EXPLICIT DEMAND MODEL FOR MULTI- STORY STEEL MOMENT RESISTING FRAMES

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ABSTRACT

Probabilistic structural demand models are considered as an essential ingredient for a seismic fragility analysis. This concept is commonly developed using statistics which needcollecting data in large quantities. Preparation of such a data-base is often costly and time-consuming. In this paper, generic seismic drift demand model for regular-multi-story steel moment resisting frames is presented to eliminate the need of time-consuming analyses. The demand model defined as a linear function of intensity measure,the spectral acceleration at fundamental period$\left(Sa(T_1)\right)$, in logarithmic space predicts overall maximum inter-story drift. In addition,the model is coupled with a set of relations to directly estimate unknown statistical characteristics of the model parameters. These relations are developed using a Bayesian regression technique to explicitly address uncertainties arise from randomness and lack of knowledge. The developed demand model is employed to perform Seismic Fragility Analysis (SFA) for three designed building. The accuracy of the results is assessed by comparison with the results directly obtained from Incremental Dynamic analysis as an alternative.

INTRODUCTION

Next-generation Performance Based-Earthquake Engineering (PBEE) proposed by Pacific Earthquake Engineering Research (PEER) center employs probabilistic framework to serve a mathematical basis for seismic performance assessment. In this framework, uncertainties embedded in an earthquake occurrence, nonlinear response of structures and vulnerability of structural components during seismic events are explicitly addressed. To this end, next-generation PBEE requires probabilistic models for seismic hazard, structural response, damage and consequence to evaluate seismic performance of a building. Recent studies have tried to meet this need by developing multifaceted probabilistic models for different part of PBEE. In the present study the focus in particular is placed on structural demand model. Demand model is commonly developed for a typical structure based on data obtained from numerous nonlinear response history analyses (Ramamoorthy et al. (2006), Berahmanand Behnamfar (2009), Garcia and Miranda (2010), Bai et al. (2011),Tondini and Stojadinovic (2012).). Albeit, this methodology is suitable for academic purpose, but cannot be appealing for practical purpose because of its computational cost. In this paper, generic probabilistic demand model is proposed for multi-story steel moment resisting frames (SMRFs) that satisfy seismic requirements of ASCE-07-10. The model estimates overall maximum inter story-drift and have linear formulation in logarithmic space respect to earthquake intensity. Also, a set of relations in terms of building characteristics is developed using Bayesian regression technique to compute unknown models parameters without requiring time-consuming nonlinear dynamic analyses. Finally, Seismic Fragility Analyses (SFA) are made based on proposed relations for three sample buildings and the results are compared with those obtained based on seismic demand model specifically developed for each of the three sample buildings using Incremental Dynamic Analysis.

DATA GENERATION FOR DEVELOPING PROBABILISTIC MODELS

GROUND MOTION RECORDS SELECTION

Developing probabilistic models based on observations obtained from nonlinear dynamic analysis requires an appropriate selection of ground motion records, called ground motion bin. As a general rule, the ground motion bin should be unbiased to any site-specific seismological characteristic of a probable future earthquake event. That is to say that the demand model proposed must keep its generality and versatility. For instant, the ground motion bin should be broadly applicable to a variety of structures located at different sites. Also, the number of records in the bin should be enough to cover record-to–record variability in a justified way. According to the mentioned objectives, the general far-field ground motions set originally introduced by FEMA-P695 and extended by Prof. C. Haselton1 is used. This set includes 41 pairs of horizontal ground motions taken from 15 seismic events that occurred in the last three decades of twentieth century. Of the 15 events, eight were earthquakes that occurred in California and the others occurred in five different countries. Event magnitudes range from M6.5 to M7.6 with an average magnitude of M7.0. Moreover, the seismic events are recorded at sites with soil shear wave velocity, in upper 30m of soil, greater than $180\frac{m}{\sec}$, and located at distance 10 to 70 km from fault rupture. This paper defines source to site distance as the average of Campbell and Joyner-Boore fault distances provided in the PEER NGA database. The selected motions were recorded in free-field or on ground floor of a small building to avoid potential soil structures interaction bias in records set. Also, to avoid potential event-based bias in the ground motion bin, maximum six records are allowed to be taken from a single seismic event. In addition, between different ground motions recorded for a single seismic event, only those with Peak Ground Acceleration, PGA, greater than $0.2g$, and Peak Ground Velocity, PGV, greater than $15\frac{cm}{\sec}$ are considered. The limits put on PGA and PGV are arbitrary, but can be considered as the representative of strong ground motions that may cause structural damage (FEMA-P695). In addition, twenty five pairs of records are from events of mainly strike-slip faulting and the others are selected from events of principally thrust faulting.

GENERIC STEEL MOMENT RESISTING FRAMES

The main purpose of the present study is to develop probabilistic drift demand model that is capable to predict seismic performance of real SMRFs. Therefore, it is important to develop analytical models that the obtained results can be extended for a wide range of SMRFs with different characteristics. To this end, the concept of generic moment resisting frame is adopted in this paper. This concept has been widely utilized by various researchers for assessing seismic behaviour of moment resisting frames (Esteva and Ruiz (1989), Chintanapakdeeand Chopra (2003), Medina andKrawinkler (2004),). These studies have shown that the response of a multi-bay steel moment resisting frames can be simulated adequately by a single- bay generic frame.However, a significant limitation is that the simulation of realistic conditions at an interior joint cannot be properly considered. Thus, a family of three-bay generic moment frames introduced by Zareian andKrawinkler (2006)is used to overcome this deficiency of one bay-generic moment frames. The generic SMRFs with the number of stories, N ,equal to 4, 6 and 8 are utilized in this paper to cover the range of low-rise to mid-rise structures. For each number of stories, three fundamental periods equal to $0.1N$, $0.15N$ and $0.2N$ are considered to cover the range of variation of the fundamental periods of SMRFs (Goel, Chopra (1997)). For each period, three different cases for beam stiffness and strength variation are considered. These three categories are denoted as: “Shear”,” Uniform” and “Intermediate”. Shear implies that moment of inertia and bending strength of beams at i^{th} story to the moment of inertia and bending strength of the beams

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at first story is equal to the ratio of shear force, obtained from subjecting the generic SMRFs to the ASCE-07-10 lateral load pattern, at i^{th} story to the shear force at first story. This alternate guarantees a straight line deformed shape under the ASCE-07-10 lateral load and indicates lower bound for distribution of beam stiffness and strength over the height. Uniform indicates that beam moment of inertia and bending strength is the same along the height of the structure. That is, the ratio of the moment of inertia and bending strength of beams at each floor to the moment of inertia and bending strength of the beams at first story is equal to 1 and represent upper bound for beam stiffness and strength distribution. Intermediate is also introduced as the average of the mentioned bounding alternates, i.e. Shear and Uniform to capture behavior of structures that fall in between two bounds. For simplicity, column moment of inertia in each story is assumed to be equal the beam moment of inertia. This assumption is supported by the fact that the most of lateral deformation of SMRFs is due to beam rotation and less due to column deformation, that is, structural deformation is not sensitive to variation along the height of column moment of inertia. This is quite reasonable and due mainly to the type of dominated mode of deformation, which is mainly shear-type for a SMRF. Moreover, columns strength are assigned with respect to strong column–weak beam concept.For each case of stiffness and strength variation along the height, based on different levels of response modification factor, i.e. R factor, different occupancy and seismic design categories (ASCE-07-10), three values for yield base shear strength are defined to sweep variation range of the designed SMRFs lateral yield strength. Lateral yield strength values are estimated by multiplying design value of the seismic base shear calculated according to ASCE-07-10by over-strength factor provided in ASCE-07-10. Concentrated plasticity is used to model nonlinear behavior of SMRFs elements. To this end, elastic beam column element associated with nonlinear rotational spring at two ends is adopted to model nonlinearity. The Bilin-Materials (Lignos, D.G. and H. Krawinkler (2011)), Modified Ibarra-Medina-Krawinkler Deterioration Model with Bilinear Hysteretic Response, are assigned to end springs to demonstrate hysteretic behavior (Fig.1). The hysteretic response of this material has been calibrated with respect to more than 350 experimental data of steel beam-to-column connections. The model incorporates three deterioration modes once the yielding point is passed in cyclic loading. These three modes are: Basic Strength Deterioration, Post capping Strength Deterioration and Unloading stiffness deterioration. In this model, the rate of cyclic deteriorations for each mode of deteriorations are controlled by the rule initially developed by Rahnama and Krawinkler (1993) .Also, the model parameters value are computed based on comprehensive data-base provided by Lignos and Krawinkler (2011) .According to above criteria , 81 generic steel moment resisting frames are developed .The OpenSees , a software proposed by PEER as the computational platform for simulating the seismic response of structural and geotechnical systems, is utilized to perform Incremental Dynamic Analysis (IDA) . Also, global P-Delta effect and Rayleigh damping equals 5% are considered when IDA is carried out.

INCREMENTAL DYNAMIC ANALYSES (IDA)

Incremental Dynamic Analysis (IDA) is a computer-intensive procedure which depicts the performance of structures over the full range of structural behavior, from initial elastic response through to global Instability, under seismic loads (Vamvatsikos and Cornell (2002)). IDA is usually referred as the dynamic equivalent of the well-known static pushover analysis. It entails performing multiple nonlinear time history analyses of a structural model under an appropriate number of ground motion records scaled to several levels of seismic intensity. The scaling levels initiate at an appropriate low value and continuously increase until global dynamic instability will occur. Seismic demand of interest is monitored during each nonlinear dynamic analysis and the maximum value of the demand is plotted versus intensity level. In this paper, the spectral acceleration at the fundamental period of buildings $Sa(T_1)$which is suitable for low to mid-rise SMRFs was employed to represent earthquake intensity (Shomeand Cornell (2000)). Also, overall maximum inter-story drift$(\bar{\ }_{max})$ is considered as a demand of interest to evaluate seismic performance of existing building. The IDA solution algorithm implemented in the present study proceeds until structure experiences excessive $\bar{\ }_{max}$ for a slight increase in earthquake intensity, this means $Sa(T_1)-\bar{\ }_{max}$ curve becomes flat. A comprehensive structural data-base is established due to these extensive nonlinear dynamic analyses. The data-base is divided into two parts, collapse and non-collapse data. The non-collapse data is applied to introduce probabilistic maximum inter-story drift model for a wide range of SMRFs in terms of some building characteristics. Based on FEMA 350, collapse point can be defined as a point proximity at which the local tangent of IDA curve reaches 20% or $\bar{\ }_{max}$ exceeds 10%, each occurs first. Nevertheless, it seems the first criterion is somewhat conservative in some cases. It is observed that structures represent acceptable level of lateral resistance after collapse point. Hence, this paper defines collapse limit as a point at which IDA curve starts to flatten i.e. the structure has exhausted most of its lateral resistance, provided that θ_{max} shall not exceed 10%.

PROBABILISTIC DEMAND MODEL FORMULATION

BAYESIAN STATISTICAL INFERENCE

Consider $h(x)$ as a vector of explanatory functions formulated in terms of independent variables collected in vector x. y is a response variable predicted by:

$$y = \theta_1 h_1(x) + \theta_2 h_2(x) + \dots\dots\dots + \theta_k h_k(x) + \sigma\varepsilon \tag{1}$$

where $\theta_i s$ are called model parameters, ε is a standard normal random variable and σ is standard deviation of model error. Traditionally, classical regression is applied to compute point estimation of model parameters (θ_i, σ). It is clear that point estimation based on information obtained from a finite–size sample population is incomplete and uncertain. Conversely, Bayesian linear regression can express our uncertainty about (θ_i, σ) by considering model parameters as random variables and determines probability distribution of the coefficients using the Bayesian updating rule (Box andTiao (2011)):

$$\mathrm{f}(\theta_i, \sigma) = \mathrm{c.L}(\theta_i, \sigma).\mathrm{P}(\theta_i, \sigma) \tag{2}$$

Where $f(\theta_i, \sigma)$ denotes posterior distribution representing our updated knowledge about the coefficients, $L(\theta_i, \sigma)$ indicates the likelihood function representing the objective information on (θ_i, σ) gained from a set of observations, $p(\theta_i, \sigma)$ denotes the prior distribution reflecting our knowledge about parameters prior to obtaining observations and c is a normalizing factor . In the case that lower bound data and/or upper bound data are not available such as data collected in this study, and the probabilistic model of interest is formulated as a linear function of θ_i , closed form solution can be found for Eq.(2) (Gardoni*et al.* (2002) . Under the normality assumption on ε and a non-informative priors, Box and Tiao(2011) show that the posterior distributions of θ and σ^2, denotes vector of model parameters θ_i , are a multivariate t distribution and an inverse chi-square distribution respectively.

$$f(\theta) = \frac{\Gamma\left(\frac{1}{2}(\nu + k)\right).s^{-k}\sqrt{\left|H^T H\right|}}{\left[\Gamma\left(\frac{1}{2}\right)\right]^k \Gamma\left(\frac{\nu}{2}\right)\left(\sqrt{\nu}\right)^k}\left[1 + \frac{\left(\theta - \hat{\theta}\right)^T H^T H\left(\theta - \hat{\theta}\right)}{\nu s^2}\right]^{\frac{\nu - k}{2}} \tag{3}$$

$$f\left(\sigma^2\right) = \nu s^2 \chi_\nu^{-2}$$

$$\hat{\theta} = \left(H^T H\right)^{-1} H^T Y \;, \nu = n - k,\; s^2 = \frac{1}{\nu}\left(Y - \hat{Y}\right)^T\left(Y - \hat{Y}\right),\; \hat{Y} = H\hat{\theta}$$

Where H is a $n-$by$-k$ dimensional matrix which contains all n observations of explanatory functions. Also, Y is the n-dimensional vector of response variable observations. Once posterior distribution is known, mean vector M_θ and covariance matrix Σ_θ can be computed as following:

DRIFT DEMAND MODEL FORMULATION

Probabilistic models are known as a central theme in probabilistic seismic performance assessment framework. Models can be developed based on both mechanics and statistics i.e. both theory and observations. The present study focuses on the use of observations obtained from numerous IDA to develop models. It should be noted, a model that matches past observations will not necessarily predict future events.

Therefore, both aleatory and epistemic uncertainties are recognized. To this end, linear model with random parameters in the logarithmic space have been developed to describe relation between overall maximum inter-story drift as the structural demand parameters (D) and earthquake intensity, the spectral acceleration at fundamental period $(Sa(T_1))$.The logarithmic transformation is also utilized to approximately satisfy the normality assumption (i.e., model error has normal distribution) and homoscedasticity assumption (i.e., Standard deviation of model error is constant). Eq. (4) illustrates general form of the probabilistic model considered in this study:

$$Ln[D(Sa(T_1),\Theta)] = a + b\,Ln(Sa(T_1)) + \pm\pounds \tag{4}$$

Where $Ln[D(Sa(T_1),\Theta)]$ is a response that the model predicts and equal to natural logarithm of the overall maximum inter-story drift and $\Theta = (a,b,\pm)$ is a vector of unknown random model parameters. In practice, estimate statistical characteristics of the model parameters require gathering large quantity observations that are often time-consuming and expansive. Therefore, in this paper, a set of relations in terms of building characteristics are proposed to estimate mean and standard deviation of the Θ without requiring time-consuming approach such as IDA. Moreover, a relation is proposed to estimate correlation between a and b

$$\text{«}_a = \sim_1 N + \sim_2 \frac{N^2 \times T}{CY} + \frac{\sim_3}{T \times CY} + \sim_4 CY + \pm\pounds \tag{5}$$

$$\pm_a = \sim_1 N + \frac{\sim_2}{T^2} + \sim_3 \frac{SSD}{T^2 \times CY \times N^2} + \frac{\sim_4}{CY} + \pm\pounds \tag{6}$$

$$\text{«}_b = \sim_1 + \frac{\sim_2}{T} + \sim_3 \frac{N^2 \times SSD}{T} + \sim_4 \frac{CY}{N \times SSD^2} + \pm\pounds \tag{7}$$

$$\pm_b = SSD[\sim_1 SSD - 2.98\sim_1 + 0.00423] + \frac{\frac{\sim_2}{N} - 0.256\sim_2 + 0.00629}{N \times T \times CY \times SSD} + \pm\pounds \tag{8}$$

$$\text{«}_\pm = \frac{\sim_1}{SSD} + \sim_2 \frac{T \times SSD^2}{N} + [0.126 - 0.462\sim_2]SSD + \frac{\sim_4}{T \times SSD \times CY} + \pm\pounds \tag{9}$$

$$\pm_\pm = \sim_1 \frac{T^2 \times CY}{N} + \sim_2 + .[0.00325 - 0.215\sim_2]SSD + \frac{0.00185 - 0.122\sim_2}{T \times SSD \times CY} + \pm\pounds \tag{10}$$

$$\mathrm{ro}_{\mathrm{ab}} = 10.12 \frac{\mathrm{T}^2 \times \mathrm{SSD} \times \mathrm{CY}^2}{\mathrm{N}^2} + 0.661\mathrm{T} + \mathrm{CY}(3.3 + 2.85\mathrm{CY}) \tag{11}$$

T is structural fundamental period which is equal to $C_u T_a$ (ASCE-7-10) , N denotes as number of stories and CY indicates yield base shear coefficient . Moreover, SSD is a numerical index for stiffness and strength distribution over the structural height and varies from 1 to 3. Its value takes 1 if the stiffness and strength distribution in height are proportioned to the story shear force obtained from ASCE-7-10 lateral load pattern. SSD is 3 for uniform stiffness and strength distribution in height. In general, for a designed steel moment frame, stiffness and strength variation along height is not governed by any of the above mentioned bounding patterns, but it falls in between these two bounds. Therefore, in this paper, according to interpolation technique and averaging over the height, following equation is suggested to calculate SSD value.

$$SSD = \frac{\sum_{i=1}^{N-1} \left(1 + 2 \frac{\left(\frac{I_i}{I_1} - \frac{V_i}{V_1} \right)}{\left(1 - \frac{V_i}{V_1} \right)} \right)}{N - 1} \tag{12}$$

Where I indicates beam moment of inertia and V represents story shear, when subjected to ASCE-7-10 lateral load pattern Also, i and 1 indicate story number. Bayesian regression technique is used to consider both aleatory and epistemic uncertainties when these equations are developed. Table 1 and 2 represent posterior mean and standard deviation of the model parameters respectively .Moreover, correlation coefficients between the parameters are presented in table 3 and 4. With these equations, demand model can be directly developed. For this purpose, it is only needed to define demand model in the form of Eq. (4). Then, Eq. (5) to Eq. (11) are implemented to compute mean and standard deviation of the random model parameters.

Table 1. Mean of model parameters of Eq. (5) ~Eq. (11)

	$\sim_1$	$\sim_2$	$\sim_3$	$\sim_4$	$\pm$
$«_a$	-0.150042437	0.001006396	-0.33537478	-4.7955413	0.013381034
$\pm_a$	0.0010861	0.002093713	0.003986602	0.001847132	0.003068312
$«_b$	0.830570868	0.174904356	0.00045382	-0.82214535	0.034379871
$\pm_b$	-0.00139821	-0.05936269	-----------	-----------	0.001937183
$«_{\pm}$	0.145450695	-0.124366258	-----------	0.042774078	0.057791202
$\pm_{\pm}$	-0.030818133	0.009743194	-----------	-----------	0.002285736

Table 2. Standard deviation of model parameters of Eq. (5) ~Eq. (11)

	$\sim_1$	$\sim_2$	$\sim_3$	$\sim_4$	$\pm$
$«_a$	0.011657642	0.000133095	0.007967072	0.143275706	0.013381034
$\pm_a$	0.000151347	0.000313397	0.000845039	0.000208831	0.000253935
$«_b$	0.012724471	0.007825274	9.08426E-05	0.160510466	0.002845298
$\pm_b$	0.000251436	0.008900826	-----------	-----------	0.000160322
$«_{\pm}$	0.028539505	0.025407578	-----------	0.005687316	0.004782834
$\pm_{\pm}$	0.0158503	0.002230867	-----------	-----------	0.000189169

Table 3. Correlation Matrix

	Correlation matrix of $«_a$				Correlation matrix of $\pm_a$				Correlation matrix of $«_b$			
	$\sim_1$	$\sim_2$	$\sim_3$	$\sim_4$	$\sim_1$	$\sim_2$	$\sim_3$	$\sim_4$	$\sim_1$	$\sim_2$	$\sim_3$	$\sim_4$
$\sim_1$	1				1				1			
$\sim_2$	-0.786	1			-0.530	1			-0.493	1		
$\sim_3$	-0.334	-0.048	1		0.4280	-0.847	1		-0.622	-0.251	1	
$\sim_4$	-0.809	0.7037	-0.148	1	-0.880	0.3407	-0.382	1	-0.365	-0.433	0.5834	1

Table 4. Correlation Matrix

Correlation matrix of $\pm_b$			Correlation matrix of $«_{\pm}$				Correlation matrix of $\pm_{\pm}$		
	$\sim_1$	$\sim_2$		$\sim_1$	$\sim_2$	$\sim_4$		$\sim_1$	$\sim_2$
$\sim_1$	1		$\sim_1$	1			$\sim_1$	1	
$\sim_2$	-0.48304	1	$\sim_2$	0.235754	1		$\sim_2$	-0.79248	1
			$\sim_4$	-0.82941	0.096458	1			

VALIDATION

To evaluate efficiency and accuracy of the proposed relations, 4 and 7 story- buildings are designed with respect to American Institute of Steel Construction (AISC) specifications. The first story is 2.8 meter high, and the height of the remaining stories is 3.2 meter. The buildings are rectangular in plane with a length of 22 meters and a width of 16 meters for seven story buildings. Square plane with a length of 20 meters is considered for four story building. The bay length is 5 meters for four story building and equal 4 meters for seven story buildings .Two perimeter steel moment frames in each direction associated with composite steel deck floor are employed to carry lateral and gravity loads, respectively. The model takes advantage of the building's regularity, so a two dimensional analytical model was used to perform IDA in longitudinal direction. The effect of gravity load system during nonlinear dynamic analysis is also considered by introducing leaning columns. Rigid zones are used to define the joint regions, and the inelastic behavior is concentrated at the end of beam and column elements. Table 5 shows beams and columns geometry.

Table 5. Beams and Columns Geometry

STORY	4 Story-Building		7 Story-Building	
	Beam-Section	Column-Section	Beam-Section	Column-Section
1	IPE 450	TUBE 400x400x12	IPE 550	TUBE 400x400x15
2	IPE 450	TUBE 400x400x12	IPE 550	TUBE 400x400x15
3	IPE 400	TUBE 350x350x12	IPE 550	TUBE 400x400x15
4	IPE 400	TUBE 350x350x12	IPE 500	TUBE 400x400x12
5	----	---	IPE 500	TUBE 400x400x12
6	----	----	IPE 400	TUBE 350x350x12
7	----	-----	IPE 400	TUBE 350x350x12

SEISMIC FRAGILITY ANALYSIS

Seismic fragility is defined as the conditional probability of attaining or exceeding a specific threshold value d for spectral acceleration equals x. Generally, fragility is computed by:

$$P\left[D(Sa,\Theta)\geq d\;|Sa=x\right]\cong\left[1-{}^{\cdot\cdot}\left(\frac{Ln(d)-a_{Ln(D|Sa)}}{\pm_{Ln(D|Sa)}}\right)\right] \tag{13}$$

Where $a_{Ln(D|Sa)}$ and $\pm_{Ln(D|Sa)}$ are the median and standard deviation of the seismic demand given Sa in the logarithmic space. ¨ indicatescumulative standard normal distribution function. According to Eq.(13), probabilistic demand model is required to perform fragility analysis . Thus, maximum drift demand model is developed once based on Non-collapse data obtained from IDA, and once again using proposed relations. The results are presented in table 6 and table 7.

Table 6. Demand model parameters computed using IDA

Number of Story	a		B		±	
	Mean	STDEV	Mean	STDEV	Mean	STDEV
4	-3.51814	0.01693	0.85823	0.01379	0.40837	0.01203
7	-3.4983394	0.016029	0.88496	0.0481477	0.42667	0.01135

Table 7. Demand model parameters predicted by Eq. (7) ~Eq. (13)

Number of Story	a		B		±	
	Mean	STDEV	Mean	STDEV	Mean	STDEV
4	-3.5144	0.1817	1.0711	0.0501	0.4469	0.0708
7	-3.3712	0.1809	1.0164	0.0484	0.4195	0.0701

Seismic fragility analyses are performed for two example buildings using models developed both based on proposed equations and IDA and the results are presented in the form of fragility curves. Fragility curves are developed for d equals 0.007,0.03 and 0.05 (Fig.2). According to FEMA 350 limitation on collapse and immediate occupancy limit-state, it is expected that selected threshold values sweep light to relative severe damage state and named SD_1, SD_2 and SD_3 individually. As shown graphically, the maximum difference observed is about 20%. Generally, the results produced based on the proposed relations give an appropriate agreement with the results obtained from building-specific demand models. Building-specific demand models are referred to the models specifically developed for each of 4 and 7-story buildings using IDA. It should also be noted, the time needed to develop fragility curves based on proposed relations is in order of few minutes whereas for convenience approach, develop fragility based on incremental dynamic analysis, is in order of few days. This time saving features associated with appropriate accuracy make these relations more efficient and appealing for practical purpose.

SUMMARY AND CONCLUSION

This paper presents generic drift demand model for a wide-range of multi-story steel moment resisting frames designed based on seismic requirements of ASCE-07-10. The model considersaleatory and epistemic uncertainties by introducing model coefficients as random variables. A set of relations in terms of building characteristics are presented to estimate unknown mean and standard deviation of random coefficients. These equations developed using Bayesian regression technique eliminates need of time-consuming collecting data procedure. To evaluate validity of the proposed relations, fragility curves are developed for three two buildings. The results are compared with the results developed due to use of buildings-specific drift demand model. The results indicate that the proposed relations provide acceptable level of accuracy when implemented in probabilistic framework to develop fragility curve. Note that this accuracy is achieved with low computational cost in comparison with the convenient method proceeded based on time-consuming nonlinear dynamic analysis. Indeed, the main advantage on the use of proposed relations in particular places on balance between accuracy and computational cost which is appealing for practical purposes.

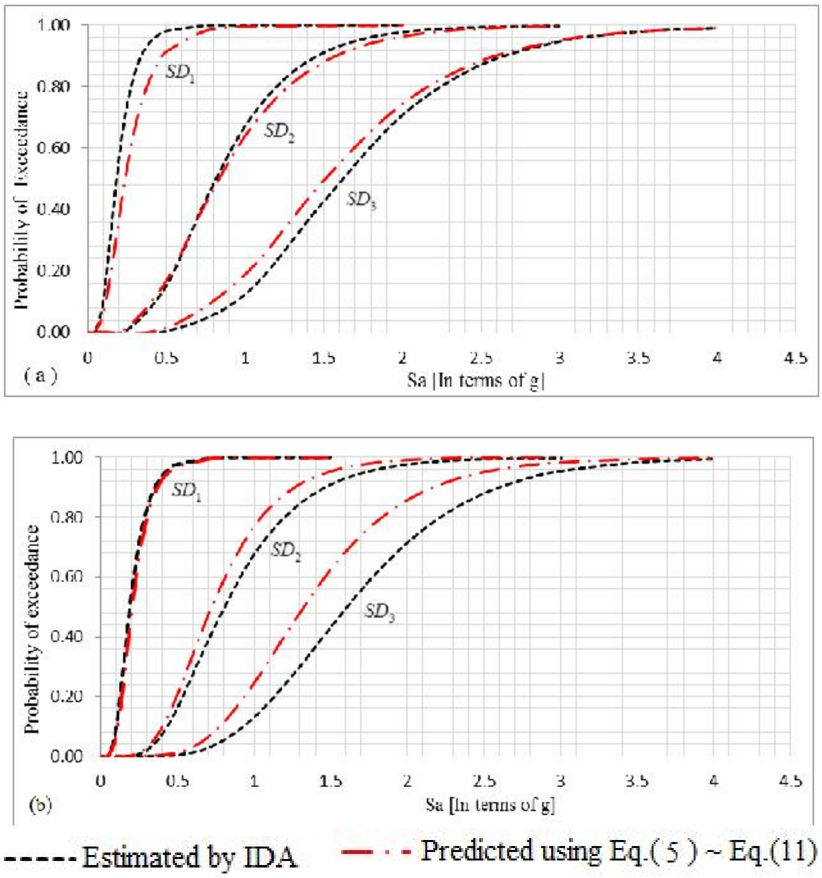

Figure 2. Fragility Curve of (a): 4-story- building, (b): Fragility 7-story-building

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