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Reliability analysis and updating of deteriorating systems with subset simulation

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ABSTRACT

An efficient approach to reliability analysis of deteriorating structural systems is presented, which considers stochastic dependence among element deterioration. Information on a deteriorating structure obtained through inspection or monitoring is included in the reliability assessment through Bayesian updating of the system deterioration model. The updated system reliability is then obtained through coupling the updated deterioration model with a probabilistic structural model. The underlying high-dimensional structural reliability problems are solved using subset simulation, which is an efficient and robust sampling-based algorithm suitable for such analyses. The approach is demonstrated in two case studies considering a steel frame structure and a Daniels system subjected to high-cycle fatigue.

1. Introduction

Engineering structures are generally subjected to deterioration processes such as fatigue and corrosion, and their structural reliability may thus reduce over time. Predictions of the deterioration progress with quantitative models are uncertain due to the simplified representation of the actual deterioration phenomena, the inherent variability of the influencing parameters and limited information on those parameters. These uncertainties must be addressed when modeling deterioration of structures [25,31,35]. Inspections and monitoring are effective means of obtaining information on the actual condition of deteriorating structures. This information should be utilized to reduce uncertainties in probabilistic models. A consistent framework for this task is provided by Bayesian analysis, in which prior probabilistic models are updated with inspection and monitoring outcomes (e.g. [64,29,11]). Ultimately, Bayesian analysis enables the quantification of the effect of inspection and monitoring results on the structural reliability, and forms the basis for decisions on maintenance actions and future inspection efforts (e.g. [66,13,37,59]).

Deterioration processes are generally correlated among structural elements within a system (e.g. [38,70,59,51]). This leads to a correlation among deterioration failures of different elements whose effect on the system reliability has to be assessed as a function of structural redundancy [57]. In addition, correlation among element deterioration is especially relevant when inspection and monitoring outcomes are considered in the reliability assessment, since it has an effect on what can be learned about the condition of the system from individual inspections or measurements [70]. An observation at one location within a structure contains more indirect information on the deterioration progress at another location if the correlation among element deterioration is high. For these reasons, the reliability of deteriorating structures should be analyzed and updated considering the structure as a whole.

A number of publications propose methods for computing the time-variant reliability of deteriorating structures, including works by Mori and Ellingwood [40], Li [22], Ciampoli [7], Estes and Frangopol [12], Stewart and Val [50] and Li et al. [23]. They consider the time-dependent characteristics of both the load and resistance, but do not account for correlation among element deterioration. More recently, a number of researchers have considered modeling and updating the system deterioration state of structures, taking into account the aspect of spatial correlation among element deterioration [38,24,14,54,44,34]. Therein, the effect of inspections and monitoring results on the probability of either reinforcement corrosion in concrete structures or fatigue failures in steel structures is quantified using Bayesian analysis. However, the impact

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of deterioration on the structural reliability is not included in these works. Such integrated system reliability analyses are proposed in [21,28,45]. Lee and Song [21] consider sequential fatigue failures taking into account the effect of stress redistribution within a structural system. They identify critical failure sequences through a branch-and-bound scheme and iteratively compute and update bounds on the system failure probability. Luque and Straub [28] and Schneider et al. [45] propose the use of hierarchical Dynamic Bayesian Network (DBN) models for probabilistically representing deterioration in structural systems and for updating deterioration probabilities as well as the system reliability with inspection and monitoring results. While they can be powerful, DBN models are rather demanding in the implementation.

To enable an integrated system reliability analysis of inspected and monitored deteriorating structures, which is computationally efficient and simple to implement, we here develop a framework using two coupled sub-models: a probabilistic system deterioration model, which considers stochastic dependence among element deterioration, and a probabilistic structural model for calculating the failure probability of the weakened system. Motivated by the work of Straub and Der Kiureghian [57], the system deterioration state is assessed at discrete time intervals and is considered constant within each interval. Information on the deteriorating structure obtained through inspection or monitoring is included in the reliability assessment through Bayesian updating of the system deterioration model. The updated system reliability is then obtained through coupling this updated model with a probabilistic structural model. The resulting structural reliability problems are high-dimensional since they include all (correlated) deteriorating elements. To solve these problems, we apply subset simulation, which is a sampling-based algorithm that can robustly and efficiently handle problems involving a large number of random variables. The method is demonstrated in two case studies considering welded steel structures subjected to fatigue deterioration.

2. System reliability analysis of deteriorating structures

2.1. Deterioration modeling

Deterioration is modeled at the element level at discrete time steps. An element may be a structural member, a welded connection or a segment of a continuous surface [57]. The state of deterioration of an element i at time t is represented by a random variable or random vector $D_{i,t}$. For example, in the context of reinforcement corrosion in concrete structures, $D_{i,t}$ may represent the loss of reinforcement cross section. Deterioration of all elements is influenced by a set of random variables $\mathbf{X} = (X_1, \ldots, X_n)$. The relationship between $\mathbf{X}$ and $D_{i,t}$ is described by a parametric deterioration model h_i, which is written in generic form as:

$$D_{i,t} = h_i(\mathbf{X}, t) \tag{1}$$

The joint probability density function (PDF) of $\mathbf{X}$ is denoted by $f_{\mathbf{X}}(\mathbf{x})$. Model uncertainties arising from a simplified representation of the actual deterioration phenomenon are included through additional random variables in $\mathbf{X}$.

All random variables describing the deterioration state of the individual elements at time t are summarized in a vector $\mathbf{D}_t = (D_{1,t}, \ldots, D_{n_E,t})$, where n_E is the number of elements considered in the system reliability analysis. This vector represents the overall deterioration state of the structural system at time t. The relationship between the system deterioration state $\mathbf{D}_t$ and the deterioration model parameter $\mathbf{X}$ is described by a function $\mathbf{h}$ as:

$$\mathbf{D}_t = \mathbf{h}(\mathbf{X}, t) = (h_1(\mathbf{X}, t), \ldots, h_{n_E}(\mathbf{X}, t)) \tag{2}$$

2.2. Modeling dependence among deterioration model parameters

Deterioration of different elements of a structural system is generally interdependent due to the spatial correlation among the uncertain parameters $\mathbf{X}$ influencing their condition. Such spatial dependencies are often due to geometrical proximity, but they mainly exist due to common factors influencing the element condition such as environmental conditions and material characteristics [28]. The aspect of spatial correlation of deterioration is especially relevant when inspection and monitoring outcomes are considered in the reliability assessment of deteriorating structures. The effect of such observations on the reliability strongly depends on the spatial correlation among the parameters $\mathbf{X}$. An observation at one location contains more indirect information on the deterioration progress at another location if the correlation among the parameters $\mathbf{X}$ is high.

There is only limited information available on modeling statistical dependence of deterioration in structural systems (e.g. [70,33,27]). For example, Vrouwenvelder [70] estimated the correlation among uncertain parameters influencing fatigue crack growth in welded connections by comparing the scatter of the parameters within one production series to the scatter in the overall population. In most applications, however, correlation among the uncertain parameters $\mathbf{X}$ has to be estimated based at least partially on engineering judgment.

Hierarchical models and random field models are commonly applied to represent spatial dependence among the uncertain parameters $\mathbf{X}$. The latter are suitable for representing parameters with inherent spatial variability (e.g. [18,51,33]). The random field approach models a spatially varying parameter X as a random variable $X(z)$ at each location z, and describes the correlation structure of the different random variables $X(z)$ in terms of a suitable correlation function. Such random fields are typically discretized to enable their numerical representation (see, for example, [6]). As a result, a random field of a spatially varying parameter is defined by a discrete set of correlated random variables, which are part of $\mathbf{X}$. The joint distribution of the variables in a random field is commonly represented by the Nataf model, also known as the Gaussian copula [26].

Hierarchical models may be applied if common influencing factors can be modeled explicitly (e.g. [32,27]). Such models represent correlation among random variables by defining different levels. The random variables within one level are linked through common influencing factors, which are modeled as random variables at a higher level in the hierarchy. The random variables at the highest level are often called hyper-parameters (see, for example, [32]). The additional random variables representing common influencing factors in a hierarchical model are included in $\mathbf{X}$. The probability distributions of the random variables in each level are defined conditional on the random variables at the next higher level in the hierarchy. Such a hierarchical dependence structure among the variables in $\mathbf{X}$ can be implemented through the Rosenblatt transformation [19].

In many instances, common influencing factors can, however, not be modeled explicitly. Instead, statistical dependence among the variables in $\mathbf{X}$ is often represented by correlation coefficients. As an example, statistical dependence of fatigue deterioration among welded connections due to common fabrication quality may be modeled by defining a correlation coefficient between the initial crack sizes at different hotspots [70]. In this case, the Nataf model can be applied to model the joint distribution of the correlated deterioration model parameters.

Parameters influencing deterioration can also be time variant. Such parameters are ideally modeled by stochastic processes (see, for example, [25,60,1]). Similar to a random field, a stochastic process represents a time-varying parameter X as a random vari-