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Multiple failure modes analysis of the dam system by means of line sampling simulation

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ABSTRACT

As the number of aging dams is increasing, an efficient and feasible probabilistic method is required to analyze the uncertainties of a dam system with multiple failure modes. Due to the limitation of huge computation of Direct Simulation Monte Carlo, a new method is introduced to solve the reliability problem of a dam system. This new method determines the failure domain of a complex structure by resorting to lines rather than random points. It is used to calculate the failure probability and reliability sensitivity of a gravity dam, which is a large, complex structure with small probability; and the basic Monte Carlo method is also used for comparison. Results show that the new method is more efficient and feasible to analyze the reliability of a dam system with small failure probability and multiple dimensionalities.

1. Introduction

Fuzziness and randomness are two inseparable uncertainty factors that influence dam safety. It is more objective to analyze dam reliability if these two attributes are taken into account. There are over 86,000 dams in China and they play a vital role in the national economy. Many of these dams have becoming increasingly dangerous due to improper design and mismanagement. And the number of dangerous dams currently accounts for over 40% of all the dams in China [1]. Therefore, the assessment of dam reliability and the probability of dam failure are more and more essential for people to recognize the safety of dams.

In the past years, great achievements have been gained in the analysis of dam system reliability. "Direct Simulation Monte Carlo" technique has always been used for calculating system failure possibility [2]. However, failures probabilities are really small when it comes to low probability events in a large complex system. Monte Carlo Simulation (MCS) is inefficient, to certain extent, as it needs a large number of samples for an accurate calculation. Another popular method called the Moment Method, which requires computational effort for high dimension problems, has also been used in the field of system reliability analysis [3], since there are multiple failure modes in large-scale structures and mutual correlations among these models, the moment method seems inapplicable to these problems, too.

Because of the shortcomings aforementioned, several novel sampling methods including Latin Hypercube Sampling (LHS) and importance sampling have been proposed [4]. Importance sampling uses an importance sampling distribution, which replaces the probability density function (PDF) in Monte Carlo simulation. It reduces the variance, but this method is more subjective because an inappropriate choice of an importance sampling distribution may lead to worse estimates. Another sampling method is stratified sampling [5]. This method divides sample space into non over-lapping stratum, and then calculates each probability of each stratum. However, it is not a practical method in real large-scale system. Although LHS is more efficient than Monte Carlo method to estimate average values and standard deviations in complex systems, it is less efficient for low probability events. To overcome this limitation, therefore, a sampling method denoted as line sampling (LS), which replaces the random points with lines, is developed to evaluate reliability in high-dimensional setting and low probability events. This technique determines the failure domain in terms of system reliability. This method has been applied widely in the area of structural reliability problems, and it is better than basic MCS in terms of robustness and accuracy. In addition, LS can resolve the problem of multiple failures in a simple and effective way.

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Therefore, LS is used to analyze the multiple failure modes of dam systems. It is the first time that LS is used in dam systems. With a series system and parallel subsystems, the dam system is a redundant structure for which the related uncertainties and multiple failure modes are accounted. The advantages of LS can be shown when compared with the method of traditional MCS and that of LHS.

2. The line sampling method

Line sampling is a new method of simulation to calculate low failure probability. It uses random points instead of lines to determine the failure domain.

2.1. Line sampling's basic theory

Apply Nataf's transformations [6] and transform a set of non-normal correlated random variables into the set of uncorrelated normal (Gaussian) variables. It can serve as a mapping which transforms the original and the physical space into the standard normal one. Let $x = [x_1, x_2, \ldots, x_n],\quad x \in R^n$ to be uncertain parameters' vectors. Transform the parameter vector x into the vector $\theta = \left[\theta_1, \theta_2, \ldots, \theta_n\right],\quad \theta \in R^n$.

$$\begin{aligned}\theta &= T_{x\theta}(x),\\ x &= T_{\theta x}(\theta).\end{aligned} \tag{1}$$

Applying Eq. (1), the performance function on the standard normal space can be defined as:

$$g^{(i)} = g_x(x^{(i)}) = g_x(T_{\theta x}(\theta^{(i)}) = g_\theta(\theta^{(i)}) \tag{2}$$

Since the function, $g_\theta(\theta)$, in some cases of practical system, is unknown explicitly, it can just be calculated point-wise. For example, when a full finite element problem is analyzed, the performance function $g_\theta(\theta^{(i)}) = g_x(x^{(i)})$ can be computed for each realization x^i. The number of finite element runs decides the computational cost when the failure probability is evaluated [7]. But before sampling, the important direction e_α should be first determined, which is called "important unit vector" or "important direction". In the standard normal space, e_α is used as pointing in the direction of "design point". And in the failure space, the most probable point is the optimal important unit vector. On the limit state space $g_\theta(\theta) = 0$, the "design point" is defined as the vector point θ^* which is the nearest to the origin. [8,9]. After that, by normalizing θ^*, α – the important unit vector – can be obtained.

Take the direction of e_α as the performance function's normalized gradient. Let $g_\theta(\theta)$ as the performance function, and the gradient $\nabla g_\theta(\theta^*)$ at the vector point θ^* is then defined as:

$$\nabla g_\theta(\theta^*) = \left[\frac{\partial g_\theta(\theta^*)}{\partial\theta_1}\frac{\partial g_\theta(\theta^*)}{\partial\theta_2}\cdots\frac{\partial g_\theta(\theta^*)}{\partial\theta_n}\right]^T \tag{3}$$

This is a new method to measure the relative importance of a given random variable: the larger the gradient $\nabla g_\theta(\theta^*)$ 'value, the larger the corresponding uncertain variable's "effect" of the performance function. By normalizing θ^*, the unit vector α can be calculated by Eq. (4)

$$e_\alpha = \nabla g_\theta(\theta^*)/\left\|\nabla g_\theta(\theta^*)\right\| \tag{4}$$

2.2. Failure probability estimation

After calculating the unit vector e_α, the conditional Monte Carlo method [6] is applied in the procedure of line sampling. The results are shown in Fig. 1. The conditional failure probabilities is calculated where x changes randomly just along the direction e_α. In Fig. 1, apply direct Monte Carlo and in the direction $\theta^\perp$, transfer the point normal into the line. The sampling density is $f(\theta)$ and the failure probability P_f is expressed in Eq. (5)

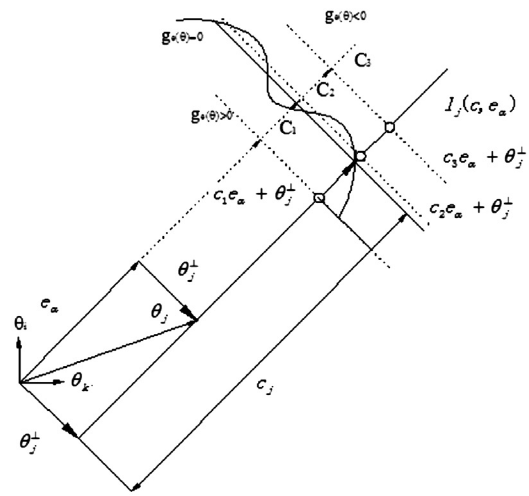

Fig. 1. Single failure mode's line sampling.

$$P_f = \int\cdots\int_F f(\theta)\mathrm{d}(\theta) \tag{5}$$

Then, the sampling $\tilde{\theta}$ is the total of a deterministic multiple of e_α and a generated vector $\theta^\perp$ is defined perpendicular to the direction of e_α.

$$\begin{aligned}\tilde{\theta} &= ce_\alpha + \theta^\perp\\ &\text{and}\\ \theta^\perp &= \theta - \left\langle e_\alpha, \theta\right\rangle e_\alpha\end{aligned} \tag{6}$$

where, θ is the input variables of the standard normal space with dimensions n; $\left\langle e_\alpha, \theta\right\rangle$ is the dot product of e_α and θ.

After that, apply direct Monte Carlo simulation to calculate N samples $\theta_j (j = 1, 2, \ldots, N)$ and solve for each sample j which is relative one-dimensional reliability issue. Here c is only random variable. The relative failure probability can be denoted as:

$$P_{fj} = \phi(-c_j) \tag{7}$$

where, c_j is the junction between the limit state equation $g(x) = 0$ and the line $l_j(c, e_\alpha)$ which is shown in Fig. 1. Select three different values of c, and evaluate the performance function, then fit a second-order polynomial to determine the root. After that, the value c_j can be calculated.

In the next step, the estimator p_f is calculated by Eq. (8) after collecting the failure probability P_{fj},

$$P_f = \frac{1}{N}\sum_{j=1}^{N} P_{fj}. \tag{8}$$

2.3. Estimation of the reliability sensitivity

Differentiating Eq. (8), μ_{x_i} and σ_{x_i} are the reliability sensitivities of P_f, which can be denoted with partial derivatives $\partial P_f/\partial\mu_{x_i}$ and $\partial P_f/\partial\sigma_{x_i}$ by Eqs. (9) and (10).

$$\frac{\partial P_f}{\partial\mu_{x_i}} = \frac{1}{N}\sum_{j=1}^{N}\frac{\partial P_{fj}}{\partial\mu_{xi}} \tag{9}$$

$$\frac{\partial P_f}{\partial\sigma_{x_i}} = \frac{1}{N}\sum_{j=1}^{N}\frac{\partial P_{fj}}{\partial\sigma_{xi}} \tag{10}$$