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Closed-form fragility analysis of the steel moment resisting frames

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Abstract. Seismic fragility analysis is a probabilistic decision-making framework which is widely implemented for evaluating vulnerability of a building under earthquake loading. It requires ingredient named probabilistic model and commonly developed using statistics requiring collecting data in large quantities. Preparation of such a data-base is often costly and time-consuming. Therefore, in this paper, by developing generic seismic drift demand model for regular-multi-story steel moment resisting frames is tried to present a novel application of the probabilistic decision-making analysis to practical purposes. To this end, a demand model which is a linear function of intensity measure in logarithmic space is developed to predict overall maximum inter-story drift. Next, the model is coupled with a set of regression-based equations which are capable of directly estimating unknown statistical characteristics of the model parameters.To explicitly address uncertainties arise from randomness and lack of knowledge, the Bayesian regression inference is employed, when these relations are developed. The developed demand model is then employed in a Seismic Fragility Analysis (SFA) for two designed building. The accuracy of the results is also assessed by comparison with the results directly obtained from Incremental Dynamic analysis.

Keywords: probabilistic demand model; seismic fragility analysis; incremental dynamic analysis; generic steel moment resisting frame; Bayesian regression

1. Introduction

Next-generation Performance Based-Earthquake Engineering (PBEE) proposed by Pacific Earthquake Engineering Research (PEER) centre 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 several probabilistic models for different part of PBEE. In the present study the focus in particular is placed on structural demand model. Demand models, in research studies, are commonly developed based on statistics with enormous, costly and time consuming data

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gathering. For example, Ramamoorthy *et al*. (2006), based on a large number of nonlinear response history analyses, constructed bilinear probabilistic demand models for a hypothetical two-story reinforced concrete (RC) frame building before and after retrofitting. The predictive models of the maximum inter-story drift are utilized in fragility analyses to evaluate retrofitting impact on reducing the vulnerability of the building during earthquake events. This approach is also applied in other studies (such as Adeli *et al*. 2011a, b, Bai *et al*. 2011, Bayat and Daneshjoo 2015, Bayat *et al*. 2015a, b, O'Reilly and Sullivan 2016, Ghowsi and Sahoo 2015, Jalali *et al*. 2012, Ruiz-García and Miranda 2010, Tang and Zhang 2011) when demand models are developed. Some other studies focus on developing demand models based on available deterministic models and experimental tests. This methodology originally presented by Gardoni *et al*. (2002) became the basis of subsequent studies to develop capacity models for structural element. Some novel works employing this methodology to develop demand models are Choe *et al*. 2008, Sharma *et al*. 2014, Tabandeh and Gardoni 2014, Zhu *et al*. 2007. Although developing probabilistic demand model based on nonlinear response history analyses or experimental test results might be justified for research purposes, it is not appealing for practical applications because of its computational cost. Therefore, availability of ready-made demand models eliminating the need of time-consuming data gathering process would be greatly interesting for practical purposes.

According to above description, in this paper, generic probabilistic demand model of low- to mid-rise multi-story steel moment resisting frames (SMRFs) is proposed. The model estimates overall maximum inter story-drift and have linear formulation in logarithmic space respect to earthquake intensity. Finally, fragility Analyses (SFA) of two sample buildings, based on proposed relations, are carried-out and the results are compared against those obtained from Incremental Dynamic Analysis (IDA), which is a computer-intensive procedure.

This paper is organized into five sections. Following this introduction, the next section discusses data generation, including a full discussion about ground motion record selection, the characteristic of generic frames and incremental dynamic analysis. Next, formulations of probabilistic demand model along with Bayesian regression-based equations predicting model parameters are presented. Finally the proposed model are implemented in seismic fragility analysis of two sample buildings to numerically demonstrate how much availability of such a ready-made demand model makes probabilistic decision making analysis feasible and practical.

2. Data generation for developing probabilistic demand model

2.1 Ground motion records selection

Developing probabilistic model based on observations obtained from nonlinear dynamic analysis requires an appropriate selection of ground motion records. As a general rule, the ground motion records should be unbiased to any site-specific seismological characteristic of a probable future earthquake event. In addition, 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 the authors is used. This set includes 41 pairs of horizontal ground motions, taken from 15 strong seismic events, recorded at sites with soil shear wave velocity, in upper 30 m of soil, greater than 180 $\frac{\text{m}}{\text{sec}}$, 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. All 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. Furthermore, 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 have a Peak Ground Acceleration and velocity greater than 0.2 g and 15 $\frac{\mathrm{cm}}{\mathrm{sec}}$, and lowest usable frequency smaller than 0.25 Hz are selected.

2.2 Generic steel moment resisting frames

The main purpose of the present study is to develop probabilistic drift demand model that is capable of predicting 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 (Chintanapakdee and Chopra 2003, Esteva and Ruiz 1989, Medina and Krawinkler 2004, Ruiz-García and Miranda 2010). 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 and Krawinkler (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 0.1 N, 0.15 N and 0.2 N are considered to cover the range of variation of the fundamental periods of SMRFs (Goel and 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" distributions. A "Shear" distribution implies that moment of inertia and bending strength of beams are distributed in proportion to the story shears obtained from applying the design code, For example ASCE-07-10, lateral load pattern. This distribution leads to a straight line deformed shape under mentioned loading (Zareian and Krawinkler 2006). A "Uniform" distribution, on the other hand, suggests equal moments of inertia and bending strengths for all beams along height. That is, the cross section assigned to the beams of the first story is also considered for the beams of other stories and provide an upper bound for beams stiffness and strength distributions. This pattern represents those structural designs in which the designer decides to use a similar cross section for beams in several stories because of availability of structural material, cost of using joints with different detailing, simplicity in design and construction, etc. Intermediate is also introduced as the average of the mentioned bounding alternates, i.e., Shear and Uniform to capture behaviour of structures that fall in between two bounds. For simplicity, column moment of inertia in each story is assumed to be equal to 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, 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 design code by over-strength factor.

Concentrated plasticity is also used to model nonlinear behaviour 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 and Krawinkler 2010) are assigned to end springs to demonstrate hysteretic behaviour. The hysteretic behavior of rotational springs is modeled using Bilin material with parameters set to the mean value of data obtained from 350 experimental tests conducted on steel beam-to-column connections (Lignos and Krawinkler 2010). Basic strength, post capping strength and unloading stiffness deterioration modes are considered in formulation of this material according to Rahnama and Krawinkler (1993) deterioration rule. 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. P-Delta effects have also been accounted for in the models and a Rayleigh damping matrix is computed using 2% of the critical damping applied in the 1st and 3rd vibration periods of the structures. It should be noted, the mentioned technique of modeling nonlinearity in combination with Rayleigh damping results in damping force becomes unrealistically large (Medina and Krawinkler 2004, Zareian and Krawinkler 2006). Thus, the simple methodology first proposed by (Medina and Krawinkler 2004) and enhanced by (Zareian and Krawinkler 2006) is implemented, in the present study, to solve this deficiency. Fig. 1 schematically describes generic moment frame and modelling techniques implemented to develop analytical model.

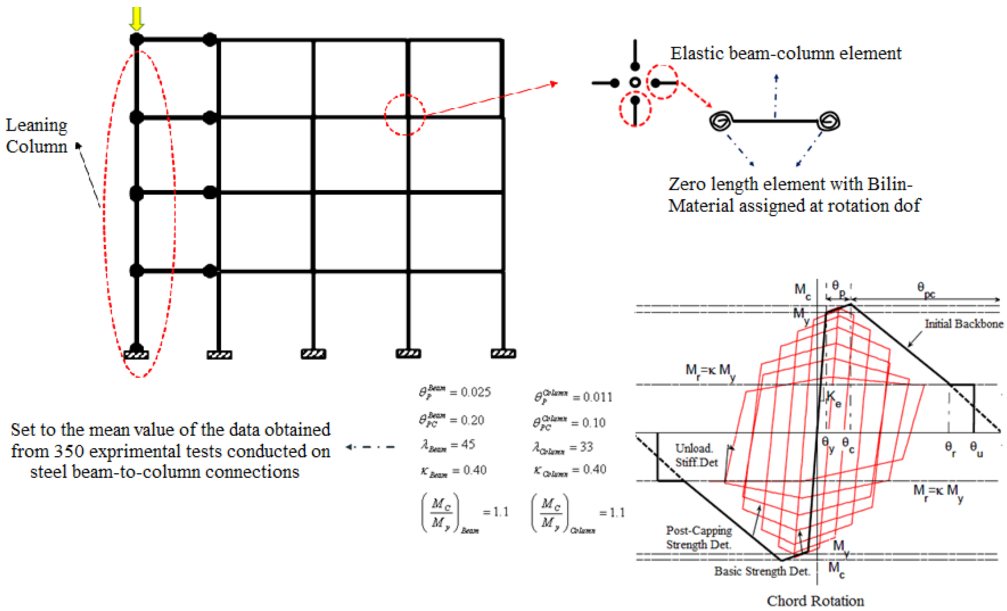


Fig. 1 Analytical model of generic steel moment frame

2.3 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 behaviour, 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 (Adeli *et al.* 2011a, b, Shome and Cornell 2000). Overall maximum inter-story drift ($\theta_{\max}$) is also 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 $\theta_{\max}$ for a slight increase in earthquake intensity, this means $Sa(T_1) - \theta_{\max}$ 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 develop 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 $\theta_{\max}$ 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 $\theta_{\max}$ shall not exceed 10%. As an example, in the following, the IDA curve related to one of 81 generic moment frames (model with Number of story = 4, Fundamental Period = 0.4, Stiffness and Strength distribution = Int, and Yield based shear = 0.3) is shown.

3. Probabilistic demand model formulation

3.1 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 θ_i indicates model parameters, ε is a standard normal random variable demonstrating model error, and σ is standard deviation of model error.

Traditionally, classical regression technique is applied to compute point estimation of model parameters, i.e., (θ_i, σ). It is clear that point estimation based on information obtained from a finite–size sample population is incomplete and uncertain. In contrast, Bayesian linear regression can express our uncertainty about (θ_i, σ) by considering model parameters as random variables and

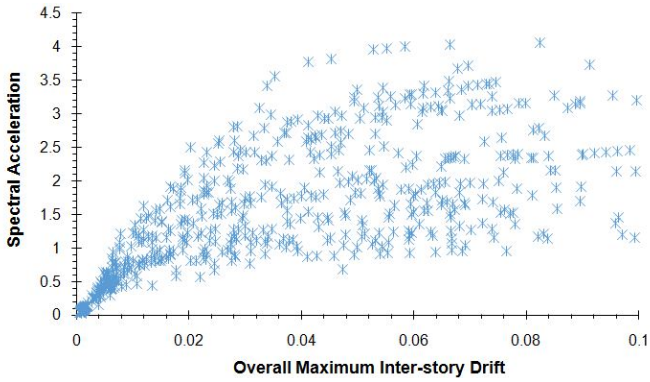


Fig. 2 An example IDA curves

determines probability distribution of the coefficients using the Bayesian updating rule (Box and Tiao 2011)

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

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, $p(\theta_i, \sigma)$ represents the prior distribution reflecting our knowledge about parameters prior to obtaining observations and c is a normalizing factor .

According to the type of obtained data, three algorithms for calculating of Eq. (2) are discussed in (Gardoni *et al*. 2002), one of which, implemented in this paper, is Close-form solution that is valid for models with linear formulation in respect to θ_i. By assuming a normally distributed error term, ε, and in case of non-informative priors, Box and Tiao (2011) demonstrated that the posterior distribution of model parameters, θ_i, and squared standard deviation, σ^2, are multivariate t and inverse chi-square distributions, respectively.

$$\begin{gathered}
f(\theta)=\frac{\Gamma(\frac{1}{2}(\nu+k)).s^{-k}\sqrt{\left|H^T H\right|}}{\left[\Gamma(\frac{1}{2})\right]^k\Gamma(\frac{\nu}{2})(\sqrt{\nu})^k}\left[1+\frac{(\theta-\hat{\theta})^T H^T H(\theta-\hat{\theta})}{\nu s^2}\right]^{-\frac{\nu-k}{2}} \\
f\left(\sigma^2\right)=\upsilon s^2\chi_\upsilon^{-2} \\
\hat{\theta}=(H^T H)^{-1}H^T Y\ ,\ \nu=n-k \\
\hat{Y}=H\hat{\theta} \\
s^2=\frac{1}{\nu}(Y-\hat{Y})^T(Y-\hat{Y})
\end{gathered} \tag{3}$$

Where H is a n–by–k dimensional matrix containing all n observations of explanatory functions, Y is the n-dimensional vector of response variable observations. Once posterior distributions are known, mean values and covariance matrix, $\Sigma_{\theta\theta}$, can be effortlessly computed as

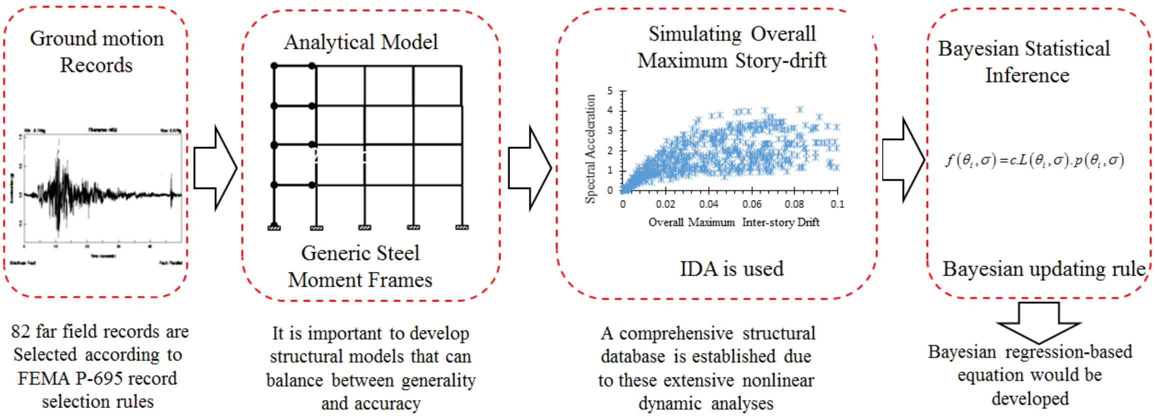


Fig. 3 Procedure of developing regression-based demand model

$$\mu_\theta = \hat{\theta} \qquad \Sigma_{\theta\theta} = \frac{\nu}{\nu-2} s^2 \left(X^T X\right)^{-1}$$
$$\mu_\sigma = \sqrt{\frac{\nu}{\nu-2} s^2} \qquad \sigma_\sigma^2 = \frac{s^2}{2(\nu-2)(\nu-4)} \tag{4}$$

According to the above description and those presented in the previous section, the procedure implemented in the present study to develop demand model is graphically exhibited in the Fig. 3.

3.2 Drift demand model formulation

Probabilistic demand model constitutes central theme of probabilistic decision-making analyses such as seismic fragility analysis. These models are commonly developed based on observations obtained from experimental tests and/or numerical analyses. It should be noted that a model that matches past observations would not necessarily predict future events. Therefore both aleatory and statistical uncertainty should be explicitly embedded within the predictive demand models. To this end, linear model with random parameters in the logarithmic space have been employed 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. (5) illustrates general form of the predictive model considered in this study

$$Ln(D) = a + b\,Ln\left(Sa\left(T_1\right)\right) + u \tag{5}$$

where D represents the target response (overall maximum inter-story drift), Ln denotes natural logarithm, u is a term reflecting model error and supposed to be a normal random variable with zero mean and unknown standard deviation equals σ_D, and $\Theta = (a, b)$ is a vector of unknown normal random model parameters.

In practice, estimating the statistical characteristics of the model parameters a, b and σ_D

requires collecting a large quantity of observations that is often time-consuming and expensive. This provides motivation for developing relations, in terms of building characteristics, to estimate mean and standard deviation of (a, b, σ_D) without conducting time-consuming building-specific nonlinear response history analyses. In each of these relations, a, b and σ_D, are regressed, separately, through Bayesian statistical inference to reflect statistical uncertainty arising due to use of finite-size sample population (See Section 3.1). Of course, in studies where the statistical uncertainty, for simplicity, are decided to be overlooked, only the mean value of regression coefficients would be used. Otherwise, this paper supposes normal marginal distribution for regression coefficients to reflect statistical uncertainty on the proposed relations. This assumption is supported with the fact that t-distribution, posterior distribution resulting from Bayesian regression, asymptotically approaches a normal distribution when the number of data is large. In addition, for improving the accuracy of the proposed Bayesian regression equations, the explanatory functions have utilized generic frame characteristics, namely T, N, SSD, CY in the form of Eq. (6) instead of considering each generic frame characteristics as an individual explanatory variable, and the power terms, m_1 to m_4, are picked from {-3,-2,-1, 0, 1, 2, 3} collection so that the coefficient of variation of the model parameters were minimized. This was achieved using the algorithm provided in the RT software (Mahsuli 2012)

$$h(x) = T^{m_1}.N^{m_2}.SSD^{m_3}.CY^{m_4} \tag{6}$$

In the following, the regression equations derived for estimating model parameters a, b and σ_D are provided

$$a = \alpha_1 N + \alpha_2 \frac{N^2 \times T}{CY} + \frac{\alpha_3}{T \times CY} + \alpha_4 CY + \sigma\varepsilon \tag{7}$$

$$b = \alpha_1 + \frac{\alpha_2}{T} + \alpha_3 \frac{N^2 \times SSD}{T} + \alpha_4 \frac{CY}{N \times SSD^2} + \sigma\,\varepsilon \tag{8}$$

$$\sigma_D = \frac{\alpha_1}{SSD} + \alpha_2 \frac{T \times SSD^2}{N} + \left[0.126 - 0.462\alpha_2\right].SSD + \frac{\alpha_4}{T \times SSD \times CY} + \sigma\,\varepsilon \tag{9}$$

Where T demonstrates the structural fundamental period, N is the number of stories and CY indicates the yield base shear coefficient. It equals $\frac{V_y}{W}$, where W represents effective seismic weight and V_y is the yield base shear strength. V_y can be directly obtained from pushover analysis or estimated by multiplying design value of the seismic base shear by over-strength factor provided in design codes. Moreover, SSD is a numerical index indicating the beams strength/stiffness distribution pattern along building height and varies from 1 to 3. It takes values ranging from 1 to 3 which correspond, respectively, to “Shear” and “Uniform” distributions described in Section 2.2. 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. This is mainly due to structural elements geometry and their configuration in structure. Therefore, in the present study, following equation is suggested to calculate SSD value.

$$SSD = \frac{\sum_{i=2}^{N}\left(1+\frac{\left(\frac{I_i}{I_1}+\frac{M_i}{M_1}-2\frac{V_i}{V_1}\right)}{\left(1-\frac{V_i}{V_1}\right)}\right)}{N-1} \tag{10}$$

where I_i and M_i indicate, respectively, moment of inertia and plastic moment of i^{th} story beams, and V_i represents design story shear calculated at i^{th} story. According to Eq. (10), the overall *SSD* of a structure is computed by, first, calculating the *SSD* index at each story level using interpolation technique and, then, averaging the story indices over building height. In the following, posterior statistical characteristics of the model parameters and correlation between

Table 1 Posterior statistics of the coefficients of the Eqs. (7)-(9)

	Eq. (7)		Eq. (8)		Eq. (9)	
	μ^*	SD^*	M	SD	μ	SD
α_1	-0.15	0.012	0.831	0.013	0.145	0.028
α_2	0.001	0.00013	0.175	0.0078	-0.1243	0.025
α_3	-0.335	0.008	0.0005	9.08e-05	-------	-------
α_4	-4.795	0.143	-0.822	0.161	0.043	0.006
σ	0.0134	0.00212	0.0344	0.0028	0.058	0.005

* μ: Mean; *SD*: Standard Variation

Table 2 Correlation coefficients of the parameters of Eqs. (7)-(9)

Correlation coefficients between parameters of the Eq. (7)				
	α_1	α_2	α_3	α_4
α_1	1.00			
α_2	-0.78	1.00		
α_3	-0.33	-0.05	1.00	
α_4	-0.81	0.70	-0.15	10
Correlation coefficients between parameters of the Eq. (8)				
	α_1	α_2	α_3	α_4
α_1	1.00			
α_2	-0.49	1.00		
α_3	-0.62	-0.25	1.00	
α_4	-0.36	-0.43	0.58	1.00

Correlation coefficients between parameters of the Eq. (9)			
	α_1	α_2	α_4
α_1	1.00		
α_2	0.24	1.00	
α_4	-0.83	0.096	1.00

them are respectively presented in the Tables 1-2. It is worthy noted that all above Bayesian regression-based relations are graphically investigated against diagnoses (such as normality, heteroscedasticity…) may suffer the reasonableness of the model.

The potential dependency between demand model parameters, i.e., *a* and *b*, is also evaluated and regressed in Eq. (11).

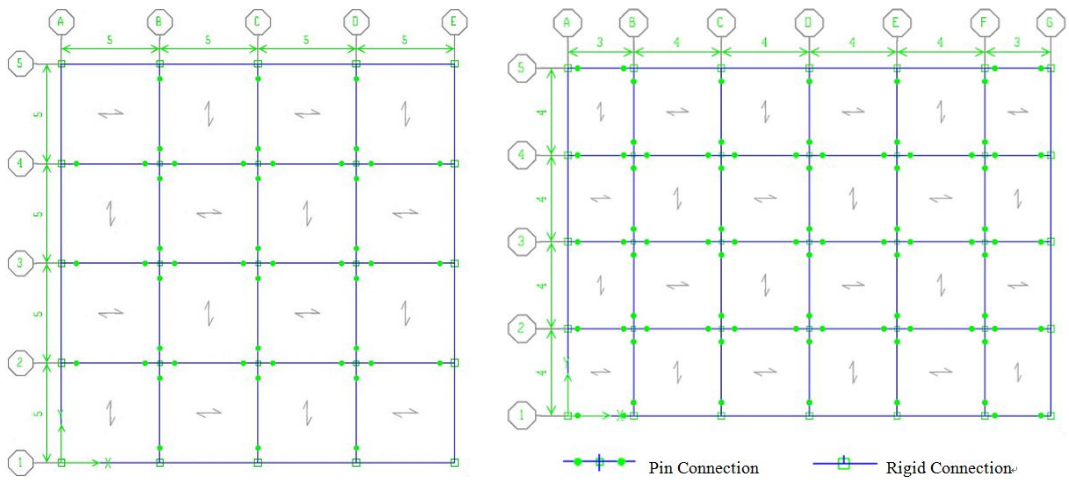
$$\rho_{a,b} = Sin\left(\frac{\pi}{2} - \left[1.66 - 0.315\frac{T^2}{N \times CY} - 1.27T \times CY + 1.61CY\right]\right) \tag{11}$$

4. Numerical example

As an application of the proposed relations, seismic fragility analysis for 4 and 5-story SMRF designed with respect to American Institute of Steel Construction (AISC) and ASCE 7-10 specifications are performed. The building is rectangular in plane with a length of 22 meters and a width of 16 meters for 5-story building. Square plane with a length of 20 meters is also considered for four story building. The first story is 2.8 meter high, and the height of the remaining stories is 3.2 meter. Two perimeter steel moment frames in each direction associated with composite steel deck floor are employed to carry lateral and gravity loads, respectively (See Fig. 4).

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 3 shows beams and columns geometry.

Also, the buildings characteristics intended for use with generic drift demand model are presented in the following table. It is worthwhile to mention that *CY* was directly obtained from pushover analysis.



(a) (b)

Fig. 4 Plan view of (a) four story-building; (b) five-story building

Table 3 Beam and column geometry

STORY	4-Story Building		5-Story Building	
	Beam-Section	Column-Section	Beam-Section	Column-Section
1	IPE 450	TUBE 400×400×12	IPE 450	TUBE 350×350×12
2	IPE 450	TUBE 400×400×12	IPE 450	TUBE 350×350×12
3	IPE 400	TUBE 350×350×12	IPE 450	TUBE 350×350×12
4	IPE 400	TUBE 350×350×12	IPE 330	TUBE 300×300×12
5	----	---	IPE 330	TUBE 300×300×12

Table 4 The example buildings characteristics

Number of stories	*T*	*SSD*	*CY*
4	0.74	2.05	0.29
5	0.88	2.06	0.26

4.1 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

$$P\left[D\left(Sa,\Theta\right)\geq d\,|\,Sa=x\right]\cong\left[1-\varphi\left(\frac{Ln\left(d\right)-\lambda_{Ln(D|Sa)}}{\sigma_{Ln(D|Sa)}}\right)\right] \tag{12}$$

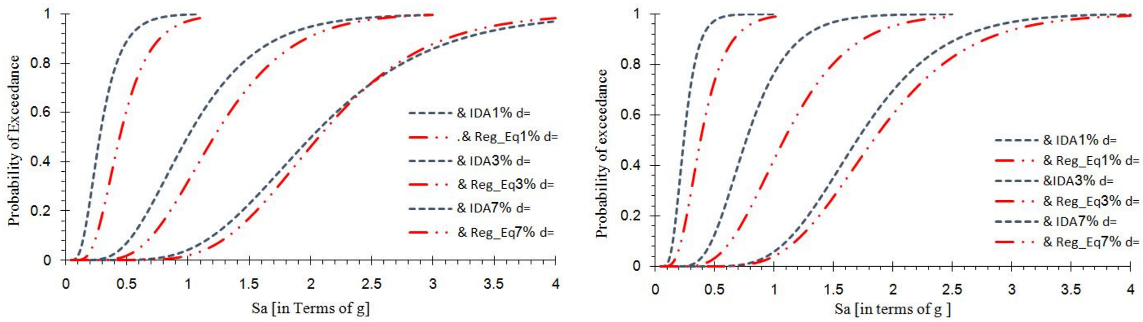
Where $\lambda_{Ln(D|Sa)}$ and $\sigma_{Ln(D|Sa)}$ are the median and standard deviation of the seismic demand given *Sa* in the logarithmic space. φ indicates cumulative standard normal distribution function. According to Eq. (12), probabilistic demand model is required to perform fragility analysis. Thus, maximum drift demand model, in the form of Eq. (5), is developed once based on Non-collapse data obtained from IDA, and once again using proposed relations. The results are presented in Tables 5-6.

Table 5 Mean value of the demand model parameters computed using IDA

Number of Story	*a*	*b*	σ_D
4	-3.520	0.858	0.408
5	-3.155	0.954	0.355

Table 6 Mean value of the demand model parameters computed by Eq. (7)~Eq. (9)

Number of Story	*a*	*b*	σ_D
4	-3.514	1.071	0.447
5	-3.376	1.049	0.437



(a) (b)

Fig. 5 Fragility curves: (a) four-story building; (b) five-story building

Table 7 Percentage errors at different exceedance probabilities

	Probability of exceedance		d = 1%	d = 3%	d = 7%
4-Story building	16%	Sa-Exact	0.185	0.64	1.37
		Sa-predicted	0.30	0.815	1.49
		Percentage-error	62 %	27%	9.0%
	50%	Sa-Exact	0.29	1.01	2.03
		Sa-predicted	0.45	1.23	2.08
		Percentage-error	55%	22%	2.5%
	84%	Sa-Exact	0.46	1.55	2.93
		Sa-predicted	0.69	1.79	2.86
		Percentage-error	50%	15%	-2.38
5-Story building	16%	Sa-Exact	0.178	0.54	1.23
		Sa-predicted	0.26	0.73	1.32
		Percentage-error	46%	35%	7.4%
	50%	Sa-Exact	0.25	0.78	1.71
		Sa-predicted	0.39	1.1	1.85
		Percentage-error	56%	41%	8.2%
	84%	Sa-Exact	0.36	1.12	2.34
		Sa-predicted	0.6	1.59	2.55
		Percentage-error	66%	42%	9%

Seismic fragility analysis, using regression/IDA-based demand model, is performed for two example buildings, and results presented in the form of fragility curves are compared. Fragility curves are developed for d equals 0.01, 0.03 and 0.07 (Fig. 5). These values are quite arbitrary choice, but according to FEMA 350 limitation on collapse and immediate occupancy limit-states, it can be expected that selected thresholds reflect light to severe damage states and named SD_1, SD_2 and SD_3 respectively.

As shown in the Fig. 5, 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 5-story buildings using IDA. It should be also noted, the computational efforts required to develop fragility curves based on proposed relations would be dramatically less than what requires to develop same curves using IDA. To numerically examine accuracy of the regression equations-based curves, percentage errors at exceedance probabilities equal 16%, 50% and 84% are computed and presented in the Table 7.

According to the results of the Table 7 and considering the regression-based fragility curves are developed with much less computational efforts, it is concluded that implementing proposed regression equations in a seismic fragility analysis provide a reasonable approximation of the exact results, especially for damage-states having high consequences, i.e., SD_2 and SD_3, and would be important for decision making. For light damage state, i.e., SD_1, albeit errors up to 66% are observed, it is not important for a decision maker due to low consequences imposed to the building.

5. Conclusions

The vision of the present study is to develop a technical basis on which probabilistic decision-making analysis could be readily implemented for practical purposes. To this end, generic drift demand model of the regular low to mid-rise steel moment resisting frames are presented. The model considers aleatory and epistemic uncertainties by introducing model coefficients as random variables. A set of relations in terms of building characteristics are presented to estimate unknown model coefficients. These equations which are based on Bayesian regression technique eliminates need of time-consuming collecting data procedure. To demonstrate a novel application of the proposed relations, fragility curves are developed for two example buildings designed according to ASCE-07-10. The results are compared with those developed based on 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 level of 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 is balance between accuracy and computational cost which is appealing for practical purposes.

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