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Quantify seismic reliability of steel moment frame structures with numerical procedures

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Abstract

Quantifying the reliability indices of structures under earthquake loading is traditionally considered to be challenging, especially when the nonlinear structural behaviour needs to be considered. With the increasing popularity of high-performance computer clusters, it is feasible to use detailed numerical procedures to quantify seismic safety margins of steel moment resisting frame (SMRF) structures under various sources of uncertainties. Two seismic reliability methods are used to examine the interaction of uncertainty from ground motions and intensity. One is a numerical integration procedure for the traditional method. The other is the Monte Carlo simulation. These methods produce cumulative probability distribution curves that can retain the accuracy of results from nonlinear dynamic analysis. These methods are applied to two SMRF structures to investigate their probabilistic behaviour with their uncertainties from earthquake loads and seismic weights. The global reliability indices of the structures are found to be between 2.5 and 2.1 under the maximum considered earthquake (MCE). When an MCE occurs, the conditional reliability indices of the structures range between 1.4 and 1.0. The results indicate that both methods can be used to accurately quantify the reliability of SMRF structures. The results also show that some conditional probability distributions may not be well-represented by simple equations with their parameters calibrated from data-fitting techniques. The results also prove that the discussed methods and numerical procedures can be further used to accurately quantify probabilistic seismic behaviour of other structures toward the community resilience.

Keywords: steel moment frames, seismic reliability analysis, seismic probability analysis, Monte Carlo method, parallel computing, seismic risk analysis

1. Introduction

Economic losses, injuries and casualties resulted from damaged and collapsed structures have been reported after many earthquakes, such as the 1994 Northridge earthquake, the 1995 Kobe earthquake and the 2011 Christchurch earthquake. Mitigating these losses and damages from earthquakes is a primary goal to build earthquake resilient communities. In order to quantify the losses and damages caused to buildings and other structures, predicting and quantifying seismic behaviour of structures is essential. Seismic behaviour of structures is nonlinear and related to many factors, such as structural configurations, material properties, occupancy loads, earthquake hazards and incomplete knowledge of the system. Since these factors have their own sources of uncertainties, seismic behaviour of structures is probabilistic in nature.

Accurately quantifying probabilistic seismic behaviour of structures provides designers and stakeholders with insights toward strategies to build safer structures and better mitigate damages and losses in future events. In the past decade, many research works have been done to

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Nomenclature

CDF	cumulative distribution function	MCE	maximum considered earthquake
HPCs	high-performance computer clusters	MCS	Monte Carlo simulation
IDA	incremental dynamic analysis	NDA	nonlinear dynamic analysis
IM	intensity measure	SDC	seismic design category
LA3	three-story building (Los Angeles)	SF2	secondary scaling factor
LA9	nine-story building (Los Angeles)	SMRF	steel moment resisting frame

examine probabilistic seismic behaviour of structures. In [24], Yun and Li reported a performance prediction and evaluation procedure based on nonlinear dynamics and reliability theory for steel moment resisting frame (SMRF) structures. Their work presented a method that calculates the probability of exceedance using the weighted summation of conditional probability distribution curves given the earthquake intensity [2]. In [20], Ribeiro et al. used this method to examine the performance of steel moment frame structures. Kazantzi et al. [10] evaluated a four-story SMRF building with a numerical model using the Monte Carlo simulation (MCS) with Latin hypercube sampling. Their work also studied the comparison of interstory drift obtained with and without the consideration of model parameter uncertainties. In [13], Li et al. investigated the collapse probability of a mainshock-damaged four-story SMRF building in aftershocks, as an essential part of developing a framework to integrate aftershock seismic hazard into performance-based engineering. Liu et al. [16] investigated a four-story three-bay SMRF to demonstrate their proposed performance based on robust design optimisation with the consideration of cost, seismic demand, performance objectives and ground motion variability. In [3], Fayaz and Zareian assessed the effect of the vertical component of ground motions on SMRF structures and evaluated the current seismic design provisions of ASCE 7 on the basis of structural reliability analysis. Mosallam et al. presented a probabilistic study [17] using the fragility function method for the performance assessment of two moment-resisting frame structures representing rigid and flexible frame structures considering the impact of the uncertainties in seismic loading and response of structures. They concluded that the adopted fragility method can serve as an effective tool for assessing the performance and safety levels of structures, and in decision making as well as financing for seismic protection. In [12], Lachanas and Vamvatsikos quantified the model-type uncertainty for a modern steel moment-resisting frame building considering different types of geometrical features. They concluded that the uncertainty stemming from 3D and distributed plasticity models is lower than the governing record-to-record variability.

With the recently developed numerical procedures of seismic reliability methods and the wide application of high-performance computer clusters (HPCs), seismic reliability analysis can be performed numerically for SMRF structures with sophisticated modelling details. With the numerical procedures, the probabilistic seismic behaviour of these buildings can be accurately quantified to examine essential factors and other assumptions used in previous studies. In this study, two post-Northridge SMRF buildings are used as examples, including one three-story and one nine-story buildings. In order to capture the accuracy of results from nonlinear dynamic analysis (NDA) for probabilistic analysis, two seismic reliability methods with their numerical procedures are discussed. One is the traditional method developed by the SAC steel moment frame project [2], with its numerical integration format. The other is to directly use MCS to produce the cumulative probability distribution, without any intermediate calculation from data-fitting techniques for probability distribution models. The examples show the feasibility to apply the numerical procedures of the reliability methods to the prediction of probabilistic seismic behaviour of SMRF structures with sophisticated modelling details. The results of the analysis can be further used to perform sensitivity analysis for different parameters and configurations. The methods and procedures in this paper can be extended to calibrate seismic design provisions toward the disaster resilient built environment in their design lifecycle.

2. Structural configurations and model

Two special SMRF buildings developed as a part of the SAC steel project [4, 5, 8] are investigated for their probabilistic behaviour under earthquake loading. The three- and nine-story frames (denoted as LA3 and LA 9 in this study, respectively) were designed following the code requirements for Los Angeles by using the post-Northridge design with reduced beam sections (RBS). The failure of buildings following the post-Northridge design is very ductile and may be well-represented by drift demand. Both buildings have a grid spacing of 9.14 m and typical story height of 3.96 m, except for the basement and ground floor of the LA9. The details for RBS connections are discussed in FEMA 355D [12] and the background documents [11, 21].

A two-dimensional frame analysis in one direction of the buildings is conducted. One additional bay of P-Delta leaning columns is used to investigate the geometrical nonlinearity from gravity columns. The models incorporate panel zones (Model M2) with shear strength and stiffness as illustrated in the original documents [4, 8]. The open source software, OpenSees [18], is used in this work to develop the frame analysis models. The panel zones are modelled with rigid boundaries. The columns and beams are modelled with elastic elements with large strength and stiffness over their clear span length. It is reported that the models with panel zones are more realistic than a bare frame model [9]. The energy dissipation system relies on plastic hinges, which are modelled with zero-length rotational springs placed away from the face of the panel zones. The modified Ibarra-Krawinkler deterioration model with bilinear hysteretic response [9, 15], "Bilin" in OpenSees, is used to simulate the plastic hinges. All hinges are assumed to have 3 % of strain hardening. Seismic masses and gravity loads are applied to the joints adjacent to the panel zones. A viscous damping of 2 % is assigned to the first mode and the mode at a period of 0.2 s, as specified in FEMA 355C [4]. The results of modal analysis from OpenSees of this work (Table 1) match the data published in the original work [10] with the results obtained from DRAIN-2DX [19]. With the structural models, drift demands are recorded from NDA and subsequently used for probability analysis.

Table 1. Results of modal analysis

		1st mode	2nd mode	3rd mode
LA3	OpenSees	1.02 s	0.31 s	0.19 s
	DRAIN-2DX	1.02 s	0.30 s	0.14 s
LA9	OpenSees	2.23 s	0.84 s	0.47 s
	DRAIN-2DX	2.21 s	0.82 s	0.46 s

3. Reliability methods

3.1. Traditional reliability method

Structural dynamic response under extreme seismic loading is typically nonlinear, which needs to be predicted using numerical methods, such as the finite element method. Since seismic demands are nonlinear functions of many factors, the random variable for any structural demand follows a multivariate probability distribution for all related factors over the integration domain defined by the limit states. Examining probabilistic behaviour of structures under earthquake loading has to examine the sources of uncertainties from essential factors, especially for earthquake loading. Two methods are discussed here to study seismic probabilistic behaviour from these sources of uncertainties.

The traditional method developed by the Pacific Earthquake Engineering Research Center determines the probability of exceedance from the weighted summation of conditional distributions given the intensity measure

$$F_D(d) = P(D \leq d) \approx \int_0^\infty P\Big[D(a) \leq d \,|\, IM = x\Big] f_{IM}(x)\,\mathrm{d}x, \tag{1}$$

where $P[D(a) \leq d\,|IM = x]$ is the conditional cumulative distribution function (CDF) of demand D not exceeding the value d, given the intensity measure (IM) of $IM = x$, a is the vector for all sources of uncertainties other than ground motions and intensity measure, and f_{IM} is the probability density function of the intensity measure. Unless noted otherwise, capital letters in all equations refer to random variables.

This method is commonly used to derive a set of simplified algebraic equations to express probabilistic behaviour. These algebraic equations use a mean value and dispersion to characterise the probabilistic nature of involved random variables. The use of the mean and the dispersion for related distributions simplifies the process of analysing the complicated probabilistic behaviour under seismic loading. However, extracting the parameters of the mean and the dispersion relies on data-fitting techniques applied to the results from incremental dynamic analysis (IDA) [22]. The accuracy of the fitted parameters depends on whether the chosen probability distribution can accurately represent the demand or capacity measure under consideration. In order to improve the accuracy for the probability analysis, a numerical integration procedure is introduced to solve the probabilistic behaviour expressed as

$$F_D(d) \approx \sum_{i=1}^{M} P\Big[D(a) \leq d \,\Big|\, IM = x_i\Big] f_{IM}(x_i)\,\Delta x_i\,, \tag{2}$$

where M is the total number of intensity levels for numerical calculation. This equation can be used to directly produce the probability distribution of demand, with which the probability of structural failure can be evaluated. The conditional probability of exceedance of drift demand, $P[D(a) \leq d\,|IM = x_i]$, describes the uncertainty from material properties and ground motions. This distribution can be generated by ranking drift demands at certain intensity, $IM = x_i$, as shown in the fragility analysis. Using the numerical procedure expressed in (2) to directly perform reliability analysis does not involve any data-fitting technique, which retains the accuracy of results from IDA. The accuracy of results from these equations only depends on the sample number and sampling techniques for related random variables, and it is independent of their certain distribution types or their intermediate numerical calculations [7].

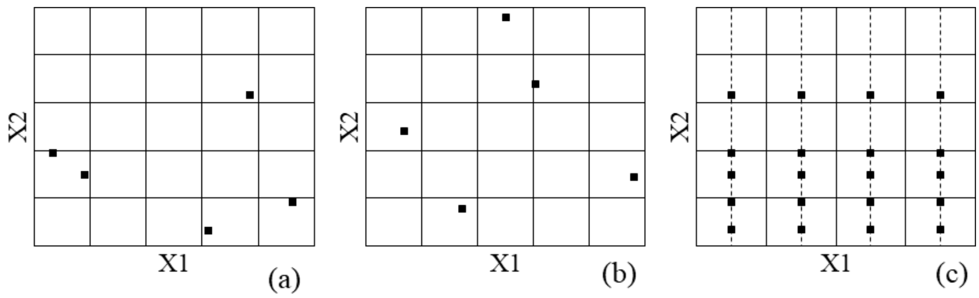


Fig. 1. Generation of samples for intensity measure

3.2. *Monte Carlo simulation*

In view of structural response under any loads, the demand of a structure is a function $[g(\cdot)]$ of the intensity (im), ground motions (r) and other sources of uncertainty (a). This function is determined by the dynamic analysis. In view of probability theories, the selected ground motion records can be treated to follow a special distribution. Each record is a natural sample representing the ground motion characteristics, although the boundary of the characteristics is unknown. Considering that the distribution of these variables can be defined with statistical data, the drift demand follows a joint multivariate distribution of material and geometrical properties, motions and intensity. If more uncertainty sources are considered, the joint distribution will have more random variables. The joint distribution of the demand may not have any closed form solution because the results of demand data are discrete as they are typically calculated from nonlinear structural analysis. It would be practical to solve this equation using numerical procedures, such as MCS.

Although MCS has been used by the fragility analysis, directly using MCS in seismic reliability analysis is established on the nature of ground motions and related sampling strategies. In the traditional MCS, samples are generated from pseudo random numbers as illustrated in Fig. 1a, with two random variables X1 and X2 shown. This method may not be computationally efficient as the sample size has to be great enough. In order to improve the efficiency of simulation, the Latin hypercube sampling (LHS) technique [14] may be employed (Fig. 1b). For both the traditional MCS and LHS techniques, the random variables must be able to be expressed in mathematical equations, so that the samples can be determined from their corresponding distribution functions. In seismic reliability analysis, it is implicitly assumed that all selected motions contribute equally to the uncertainty of seismic demands. In the view of probability analysis, ground motions are discrete samples in their representing ground vibrational characteristics. Therefore, these discrete samples should be viewed as grid samples. The grid samples have their implied probability values, as illustrated by the variable X1 in Fig. 1c, in which X2 is the same with that in Fig. 1a. Compared with commonly used random variables, the selected motions are natural samples. Such samples do not need to and cannot be calculated from their inverse functions. In order to combine this special random variable with other variables, the scheme in Fig. 1c illustrates the sampling process.

3.3. *Ground motions and scaling method*

A set of 22 ordinary earthquake ground motions by FEMA P695 [6] is used as the input for NDA. These ground motion records are scaled to multiple levels of IM using a scaling method to account for the variation of earthquake loads. The scaling process has three steps: i) the normalisation, ii) the basic scaling, and iii) the secondary scaling. The first two steps are defined by FEMA P695. During the normalisation, all records are scaled to their median peak ground velocity. In the second step, all records are scaled to have a median spectral acceleration (S_a) to match the targeted spectral acceleration for the maximum considered earthquake (MCE) at the fundamental period. With the second step, the ground motion records are scaled to a deterministic level of intensity. To ensure a probabilistic analysis, the targeted intensity level should not be deterministic. The third step, the scaling factor for the second scaling (SF2) is used to consider the uncertainty of intensity measure for reliability analysis with the SF2 scaling factors dependent on the selected distribution types as discussed below.

3.4. Other sources of uncertainties and their distributions

The annual occurrence probability of intensity $H(S_a)$ is traditionally assumed to be linear on a log-log plot and given as [2]

$$H(S_a) = cS_a^{-b}. \tag{3}$$

Based on previous research [2, 6, 13], the parameters b and c are chosen to be 3.2 and 0.014 4, respectively. These numbers correspond to the median peak spectral acceleration of normalised records. With these parameters, SF2 is defined as the ratio of a sample for the distribution to the median spectral acceleration for the Seismic Design Category (SDC) of $D_{\max}$ as defined in FEMA P695. This case is referred to as the ”extreme distribution” in the following discussion.

There is no doubt that this type of distributions is reasonable to describe the occurrence probability of earthquakes for earth scientists. In terms of construction practice, most structures, if not all, have been designed or proved to resist certain levels of earthquakes. Engineers, owners and stakeholders may not be interested in the consequence of small earthquakes to structures. Rather, they may be more interested in the consequence of reasonably large earthquakes within the life period of structures. Their concerns to the performance at targeted intensity levels may be described by this question: ”What are the consequences if a 7.0-magnitude earthquake hits this region?” If the 7.0-magnitude earthquake is a fixed value, the problem becomes a fragility analysis. Reliability analysis targeted at certain intensity levels with their uncertainties may provide much information for disaster prediction and mitigation.

In terms of reliability analysis, the extreme distributions produce many samples at low intensity levels. The engineering demand measures calculated from these low-intensity samples may not exceed the threshold that contributes to damages or failure probabilities. Samples near targeted design intensity levels may be scarce but useful for analysis. In order to address the concerns of users of construction practice and reliability analysis, the log-normal or other distributions with a mean or median near the targeted intensity levels may be employed. Such distribution types not only address the concerns about the risk conditioned on existing knowledge, but also allow samples concentrating around the targeted intensity level for reliability analysis. The variation for IM is used to consider the aleatoric and epistemic uncertainties associated with the targeted earthquake level. The probabilistic analysis conducted with this type of distribution may be viewed as an extension of the fragility analysis. In this paper, a log-normal distribution is used with the mean value set to the median spectral acceleration at the fundamental period for the SDC of $D_{\max}$ in FEMA P695. The coefficient of variation (COV) is set to 0.3, which is chosen with the reference to typical live loads. This case is referred to as the ”log-normal distribution”. The results from this distribution are cited as the conditional probability of failure or the conditional reliability index in the following discussion.

Some other sources of uncertainties are also important. As an example of applications using the discussed numerical procedures, only the effect of seismic weights is considered here.

A log-normal distribution with a COV of 0.1 is assumed for seismic weights of all floors and roofs. This distribution avoids near-zero or negative samples for seismic weights. It is noted that the floor assembly for one building is commonly identical or similar for all floors. The materials for all floors are, therefore, assumed to come from the same suppliers or perhaps even the same shipment. Thus, it would be reasonable to assume that seismic weights at different floor levels are highly correlated. It is practical and reasonable to assume the correlation coefficients between any two floors as unity. Two types of analysis are conducted, one considering the uncertainty from seismic weights and the other without. When the uncertainty of seismic weights is considered, each NDA requires three types of random samples including one for ground motions, one for intensity levels and one for seismic weights. As the samples for ground motions are viewed as special nature ones (represented by the variable X1 in Fig. 1c), only two other types of samples need to be generated, both of which are represented by the variable X2 in Fig. 1c. Strictly speaking, the variable X2 is a vector with two random variables for both intensity levels and seismic weights together. Thus, Fig. 1c has been effectively expanded to a three-dimensional case. When the uncertainty of seismic weights is not considered, each NDA only requires two random samples including one for ground motions represented by the variable X1 in Fig. 1c, and the other for intensity levels represented by the variable X2 in Fig. 1c.

3.5. Parallel computing using high performance clusters

Using the discrete format of the traditional method or MCS requires repeatable NDA. These repeatable calculations are for the same system with different vector inputs to consider their uncertainty sources. On one hand, the process of each NDA is performed step by step in the time domain. In each time step, the iteration to achieve the convergence involves some algorithms, such as the Newton-Raphson method. All these iteration steps are to be performed in a serial manner, the order of which cannot be alternated easily. Therefore, each NDA is in a sequence-based calculation, the efficiency of which is primarily dominated by the speed of the processor. The parallel computing technology may not be directly applied to speed up the computational process for typical individual NDA. On the other hand, all NDA are independent from one another, every one of which does not need any communication with other NDA during their execution. Since only the peak demand measure are needed for probabilistic analysis, the demand for information sharing and communication within different NDA is minimised. Therefore, these NDA can be viewed as parallel and easily executed by different processors on any parallel computing system, regardless of whether the computer processors are located locally or remotely. The parallel version of OpenSees streamlines the communication process among multiple processors over the network in a convenient way, so that structural engineers can focus on structural modelling, rather than on the network of the clusters. In this work, OpenSees are executed on three HPCs with a maximum allocation of 450 processors each.

4. Results and discussions

4.1. Results from the traditional method for LA3

With the combination of samples from records, IM and seismic weights, IDA can be performed. Since multiple levels of seismic weights are used in the analysis corresponding to the same intensity level, the results of IDA may not be easily expressed and fairly compared as traditional IDA curves that are only for a single source of uncertainty, i.e., records. Therefore, the analysis results are normalised as conditional distributions, see Fig. 2. In this figure, each curve is a

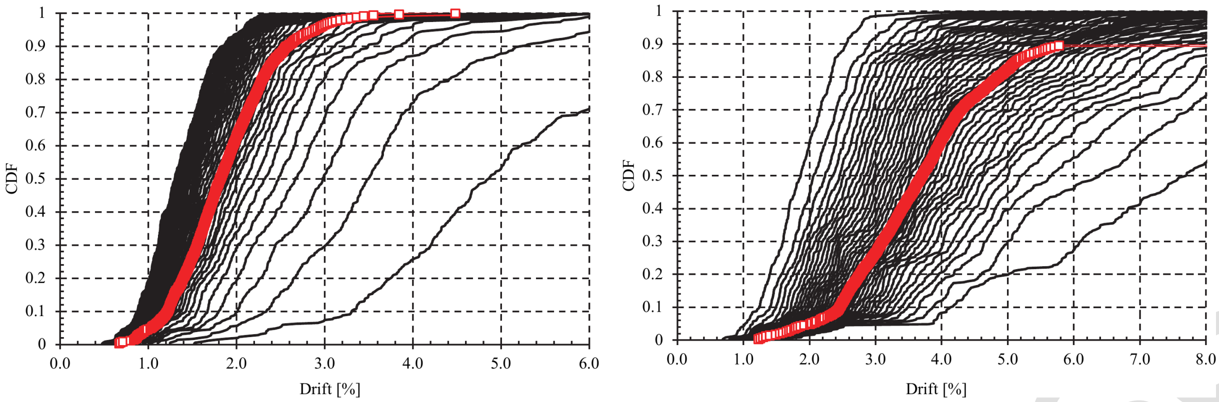


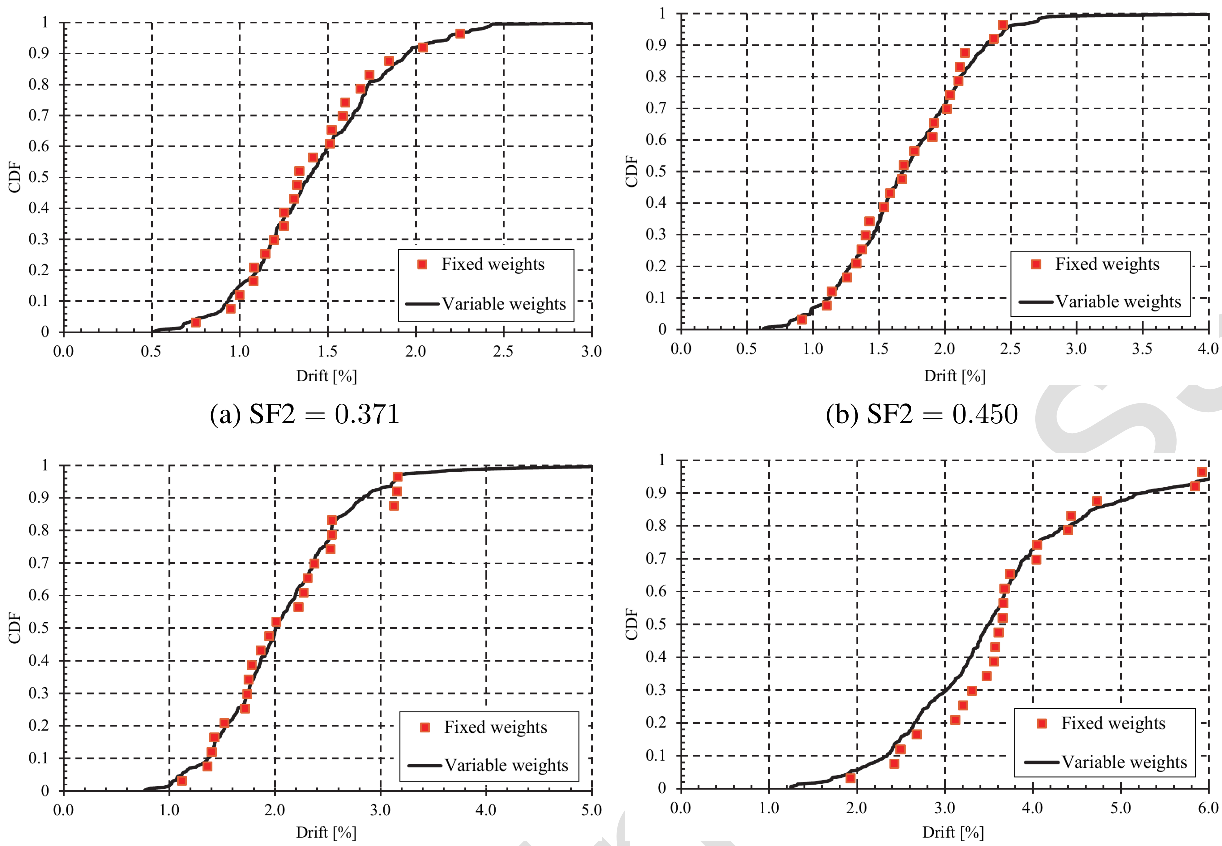
Fig. 2. All conditional distributions of LA3 for IM following (*left*) the extreme distribution and (*right*) the log-normal distribution

conditional cumulative probability distribution for the traditional method given by (2) at one level of IM with their uncertainties from records and seismic weights.

Since IM with a log-normal distribution used in the analysis represents earthquakes greater than that of the extreme distribution, the demand for the log-normal distribution in Fig. 2 (right) is greater than that of the extreme distribution in Fig. 2 (left). This figure also shows that a few curves are overlapped in the left portion, while the curves in Fig. 2 (right) spread over the entire region. This observation indicates that many samples at lower intensity levels are generated only for the extreme distribution. The relatively steep slope of the curves within this overlapped region indicates the structural response is not very sensitive to the variation from records and seismic weights.

In order to further examine the results, four conditional distributions for the intensity following the extreme distribution are shown in Fig. 3. They represent four levels of IM resulting from different secondary scaling factors (SF2). The curve for ”fixed weights” means a result curve for seismic weight without considering the uncertainty for weights. In this case, no variation for seismic weights is considered. This curve has 22 squares, each of which represents one record. This curve is similar to the traditional IDA curve, except with the CDF as the ordinate. The curve for ”variable weights” means that the result curve has considered the uncertainty from seismic weights. In this case, the seismic weight of each floor is correlated with the correlation coefficient of 1.0. In different NDA, these seismic weights may be different, as they are random samples following the probability distribution of the seismic weight as discussed above. The curves for fixed weights generally match those for variable weights well, which indicates that the uncertainty in seismic weights does not appear to contribute much to the results of probability analysis at low intensity levels. However, Fig. 3d shows that the uncertainty in seismic weights does influence the resulted distribution curve at high intensity levels. This observation may be explained by the fact that significant structural nonlinearity at high intensity levels ”amplifies” the variation of seismic weights.

As a further illustration of Fig. 2 (right), four conditional distributions for IM following the log-normal distribution are shown in Fig. 4. This figure further confirms that the uncertainty from seismic weights does not affect the results significantly at their low intensity levels. It is also noted that the curves in this figure are not as smooth as those in Fig. 3. Considering that the major difference between the assumptions of the two figures is the secondary scaling factor, one can conclude that, at high intensity levels, the probabilistic behaviour appears to be affected



(a) SF2 $= 0.371$ (b) SF2 $= 0.450$

(c) SF2 $= 0.554$ (d) SF2 $= 0.952$

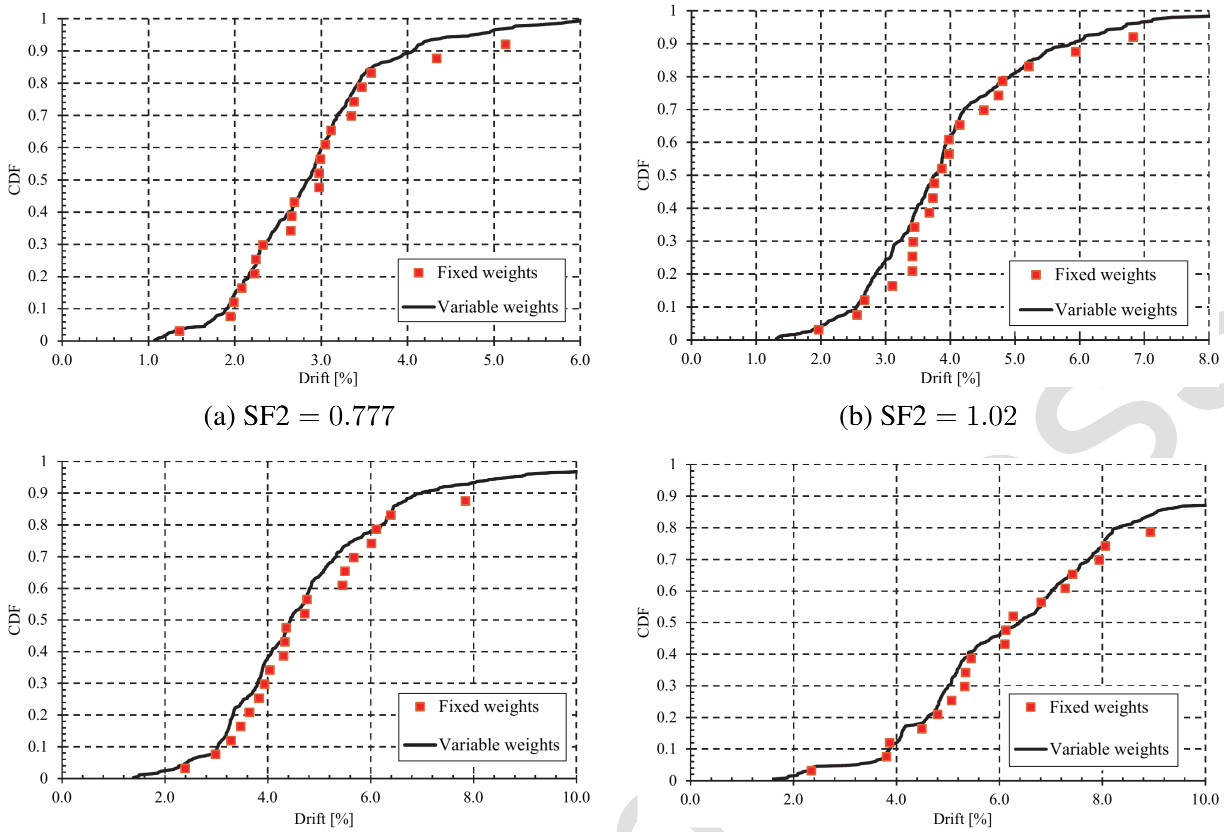
Fig. 3. Some conditional distributions of LA3 for IM following the extreme distribution

much by seismic weights. The shape of some curves at high intensity levels, such as in Fig. 4d, is zigzagged, which indicates that CDF may not be fitted well with a normal or log-normal distribution. With this type of CDF, a numerical procedure may be suitable to obtain accurate results of the probability of exceedance.

With these conditional probability distributions, the probability of structural failure under the extreme distribution and the conditional probability of failure under the log-normal distribution is evaluated using the weighted summation, as shown in (2). The results are presented in Table 2. The second row of this table shows the inter-story drift capacity. The inter-story drift capacity of 2.5 % is chosen from ASCE 7 [1] and the 6.3 % is chosen from FEMA P695. The numbers in the brackets are reliability indices or conditional reliability indices, defined as $\Phi^{-1}(1 - P_f)$, where $\Phi(\cdot)$ is the standard normal distribution. For the extreme distribution, the probability exceeding the drift capacity of 2.5 % and 6.3 % is 14.6 % and 0.78 %, respectively. For the log-normal distribution, the conditional probability of exceedance is 76.7 % and 16.5 %, respectively.

4.2. *Results from MCS for LA3*

MCS generates a CDF of drift demand, as shown in Fig. 5. In this figure, the term ”extreme” refers to the extreme distribution while the term ”log-normal” refers to the log-normal distribution. The CDF curves for ”variable weights” incorporate uncertainties from IM and seismic weights. It can be observed that both types of curves are very close, except for some difference at the tails.



(a) SF2 = 0.777 (b) SF2 = 1.02

(c) SF2 = 1.21 (d) SF2 = 1.62

Fig. 4. Some conditional distributions of LA3 for IM following the log-normal distribution

CDF in Fig. 5 can be used to determine the probability of exceedance for any drift capacity directly. The results are also listed in Table 2. The results from two MCS curves with and without the uncertainty from seismic weights are slightly different. The drift capacity of 2.5 % appears to be very stringent, as the corresponding probability of exceedance for the extreme and log-normal distributions ranges about 13–15 % and 76–78 %, respectively. This can be explained by that this drift capacity is for life safety rather than for collapse prevention. With the drift capacity of 6.3 %, the probability of exceedance for the extreme distribution is less than 1 % while the probability for the log-normal distribution is about 8–10 %. Considering that the

Table 2. The probability of failure and the conditional probability of failure for LA3

	Probability of failure under the extreme distribution		Conditional probability of failure under the log-normal distribution	
	2.5 %	6.3 %	2.5 %	6.3 %
Traditional method	14.6 % (1.06)	0.780 % (2.42)	76.7 % (−0.729)	10.5 % (1.26)
MCS (fixed weights)	13.4 % (1.11)	0.671 % (2.47)	77.6 % (−0.733)	8.46 % (1.38)
MCS (variable weights)	14.6 % (1.06)	0.766 % (2.42)	76.8 % (−0.733)	10.5 % (1.25)

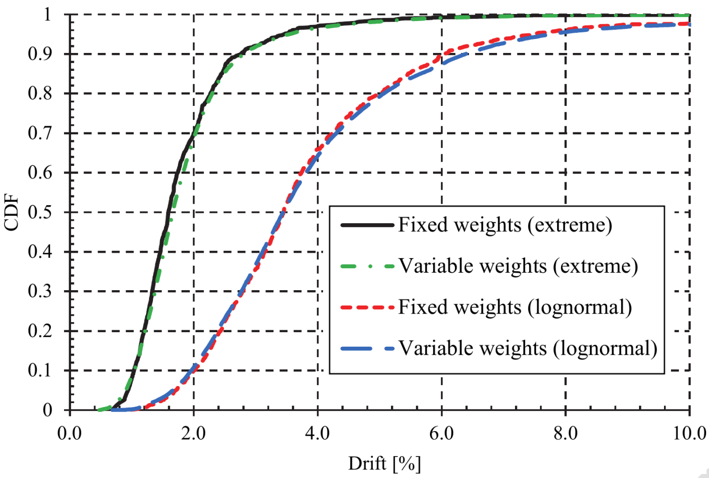


Fig. 5. Probability distributions of LA3 from MCS

MCE of SDC $D_{\max}$ is for extreme events, the probability of failure at 8–10 % may be judged to be acceptable. Therefore, the drift capacity of 6.3 % appears to be acceptable for this SMRF building.

4.3. *Results from both methods for LA9*

The conditional distribution curves used by the traditional method for LA 9 are shown in Fig. 6. Similar to the results for LA3, the conditional distribution curves for the extreme distribution of the intensity are concentrated around the lower region. Several conditional distribution curves are shown in Figs. 7 and 8. The shapes of some curves appear to be zigzagged. Some curves, such as in Figs. 8c–d, tend to have two distinct regions: the region at the lower and intermediate portion, and the region at the upper tail. It is difficult to fit these curves with normal or log-normal distributions. The CDF curves obtained from MCS are shown in Fig. 9. The probability of failure under the extreme distribution and the conditional probability of failure under the log-normal distribution exceeding the drift capacity of 2.5 % and 6.3 % are listed in Table 3.

Overall, the results for LA9 have similar features with those for LA3, except that LA9 has larger drift demand. These results further confirm some observations obtained from LA3. The probability of LA9 exceeding 6.3 % for the extreme distribution ranges between 1–2 %.

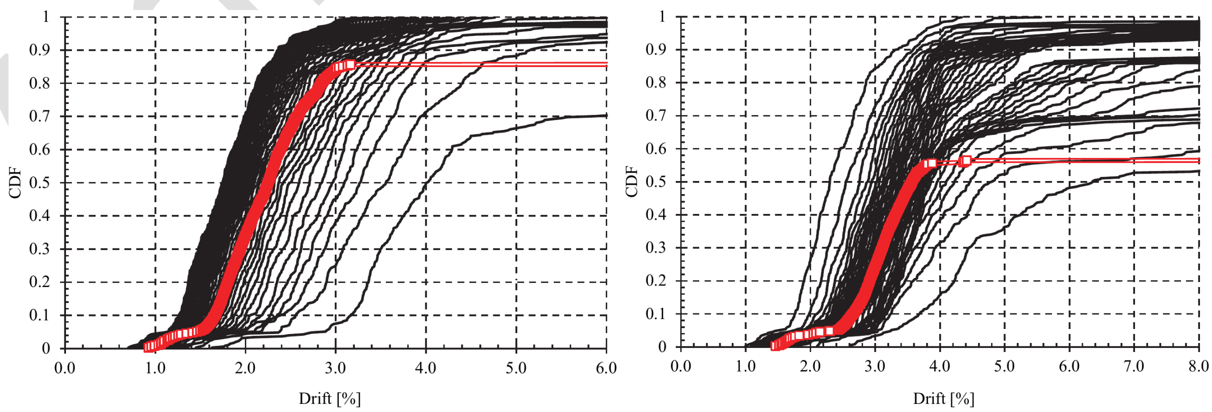
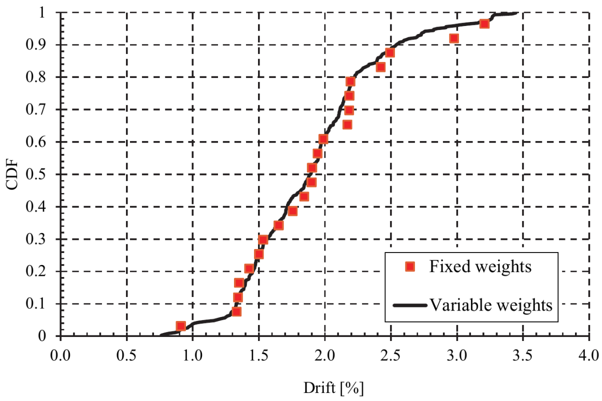
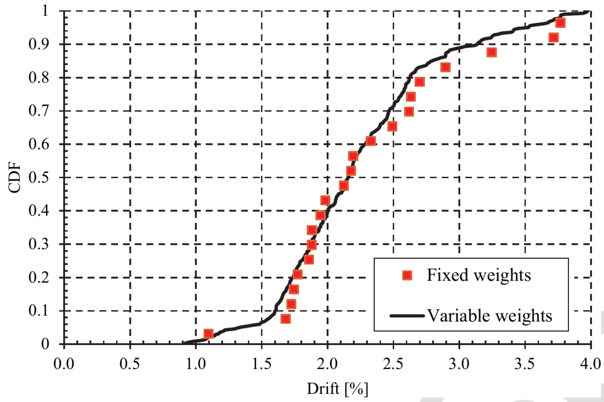


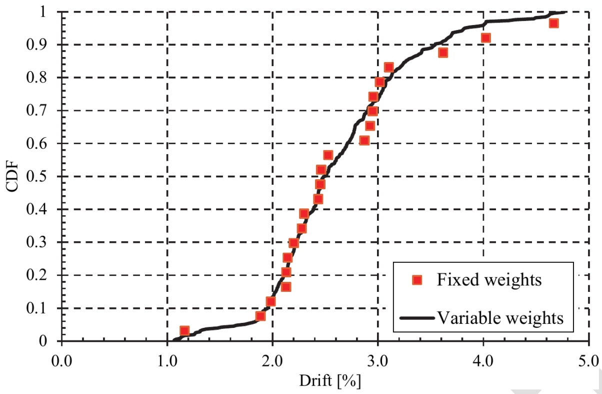
Fig. 6. All conditional distributions of LA9 for IM following (*left*) the extreme distribution and (*right*) the log-normal distribution



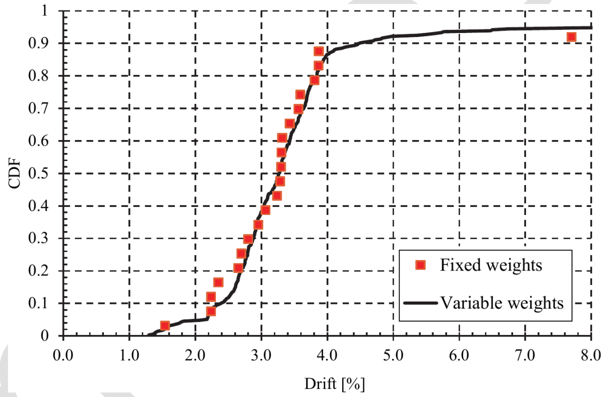
(a) SF2 $= 0.371$



(b) SF2 $= 0.450$



(c) SF2 $= 0.554$



(d) SF2 $= 0.952$

Fig. 7. Some conditional distributions of LA9 for IM following the extreme distribution

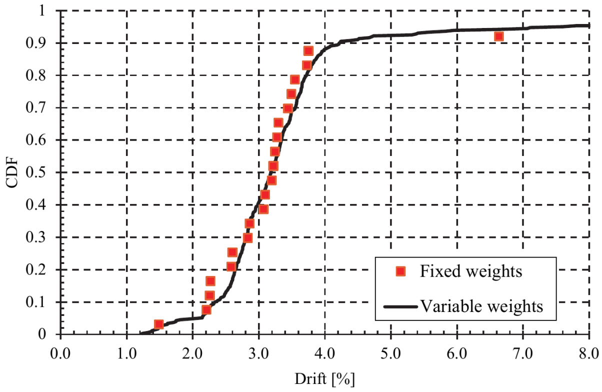
The conditional probability of LA9 exceeding the drift capacity of 6.3 % for the log-normal distribution is about 13–15 %. Under some large events, this conditional probability of failure may be judged to be acceptable for ductile systems such as the considered SMRF building.

4.4. *Discussion of results*

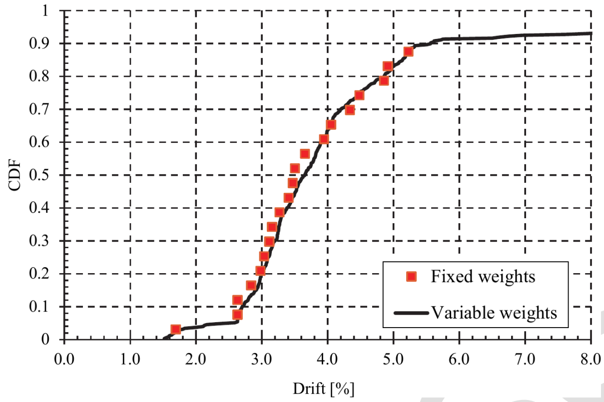
Seismic reliability analysis is performed to investigate the interaction between ground motions and intensity as well as the uncertainty from seismic weights. The results from LA3 and LA9

Table 3. The probability of failure and the conditional probability of failure for LA9

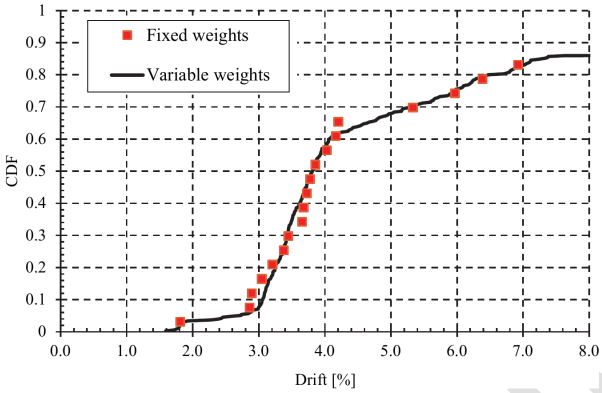
	Probability of failure under the extreme distribution		Conditional probability of failure under the log-normal distribution	
	2.5 %	6.3 %	2.5 %	6.3 %
Traditional method	32.4 % (0.456)	1.32 % (2.22)	88.4 % (– 1.19)	13.4 % (1.11)
MCS (fixed weights)	33.7 % (0.420)	1.63 % (2.14)	86.3 % (– 1.10)	14.6 % (1.05)
MCS (variable weights)	32.5 % (0.454)	1.32 % (2.22)	88.6 % (– 1.20)	13.4 % (1.11)



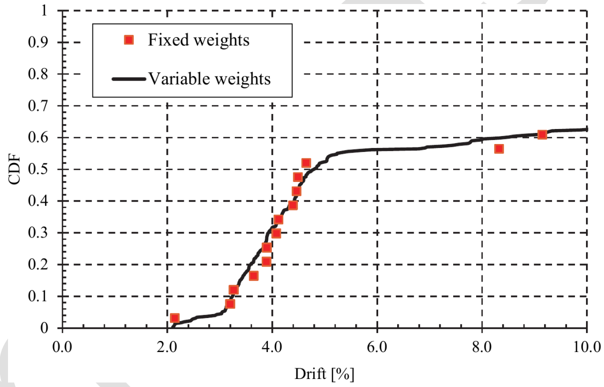
(a) SF2 = 0.777



(b) SF2 = 1.02



(c) SF2 = 1.21



(d) SF2 = 1.62

Fig. 8. Some conditional distributions of LA9 for IM following the log-normal distribution

come from numerical procedures that retain the accuracy from nonlinear structural analysis. These results enable us to investigate the details of seismic reliability analysis. The traditional method determines the failure probability from the summation of conditional distributions from ground motions. As the number of ground motions is typically limited, some errors to the conditional failure probability are likely caused by the limited number of data points, as shown in Figs. 3, 4, 7 and 8. Some of these figures are truncated for the comparison with the results

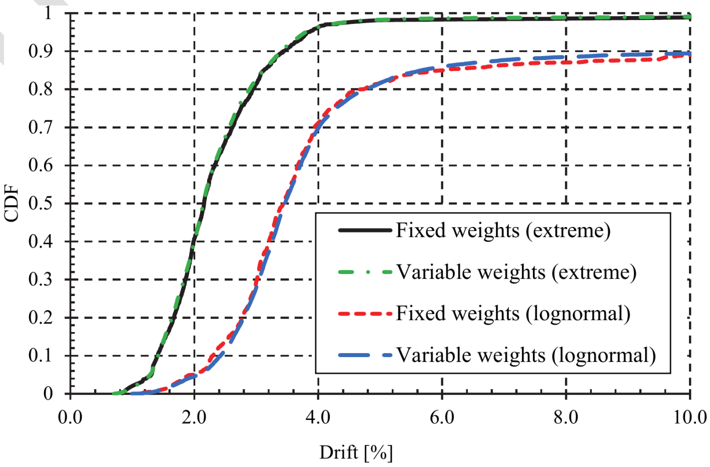


Fig. 9. Probability distributions of LA3 from MCS

of LA3. These errors are likely propagated to and accumulated in the final results of the failure probability in (2). Meanwhile, the failure probability with MCS is directly determined from the ranked results with the interaction between ground motions and intensity. Therefore, the results with MCS are expected to be relatively accurate.

The effect of seismic weights to the final results of the probability of failure does not appear to be significant in general. However, some conditional distribution curves show that seismic weights do affect the results. This observation can also be seen from the results of MCS (Figs. 5 and 9), especially at the tail of the distribution curves. It can be explained by structural nonlinearity from plastic hinges and P-Delta effect that amplifies the uncertainty from seismic weights. It also implies that the reliability of certain other structures with significant nonlinearity could be affected by the uncertainty of seismic weights for large events.

The conditional probability distributions from the traditional method and the CDF from MCS appear to have various shapes, some of which may not be fitted well with common distribution types used in engineering analysis, such as the normal or log-normal distribution. Therefore, using algebra-based equations with their parameters calibrated from data-fitting techniques may not produce accurate results. It would be reliable to use the numerical procedures to determine the probability of failure. Although the numerical procedures may need more NDA compared to traditional analysis, the additional computational demand can be alleviated by the use of advanced computing technology, such as HPCs.

It can be seen from Tables 2–3 that the conditional probability exceeding the drift capacity of 2.5 % for log-normal distributions appears to be greater than 75 %. This large conditional failure probability indicates that the 2.5% drift capacity is only for the purpose of reference and may not be suitable to investigate collapse prevention. For the studied sample buildings, the drift capacity of 6.3 % appears to be reasonable, as the drift is used as the demand measure to study collapse safety. With the extreme distribution for IM, the calculated probability of failure is between 0.67 % and 1.7 %, corresponding to the reliability indices of 2.5 to 2.1. This result is interpreted as the global reliability of structures. As the occurrence probability of extreme earthquake events is very low, this level of probability of failure can be judged to be sound considering the tremendous cost to increase the capacity for earthquake design of such structures. With the log-normal distribution, the calculated probability of failure ranges between 8 % and 15 %, equivalent to the reliability indices of 1.4 to 1.0. This result is interpreted as the conditional reliability of structures when MCE occurs. Although these reliability indices appear to be lower, they should be interpreted as the safety margin at the targeted design earthquake, i.e., MCE, with its uncertainty associated with design intensity levels. It should be mentioned that these results are based on two frame buildings with the intensity measure of spectral acceleration scaled at the fundamental period.

5. Conclusions

Accurately quantifying seismic reliability of SMRF structures needs to incorporate the results from nonlinear structural dynamic analysis with seismic reliability methods and their numerical procedures. This paper presents the application of two seismic reliability methods, the traditional method and MCS. In order to capture the accuracy of results from NDA, numerical procedures of these methods are introduced to quantify the probability of failure. A novel application of these methods is to quantify seismic reliability with numerical procedures, which can provide accurate information toward safe structures. These methods can also be used to perform sensitivity analysis of various factors. The uncertainties from intensity, ground motions, and seismic weights are calculated for their contribution to seismic probabilistic behaviour of the buildings. The random variables are sampled and combined to generate vector inputs, which are fed to structural models for NDA on clusters. One three-story and one nine-story SMRF building are used as archetype buildings with the consideration of plastic hinges and panel zones. Peak drift demands of dynamic analysis from the structural models are extracted for seismic reliability analysis.

The results of reliability analysis indicate that both the traditional method and MCS can be used to numerically evaluate the reliability of structures. The results also indicate the probability of failure of the structures ranges between 0.67 % and 1.7 % for MCE (or reliability indices of 2.5 and 2.1). If an MCE does occur (corresponding to the log-normal distribution), the conditional probability of failure would be between 8 % and 15 % (or conditional reliability indices of 1.4 and 1.0). The results of the analysis reveal that algebra-based equations with their parameters calibrated from data-fitting techniques may not be accurate. Such results can be used to calibrate seismic provisions toward life-cycle design and management. The methods and procedures discussed in the paper can be further extended to quantify other indices for community resilience under earthquake disasters.

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References

[1] American Society of Civil Engineers, Minimum design loads for buildings and other structures (ASCE 7-22), Reston, USA, 2010.

[2] Cornell, C. A., Jalayer, F., Hamburger, R. O., Foutch, D. A., Probabilistic basis for 2000 SAC Federal Emergency Management Agency steel moment frame guidelines, Journal of Structural Engineering 128 (4) (2002) 526–533. https://doi.org/10.1061/(ASCE)0733-9445(2002)128:4(526)

[3] Fayaz, J., Zareian, F., Reliability analysis of steel SMRF and SCBF structures considering the vertical component of near-fault ground motions, Journal of Structural Engineering 145 (7) (2019) No. 0002330. https://doi.org/10.1061/(ASCE)ST.1943-541X.0002330

[4] Federal Emergency Management Agency (FEMA), State of the art report on systems performance of steel moment frames subjected to earthquake ground shaking (FEMA-355C), Washington D.C., USA, 2000.

[5] Federal Emergency Management Agency (FEMA), State of the art report on connection performance (FEMA-355D), Washington D.C., USA, 2000.

[6] Federal Emergency Management Agency (FEMA), Quantification of building seismic performance factors (FEMA-P695), Redwood City, USA, 2009.

[7] Gu, J., Seismic reliability analysis of wood shear walls using different methods, Journal of Structural Engineering 140 (2) (2014) No. 04013054. https://doi.org/10.1061/(ASCE)ST.1943-541X.0000841

[8] Gupta, A., Krawinkler, H., Seismic demands for performance evaluation of steel moment resisting frame structures, Report No. 132, John A. Blume Earthquake Engineering Research Center, Stanford University, Stanford, USA, 1999.

[9] Ibarra, L. F., Krawinkler, H., Global collapse of frame structures under seismic excitations, Report No. 152, John A. Blume Earthquake Engineering Research Center, Stanford University, Stanford, USA, 2005.

[10] Kazantzi, A. K., Vamvatsikos, D., Lignos, D. G., Seismic performance of a steel moment-resisting frame subject to strength and ductility uncertainty, Engineering Structures 78 (11) (2014) 69–77. https://doi.org/10.1016/j.engstruct.2014.06.044

[11] Krawinkler, H., Gupta, A., Benchmarking of analysis programs for SMRF system performance studies, Report No. SAC/BD-00/09, SAC Joint Venture, USA, 2000.

[12] Lachanas, C. G., Vamvatsikos D., Model type effects on the estimated seismic response of a 20-story steel moment resisting frame, Journal of Structural Engineering 147 (6) (2021) No. 0003010. https://doi.org/10.1061/(ASCE)ST.1943-541X.0003010

[13] Li, Y., Song, R., van de Lindt, J. W., Collapse fragility of steel structures subjected to earthquake mainshock-aftershock sequences, Journal of Structural Engineering 140 (12) (2014) No. 04014095. https://doi.org/10.1061/(ASCE)ST.1943-541X.0001019

[14] Li, Y., Yin, Y., Ellingwood B. R., Bulleit W. M., Uniform hazard versus uniform risk bases for performance-based earthquake engineering of light-frame wood construction, Earthquake Engineering and Structural Dynamics 39 (11) (2010) 1 199–1 217. https://doi.org/10.1002/eqe.989

[15] Lignos, D. G., Krawinkler, H., Deterioration modeling of steel components in support of collapse prediction of steel moment frames under earthquake loading, Journal of Structural Engineering 137 (11) (2011) 1 291–1 302. https://doi.org/10.1061/(ASCE)ST.1943-541X.0000376

[16] Liu, Z., Atamturktur, S., Juang, C. H., Performance based robust design optimization of steel moment resisting frames, Journal of Constructional Steel Research 89 (10) (2013) 165–174. https://doi.org/10.1016/j.jcsr.2013.07.011

[17] Mosallam, A., Zirakian, T., Abdelaal, A., Performance assessment of steel moment-resisting frame structures using fragility methodology, Journal of Structural Engineering 144 (3) (2018) No. 0001964. https://doi.org/10.1061/(ASCE)ST.1943-541X.0001964

[18] Pacific Earthquake Engineering Research Center (PEER), Open system for earthquake engineering simulation – OpenSees (Version 2.4.2.2), Berkeley, USA, 2014.

[19] Prakash, V., Powell, G. H., Campbell S., DRAIN-2DX base program description and user guide version 1.10, Report No. UCB/SEMM-93/17, University of California, Berkeley, USA, 1993.

[20] Ribeiro, F. L. A., Barbosa, A. R., Neves, L. C., Application of reliability-based robustness assessment of steel moment resisting frame structures under post-mainshock cascading events, Journal of Structural Engineering 140 (8) (2014) No. A4014008. https://doi.org/10.1061/(ASCE)ST.1943-541X.0000939

[21] Shi, S., Foutch, D. A., Evaluation of connection fracture and hysteresis type on the seismic response of steel buildings, Structural Research Series No. 614, University of Illinois at Urbana-Champaign, Urbana-Champaign, USA, 1997.

[22] Vamvatsikos, D., Cornell, C. A., Incremental dynamic analysis, Earthquake Engineering and Structural Dynamics 31 (3) (2002) 491–514. https://doi.org/10.1002/eqe.141

[23] Yin, Y. J., Li, Y., Seismic collapse risk of light-frame wood construction considering aleatoric and epistemic uncertainties, Structural Safety 32 (4) (2010) 250–261. https://doi.org/10.1016/j.strusafe.2010.03.012

[24] Yun, S. Y., Hamburger R. O., Cornell C. A., Foutch D. A., Seismic performance evaluation for steel moment frames, Journal of Structural Engineering 128 (4) (2002) 534–545. https://doi.org/10.1061/(ASCE)0733-9445(2002)128:4(534)