Reliability Engineering and System Safety 142 (2015) 346–356

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

A double-loop adaptive sampling approach for sensitivity-free dynamic reliability analysis

Zequn Wang, Pingfeng Wang *

Department of Industrial and Manufacturing Engineering, Wichita State University, Wichita, KS 67260, USA

ARTICLE INFO

Article history:
Received 2 November 2013
Received in revised form
24 April 2015
Accepted 15 May 2015
Available online 6 June 2015

Keywords:
Reliability analysis
Surrogate model
Sequential sampling
Dynamic
Sensitivity free

ABSTRACT

Dynamic reliability measures reliability of an engineered system considering time-variant operation condition and component deterioration. Due to high computational costs, conducting dynamic reliability analysis at an early system design stage remains challenging. This paper presents a confidence-based meta-modeling approach, referred to as double-loop adaptive sampling (DLAS), for efficient sensitivity-free dynamic reliability analysis. The DLAS builds a Gaussian process (GP) model sequentially to approximate extreme system responses over time, so that Monte Carlo simulation (MCS) can be employed directly to estimate dynamic reliability. A generic confidence measure is developed to evaluate the accuracy of dynamic reliability estimation while using the MCS approach based on developed GP models. A double-loop adaptive sampling scheme is developed to efficiently update the GP model in a sequential manner, by considering system input variables and time concurrently in two sampling loops. The model updating process using the developed sampling scheme can be terminated once the user defined confidence target is satisfied. The developed DLAS approach eliminates computationally expensive sensitivity analysis process, thus substantially improves the efficiency of dynamic reliability analysis. Three case studies are used to demonstrate the efficacy of DLAS for dynamic reliability analysis.

1. Introduction

Engineered systems generally degrade over time and could fail due to time-variant operational conditions and component deterioration, which may lead to catastrophic consequences such as substantial economic and societal losses. To measure the performance of engineered systems against potential system failures, reliability is defined as the probability that the system or component will perform the required function for a given period of time under inherent uncertainties and certain operation conditions. In the literature, two types of reliability analysis have been conducted, referred to as static reliability analysis and dynamic reliability analysis, depending on whether time-variant characteristics are considered in reliability analysis processes.

To conduct static reliability analysis, various numerical methods, including both analytical and simulation-based approaches, have been developed, such as most probable point (MPP) based methods [1–3], dimension reduction method (DRM) [4–6], polynomial chaos expansion (PCE) [7–10] and Kriging-based methods [11–14]. In addition, studies have also been done to handle multiply limit states [15,16] and epidemic uncertainty [17–19] in static reliability analysis. In MPP-based methods such as the first order reliability method (FORM), reliability index is calculated as the distance between the MPP and the origin in the U-space by iteratively locating MPP on the limit state function. Due to an iterative MPP searching process, sensitivity information of performance functions with respect to random variables is required in order to pinpoint the next potential MPP point and carry forward the searching process. However, accurate sensitivity information of the performance function is usually not readily available in practical engineering applications. The DRM simplifies a single multi-dimensional integration for reliability analysis to multiple one-dimensional integrations using an additive decomposition formula, and then estimates reliability based on statistical moments of system performance functions. Although it is a sensitivity-free approach for reliability analysis, the DRM may introduce significant error for limit state functions with high nonlinearity. The PCE method constructs a stochastic response surface with multi-dimensional polynomials over the sample space of random variables, updates the stochastic response surface by incorporating more samples and then approximates reliability directly using Monte Carlo simulation (MCS) based on the developed stochastic response surface. The accuracy of the PCE can be

* Corresponding author.
E-mail addresses: zxwang5@wichita.edu (Z. Wang), pingfeng.wang@wichita.edu (P. Wang).

http://dx.doi.org/10.1016/j.ress.2015.05.007
0951-8320/

Nomenclature

R	reliability
Φ	standard Gaussian cumulative distribution function
β_t	target reliability index
EI	expected improvement
$f_x(x)$	probability density function
$f(\cdot\|\cdot)$	conditional probability density function or likelihood function
I_f	indicator function
P_f	probability of failure
ν^+	out-crossing rate

improved by increasing the order of stochastic polynomial terms; however, the computational cost can be prohibitively high for problems with a large number of random input variables. Surrogate models have also been employed for reliability analysis to replace original computationally expensive simulation models, so that reliability can be approximated less expensively. For this type of approaches, major challenges include proposing appropriate metrics to quantify the accuracy of reliability estimation and developing efficient sampling schemes for surrogate models.

Compared with static reliability analysis, performing dynamic reliability analysis is even more computationally expansive in practical engineering applications, because of the time-dependency of system failure events. In the literature, two categories of methods: extreme performance based approaches [20–22,26] and first-passage based approaches [23–25], have been developed for dynamic reliability analysis. The extreme performance approaches define the failure event according to extreme value of the performance function, and then quantify uncertainty of the extreme performances in order to approximate dynamic reliability. Instead of extreme performances, first-passage based approaches focus on out-crossing events, when the performance function exceeds the upper bound or falls below the lower bound of the safety threshold, and estimate dynamic reliability by computing an out-crossing rate measure. In the first category of dynamic reliability methods, the composite limit state (CLS) approach [26] has also been developed to tackle the time-dependency issue and calculate the cumulative probability of failure based on MCS. As the CLS converts the continuous time to discrete time intervals and constructs a composite limit state by combining all instantaneous limit states of discretized time intervals in a series manner, it is extremely expensive to perform the dynamic reliability analysis using the CLS, as illustrated by reported case studies [26]. Recently, the nested extreme response surface method (NERS) [22] utilized the Kriging technique to efficiently identify extreme time responses corresponding to extreme performances, so that dynamic reliability can be performed by only focusing extreme events using existing static reliability tools such as the FORM and MCS. Although NERS can tackle the time-dependent issue efficiently, error can also be induced by using FORM as a static reliability analysis tool. As a representative of the first-passage methods, the PHI2 approach [27] was developed for dynamic reliability estimation, in which the FORM was also utilized to calculate out-crossing rates. Although static reliability analysis tools such as FORM can be integrated with the PHI2 method, the error of dynamic reliability estimation could be very significant for two reasons: high nonlinearity of the limit states and improper time step while discretizing the time variable. Another limitation of PHI2 is that it requires accurate sensitivity information of the performance function with respect to random input variables, which is usually not available in practical engineering applications.

To handle time-dependency of system failure events and reduce extremely high computational costs in dynamic reliability analysis, this paper presents a confidence-based meta-modeling approach, referred to as double-loop adaptive sampling (DLAS), for efficient sensitivity-free dynamic reliability analysis. In order to evaluate dynamic reliability directly by MCS, Gaussian Process (GP) regression is adopted to construct a meta-model for extreme performance function over time while the DLAS technique is developed to enhance the fidelity of meta-model sequentially by considering the model input variables and time concurrently in two sampling loops. The rest of paper is organized as follows. Section 2 introduces dynamic reliability analysis and existing methods. Section 3 details the developed DLAS approach for dynamic reliability analysis. Three case studies are used to demonstrate the effectiveness of the developed methodology in Section 4.

2. Review of dynamic reliability analysis

For engineered systems, system failure events occur if system performance function goes beyond its failure thresholds. Consequently, a limit state function, denoted as $G(x)=0$, can be defined which separates the safe and failure events in the random input space. For static reliability analysis, the probability of failure is defined as

$$P_f = \Pr(G(x)<0) = \int \cdots \int_{G(x)<0} f_x(x)dx \qquad (1)$$

where $f_x(x)$ is the joint probability density function. However, the performance function is also governed by the time-variant uncertainties such as loading conditions and component deterioration. Time parameter can be implicitly involved in the limit state function when input random processes are taken into account. In this work, we assume that the limit state function is an explicit function of the random variable x and time parameter t. Thus, a time-variant limit state function can be generally derived as $G(x, t)=0$ by taking the time parameter t into account in reliability analysis. Let t_l be the designed system life time of interest, the probability of failure within $[0, t_l]$ can be described as

$$P_f(0,t_l) = \Pr(\exists t \in [0,t_l], G(x,t)<0) \qquad (2)$$

Thus, the task of dynamic reliability analysis is to estimate the P_f in an efficient and accurate manner. The rest of this section provides a brief review of three representative dynamic reliability analysis approaches: the composite limit state (CLS) approach, the nested extreme response surface (NERS) approach, and the out-crossing rate approach.

2.1. Composite limit state approach

If the CLS is used, the time interval $[0, t_l]$ will be discretized to N_T time nodes with a fixed time step Δt. Let $G(x, t_n) = 0$ ($n=1,\ldots, N_T$) denotes the instantaneous limit state at the nth time node t_n, the composite limit state is defined as the union event of all instantaneous limit states. The cumulative probability of failure can then be described as

$$P_f(0,\ t_l) = \Pr\left(\cup_{n=0}^{N} G(x,t_n)<0\right) \qquad (3)$$

where failure occurs if any of the instantaneous limit states is violated.

With the development of the composite limit state, dynamic reliability can be estimated using existing static reliability analysis tools; however, identifying composite limit states is computationally very expensive because it requires evaluations of all instantaneous performances for each design point. While using the CLS method, time variable is discretized to simplify the dynamic reliability