Chapter 18
Structure Reliability and Response Prognostics under Uncertainty Using Bayesian Analysis and Analytical Approximations

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ABSTRACT
This study presents an efficient method for system reliability and response prognostics based on Bayesian analysis and analytical approximations. Uncertainties are explicitly included using probabilistic modeling. Usage and health monitoring information is used to perform the Bayesian updating. To improve the computational efficiency, an analytical computation procedure is proposed and formulated to avoid time-consuming simulations in classical methods. Two realistic problems are presented for demonstrations. One is a composite beam reliability analysis, and the other is the structural frame dynamic property estimation with sensor measurement data. The overall efficiency and accuracy of the proposed method is compared with the traditional simulation-based method.

INTRODUCTION
Diagnostics and prognostics of modern engineering systems have drawn extensive attentions in the past decade due to their increasing complexities (Brauer & Brauer, 2009; Melchers, 1999). In particular, time-dependent reliability estimate for high reliability demanding systems such as aircraft and nuclear facilities must be quantified in order to prevent system failures. The central idea of reliability analysis involves computation of a multi-dimensional integral over the failure domain of the performance function (Ditlevsen & Madsen, 1996; Madsen, Krenk, & Lind, 1986; Rackwitz,
2001). For problems with high-dimensional parameters, the exact evaluation of this integral is either analytically intractable or computationally prohibitive (Yuen, 2010). Analytical approximations and numerical simulations are two major computational methods to solve such problems.

The simulation-based method includes direct Monte Carlo (MC) (Kalos & Whitlock, 2008), Importance Sampling (IS) (Gelman & Meng, 1998; Liu, 1996), and other MC simulations with different sampling techniques. Analytical approximation methods, such as first- and second-order reliability methods (FORM/SORM) have been developed to estimate the reliability without large numbers of MC simulations. FORM and SORM computations are based on linear (first-order) and quadratic (second-order) approximations of the limit state surface at the most probable point (MPP) in the standard normal space (Ditlevsen & Madsen, 1996; Madsen, Krenk, & Lind, 1986; Rackwitz, 2001). Under the condition that the limit state surface at the MPP is close to its linear or quadratic approximation and that no multiple MPPs exist on the limit state surface, FORM/SORM are sufficiently accurate for engineering purposes (Bucher & Bourgund, 1990; Cai & Elishakoff, 1994; Zhao & Ono, 1999). If the final objective is to calculate the system response given a reliability index, the inverse reliability method can be used. The most well-known approach is inverse FORM method proposed in (Der Kiureghian & Dakessian, 1998; Der Kiureghian, Zhang, & Li, 1994; Li & Foschi, 1998). Du, Sudjianto, and Chen (2004) proposed an inverse reliability strategy and applied it to the integrated robust and reliability design of a vehicle combustion engine piston. Saranyasooontorn and Manuel (2004) developed an inverse reliability procedure for wind turbine components. Lee, Choi, Du, and Gorsich (2008) used the inverse reliability analysis for reliability-based design optimization of nonlinear multi-dimensional systems. Cheng, Zhang, Cai, and Xiao (2007) presented an artificial neural network based inverse FORM method for solving problems with complex and implicit performance functions.

Conventional forward and inverse reliability analyses are based on existing knowledge about the system (e.g., underlying physics, distributions of input variables). Time-dependent reliability degradation and system response changes are not reflected. For many engineering problems, usage monitoring or inspection data are usually available at a regular time interval either via structural health monitoring system or non-destructive inspections. The new information can be used to update the initial estimate of system reliability and responses. The critical issue is how to incorporate the existing knowledge and new information into the estimation. Bayesian updating is the most common approach to incorporate these additional data. By continuous Bayesian updating, all the variables of interest are updated and the inference uncertainty can be significantly reduced, provided the additional data are relevant to the problem and they are informative (Guan, Jha, & Liu, 2011). Hong (1997) presented the idea of reliability updating using inspection data. Papadimitriou, Beck, and Katafygiotis (2001) reported a reliability updating procedure using structural testing data. Graves, Hamada, Klamann, Koehler, and Martz (2008) applied the Bayesian analysis for reliability updating. Wang, Rabiei, Hurtado, Modarres, and Hoffman (2009) used Bayesian reliability updating for aging airframe. A similar updating approach using Maximum relative Entropy principles has also been proposed in (Guan, Giffin, Jha, & Liu, 2011). In those studies, Markov chain Monte Carlo (MCMC) simulations have been extensively used. For practical problems with complicated performance functions, simulations are time-consuming and efficient computations are critical for time constrained reliability evaluation and system response prognostics. In structural health management, simulation-based method may be not feasible because updating is frequently performed upon the arrival of sensor data. All these applications require efficient and
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