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Hybrid approach to seismic reliability assessment of engineering structures

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ABSTRACT

Although the direct Monte Carlo simulation (MCS) method can estimate the seismic failure probability accurately, it is inefficient when small failure probabilities are of interest, and especially so if finite element transient analysis is required. For seismic reliability assessment of practical complex structure with large number of random parameters and small failure probability, a hybrid approach which combines subset simulation (SS), explicit time domain method (ETDM) and back propagation neural network (BPNN), is proposed herein. In this methodology, SS with modified Metropolis-Hastings (MMH) algorithm reduces the number of simulation samples required to estimate the failure probability; the use of ETDM with BPNN technique in lieu of many repeated finite element transient analysis reduces the computational effort for each realization dramatically. It should be emphasized that the separate treatment of uncertain structural and earthquake load parameters having low and high variabilities make the presented method successful. The seismic reliability analyses of an in-service self-anchored suspension bridge (modeled using a 15,530 nodes and 20,875 elements) with 31 random parameters subjected to earthquake motion are performed to illustrate the comparable much higher efficiency of the proposed method (especially for low failure probability cases) compared to using the direct Monte Carlo simulation (MCS). In terms of computational efficiency, if the suspension bridge has a failure probability of 1.0×10^{-3} and a COV of less than 0.3 is desired, the direct MCS requires 12,000 simulations, which will take about 250 days using a notebook with i5-core. The proposed hybrid approach only needs 18 days, which includes the FE analysis to obtain expressions for impulse response matrix through BPNN and three levels in the SS.

1. Introduction

For large scale engineering structures, evaluating their performances under seismic conditions is a necessary step and the deterministic approach is often taken for reasons of simplicity and minimal computational effort. However, to obtain a more complete evaluation, the existence of uncertainties such as those associated with structural parameters including material characteristics as well as load conditions must be accounted for in the analysis [1–3]. There are limited works published or actual computation performed on the seismic reliability of real large scale engineering structures, especially bridges, due to its complexity and lengthy computation [4–9].

The straightforward approach to reliability analysis of large scale structures like bridges is to perform direct Monte Carlo simulation (MCS) to obtain an accurate estimate of the failure probability. This method provides results for reference purpose rather than for performing all cases of interest due to the volume of computation needed especially for real engineering structures [10]. The latter involves not only thousands of repeated structural analyses, but in cases involving rare events and nonlinear dynamics, the effort is exponentially formidable. Methods which can reduce the number of sample points required, such as through advanced sampling techniques, and shorten the computation effort of the nonlinear dynamic finite element (FE) analysis, are needed.

Several variance reduction based strategies have been developed to reduce the simulation samples, such as importance sampling and line sampling [10–12]. The basic concept is the choose a new sampling distribution to generate samples leading to failure occurring more frequently on a conditioned domain. This has been illustrated to be feasible for problems involving low number of random parameters but the choice of an appropriate sampling distribution is by no means easy [10,13]. To address this limitation, Au and Beck [11] proposed the subset simulation (SS) method which decomposed a rare failure event into several conditional events with relatively higher occurrence frequency. To generate the samples at the conditional event level, the Markov chain Monte Carlo (MCMC) simulation and Metropolis-

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Hastings (MH) algorithm are adopted [11,14,15]. The advantage of this sampling method is that the target distribution need not to be known fully and the samples under the conditional event level could be generated without prior knowledge of the failure probability. The disadvantage is the relatively high coefficient of variation (COV), used as a measurement criteria of the error of estimator, leading to frequent 'repeated' samples. Hence, the modified MH (MMH) algorithm was proposed subsequently to reduce the COV [14,15] through modifying the rejection rate of the pre-candidate sample generated by proposed PDF. From step c of Appendix A, in MMH, all the generated candidate samples satisfy the acceptance condition and are only rejected in step d if lying outside the limitation region. While in original MH, the rejection starts at step c and this operation of frequent rejection obviously increases the appearance of 'repeated' samples which causes the high correlation between the generated Markov chain samples.

Although SS has been employed to reduce the amount of samples, but the finite element analysis still needs to be performed for each sample, the calculation effort is formidable as usual. The natural way to shorten the computation time for repeated finite element analyses is to use approximation methods, of which meta model approach such as employing neural network (NN) has been successfully implemented together with MCS to estimate the failure probability [13]. Simply speaking, meta model is an explicitly mathematical expression, constructing the relationship between parameters and interested performances (e.g. response) and replacing performing the FE analysis. Due to the high nonlinear relationship between parameters and structural responses, NN meta model which has more fitting ability and efficiency compared to traditional meta model like polynomial expressions was employed. But such method has proven to be accurate for problems with random parameters having low coefficients of variation and may not work well if the parameters have high variability [16,17]. For example, in dealing with meta models between parameters (including the structural and random earthquake load parameters) and random seismic performances, using this technique may not be able to produce accurate relationships considering all the parameters together. Because the structural parameters has low degree of randomness, but the earthquake loads having parameters with high variability. This has not been explicitly addressed.

To overcome this deficiency, this paper proposes to treat the two classes of uncertain parameters (structural parameters and earthquake load parameters) separately. For an ground acceleration time history generated by earthquake load parameters, an explicit time domain method (ETDM) [18,19] is adopted to obtain the seismic response history. In ETDM, two unit impulse acceleration time history loads are employed and the responses at each time instant of these two loads are obtained by time domain FE analysis. Then the response of the structure can be estimated by multiplying the coefficient matrix, where elements at each column are responses of each time instant of impulse loads, with the vector where the elements are acceleration load values of each time instant. That means, for a deterministic structure, if there are one thousand samples of random earthquake acceleration time history loads generated by one thousand groups of earthquake load parameters, only twice FE transient analyses are needed to obtain the responses of the two impulse loads to form the coefficient matrix in ETDM, then the responses of structure for each earthquake acceleration time history are obtained by multiplying this matrix with corresponding acceleration vector. Compared with conventional FE analysis, a total of one thousand times of transient analyses are needed, which seems like a huge project. But in seismic reliability analysis, not only the earthquake loads are uncertain factors, but also are the structural parameters. Different groups of structural parameters means different structural responses under the same earthquake load. Hence, the coefficient matrix, namely the responses of the two unit impulse loads, is based on the structural parameters. To improve the calculation efficiency, the NN meta model is employed by constructing explicit expressions between each element in coefficient matrix and structural parameters. Then in the SS process, for each parameter vector, the structure response is calculated by multiplying coefficient matrix, obtained by the aforementioned explicit expressions and structural parameters, with earthquake acceleration vector, obtained by earthquake load parameters. Hence, there is no need to perform numerous time domain finite element analyses.

In summary, this paper presents a more efficient hybrid method of seismic reliability assessment for large scale structures, which is based on the integrated use of the aforementioned ETDM, NN and SS. SS is employed to reduce the simulation samples, and in the SS process, the structural response can directly be obtained by ETDM, where the coefficient matrix has been transferred to explicit expressions, trained by NN technique, only having relationship with structural parameters. The paper is organized as follows. Section 2 touches on the basics of SS, ETDM, NN, non-stationary stochastic earthquake acceleration simulation, as well as the procedure of the proposed hybrid approach. Section 3 demonstrates the detailed process and results of applying the hybrid approach to the seismic reliability assessment of a self-anchored suspension in-service bridge which is a complex and larger structure. The conclusions are drawn in Section 4.

2. Hybrid method for seismic reliability assessment

2.1. Subset simulation with MMH algorithm

Seismic reliability of engineering structures is usually small failure probability event and needs large amount of samples in analysis. But SS method [11,13] divides a small failure probability event F into a sequence of m more frequently occurring conditional events, F_i, $i = 1, 2, \ldots, m$, such that $F_1 \supset F_2 \supset,\ldots,\supset F_m = F$. Thus this operation reduces the number of samples greatly compared to direct MCS. The probability of event F occurring can be expressed as

$$P(F) = P(F_1)P(F_2|F_1)P(F_3|F_2),\ldots,P(F_m|F_{m-1}) \tag{1}$$

where $P(F_1)$ is the probability of event F_1 occurring; and $P(F_\mathrm{m}|F_{\mathrm{m}-1})$ represents the conditional failure probability. Each event F_i represents the event $\{G(\mathbf{X}) < c_i\}$, where $G(\mathbf{X})$ is the performance function value with vector of random parameters $\mathbf{X}$ and c_i is the intermediate threshold for each level, which usually has a relationship of $c = c_m < c_{m-1} < \ldots < c_1$.

Usually, the number of samples in each subset level, N, is pre-determined, such as 500 depending on the accuracy required, and a fixed p is used as the failure probability for each level except the final level, and c_i is then determined as the $(pN + 1)$-th smallest value of $G(\mathbf{X}_k^{(i)})$ in each level i, where $\mathbf{X}_k^{(i)} = [x_{k1}, x_{k2}, \ldots, x_{kd}]$, $k = 1, 2, \ldots, N$ is the number of samples, $i = 1, 2, \ldots, m-1$, d is the number of parameters. If the $(pN + 1)$-th smallest value of $G(\mathbf{X}_k^{(m)})$ in level m is smaller than final limitation c, it means this is the final conditional level and the SS process ends. Hence, the estimator of $P(F)$ is given by $p^{m-1}P_m$, where $P_m = P(F_m|F_{m-1})$. In practice, p is often set as 0.1 where researchers have shown this to be efficient for failure probability up to 10^{-6} [11,14].

In the first conditional level of SS, the N samples are generated according to the original PDF of each parameter and pN samples whose performance function value lower than c_1 are selected as so-called seeds. For each seed, $1/p$ Markov chain samples need to be generated according to proposal PDF of each parameter. The number of simulation samples generated will be N, which will be used in conditional level 2 simulation. Repeat the former process to generate N samples for conditional level 3 to m. As to the selection of the proposal PDF, which is suggested as a one-dimensional PDF with a symmetry characteristic for each parameter, that is, $\varphi_i(y|x) = \varphi_i(x|y)$, where $\varphi_i(\cdot)$ is the proposal PDF and y, centered at x, is also a sample generated by x. To ensure the efficiency of the Markov chain samples and generate samples over a constrained domain, a uniformly distributed proposal PDF around the seed has been suggested [13]. A typical procedure of generating samples for conditional level i with the aforementioned process using MMH