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Bayesian networks inference algorithm to implement Dempster Shafer theory in reliability analysis

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Abstract

This paper deals with the use of Bayesian networks to compute system reliability. The reliability analysis problem is described and the usual methods for quantitative reliability analysis are presented within a case study. Some drawbacks that justify the use of Bayesian networks are identified. The basic concepts of the Bayesian networks application to reliability analysis are introduced and a model to compute the reliability for the case study is presented. Dempster Shafer theory to treat epistemic uncertainty in reliability analysis is then discussed and its basic concepts that can be applied thanks to the Bayesian network inference algorithm are introduced. Finally, it is shown, with a numerical example, how Bayesian networks' inference algorithms compute complex system reliability and what the Dempster Shafer theory can provide to reliability analysis.

Keywords: Reliability; Epistemic uncertainty; Dempster Shafer theory; Bayesian networks; Evidence networks

1. Introduction

There are many quantitative analysis methods of system reliability. The use and efficiency of these methods depends on the type and the structure of the system as well as on the experience of the reliability engineer. In the industry, some tools are recommended and explicitly referenced in standards such as IEC 61508 [1] and IEC 61025 [2]. More precisely, the IEC 61025 standard describes the symbols and method to make quantitative reliability analysis. Among these methods, fault trees and Markov chains have often been employed and remain the reference methods for the reliability engineer.

However, systems become increasingly complex and consequently the number of failures to be taken into account increases. As it has been introduced in [3], in a complex system composed of n components with positive random lifetimes, two or more components can fail at the same time. Moreover, the system as well as the components are allowed to have an arbitrary (finite) number of states (in the following: a multistate system or component). In addition, no assumption of independence is made concerning the component lifetime. Moreover, taking into account the effects of the combinations of failure within scenarios renders the calculation of the reliability of such complex systems very difficult. The classical modelling methods reach their limit.

The use of the fault tree method [4,5] assumes the independence of elementary probabilities of failures and boolean variables. Fault trees (FT) are very powerful especially when they are solved using binary decision diagrams (BDD). Unfortunately, when multiple failures are assumed to affect a component, the model needs a representation as multiple states variables. Then the fault tree approach is close to its limit.

The state space representation has been recognized by academic literature [3,4,6] and industrial IEC61511 standards [7,8]. Usually, the structure function of the system reliability is modelled with a Markovian process. Each accessible state of the system is represented by a node and the transitions between nodes are represented by arcs

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modelling the transition rates. This method is well adapted to study the reliability of various systems and allows an exact analysis of their probability of failure. However, the system complexity induces a combinatorial explosion of the number of states, which makes the modelling step more difficult.

Apart from current standards, Stochastic Petri Net [9,10] is a method traditionally used to model the system reliability. They provide a powerful modelling formalism but, unfortunately, the reliability analysis relies on a Monte Carlo simulation procedure that usually requires a great number of simulation runs in order to get accurate results.

This work focus on Bayesian networks, which provides solutions to the problems mentioned above by concentrating on the modelling in a compact structure built from the states of component. Recently, works on system safety and Bayesian networks, developed by Boudali and Dugan [11] and Bobbio et al. [12], explain how the fault tree methodology can be implemented by using Bayesian networks. In [13], the authors describe stochastic modelling techniques as fault trees, Bayesian networks and Petri nets. They present some application cases and highlight the advantages of each technique with respect to the others. In order to improve reliability analysis and maintenance decision process, Weber [14] has defined a dynamic Bayesian network model of the process reliability, that allows to compute state probability distributions by taking into account multistate components, age of the components and the latest maintenance operations. In [15], a study is dedicated to the comparison between Markov chains and dynamic Bayesian networks for the system reliability estimation and [16] describes model of reliability to simulate a stochastic process with exogenous constraints. From a general point of view, Langseth and Portinale [17] investigate the properties of Bayesian networks that make this formalism particularly well suited for reliability applications.

In all mentioned methods, a priori probabilities expressing the probability of component elementary failure are considered as precise values even if they are derived from statistical information based on experiments or from subjective experts' opinion. In Bayesian networks, conditional probabilities allowing the realization of the inference are also precise values. Indeed, Bayesian network formalizes the knowledge under a frequentist or subjectivist point of view and translates the uncertainty in its random sense but not in an epistemic way. In this case, the probabilistic framework is not suitable and another reasoning framework such as the evidence theory should be preferred. This discussion about choosing a suitable framework to take into account this kind of uncertainty remains a great debate. The purpose of this paper is not to provide such a discussion. The reader can refer to [18–23] to get some elements on this controversy.

Nevertheless, from an industrial point of view, it is classically accepted that observations made on the system are partially realized [24]. For instance, the observations can be done after inspection or maintenance action or intervention; therefore the knowledge is not available at any time. During the use of data from databases or with uncensored measures, some incompleteness and incoherencies may be encountered. In the probability framework, incomplete data should be censored or completed according to the principle of minimal commitment. It corresponds to the maximum entropy principle. The corresponding probability masses are equally distributed on each possible state called focal element. In the evidence framework, the belief mass associated to the incomplete data (i.e. uncertainty on the state) is allocated to the uncertain focal element according to the minimal commitment principle. Thanks to the evidence theory formalism, the principle of minimal commitment formalizes the idea that we should never give more information than justified to any subset of the frame of discernment [25]. Consequently, the probability framework imposes a random view of uncertainty that is debatable. The reliability engineer can be interested in predicting the influence of the component's states epistemic uncertainty on the system state.

Bayesian networks are powerful modelling tools when the problem is handled under a subjectivist point of view [26]. In addition, Valuation networks [27,28] are powerful tools, well adapted when the modelling problem is handled under a knowledge point of view. Shenoy [29] has shown the advantages and drawbacks of these tools and proved their equivalence under some conditions.

The probabilistic representation of uncertainty have been successfully employed in reliability analyses but also criticized for inducing an appearance of more knowledge with respect to the existing uncertainty than is really present [30,31]. Much of these criticisms are induced by the use of uniform distribution to characterize uncertainty in the presence of incomplete knowledge. Uniform distribution is the best representation of the minimal commitment in the probabilistic representation [32]. As a result, a number of alternative mathematical structures for the representation of epistemic uncertainty have been proposed, including evidence theory, possibility theory and fuzzy set theory [33,34]. Evidence theory is a promising alternative that allows a fuller representation of the implications of uncertainty in knowledge than is the case in the probabilistic representation [35].

In this article, we propose to combine the evidence theory with Bayesian networks to model system reliability. The goal is to obtain a powerful tool to compute the reliability of a system by taking random and epistemic uncertainties into account. The manipulation of these uncertainties by the evidence theory thanks to the appropriate Bayesian network algorithms is presented. The paper shows how exact inference algorithms used by Bayesian networks software tools provide a support to the evidence theory applied to reliability evaluation. In Section 2, a simple system that characterizes the drawbacks of standard methods is studied. In Section 3, principles of the Bayesian network modelling and their application to the