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Bayesian approach for determination of drift hazard curves for generic steel moment-resisting frames in territory of Tehran

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Abstract

The objective of this paper is to determine the drift demand hazard curves of steel moment-resisting frames with different number of stories in territory of Tehran; this is done through the combination of the results obtained from probabilistic seismic hazard analysis and the demand estimated through the best probabilistic seismic demand models. To select the best demand model, in this paper, a Bayesian regression has been used for the statistical analysis of the results obtained from incremental dynamic analysis in order to estimate the unknown parameters of model and to select the best Intensity Measure (IM) parameter; also the probability of overall collapse of structures has been computed. Considering the efficiency and sufficiency of the models, the results indicate that the accuracy of models with one single IM is a function of the number of stories, consequently the current widely used model with spectral acceleration in first period as IM is not suitable for all structural heights. Furthermore, regarding the fact that it is difficult to prepare a seismic hazard curve for a combined IM, it seems that the best model can be found among models with two single IMs. In other words, the best model to cover all structural heights is the one with linear combination of spectral acceleration of the first and the second period. Furthermore, using different models to calculate the curves shows that regardless of the number of IMs, estimated demands strongly depend on the standard deviation of model.

Keywords: Drift hazard curves, Steel moment-resisting frame, Bayesian, Tehran

1. Introduction

Huge economical losses due to recent earthquakes in countries such as USA (Loma Prieta, 1989 & Northridge, 1994), Japan (Kobe, 1995), Taiwan (chi-chi, 1999), Turkey (Izmit, 1999) and Iran (Bam, 2003) can be viewed as strong evidences for the fact that the classical structural seismic design philosophy based on collapse prevention is not a reliable method to mitigate the adverse effect of earthquake events in 21st century [1].This is why a framework has been established for seismic structural design to overcome the inability in realistic prediction of earthquake consequences which is termed as Performance Based Design (PBD). In this new method, which is based on the reliability assessment of structural performance, structural behavior is defined in terms of seismic demand parameters, structural capacity characteristics and performance limit states [2]. Therefore PBD itself includes different components; one of the most important is the estimation of the seismic demand.

Although any parameter in structural seismic response can be regarded as a demand parameter, the one which is suitable must be able to indicate the realistic performance of the structures against a seismic event. Regardless of the type of selected demand parameter, the challenge in estimation of this parameter is the existence of large uncertainty associated with the seismic events and structural response. Uncertainty in estimation of a seismic demand value can be classified in two categories; those originated from inherent randomness (aleatory) and those originated from modeling errors (epistemic) [3]. Hence, it is inevitable to apply a reliable probabilistic method for treating both randomness and uncertainty of demand estimation. This method is known as Probabilistic Seismic Demand Analysis (PSDA) [4].

PSDA, an integral part of PBD methodologies, is an approach to estimate the mean annual probability exceeding of a specified seismic demand for a given structure at a designated site [5]. Analogous to a ground motion hazard curve estimated through Probabilistic Seismic Hazard Analysis (PSHA), the main result of PSDA is a structural demand hazard curve, which means annual frequency that the

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displacement-based demand exceeds a given value. The main aim of this article is to determine the drift hazard curves of Steel Moment-Resisting Frames (SMRFs) in territory of Tehran, which is the populous capital of Iran and located in a relatively high level seismic risk zone.

Nowadays the approach suggested by Cornell and co-workers [1, 2 and 6], is the main method in PBD to estimate the seismic demand. In this approach the PSDA problem is simplified by introducing an intermediate parameter known as the ground motion Intensity Measure (*IM*), and decoupling the ground motion hazard and Nonlinear Dynamic Analysis (NDA). Briefly in PSDA, the IM which is a dependent random variable within a PSHA is combined with the demand parameter which itself could be a dependent random variable for considering modeling uncertainty through an application of total probability theorem. In this approach PSDA is expressed mathematically as follow [6]:

$$\lambda_{DR}(z) = \int_0^\infty G_{DR|IM}(z \mid x). \mid d\lambda_{IM}(x) \mid \quad (1)$$

Where *DR* is the maximum inter-storey drift and *IM* is the ground motion intensity measure. In this equation the drift hazard function expressing the mean annual frequency of *DR* exceeding the value z, is denoted by $\lambda_{DR}(z)$. IM hazard function is $\lambda_{IM}(x)$ (evaluated at x), typically computed through PSHA and $|d \ldots|$ denotes its differential with respect to *IM* (also evaluated at x). The term $G_{DR|IM}(z|x)$, which can be customarily estimated using NDA results for a suite of earthquake records, denotes the probability of *DR* exceeding the value z conditioned that *IM* equals x. This conditional term is usually calculated by using a probabilistic seismic demand model.

In some recent studies, instead of using one *IM* parameter, a vector of two ground motion parameters, *IM1* and *IM2* is used to estimate the drift [7]. In this case the Eq.1 changes to:

$$\lambda_{DR}(z) = \int_0^\infty \int_0^\infty G_{DR|IM1,IM2}(z \mid x, y).f_{IM2|IM1}(y \mid x) \mid d\lambda_{IM1}(x) \mid \quad (2)$$

In this equation the term $f_{IM2|IM1}(y|x)$ denotes the conditional probability density function of *IM2* given *IM1* and the other terms are similar to Eq.1.

In this article maximum inter-storey drift (*DR*) is chosen as the displacement-based structural demand (the maximum is obtained as the peak in response time histories over all stories in the building). *DR* is an adequate seismic demand parameter for describing the seismic behavior of SMRFs to assess the structural overall collapse [2 and 8]. Also the Bayesian statistical approach, a robust statistical framework for simultaneous modeling of the uncertainty and randomness has been adopted in this paper to estimate the unknown parameters of different demand models [9]. In the following, the procedures for computing the components of Eq.1 and 2 are presented. First, the structural model of SMRFs has been presented, and then selected ground motion records for NDA are introduced. In the next step, Bayesian statistics and its application as well as advantages are discussed. Then the best models for prediction of the seismic demand are determined. Later the PSHA for selected *IM* parameters has been carried out for the territory of Tehran and *IM* hazard functions are obtained. Then the selected models are recalibrated with results obtained from the Incremental Dynamic Analysis (IDA) in order to introduce the effect of structural overall collapse in a PSDA. Finally by combining these results, the drift hazard curves for steel moment-resisting frames in Tehran are determined.

2. Generic archetype steel moment-resisting frames

It is important to note that the obtained results in this article can be extended for a wide range of all type of SMRFs with different characteristic such as the number of stories. In order to cast a reliable archetype of SMRFs, the concept of generic frames is adopted in this paper. NDA is carried out using a family of two-dimensional [11] single-bay generic SMRFs for 3, 6, 9, 12 and 15-storey structures, and the first mode period equals to 0.3, 0.6, 0.9, 1.2 and 1.5 second and the second mode period equals to 0.1, 0.23, 0.35, 0.48 and 0.6 respectively. The results of different studies show that using a single-bay generic frame can properly demonstrate the behavior of multi-bay frames [12]. Nonlinear beam-column elements with concentrated plastic hinges in two ends, connected by an elastic element, are adopted for modeling the frames. The nonlinear behavior in plastic hinges is modeled implementing rotational springs (with stiffness and strength deterioration). The peak-oriented model is applied to specify the hysteretic behavior (Fig. 1).

Also, in order to consider the cyclic deterioration, the modified model suggested by Ibarra and co-workers have been used [13]. In this model, cyclic deterioration parameter is accounted for deterioration criterion by using energy dissipation. The following four modes of deterioration are included: basic strength, post-capping strength, unloading stiffness, and accelerated reloading stiffness deterioration. Although this model is calibrated for explaining real behavior of steel frames, it is demonstrated in some researches that this model is also appropriate for defining the real behavior of steel structures in generic frames. In fact it is shown this model can even be used for the prediction of very complicated behaviors such as overall collapse of steel frames [13].

The open source for simulation in earthquake engineering established by PEER, known as Opensees, is selected to perform the NDA. Some main characteristics of this family of frames are as follow, more details can be found in [12]:

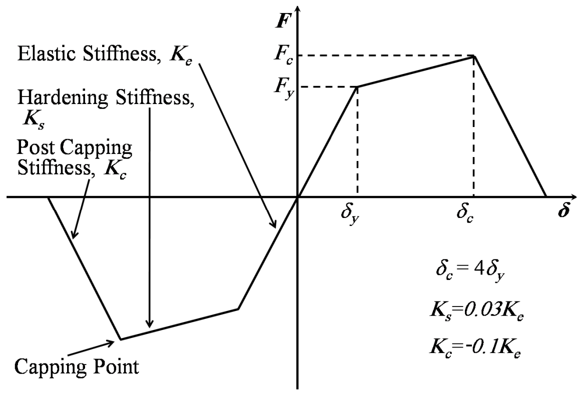


Fig. 1. Used peak-oriented hysteretic model and its specifications

• The frames are two dimensional;
• The same mass is used at all floor levels;
• One-bay frames have constant storey height equal to 3.66 m and beam span equal to 7.32 m;
• Centerline dimensions are used for beam and column elements;
• The same moment of inertia is assigned to the columns in a storey and the beam above them;
• Relative stiffness are tuned so that the first mode is a straight line (a spring is added at the bottom of the first-storey columns to achieve a uniform distribution of moments of inertia;
• Plasticization just occurs at the end of the beams and the bottom of the first storey columns
• Frames are designed so that simultaneous yielding at all plastic hinge locations is attained under a parabolic (NEHRP, k=2) load pattern;
• Global (structure) P-delta is included (member P-delta is ignored);
• Axial deformations and M-P-V interaction are not considered;
• Moment-rotation hysteretic behavior is modeled by using rotational springs with peak-oriented hysteretic rules and cyclic deterioration parameter equal to 30 and 3% strain hardening;
• For the NDA, 5% Rayleigh damping is assigned to the first mode and the mode at which the cumulative mass participation exceeds 95%.

3. Selection of ground motion records

An appropriate estimation of seismic demand through NDA requires a suitable selection of ground motion records which must represent the seismic hazard condition of target territory at different return periods. In this article, using a bin strategy, 80 records are selected from the PEER Center Ground Motion Database (http://peer.berkeley.edu/smcat/) and classified into four magnitude-distance bins for the purpose of NDA of SMRFs [12]. The record bins are designated as follow:
• Large Magnitude-Short Distance Bin, LMSR, (6.5 < Mw < 7.0, 13 km < R < 30 km),
• Large Magnitude-Long Distance Bin, LMLR, (6.5 < Mw <7.0, 30 km < R < 60 km),
• Small Magnitude-Short Distance Bin, SMSR, (5.8 < Mw < 6.5, 13 km < R < 30 km), and
• Small Magnitude-Long Distance Bin, SMLR, (5.8 < Mw < 6.5, 30 km < R < 60 km).
These ground motions were recorded on NEHRP site class D and no aftershocks or near-fault cases are included. Although using the ground motion records which directly belong to the Tehran territory is an ideal option, because of unavailability of such records, implementation of a bin-strategy using PEER record is an unavoidable alternative.

4. Bayesian statistical approach

In the framework of data analysis based on probability models, three principal approaches are possible: frequentist, likelihood and Bayesian. The frequentist approach is based on imagining repeated sampling from a particular model (the likelihood), which defines the probability distribution of the observed data conditional on unknown parameters. The likelihood (or Fisherian) approach is based on a sampling model, and the inferences are based only on the likelihood function. Finally the Bayesian approach requires a sampling model and, in addition, a prior distribution for the unknown parameters. The prior and the likelihood are combined to construct the posterior distribution.

The eventual goal of developing seismic demand hazard curves is seen in the context of making decisions with regard to the seismic events and nonlinear response of structures. In this context, it is essential for the approach to be capable of incorporating all types of available information, including mathematical models of seismic sources and structural behavior, data related to attenuation relations, field observations, past experience, and engineering judgment. It is equally important that the approach explicitly account for all the relevant uncertainties, including those that are aleatory in nature and those that are epistemic. The Bayesian framework employed in this work is ideally suited for this purpose [9 and 10]. Another advantage of Bayesian approach is its probabilistic treatment with uncertainty instead of dealing with confidence interval which makes it be considered as an ideal option within the framework of performance- based design. Considering these advantages, all the statistical calculations have been done through Bayesian statistics instead of classic statistics.

Here only a brief description of this method is presented. Details can be found in [9]. Let

$$y(x,\theta,\sigma)=d(x,\theta)+\sigma.\varepsilon \tag{3}$$

be a mathematical model for predicting variable y in terms of a set of observable variables x, in which $d(x,\theta)$ is the deterministic model, θ is the vector of unknown model parameters, ε is a random variable, representing the uncertainty in the model and σ is the unknown standard deviation. So the set of unknown parameters must be estimated by using Bayesian statistics and available information is $\psi(\theta,\sigma)$. In the Bayesian approach, this is done by using the well-known updating rule:

$$f(\psi)=c.L(\psi).p(\psi) \tag{4}$$

Where $p(\psi)$ can be viewed as the prior distribution reflecting the state of knowledge about ψ prior to obtaining the information, $L(\psi)$ is the likelihood function, which is a function proportional to the conditional probability of making the observation on x and y for a given value of the parameters and reflect the objective information, $f(\psi)$ is posterior distribution reflecting the updated information about ψ and c is a normalizing factor necessary to ensure that the posterior distribution integrates to one.

Clearly, because of complexity of defined equations, it is impossible to introduce a closed-form solution for required likelihood function, posterior mean or posterior mode estimation. Consequently, a numerical method must be used to perform the calculations. In this article, for this purpose, the regression tool relies on Markov chain Monte Carlo simulation techniques and yields fully Bayesian posterior mean or posterior mode estimation. In this method, all the data points are produced by simulations and the functions are estimated based on these points. Details can be found in [13].

5. Selection of probabilistic seismic demand model

In order to determine the probability of seismic demand exceeding over a certain level of *IM* parameter, a model of conditional probability prediction of seismic demand is required. This model, namely Probabilistic Seismic Demand Model (PSDM), calculates the average of seismic demand for a certain level of *IM*. The selection of PSDM is based on several inherent properties such as practicality, sufficiency, effectiveness and efficiency [15]. In this section, the best PSDMs are selected.

Generally, the following mathematical form is adopted for a demand model [1]:

$$D(IM,\theta,\sigma) = d(IM,\theta) + \sigma.\varepsilon \qquad (5)$$

In the above expression, *D* is the demand parameter, *d* is the selected deterministic model and ε is a standard normal random variable with zero mean and unit standard deviation. Furthermore *IM* is the ground motion intensity measure parameter (may be one or more parameters), θ is the vector of model parameters and σ is the standard deviation of model error. The vector of θ and amount of σ are the unknown parameters and must be estimated based on the results of NDA.

In this article, 16 different demand models, with various types and numbers of *IM* parameters are defined and evaluated to select the best PSDM. Efficiency of models can be defined as minimal standard deviation of model and their sufficiency can be defined as constant standard deviation of model over a range of structural heights, these two are considered as the best rules to select the best model. In these model, listed follow, first (S_{a1}), second (S_{a2}) and third (S_{a3}) mode spectral acceleration, Peak Ground Acceleration (*PGA*), moment magnitude (*M*), site to fault distance (*R*) and strong ground motion time duration (*T*) of casual earthquake are used as *IM* parameter. Fig. 2 shows the estimated standard deviations of these models, divided into 4 groups.

Model No01: $\ln(DR) = a.\ln(PGA) + w + \sigma.\varepsilon$

Model No02: $\ln(DR) = a.\ln(S_{a1}) + w + \sigma.\varepsilon$

Model No03: $\ln(DR) = a.\ln(S_{a2}) + w + \sigma.\varepsilon$

Model No04: $\ln(DR) = a.\ln(S_{a3}) + w + \sigma.\varepsilon$

Model No05: $\ln(DR) = a.\ln(\frac{S_{a1} + S_{a2}}{2}) + w + \sigma.\varepsilon$

Model No06: $\ln(DR) = a.\ln(\sqrt{S_{a1}^2 + S_{a2}^2}) + w + \sigma.\varepsilon$

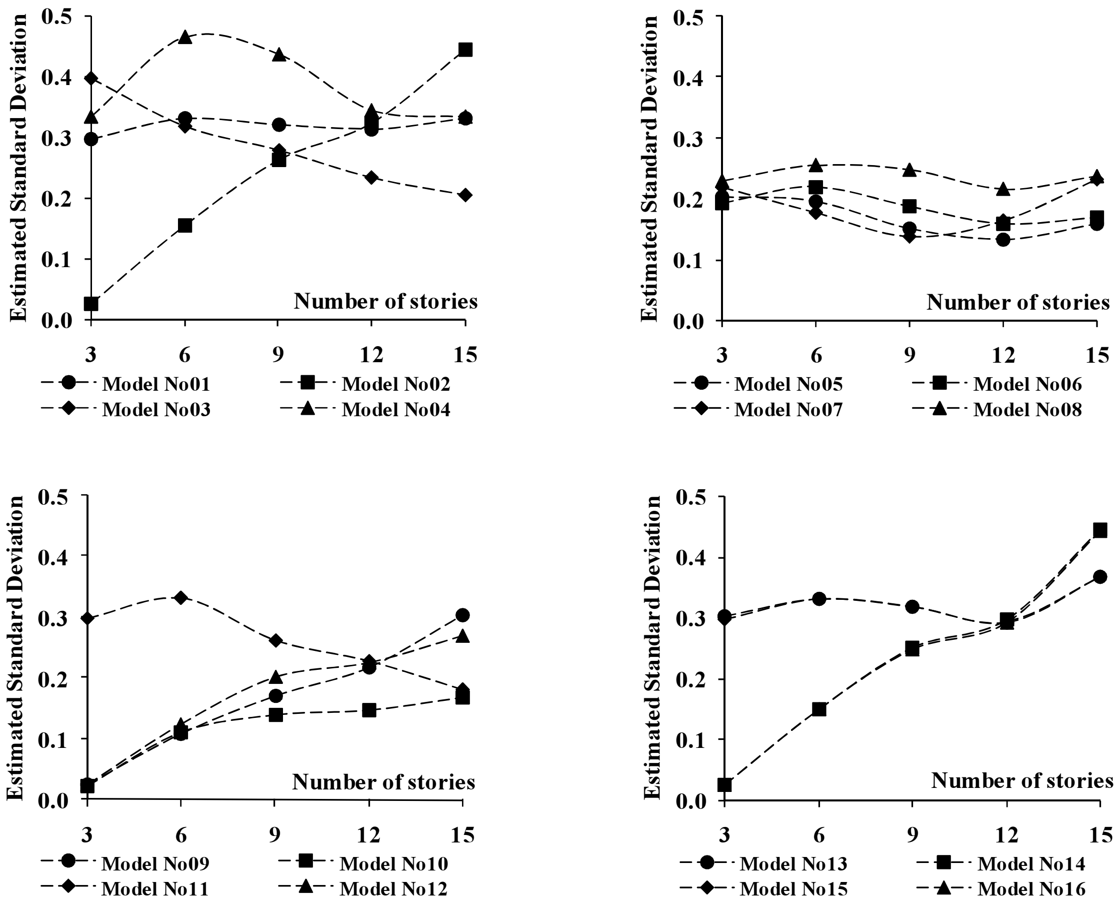


Fig. 2. Estimated standard deviation of 16 defined demand model, using Bayesian regression

Model No07: $\ln(DR) = a.\ln(\sqrt{S_{a1}.S_{a2}}) + w + \sigma.\varepsilon$

Model No08: $\ln(DR) = a.\ln(\frac{S_{a1} + S_{a3}}{2}) + w + \sigma.\varepsilon$

Model No09: $\ln(DR) = a.\ln(PGA) + b.\ln(S_{a1}) + w + \sigma.\varepsilon$

Model No10: $\ln(DR) = a.\ln(S_{a1}) + b.\ln(S_{a2}) + w + \sigma.\varepsilon$

Model No11: $\ln(DR) = a.\ln(PGA) + b.\ln(S_{a2}) + w + \sigma.\varepsilon$

Model No12: $\ln(DR) = a.\ln(S_{a1}) + b.\ln(S_{a3}) + w + \sigma.\varepsilon$

Model No13: $\ln(DR) = a.\ln(PGA) + bM + c.R + w + \sigma.\varepsilon$

Model No14: $\ln(DR) = a.\ln(S_{a1}) + bM + c.R + w + \sigma.\varepsilon$

Model No15: $\ln(DR) = a.\ln(PGA) + bM + c.\ln(R) + d.T + w + \sigma.\varepsilon$

Model No16: $\ln(DR) = a.\ln(S_{a1}) + bM + c.\ln(R) + d.T + w + \sigma.\varepsilon$

It is clear that the standard deviations of models No01 to No04, which include single *IM* parameter consisting of single parameter, depend on the number of stories, i.e. although model No02, which is commonly used in PBD, has small standard deviation and good accuracy to estimate the demand in the case of 3-storey frame, it is not suitable in 15-storey frame because of its considerable standard deviation. Besides, model No3 is the weakest estimator in 3-storey and the best estimator in 15-storey frame. Furthermore, model No01 is a sufficient model because of its constant standard deviation, but it is not an efficient model because of its large standard deviation. As a general rule, results show that there is no efficient and sufficient one-parameter model to cover all structural height.

Although all of the models with single *IM* including two spectral values, i.e. models No05 to No8 are sufficient because of their nearly constant standard deviation, they are not recommended as demand model in PBD framework due to extreme difficulty of producing a multiple parameters seismic hazard curve.

Considering the standard deviations of models No09 to No12, on the condition that appropriate parameters are selected, it is best to construct a model through two spectral parameters as *IM*. When two *IM* parameters are applied for the estimation of the demand, the model can benefit from each *IM* in different cases. For instance in model No10, a linear combination of S_{a1} and S_{a2}, when the target frame is 3-storey, S_{a1} has the most participation in estimating the demand (so the standard deviation is similar to model No02) and when the target frame is 15-storey, S_{a2} is the dominant parameter in estimation (so the standard deviation is similar to model No03).

In order to investigate the ability of earthquake parameters, such as magnitude, distance and time duration to predict the demand, models No13 to No16 are defined. It is interesting to note that there is no difference between models No13, No15 and N01 and models No14, No16 and No02 in respect of standard deviation. In the other words in these models the spectral parameters are always dominant and making use of earthquake parameters is not recommended.

Generally and by considering all the discussed matters it seems that model No02 is the best one- parameter model and model No10 is the best two-parameter model and the best one among all models. However when using model No02 for high-rise care should be taken, in the present article, this model and model No10 are selected to determine the drift hazard curves in following section.

6. Probabilistic seismic hazard analysis for territory of Tehran

As mentioned in previous section, the S_{a1} was selected as *IM* parameter. So in this section, the calculation of hazard function of spectral accelerations at 0.3, 0.6, 0.9, 1.2 and 1.5 second for territory of Tehran, which is defined as an area between 50.8° to 52.2° longitude and 35.5° to 36.2° latitude, has been considered by means of well-known PSHA method. In order to solve this problem, a project area, which is located between 49.5° to 53.3° longitude and 34.0° to 37.0° latitude, has been developed in a way that all the sources which can cause seismic events in Tehran territory, be considered. Then by dividing this area into two seismic zones and identifying active faults and defining their geometries, the probability density function of distance has been calculated and by collecting the data related to historical and instrumental earthquakes, the probability density function of magnitude and the rate of seismic activity for each source have been calculated. Also in this study, a valid spectral attenuation relation for Iran which is suggested by Zare in 1999 has been used [16].

By using the routine PSHA method [17] and dividing Tehran territory to a grid of points, spacing of 0.1 degrees in latitude and longitude and hazard analysis for all points, a map of *PGA* is generated with 475 years return period. This map, shown in Fig. 3, is used to divide the Tehran territory into 3 seismic zones with different seismic hazard levels in terms of PGA. Then, by using the selected spectral attenuation relation and PSHA, $\lambda_{Sa}(x)$ is computed for all of these points and for each of five mentioned periods. The spectral acceleration hazard function of each zone is defined as the average of spectral acceleration hazard function of every point in that zone. In Fig. 4 such curves are shown. As shown in this figure these curves can be regressed by a power equation as follow:

$$\lambda_{Sa}(x) = k.(x)^t \tag{6}$$

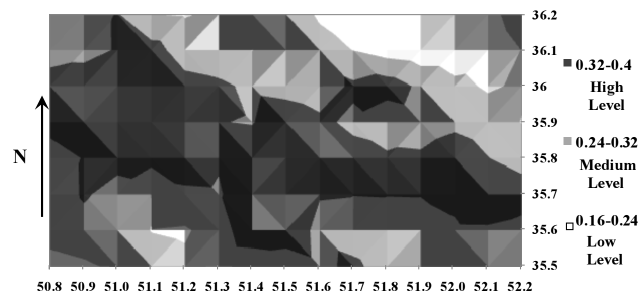


Fig. 3. The map of Pick Ground Acceleration (g) calculated for territory of Tehran city with 475 years return period and 3 defined seismic zones based on the PGA

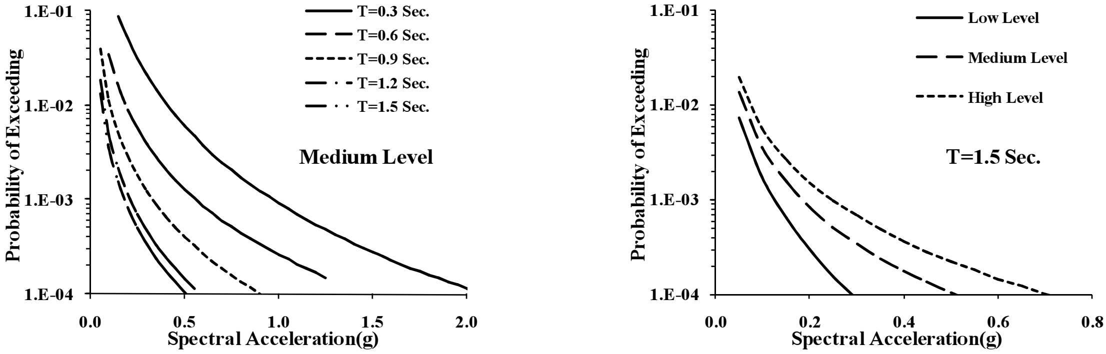


Fig. 4. Calculated seismic hazard curves for different spectral acceleration and different seismic zones in territory of Tehran city

This approximation, which has been authenticated by different studies and whose regression coefficient is above 0.99, can simplify the integrations in Eq.1 and 2 without decreasing the accuracy. The required parameters of this relation for different zones are listed in Table 1.

Applying two-parameter PSDM No10 requires the conditional probability density function of S_{a2} given S_{a1} additional to these hazard curves. By assuming a normal distribution for dispersion of S_{a2} given S_{a1}, this function can be defined as:

$$f_{IM\,2|IM\,1}(y\,|\,x)=\frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{1}{2\sigma^2}(y-\mu(x))^2} \tag{7}$$

The required parameters of this distribution (σ and μ(x)) are estimated by using Bayesian regression analysis based on S_{a2} and S_{a1} amounts of 80 selected ground motion records. The estimated parameters are listed in Table 2 for modeled SMRFs.

7. Consideration of collapse probability by using IDA to calibrate PSDMs

The ground motion records which have been used in this study are not strong enough to cause collapse or even severe nonlinear behavior in modeled SMRFs. While regarding the results obtained from the PSHA in previous section, the occurrence of spectral acceleration which can cause overall collapse of these structures in territory of Tehran is expected, so applying these ground motions cannot represent the real behavior, including the overall collapse case which is considered here as the ultimate limit state in which dynamic sideway instability in one or several stories of structural system is attained or a maximum inter-storey drift which is defined as collapse by codes (here 10%). In order to conquest this shortage, the applied ground motion records in NDA should be scaled in such a way that they have the ability to create extreme nonlinear conditions in SMRFs. An IDA, the dynamic equivalent to familiar static pushover analysis, is used in this research for making this condition.

Given a structure and a ground motion, IDA is done by conducting a series of NDA. In this process the *IM* of ground motion increases incrementally and the selected seismic demand parameter is monitored during each analysis [18]. The extreme values of demand parameter are plotted against the corresponding value of the *IM* for each level to produce a database which is used to estimate the unknown parameters. In this article, by a scale factor which can be less or more than

Table 1. Calculated parameters for seismic hazard curves in 3 different seismic zones

Spectral acceleration	High Level Hazard		Medium Level Hazard		Low Level Hazard	
	k	*t*	*k*	*t*	*k*	*t*
$S_a(0.30)$	1.890 E-3	-2.653	8.422 E-4	-2.683	1.861 E-4	-2.888
$S_a(0.60)$	5.653 E-4	-2.131	2.661 E-4	-2.191	6.416 E-5	-2.510
$S_a(0.90)$	1.787 E-4	-2.005	8.947 E-5	-2.105	2.311 E-5	-2.367
$S_a(1.20)$	7.460 E-5	-2.021	3.444 E-5	-2.140	7.434 E-6	-2.451
$S_a(1.50)$	5.356 E-5	-2.021	2.473 E-5	-2.140	5.337 E-6	-2.451

Table 2. Estimated parameters for conditional probability density function of S_{a2} given S_{a1}

		Conditional Probability Density Function	Mean	Standard Deviation
Number of Stories	3-Storey	$f(S_a(0.10)\,|\,S_a(0.3))$	$\mu(x)=0.6973x+0.0506$	0.128065
	6-Storey	$f(S_a(0.23)\,|\,S_a(0.6))$	$\mu(x)=0.6439x+0.1801$	0.169600
	9-Storey	$f(S_a(0.35)\,|\,S_a(0.9))$	$\mu(x)=1.1697x+0.1240$	0.152442
	12-Storey	$f(S_a(0.48)\,|\,S_a(1.2))$	$\mu(x)=1.4134x+0.1155$	0.130762
	15-Storey	$f(S_a(0.60)\,|\,S_a(1.5))$	$\mu(x)=2.0902x+0.0881$	0.181576

one, S_{a1} of the ground motion records is scaled from a very low level to a high level limit which is defined as the amount of first mode spectral acceleration with the probability of exceeding equal to 0.0001. This limit for S_{a1} at 0.3, 0.6, 0.9, 1.2 and 1.5 second is calculated 2.1g, 1.35g, 0.95g, 0.6g and 0.55g respectively in Tehran by PSHA in previous section. Actually each record scaled from S_{a1} =0.05g to the defined high level limit with 0.05g steps and a NDA is done by using this scaled record.

In order to contribute all data points, both non-collapse and collapse data, in estimation of drift, the following form is applied to calculate the term $G_{DR|IM}(z|x)$:

$$G_{DR|IM}(z\mid x)=(1-P_{Collapes|IM}(x)).[1-\Phi(\frac{\ln(z)-d(x,\theta)}{\sigma})]+P_{Collapes|IM}(x) \qquad (8)$$

In this equation, Φ is cumulative normal distribution function and $d(x,\theta)$ and σ are the deterministic part (or mean) and standard deviation of the selected demand model, respectively. The IDA resulted data points which do not lead to collapse of SMRFs, are used in a Bayesian regression analysis to estimate model parameters (a and w for model No02 and a, b and w for Model No10) and standard deviations of these demand models. The results for model No02 and model No10 are listed in Table 3. As it can be seen from this table, all these parameters are computed for different probabilities, i.e. mean, occurrence probability 2.5%, 10%, 50% (median), 90% and 97.5%. These capabilities are unique characteristics of Bayesian method to simultaneous modeling of randomness and uncertainties. The remained IDA data points, which lead to collapse of SMRFs, are used to calculate the probability of collapse at the given IM level i.e. $P_{Collapes|IM}(x)$. This probability is defined as the number of scaled records, which leads to collapse, divided to the number of all records i.e. 80, at any given IM level. Fig. 5 shows such a probability calculation for 3 and 15-storey SMRFs. Although some studies show that a normal distribution can be a suitable probabilistic model to predict the collapse probability [7], as seen in Fig. 5, when a high level limit is defined for S_{a1} a linear model may lead to better results for prediction of collapse probability in comparison with the normal model. For this reason, a linear

Table 3. Estimated parameters for probabilistic seismic demand and collapse models, using Bayesian regression of IDA results with different probabilities of exceeding

Model No02: $\ln(DR)=a.\ln(S_{a1})+w+\sigma.\varepsilon$

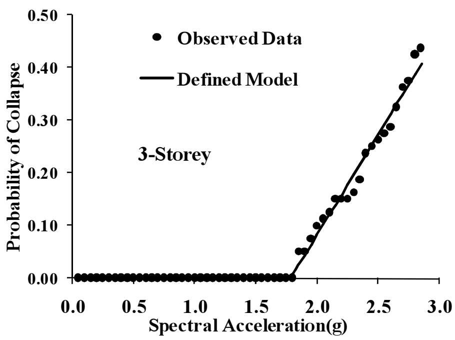
	Parameter	Mean	Standard deviation	%2.5 Prob.	%10 Prob.	Median	%90 Prob.	%97.5 Prob.
3	w	-5.8825	0.0026	-5.8875	-5.8857	-5.8825	-5.8791	-5.8771
Storey	a	1.0200	0.0028	1.0142	1.0165	1.0200	1.0235	1.0255
frame	σ^2	0.0268	0.0006	0.0257	0.0260	0.0268	0.0276	0.0280
6	w	-4.9563	0.0034	-4.9633	-4.9607	-4.9563	-4.9519	-4.9496
Storey	a	1.0226	0.0038	1.0152	1.0177	1.0227	1.0275	1.0300
frame	σ^2	0.0326	0.0008	0.0310	0.0316	0.0326	0.0337	0.0343
9	w	-4.3029	0.0074	-4.3172	-4.3124	-4.3030	-4.2931	-4.2892
Storey	a	1.0085	0.0071	0.9947	0.9994	1.0085	1.0173	1.0226
frame	σ^2	0.0708	0.0023	0.0665	0.0681	0.0707	0.0736	0.0755
12	w	-3.7765	0.0144	-3.8047	-3.7955	-3.7763	-3.7582	-3.7497
Storey	a	0.9862	0.0118	0.9637	0.9708	0.9866	1.0015	1.0092
frame	σ^2	0.1276	0.0047	0.1185	0.1219	0.1275	0.1338	0.1369
15	w	-3.4132	0.0242	-3.4630	-3.4437	-3.4140	-3.3813	-3.3655
Storey	a	0.9519	0.0176	0.9157	0.9291	0.9519	0.9740	0.9846
frame	σ^2	0.2028	0.0085	0.1852	0.1922	0.2027	0.2136	0.2190

Model No10: $\ln(DR)=a.\ln(S_{a1})+b.\ln(S_{a2})+w+\sigma.\varepsilon$

	Parameter	Mean	Standard deviation	%2.5 Prob.	%10 Prob.	Median	%90 Prob.	%97.5 Prob.
3 Storey frame	w	-5.8693	0.0029	-5.8749	-5.8729	-5.8694	-5.8656	-5.8635
	a	0.9617	0.0061	0.9501	0.9539	0.9615	0.9696	0.9739
	b	0.0588	0.0055	0.0483	0.0515	0.0588	0.0658	0.0695
	σ^2	0.0262	0.0006	0.0251	0.0254	0.0262	0.0269	0.0272
6 Storey frame	w	-5.0238	0.0026	-5.0289	-5.0269	-5.0239	-5.0204	-5.0187
	a	0.7740	0.0052	0.7639	0.7676	0.7740	0.7807	0.7838
	b	0.2504	0.0044	0.2419	0.2449	0.2504	0.2562	0.2594
	σ^2	0.0157	0.0004	0.0150	0.0152	0.0157	0.0162	0.0166
9 storey frame	w	-4.6076	0.0059	-4.6185	-4.6149	-4.6077	-4.5998	-4.5961
	a	0.5208	0.0079	0.5055	0.5108	0.5206	0.5311	0.5365
	b	0.4972	0.0068	0.4839	0.4884	0.4970	0.5063	0.5105
	σ^2	0.0211	0.0006	0.0198	0.0203	0.0211	0.0219	0.0224
12 Storey frame	w	-4.2935	0.0096	-4.3124	-4.3053	-4.2937	-4.2806	-4.2743
	a	0.3616	0.0098	0.3427	0.3491	0.3613	0.3743	0.3805
	b	0.6478	0.0085	0.6319	0.6370	0.6477	0.6590	0.6639
	σ^2	0.0242	0.0009	0.0225	0.0230	0.0242	0.0255	0.0260
15 Storey frame	w	-4.1439	0.0135	-4.1710	-4.1614	-4.1439	-4.1274	-4.1165
	a	0.2238	0.0117	0.2005	0.2090	0.2239	0.2380	0.2479
	b	0.7813	0.0101	0.7613	0.7686	0.7814	0.7946	0.8014
	σ^2	0.0303	0.0012	0.0279	0.0288	0.0302	0.0319	0.0326

Defined model to predict the collapse probability: $0\le P_{Collape|IM}(x)=\alpha x+\beta\le 1$

	3-Storey	6-Storey	9-Storey	12-Storey	15-Storey
α	0.381	0.051	0.076	0.121	0.311
β	-0.679	-0.061	-0.049	-0.036	-0.088



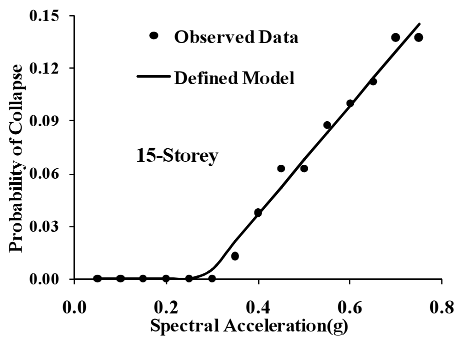


Fig. 5. Calculated probability of collapse at the given S_{a1} for 3 and 15-storey SMRFs. The solid line shows the defined collapse model in Table 4

model like follow can be used to predict the probability of collapse:

$$0 \le P_{Collape|IM}(x) = \alpha x + \beta \le 1 \tag{9}$$

In table 3, the required parameters for linear models of prediction probability of structure overall collapse have been calculated. These models are plotted in Fig. 5 along with observed data.

8. Determination of drift Hazard curves of SMRFs for territory of Tehran

The main objective of this study is to determine drift hazard curves of SMRFs in territory of Tehran. Such curves which are obtained from Eq. 1 and 2 can directly be applied to PBD framework of SMRFs. In this section, by coupling the terms calculated in previous sections, the target curves are determined. At first, by using one-parameter model No02 and considering the collapse probability, the drift hazard curves of 3, 6, 9, 12 and 15-storey frames for three different seismic zones in territory of Tehran are generated and shown in Fig. 6.

In order to study the effects of using two-parameter model instead of one-parameter on estimated demand, the drift hazard curves of 3 and 15-storey frames are calculated by using model No10 and the results along with the results of using model No2 are shown in Fig. 7. For 3-storey frame the estimated drifts by applying one and two-parameter model are almost similar in all ranges except the saturated region of curves, such results are expected because of similar standard deviation of the model No02 and the model No10. But in the case of 15-storey frame, as seen in Fig. 7, the estimated drift demands by using these two models are totally different. The main reason for such a large dissimilarity in estimated drift of 15-storey frame is the large difference in estimated standard deviations of demand models.

9. Discussion and conclusion

In this article a comparative study is carried out on spatial distribution of probabilistic drift demand estimation for steel moment-resisting frames in territory of Tehran in terms of annual frequency of exceeding, namely seismic drift hazard curve, through different demand models. In order to make the obtained curves applicable in designing steel moment-resisting frames within the framework of performance based design, generic frames have been used for the modeling of steel structures and a considerable number of ground motion records, selected based on Bin Strategy, have been applied in nonlinear dynamic analysis of structures; furthermore, a specific probabilistic seismic hazard analysis for Tehran has been done in order to compute the seismic hazard functions.

In order to determine the drift hazard curves 16 seismic demand models have been studied which were divided into 4 groups. The results show that the accuracy of first group models, where a single parameter was used as *IM* in their definitions, is a function of the number of stories. As an example the model in which the first mode spectral acceleration is used as *IM* and is considered as the best model for the estimation of seismic demand of stiff and low-rise structures such as 3 and 6-storey frames, however this model is not suitable for deformable structures such as 12 and 15-storey frames. Generally, because of variable accuracy, a certain model from this group is not recommended to estimate the drift demand for all structures with different numbers of stories. However the models of second group in which *IM* is a combination of two parameters can overcome this problem because of having standard deviation and accuracy independent of the number of stories. But it should be noted that there is no common method for seismic hazard analysis of such IM parameter and it needs a new attenuation relation which makes using of these models in PBD problematic. Third group model in which two independent IMs have been used might be the solution for this problem. The results show that in the case of selecting two proper parameters, the accuracy of these models is better than others, e.g. a model in which a linear combination of first and second mode spectral acceleration is used as *IM* has acceptable accuracy in estimation of seismic demand analysis for all frames defined in this study. But using these models required more data and calculations. Finally the fourth group of models indicates that using the earthquake parameters in estimation of seismic demand is not beneficial.

In this research, in addition to one-parameter model, a two-parameter model has been used to estimate the seismic demand. For 3-storey frame, the obtained curves are the same in both models, because their standard deviation is the same;

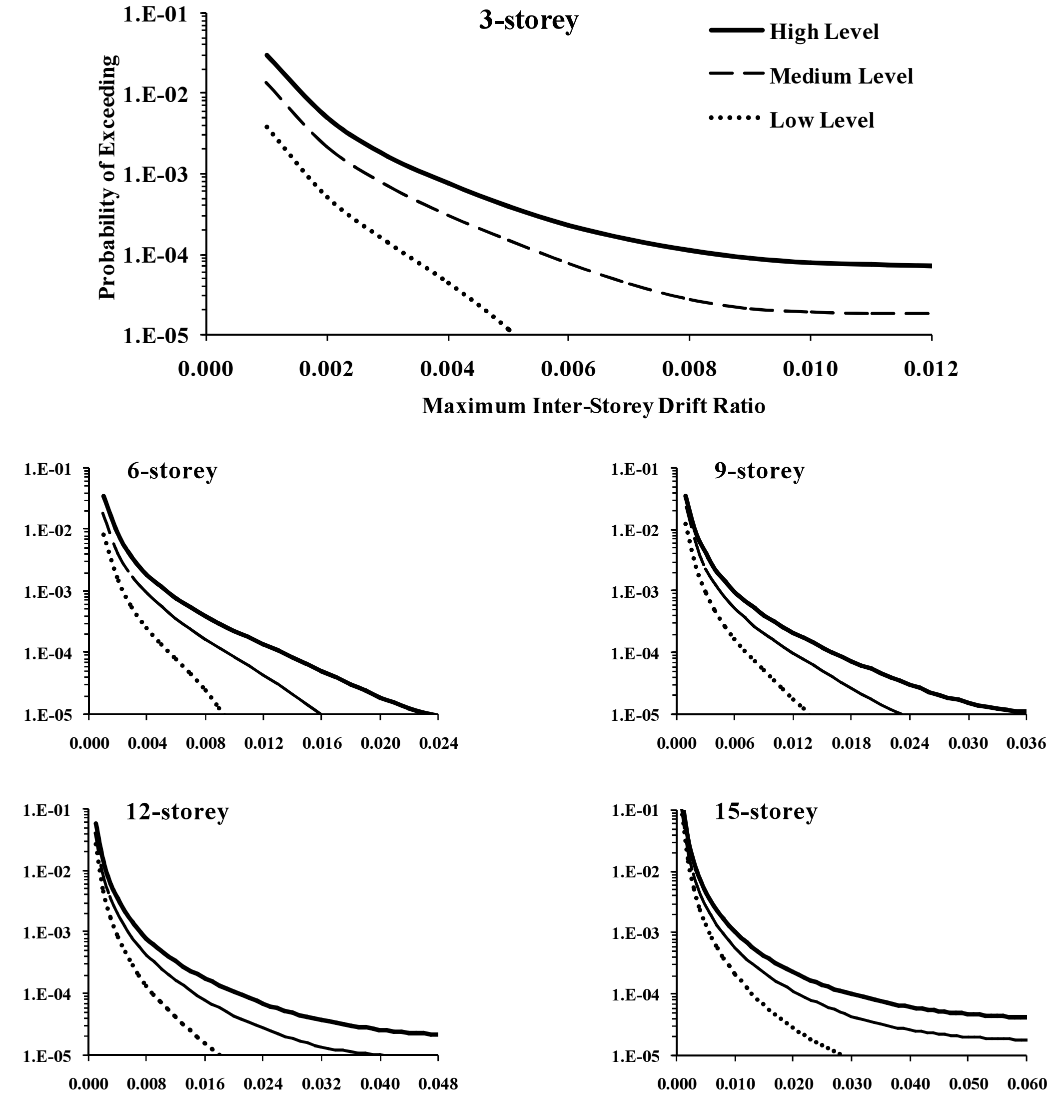


Fig.6. Determined drift hazard curves of SMRFs for territory of Tehran city in three different seismic zones, using one-parameter PSDM No02

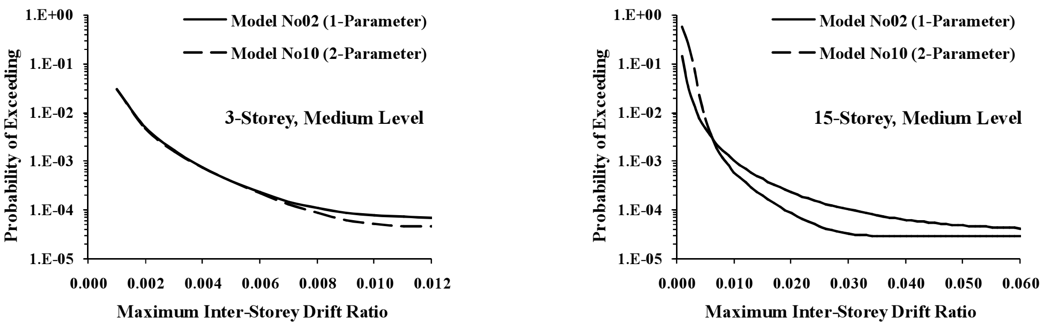


Fig. 7. Comparison of estimated seismic drift demand in 3 and 15-storey frames through using one-parameter model No02 and two-parameter model No10

however obtained curves with these two models in 15-storey frame differ significantly, because the standard deviations of these two models are totally different in this frame. This shows that regardless of the number of used IM, estimated demands strongly depend on the standard deviation of model.

Finally it should be noted that the results show the selection of seismic demand model has a great influence on the estimation of seismic demand, and considering the fact that seismic demand is itself a crucial and significant component in performance based design, it is necessary to pay much attention to the selection of applied model for different structures in performance based design.

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