference between seismic demand model based fragility and foregoing approach is that "Method A" and MLE formulation uses only a single IM value associated with its onset of collapse for each ground motion, while probabilistic model based methodology uses entire data point of IDA because the model developed using all IDA data points can quantify the relationship between capacity and demand of structure against collapse probabilistically. Although a nonlinear regression model can be used for developing fragility function, this section describes a simple statistical procedure using a linear regression model.

A linear regression model of demand, D, is developed as shown in Equation (2.8) while the conditional mean and variance are shown in Equation (2.9) and (2.10), respectively.

$$D = a_1 \cdot \ln IM + a_2 + \sigma \cdot \varepsilon \tag{2.8}$$

$$E[D \mid \ln IM] = a_1 \cdot \ln IM + a_2 \tag{2.9}$$

$$Var[D \mid \ln IM] = \sigma^2 \tag{2.10}$$

where IM is an intensity measure used in IDA, a_1 and a_2 are coefficients computed from regression analysis, σ^2 represents the conditional variance of linear regression error, and ε is a normal random variable with zero mean and unit standard deviation. In order to make a reasonable assumption that demand model has constant variance along the regression curve, i.e., homoscedasticity, natural logarithms are applied to IM before regression.

The probability that structural demand exceeds a structural capacity at a given IM, x, can be described as:

$$P(x) = P\left(C - D \leq 0 \mid \ln IM = \ln x\right) = \Phi\left(-\frac{\mu_C - \mu_D(x)}{\sqrt{\sigma_C^2 + \left[\sigma_D(x)\right]^2}}\right) \tag{2.11}$$

where C represents structural capacity, its mean and standard deviation is denoted as μ_C and σ_C, respectively and D represents structural demand at given x and the mean and standard deviation is denoted as same manner. Mean and standard deviation of collapse capacity are defined using the collapse or last non−collapse point of the IDA results.

Chapter 3. New Seismic Intensity Measure for Collapse Prediction Combining Cumulative and Peak Indices

The main tasks of the proposed intensity measure are as follows: First, identify IMs that can account for seismic input energy (E_I) and dissipated hysteretic energy (E_{SPR}) effectively, especially with respect to near-collapse behavior. Then, combine the identified measures using an inverse form of equivalent velocity ratio, which is the ratio of the earthquake energy applied on the structure to the energy dissipated through structural degradation. Therefore, this chapter first summarizes and categorizes existing IMs for comprehensive understanding about properties of ground motion intensities. After literature reviews of existing seismic intensities, energy-based collapse criterion and descriptor are introduced, which are used for developing new IM (Deniz 2014, Deniz *et al.* under review). Next, IMs that highly correlated with E_I and E_{SPR} are presented. Finally, a four-story ductile structural frame collapse case study is provided which was used for investigating the "energy measure" and is also employed in this paper (Deniz *et al.* under review).

3.1. A Four-Story Ductile Structural Frame Collapse Case Study

A series of shaking table test of 1:8 scale models of a 4-story, 2-bay steel moment-resisting frame with reduced-beam sections (RBS) was performed by Lignos *et al.* (2008). The steel frame was tested on the earthquake simulator of the Network for Earthquake Engineering Simulation (NEES) facility at the University at Buffalo. Figure 3.1 (Lignos *et al.* 2009) shows the setup of the ductile structural model that mass simulator is connected to the test frame with axially rigid links at each floor level to transfer P-Delta effects acting as leaning columns on the prototype frame.

Deniz *et al.* (under review) developed an equivalent 2D computational model, based on the study by Lignos *et al.* (2008). The analytical model was developed in OpenSees (2004) using linear elastic elements for the beams and columns with plastic hinge at the elements ends. In order to take RBS into account, offsets from the connection of the element ends were applied and nonlinear geometry effects were also considered using a co-rotational transformation. The rotational springs were used to analytically model the plastic hinges with a modified Ibarra-Krawinkler deterioration model available as "Bilin" model in OpenSees (Lignos *et al.* 2008). These nonlinear rotational springs at the ends of beams and columns are only locations that exhibit the inelasticity of this ductile frame. Therefore, the sum of elastic strain energy and hysteretic energy in the spring can be represented as the dissipated hysteretic energy - total area under the hysteretic curve of the degrading element.

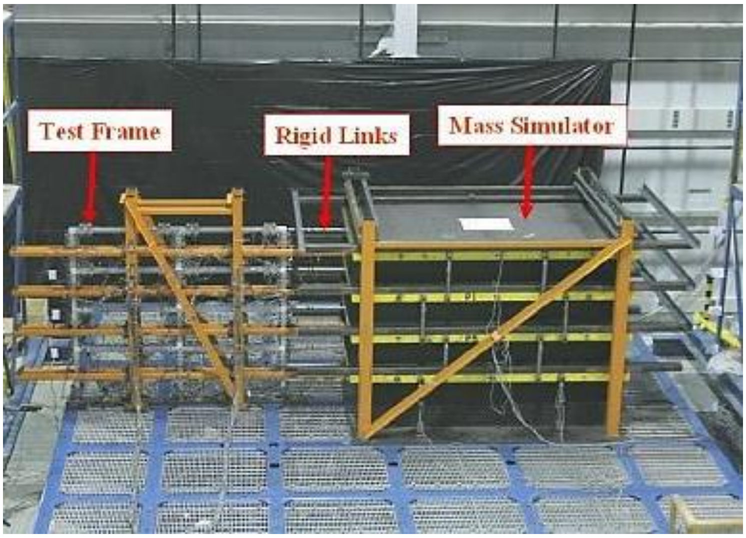

Figure 3.1 Shake-table-test of a 4-story, 2-bay steel frame by Lignos *et al.* (2008, 2009).

A series of nonlinear dynamic analysis is performed sequentially under the application of the Canoga Park ground motion record from the 1994 Northridge earthquake at the scale factors of 0.4, 1.0, 1.5, 1.9, and 2.2 following the experiment procedure. The lateral displacement at roof top of computational results were matched closely with that of the experimental results as shown in Figure 3.2 (Deniz *et al.* under review). Further details of this work are available in Deniz *et al.* (under review).

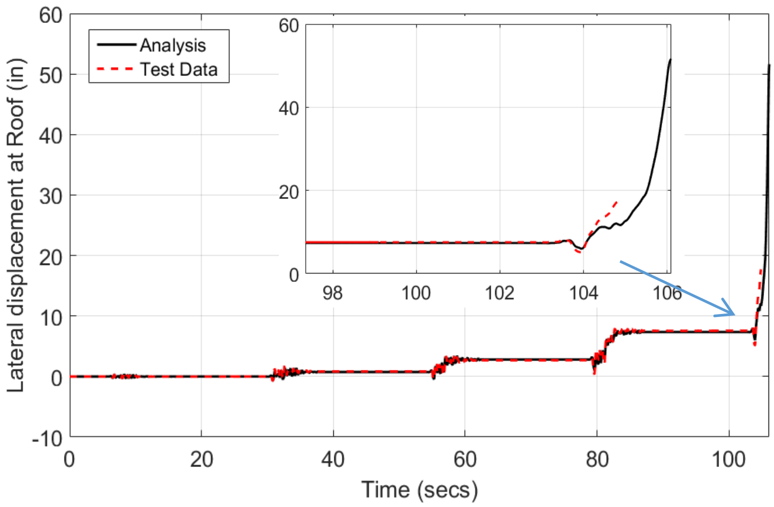

Figure 3.2 Lateral displacement of both experimental and computational test at the roof top of the frame from Deniz *et al.* (under review).

3.2. Existing IMs for Ground Motions

For reliable estimation of the existing buildings or earthquake-resistant design of new structures, it is important to understand the key features of both ground motion and structural system that are likely to affect the collapse potential of structures. Thus, numerous research efforts have been made to characterize the strength of ground motion combining with structural information. Since the complex phenomenon is described by a single feature, a great deal of information is inevitably lost. The interpretation of affecting features of ground motion to structural system can vary accordingly. It thus seems useful to distinguish and describe the different types of IMs and to attempt a classification on that basis. This study classifies IMs into following four groups based on their fundamental properties: basic, peak, cumulative, and mixed index. Table 1 summarizes the IMs studied by Riddell (2007) and some other measures proposed in other papers which are either widely−used or recently proposed in the field of earthquake engineering (Arias 1970, Housner 1952, Marafi et al. 2016, Trifunac and Brady 1975). Note that since mixed index is an IM that contains more than one property of ground motion (i.e., one can make a mixed index combining basic, peak, and cumulative indices), it will not be handled in this paper.

3.2.1. Basic Index

Basic index is defined as the intensity using only fundamental characteristics of earthquake ground motions. It does not contain any strength of ground motions but just include primary information of time histories. Total duration of ground motion time history or average period of zero−crossing per unit time of the acceleration are examples of basic index. These features are mostly employed to help characterize peak and cumulative index more specifically rather than using alone.

3.2.2. Peak Index

As the term implies, the peak index is based on its maximum value, or *peak*, often regardless of its sign. Although various intensity measures have been developed, this type of IM such as peak ground acceleration (PGA) and elastic spectral acceleration at first mode period ($Sa(T_1)$) are most widely used to characterize the seismic hazard at given site. A fundamental reason is that PGA is the simplest index providing the strength of ground motion. Likewise, $Sa(T_1)$ is the most practical measure that contains information about both ground motion and structure. The most important reason, however, is that almost every attenuation relationship which was developed for providing seismic hazard information at site of interest uses PGA and $Sa(T_1)$. It is, however, noted that PGA and $Sa(T_1)$ may not fully cover the near−collapse structural responses. In particular, when structure shows significant nonlinear behavior due to large ductility demand of structural system, first mode period cannot represent severe damage potential of ground motion. Although some researchers have investigated the effects of higher modes (Tothong and Cornell 2007, 2008, Bianchini *et al.* 2009), this paper also handles the higher nonlinearity of structures under strong earthquake load based on statistical method.

3.2.3. Cumulative Index

The cumulative index is a measure that considers total behavior of the time history by *accumulating* the quantities as time goes on, e.g., integral of square of total ground motion acceleration. The cumulative index is useful than peak index when structural system needs to be understood from the perspective of aggregated quantities such as energy parameters. This is due to the fact that cumulative index such as AI characterizes the earthquake behavior during time interval which can represent overall impact of ground motion to structural system, while peak index provide only peak amplitudes at a time instant. It is, thus, noted that no one can clearly state that any single parameter is dominant than other measures.

Since there is no ground motion whose intensity measures are equivalent to each other, the damage potential of structural system at near collapse can be different even ground motions are scaled to get same intensity level. In other words, if one scales the ground motions to get same peak index, PGA=1g, cumulative index, AI, can be different for each ground motion. Then, completely different structural responses can be obtained even the same structure is employed. Therefore, comprehensive studies about the effect of earthquake characteristics on structural collapse capacity should be needed. In this study, in order to enhance the field of seismic intensities, new IM will be developed using existing IMs based on comprehensive understanding of complex collapse mechanism.

Table 3.1 The intensity measures categorized in three groups in terms of characteristic.

Group	IM	Unit	Description
Basic	t_T	s	Total duration of ground motion time history
	t_S	s	Strong earthquake duration which is defined as the time interval over 5% and 95% of the AI (Trifunac and Brady 1975)
	v_T v_S	-	Number of zero-crossings of acceleration time history in t_T and t_S
	$T_{v,total}$ $T_{v,strong}$	s	Average period of a zero-crossing in t_T and t_S
	$f_{v,total}$ $f_{v,stomg}$	Hz	Average frequency of a zero-crossing in t_T and t_S
Peak	PGA PGV PGD	in/s^2 in/s in	Peak ground acceleration, velocity, and displacement
	$Sa(T_1)$ $Sv(T_1)$ $Sd(T_1)$	in/s^2 in/s in	Maximum pseudo acceleration, pseudo velocity, and displacement that a ground motion will cause in a linear oscillator with a specified period (T_1) and damping level
	$Sa_{avg}(T_1)$ $Sv_{avg}(T_1)$ $Sd_{avg}(T_1)$	in/s^2 in/s in	Average spectrum intensity which are geometric mean of elastic spectral properties. Period interval can be changed along with mode effects and nonlinearity of structure
	S_I	in	Housner's spectral intensity (Housner 1952)
	$SS_a(T_n, \alpha)$	-	Integral of ground motion response spectrum between the fundamental period of the structure and the nominal elongated structure, then normalized by the area (Marafi *et al*. 2016)
Cumulative	a_{sq} v_{sq} d_{sq}	in^2/s^3 in^2/s $in^2 \cdot s$	Integral of squared ground motion acceleration, velocity, and displacement
	CAA CAV CAD	in/s in $in \cdot s$	Cumulative of absolute value of ground motion acceleration, velocity, and displacement
	AI	in/s	Arias intensity (Arias 1970)

3.3. Energy-based Collapse Criteria and Descriptor

3.3.1. Energy-based Collapse Criteria

During seismic excitation, earthquake loads applied on the structure introduce energy into the system. Such seismic energy into the system (E_{EQ}) is absorbed as kinetic energy (E_K), strain energy (E_S), and the rest is dissipated as work done by the damping forces (E_D). In addition, repeated loading and unloading of the external forces makes excessive deformations of structural system, which induces gravity forces applied on the structure to release gravity energy (E_G) (Akiyama 2002). Taking the integral of the dynamic equation of motion with respect to relative nodal displacement, the components of the energy balance can be described as follows (Deniz *et al.* under review):

$$E_K + E_D + E_S = E_{EQ} + E_G \tag{3.1}$$

Global collapse capacity of structure under strong earthquake can be defined as the point just before the structure shows dynamic instability which is defined as the loss of the structural resistance against the gravity load. That is, a structural system starts to shows boundless lateral drift, i.e., dynamically unstable. The accumulation of permanent lateral drifts eventually makes gravity energy as dominant parameter in structural system compared to other energy responses. Deniz *et al.* (under review), thus, proposed a new collapse criterion based on the incidence of gravity energy exceeding dynamic input energy with a sudden increase, that is $E_G > E_{EQ}$. This energy-based criterion was verified by checking energy time histories of the three experimental case studies for steel frames reported in the literature using OpenSees (2004) with 78-ground motion records provided by Haselton and Deierlein (2007). It was observed that the new collapse criterion indicates the dynamic instability more accurately and effectively compared to subjective-based collapse criteria. Therefore, it can serve as more reliable indicator for the purpose of collapse prediction, which helps developing structural fragility accurately and assessing the risk of collapse capacity properly.

3.3.2. Energy-based Collapse Descriptor

Using a ductile steel frame computational model by Lignos *et al.* (2008), IDA was performed using the far-filed set of 78 ground motions by Haselton and Deierlein (2007). During IDA, spectral acceleration at the first-mode period ($Sa(T_1)$) and maximum inter-story drift ratio (IDR) are selected as intensity measure (IM) and damage measure (DM), respectively. As shown in Figure 3.3 (Deniz 2014), IM-based (green triangle), DM-based (blue square), and Energy-based (red circle) criterion are denoted. Due to uncertainty of ground motions, large variability is observed in the collapse capacity for two collapse criteria except for the DM-based rule which depends on predetermined threshold value. For reliable collapse risk assessment, a new DM which shows stable structural response at near collapse level is needed.

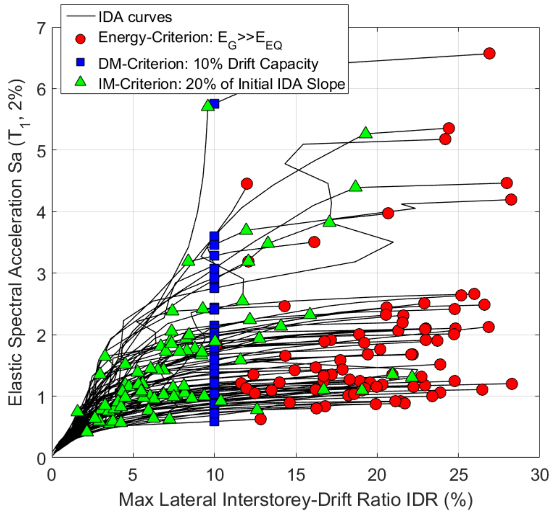

Figure 3.3 Comparison of collapse data points obtained by three different collapse criteria when IDR is selected as DM by Deniz (2014).

The energy based descriptor, termed as equivalent ratio (V_R), which is related to the ratio of the system's degrading energy ($E_{Degrading}$) to the earthquake total input energy (E_I) is defined as follows:

$$V_R = \sqrt{\left.\frac{E_{Degrading}}{2E_{EQ}}\right|_{time=at\ the\ end}} \approx \sqrt{\frac{\max(E_{Degrading})}{2\max(2E_{EQ})}} \tag{3.2}$$

Since the gravity energy becomes equal to the seismic input energy at near collapse, the total input energy then become almost twice the seismic energy (i.e., $E_I \approx 2E_{EQ}$). It is, thus, reasonable to introduce $2E_{EQ}$ for the denominator in Equation (3.2). Furthermore, the ratio at the end of the excitation can be approximated by the ratio of the maximum value as shown in the right hand side of Equation (3.2) because energy parameters are cumulative values. Given that most of hysteretic energy occurs from degrading rotational springs in the ductile frames, one can replace degrading energy as total strain energy dissipated from spring energy (E_{SPR}). Moreover, using a corresponding equivalent velocities for energy terms in Equation (3.1), one can finally get V_R, which is the ratio of the maximum equivalent velocities.

$$V_R = \sqrt{\frac{\max(E_{SPR})}{2\max(2E_{EQ})}} = \sqrt{\frac{\max\left(\frac{1}{2}mV_{SPR}{}^2\right)}{2\max\left(\frac{1}{2}mV_{EQ}{}^2\right)}} = \frac{\max(|V_{SPR}|)}{\sqrt{2}\max(|V_{EQ}|)} \tag{3.3}$$

An alternative IDA result is presented in Figure 3.4 (Deniz 2014) with replacing IDR to V_R and employing energy-based collapse criterion for circumventing sensitivity of collapse point due to assumed value. As shown in the last non-collapse case from each IDA curve (red asterisks), the collapse capacity defined by V_R exhibits a significantly reduced variability (Deniz 2014). Due to redistribution and variation of damage within structure, most widely used DM, IDR, may not accurately represent the overall collapse behavior. It is, however, noted that one can overcome the limitation by employing energy parameters at system-level which allows for considering each individual component damage within the structural system. Thus, using the energy based collapse criterion and descriptor, one can estimate the structural collapse more effectively.

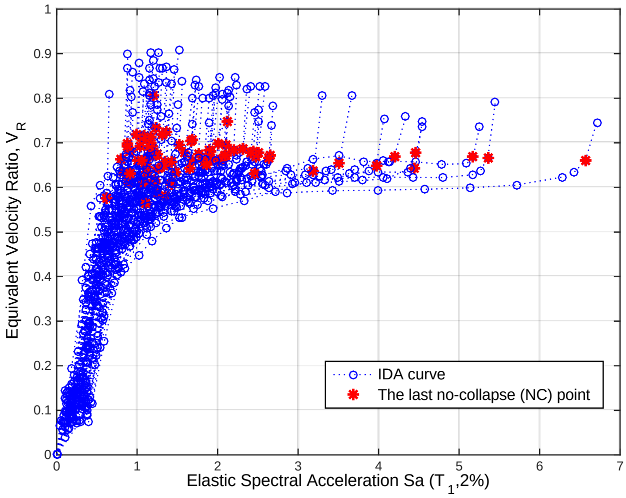

Figure 3.4 Last non-collapse points (red asterisks) from IDA curves when energy-based collapse criterion and descriptor are employed by Deniz (2014).

3.4. Development of a New Intensity Measure

3.4.1. Seismic Input Energy

Arias intensity (AI), mathematically defined as the integral of squared ground motion acceleration, is interpreted as the total energy per unit weight stored by a set of undamped simple oscillators at the end of an earthquake (Arias 1970).

$$AI = \frac{\pi}{2g}\int_0^{t_T} a(t)^2 dt \tag{3.4}$$

where, t_T is total duration of ground motion and $a(t)$ represents ground motion acceleration. Although AI is considered as one of the most commonly used IMs for describing seismic input energy, it does not take any structural information into account. This is the reason that new intensity measure is needed incorporating both input stochastic properties and structural characteristics for seismic input energy. In order to characterize the seismic input energy, average modified Arias intensity with strong earthquake duration ($AI^*_{avg}(T_1)$) is proposed in this section. To begin with, modified

Arias intensity with strong earthquake duration ($AI^*(T_1)$) is developed first that accounts for combining both total energy for ground motion and first mode period of structure.

Spectral acceleration ($Sa(T_1)$) is the most commonly used IM in earthquake engineering defined as the value representing the maximum acceleration that a ground motion will cause in a linear oscillator with a specified period and damping level (Baker 2006). Likewise, rather than using a maximum value, $AI^*(T_1)$ uses a whole pseudo spectral acceleration responses of specified natural period with strong earthquake duration. The definition of $AI^*(T_1)$ is obtained by replacing ground acceleration from AI to pseudo spectral acceleration responses of linear single degree of freedom (SDF) oscillator for specific damping value (5% damping has been introduced in this paper) at first mode period of structure, then integrating squared of pseudo spectral acceleration accumulated for corresponding period. Strong earthquake duration is defined as the time interval over 5% and 95% of the integral of square of pseudo spectral acceleration, $\int Sa_g^2(t)dt$. Mathematical form of $AI^*(T_1)$ is as follows:

$$AI^*(T_1) = \int_{Ds_5}^{Ds_{95}} Sa_g^2(t)dt \tag{3.5}$$

where, Sa_g and Ds_{5-95} indicates pseudo spectral acceleration and strong earthquake duration, respectively. Although $AI^*(T_1)$ incorporates both characteristics of ground motion and information of structure’s first mode period, it cannot properly interpret the ground motion’s impact on the responses due to lack of accounting for the effects of softening nonlinearities on the structure. Since not only stiffness and strength of structural system but also their ability to dissipate earthquake energy degrades under the earthquake excitation, the effect of period elongation caused by stiffness degradation should be taken into account (Katsanos and Sextos 2015).

Considering the effects of softening nonlinearities on the structure, $AI^*_{avg}(T_1)$ is defined as the arithmetic mean of modified Arias intensity over the interval between the structure's relative frequency drop (i.e., elongated fundamental period (T_1/α)) to fundamental period (T_1) as follows (De Biasio *et al.* 2014):

$$AI^*_{avg}(T_1) = \frac{1}{f_1(1-\alpha)}\int_{\alpha \cdot f_1}^{f_1} AI^*(T_1)dT = \frac{\alpha}{T_1(1-\alpha)}\int_{T_1}^{T_1/\alpha} \frac{AI^*(T_1)}{T^2}dT \tag{3.6}$$

where f_1 and T_1 are the first mode of frequency and period of structure, respectively and α indicates the ratio of structure's relative frequency drop (i.e., period elongation due to stiffness degradation of structural system). IDA data in terms of $\ln\left(AI^*_{avg}(T_1)\right)$ and $\ln\left(E_I\right)$ which is transformed using natural logarithm with 85% of relative frequency drop is shown in Figure 3.5. This figure confirms that one can estimate E_I precisely using $AI^*_{avg}(T_1)$ without performing dynamic analysis due to high correlation between E_I and its corresponding intensity measure, $AI^*_{avg}(T_1)$. It is noted that the period elongation of structure under strong earthquake is hard to evaluate, particularly, when structural system is complex and sophisticated. To circumvent the complicated procedure, optimal α is determined through comparing sum of squared error (SSE) of linear regression. In other words, the alpha value is chosen such that SSE of linear regression is minimized, which makes E_I and $AI^*_{avg}(T_1)$ most highly correlated. It should be noted that quantifying the structure's nonlinear behavior based on statistical inference can be useful considering chaotic nature of the dynamic behavior of a structure.

In Equation (3.6), it is found that $AI^*(T_1)$ is integrated over the frequency interval rather than period interval which is more common feature to describe the IM. The integration over the frequency domain gives higher weight to lower frequency spectral ordinate that integration over the period domain as shown in Equation (3.6). Moreover, the accumulation of the $AI^*(T_1)$ over frequency domain would give higher weight to spectral ordinate closer to "known" fundamental frequency and lower weight to spectral ordinate closer to "less-known" elongated frequency (De Biasio *et al.* 2014).

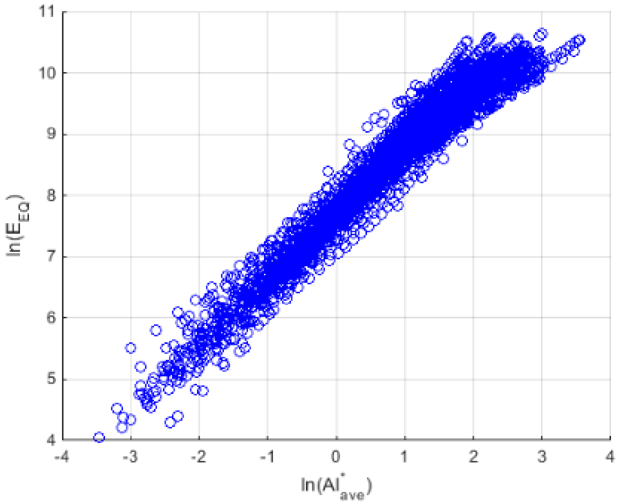

Figure 3.5 Relationship between natural logarithms of $AI^{*}_{avg}(T_1)$ and E_I with 85% frequency drop.

3.4.2. Dissipated Hysteretic Energy

As shown in Equation (3.1), some part of E_I is dissipated through structural degradation, so called degrading energy ($E_{Degrading}$). $E_{Degrading}$ is defined as the area under the hysteric curve of the degrading elements which is the sum of E_E and E_H for the rotational spring of the ductile structure. The cumulative energy component E_H reaches the maximum value at the end of the time series analysis while E_E becomes zero. Moreover, most of hysteretic energy occurs from degrading rotational spring of ductile frames, it is natural that $E_{Degrading}$ can be described in terms of spring energy termed as E_{SPR} (Deniz 2014).

E_{SPR} is dependent on the complex mechanism which is characterized by such as number of inelastic load cycle, ductility of structure, and the hysteresis loop. Thus, it is hard to estimate E_{SPR} without performing dynamic analysis or using parameters of degrading model. The proxy measure of degrading energy can then be obtained approximately. Given that energy is proportional to the force from the fundamental theory of structural mechanics, higher strength of ground motion leads to more degrading energy in the structures, even though same energy is applied on the system. It is thus noted that IM whose property represents the strength of ground motion can be a good candidate for describing E_{SPR} such as peak ground acceleration or $Sa(T_1)$. Moreover, to find a peak IM that not only take structural characteristic and seismic properties into account but also consider period elongation of structural system during dynamic analyses, average spectral acceleration ($Sa_{avg}(T_1)$) introduced by Baker and Cornell (2005) is identified as the best proxy of E_{SPR}. The average spectral acceleration is defined as a geometric mean of a series of spectral acceleration which is computed as

$$Sa_{avg}(c_1 T_1, \cdots, c_N T_1) = \left(\prod_{i=1}^{N} Sa(c_i T_1) \right)^{1/N} \tag{3.7}$$

where N represents the number of periods used to compute $Sa_{avg}(T_1)$ and the c_i is a non-negative values range between 1 to $1/\alpha$ with a uniform period spacing 0.01s (Bojórquez and Iervolino 2011), where α should coincide with the value for $AI^{*}{}_{avg}(T_1)$ in Equation (3.6). For dissipated hysteretic energy, geometric mean is used for AI instead of the arithmetic mean for $AI^{*}{}_{avg}(T_1)$. This is due to the fact that peak IM should take the effects of compounding into account when describing E_{SPR}. Contrast to E_I which just piles up the applied energy on the structure during earthquake, E_{SPR} should consider previously affected structure’ s period elongation because of influence on the state of stiffness degradation of structural system.

The results of nonlinear dynamic analysis regarding $\ln(Sa_{avg}(T_1))$ and $\ln(E_{SPR})$ which is linear transformation of $Sa_{avg}(T_1)$ and E_{SPR} using natural logarithm are shown in Figure 3.6. The plot begins to diverge at the point where $\ln(Sa_{avg}(T_1))$ is around at −1.3, which coincides with the point where the deterioration model, rotational spring in the frame, reaches their peak strength and the first mode period of structure starts to change. Much variability is observed in Figure 3.6 compared to Figure 3.5 because each ground motion makes different influence on the structure that may result in different deterioration level of structural system. Using "specific" parameters such as modified Ibarra−Krawinkler deterioration model (Lignos *et al.* 2008), one may be able to find or develop a "limited−IM" which reduce the variability of E_{SPR}. However, this would lead to losing general applicability to other structures which do not use "specific" parameters. Thus, it is reasonable that even without relying on nonlinear analysis using a particular deterioration model, $Sa_{avg}(T_1)$ correlates reasonably well with E_{SPR}.

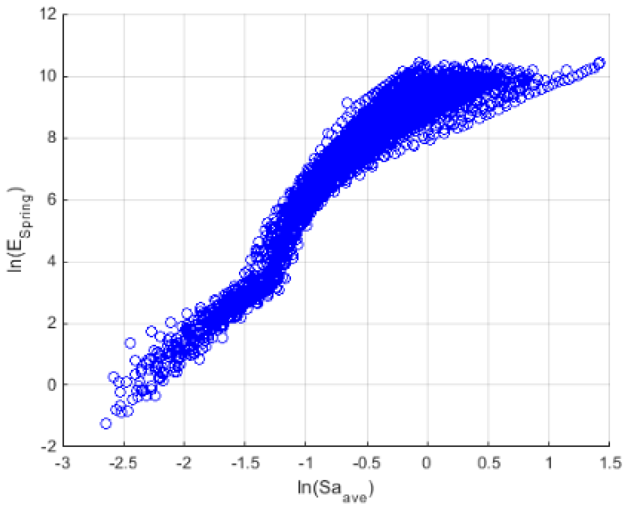

Figure 3.6 Relationship between natural logarithms of $Sa_{avg}(T_1)$ and E_{SPR} with 85% frequency drop.

3.4.3. A New Intensity Measure

This paper proposes a new cumulative IM, $AI^*_{avg}(T_1)$, for seismic input energy and find a proper peak IM, $Sa_{avg}(T_1)$, for dissipated hysteretic energy. Using the inverse relation of equivalent velocity ratio which is the ratio between seismic input energy and hysteretic energy, new IM can be defined as follows:

$$IM = \sqrt{\frac{AI^{*}_{avg}(T_1)}{Sa_{avg}(T_1)}} \tag{3.8}$$

The new IM involves the cumulative IM, peak IM, strong earthquake duration, and the effects of softening nonlinearities on the structure. Due to the inverse relation of V_R, the new IM is scalable, in that its value is proportional to the ground motion scaling factor. Therefore, it can be used in IDA and also employed in performance−based earthquake engineering (PBEE) framework.

The efficiency of the IM can be tested by comparing the dispersion of the point where the seismic intensity indicates the collapse of a structure. Comparison are made between the dispersion of the new IM and a most widely used IM, $Sa(T_1)$, at last non−collapse level of IDA. V_R is selected as DM and collapse is defined using energy−based collapse criterion. To facilitate direct comparison between IMs, both fragility curves have been normalized by those of median values. Figure 3.7 shows both fragility curves of the IM for a steel moment resisting frames by Lignos *et al.* (2008). The coefficient of variation (c.o.v) of the new IM is 0.1869, lower than 0.4378 of $Sa(T_1)$. This result shows that new IM can serve as more reliable measure for the purpose of predicting collapse.

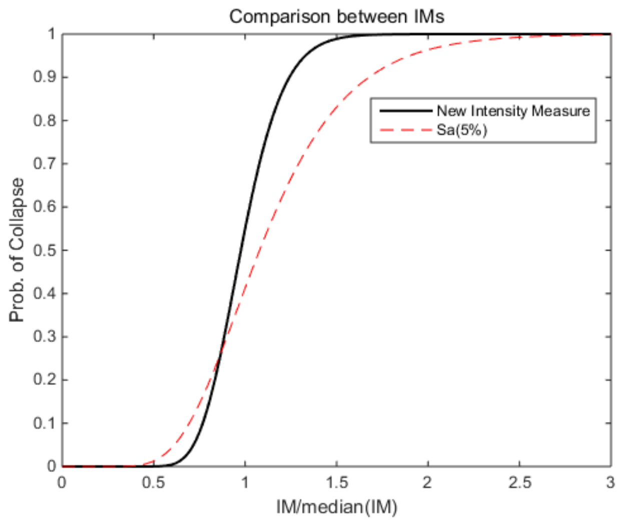

Figure 3.7 Collapse fragility curve for steel frame structure using the new IM and $Sa(T_1)$ which are normalized by each median value.

3.4.4. Application of New IM to Reinforced Concrete Structural Frame

Even though the structural system used to develop the new IM was validated by the experimental results, there is a chance that the new IM is applicable only to steel frame structure. Therefore, the applicability and effectiveness of the new IM need to be checked for other type of structures. In order to further quantify the efficiency of new IM at collapse, one of the RC SMF buildings developed by Haselton *et al.* (2011), 4-story perimeter frame (ID 1004), is selected. Haselton *et al.* (2011) report the results of nonlinear dynamic analyses for a set of 30 representative reinforced concrete (RC) special moment-frame (SMF) building to assess the risk of collapse under the ground motion set used in federal emergency management agency (FEMA) P-695. To demonstrate the applicability of the new IM, "traditional" IDA is performed instead of using energy-based descriptor and criterion: IDR, one of the most widely-used DM, is selected as a damage measure instead of V_R. Moreover, rather than using energy based collapse criterion, collapse is defined as the point where the lateral story drifts of the building increase without bounds, i.e., the point where the IDA curves become almost flat. The same method is used for calculating the period elongation of the RC structure which is determined through comparing SSE of linear regression between $\ln\left(AI^{*}_{avg}(T_1)\right)$ and $\ln(E_I)$ by varying α. The optimal period elongation value for RC building is computed as 0.96. This result is reasonable that structure' s relative frequency drop of RC structure (0.96) is much bigger than that of more ductile steel frame structure (0.85), which in turn shows that α can effectively account for the behavior of structural nonlinearities.

IDA is performed for an RC SMF building subjected to the 78 ground motion records in the expanded FEMA set, incrementally increase intensity level until collapse. Figures 3.8 and 3.9 show IDA curves of $Sa(T_1)$ and new IM to IDR, respectively. Comparing the IDA curves of Figure 3.8 and 3.9, it is found that the new IM gives gradual slope at near collapse area which can provide more reliable collapse limit states when IM-based collapse rule is employed. The dispersion in the collapse fragility curves of the RC SMF building is smaller for new IM than that of $Sa(T_1)$ as shown in Figure 3.10. The c.o.v of the new IM is 0.2421 compared to the 0.3762 of spectral acceleration. It should be noted that one can predict the collapse for a structural system with less uncertainty not only with energy-based collapse criterion and descriptor but also with existing collapse criterion and widely used DM such as IDR.

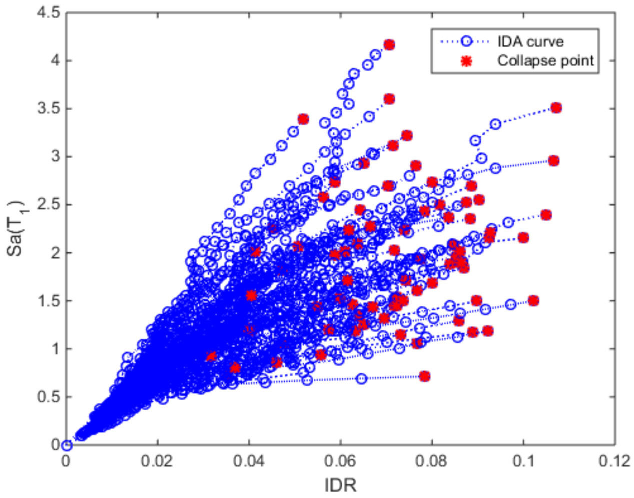

Figure 3.8 IDA curves for $Sa(T_1)$ and IDR using RC structure subject to 78 ground motions.

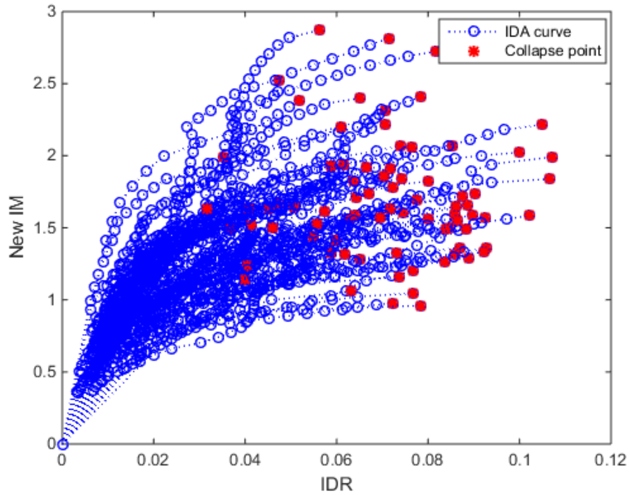

Figure 3.9 IDA curves for new IM and IDR using RC structure subject to 78 ground motions.

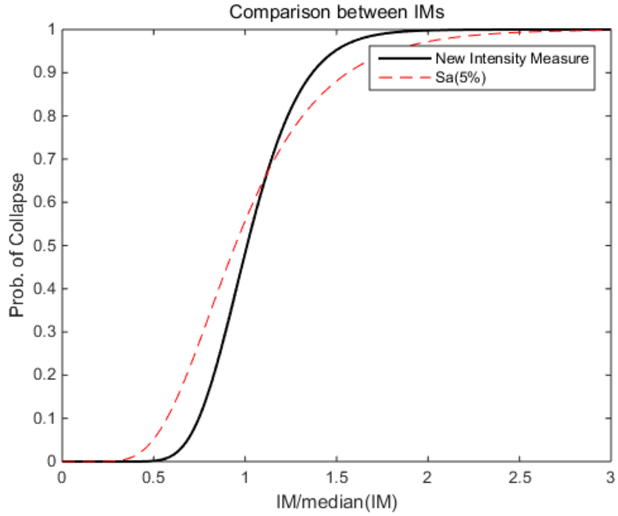

Figure 3.10 Collapse fragility curves for one of test specimen by Haselton *et al.* (2011) using $Sa(T_1)$ and new IM which is normalized by each median value.

3.5. Influence of Energy Balance Ratio Between E_I and $E_{Degrading}$ on Structural Collapse Capacity

During earthquake excitation, structural system can be understood from the viewpoint of the energy parameters such as energy balance between earthquake input energy and dissipated hysteretic energy (Uang and Bertero 1990). Although this is the topic that has been researched extensively in the literature, the influence of energy balance between E_I and $E_{Degrading}$ on structural demands does not have a well-defined framework when selecting ground motions for dynamic analysis, particularly emphasis on predicting structural collapse. This section, therefore, aims to highlight the effects of energy parameters when evaluating structural collapse. First, IM which can illustrate energy balance between E_I and $E_{Degrading}$ is proposed using the relation between $AI^*_{avg}(T_1)$ and $Sa_{avg}(T_1)$, which is demonstrated as proxy measure for E_I and $E_{Degrading}$, respectively. Collapse fragility curve is then computed for the test specimen of Lignos *et al.* (2008) subjected to a set of different energy balance ratio of ground motions.

A new measure of seismic intensity is developed here as an indicator of energy balance ratio between E_I and $E_{Degrading}$ of a ground motion. To begin with, a set of ground motions have to be scaled to get the same target value of $Sa_{avg}(T_1)$ (e.g., each ground motion is scaled to make $Sa_{avg}(T_1)$ get $1g$). The energy balance ratio denoted by ε_{AI}, is then defined as a discrepancy between the value of $AI^*{}_{avg}(T_1)$ and the median of the ground motion record set. Thus, energy balance ratio for k^{th} ground motion, $\varepsilon_{AI,k}$ is mathematically expressed as follows:

$$\varepsilon_{AI,k} = \exp\left(\ln\left(AI^*{}_{avg,k} \mid Sa_{avg,k} = x^*\right) - \frac{1}{N}\sum_{k=1}^{N}\ln\left(AI^*{}_{avg,k} \mid Sa_{avg,k} = x^*\right)\right) \tag{3.9}$$

where, x^* denotes any positive integer (e.g., 1g), and N indicates the number of ground motions employing in the IDA. Suppose ground motions are scaled to get the same target value of $Sa_{avg}(T_1)$, it is natural to think that same amount of energies are dissipated through structural system under the set. Each ground motion, however, has different $AI^*{}_{avg}(T_1)$ value so that higher value of $AI^*{}_{avg}(T_1)$ indicates more seismic input energies are applied on the structural system given same energy is dissipated.

In order to estimate collapse fragility regarding energy balance ratio, a set of ground motions should be grouped in terms of ε_{AI}, "high" energy balance ratio record set is defined as a value of ε_{AI} belongs to intervals of 67$^{\text{th}}$ percentile to 100$^{\text{th}}$ percentile among the set and "medium" and "low" energy balance ratio group consist of 34$^{\text{th}}$ percentile to 66$^{\text{th}}$ percentile and 0$^{\text{th}}$ percentile to 33$^{\text{th}}$ percentile of ε_{AI} among the records, respectively. For effective risk assessment of structural collapse, energy based collapse criterion and descriptor are used for estimating collapse fragility under 155 ground motions. Collapse fragility curves resulting from IDA conducted using high, medium, and low energy balance ratio records sets are illustrated in Figure 3.11. The median spectral acceleration value of collapse capacity estimated using high, medium, and low record sets are 1.004g, 1.129g, and 1.435g, and c.o.v of each set are 0.191, 0.303, and 0.4767, respectively. It is found that ground motions whose energy balance ratio belongs to low group make buildings vulnerable to collapse and increase the uncertainty in terms of structural demand. The results serve to illustrate the significant impact of energy balance ratio of ground motion to collapse prediction. Thus, one can reliably predict the structural collapse when IDA is performed using a ground motion sets which are selected considering an energy balance ratio.

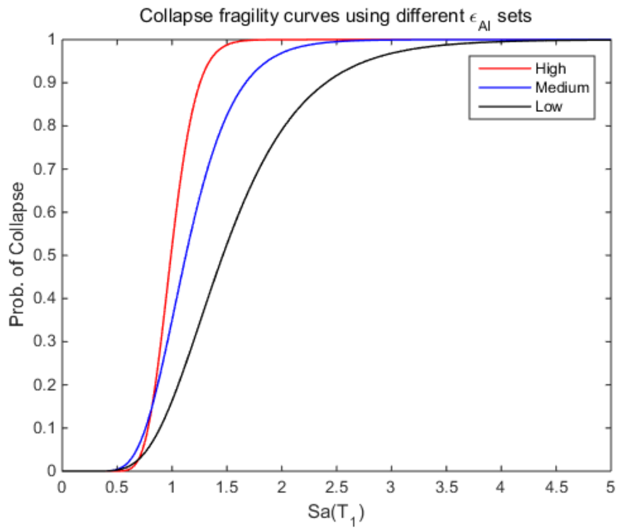

Figure 3.11 Collapse fragility curves estimated using the high, medium, and low energy balance ratio record sets.

Chapter 4. A Ground Motions Selection Procedure Using Clustering-based Adaptive Sampling

For accurate and reliable collapse risk assessment, nonlinear dynamic analyses coupled with probabilistic seismic hazard analysis need to be performed. To begin with, ground motions whose response spectra is closely matched with a site−specific target response spectrum should be selected for nonlinear dynamic analyses of structural system. For comprehensive reflection of hazard characteristics at a given site, a large set of ground motions are needed, which incur high computational cost of dynamic seismic response analysis. To reduce the number of ground motion time series used in nonlinear stochastic analyses while providing proper information about given site, this chapter develops a new algorithm about selecting ground motion time series. The main idea of the framework is that a set of ground motions are grouped regarding their critical features which affect the likelihood of structural collapse, and ground motions are selected from the identified clusters until the estimated fragility is converged. To this end, statistical learning algorithm such as subset selection method and clustering analysis are employed. Using the developed algorithm, one can obtain reliable estimation on collapse fragility using far less number of ground motions.

4.1. Ground Motion Selection Algorithm

The main goal of the algorithm is to reduce the number of dynamic analysis when estimating collapse capacity of structural system. A large ground motion set, however, is needed for reflecting information about probabilistic seismic hazard analysis when evaluating structural collapse. In this study, a new ground motion selection algorithm is proposed to reduce the computational cost effectively while keeping consistency with seismic hazard analysis. The main idea of the algorithm is that ground motions in a given set are grouped distinctively in terms of the relationship between IM and corresponding calculated DM in IDA. Then, select one ground motion from each identified cluster and perform nonlinear time history analyses. This is based on premise that if ground motions are clustered properly regarding a behavior of IDA curves, the results of dynamic analyses using ground motions in the same cluster shows similar to each other.

Clustering analysis is a standard technique in statistics that is commonly used to cluster a set of data so that data in the same group show more similar characteristics compared to data from other groups. Although many clustering methods have been developed, K-means clustering analysis, a simple and most widely used technique, is employed in this study. Given an initial set of center, K, the procedure of K-means clustering algorithm is consisted of two steps (Friedman *et al.* 2001):

- For each center, the subset of data which is closer to its center than any other center is identified.
- In each cluster, the mean vector of each feature for data points is computed and becomes the new center for that cluster.

These two steps are performed iteratively until the mean vector converges to a certain value. As shown in the procedure, a fundamental task of clustering method is the choice of distance or dissimilarity measure between two data points (Friedman *et al.* 2001). In order to apply clustering algorithm, ground motions should be denoted as vector of intensity measures which can explain the relationship between IM and DM. If vector of intensity measures has been already figured out regarding IDA curves, one can use chosen IMs. If not, the procedure to find these vector of intensity measure so called "critical features" may be helpful, which will be explained in the next section.

Using clustering method, a new ground motion selection algorithm is developed as follows:

1. Initialize: Choose initial values of the number of cluster, n, and target coefficient of variation (c.o.v), ε^*. A lower level of target c.o.v would lead to higher total computational cost.
2. Cluster: Perform K-means clustering analysis based on critical features so that distinct groups of ground motion are identified. When performing clustering analysis, some statistical issues have been occurred such as data splitting and scale problem due to different scale between each critical feature. To address such issues, it is noted that natural logarithm is applied to each variable in order to satisfy the homoscedasticity assumption and normalized by its own standard deviation value to make scaleless variables. Please note that K-means clustering sometimes converges to local-minima, thus one has to perform a few times of clustering analysis to find the global optimization result.
3. Sample: Although ground motions in the same group show similar characteristics, a ground motion that located near at the center point of each cluster can represent the characteristics of the group most properly. Therefore, this study selects a "dominant" ground motion rather than randomly sample a ground motion from each cluster for nonlinear dynamic analysis. IDA is then carried out using selected ground motions.
4. Estimate initial fragility: Assign the result of IDA to other ground motions in the same cluster and fit fragility function to dynamic analysis results using statistical procedure.
5. Update: Perform clustering analysis with increasing the number of cluster and sample one ground motion from each cluster. Since the ground motions from the previous stage are re-used, it is not necessary to sample a new ground motion from the clusters including the ground motion employed previous step.
6. Estimate fragility: IDA is carried out using recently sampled ground motion(s) then estimate new fragility curve.
7. Convergence check: Compute distance between previous

and current fragility curves using MD. If c.o.v of MD is greater than target c.o.v, return to step 5. Otherwise, stop the algorithm. The fragility stabilizing parameter, MD, will be discussed later.

The aforementioned procedure is explained by a flow chart in Figure 4.1. This procedure is based on the "Method A" fragility fitting method. If one cannot guarantee the set of ground motions from probabilistic seismic hazard analysis, i.e., most ground motions in the set represent similar IDA curves, probabilistic seismic demand model based fragility fitting method is better choice for reliable estimation. Then, some modification in ground motion selection algorithm is needed. First of all, estimation technique should be changed from "Method A" to probabilistic seismic demand model based fitting method. In addition, since fragility curve is a function of probabilistic model, MD will not be required any longer in convergence check step. Thus step 4 and 7 will be changed as follows:

4. Estimate: Rather than assign the results of dynamic analysis to other ground motions in the same cluster, use just analyzed ground motion results to fit fragility function based on Equation (2.8) to (2.11). For example, if the number of ground motions which is used in dynamic analysis is 15 among 155, "Method A" procedure uses 155 collapse data points because of assigning the result to other ground motions, while probabilistic seismic demand model based approach uses 15. However, the latter not only uses collapse data point but also employs non-collapse data point to develop probabilistic model. Thus one can overcome the limitation of bias of structural responses result from record set.
7. Convergence check: Instead of employing MD, the fragility curve is updated until the parameters of safety margin against the collapse of structural system (i.e., $\mu_C - \mu_D(x)$

and $\sqrt{\sigma_C^2 + [\sigma_D(x)]^2}$ in Equation (2.11)) converges to certain value. It is, however, noted that algorithm only check convergence of $\sqrt{\sigma_C^2 + [\sigma_D(x)]^2}$ due to the fact that the value, $\mu_C - \mu_D(x)$, varies with respect to given x.

From experience of the study, the target c.o.v in Step 2, is typically on the order of 2%. A good rule of thumb for the initial number of ground motion is more than 15 because the proposed method is based on statistical approach. Furthermore, the convergence of the iteration is sensitive to critical features so that well defined IM vector makes the fragility curve converged with a few times of nonlinear dynamic analyses.

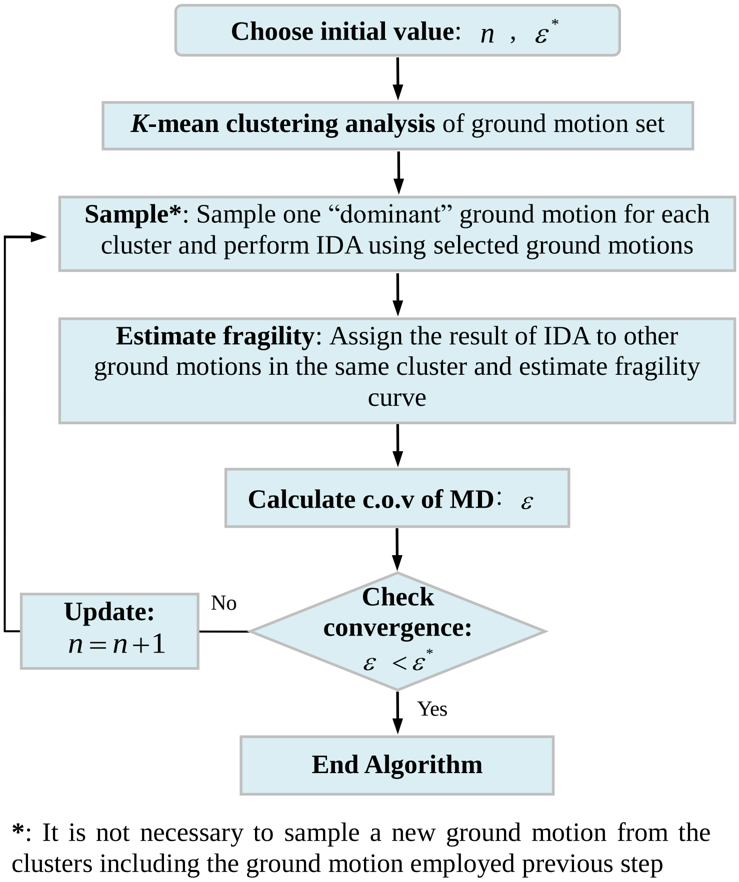

Figure 4.1 Flowchart of ground motion selection algorithm procedure.

4.2. Identification of Critical Features for Incremental Dynamic Analysis

Critical features are the characteristics of ground motions that are well correlated with behavior of IDA−curve. Since IDA−curves are significantly affected by the choice of IM and DM used in IDA, it is important to identify critical features corresponding the selected IM and DM. To begin with, formulation which can interpret seismic demand and structural capacity should be identified. Based on theories of structural mechanics and/or expert opinions, following mathematical form is usually adopted to construct a probabilistic model when drift ratio is selected as DM (Cornell *et al.* 2002).

$$DM = b \cdot \prod_i \left(IM_i\right)^{a_i} \tag{4.1}$$

where IM_i represents a possible relevant feature of ground motion and a_i accounts for its sensitivity to IM_i and b is an intercept of the model. The coefficients can be found by regression analyses. The formulation, however, can be changed along with DM used for IDA. For example, if an energy−based descriptor named as equivalent velocity ratio (V_R) is used as DM, Equation (4.2) is more useful than Equation (4.1).

$$DM = \frac{e^{\mathbf{c}^{\mathrm{T}} \cdot \mathbf{IM}}}{1 + e^{\mathbf{c}^{\mathrm{T}} \cdot \mathbf{IM}}} \tag{4.2}$$

where $\mathbf{IM}$ represents the vector of candidate IMs and $\mathbf{c}$ denotes the corresponding coefficients vector. Since V_R is related to the ratio of the system' s degrading energy to earthquake input energy, it should be smaller than 1 (Deniz 2014). Therefore, formulation of logistic regression is more reasonable choice for V_R.

Since the goal of the procedure is to find additional features of ground motion which can minimize "remaining uncertainty" that are not fully covered by originally selected IM for IDA, each ground motion is first scaled to get the same intensity level of selected IM. For example, when spectral acceleration ($Sa(T_1)$) is originally selected for IM, ground motions are respectively scaled to get the same spectral acceleration value, e.g. 1g. Next, the best subset of intensity measures that properly reduces the remaining uncertainty is found using best-subset selection method which is one of the subset selection methods in statistical field. The procedure starts with empty set of features and generates all possible probabilistic model using a single feature. Then, the model is expanded in the same manner by sequentially adding another features. The best subset of features can be determined through comparing the sum of squared error (Friedman *et al.* 2001). Since best-subset selection method explores the entire search space (2^p possible model, where p is the number of predictors), it is common to limit the number of subsets that are expanded for computational efficiency. In summary, the procedure to find key characteristics of IDA-curve can be used not only for ground motion selection algorithm but also for comprehensive understanding between seismic demand and structural capacity.

4.3. Euclidian Metric Distance

The metric distance measure is originally developed to measure a fuzziness in information theory (Klir and Folger 1988), but its concept can also be used to measure the distance between two different fragility curves expressed as probabilistic manner. A general form of metric distance, Minkowski class of distance, would mathematically be stated

$$M = \left(\sum_{x \in X} \left| f_1(x) - f_2(x) \right|^w \right)^{1/w} \tag{4.3}$$

where $f_1(x)$ and $f_2(x)$ denote functions of x, and w represents a number greater than 1. For $w=1$ and $w=2$ are special case of Minkowski class of distance, which are called as Hamming and Euclidian distance, respectively.

In this paper, normalized Euclidian metric distance, MD (Chun *et al.* 2000) which is normalized by the mean of previous fragility curve is used as criteria of convergence of the fragility curve

$$MD = \frac{\left(\int_0^1 \left(y_p^i - y_p^o\right)^2 dp\right)^{1/2}}{\mu_{y^i}} \tag{4.4}$$

where y_p is p^{th} quantile of cumulative density function (CDF), the superscript i and o means previous and current fragility, respectively and μ_{y^i} represents the mean of previous fragility curve. Normalization using mean of previous fragility curve can make the MD a dimensionless quantity. If the value of y_p^i is equal to y_p^o in overall ranges of 0 to 1, the two CDFs become identical and MD goes to zero. The MD defined in this study can provide the information on how much an updated dynamic analyses can effect on the fragility curve. A larger MD means that clustering analysis has not yet grouped a set of ground motions properly so that fragility curve fluctuates a lot. It is thus natural that stable and small values of MD guarantee that the fragility curve is converged, i.e., c.o.v of MD smaller than target c.o.v can be a criterion for algorithm.

As previously mentioned, lognormal cumulative distribution is often used to define a fragility function which includes scale and shape factor or mean and standard deviation of $\ln x$, λ and ξ. The probability density function is given by (Ang and Tang 2007):

$$f_X(x) = \frac{1}{\sqrt{2\pi}\xi x} \exp\left[-\frac{1}{2}\left(\frac{\ln x - \lambda}{\xi}\right)^2\right], \qquad 0 < x < \infty \tag{4.5}$$

For mathematical simplicity, let β represents a natural logarithm of scale factor, $\exp(\lambda)$, one can analytically derive closed form of general MD follows lognormal distribution as follows (Chun *et al.* 2000):

$$MD = \frac{\sqrt{(\beta_i)^2 \cdot \exp(2\cdot\xi_i^2) + (\beta_o)^2 \cdot \exp(2\cdot\xi_o^2) - 2(\beta_i)\cdot(\beta_o)\exp\left(\frac{(\xi_i + \xi_o)^2}{2}\right)}}{\beta_i \cdot \exp\left(\xi_i^2/2\right)} \tag{4.6}$$

where β and ξ with subscription i and o represent scale and shape parameter of previous and current fragility curve, respectively. Using explicit form of MD, one can easily stabilize the fragility curve in ground motion selection algorithm.

4.4. Numerical Examples

The breadth of applications and performance of the proposed ground motion selection algorithm are demonstrated by numerical examples. First, roof drift ratio (D_x) and spectral acceleration at the first mode period ($Sa(T_1)$) which is most commonly used DM and IM is selected for demonstrating the efficiency of the algorithm. Second, applicability of the algorithm is tested using different combination of IM and DM such as V_R and $Sa(T_1)$. Since proposed algorithm and selected critical features are developed based on the steel frame structure even though the test specimen was validated by the experiment results, it is needed to evaluate its applicability and effectiveness. In order to further check the applicability of the algorithm and the effectiveness of critical features identified through steel frame structure, the algorithm with selected critical features are evaluated using one of RC SMF building reported by Haselton *et al.* (2011). Finally, to test the proposed algorithm with different fragility fitting method, the collapse risk assessment of steel frame structure developed by Lignos *et al.* (2008) is assessed under biased record set with the probabilistic seismic demand model based collapse fragility fitting method.

4.4.1. Numerical Example 1

In the first example, $Sa(T_1)$ and D_x is selected as IM and DM for IDA and 20% IM-based criteria is used to define structural collapse. In order to employ ground motion selection algorithm, critical features should be first identified. Various measures mostly from Riddell (2007) and some other seismic intensities proposed in recent studies (Chandramohan *et al.* in print, Marafi *et al.* 2016) have been considered as candidates for critical features. To identify critical features, each ground motion is respectively scaled to get same $Sa(T_1)$, 1g. Using the best−subset selection method and the model in Equation (4.1), three additional features are identified as critical features: Arias intensity (AI) (Arias 1970), peak ground acceleration (PGA) and average modified Arias intensity with strong earthquake duration ($AI^*_{avg}(T_1)$). Thus, the ground motions are denoted as vector that has four components, $\left[Sa(T_1)=1g,\ AI,\ PGA,\ AI^*_{avg}(T_1)\right]$.

Initial values of parameters, the number of initial cluster and target coefficient of variation, are selected as 20 and 0.02, respectively. To illustrate the process, MD computed from each step of adaptive selection with respect to the fragility curve of previous step is shown in Figure 4.2. Using the ground motion selection algorithm, one can obtain small MD value even using small number of ground motions as shown in blue asterisk mark. Furthermore, while large variability is observed when using randomly selected ground motions (red plus mark), the ground motion algorithm make fragility curve converged quickly to a certain value.

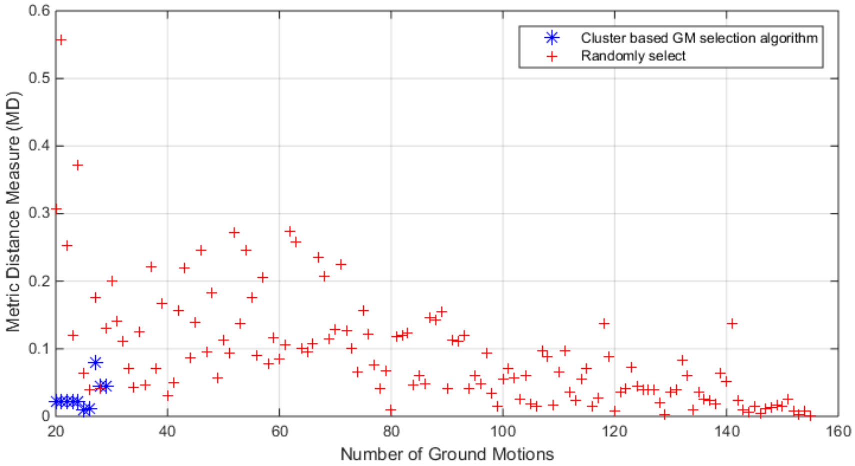

Figure 4.2 Metric distance measure (MD) of the fragility model at each step of updates with respect to the fragility curve from the previous step.

To test whether the “certain value” is local optimum or not, the MD values are computed with respect to the fragility curve calculated using the entire set of ground motions which is called as "real fragility curve" in this study. Please note that this is done only for the test purpose, and in practical situation, MD will be computed with respect to fragility curve of previous step. Figure 4.3 and 4.4 show the distance from the fragility curve based on "real fragility curve". The MD will be zero when fragility curve is estimated using total 155 ground motions, as shown in the last green triangle point of Figure 4.3 at the number of ground motion is equal to 155. While the MDs of randomly selected ground motion denoted as green triangle show large variability as expected, that of proposed algorithm decrease steadily in this case well as shown in Figure 4.4 (yellow square). Finally, fragility curve calculated using only 30 ground motions is compatible with the one computed by the original set as shown in Figure 4.5.

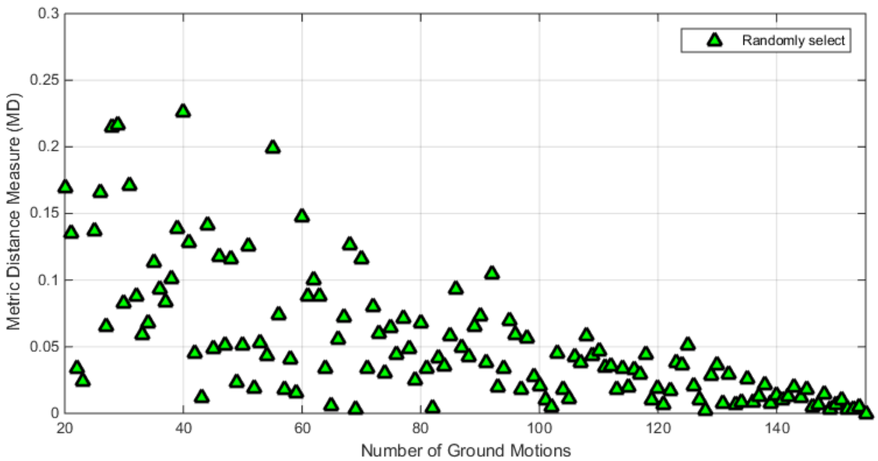

Figure 4.3 MDs of randomly selected ground motion at each step of updates with respect to the fragility curve based on the entire set.

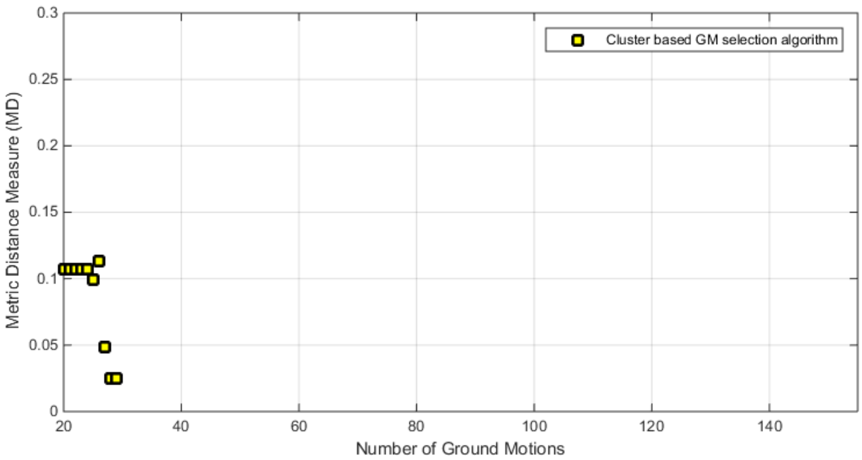

Figure 4.4 MDs of ground motion selection algorithm at each step of updates with respect to the fragility curve based on the entire set.

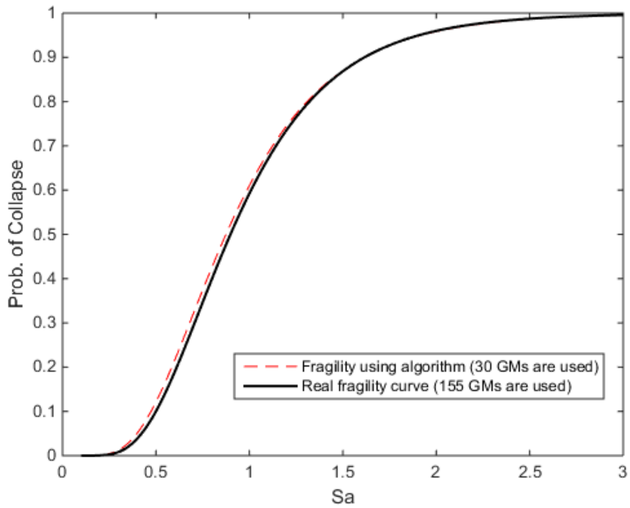

Figure 4.5 Fragility curves by the developed algorithm (30 ground motions) and the entire set of 155 ground motions.

4.4.2. Numerical Example 2

It is noted that even using the same structural system under the same set of ground motions, different IDA−curves may be obtained along with selection of IM and DM for IDA. To test the applicability of proposed algorithm considering such an issue, the second example is explored. Instead of employing D_x, V_R is used as damage measure and $Sa(T_1)$ is selected as IM. In addition, the energy collapse criterion is introduced with V_R so that the dispersion due to record-to-record variability can be decreased, which in turn leads to a reduction on uncertainty level of predicting collapse (Deniz 2014, Deniz *et al.* under review).

Through best-subset selection method with Equation (4.2), three additional features are identified as critical features: AI, $AI^*_{avg}(T_1)$ and strong earthquake duration (t_s) (Trifunac and Brady 1975). The ground motion selection algorithm was employed under same condition of the first example. Figure 4.6 shows MD computed with respect to previous step of fragility curve. One can see significant savings in computational time when compared with randomly selected ground motion as shown in Figure 4.6. Figure 4.7 also confirms that fragility curve using 30 ground motions can provide a fragility curve that is almost same as "Real fragility curve". Thus, one can demonstrate that proposed algorithm is not sensitive to selected IM and DM for IDA.

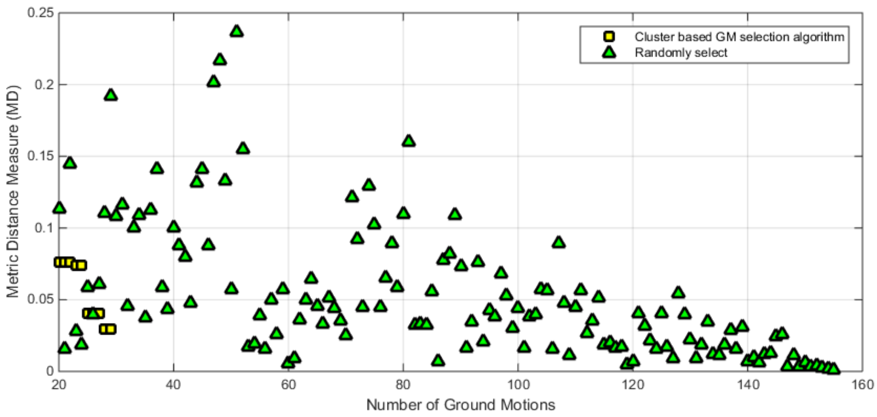

Figure 4.6 MDs of the fragility model at each step of updates with respect to the fragility curve based on the entire set when V_R is selected as DM.

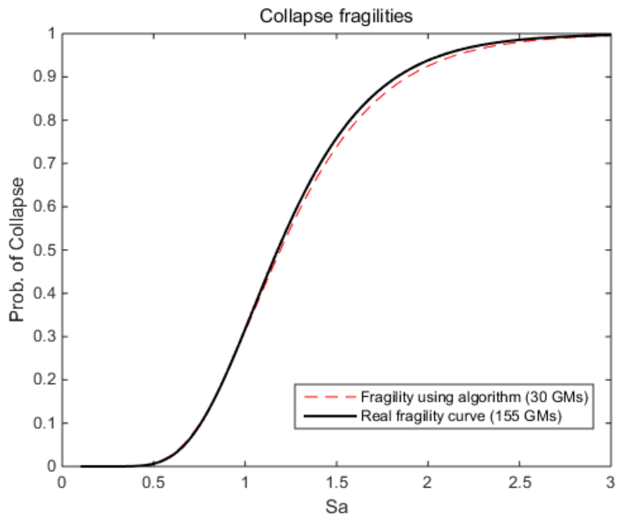

Figure 4.7 Fragility curves evaluated by using developed algorithm (30 ground motions) and employing the entire record set (155 ground motions) when V_R is selected as DM.

4.4.3. Numerical Example 3

In order to find the additional features which are used in ground motion selection algorithm, the results of incremental dynamic analysis for the steel frame structure are employed. Thus, the determined critical features should be checked its effectiveness and applicability subject to other structure. To test the efficiency of identified critical features with ground motion selection algorithm, one of RC SMF building, 4-story perimeter frame (ID 1004), developed by Haselton *et al.* (2011) is examined under 78 ground motion records in the expanded FEMA set. $Sa(T_1)$ and D_x is selected as IM and DM for IDA. To perform algorithm, previously identified AI, PGA, and $AI^*_{avg}(T_1)$ is used as critical features for clustering analysis. The results are obtained based on 15 of the number of initial cluster and 2% of target c.o.v. Figure 4.8 and 4.9 shows that ground motion selection algorithm shows quick convergence of MD and provide reliable structural collapse likelihood using 22 ground motions.

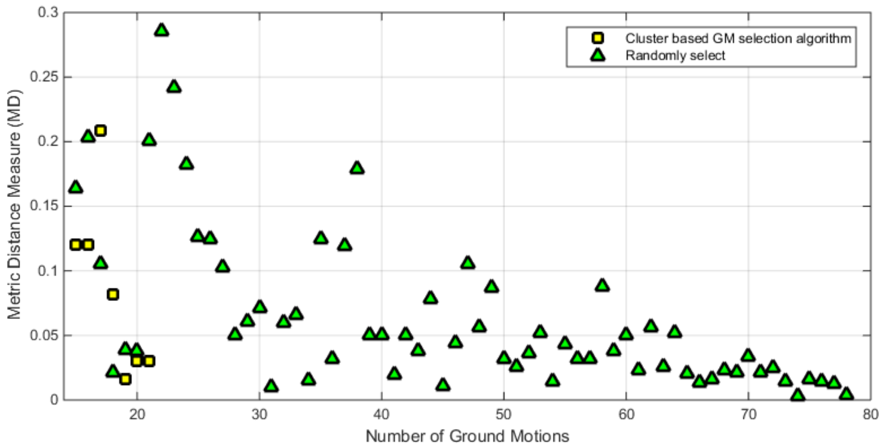

Figure 4.8 MDs of the fragility model at each step of updates with respect to the fragility curve based on the entire set for RC SMF building.

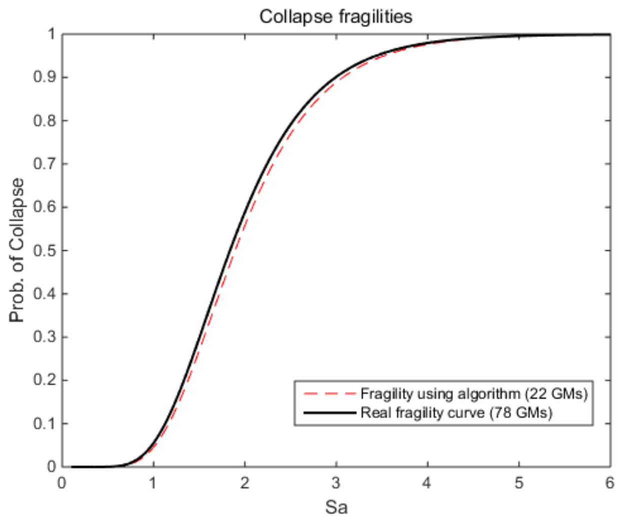

Figure 4.9 Fragility curves by the developed algorithm (22 ground motions) and the entire set of 78 ground motions for structure developed by Haselton *et al.* (2011).

Based on the critical features of the Example from 1 through 3, one can infer that both AI and $AI^{*}_{avg}(T_1)$ are the most critical seismic intensities which can properly capture the remaining variability that are not fully covered by spectral acceleration at first mode period in IDA. It is noted that selected critical features are in line with new IM combined with peak (e.g., $Sa(T_1)$) and cumulative (e.g., $AI^{*}_{avg}(T_1)$) indices. Therefore, one can predict the structural responses with less uncertainty using new IM, particularly for estimating the collapse risk assessment of structural system.

4.4.4. Numerical Example 4

In developing collapse fragility, a linear regression model can be used for providing more reliable probabilistic evaluation of collapse likelihood, particularly a set of ground motions are biased. Following the statistical procedure described above, a linear regression model of demand is developed as in Equation (2.8) for the test case of Lignos *et al.* (2008). To test the efficiency and applicability of the algorithm with probabilistic model, 99 ground motions are selected by intention to make biased record set. To show a level of bias in record sets, comparison is made between the fragility curve which is estimated using 99 ground motions and the one by the original set (i.e., 155 ground motions are used) based on "Method A" statistical fitting procedure. As shown in Figure 4.10, the biased fragility function (blue curve) seems to slightly overestimate the structural collapse compared to "real fragility function" due to the fact that the biased record set is mostly consisted of weak ground motions which can make structural collapse at relatively large $Sa(T_1)$ level.

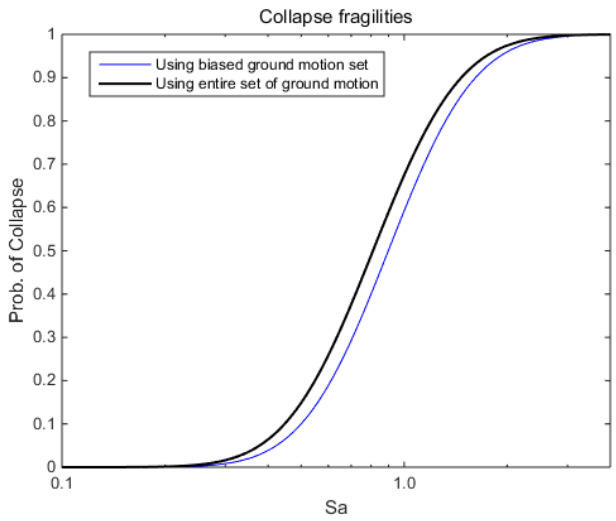

Figure 4.10 Collapse fragility curves estimated using biased ground motion set and the entire set of 155 ground motions.

As stated previously, structural collapse estimated using probabilistic demand model based fragility fitting procedure is less sensitive to biased record set because of IM–DM regression model. Figure 4.10 compares the fragility model based on regression IM–DM model: a fragility curve subject to 155 ground motions (black curve), the one subject to 99 ground motions (blue curve), and the structural fragility subject to proposed algorithm among biased record set (red dashed curve) estimated using regression model. Although, blue curve is compatible with the black curve and closely matched compared to the fragilities estimated based on method of moment fitting procedure, the one assessed based the proposed algorithm seems more accurate and reliable. Due to clustering analysis, ground motions are equally selected in record sets so that one can address the bias of a ground motion set. Furthermore, in order to quantify the effectiveness of the regression based fragility method, the MD value of three different fragilities are calculated. First, fragility curve based on method of moment procedure with respect to "real fragility curve", i.e., distance between two fragility curves in Figure 4.10 is 0.6036. Second, fragility curve using regression model based procedure with respect to "real" one, i.e., distance between blue and black curves in Figure 4.11 is 0.0573. Finally, regression model with the proposed algorithm procedure with respect to "real fragility curve", i.e., distance between red and black curves in Figure 4.11 is 0.0302. Therefore, the numerical example confirms that probabilistic demand model based fragility fitting procedure with proposed algorithm yields more reliable results when record sets are biased.

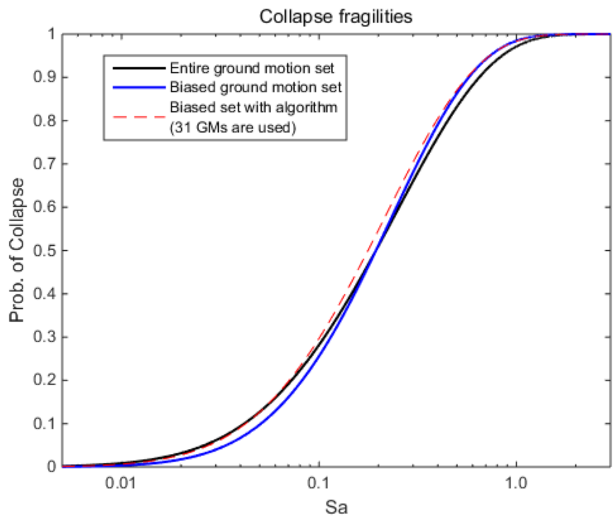

Figure 4.11 Collapse fragility curves estimated using the entire ground motion set, biased ground motion set, and biased set with ground motion selection algorithm (31 ground motions are used).

Chapter 5. Conclusions

IDA is a most widely used methodology to assess collapse potential of structural system. It is however noted that there exist critical issues in seismic fragility assessment associated with variability of structural responses and high computational cost. To address the limitations and to further enrich the field of performance based earthquake engineering, especially when evaluating risk of structural collapse, a new IM based on comprehensive understanding of collapse mechanism under seismic excitation as well as a new clustering based ground motion selection algorithm coupled with Euclidian metric distance has been developed. It is noted that one can get more gradual slope of IDA curve near collapse point using the proposed IM, which may serve as more reliable collapse criterion when using IM−based rule to identify structural collapse capacity. Furthermore, using a clustering analysis coupled with the relevant features of ground motion, a set of ground motions are clustered regarding relationship between IM and corresponding DM, which can reduce the number of ground motion used in dynamic analyses while keeping consistency with probabilistic seismic hazard analysis at given site. Since clustering analysis make sampling points equally distributed in whole domain of record set, convergence of structural collapse capacity can be quantified even using small number of ground motions in dynamic analysis and also avoid false convergence or converging to local optimum value that may result in inaccurate estimation of structural collapse capacity. The breadth of applications of new IM and ground motion selection algorithm was demonstrated using ductile steel frame and RC SMF building.

Along with two main developments, there are several additional findings in this study. First, this paper introduces a new parameter (α) and statistical procedure for quantifying the structure’s softening, which can be useful particularly when structural system is sophisticated and complex. Second, it is found that the energy balance ratio of seismic energy to dissipated hysteretic energy significantly influence on structural capacity. Therefore, energy balance ratio should be considered when ground motions are selected for estimating performance of structural system. Finally, identified critical features and proposed algorithm is helpful not only for reducing computational cost but also for comprehensive understanding between seismic demand and structural capacity.

Several possible improvements for future work can be proposed for both methods. For the new IM, it would be necessary to develop ground motion prediction equations(GMPEs), at which time the predictability of the IM could be evaluated. For the ground motion selection algorithm, more advanced method to find critical features is needed, which are used in the algorithm. This is necessary for a more accurate and stable estimation of the collapse fragilities. From these two methods, adequacy and efficiency of current collapse risk assessment of structural system can be enhanced.

Appendix A

The ground motion selection criteria set used in this study are provided by Haselton and Deierlein (2007) using NGA-West2 database (Ancheta *et al.* 2013), except some criteria for obtaining large dynamic analysis data. The ground motion records used in the nonlinear dynamic analyses are summarized in Table 1. 22 earthquakes and total 155 ground motions are selected using the following criteria:

- Distance from source to site > 10 km (average of Joyner-Boore and Campbell distances)
- Soil shear wave velocity, in upper 30 m of soil, greater than 180 m/s (NEHRP soil types A-D; note that all selected records happened to be on C/D sites)
- Limit of six records from a single seismic event (each record set has two-lateral components)
- Lowest useable frequency < 0.25 HZ, to ensure that the low frequency content was not removed by the ground motion filtering process
- Strike-slip and thrust faults (consistent with California)
- No consideration of spectral shape (ε)
- No consideration of station housing, but PEER-NGA records were selected to be "free-field"

Table A.1. Summary of the number of ground motions used in this paper

Earthquake	Magnitude	Number of ground motions
1966 Parkfield	6.19	6
1976 Friuli, Italy-01	6.50	4
1979 Imperial Valley-06	6.53	11
1986 N. Palm Springs	6.06	7
1987 Whittier Narrows-01	5.99	8
1987 Superstition Hills-02	6.54	8
1989 Loma Prieta	6.93	12
1992 Landers	7.28	9
1992 Big Bear-01	6.46	9
1994 Northridge-01	6.69	11
1995 Kobe, Japan	6.90	12
1999 Kocaeli, Turkey	7.51	5
1999 Chi-Chi, Taiwan	7.62	10
1999 Duzce, Turkey	7.14	6
1999 Hector Mine	7.13	7
1999 Chi-Chi, Taiwan-03	6.20	3
1999 Chi-Chi, Taiwan-04	6.20	1
1999 Chi-Chi, Taiwan-05	6.20	3
1999 Chi-Chi, Taiwan-06	6.20	5
1992 Cape Mendocino	7.01	12
2003 San Simeon, CA	6.50	1
2004Parkfield-02, CA	6.00	5

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국 문 초 록

도시 인프라 시스템의 복잡성이 증대함에 따라 지진에 대한 사회경제적 취약도 역시 나날이 증가하고 있어, 지진하중에 대한 구조물의 손상과 붕괴를 예측하고 피해 및 인명손실을 최소화할 수 있는 내진설계의 중요성은 나날이 증대되고 있다. 효과적인 내진설계를 통한 지진재해의 경감 및 복원력의 효과적 강화를 위해서는 지진하중에 대한 구조물의 내진성능을 정확히 평가하는 것이 필수적이다. 이를 위해 최근 지진동의 변동성과 구조 시스템 내 잠재된 여러 불확실성을 고려하여 구조물의 붕괴 확률을 산정하는 여러 가지 해석 및 평가방법이 개발되었고, 근래에는 구조물의 취약도를 평가하는 해석 방법의 하나로서 증분동적해석법(Incremental Dynamic Analysis, IDA) - 지진의 강도와 구조물의 응답의 상호관계를 분석하기 위하여 지진의 강도를 점진적으로 증가시키면서 비선형 동적해석을 수행하는 방법 - 이 많이 사용되고 있다. 증분동적해석법은 지진동과 구조물에 내재하는 불확실성과 변동성을 체계적으로 고려할 수 있어, 성능기반지진공학(Performance Based Earthquake Engineering, PBEE)에서 자주 사용되고 있지만 해석 시 주로 사용되는 지진강도척도(Intensity Measure)인 가속도 스펙트럼($Sa(T_1)$)은 지진동의 강도 및 특성을 효과적으로 나타내지 못하는 단점이 있으며 다양한 지진동 필요와 더불어 많은 횟수의 비선형 동적해석 수행을 요하는 근본적인 한계점을 가지고 있다. 이에 본 연구는 구조물의 붕괴 영향 관점에서 지진동의 불확실성을 감소시키기 위해, “누적” 지진강도척도와 “최대” 지진강도척도를 조합한 새로운 지진강도척도의 개발하였고, 구조물의 붕괴 여용력(Collapse Capacity) 예측 시 사용되는 지진동 수를 효과적으로 줄이기 위해 클러스터링 기반 적응형 샘플링 기법을 활용한 지진동 선택알고리즘을 제안하였다. 정량적이며 신뢰성 있는 방법론 개발을 위하여 다양한 통계 분석 기법이 사용되었으며, 그 적용성 및 효용성 검증을 위하여 Lignos 등(2008)에 의해 실험될 철골 구조물 및 Haselton 등(2011)에 의해 모델링 된 RC 구조물을 대상으로 155개의 지진동 시간이력을 이용 각각 증분동적해석을 수행하였다. 증분동적해석 결과를 분석한 결과, 새로운 지진강도 척도와 알고리즘을 사용하면 지진동에 내재하는 변동성을 크게 줄일 수 있었으며 매우 적은 수의 동적해석으로도 구조물의 지진 취약도를 구할 수 있음을 확인하였다. 본 연구에서 제시된 방법론은

향후 성능기반지진공학에 폭넓게 적용이 가능할 것으로 예상된다.

주요어: 지진강도척도, 지진동 선택, 취약도 해석, 증분동적해석, 에너지 평형비, 중요강도척도

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