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Updating real-time reliability of instrumented systems with stochastic simulation

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ABSTRACT

In this research, a new method is proposed to update real-time reliability based on data recorded by instruments and sensors installed on a system. The method is founded on Bayesian analysis and subset simulation and is capable of estimating the functional relationship between the real-time failure probability and the monitoring value. It is shown that as long as the monitoring data can be reasonably deduced into a single index, this relationship can be obtained; moreover, it can be obtained prior to the monitoring process. Three examples of civil engineering systems are used to demonstrate the new method. This new method may be applied to safety monitoring of in-construction civil systems and monitoring of existing civil systems.

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1. Introduction

Uncertainties are abundant in civil engineering. Major sources of these uncertainties may include uncertainties in material properties, model uncertainties and measurement uncertainties. Reliability analyses [1–4] are the main tool of quantifying these uncertainties. However, it is sometimes the case that the amount of uncertainties associated with civil systems is so significant that the resulting failure probability is unacceptably large. For one of the examples in this paper (a deep excavation case study), where the probability distributions of the uncertainties are reasonably chosen according to the laboratory test results and literature, the probability that the maximum ground settlement is greater than 10 cm is as high as 30%. Such a high failure probability usually reflects insufficient information. Similar issues may exist in various civil systems if they are subjected to a large amount of uncertainties. How to reduce the uncertainties in civil systems is an important research topic.

The goal of this paper is to develop a method of updating real-time reliability by using the monitoring data obtained from an instrumented system to reduce uncertainties. Please note that the goal is to update "real-time" reliability rather than "future" reliability, i.e. to "monitor" the reliability of the system, not to update the reliability due to future excitation. The applications of updating real-time reliability are exemplified by the following examples:

(a) Monitoring of serviceability: A semiconductor factory may be vulnerable to small vibrations that can do major damage during the production process. This damage may be difficult to detect since it does not induce obvious "failure" but rather is a serviceability issue. It would be beneficial to monitor this "serviceability" reliability during the production process to minimize the impacts of the damage.
(b) Early warning: Another benefit for routinely updating real-time reliability is "early warning", i.e. warnings prior to possible failures. Before failures occur, there may be "signs" prior to failures. A high updated real-time failure probability may be a good indicator of the "signs". By routinely updating real-time reliability, the users of the target system can have a better grasp of how the reliability changes with time, so that the issue of an early warning is possible.
(c) Hazard forecasting: In the case that the monitoring data can be forecasted, the proposed method can be combined with the forecast results to quickly predict future reliability. For instance, if the functional relation between failure probability of a slope and rainfall amount is established by the proposed method, this functional relation combined with rainfall forecast results can be used to obtain a quick prediction for failure probability of the slope during a future rainfall.

In the literature [5–7], updating reliability has been discussed under a FORM (First-Order Reliability Method) framework. With minimal amount of computation, the FORM approach works

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reasonably well for problems with few uncertainties. However, the limitation is that when there are lots of uncertainties or multiple design points, FORM may not be suitable.

In the case that more computation resource is available, a more general reliability updating approach based on Bayesian methods can be employed. To explain the approach, let us divide the uncertain variable Z into two parts $Z = \{\theta, X\}$: θ denotes the uncertain system (structural) parameters, and X denotes the uncertain excitation. The following equation can be used to update the reliability:

$$P(F|\varphi, M) = \int P(F|\theta, M) f(\theta|\varphi, M)\, \mathrm{d}\theta \tag{1}$$

where φ denotes the monitoring data; $P(F|\theta, M)$ is the failure probability given the system parameters θ and the chosen model class M; $f(\theta|\varphi, M)$ is the posterior probability density function (PDF) of θ. Note that $P(F|\theta, M)$ can be determined by an ordinary reliability analysis. This approach was taken by Papadimitriou et al. [8] to update the reliability by assuming that the problem is identifiable and the amount of data is large. If the data amount is insufficient or the problem is unidentifiable, the approach may not be applicable.

The integral in (1) can be evaluated through stochastic simulations: if samples $\left\{\theta^{(i)} : i = 1, \ldots, N\right\}$ can be drawn from the posterior PDF $f(\theta|\varphi, M)$, according to the Law of Large Number:

$$P(F|\varphi, M) \approx \frac{1}{N} \sum_{i=1}^{N} P\left(F|\theta^{(i)}, M\right). \tag{2}$$

Compared to the FORM approach, this approach is more general since it is applicable for general problems, even those with multiple design points, as long as the conditional samples can be drawn from $f(\theta|\varphi, M)$. However, there are, at least, two challenges in this approach: (a) drawing samples from $f(\theta|\varphi, M)$ can be highly non-trivial, especially when the θ dimension is high; (b) for each sample of $f(\theta|\varphi, M)$, a reliability analysis is required to determine $P\left(F|\theta^{(i)}, M\right)$. This implies that in order to evaluate $P(F|\varphi, M)$, repetitive reliability analyses may be needed.

One exception is described in Ching and Beck [9], where they proposed a method based on ISEE [10] to update the real-time reliability of linear systems. Their approach does not have the aforementioned constraints, but it can be only applied to linear systems with Gaussian uncertainties. For general problems, Cheung and Beck [11] recently proposed an interesting method of updating the reliability that bypasses the second challenge. The idea is to implement the following equation:

$$P(F|\varphi, M) = \frac{f(\varphi|F, M)\, P(F|M)}{f(\varphi|F, M)\, P(F|M) + f\left(\varphi|F^C, M\right)[1 - P(F|M)]} \tag{3}$$

where F^C is the non-failure event; the two normalizing constants $f(\varphi|F, M)$ and $f\left(\varphi|F^C, M\right)$ can be directly estimated with more advanced Bayesian methods, e.g. the transitional Markov chain Monte Carlo method proposed by Ching and Chen [12]. Hence the reliability can be updated without further repetitive reliability analyses. This approach is quite general but still requires drawing samples from $f(\theta|\varphi, M)$. To the authors' best knowledge, a method that completely resolves the two challenges is not yet available.

The intention of this paper is to provide a partial solution to the two challenges: it will be shown that the aforementioned two challenges can both be bypassed if the monitoring data is a scalar. In particular, an approach based on subset simulation (SubSim) [13–15] will be developed so that updating the reliability no longer requires drawing samples from $f(\theta|\varphi, M)$ but from $f(\varphi|F, M)$; also, the repetitive reliability analyses are not necessary. When the monitoring data is high dimensional, the proposed method may be not applicable; however, whenever it is possible to effectively condense the high-dimensional data into a scalar, the method can still be applied at the cost of losing information.

The structure of the paper is as follows. In Section 2, the problem of updating reliability is formally defined. In Section 3, a simple procedure for reliability updating via Monte Carlo simulation (MCS) is presented, while a more efficient method based on SubSim is presented in Section 4. In Section 5, examples are used to demonstrate the new approach, and in Section 6, discussions and a conclusion will be given.

2. Problem definition

The goal of regular reliability analyses is to estimate the failure probability given the probability distribution of the uncertainties in the target system and the mathematical model M of the system, i.e. to compute $P(F|M)$, where F is the failure event. When new information φ is available, it is essential to incorporate it to reduce the uncertainties (i.e. update the reliability). This is especially the case if the new information φ is the direct measurement on the target system: this measurement directly reflects the system status and may contain much information. Therefore, it is desirable to develop a methodology to update the reliability based on these measurements, i.e. to compute $P(F|\varphi, M)$. In this paper, φ is assumed to be a scalar. For vectorial φ, the problem of updating $P(F|\varphi, M)$ is much more difficult, so it is left as future research.

A naïve way of achieving the aforementioned task is as follows: employ brute-force MCS to draw many samples of the uncertain variables; each sample corresponds to a monitoring value. Suppose that there are m samples whose monitoring values are identical to the actual monitoring value, and that among the m samples, there are n samples satisfying the prescribed failure condition (called failure samples). The failure probability can therefore be updated as n/m. However, this approach is infeasible in practice since the chance that the sampled monitoring value is equal to the actual one is zero, so obtaining such m samples requires an infinite amount of computational time.

For convenience of discussion, (3) is re-written in the following form:

$$P(F|\varphi, M) = \frac{f(\varphi|F, M)\, P(F|M)}{f(\varphi|F, M)\, P(F|M) + f\left(\varphi|F^C, M\right)[1 - P(F|M)]} \tag{4}$$

where $f(\varphi|F, M)$ and $f\left(\varphi|F^C, M\right)$ are the PDFs of the monitoring value conditioned on the failure and non-failure events, respectively; $P(F|M)$ is the failure probability without the monitoring information, called the prior failure probability. For our purpose, the goal is to find $P(F|\varphi, M)$. According to (4), if $f(\varphi|F, M)$, $f\left(\varphi|F^C, M\right)$ and $P(F|M)$ are all available, $P(F|\varphi, M)$ can be readily obtained. Therefore, it is not necessary to draw samples from $f(\theta|\varphi, M)$ nor to conduct repetitive reliability analyses.

In the following two sections, the detailed descriptions for estimating $f(\varphi|F, M)$, $f\left(\varphi|F^C, M\right)$ and $P(F|M)$ by using MCS and SubSim, respectively, will be given. For notational simplicity, the symbol M in the conditions will be dropped in all the following discussions. Readers should keep in mind that all results are conditioned on the assumed mathematical model M.

3. Estimation of $P(F|\varphi)$ via MCS

An approach of estimating $P(F|\varphi)$ based on MCS is presented in this section. This approach is inefficient when $P(F|\varphi)$ is small. However, the MCS approach is worth mentioning because of its simplicity. A more technically involving technique that is efficient for small $P(F|\varphi)$ based on SubSim will be presented in the next section.

Let Z denote the uncertain variables of the target system, and let $R(Z)$ denotes the limit-state function that defines failure event F, i.e. a failure event is defined as $R(Z) \geq 1$. The MCS

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