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A computational Bayesian approach to dependency assessment in system reliability

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ABSTRACT

Due to the increasing complexity of engineered products, it is of great importance to develop a tool to assess reliability dependencies among components and systems under the uncertainty of system reliability structure. In this paper, a Bayesian network approach is proposed for evaluating the conditional probability of failure within a complex system, using a multilevel system configuration. Coupling with Bayesian inference, the posterior distributions of these conditional probabilities can be estimated by combining failure information and expert opinions at both system and component levels. Three data scenarios are considered in this study, and they demonstrate that, with the quantification of the stochastic relationship of reliability within a system, the dependency structure in system reliability can be gradually revealed by the data collected at different system levels.

1. Introduction

Due to increasing demands of product functionality, engineered products have become more and more complex over time. Traditional reliability assessment methods for simple systems are often inadequate in analyzing more complex systems. Conducting full system tests is often too expensive to be implemented on such systems. This situation calls for a method to develop reliability models for complex systems and to integrate all available information for predicting system reliability.

There are situations that we do not have complete information of how a complex system would fail in its operating environment. We would like to learn more about the interaction between the system and its components and how they work together. In this paper, we use a Bayesian network (BN) to represent the probabilistic relationship between system and component reliability, which is a natural extension of the deterministic relationship typically modeled by block diagrams or fault trees when the failure structure is well understood.

The BN model has been proved to be a powerful tool that provides important methodological advantages over traditional techniques in reliability assessment. Traditional methods, such as fault trees or reliability block diagrams, are still common representations in system reliability analysis; however, they are not flexible enough to capture the uncertainties in the dependencies among component, subsystem and system (see [1,19,2,17,34]). BNs generalize fault trees by allowing components and subsystems to be related by conditional probabilities, instead of deterministic "AND" and "OR" relationships; thus, they provide analytical advantages to the situation when we have less confidence to the reliability structure of a complex system, especially during the early stage of a product's design process. Another important advantage of BN over the traditional approach is its ability of combining information from multiple sources at multiple levels for system reliability prediction when the BN model is coupled with statistical Bayesian inference techniques. As a result, it is worthwhile to explore the use of BN model and Bayesian inference together for the dependency assessment of system reliability.

A BN model requires conditional probabilities to model the dependencies among components, subsystems and system. These conditional probabilities are capable of representing complex, probabilistic failure relationships in a multilevel system configuration. In a complex system, the failure relationship between system and components could be significantly more complicated than a typical series or parallel system, especially when the specific failure cause and failure mechanism has yet to be understood; for example, a newly developed system [35]. Therefore, investigating the conditional probability tables of a BN model can help engineers to sort out those unknown influential factors.

The conditional probabilities in a BN model can be estimated by combining information from different sources. There are objective information sources, such as failure records of older generation products, life tests of components and available field data; on the other hand, there are subjective sources too, such as expert

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opinions. These data come with different types and different structures, causing difficulties in the estimation of conditional probabilities. Furthermore, as system designs evolve over time, assigning fixed values to these probabilities limits the flexibility to account for the evolution process of system development. Therefore, we choose Bayesian inference for parameter estimation in the BN model. Bayesian inference is a statistical inference method that enables model parameter estimation by deriving the posterior distribution from a combination of prior distribution and likelihood function. It allows us to integrate both the prior information of model parameters and the data coming from different sources for model inference; therefore, we can obtain a more precise estimation of BN model parameters.

The goal of this research is to develop the methodology of estimating conditional probabilities of BN models using Bayesian inference so that the reliability-relevant information from different sources at different reliability structure levels of a complex system can be combined together. The next section presents a literature review of BN models and Bayesian inference in reliability assessment. Our BN framework for system reliability and its inference method are discussed in Section 3. We start by discussing how to infer conditional probabilities using a conjugate model for a simple 2-state Bayesian network and then extend it to a multi-state model. We also briefly discuss the case where we have only system failure records. Finally, we develop a data analysis method for the scenario of having incomplete information of components. We illustrate the proposed method with a case study in Section 4 and conclude the paper in Section 5.

2. Background

2.1. Models for multilevel system reliability assessment

One of the primary goals in system design evaluation is to predict the reliability of the full system. A system is comprised of subsystems and components, or on functional wise, sub-functions and elementary functions, which can be represented by nodes in the system's reliability topology. All nodes are potential sources of failure. Consequently, reliability information may come from different levels of the system and it tends to be heterogeneous. With data available at different system levels, the challenge becomes how to combine them to learn about the reliability of the system. The Bayesian method is very appealing for this challenging problem. Martz et al. [21] and Martz and Wailer [20] addressed the problem of integrating multilevel binary data from various levels of the system and from expert guesses about the reliability of system components. These papers focused on series and parallel systems, where component failure data were modeled using binomial distributions, and beta distributions were used for the prior information at components, subsystem and system levels. Several follow-up papers considered other computational Bayesian approaches to model inference and system reliability prediction. For example, Johnson et al. [14] proposed a hierarchical Bayes model approach to system reliability prediction. Their approach utilized Markov chain Monte Carlo (MCMC) to infer model parameters, thus avoided analytical approximation. Hamada et al. [11] applied the same approach on the non-overlapping, continuous failure time data of basic and higher-level failure events in a fault tree. Graves et al. [7] further extended this line of research by considering multi-state fault trees. They used Dirichlet distribution to define the prior information about the probabilities of the states in the model. In addition, Graves et al. [8] proposed a Bayesian approach to properly account for simultaneous multilevel data, i.e., use the simultaneous higher-level and partial lower-level data to determine the event of component failure. In another follow-up study, [26] considered lifetime data throughout the system. They presented a Bayesian model that accommodates multiple lifetime information sources and provided a method to model the time evolution of a system's reliability. Wilson et al. [30] proposed a methodology that allowed for the combination of different types of data at the component and system levels, and took a Bayesian approach to the estimation of reliability measure. Wilson et al. [29] showed how to combine different types of reliability data with an example that had binomial data (modeled with a logistic regression) from the system and one component, lifetime data from another component, and degradation data from a third component. Guo [10] discussed a unified Bayesian approach for simultaneously predicting system, subsystem, and component reliabilities when there are pass/fail, lifetime, degradation, or expert judgment data at any level of the system, which extended the work in Wilson et al. [30]. However, these studies were mostly based on fault trees and reliability block diagrams and did not cover the BN representation of system reliability.

In the system reliability literature, the idea of using BN model as an alternative to fault tree or reliability block diagram for representing system reliability structure has been discussed by many authors (e.g., [1,19,2,17]; Wilson and Huzurbazar, 2007; [18]). However, previous studies do not address the problem of assessing reliability dependencies between system and its components. In this paper, we will assess these dependencies using a computational Bayesian inference method; that is, given reliability information from multiple sources and at multiple levels of a system, we will provide the Bayesian estimation of the conditional probability parameters required in the BN model. The posterior distribution of these parameters can be used to quantify the variability of the dependency of system reliability to its components. Furthermore, previous study has not addressed the effect of simultaneous, incomplete data, drawn from different system levels, on BN inference. Since we aim to measure the reliability dependencies within a system, system and component data should be collected simultaneously, as independent datasets will not be able to capture these dependencies. However, getting simultaneous data from all components/subsystems may not be possible due to lack of sensors or other observation limitations. Graves et al. [8] and Jackson [13] analyzed the effect of simultaneous data on system reliability prediction using a fault tree model. The BN model is different from fault trees because it represents the probabilistic relationship between system and components. In this paper, we will discuss the Bayesian inference method that allows us to analyze simultaneous data that are drawn from the system and a subset of its components.

2.2. Computational methods in Bayesian inference

The posterior distribution resulting from a complex Bayesian model often cannot be written in a closed form. This difficulty has hindered the adoption of Bayesian reliability assessment for many years. However, since the 1990s, advances in Bayesian computation through Markov chain Monte Carlo (MCMC) have facilitated inference based on samples from the targeted posterior distribution [5]. MCMC is a simulation-based algorithm for performing Bayesian inference when conjugation is impossible (thus analytical result is impossible). It is particularly useful for high-dimensional Bayesian inference. MCMC algorithms draw samples from the targeted joint posterior distribution of model parameters. Gibbs sampler, the most popular MCMC algorithm, relies on the fact that samples drawn sequentially from complete conditional distributions will converge to the joint posterior distribution as long as distribution parameters are constantly updated. So, after a certain number of preliminary iterations, the samples drawn from