KRIGING METAMODELING BASED MONTE CARLO SIMULATION FOR IMPROVED SEISMIC FRAGILITY ANALYSIS OF STRUCTURES

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Abstract:

The polynomial response surface method (RSM) is mostly adopted to overcome computational challenge of Monte Carlo Simulation (MCS) based seismic fragility analysis (SFA) of structure. However, such SFA approach is primarily based on dual RSM involving lognormal assumption which lacks desired accuracy. The present study explores the advantage of adaptive nature of Kriging approach for improved SFA by random selection of metamodel to implicitly consider record to record variations of earthquakes. Without additional computational burden, the approach avoids a prior distribution assumption unlike dual RSM. The effectiveness of the approach over the usual polynomial RSM for SFA is elucidated numerically.

Keywords: *Seismic fragility analysis; Monte Carlo Simulation; Nonlinear Dynamic Analysis; Direct Response Approximation; Kriging interpolation*.

Short Title: KRIGING METAMODELING FOR IMPROVED SFA OF STRUCTURES

1. Introduction

In recent years, significant progress has been made in the field of seismic vulnerability assessment (SVA) of structures and the issue has also been addressed in various international codes explicitly defining the criteria of assessment of existing structures by linear, nonlinear or approximate nonlinear analysis approaches [Lupoi et al., 2004]. Such SVA approaches are usually performed based on response evaluation in deterministic framework. Whereas, the recent development of Performance Based Earthquake Engineering (PBEE) is supposed to serve the purpose of quantifying seismic risk of structures considering uncertainties in ground motion characteristics, structural parameters, physical damage, economic and human losses, etc. [Günay and Mosalam, 2013]. In fact, numerical simulation based seismic fragility analysis (SFA) has emerged as an integral platform for seismic safety assessment of structures in the PBEE framework. Fundamentally, SFA requires to solve a time dependent structural reliability analysis problem in which the limit state of interest is the difference between structural resistance and seismic demand. In PBEEE, SFA of structure considering nonlinear seismic responses is simply defined as the failure probability that the maximum response quantity of interest exceeds a known threshold over the entire period of an earthquake [Buratti et al., 2010]. Thereby, the limit state function (LSF) is expressed as,

$$g(\mathbf{X}) = \min_t C(\mathbf{X}_\mathbf{C}, t) - D(\mathbf{X}_D, t) \tag{1}$$

where, $\mathbf{X}_\mathbf{C}, \mathbf{X}_\mathbf{D}$ are the variables representing capacity and demand and *t* is the time parameter. The probability that the LSF is negative represents seismic risk. Thus, mathematically, the SFA is the evaluation of a multi-dimensional integral,

$$P_f = \int_{g(\mathbf{X}) \leq 0} f_\mathbf{X}(\mathbf{X}) d\mathbf{X} \tag{2}$$

where, $\mathbf{X}$ is an N dimensional vector of $\mathbf{X}_\mathbf{C}$ and $\mathbf{X}_\mathbf{D}$ and $f_\mathbf{X}(\mathbf{X})$ is the joint pdf of **X.** The exact evaluation of this integral is often computationally demanding and various approximations are typically adopted to obtain probability of exceeding different limit state conditions. This is customarily termed as SFA. The numerical simulation based SFA in the probabilistic framework is performed by two approaches: (i) analytical SFA based on probabilistic seismic demand and capacity models and (ii) simulation based SFA using random field theory and statistical simulation. The reviews of the related developments focusing on seismic performance assessment of structures encompassing modelling of seismic inputs, structural response analysis and fragility assessment may be seen elsewhere [DerKiureghian, 1996; Fragiadakis et al., 2015; Ghosh et al. 2018a]. The analytical SFA is a balance approach of accuracy and computational involvement under certain assumed conditions [Shome et al., 1998; Vamvatsikos and Cornell, 2002; Gardoni et al., 2003; Marano et al., 2008]. But, the most accurate and conceptually straightforward means of SFA without the necessity of assumption about the shape of the failure surface is based on Monte Carlo Simulation (MCS) technique. The validity and robustness of MCS based SFA is well known [Kwon and Elnashai, 2006; Kazantzi et al., 2008]. However, such full simulation approach needs a large number of repetitions to achieve acceptable confidence in the estimated probability of failure of a structure which is usually 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) of the structural model. This is computationally demanding for large complex structures [Kwon and Elnashai, 2006]. Hence, alternative techniques for efficient computation of responses of complex structures by overcoming aforesaid drawbacks while preserving accuracy of estimated fragility is of paramount importance for SFA of structures. Various metamodeling techniques have emerged as an effective solution to such problems and find wide application in SFA of structures. The present study focuses on the application of metamodeling approach for SFA of structures.

The polynomial response surface method (RSM) based metamodeling approach had been studied extensively for SFA of structures [Franchin et al., 2003; Towashiraporn, 2004; Möller et al., 2009; Saha et al., 2016; Gaxiola-Camacho et al., 2017]. In this regard, the application of various adaptive metamodeling techniques e.g., the application of hybrid high dimensional model representation (HDMR) [Unnikrishnan et al., 2013], moving least square method (MLSM) based RSM [Ghosh and Chakraborty, 2017a; 2018b], Artificial Neural Network (ANN) [Lagaros and

Fragiadakis, 2007, Lagaros et al., 2009], support vector machines [Khatibinia et al., 2013; Long et al., 2013, Ghsoh et al. 2018b] for SFA of structures are notable. With the convenience of the Kriging toolbox DACE in MatLab [Lophaven et al., 2002], the application of Kriging interpolation is getting wide attention to approximate complex structural response for reliability analysis [Kaymaz, 2005]. A critical comparative assessment of various Kriging model for uncertainty quantification to address the accuracy and computational efficiency is of worth mentioning in this regard [Mukhopadhyay et al., 2017]. The Kriging based metamodeling is also applied for SFA of structures. For example, Gidaris et al. [2015] proposed a metamodel framework based on a Kriging surrogate model to approximate the median and standard deviation (SD) of seismic demand for analytical SFA of structures. Azizsoltani and Haldar [2017] demonstrated significant improvement of basic RSM by using advanced factorial design and Kriging approach for improved seismic damage-tolerant design of structures. Zhang and Wu [2017] demonstrated the applicability of Kriging model-based MCS method for SFA of an elasto-plastic single degree of freedom (SDOF) system and a reinforced concrete (RC) bridge where the mean and the SD of the response are obtained and those are combined to obtain the overall model for seismic response approximation. The MCS is performed on the metamodel thus obtained for SFA of structures following lognormal assumption of seismic responses. In this regard, it is important to note that the number of training samples required to construct a metamodel largely increases with number of random variables. Thus, metamodeling approach can be a viable alternative only when the number of variables involve in a response prediction model is low. But, SFA requires to take into account the variability of seismic action and mechanical properties of a structure. The seismic motion is a non-stationary process with time varying amplitude and frequency content variables and the mathematical description of these quantities will involve large number of random variables. Thus, unlike reliability analyses of structures under static or deterministic dynamic loads, the application of metamodeling approach for SFA is a difficult task as the input parameters required to accurately approximate the entire input-output relationships become exorbitantly large due to high-dimensional nature of stochastic earthquake load.

To circumvent the difficulty as mentioned in the above, the input variable space is usually separated into two groups i.e. the structural parameters and the stochastic sequences. For example, SFA proposed based on RSM with random factor [Franchin et al., 2003; Buratti et al., 2010]. Using the same basic concept of separating the input space into two vectors, the dual RSM approach [Lin and Tu, 1995] is more frequently used for SFA where the overall responses are obtained by assuming some statistical distribution (usually lognormal). Furthermore, the RSM adopted in most of these studies for SFA of structures are mostly based on global approximation of scatter position data, obtained by using the least squares method (LSM) which is one of the major sources of error in response approximation. The predicted responses by the LSM based RSM that basically performs a global approximation over the entire domain may fail to capture the actual trend of a desired response within a local domain [Kim et al., 2005]. Therefore, SFA of structures by various adaptive metamodeling approaches e.g. ANN, Kriging, support vector regression (SVR), etc. are gaining momentum. The advantage of Kriging method is that it is exact at the training points as obtained from design of experiment (DOE) scheme and in other location Kriging based approximation is an improvement over the usual LSM based prediction as it provides higher weights to the response values at nearby data points. Moreover, Kriging based metamodel can quantify the error of prediction. In fact, its improved capability of response approximation is noted in uncertainty quantification and reliability analysis [Kaymaz 2005, Mukhopadhyay et al., 2017]. However, the application of Kriging metamodeling approach for SFA is found to be very limited

[Gidaris et al., 2015; Zhang and Wu, 2017]. These studies primarily adopt the dual RSM approach to construct the metamodels for predicting median and SD of seismic demand variable and these are subsequently used for SFA of structures based on lognormal distribution assumption of overall seismic response.

A Kriging based metamodeling approach in the framework of MCS technique is explored in the present study for more accurate SFA of structure. Specifically, the core numerical simulation in the framework of Kriging based metamodel (denoted as K-RSM) is proposed to approximate nonlinear seismic response of structure. However, instead of commonly adopted dual RSM, the present study proposed to construct the metamodel directly without additional computational burden to approximate a desired response. Once, the metamodels are obtained, the MCS technique is readily applied for SFA of structures by generating random samples of input parameters according to the probability density functions (pdfs) and random selection of metamodels from the suite. The random selection of metamodel assumes that each earthquake of a given intensity is equally likely to occur. This implicitly takes into account the stochastic nature of earthquake to closely follow the usual notion to consider record to record variation of earthquake motion. It may be noted here that the seismic response approximation by the proposed approach does not require a prior assumption on its distribution as is prerequisite in case of dual RSM. Furthermore, for efficient fragility computation, seismic intensity parameter is included as one of the predictors to serve as a control variable in the response prediction model [Towashiraporn 2004, Saha et al., 2016]. The SFA results are obtained by the usual polynomial RSM (termed as P-RSM) and the proposed K-RSM based approaches and compared with the similar results obtained by the most accurate brute force MCS technique to study the effectiveness of the proposed K-RSM approach. The accuracy possible to achieve to estimate seismic fragility is demonstrated numerically by considering a simple nonlinear SDOF system and a more realistic four-storied RC building frame.

2. Metamodeling Based SFA of Structures

The metamodeling approach typically starts with defining the input system parameters (**x**) and desired output variables. As discussed earlier, the application of metamodeling approach for SFA is a difficult task due to high-dimensional nature of earthquake and the dual RSM is usually adopted. Uncertainty due to earthquake ground-motion is implicitly incorporated in the dual RSM approach by using a suite of ground motions to consider record wise variations. The responses are evaluated at each DOE point for all the input ground motions in the suite. Then, the mean, μ_Y and SD, σ_Y of any desired response 'y' are computed at the considered intensity level. The metamodels to approximate the mean and the SD of the considered response are then constructed based on the training data set i.e.

$$\mu_Y \cong \hat{g}(\mathbf{x}) \;\; and \;\; \sigma_Y \cong \hat{h}(\mathbf{x}) \tag{3}$$

In the above, $\hat{g}(\mathbf{x})$ and $\hat{h}(\mathbf{x})$ represent the metamodels for the mean and the SD of the considered response, respectively. The overall metamodel to approximate the selected response is finally obtained based on lognormal distribution assumption of seismic responses.

In the present study, instead of using the mostly adopted dual RSM approach as discussed above, the metamodel is constructed directly for approximating response quantity of interest for each ground motion in the bin i.e. the metamodel for l-th ground motion in the suite is expressed as,

$$y_l = \hat{g}_l(\mathbf{x}),\;\; l = 1, 2, ..., M \tag{4}$$

where, 'M' is the total number of ground motions considered in the suite. Once, the metamodels are constructed for all the ground motions in the suite, the brute force MCS technique can be readily performed for SFA analysis of the considered structure by generating random sample input parameters, **x** based on the associated pdfs and random selection of metamodel from the suite. This is based on the fact that the ground motions in the considered suite are obtained for a target hazard level having an equal probability of occurrence i.e. an earthquake of specific intensity at the considered study area is equally likely to occur. Thereby, random selection of metamodel from the bin implicitly incorporates the conventional notion to consider nature of record to record variations of stochastic earthquake motion. It can be noted that the total number of NLTHA run necessary by the usual dual RSM and the proposed direct response approximation approach remain same. For M ground motion records in a suite and P number of training data points obtained as per the DOE, the dual RSM first computes the mean and the SD of a desired response at each training data point involving M number of NLTHA runs for each point and repeat it for all the data points. Thus, the total number of NLTHA runs are $\left(P \times M\right)$. Whereas, the proposed direct response approximation approach first performs NLTHA at all the DOE points i.e. P numbers of runs to obtain responses for one ground motion in the suite to construct a metamodel and repeat it for all the ground motions in the considered suite to obtain total M numbers of metamodels. Thus, the total NLTHA runs remain same in both the approaches. However, seismic response approximation by the proposed approach does not require a prior assumption on its distribution as is necessary in case of commonly adopted dual RSM.

It may be noted here that the metamodel to approximate structural response using Eq. (4) is conditioned on a specific level of earthquake intensity and the entire process of constructing metamodels need to be repeated for different intensity. Thus, a new set of DOE points is required for each intensity involving a fresh set of NLTHA of the structural model. Hence, the computational time and effort required to generate a complete fragility curve will be enormous. To circumvent this, the earthquake intensity parameter is suggested to include as an added dimension in the metamodel in addition to the structural uncertain parameters [Towashiraporn 2004, Saha et al., 2016]. Thus, the peak ground acceleration (PGA) considered as the intensity measure in the present study is also included within the metamodel as one of the predictors and Eq. (4) is modified as,

$$y_l = \hat{g}_l(\mathbf{x}, PGA) = \hat{g}_l(\mathbf{X}) \tag{5}$$

In the above, the input vector **X** now consists of structural parameters (**x**) as well as the intensity measure, PGA. The response approximation is no longer conditional to a specific intensity of earthquake but depends on the structural properties and the PGA as well. In order to obtain fragility for different seismic intensity level, the process can be repeated at simulation level by regulating the control variable (PGA herein). As already mentioned, the present work is intended to study the effectiveness of K-RSM approach compare to the usual P-RSM approach for SFA of structures, the related formulations are presented in the following.

2.1 Polynomial RSM based Metamodeling

Let the response of a structure, y_l due to l-th ground motion in the considered suite needs to be approximated by RSM. The *k*-th observation of the i-th input variable x_i in a DOE is denoted by x_i^k and y_l^k is the output response quantity of interest correspond to the k-th DOE point under *l*-th ground motion. For a chosen DOE scheme, a set of experimental points P are generated and P number of corresponding response values are obtained for each ground motion in the suite. The relationship between the response and the input variables i.e. Eq. (5) can be expressed by the following quadratic polynomial form (typically used in the RSM):

$$\mathbf{y}_l = \beta_0 + \sum_{i=1}^{N} \beta_i x_i + \sum_{i=1}^{N} \sum_{j=i}^{N} \beta_{ij} x_i x_j \tag{6}$$

The parameters β_0, β_i and β_{ij} are the unknown coefficients obtained by using the least square regression to fit the training as obtained from a chosen DOE scheme. In the least squares estimation, the unknown coefficients are obtained by minimizing the error norm defined as:

$$e = \sum_{k=1}^{P}\left(y_l^k - \beta_0 - \sum_{i=1}^{N} \beta_i x_i^k - \sum_{i=1}^{N}\sum_{j=i}^{N} \beta_{ij} x_i^k x_j^k \right)^2 = \left(\mathbf{y} - \mathbf{Q\beta}\right)^T \left(\mathbf{y} - \mathbf{Q\beta}\right) \tag{7}$$

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

$$\boldsymbol{\beta} = \left[\mathbf{Q}^T\mathbf{Q}\right]^{-1}\left\{\mathbf{Q}^T\mathbf{y}\right\} \tag{8}$$

In the above, the square matrix $\mathbf{Q}^{\mathrm{T}}\mathbf{Q}$ has the order of (N+1)(N+2)/2, where, N is the total number of random variables involved and $\mathbf{Q}$ is the design matrix. Once the polynomial coefficients $\boldsymbol{\beta}$ are obtained from Eq. (8), the response y can be readily evaluated for any new set of input parameters.

2.2 Kriging Metamodeling

Kriging model is an interpolation method that basically underlies spatial correlation among the response values obtained from the data samples. Therefore, a Kriging based interpolation of response value is biased by the response values at nearby data points i.e. higher weights are specified to response values at nearby data points. The relationship between the output response and the input variables for l^{th} ground motion in a considered suite can be expressed by Kriging interpolation as [Sacks et al., 1989]:

$$y_l(\mathbf{X}) = \mathbf{f}\left(\mathbf{X}\right)^{\mathrm{T}}\boldsymbol{\beta} + \mathbf{Z}\left(\mathbf{X}\right) \tag{9}$$

where, $\mathbf{f}\left(\mathbf{X}\right) = \left[f_1\left(\mathbf{X}\right), .., f_K\left(\mathbf{X}\right)\right]^{\mathrm{T}}$ is the vector of K numbers of known basis functions, $\boldsymbol{\beta} = [\beta_1, .., \beta_K]^{\mathrm{T}}$ is the regression coefficient vector and $\mathbf{Z}\left(\mathbf{X}\right)$ is assumed to be a Gaussian stationary process with zero mean and covariance as following,

$$\mathrm{Cov}\left(\mathbf{X}^i, \mathbf{X}^j\right) = \sigma^2 R\left(\mathbf{X}^i, \mathbf{X}^j\right) \tag{10}$$

where, σ^2 is the process variance and $R\left(\mathbf{X}^i, \mathbf{X}^j\right)$ is the correlation. It may be noted here that unlike P-RSM, the approximation function of K-RSM has two terms. The first term i.e. $\mathbf{f}\left(\mathbf{X}\right)^{\mathrm{T}} \boldsymbol{\beta}$ in Eq. (9) indicates a global model of the random variables and is similar to the polynomial model typically used in RSM. The second part in Eq. (9) is used to model the deviation from $\mathbf{f}\left(\mathbf{X}\right)^{\mathrm{T}} \boldsymbol{\beta}$ and takes care about the correlation with the training points. The DACE toolbox provides regression models with polynomials of orders 0, 1 and 2. The minimum number of sample points requires to train a K-RSM model depends on the type of regression function chosen. It may be note that even a first-degree polynomial regression function in the Kriging approach is capable of capturing nonlinear trend of an implicit LSF due to the introduction of correlation model in the interpolation model.

For a chosen DOE scheme, a set of experimental points are generated as, $\mathbf{S} = \left[\mathbf{S}_1, .., \mathbf{S}_P\right]^{\mathrm{T}}$. The deterministic outputs for the DOE points are given as: $\mathbf{Y}_{\mathrm{S}} = \left[y\left(\mathbf{S}_1\right), .., y\left(\mathbf{S}_P\right)\right]^{\mathrm{T}}$. The regression problem $\mathbf{F}\boldsymbol{\beta} \simeq \mathbf{Y}_{\mathrm{S}}$ has the generalized least squares solution as [Kaymaz, 2005],

$$\hat{\boldsymbol{\beta}} = \left(\mathbf{F}^{\mathrm{T}} \mathbf{R}^{-1} \mathbf{F}\right)^{-1} \mathbf{F}^{\mathrm{T}} \mathbf{R}^{-1} \mathbf{Y}_{\mathrm{S}}, \tag{11}$$

And the variance estimate is,

$$\hat{\sigma}^2 = \frac{1}{P}\left(\mathbf{Y}_{\mathrm{S}} - \mathbf{F}\hat{\boldsymbol{\beta}}\right)^{\mathrm{T}} \mathbf{R}^{-1} \left(\mathbf{Y}_{\mathrm{S}} - \mathbf{F}\hat{\boldsymbol{\beta}}\right), \tag{12}$$

where, $\mathbf{F} = \left[\mathbf{f}\left(\mathbf{S}_1\right), .., \mathbf{f}\left(\mathbf{S}_P\right)\right]^{\mathrm{T}}$ is the $\left(P \times K\right)$ design matrix, $\mathbf{R} = \left\{R\left(\mathbf{S}_i, \mathbf{S}_j\right)\right\}$, $1 \leq i, j \leq P$ is $P \times P$ matrix of stochastic-process correlations between $\mathbf{Z}$'s at the DOE points.

A correlation function of the type $R\left(\mathbf{X}^i, \mathbf{X}^j\right) = R\left(\mathbf{X}^i - \mathbf{X}^j\right)$ is generally selected and one-dimensional product correlation rule as following is used for mathematical convenience [Sacks et al., 1989],

$$R\left(\mathbf{X}^i, \mathbf{X}^j\right) = \prod_{k=1}^{N} R_k\left(\mathbf{X}_k^i - \mathbf{X}_k^j\right), \tag{13}$$

where, $\mathbf{X}_k^i$ and $\mathbf{X}_k^j$ denotes the k-th dimension of $\mathbf{X}^i$ and $\mathbf{X}^j$, respectively and N represents the dimension of the input space. The most commonly used correlation function is of the following form,

$$R\left(\theta, \mathbf{X}^i, \mathbf{X}^j\right) = \prod_{k=1}^{N} \exp\left(-\theta_k \left|\mathbf{X}_k^i - \mathbf{X}_k^j\right|^m\right) \tag{14}$$

where, $0 < m \leq 2$. For $m = 2$, it is termed as Gaussian correlation function (a process with infinitely differentiable paths in mean square sense) and is useful when the response is analytic. Finally, the best linear unbiased prediction of the response can be obtained as,

$$\hat{y}(\mathbf{X}) = \mathbf{f}(\mathbf{X})^{\mathrm{T}} \hat{\boldsymbol{\beta}} + \mathbf{r}(\mathbf{X})^{\mathrm{T}} \mathbf{R}^{-1}\left(\mathbf{Y}_{\mathrm{S}} - \mathbf{F}\hat{\boldsymbol{\beta}}\right), \tag{15}$$

where, $\mathbf{r}(\mathbf{X}) = \left[R(\mathbf{S}_1, \mathbf{X}), .., R(\mathbf{S}_P, \mathbf{X})\right]^{\mathrm{T}}$ is the vector of correlations between the $\mathbf{Z}$'s at the DOE points and a new input point of interest, $\mathbf{X}$. The Kriging based metamodel as described here can be readily implemented numerically by using DACE toolbox. It is to be noted that for estimating $\hat{\boldsymbol{\beta}}$ and $\hat{\sigma}^2$ using Eq. (11) and (12), first the parameters (θ) of the correlation function need to be chosen as the matrix $\mathbf{R}$ and thereby $\hat{\boldsymbol{\beta}}$ and $\hat{\sigma}^2$ depends on θ. The optimal choice of the parameters ($\hat{\theta}$) are obtained as the maximum likelihood estimator by minimizing $\psi(\theta) = \left|R(\theta)\right|^{\frac{1}{P}} \cdot \sigma(\theta)^2$.

The 'dacefit' algorithm of the DACE toolbox can find the local minima of $\psi(\theta)$ for a specified domain of θ[Lophaven et al., 2002].

2.3 DOE Scheme for Metamodel Construction

To construct metamodels, various classical DOEs e.g. saturated design, factorial design, central composite design etc. are usually adopted. But, such classical designs are more appropriate for physical experiments where replication errors exist. But, the experiments here will be computer analysis of nonlinear seismic responses. Thus, constructing metamodel by such artificially performed experiment through computer simulation, the outcome obtained by running the code with the same input several times will be identical i.e. the random or replicating error term will be absent. This means that there will be no variance; but bias only. It is this lack of random error that makes computer experiments different from physical experiments calling for distinct DOE scheme i.e. the DOE should have its design points filling the design space [Simpson et al. 2001]. The space-filling designs attempt to bound the bias by spreading the design points out as far from each other as possible consistent with staying inside the experimental boundaries and by arranging the points evenly over the region of interest. The Uniform Design (UD) and Latin Hypercube methods are the two most popularly used space-filling designs. The UD has the distinctive feature of accommodating the largest possible number of levels for each variable and the discrepancy for UD is the smallest [JMP® 10, 2012]. Thus, in order to construct an efficient metamodel, the UD scheme [Fang et al., 2000] is adopted in the present study. The UD table used for numerical study is readily available at http://www.math.hkbu.edu.hk/UniformDesign for different levels of sampling points for a given numbers of factors. The UD tables have notations as $U_n\left(q^s\right)$, where n is the number of experiments (or runs), s is the number of factors, and q is the number of levels for each factor.

3. Numerical Study

The effectiveness of the proposed direct response approximation approach based on K-RSM metamodeling approach for SFA of structure is demonstrated numerically by considering two examples. The first example is a nonlinear SDOF system for which large number of non-linear responses of the system with reasonable time for SFA by brute force MCS technique. The second example is a more realistic one i.e. a four-storied RC building frame considered to be located in the Guwahati city of Northeast India that involves NLTHA of the finite element model of the structures with realistic fibre section modelling approach using the OpenSees software [McKenna and Feneves, 2005]

In the context of SFA in the framework of PBEE, the ground motion record selection is very much important as it governs the level of uncertainty in the seismic response outcome of a structure obtained through NLTHA. Usually, a suite of ground motion records, the intensity of which exceeds to a specified probability for a site and the other properties are typically determined by probabilistic seismic hazard analysis (PSHA) [Hines et al. 2011] is considered. The basic choices for selecting ground motion are: recorded accelerograms from strong motion database, simulation of artificial accelerograms to match the target response spectra and simulation of synthetic accelerograms from theoretical seismological model of seismic fault rupture of the study area.

The most acceptable form for this is the use of recorded accelerograms. However, due to limited number of recorded accelerograms available for the considered region of the study area (the Guwahati city of northeast India), the choice of natural ground motions is limited to eight numbers. These are selected from the past earthquake data in the region which covers a surface wave magnitude range from 6.0 to 8.0 and epicentral distance within 300 km for rock site. Due to limited availability of recorded ground motions, accelerograms from northern Himalayan earthquakes are also included. Further, to supplement the limitation of available recorded ground motion, eight numbers of accelerograms are generated artificially and another eight numbers are synthetically generated identifying the most vulnerable magnitude (M_j) and distance (R_i) combination for the specific hazard level of the location under consideration as identified from the disaggregation of PSHA results of the study region [Ghosh et al., 2017b]. This is to ensure the variability in the input ground motion. The artificial accelerograms compatible to the acceleration response spectra for rock and hard soil for 5% damping [IS 1893, 2016] are generated following the methodology proposed by Gasparini and Vanmarcke [1976]. To simulate the transient nature of earthquake, the steady state motions are multiplied by a deterministic envelope function [Saragoni and Hart 1974]. The stochastic ground motion model as proposed by Boore [2003] that combines parametric descriptions of amplitude spectrum with a random phase as a function of the magnitude and distance from the source is used for generation of synthetic acceleration for different magnitudes between 6.0 to 8.0 and epicentral range within 300km.

3.1 Example 1: A nonlinear single degree of freedom system

A SDOF system, characterized by a nonlinear spring connecting a lumped mass (m) to the ground as shown in Figure 1 is considered. 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 random variables considered for numerical study are: frequency (ω rad/s), damping (ξ), yield force (F_y in N) and ratio of the post-yield to elastic stiffness (α). These are assumed to be uncorrelated normal random variables. The input variables are composed of two types i.e. random variables and control variable. 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 1. The PGA (X_5) that represents earthquake intensity is considered as the control variable. For developing metamodels, the control variable is treated in the similar manner like the other random variables. The DOE points are constructed within the range of the random variables by arranging twenty equidistant levels of each variable according to the UD table, $U_{20}\left(20^5\right)$ and transformed into real values of factors to implement the experiment. The ground motion suite consists of twenty artificially generated accelerograms consistent with the design spectrum of the study region and another twenty synthetically generated as described earlier.

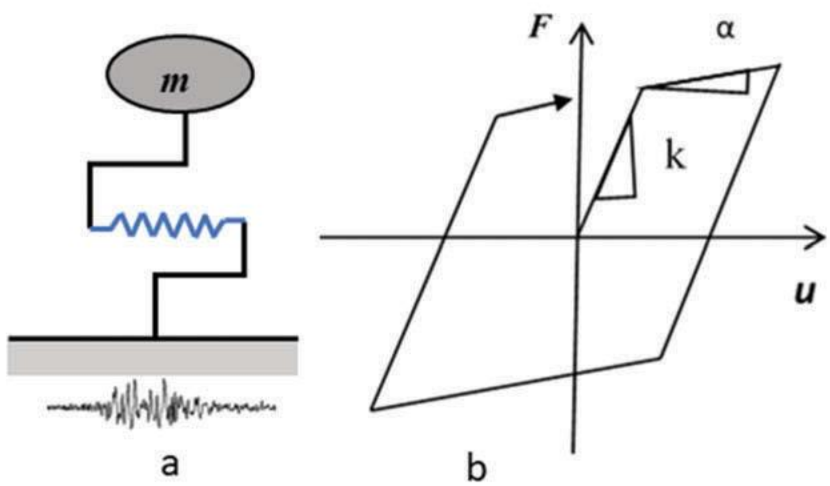

Figure 1. (a) The spring mass system and (b) the force deformation behavior of the nonlinear spring.

Table 1. The range of input variables for the SDOF system.

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

The NLTHA is performed at for twenty data set selected as per the UD scheme to obtain the maximum response for each ground motion in the suite. The metamodel is then constructed by the proposed K-RSM approach and also by the usual P-RSM approach for each ground motion in the suite yielding a bin of metamodels having forty metamodels. For construction of P-RSM based metamodels, a second-degree polynomial without cross term mostly adopted in the RSM based structural reliability analysis study has been adopted. For uncorrelated random variables involve in the LSF, for constructing efficient P-RSM, a quadratic form without cross-terms, which needs very fewer training data can capture the nonlinearity of the implicit LSF. The Kriging based metamodel is obtained by using the first-order polynomial as regression function and its appropriateness is checked based on a generalized mean square error (GMSE) estimated by leave-one-out cross-validation method [Roy et al. 2018]. The Gaussian correlation function available in the DACE toolbox is used as the process correlation model. To get the optimum choices of the correlation parameters (θ) involve in the correlation model, the initial choice, the lower and the upper bounds are used as 0.05, 0.001 and 10, respectively for all θ. The training data points for both the K-RSM and the P-RSM based metamodels remain same. For SFA by the proposed direct response approximation approach, the simulation is performed on the metamodel of random variables for any desired level of PGA (X_5). The random structural parameters (i.e. X_1 to X_4) are simulated corresponding to their respective pdf and are combined at random to generate a large number (thirty thousand herein) of SDOF system. The maximum displacement is obtained for each such SDOF system by randomly selecting a metamodel from the forty metamodels in the bin. The process is repeated for all the simulated samples of the SDOF system. 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 PGA. The process is repeated for different PGA levels to obtain the fragility curves by both the P-RSM and the proposed K-RSM based metamodels. For applying the dual RSM approach, the NLTHA is carried out and the maximum responses of the SDOF system for the forty scaled ground motions are estimated at each of the twenty sample points. The mean and the SD of the maximum response at each DOE point are computed to construct the metamodels for approximating the mean and SD of the responses. Once, the metamodels for the mean and the SD of the considered response are obtained, the overall response is obtained based on the lognormal distribution assumption of seismic responses. To obtain the fragility by the brute force MCS, following the assumption that each earthquake of a specific intensity in a suit are equally likely to occur, the ground motions are selected randomly from the suit to associate 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 estimated accordingly for a given threshold response.

To study the improved capability of the proposed direct response approximation approach, the SFAs are performed by the proposed direct response approximation approach and the usual dual RSM approach based on Kriging metamodel and compared in Figure 2. The SFA results are also obtained by the most accurate brute force MCS technique (denoted as D-MCS in the plots). The fragility curve is obtained by considering allowable displacements of 0.4m. The improvement possible to achieve in estimating seismic fragility by the proposed direct response approximation approach (denoted as Ptaroposed direct-K-RSM) compare to the dual K-RSM approach can be readily observed from the plots by comparing with the similar results obtained by the most accurate brute force MCS based results.

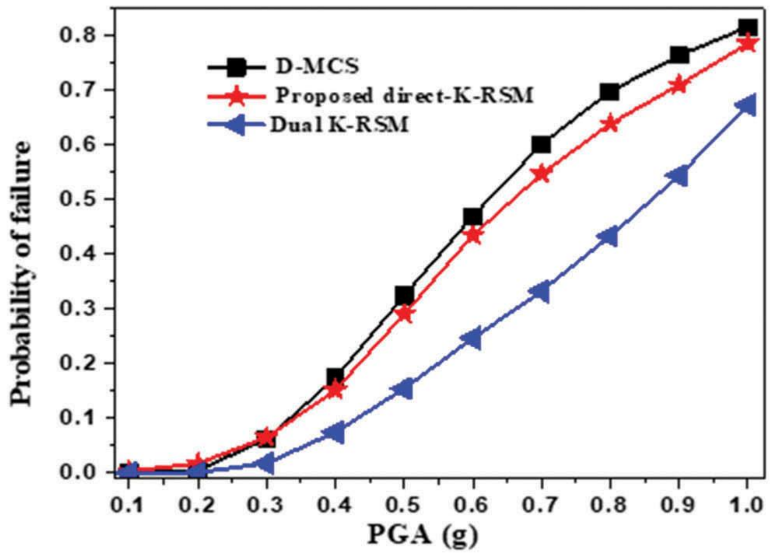

Figure 2. Comparison of fragility of the SDOF system by the dual K-RSM and the proposed direct K-RSM approaches.

To study the accuracy of the proposed K-RSM based metamodel to approximate seismic responses, the mean and the SD of the response of the SDOF system are computed for different PGA values by the usual P-RSM and the proposed K-RSM approaches. The variations of the mean and the SD of the responses with varying PGA level are shown in Figure 3. The improvement possible to achieve by the proposed K-RSM based approach compare to the conventional P-RSM approach to estimate the mean and the SD of the nonlinear seismic responses can be readily observed in these plots by comparing those with the brute force MCS based similar results. Furthermore, to study the quality of response approximation capability of the proposed K-RSM based metamodeling, the normalized root mean square error (NRMSE) and the co-efficient of determination (R^2) as defined by the following equations are further computed:

$$\text{NRMSE} = \frac{\sqrt{\sum_{i=1}^{N_{sim}} (\hat{y}_i - y_i)^2 / p}}{\bar{y}} \quad \text{and} \quad R^2 = \frac{\sum_{i=1}^{N_{sim}} (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{N_{sim}} (y_i - \bar{y})^2} \tag{15}$$

where, N_{sim} is the total number of samples (thirty thousand for the present numerical computation), $\hat{y}_i$ is the predicted response obtained from the respective metamodel, y_i is the actual response for the i^{th} sample point obtained directly from NLTHA of the corresponding SDOF system and $\bar{y}$ is the mean value of the actual responses obtained from the brute force MCS. The results of statistical tests i.e. the NRMSE and R^2 values as obtained from the P-RSM and the K-RSM based metamodels are show in Table 2. The results are shown here for four PGA levels only. However, the observations are similar for other PGA values. As expected, it can be noted that the lesser values of NRMSE as well as R^2 value closer to unity are attained by the proposed K-RSM based metamodel compare to that of obtained from the P-RSM based metamodel. This, clearly indicates improved accuracy of the proposed K-RSM based metamodeling approach to approximate nonlinear seismic responses.

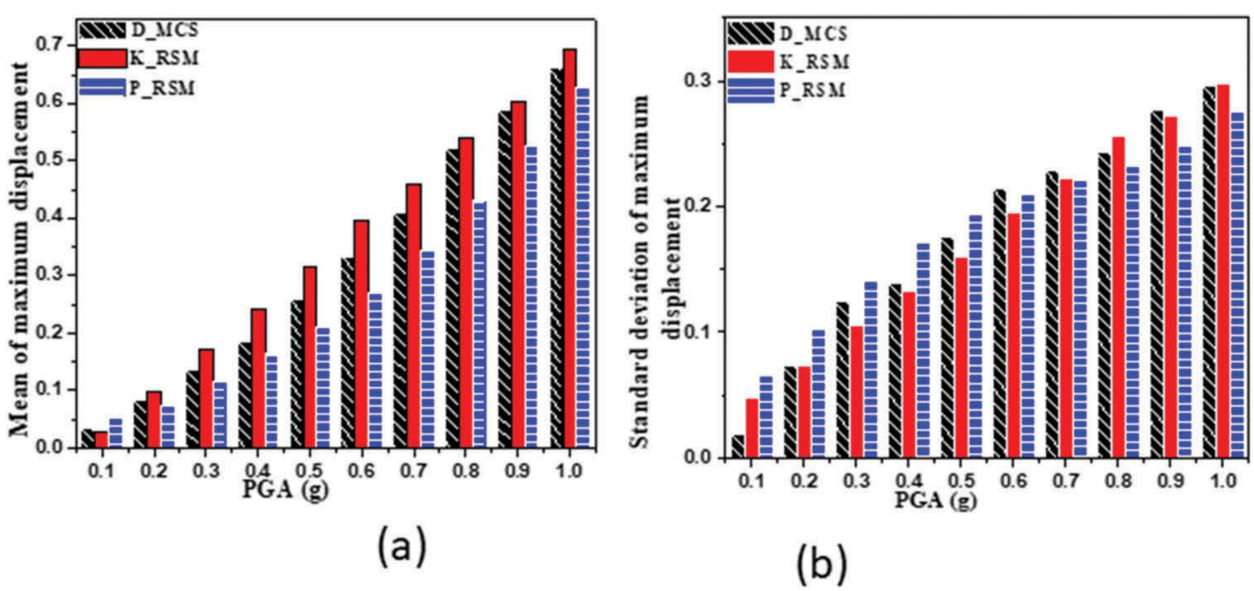

Figure 3. (a) Comparison of (a) the mean and (b) the standard deviation of the maximum displacement by the K-RSM and the P-RSM based on the proposed direct response approximations approach.

Table 2. The performances of the P-RSM and the K-RSM-based metamodel for the SDOF System.

	N-RMSE (%)		R^2	
PGA (in g)	P-RSM	K-RSM	P-RSM	K-RSM
0.3	13.1407	9.96478	0.9503	0.9714
0.5	13.0558	5.96891	0.9422	0.9879
0.7	12.9345	4.22912	0.9275	0.9923
0.9	4.6041	3.1182	0.9887	0.99408

The SFA is now performed by the proposed K-RSM and the usual P-RSM approaches based on the direct response approximation approach. The SFA results are also obtained by the brute force MCS approaches to study the effectiveness of the K-RSM approach compare to the widely adopted P-RSM approach. The improvement possible to achieve to estimate seismic fragility by the proposed K- RSM with respect to the P-RSM when compared with the most accurate brute force MCS based fragility results are quite apparent from Figure 4. The K-RSM based fragility estimates are closer to the brute force MCS fragility estimates than that of obtained by the usual P-RSM approach for all intensity levels showing the enhanced accuracy of the proposed K-RSM based approach.

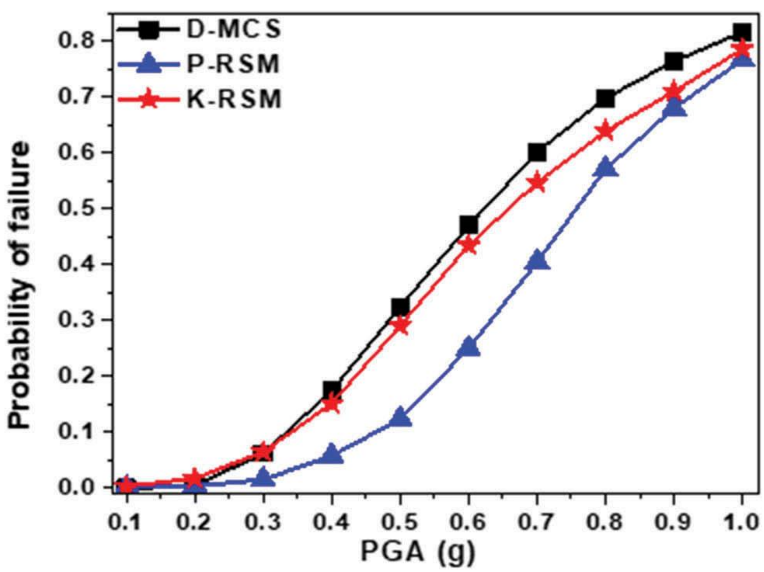

Figure 4. Comparison of fragility of the SDOF system by the proposed K-RSM and the P-RSM based on the direct response approximation approach.

3.2 Example 2: A four storied RC frame

A four storied RC building frame considered to be located in the Guwahati city of northeast India is further undertaken to study the effectiveness of the proposed K-RSM based metamodeling approach for SFA of structures. The building plan is shown in Figure 5. A transverse 2-D frame as shown in Figure 6(a) is 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. 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 columns and the beams sections are: (i) Beams: 300mm x 400mm, 12 numbers of 16mm diameter bars at top and bottom with 8mm diameter stirrups @200c/c and (ii) Columns: 400mm x 400mm with 12 numbers of 16mm diameter bars placed equally with 8mm diameter stirrups @200c/c.

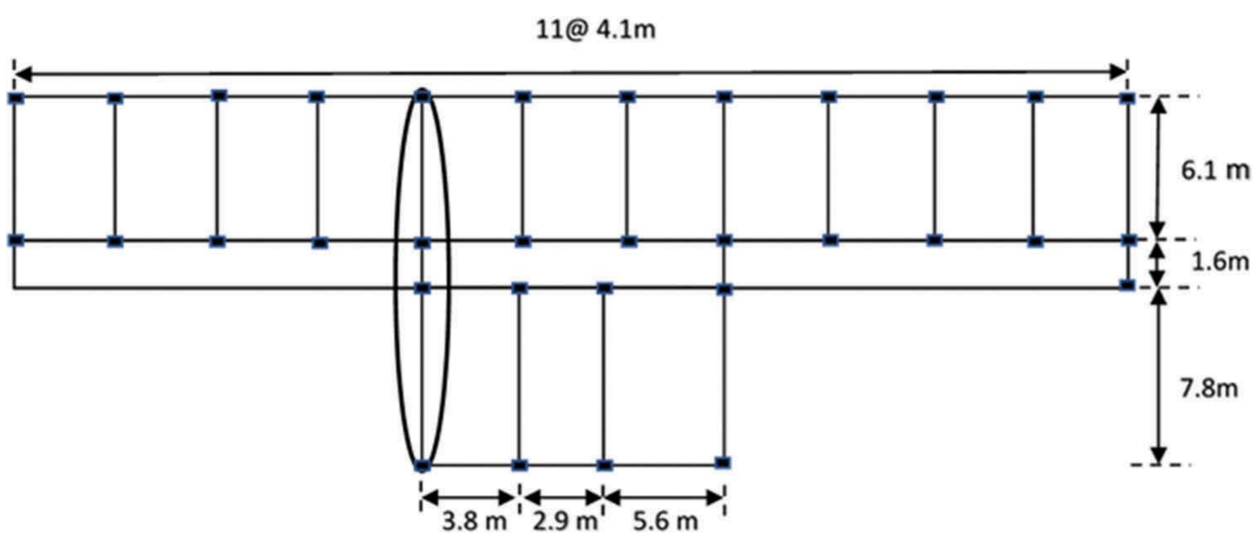

Figure 5. The details of the RC building plan.

The computational model of the considered frame is developed in the OpenSees for NLTHA. The beams and columns are modelled with displacement-based beam-column element with associated fibre sections. The concrete core section is discretized into eight fibres vertically and four fibers horizontally. The cover sections are discretized into 4 x1 fibers at sides and 8x1 fibers at top and bottom. The reinforcing steels are considered as separate fibers for both beams and columns. The assumed fibre discretization of beams and columns are shown in Figure 6(b) and (c), respectively. The core sections are modelled with confined concrete and for cover section unconfined concrete model is used. The available material model in the OpenSees i.e. the concrete04 material model for core concrete, the concrete01 model for cover concrete with zero tensile strength and the steel02 material model with isotropic strain hardening property for reinforcing steels are used. The ultimate strength of the confined concrete is considered at the stress level correspond to the first hoop fracture. The fibre cross sections thus developed by adopting the above material models are used to characterize model the displacement beam-column elements in the OpenSees. Each segment of these beam-column element is assigned with five integration points to capture the response of the components during analysis.

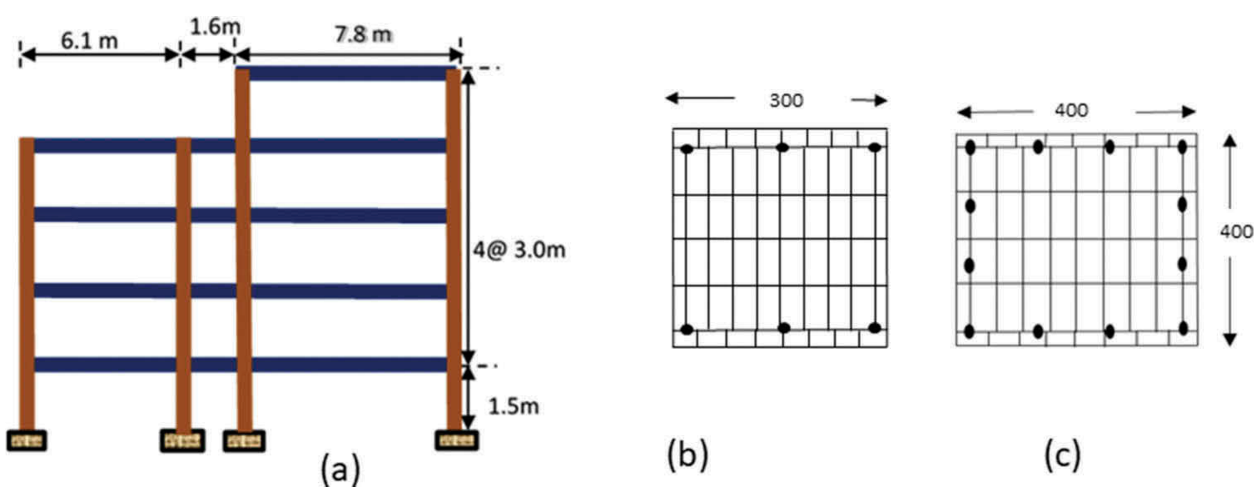

Figure 6. (a) The details of (a) the extracted the 2D frame, (b) the fiber discretization of the beams, and (c) the fiber discretization of the columns.

The parameters that are considered to be random are: concrete characteristic strength (f_{ck}), steel yield strength (f_y), structural damping values (ξ). The statistical values of these uncorrelated normal parameters are provided in Table 3. As earlier, the PGA (X_4) is taken as the control variable.

The DOE points are constructed within the range of the random variables by arranging 30 equidistant levels of each variable according to the UD table, $U_{30}\left(30^4\right)$. The ground motion bin consists of twenty-four numbers of earthquake time histories (natural, artificial and simulated, eight each) as described earlier. The training data points remain same for the proposed K-RSM and the usual P-RSM based metamodels constructions.

Table 3. The details of the various parameters of the RC frame.

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

The seismic fragility estimates by the proposed direct response approximation approach and the conventional dual RSM approach based on Kriging metamodel are now obtained for three structural performance levels i.e. the Immediate Occupancy (IO), the Life Safety (LS) and the Collapse Prevention (CP). The permissible maximum storey drift (MSD) ratio values for the IO, LS and CP levels associated with various performance levels of the RC frame are taken as 1%, 2% and 4%, respectively [FEMA 356, 2000]. 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 (five thousand simulations for each intensity level) is performed to get the trend of the brute force MCS based fragility estimate so that the quality of the proposed K-RSM based fragility estimate could be judged. Figures 7 to 9 show the SFA analysis results obtained for different performance levels. As may be noted from these plots, the proposed direct K-RSM based fragility estimates are closer to the brute force MCS based fragility estimates compare to that of obtained by the dual K-RSM based approach. Thus, the enhanced accuracy of the proposed direct response approximation approach is valid for this problem also.

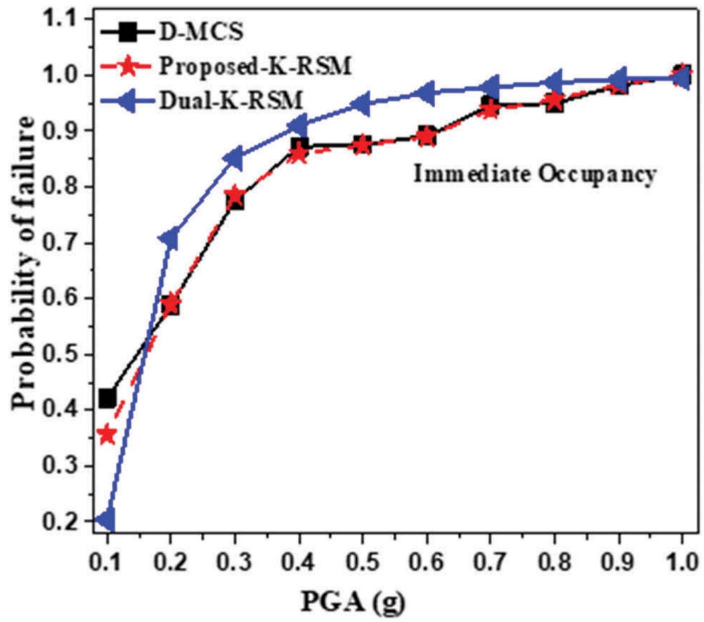

Figure 7. Comparison of fragility of the RC frame at IO level by the dual K-RSM and the proposed direct K-RSM approaches.

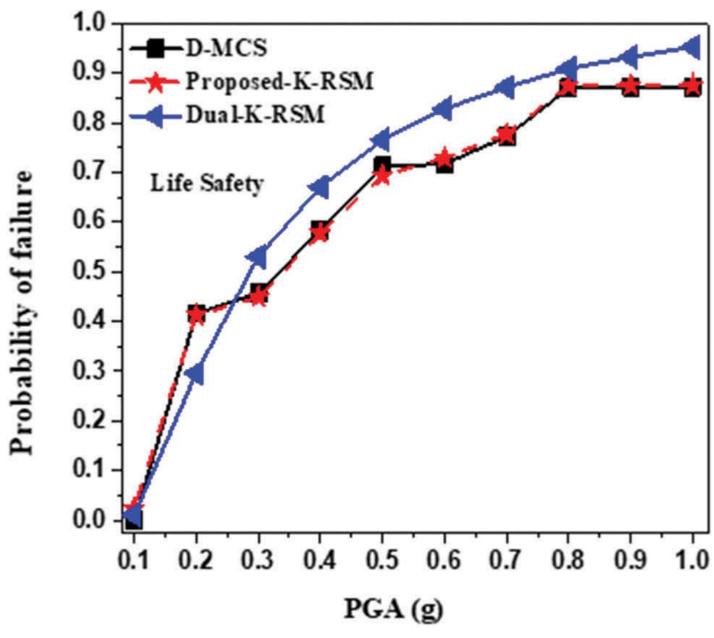

Figure 8. Comparison of fragility of the RC frame at LS level by the dual K-RSM and the proposed direct K-RSM approaches.

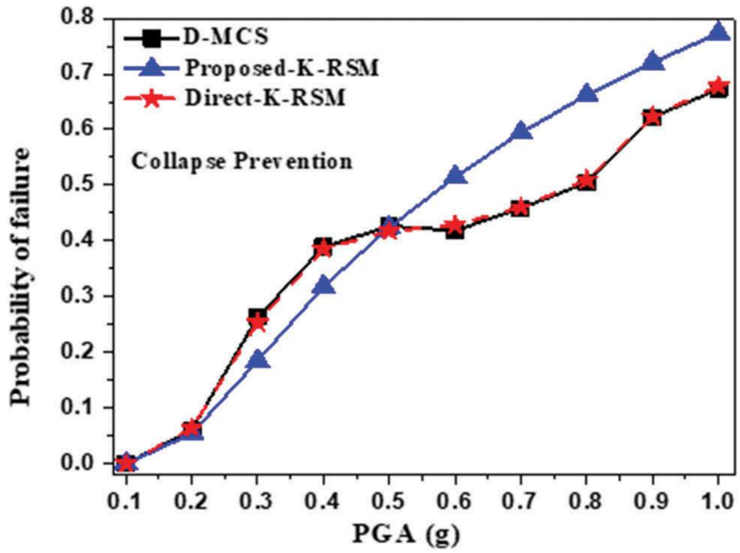

Figure 9. Comparison of fragility of the RC Frame at CP level by the dual K-RSM and the proposed direct K-RSM approaches.

To demonstrate the improved capability of the propose K-RSM based metamodel compare to the P-RSM based metamodel to approximate the nonlinear dynamic responses of the RC frame, the mean and SD of MSD values are compared with varying PGA values in Figure 10. The brute force MCS based similar results are also obtained directly from the NLTHAs of the frame considering the same twenty-four ground motions in the bin. The improved capability of the proposed K-RSM approach compare to the conventional P-RSM approach to estimate the mean and SD of the nonlinear seismic responses of the frame can be readily observed in the plots by comparing those with the direct MCS based results. The estimated response values by the proposed K-RSM based approach are closer to the brute force MCS based such results than the P-RSM based values clearly indicating the enhanced accuracy of the proposed K-RSM based metamodel to approximate seismic response. The NRMSE and R^2 values are compared in Table 4. The lesser NRMSE and R^2 value closer to unity by the proposed K-RSM based metamodel compare to that of obtained from the P-RSM based metamodel can also be noted from the table confirming the improved approximation capability of the K-RSM based metamodel for this frame problem as well.

Table 4. The performances of the P-RSM and the K-RSM-based metamodels for the RC frame.

	N-RMSE (%)		R^2	
PGA (in g)	P-RSM	K-RSM	P-RSM	K-RSM
0.3	19.8216	7.2336	0.9311	0.9908
0.5	16.8972	4.8517	0.9639	0.9970
0.7	18.8131	4.2439	0.9539	0.9976
0.9	16.6504	3.0331	0.9619	0.9987

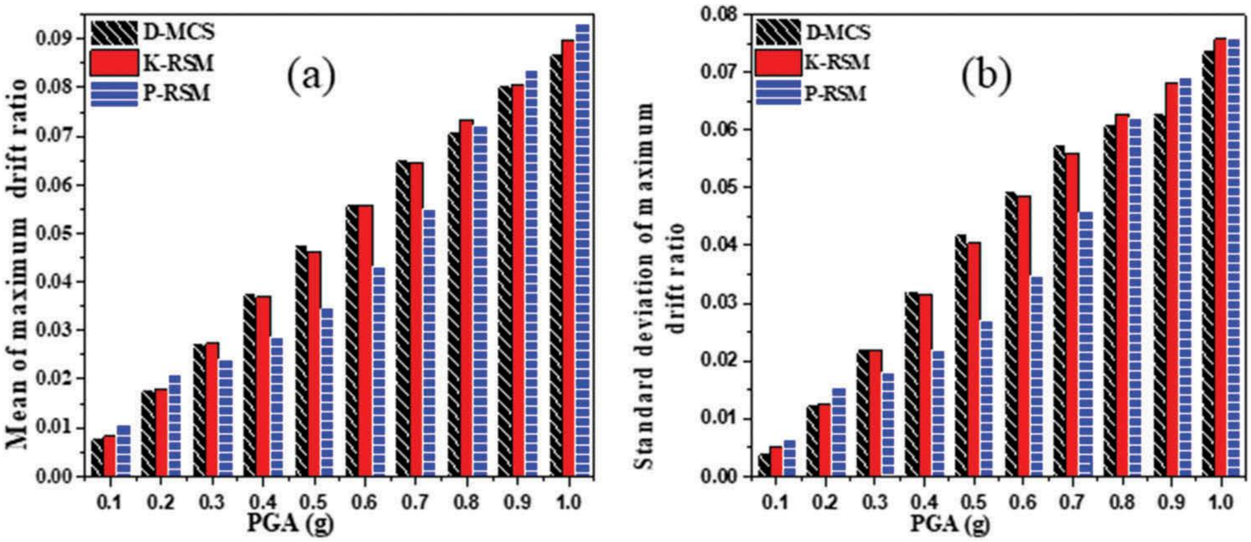

Figure 10. The comparison of (a) the mean and the SD of the maximum displacement.

The SFA is now performed by the proposed K-RSM and the usual P-RSM based metamodels. The fragility curves are shown in Figs. 11 to 13 for IO, LS and CP performance levels, respectively. The improve capability to estimate seismic fragility by the proposed K- RSM based metamodel with respect to the P-RSM is also quite apparent from these plots.

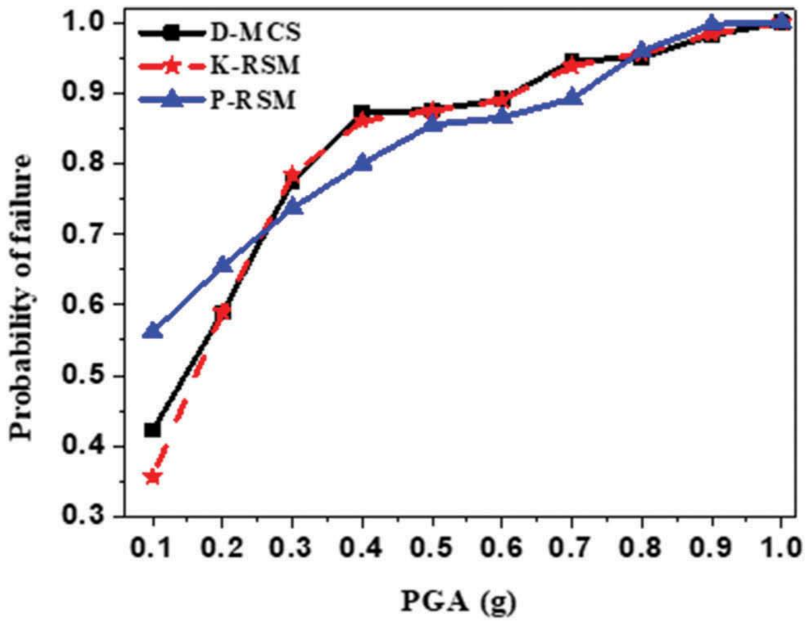

Figure 11. Comparison of fragility of the RC frame at IO level.

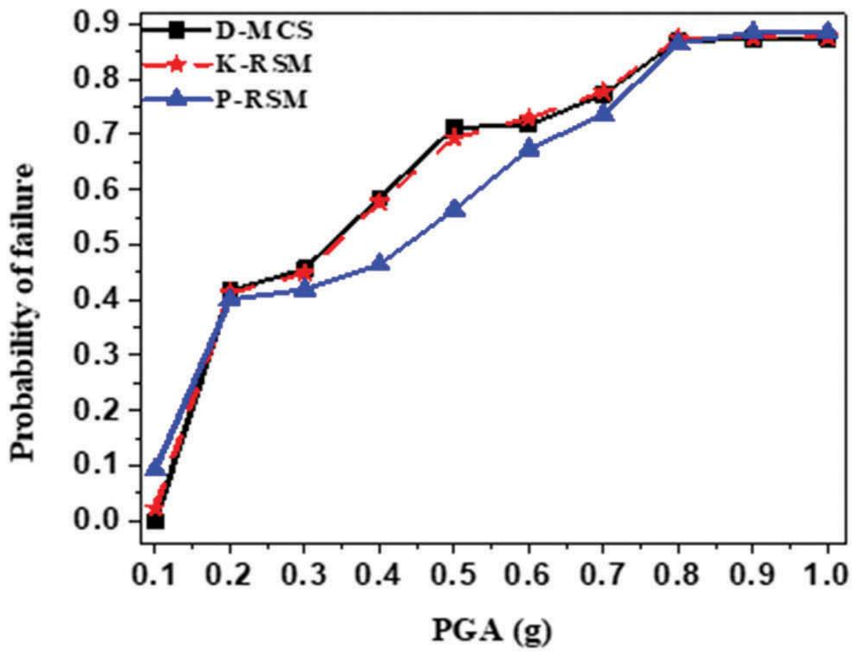

Figure 12. Comparison of fragility of the RC frame at LS level.

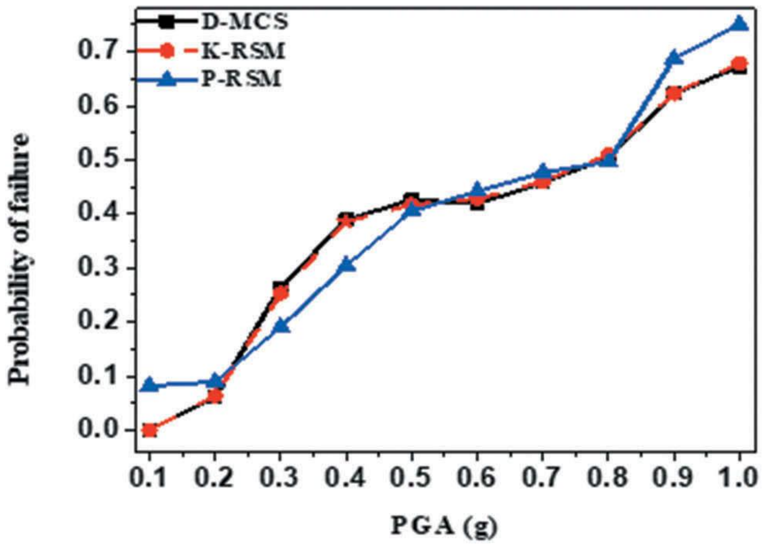

Figure 13. Comparison of fragility of the RC frame at CP level.

4. Summary of Observations and Conclusions

A metamodeling approach based on Kriging interpolation method is explored for improved SFA of structures in the framework of MCS technique. Without further computational burden compare to usual dual RSM approach, the metamodel is proposed to construct directly to avoid a prior assumption on statistical distribution of seismic responses as necessary in case of dual RSM approach. For efficient SFA of structure, seismic intensity parameter is included as one of the predictors in the response prediction model. Though, the required computational cost increases marginally for metamodel building process due to this added parameter; the overall process of complete fragility curve generation is much more efficient as the repetitive construction of metamodels are avoided. The superiority of the proposed direct response approximation approach for predicting seismic response and fragility estimation are noted consistently compare to those obtained by the usual dual RSM approach for all the PGA values for both the examples studied here. The comparative assessments of the capability of the proposed K-RSM with respect to the P-RSM based metamodel reveal that there is a substantial improvement in the accuracy to approximate nonlinear seismic response and fragility estimate by the K-RSM approach. The computed statistical metrics i.e. the NRMSE and R^2 values also confirm the superiority of the K-RSM based metamodel. The observation of the present study is based on a specific ground motion bin and single DOE scheme based on UD. It is felt important to address the sensitivity of the performance for different choices of ground motion bin and DOE scheme. The present study is focused on specific examples and particular study area. However, the basic steps are generic enough to readily adapt to any other structures by replacing the mechanical model and generation of ground motion data for the location of the structure. Thus, the proposed Kriging based metamodeling approach can be applied generically for improved SFA of structures.

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