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Simulation based improved seismic fragility analysis of structures

Shyamal Ghosh[a] and Subrata Chakraborty*

Department of Civil Engineering, Indian Institute of Engineering Science and Technology, Shibpur, Howrah 711103, India

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Abstract. The Monte Carlo Simulation (MCS) based seismic fragility analysis (SFA) approach allows defining more realistic relationship between failure probability and seismic intensity. However, the approach requires simulating large number of non-linear dynamic analyses of structure for reliable estimate of fragility. It makes the approach computationally challenging. The response surface method (RSM) based metamodeling approach which replaces computationally involve complex mechanical model of a structure is found to be a viable alternative in this regard. An adaptive moving least squares method (MLSM) based RSM in the MCS framework is explored in the present study for efficient SFA of existing structures. In doing so, the repetition of seismic intensity for complete generation of fragility curve is avoided by including this as one of the predictors in the response estimate model. The proposed procedure is elucidated by considering a non-linear SDOF system and an existing reinforced concrete frame considered to be located in the Guwahati City of the Northeast region of India. The fragility results are obtained by the usual least squares based and the proposed MLSM based RSM and compared with that of obtained by the direct MCS technique to study the effectiveness of the proposed approach.

Keywords: seismic fragility analysis; Monte Carlo simulation; response surface method; adaptive moving least squares method

1. Introduction

The issue of seismic vulnerability analysis (SVA) of infrastructures has been addressed in various international codes which explicitly define the criteria of assessment of existing structures by linear, nonlinear or approximate nonlinear analysis methods. The most important contributions to the field of SVA over the past 30 years covering the advantages and draw backs of various methodologies are well documented by Calvi *et al*. (2006). Such SVA approaches are usually performed based on the evaluation in the deterministic framework. But, uncertainties in various system parameters are inevitable to model earthquake action as well as structure itself. This causes significant deviations of various system responses obtained by the deterministic approach and the commonly used deterministic procedures disregarding the presence of system parameter uncertainty may lead to an improper assessment. Therefore, random nature of earthquake and uncertainty with regard to various system parameters should be considered properly in the assessment. With enormous computational growth and availability of commercial software for nonlinear structural analysis in the recent past, the highly-refined methods of structural analysis tools have facilitated SVA of existing structures realistically considering uncertainty in collected information data base. In fact, seismic fragility analysis (SFA) has emerged as an integrated platform for SVA in the context of performance base earthquake engineering (PBEE) considering parameter uncertainty. Such analyses are gaining much importance for identifying seismic vulnerability of structure providing useful information for damage and loss estimations required for disaster response planning and decision-making towards retrofitting of existing structures. The present study deals with SFA of structures.

The SFA is basically a time dependent structural reliability analysis problem. The methods commonly used for SFA of structures include empirical, statistical and numerical analysis. In empirical approach, structural damage is evaluated by establishing seismic fragility curves based on the post-earthquake statistical data. But the real statistical record of data obtained by this method are very limited in most of the cases. Thus, the applicability of such approach is restricted to situations with similar conditions and cannot be used generically. On the contrary, the applicability of numerical analysis method is more generic in nature and are more commonly used for SFA of structures. An excellent state-of-the art development focusing on the seismic performance assessment of structures and life lines encompassing modelling of seismic actions, analysis and performance assessment of structures in probabilistic format is worth mentioning in this regard (Fragiadakis *et al*. 2015). The development of SFA by numerical analysis in the PBEE framework can be studied under two major subheads i.e., (i) the analytical SFA based on probabilistic seismic demand and capacity models and (ii) the simulation based SFA based on non-linear PBEE using random field theory and statistical simulation. The analytical SFA is a balance approach of accuracy and computational involvement under certain assumed conditions. Further, on analytical SFA can be seen

*Corresponding author, Professor
E-mail: schak@civil.iiests.ac.in
[a]E-mail: shyamalemail@rediffmail.com

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elsewhere (Marano 2008, Eads *et al*. 2013, Lu *et al*. 2014, Esra and Nazli 2014, Nicholas *et al*. 2014, Mandal 2016). A conceptually straightforward but computationally demanding methodology for SFA is based on direct Monte Carlo Simulation (MCS) technique. The validity and robustness of MCS based SFA by non-linear performance based analysis is well known (Dymiotis *et al*. 1999, Kwon and Elnashai 2006, Kazantzi *et al*. 2008, Balasubramanian *et al*. 2014, Gerard and Timothy 2016, Saha *et al*. 2016). In the brute-force MCS, uncertainty in structural parameters and seismic inputs are randomly selected, based on their probability distributions to create multiple structure-earthquake combinations. Seismic response analysis is performed on each such combination. The process is repeatedly performed to obtain the probability of response exceeding certain threshold value. Further, one needs to repeat the evaluation of failure probability for each intensity for complete generation of a fragility curve. Such direct simulation approach is desirable as it does not require an assumption about the shape of the failure surface. However, the full simulation approach needs a large number of replications to obtain acceptable confidence in probabilities of failures of structures, typically very small in magnitude. For each replication in the simulation process, the computation of maximum response requires to perform complete nonlinear time history analysis (NLTHA) which is computationally demanding for real building structures. The enormous time requirement for such simulation analysis of building frame to extract story drifts for statistical analysis is studied by Kwon and Elnashai (2006). The number of simulations necessary might be of the order of several thousand for sufficient reliable estimate of probability of failure depending on the function being evaluated and the magnitude of probability of failure (Mann *et al*. 1974). The response surface method (RSM) based metamodeling technique is found to be useful in this regard to replace the complex mechanical model of a structure which otherwise involve large computational need for response analysis. The applications of RSM for SFA of structures are numerous in the recent past (Franchin *et al*. 2003, Towashiraporn 2004, Buratti *et al*. 2010, Unnikrishnan *et al*. 2013, Park and Towashiraporn 2014, Saha *et al*. 2016). A comparison between various RSMs for SFA of structures in this regard is notable (Möller 2009). Generally, the RSM is based on global approximation of scatter position data, obtained by using the least squares method (LSM). However, the LSM is one of the major sources of error in the prediction by the RSM. The RSM based on the moving least squares method (MLSM) is found to be more efficient in this regard (Kim 2005). This has been successfully applied in approximation of complex responses in reliability analysis (Kang *et al*. 2010, Taflanidis and Cheung 2012, Minas and Chatzi 2015, Goswami *et al*. 2016).

In the present study, an adaptive RSM based metamodeling technique is attempted as an effective alternative for improved approximation of nonlinear seismic responses. This will enable to apply the brute-force MCS technique to the metamodels formed based on limited NLTHA (i.e., at the design of experiment points only) of the structure to extract story drifts for statistical analysis. Specifically, the core numerical simulation in the framework of MLSM based RSM is adopted to approximate the nonlinear dynamic response of structure. It is well known that the simulation based SFA largely hinges on proper evaluation of structural demand parameters through NLTHA. As the LSM yields a global approximation, the predicted responses by the LSM based RSM may fail to capture the actual trend of the responses within a local domain. On the contrary, the MLSM based RSM; basically, a local approximation approach is expected to be more effective in approximating the nonlinear responses. The purpose of the present study is to explore the effectiveness of the MLSM based RSM to estimate seismic fragility of structures compare to that of obtained by the usual LSM based RSM. In doing so, the repetition of seismic intensity for complete generation of fragility curve is avoided by including this as one of the predictors in the seismic response estimate model. For NLTHA, a representative ground motion bin corresponds to the specified hazard level of the location of the structure is prepared so that statistically meaningful study can be performed for seismic demand analysis. The study area is considered to be the Guwahati City of the Northeast (NE) region of India. As the recorded accelerograms in the focused region of the present study is very scarce, apart from recorded accelerograms, the ground motion bin also includes artificially and synthetically generated accelerograms. The accuracy possible to achieve to approximate nonlinear seismic response and subsequently to estimate seismic fragility is first demonstrated by considering a SDOF non-linear spring mass model. Finally, the superiority of the proposed MLSM based RSM over the conventional LSM based RSM for SFA of structures is elucidated by considering a moment resisting reinforced concrete (RC) frame of a typical multi storied building.

2. Simulation based seismic fragility analysis

The seismic fragility evaluation primarily involves the solution of a time dependent structural reliability analysis problem. The limit state of interest in the reliability analysis problem is the difference between the seismic demand (D) and capacity (C) of a structure considering uncertainty due to earthquake motions, structural properties, physical damage, economic and human losses etc. The problem can be envisaged as

$$Z(\mathbf{X_C},\mathbf{X_D},t)=C(\mathbf{X_C},t)-D(\mathbf{X_D},t) \quad (1)$$

In the above, $\mathbf{X_C}$ and $\mathbf{X_D}$ are the variables governing the capacity and demand, t is the time parameter. The computation of the probability that the limit state function is negative means to evaluate the seismic risk of the structure i.e.

$$Z<0\rightarrow \text{Failed},\ \ Z=0\rightarrow \text{Limiting and } Z>0\rightarrow \text{Safe} \quad (2)$$

Therefore, the seismic risk estimate is mathematically the evaluation of the following multi-dimensional integral

$$P_f = \int_{Z<0} f_Z(\mathbf{X})dZ \tag{3}$$

Where, $\mathbf{X}$ is an 'n' dimensional vector of variables involving $\mathbf{X_C}$ and $\mathbf{X_D}$, $f_Z(\mathbf{X})$ is the joint probability density function (pdf) of the involved random variables. The exact computation of the above is often computationally demanding. In fact, the joint pdf of $f_Z(\mathbf{X})$ is hardly available in closed form. Various approximations i.e. the analytical and simulation based fragility analysis as mentioned earlier are usually adopted to obtain the probability of exceeding a response parameter for different limit states of damage considering a specific seismic intensity measure. This is customarily termed as SFA. Considering the focus of the present study, the rest of the paper focuses on the simulation based SFA approach.

The simulation based approach allows defining an approximate relationship between the failure probability and seismic intensity in the context of performance based SFA by realistic modelling of seismic input, non-linear performance based analysis and use of random field theory in the framework of statistical simulation. As already mentioned, the approach requires simulating large number of NLTHAs of structure for reliable estimate of fragility and makes the approach computationally challenging. The RSM based metamodeling to replace the computationally involve complex mechanical model of a structure is found to be a viable alternative in this regard. The present study attempted to explore the effectiveness of MLSM based RSM for SFA of structures. The related formulations are presented in the following section. In doing so, the basic concept of RSM based SFA is first introduced to set the background of the proposed approach.

3. Fragility analysis by RSM

The RSM primarily uncovers analytically complicated or an unknown relationship between several inputs and desired output through empirical models (non-mechanistic) in which the response function is replaced by a simple function (often polynomial) that is fitted to data at a set of carefully selected points referred as design of experiment (DOE), normally obtained from experimental investigation or numerical simulation.

The SFA in the framework of metamodel technique starts with defining the input system parameters and desired output response variables. A response measure that best describes damage from seismic effect is selected as the output variable. These could be base shear, maximum roof displacement, peak inter-storey drift, damage indices, ductility ratio, and energy dissipation capacity to identify the damage states depending on the type of structure being investigated. Uncertainty due to earthquake is implicitly incorporated in the analysis by using a suite of accelerograms. In doing so, the dual response surface approach (Lin and Tu 1995) is adopted opportunely to overcome an unwieldy process of generating response surface models for individual earthquakes. The responses are evaluated at each DOE point for all the input ground motions in the suit. The vector of the mean, y_μ and standard deviation (SD), y_σ of any desired response 'y' are then computed at the considered intensity level. The response surface (RS) for mean and SD are then obtained for the considered responses i.e.

$$y_\mu = g(\mathbf{X}) \quad and \quad y_\sigma = h(\mathbf{X}) \tag{4}$$

Finally, the overall RS model to approximate the selected response is obtained as

$$y = y_\mu + Z(\mathbf{X}) = g(\mathbf{X}) + Z(\mathbf{X}) = g(\mathbf{X}) + LN[0, h(\mathbf{X})] \tag{5}$$

The above is based on the fact that Z(X) follows lognormal distribution with zero mean and SD of magnitude y_σ. It is to be noted here that obtaining fragility using Eqs. (4) and (5) is highly inefficient. The overall response of the structures approximated as above is conditioned on a specific level of earthquake intensity. Hence, the entire process of generating the RS models need to be repeated for different earthquake intensity involving a new set of DOE points for each intensity level. And for each DOE, one needs to perform a fresh set of NLTHA to obtain response output required for generation of RS at each intensity level. Thus, the computational time and effort required to generate a complete fragility curve will be enormous. To circumvent this, the earthquake intensity parameter can be included as an added dimension in the RS model in addition to the structural uncertain parameters (Towashiraporn 2004, Saha *et al*. 2016). The intensity measure i.e., the peak ground acceleration (PGA) herein is included within the RS model as one of the predictors in the RS model and Eq. (4) becomes

$$y_\mu = g(\mathbf{X}, PGA) \quad and \quad y_\sigma = h(\mathbf{X}, PGA) \tag{6}$$

The selected response is now obtained as earlier i.e.

$$y = y_\mu + Z(\mathbf{X}) = g(\mathbf{X}, PGA) + LN[0, h(\mathbf{X}, PGA)] \tag{7}$$

It may be noted that the response approximation as described above is no longer conditional to a specific intensity of earthquake. The response obtained from the above metamodel depends on the structural properties as well as the level of seismic intensity. Therefore, the response surface described by Eq. (6) is used in the present study instead of Eq. (4) to estimate the mean and SD of seismic responses. Thus, the overall response of the structure approximated subsequently through Eq. (7) is not specific to a certain level of earthquake intensity. The required computational cost may increase in the initial metamodel building process due to this additional parameter. However, the overall process is much more efficient since the needs of repetitive generation of RS models are eliminated. Metamodels for different levels of seismic intensity can be obtained directly by evaluating the RS at specific values of intensity measures. In order to draw a fragility curve, the process is repeated at simulation level by adjusting the control variable i.e. the seismic intensity parameter to other intensity values. It becomes computationally much viable avoiding repeated construction of RS models for each PGA values. The present work is intended to study the effectiveness of the

MLSM based efficient RSM compare to LSM based RSM to approximate the nonlinear seismic responses. The LSM and MLSM based RSMs are presented in the following subsections.

3.1 LSM based RSM

If there are n response values y_i corresponding to n numbers of observed data, x_{ij} (denotes the i-th observation of the j-th input variable x_j in a DOE), the relationship between the response and the input variables can be expressed as

$$\mathbf{y} = \mathbf{X\beta} + \varepsilon_y \tag{8}$$

In the above multiple non-linear regression model, $\mathbf{X}$, $\mathbf{y}$, $\boldsymbol{\beta}$ and $\boldsymbol{\varepsilon}_\mathbf{y}$ are the design matrix containing the input data from the DOE, the response vector, the unknown co-efficient vector and the error vector, respectively. Typically, the quadratic polynomial form used in the RSM is as following

$$\mathbf{y} = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k}\sum_{j=1}^{k} \beta_{ij} x_i x_j \tag{9}$$

In the LSM of estimation technique, the unknown polynomial coefficients are obtained by minimizing the error norm defined as

$$L = \sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{i=1}^{k}\beta_i x_i - \sum_{i=1}^{k}\sum_{j=1}^{k}\beta_{ij} x_i x_j \right)^2 = (\mathbf{y} - \mathbf{X\beta})^T (\mathbf{y} - \mathbf{X\beta}) \tag{10}$$

And, the least squares estimate of $\boldsymbol{\beta}$ is obtained as,

$$\boldsymbol{\beta} = \left[\mathbf{X}^T\mathbf{X}\right]^{-1}\left\{\mathbf{X}^T\mathbf{y}\right\} \tag{11}$$

Once the polynomial coefficients $\boldsymbol{\beta}$ are obtained from the above, the response y can be readily evaluated for any set of input parameters.

3.2 MLSM based RSM

The MLSM based RSM is a weighted LSM that has varying weight functions with respect to the position of approximation. The weight associated with a particular sampling point x_i decays as the prediction point x moves away from x_i. The weight function is defined around the prediction point x and its magnitude changes with x. The least-squares function $L_y(x)$ can be defined as the sum of the weighted errors as following

$$L_y(x) = \sum_{i=1}^{n} w_i \varepsilon_i^2 = \boldsymbol{\varepsilon}^{\mathrm{T}}\mathbf{W}(x)\boldsymbol{\varepsilon} = (\mathbf{y} - \mathbf{X\beta})^{\mathrm{T}}\mathbf{W}(x)(\mathbf{y} - \mathbf{X\beta}) \tag{12}$$

Where, $\mathbf{W}(x)$ is the diagonal matrix of the weight function. It can be obtained by utilizing the weighting function such as constant, linear, quadratic, higher order polynomials, exponential functions etc. In the present study, the following exponential function has been used (Taflanidis and Cheung 2012)

$$w(d) = \frac{\exp(-(d/cD)^{2k}) - \exp(-(1/c)^{2k})}{1-\exp(-(1/c)^{2k})} \quad \text{if } d < D, \text{ else '0'} \tag{13}$$

In the above, d is the distance of the point where approximate response is required to the origin of the approximating domain and D is the radius of the sphere of influence, chosen at any point of interest such that it contains sufficient numbers of DOE points to avoid singularity in the solution. The parameters, c and k are used for better efficiency. Eventually, a weight matrix $\mathbf{W}(x)$ can be constructed by using the weighting function in the diagonal terms as follows

$$\mathbf{W}(x) = \begin{bmatrix} w(x-x_1) & 0 & 0 & 0 \\ 0 & w(x-x_2) & .. & 0 \\ .. & .. & .. & .. \\ .. & .. & .. & .. \\ 0 & 0 & .. & w(x-x_n) \end{bmatrix} \tag{14}$$

The weighting function has its maximum value of unity at a normalized distance of zero and zero value (minimum) outside of unit normalized distance, i.e., w (0.0) = 1.0 and w (d/D>1.0)=0.0. The function decreases smoothly from 1.0 to 0.0. By minimizing the least-squares estimators $L_y(x)$, the coefficients $\boldsymbol{\beta}(x)$ can be obtained by the matrix operation as below

$$\boldsymbol{\beta}(x) = \left[\mathbf{x}^T\mathbf{W}(x)\mathbf{x}\right]^{-1}\mathbf{x}^T\mathbf{W}(x)\mathbf{y} \tag{15}$$

It is important to note here that the coefficients $\boldsymbol{\beta}(x)$ are the function of the location x, where the approximation is sought. Thus, the procedure to calculate $\boldsymbol{\beta}(x)$ is a local approximation and the moving processes performs a global approximation throughout the whole design domain.

For constructing the response surface model, various DOE are used e.g., Saturated Design, Factorial Design, Central Composite Design etc. But, such classical designs are more appropriate for physical experiments where replication errors exist. It may be noted in this regard that the experiment here will be a computer analysis of nonlinear seismic response in which the random or replicating error term is missing. Thus, the absence of random error term leaves the least-square fit of a model without obvious statistical meaning (Simpson 2001). It is mentioned that for constructing the RS where experiments are performed artificially through computer simulation, DOE should have its design points filling the design space and treat all the regions of the design space equally (Park and Towashiraporn 2014). Thus, in order to construct an efficient RS model, a uniform design (UD) as proposed by Fang (1980), basically a space filling design appropriate for deterministic computer experiments is adopted in the present study. The UD table used in the numerical study to obtain the various design points is readily available at http://uic.edu.hk/isci/UniformDesign/UD%20Tables.html for different levels of sampling points for a given numbers of factors.

4. Selection of ground motion bin

Proper selection of ground motion record is the most important aspect for NLTHA of structure governing the seismic response outcome (Zeinab and Masoud 2016). The most acceptable form for this is the use of recorded accelerograms. However, due to limited resource of recorded accelerograms for the focused region of the present case study (the Guwahati city of NE India), the choice of natural ground motions is limited to eight numbers. To supplement this limitation, the accelerograms are further generated artificially and also synthetically by identifying the most vulnerable magnitude (M_j) and distance (R_i) combination for the specific hazard level of the location under consideration to ensure the variability in the input ground motion. These are briefly discussed in the following.

4.1 Natural accelerogram records

The eight natural accelerogram records are selected from the past earthquake data in the region which covers a surface magnitude range from 6.0 to 8.0 and epicentral distance within 300 km for rock site, corresponding to the considered hazard level as identified from the disaggregation of PSHA of the Guwahati city. Due to the limited recorded accelerograms in the region, the records are also selected from Northern Himalayan earthquakes with similar subsoil sites available in the COSMOS virtual data centre (http://strongmotioncenter.org/vdc/scripts/default.plx). Table 1 shows the details of the selected earthquake accelerograms.

4.2 Artificial accelerograms

The artificial accelerograms are generated following the iterative methodology proposed by Gasparini and Vanmarcke (1976). The power spectral density (PSD) function compatible to the acceleration response spectra for rock and hard soil for 5% damping (IS 1893 2002) is obtained following Kaul (1978). For each cycle, the response spectrum generated for the simulated ground motion is compared with the target one. The ratio between the desired and the computed response is defined at each cycle and the corresponding PSD is recalculated as a function of the square of the aforementioned ratio. Using the modified PSD, a new ground motion is simulated and a new response spectrum is obtained, otherwise the procedure is repeated until convergence. The steady state motions are further multiplied by a deterministic envelope function (Saragoni and Hart 1974) to simulate the transient nature of earthquakes.

Table 1 Selected accelerograms records for NE region of India

Name	Date	Station	Comp.	Mag. (Ms)	Dist. (km)	Depth (Km)	Site Geology	PGA (g)
Indo-Burma Border	6 Aug, 1988	Baigao	S28W	7.2	230	90	Soft Rock	0.217
Indo-Burma Border	6 Aug, 1988	Berlongfer	N14W	7.2	201	90	Soft Rock	0.337
Indo-Burma Border	8 May, 1997	Jellalpur	N02E	6.0	24	34	Soft Rock	0.136
Indo-Burma Border	8 May, 1997	Katakhal	S01W	6.0	40	34	Soft Rock	0.159
Uttarkashi, India	19 Oct, 1991	Bhatwari	N85E	7.0	53	10	Rock	0.248
Uttarkashi, India	19 Oct, 1991	Uttarkashi	N75E	7.0	31	10	Rock	0.304
Chamoli, India	28Mar, 1999	Gopeswar	N20E	6.6	14	15	Rock	0.353
Chamoli, India	28Mar, 1999	Ukhimath	N75W	6.6	19	15	Rock	0.091

4.3 Synthetic accelerograms

The stochastic ground motion model as proposed by Boore (2003) is used for generation of synthetic acceleration time histories. The Fourier amplitude spectrum of ground motion at a site is expressed in terms of source and wave propagation functions as

Ground motion (f) = C × Source (f) × Path (f) × Site (f) (16)

Where, $C = R_{\theta\varphi} FH / 4\pi\sigma\beta^3$ is the scaling factor in which $R_{\theta\varphi}$ represents the radiation pattern for a range of azimuths θ and take-off angles φ, F represents the free surface effect and H is the reduction factor accounting the partitioning of energy into two horizontal components. The crustal density and shear wave velocity are represented by σ and β, respectively.

By using the ω-square model (Brune 1970), the source spectrum is obtained as

$$\mathrm{Source(f)} = (2\pi f)^2 \frac{\mathrm{M}_0}{[1+(f/f_c)^2]} \tag{17}$$

Where, M_0 is the seismic moment and the corner frequency, $f_c = 4.9\mathrm{x}10^6 \beta(\Delta\sigma / \mathrm{M}_0)^{1/3}$ in which, f_c is in hertz, β is in km/s, the stress drop, $\Delta\sigma$ is in bars and M_0 is in dyne-cm. The path term is interpreted in terms of geometrical spreading (GSP) factor and frequency dependent quality factor $Q(f)$ and given as

$$\mathrm{Path}(f) = \mathrm{GSP}(r).\exp(-\pi fr / Q(f)\beta) \tag{18}$$

The site term is obtained in terms of frequency dependent amplification and diminution factor as

$$\mathrm{Site}\ (\mathrm{f}) = \mathrm{A}\ (\mathrm{f}) \times \mathrm{D}\ (\mathrm{f}) \tag{19}$$

Where, A(f) represents the site amplification due to propagation of earthquake waves from the source region. The diminution factor is represented as, $D(f)=\exp(-\pi k_0 f)$ in which k_0 is the distance-independent high frequency attenuation operator (Kappa factor). Several methods are available in the literatures for evaluating site amplification. In this study, the amplification function A(f) is estimated from H/V ratio. In COSMOS virtual database, only one earthquake record is available for Loharghat station, 33 km away to Guwahati (Indo-Burma Border earthquake 6th August, 1988). The three orthogonal components of this record are used to calculate H/V spectrum. Fourier spectra of the three orthogonal components are calculated and smoothed by spectral smoothing algorithm (Konno and

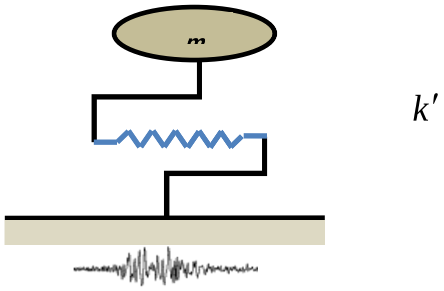


Fig. 1 (a) The spring mass system

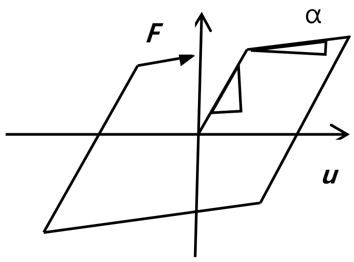


Fig. 1 (b) The force deformation behaviour of the nonlinear spring

Table 2 The parameters adopted for synthetic ground motion generation

Parameters	Values	References
Stress Drop ($\Delta\sigma$)	250 bars	Raghukanth and Somala (2009)
Quality Factor (Q_f)	$224f^{\,0.93}$	Raghukanth and Somala (2009)
Geometrical spreading factor (GSP)	1/r for r < 100 km 1/10√r for r > 100 km	Singh *et al*.(1999)
Distance dependent factor (b)	0.05	Boore (2003)
Shear Wave Velocity (β)	3.6 km/sec	Mitra *et al*. (2005)
Crustal Density (σ)	2900 kg/m^3	Mitra *et al*. (2005)
kappa factor (k_0)	$(0.057/V_{s,30}^{0.8})-0.02$	Chandler *et al*. (2006)
V_{s30}	1.97 km/s	Chandler *et al*. (2006)
Reduction Factor (H)	1/√2	Boore and Boatwright (1984)
Radiation Pattern ($R_{\theta\phi}$)	0.55	Atkinson and Boore (1998)
Free Surface Amplification (F)	2.0	Boore (1996)

Ohmachi 1998). Smoothed Fourier spectrums of the two horizontal motions are then averaged using a quadratic mean. The average spectrum is divided by the smoothed vertical spectrum to obtain the H/V ratio and multiplied by the near-surface attenuation term exp($-\pi k_0 f$) to get the overall site amplification. Now, for generating synthetic accelerograms, white Gaussian noise is generated with zero mean and unit SD. This is filtered to retain the frequencies between 0 to 50 Hz and the filtered Gaussian noise is further windowed by envelope function (Saragoni and Hart 1974). This windowed noise is now Fourier transformed and normalized with its root mean square value. The normalized ordinates of the Fourier amplitudes are then multiplied with the Fourier amplitude as obtained from the stochastic point source model to get the Fourier spectrum of the ground motion. This Fourier spectrum is then inverse Fourier transformed to obtain the synthetic accelerograms. Following this procedure, eight accelerograms are generated for different magnitudes between 6.0 to 8.0 and epicentral range within 300 km around the focused study area. Table 2 summarizes the various parameters necessary for generation of synthetic ground motion and the specific values adopted in the present study along with useful references.

5. Numerical study

To demonstrate the effectiveness of the proposed MLSM based RSM over the conventional LSM based RSM for SFA of structures, two examples are taken up. The first example is a simple nonlinear single degree of freedom (SDOF) system. Because of its simplicity, it is feasible with reasonable time to obtain large number of non-linear responses of the SDOF system with random system properties and earthquake inputs necessary for fragility computation by brute force MCS. Thus, this problem has been taken up to make a comparative study of the accuracy possible to achieve in seismic fragility computation by the LSM and MLSM based RSMs compare to that of obtained by the brute force MCS based approach. The second example is a more realistic case study problem. A four-story RC frame building considered to be located in the Guwahati city of NE India involving NLTHA by using commercial structural analysis software is taken up to elucidate the effectiveness of the proposed MLSM based RSM for efficient SFA of structure.

5.1 Example 1: Simple nonlinear SDOF system

The nonlinear spring-mass SDOF system as shown in Fig. 1(a) is characterized by a nonlinear spring connecting a lumped mass (m) to the ground. The nonlinear spring behaviour is described in Fig. 1(b). The damping is assumed to be proportional to system mass and stiffness. The system is subjected to seismic acceleration at the base and its response is obtained at each time step by numerical integration in Matlab platform.

The fragility analysis requires that the computed responses are described probabilistically. This can be accomplished by simulating cases with random structural properties and earthquake inputs. To consider the record to record variation of stochastic earthquake motion, a suite of ground motion records is considered. The ground motion bin consists of twenty artificially generated accelerograms consistent with the design spectrum of the study region and another twenty synthetically generated for the Guwahati city as detailed in section 4. The mean and SD of the nonlinear response of the system is obtained based on these ground motions. The random variables considered are the frequency (ω rad/s), damping (ξ in percentage), yield force (F_y in N) and ratio of the post-yield to elastic stiffness (α). These are assumed to be statistically independent normal random variables. The ranges of the variables are depicted in Table 3. The PGA value is considered as control variables whose range varies from 0.1 g to 1.0 g. The maximum displacement of the mass is taken as the output response variable.

The input variables in the RS models are composed of two components, the random variables (X_1 to X_4) and the control variable (X_5). The random variables are those representing the uncertainties in the structural properties i.e. ω (X_1), ξ(X_2), F_y(X_3) and α(X_4) as detailed in Table 3. The control variable is the PGA that represents earthquake intensity level. It may be noted that the evaluation of RS at different values of PGA yield models for predicting the mean and SD of the response of the SDOF system due to specific levels of PGA for generating fragility curve. For developing RS model, the control variable is treated in a similar way as other random variables. As already discussed in section 3.3, the UD is adopted in the present study for DOE. For this, total thirty levels of sampling points for five factors are prepared following the UD table and transformed into real values of factors to implement the experiment. The NLTHA is carried out and the maximum responses of the SDOF system for forty scaled ground motions are estimated at each of these thirty sample points. The mean and SD of the maximum response for each of these cases (required as the input responses at the DOE points for constructing RS models) are then computed. For generation of LSM and MLSM based RS models, the quadratic polynomial with cross terms has been adopted which contains twenty-one unknown coefficients. The design matrices and the response vector for the MLSM and LSM based RSM remain same. Only the coefficient vector of the MLSM based approach changes at each point of interest due to the change in the weight matrix. The influence radius D for computing the weight matrix is chosen to ensure sufficient number of neighbouring supporting points (twenty-two for this problem) and the values of c and k are taken as 0.15 and 1, respectively (Taflanidis and Cheung 2012). The mean and SD of the responses at any point of interest can be evaluated with the help of these RS models and the total response is evaluated accordingly.

To study the accuracy of the RS models in approximating the seismic responses, the mean and SD of response values are computed for different PGA values with the mean values of the random parameters by the usual LSM based and the proposed MLSM based RSM. The results are shown in Figs. 2-3. For comparative study, the mean and SD of the response are also obtained at these points by the brute force MCS method. For this, the NLTHA is performed at these checking points considering

Table 3 The range of input variables

Parameters	ω (X_1)	ξ(X_2)	F_y(X_3)	α(X_4)
Upper limit	9.27	0.03	2.913	0.075
Lower limit	3.29	0.01	1.035	0.025
Mean	6.28	0.02	1.974	0.05
COV	0.2	0.25	0.2	0.25

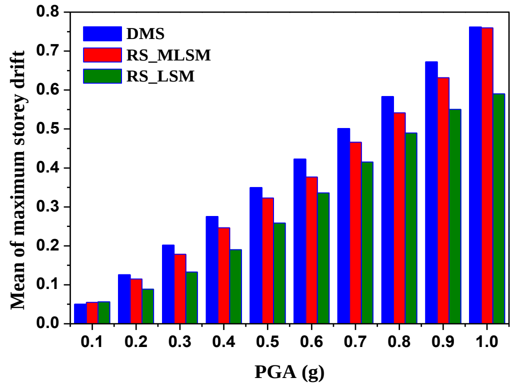


Fig. 2 Comparison of mean maximum displacement

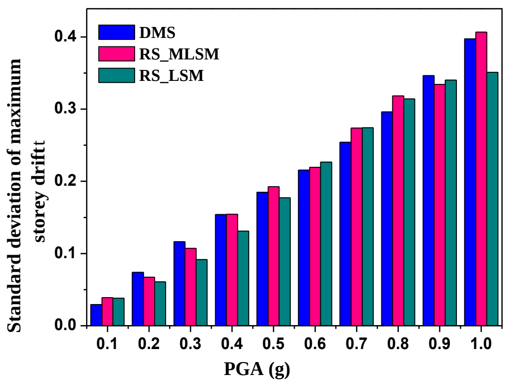


Fig. 3 Comparison of SD maximum displacement

all the ground motions of the bin and the mean and SD of the response are computed. The results are denoted as DMS and are shown in the same plots. The improvement possible to achieve by the proposed MLSM based RSM compare to the conventional LSM based RSM to estimate the mean and SD of nonlinear dynamic responses can be readily noted in these plots by comparing those with the direct MCS based results. The estimated response values by the MLSM based approach are closer to the brute force MCS based estimated response values than the LSM based values. This clearly implies the enhanced accuracy of the proposed MLSM based RSM.

Furthermore, to study the improved response approximation capability of the proposed MLSM based RSM, various statistical metrics i.e., the Root Mean Square Error(RMSE), the co-efficient of determination (R^2) and the average prediction error (ε_m) usually used to check the validity of the metamodels are computed for both the LSM and MLSM based RSMs. The expressions of those metrics are as following

$$\text{RMSE} = \sqrt{\sum_{i=1}^{p}(\hat{y}_i - y_i)^2 / p}, \quad R^2 = \frac{\sum_{i=1}^{p}(\hat{y}_i - \bar{y}_i)^2}{\sum_{i=1}^{p}(y_i - \bar{y}_i)^2} \quad \text{and} \quad \varepsilon_m = \frac{\sum_{i=1}^{p}(100\frac{|\hat{y}_i - y_i|}{y_i})}{p} \tag{20}$$

Where, $\hat{y}_i$ is the predicted response obtained by the metamodel and y_i is the actual response obtained by the direct MCS for i^{th} sample point; p is the total number of samples (thirty thousand for the present numerical computation). The results of statistical tests for both the mean and SD using the LSM and MLSM based RSMs are shown in Table 4. As expected, it can be noted from the table that the lesser values of RMSE, ε_m and also R^2 value closer to unity are attained by the MLSM based RSM which clearly indicate the improved accuracy of the proposed MLSM based approach to estimate the response statistics. Results are shown here for two PGA levels only and similar observations are noted for other cases.

The seismic fragility is now computed by the usual LSM-RSM based, the proposed MLSM-RSM based MCS and also by the brute force MCS method. For fragility computation by RSM based MCS, the simulation is performed on the RS models of random variables for any desired level of PGA (X5). The random structural parameters (i.e., X1 to X4) are simulated corresponding to their respective pdf and are combined at random to generate a large number (thirty thousand herein) of SDOF system. The mean and SD values are computed from the respective RS model. The maximum displacement is obtained for each such SDOF system using Eq. (7) to obtain an ensemble of random responses for the considered seismic intensity level. The probability of exceeding a given threshold displacement is obtained accordingly from the ensemble yielding the probability of failure of the system for the considered level of seismic intensity. The process is repeated for different PGA levels to obtain the fragility curves by RSM. To obtain the fragility by brute force MCS, following the assumption that earthquake in a suit are equally likely to occur, the ground motions are selected randomly from the suit to associate it with each randomly simulated SDOF system. The NLTHA is performed on each earthquake structure combination and the maximum displacement is obtained and the probability of failure is computed with respect to the given threshold displacement. Figs. 4-6 shows the fragility curve obtained for different allowable displacements i.e., 0.203 m, 0.406 m and 0.812 m, respectively. The improvement possible to achieve in seismic fragility computation by the proposed MLSM based RSM with respect to LSM based RSM when compared with the brute force MCS based fragility results can be readily noted from these plots. It may be noted here that the brute force MCS is still time consuming even for simple SDOF system as it needs thirty thousand NLTHA to obtain converged probability of failure values for each PGA levels.

Table 4 The performance of LSM and MLSM based RSM

			RMSE	R^2	ε_m
0.6 g	Mean	LSM	2.77%	1.112	6.22%
		MLSM	2.44%	1.104	5.37%
	SD	LSM	3.27%	1.117	11.36%
		MLSM	3.01%	1.016	10.97%
0.3 g	Mean	LSM	2.76%	1.6498	15.74%
		MLSM	2.16%	1.5826	11.59%
	SD	LSM	3.12%	1.7886	22.66%
		MLSM	2.87%	1.1542	20.30%

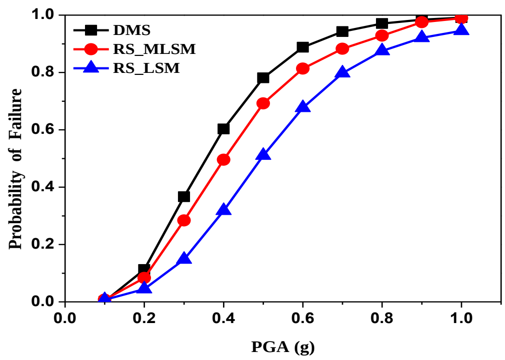


Fig. 4 Comparison of fragility curves for SDOF system (allowable displacements of 0.203 m)

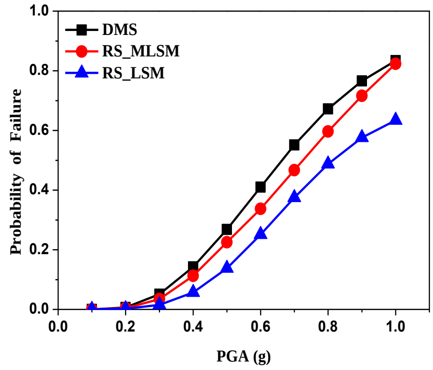


Fig. 5 Comparison of fragility curves for SDOF system (allowable displacements of 0.406 m)

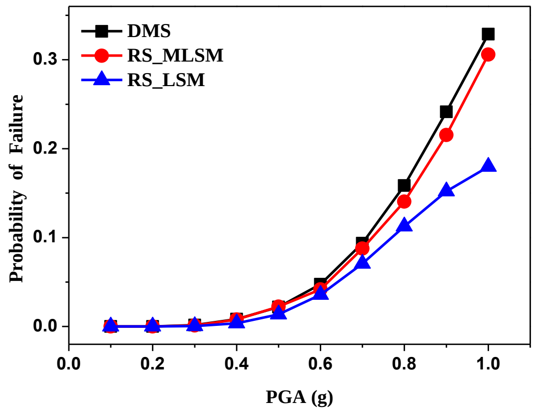


Fig. 6 Comparison of fragility curves for SDOF system (allowable displacements of 0.812 m)

Therefore, the task of fragility computation of realistic building frame by brute force MCS will be computationally challenging as simulating even few thousands of NLTHA will involve enormous time.

5.2 Example 2: A four storied RC framed building

A four storied RC framed building considered to be located in the Guwahati city is further undertaken for numerical elucidation of the proposed SFA procedure. The

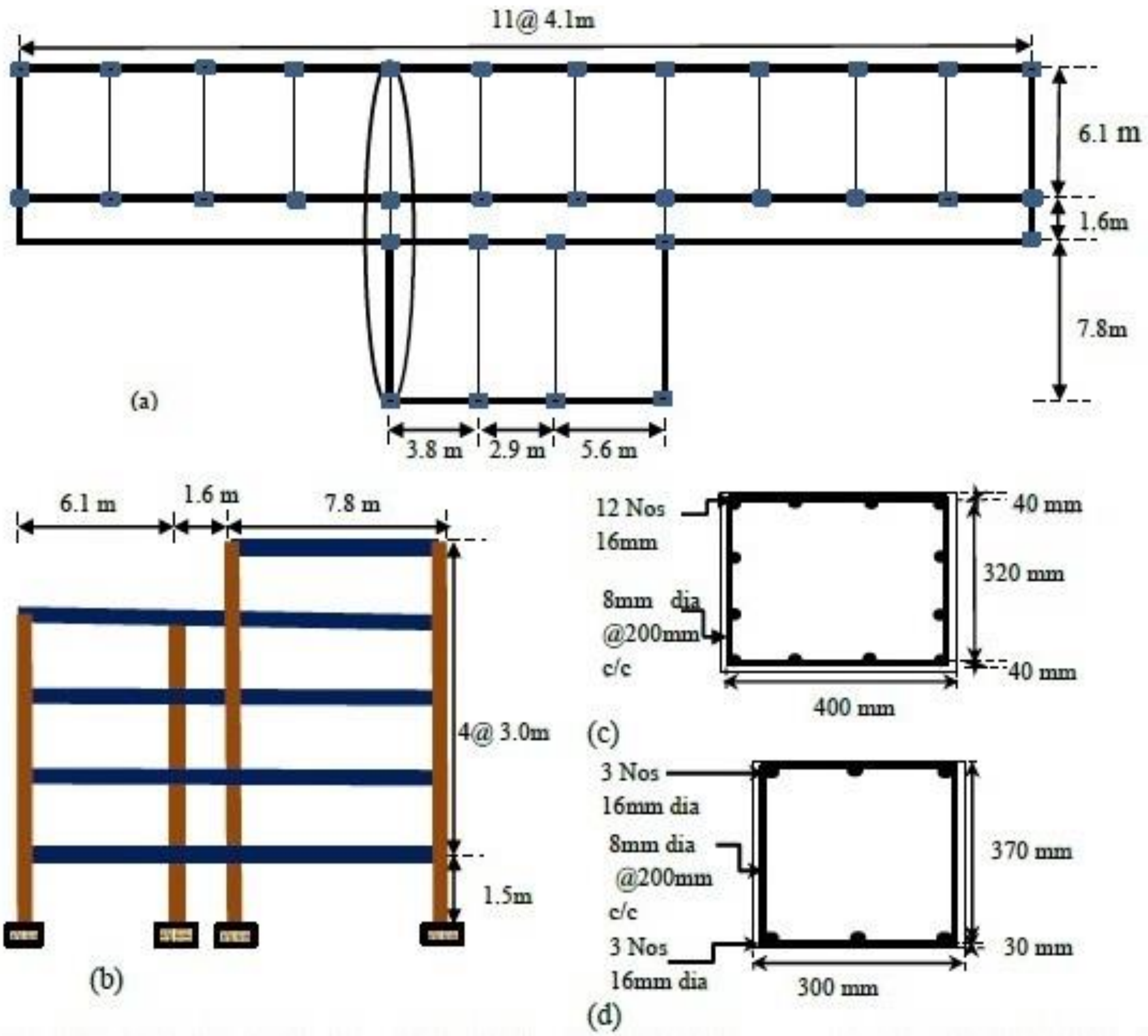
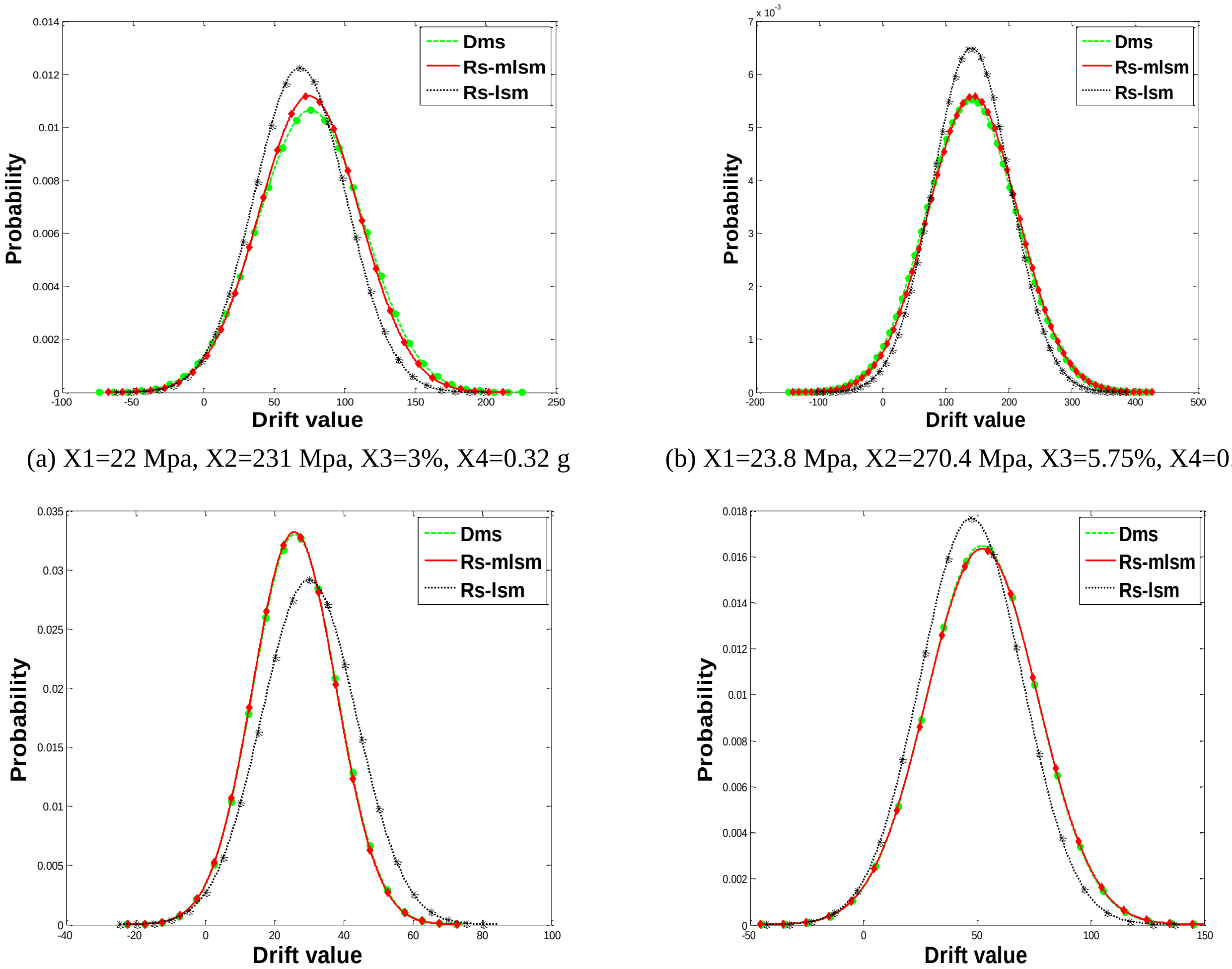


Fig. 7 The details of the building frame (a) the building plan, (b) the 2D frame, (c) the details of the column sections and (d) the details of the beam sections considered for SFA

building plan is shown in Fig. 7(a). A transverse 2-D frame as shown in Fig. 7(b) is extracted from the building and considered for SFA. The dead load consists of self-weight of the structural and non-structural members. The live load is assumed to be 2 KN/m^2. Based on onsite non-destructive test, the concrete grade is considered to be M25 i.e., the characteristic strength of 25 N/mm^2 and reinforcing steel grade is mild steel having yield strength of 250 N/mm^2. The reinforcement and geometric dimension details of the column and beam sections of the identified frame are shown in Figs. 7(c)-(d), respectively.

The responses of the structure are obtained by NLTHA using commercial software SAP2000NL. The stress-strain characteristic of concrete is considered as per Mander's confined model (Mander *et al*. 1988) for the column members and unconfined concrete model for the beam members. For reinforcing steel, the simple stress-strain model with isotropic strain hardening behaviour is considered. These models are readily available as in-built model in the software. The beams and columns are characterized by the lumped plasticity model. For this purpose, the nonlinear hinges are assigned at the beam and column ends. The beams are modelled with moment hinges (M3) whereas the columns are modelled with axial-moment (P-M3) interacting hinges. Auto hinges are assigned according to the tables of FEMA 356 (2000). The NLTHA is carried out by the Hilber-Huges-Taylor (HHT) integration scheme. From the NLTHA, the maximum storey drift (MSD) values are obtained representing the structural demand.

The uncertainty in the computed displacement demand obtained by the NLTHA occurs due to the uncertainty in the structural model parameters and random nature of ground motion. The parameters that are considered to be random are the concrete characteristic strength (f_{ck}), steel yield strength (f_y), structural damping values (ξ). The statistical values of these parameters assumed to be statistically independent normal are provided in Table 5. As earlier, the



(a) X1=22 Mpa, X2=231 Mpa, X3=3%, X4=0.32 g (b) X1=23.8 Mpa, X2=270.4 Mpa, X3=5.75%, X4=0.7 g

(c) X1=25.1 Mpa, X2=265.5 Mpa, X3=3.4%, X4=0.12 g (d) X1=29.5 Mpa, X2=240 Mpa, X3=3.8%, X4=0.22 g

Fig. 8 The comparison of probability distribution of MSD values for various combinations of input parameters (other than the DOE points) of RS model i.e., a) for X1=22 Mpa, X2=231 Mpa, X3=3%, X4=0.32 g, (b) for X1=23.8 Mpa, X2=270.4 Mpa, X3=5.75%, X4=0.7 g, (c) for X1=25.1 Mpa, X2=265.5 Mpa, X3=3.4%, X4=0.12 g and (d) for X1=29.5 Mpa, X2=240 Mpa, X3=3.8%, X4=0.22 g

Table 5 The details of the various random parameters

Variable	Mean	COV	Upper	Lower
f_{ck} (Mpa) (X_1)	25	0.2	30	20
f_y (Mpa) (X_2)	250	0.2	300	200
ξ (%) (X_3)	5	0.4	3	7

PGA is considered as control variable. The random nature of the ground motion is taken into account by using a suit of ground motion of the considered region. The ground motion bin consists of twenty-four numbers of earthquake time histories (natural, artificial and simulated, eight each) which are obtained as described in section 4. The input variables in the RS models are composed of two components. The variables X_1, X_2, and X_3 (ref. Table 5) describe structural properties, while X_4 indicates the intensity level of earthquake. The UD table consists of thirty different combinations of the input parameters. In turn, the bin of twenty-four acceleration records are used for the NLTHA at these thirty DOE points to obtain the mean and SD of MSD values required as the input responses at the design points for constructing RS models. The quadratic polynomial with cross terms has been adopted which contains fifteen unknown coefficients. The number of neighbouring supporting points taken is sixteen to obtain the D value and the values of c and k are taken as 0.15 and 1, respectively.

To study the capability of the LSM and MLSM based RS models to approximate the nonlinear dynamic responses of the building frame, the mean and SD of the MSD values are evaluated at various combinations of the four input variables (other than those which are considered in the DOE). The pdf of the response approximated by the LSM and MLSM based RS models are shown in Figs. 8(a)-(d). The pdf of the responses considering the mean and SD of MSD values are also evaluated directly from NLTHA at these points when subjected to the same twenty-four ground motion time histories and are shown in the same plot for ease in comparison. The improved capability of the proposed MLSM based approach compare to the conventional LSM-RSM based MCS approach to capture the probability distribution trend of the MSD when compare with that of obtained by the brute force MCS method can be readily noted from these plots. This clearly demonstrates the improved response prediction capability of the proposed MLSM based approach compare to the LSM based approach.

The seismic fragility is now computed by the usual LSM based RSM and the proposed MLSM based RSM. As earlier, for fragility computation by RSM, the MCS is performed over the RS models of the random variables for any desired level of PGA (X4). The random structural parameters (i.e., X1, X2 and X3) are simulated corresponding to their respective pdf and are combined at random to generate a large number of sample frames. The mean and SD are computed from the respective RS model at each simulated random variables pair. Now, the maximum displacement is obtained for each such frame to obtain an ensemble of random responses. The probability of exceeding a given threshold displacement (for specified damage level) is now obtained accordingly from the ensemble providing the probability of failure of the system for the considered level of seismic intensity. The process is repeated for different PGA level to obtain the fragility curves by the LSM-RSM and MLSM-RSM based MCS method.

The three structural limit states or performance levels, to be specific the Immediate Occupancy (IO), the Life Safety (LS) and the Collapse Prevention (CP) as per FEMA 356 (2000) are considered for seismic risk evaluation. The permissible MSD values of the IO, LS and CP levels associated with various performance levels of RC frame are taken as 1%, 2% and 4%, respectively as per FEMA 356. The fragility curves are shown in Figs. 9-11 for IO, LS and CP performance levels, respectively. Like the previous example, following the assumption that earthquake in a suit are equally likely to occur, the ground motions are selected randomly from the suit to associate with each random sample frame.

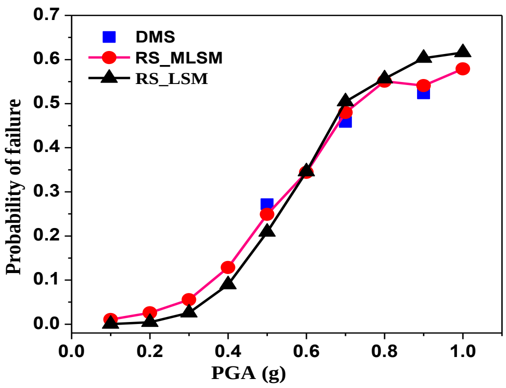


Fig. 9 Comparison of fragility curves of the considered building frame at IO level

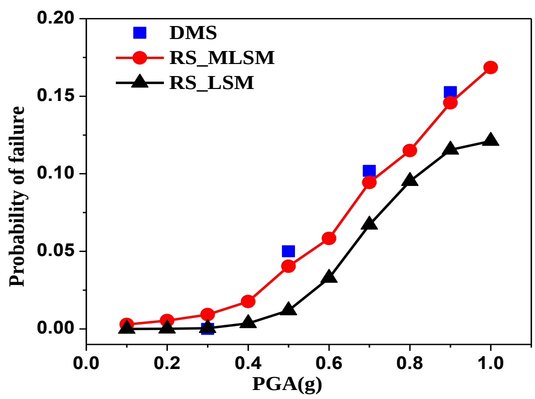


Fig. 10 The Comparison of fragility curves of the considered building frame at LS level

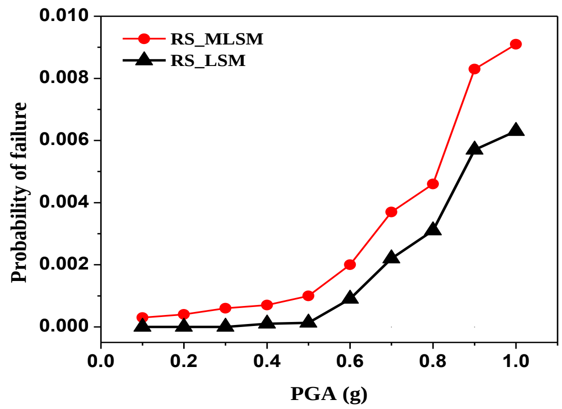


Fig. 11 Comparison of fragility curves of the considered building frame at CP level

The NLTHA is performed on each earthquake structure combination and the MSD value is obtained and the probability of failure is estimated with respect to the given threshold displacement. As already discussed, it needs enormous computation time to obtain fragility by the brute force MCS for this problem. Thus, a limited brute force MCS study (2000 number of simulations) is performed to get the trend of the brute force MCS based solution so that the quality of the proposed MLSM based fragility estimates could be judged with respect to that of by LSM based RSM. However, it is realized that the number of simulation required will be much higher than 2000 for getting converged fragility by the brute force MCS for the cases where probability of failure is very small e.g., fragility correspond to smaller PGA level and for CP limit state condition. Therefore, the trend based on 2000 simulations for 3 PGA levels i.e., 0.5, 0.7 and 0.9 for IO and LS limit state cases are only shown. The MLSM based results are found to be closer to the direct MCS results. Moreover, from the comparison of the estimate of the mean and SD of the MSD values, the accuracy of the proposed MLSM based RSM over the conventional LSM based RSM can be readily recognised. Thus, the capability of more accurate estimate of fragility by the proposed MLSM based RSM compare to that of obtained by the LSM based conventional RSM is apparent.

6. Conclusions

An adaptive algorithm to improve the accuracy of nonlinear dynamic response approximation for SFA of structures using MLSM based RSM in the framework of MCS technique is presented. The repetition of intensity for complete generation of fragility curve is avoided by including this as one of the predictors to serve as a control variable in the seismic response prediction model. The improvement possible to achieve by the proposed MLSM based approach in nonlinear dynamic response approximation is quite apparent from the numerical results. Furthermore, the various computed statistical metrics i.e., the RMSE, R^2 and ε_m values usually used to check the validity of the metamodels also confirm the superiority of the proposed MLSM based RSM approach. The MLSM based results come closer to the brute force MCS fragility results whereas the LSM based results are far away. The improvement in seismic fragility computation by the proposed MLSM based RSM with that of obtained by the conventional LSM based RSM when compared with the brute force MCS based fragility is clearly noted in the first example and also in the second example based on limited simulation study. It is also important to note that the conventional LSM provides non-conservative estimate of fragility over the MLSM. However, further study is felt essential to understand the accuracy of the proposed MLSM based approach considering more number of simulations or applying subset simulations algorithm particularly for the cases when probability of failures values are very small. Although the example application is focused to the particular building and location, the basic steps are generic enough to readily adopt to other structures i.e., bridges, water and energy supplies facilities etc. One only needs to change the mechanical model of the structure required to be evaluated. Thus, the proposed procedure can be used for efficient evaluation of SFA of structures.

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