Structural Safety 62 (2016) 34–46

Contents lists available at ScienceDirect

Structural Safety

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

Reliability analysis and updating of deteriorating systems with dynamic Bayesian networks

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ARTICLE INFO

Article history:
Received 22 May 2015
Received in revised form 22 March 2016
Accepted 31 March 2016
Available online 8 June 2016

Keywords:
Bayesian analysis
System reliability analysis
Deterioration
Inspection
Fatigue

ABSTRACT

To estimate and update the reliability of deteriorating structural systems with inspection and monitoring results, we develop a modeling and computational framework based on dynamic Bayesian networks (DBNs). The framework accounts for dependence among deterioration at different system components and for the complex structural system behavior. It includes the effect of inspection and monitoring results, by computing the updated reliability of the system and its components based on information from the entire system. To efficiently model dependence among component deterioration states, a hierarchical structure is defined. This structure facilitates Bayesian model updating of the components in parallel. The performance of the updating algorithm is independent of the amount of included information, which is convenient for large structural systems with detailed inspection campaigns or extensive monitoring. The proposed model and algorithms are applicable to a wide variety of structures subject to deterioration processes such as corrosion and fatigue, including offshore platforms, bridges, ships, and aircraft structures. For illustration, a Daniels system and an offshore steel frame structure subjected to fatigue are investigated. For these applications, the computational efficiency of the proposed algorithm is compared with that of a standard Markov Chain Monte Carlo algorithm and found to be orders of magnitude higher.

1. Introduction

Engineering structures are commonly subjected to deterioration processes, which can reduce their service life and affect the safety of the environment, people and the structure itself. For this reason, significant resources are invested to identify, model, quantify, mitigate and prevent deterioration processes in structures [61,3,9]. Structural deterioration, such as metal corrosion and fatigue, is mathematically represented using mostly empirical or semi-empirical models [51,12,45,67]. Because of their empirical nature, predictive deterioration models are typically associated with significant uncertainty. Hence deterioration is ideally modeled probabilistically [29,23,37,10].

Probabilistic deterioration models are developed mainly at the structural component level. However, deterioration at different locations in a structural system is typically correlated, and system considerations should be made [40,65,59]. Probabilistic models of deterioration in large structural systems have been proposed and applied to different types of structures and deterioration processes [14,18,56,26,48].

Bayesian methods have been used to combine probabilistic deterioration models with inspection and monitoring outcomes [62,29,33,54]. They allow quantifying the impact of inspections and monitoring on the reliability of the structure, and so facilitate maintenance decisions and the planning of future inspections [64,7,39,59]. Bayesian analysis is mainly performed at the component level, where the probability of failure of a structural component due to deterioration is updated with the inspection and monitoring outcomes. Only a few publications consider the updating of the reliability at the structural system level. Therein, the dependence among component deterioration states is modeled either through the correlation among the deterioration limit states [40,22,28] or through a hierarchical model [34,8,32,53,49]. More recently, a number of researchers have considered the planning and optimization of inspection and maintenance actions in structural systems with dependent component deterioration [59,44,43,38].

A challenge in Bayesian system reliability analysis is to keep the computation time at a feasible level. Methods belonging to classical structural reliability methods are efficient for estimating the probability of system failure, but do not facilitate Bayesian analysis or have computation times that increase exponentially with the number of observations. Recently, a class of methods has been proposed that efficiently combine structural reliability methods with

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http://dx.doi.org/10.1016/j.strusafe.2016.03.004
0167-4730/

Bayesian updating [55,60]. Nevertheless, also this approach has the drawback that its performance is a function of the number of inspection and monitoring data, which can be considerable in structural systems.

Bayesian networks (BNs) have become popular in engineering risk analysis due to their intuitive nature and their ability to handle many dependent random variables in a Bayesian analysis [17,58,66]. The graphical structure of the BN is formed by nodes and directed links. The nodes represent random variables or deterministic parameters, and the links the dependence among nodes. Ideally, the link between two nodes is based on a causal relation, but this is not necessary. As an example, if deterioration D is modeled as a function of an external random load S and a material parameter M, then a corresponding BN may look like the one in Fig. 1. Here, an additional node Z is included, representing an outcome of an inspection. Since each random variable in the BN is specified by its conditional probability distribution given its parents, the inspection outcome is defined by $p(z|d)$, i.e. the probability of the inspection outcome $Z = z$ given the damage state $D = d$. This is known as the likelihood function, and corresponds to classical models used for describing inspection or monitoring performance, such as Probability of Detection (POD). Generally, the BN is established using commonly available probabilistic models; it allows combining these in a consistent and (in most cases) intuitive manner.

Using BNs it is possible to obtain the posterior distribution of a set of random variables given a set of observations. This task is called inference. For instance, if an inspection result is included in the previously presented example, i.e. if Z is given, then the (joint) probability distribution of the random variables S, M and D conditional on the observed value of Z is calculated using inference algorithms. There are many algorithms available for inference in BNs [15,21,50]. In this paper, the focus is on BN with discrete random variables, for which exact inference algorithms exist [41,17].

The links in the BN provide information on the dependence between random variables in the model. For example, in the BN of Fig. 1, M and S are assumed to be independent a-priori, and hence no direct link between them is present. The link from D to Z indicates that the inspection provides information on the damage state. It provides no direct information on S and M. However, it does so indirectly, because the information obtained on D also updates the probability distribution of S and M, as long as D is not known with certainty. In this way, by observing one random variable, potentially all others are updated. For efficient computation, all BN inference algorithms make use of the graphical structure by performing computations locally, exploiting the conditional independence assumptions encoded in the graph.

Modeling of deterioration often involves random processes, which can be represented in a discrete-time manner by dynamic Bayesian networks (DBN), as proposed in [54]. For illustration, we extend the BN of Fig. 1 to include a time-variant load S_t and inspection results at multiple points in time $t = 1, \dots, T$. The resulting DBN is shown in Fig. 2. Each "slice" of the DBN represents

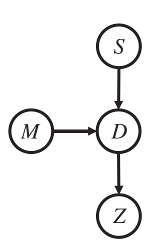

Fig. 1. BN deterioration model example. D is the deterioration state, S is an external load, M is a material parameter and Z is an observation of the deterioration state.

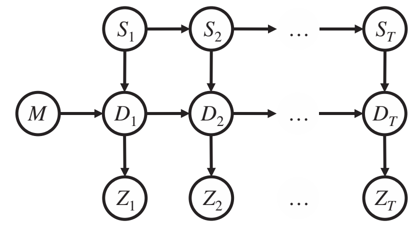

Fig. 2. DBN deterioration model example.

a time step in the analysis. The random process $\{S_1, S_2, \dots, S_T\}$ is a Markov chain where each random variable is defined conditionally on the random variables of the previous time step. The deterioration D_t at time t is a stochastic function of the previous deterioration state D_{t-1} and the current load S_t. The probability distributions of the material parameter M, the loads $\{S_1, S_2, \dots, S_T\}$, and the deterioration states $\{D_1, D_2, \dots, D_T\}$ are all updated once inspection outcomes Z_1, …, Z_T, or a subset thereof, are observed.

In this paper, the DBN model for structural deterioration from Straub [54] is extended from the component to the system level, based on work presented by the authors in Luque and Straub [27]. An efficient algorithm is developed, which assesses the reliability of a deteriorating system when partial observations of its condition are available. The deterioration factors of the system components are interrelated using a hierarchical structure and a set of hyperparameters, which model the correlation structure among components. In the following section, the concept of dynamic Bayesian networks and its application to efficiently model component deterioration are presented. Thereafter, in Section 3, the model is extended to represent the complete structural system. Sections 4.1 and 4.2 present two case studies where the model and algorithm are applied and compared to other methods for estimating the system probability of failure. To demonstrate the advantages of the proposed algorithm, the number of system components is increased to a point where classical Markov Chain Monte Carlo (MCMC) algorithms are no longer efficient for estimating the system reliability.

2. Dynamic Bayesian network for assessing component deterioration

2.1. DBN model of a single component

The DBN model framework developed in [54] is used to represent the deterioration of components. This model includes the following elements:

- Time-invariant model parameters $\boldsymbol{\theta}$, which are constant in time.
- Time-variant model parameters $\boldsymbol{\omega}_t$, which vary with time steps $t = 0, \dots, T$.
- Deterioration model: A parametric function h for describing the deterioration D as a function of t, $\boldsymbol{\theta}$, $\boldsymbol{\omega}_0, \dots, \boldsymbol{\omega}_t$ and the deterioration level at the previous time step D_{t-1}, i.e.

$$D_t = D(t) = h(t, D_{t-1}, \boldsymbol{\theta}, \boldsymbol{\omega}_0, \dots, \boldsymbol{\omega}_t), t = 1, \dots, T \quad (1)$$

- Observations: At any time step t, information on the condition of a model parameter or the deterioration D_t may be available from inspections, monitoring systems, recordings of environmental parameters or other measurements, which are related to the model parameters. These observations are denoted by $Z_{\boldsymbol{\theta},t}$, $Z_{\boldsymbol{\omega},t}$, and $Z_{D,t}$, depending on the random variables to which they relate.

Fig. 3 depicts the generic DBN deterioration model for a single component, where vectors $\boldsymbol{\theta}_1, \dots, \boldsymbol{\theta}_T$ are added in order to have a