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Application of Valuation-Based Systems for the availability assessment of systems under uncertainty

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ABSTRACT

The aim of the paper is twofold. First, it proposes an original application of the Valuation-Based System (VBS) for the availability assessment of systems under uncertainty in a time-varying fashion. Uncertainties related to failure data of components (data uncertainty) and the system structure (model uncertainty) are analysed in the proposed model. Second, it proposes the application of the VBS for the availability assessment of the European Rail Traffic Management System (ERTMS) Level 2 under uncertainty according to the railway dependability standards. The originality of this work lies in the application of the VBS for the availability assessment of systems under data and model uncertainties, and the proposition of a temporal VBS to evaluate the instantaneous system availability.

1. Introduction

Defined as the ability of a system to perform a required function without failure under specified conditions for a given interval (Zio, 2009), reliability is an important attribute of real-world engineering systems (Fang, Blanke, & Leira, 2015; Robles, Puig, Ocampo-Martinez, & Garza-Castañón, 2016). Uncertainty analysis is a major issue in reliability and risk analysis (Aven, 2011; Winkler, 1996). Different classifications of uncertainties are proposed in the literature. The most common one is to divide uncertainties into aleatory and epistemic uncertainties (Pate-Cornell, 1996). Aleatory uncertainty arises from the randomness of natural phenomena, while epistemic uncertainty is due to the insufficiency of data or the lack of knowledge. Aleatory uncertainty cannot be reduced, while epistemic uncertainty can be reduced by acquiring more information or data. In our previous work (Qiu, Sallak, Schön, & Cherfi-Boulanger, 2014a), epistemic uncertainties related to reliability data were discussed. In this work, both aleatory and epistemic uncertainties related to failure data of components (data uncertainty) and the system structure (model uncertainty) will be analysed. Model uncertainty has also other definitions in the literature. For example, Nilsen and Aven (2003) defined model uncertainty to be deviations between the real world and its simplified representations in models.

In the literature, many graphical models were developed to evaluate the system performance, e.g. Reliability block diagrams, Fault trees, and Bayesian Networks (BNs). Shenoy (1989) introduced a graphical model called Valuation-Based System (VBS) as a general framework for representing knowledge and drawing inferences under uncertainty in expert systems. The VBS has following advantages:

- it provides a compact representation of system components and their dependencies;
- it is well adapted to represent and propagate all types of uncertainties in models;
- it can model and evaluate the performance of multi-state systems.

The VBS is usually used to handle problems under uncertainty. Xu (1997) proposed a decision calculus in VBS to select an appropriate decision alternative when there are uncertainties concerning the states of events. Benavoli, Ristic, Farina, Oxenham, and Chisci (2009) developed an automatic information fusion system in evidential networks (also called VBS) to support a commander's decision making under uncertainty. Qiu, Sacile, Sallak, and Schön (2015) modelled the Hazardous Material transportation accidents under epistemic uncertainties in VBS and evaluated its occurrence probability of accidents. In this work, the VBS is used to model systems under uncertainty because of the following two reasons:

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- It can assign probabilities to subsets of events instead of events and thus taking into account both aleatory and epistemic uncertainties related to failure data of system components.
- It can represent quantitatively model uncertainty which is supposed to exist in the structure function of the system (i.e., the analyst is not 100% sure of the system structure). However, this type of uncertainty is usually taken into account by introducing mixture models in other probabilistic models such as BNs, Reliability block diagrams, etc.

This work proposes the application of the VBS to assess the availability of systems under uncertainty. To our knowledge, the use of the VBS to evaluate the availability considering uncertainties in failure data and system structure was not proposed before. Besides, the VBS can only evaluate the time-independent availability. Motivated by the above reasons, we propose a temporal VBS in this paper to evaluate the instantaneous availability of systems under data and model uncertainties. The proposed temporal VBS is validated by the comparison with the Dynamic Bayesian Network (DBN).

To perform the comparison, a method transforming BN into VBS is provided in this paper. Similarly, Simon and Weber (2009a, b) proposed the use of probabilistic BNs extended to belief masses instead of probabilities in order to handle epistemic uncertainty. They called their networks "evidential networks". However, their approach is different from the approach proposed in this paper. In their evidential networks, conditional belief mass tables of logical gates (AND, OR, etc.) were defined to represent epistemic uncertainty about the state of components, and Bayesian inference was used for uncertainty propagation. The proposed approach in this paper is fully defined under the framework of belief functions theory and does not use the Bayesian inference. It uses the operations defined in the belief functions theory: belief masses, focal sets (which allow one to assign masses representing uncertainty about the whole truth tables), combination, and marginalization. It allows one to represent adequately: the epistemic uncertainty about the state of components (such as done in Simon and Weber, 2009a, b), and the uncertainty of the model (i.e, the uncertainty of the relationship between variables by adding another level of uncertainty allowing us to represent a doubt about the whole truth table represented by focal sets and joint masses on the product space of the involved variables). The latter possibility was not proposed in the work of Simon and Weber (2009a, b).

Furthermore, the VBS is applied to evaluate the availability of the European Rail Traffic Management System (ERTMS) under uncertainty according to railway dependability standards. As a system involving humans and a large number of components and subsystems, high availability is strictly required for the ERTMS (EEIG ERTMS Users Group, 1998; UNISIG SUBSET-091, 2009).

The reminder of the paper is organized as follows: Section 2 presents basic notions of the VBS and the VBS-based methods for availability assessment under uncertainty. Section 3 applies the VBS-based methods to evaluate the availability of the ERTMS under uncertainty. Section 4 concludes this paper.

2. VBS-based methods for availability assessment

In this section, first, basic notions of the VBS are presented and the differences between BN and VBS are discussed. Then, VBS-based methods are proposed to evaluate the availability of systems under uncertainty, and the proposed temporal VBS is validated by the comparison with DBN.

2.1. Valuation-based system

VBS was first proposed by Shenoy (1989, 1992) as a framework for representation and reasoning with knowledge under uncertainty. Within this framework, knowledge is represented by a set of variables (for example components of the studied system) and their states, and of valuations representing relations between these variables. The set of all possible values of a variable is called the frame of discernment of the variable. Uncertain knowledge can be represented in different domain, including probability theory, belief functions theory, possibility theory, etc. Therefore, valuations can be expressed by probabilities, masses, possibilities, etc. Making inference involves two operators called combination and marginalization. A VBS consists of a 5-tuple $(X, \Omega_X, \mathcal{M}_X, \otimes, \downarrow)$, where X is the set of variables, Ω_X is the set of frames of discernment of variables, $\mathcal{M}_X$ is the set of valuations, $\otimes$ and $\downarrow$ are combination and marginalization operators.

2.1.1. Valuations and basic probability assignment

A variable x_i takes values from its frame of discernment Ω_i. For a finite set of variables $X = \{x_1, x_2, \dots, x_n\}$, the frame of discernment $\Omega_X = \times\{\Omega_i | x_i \in X\}$ represents the product space of frames of discernment of variables in X. For example, if there is a set of variables $X = \{x_1, x_2\}$, and their frames of discernment are $\Omega_1 = \{t_1, f_1\}$ and $\Omega_2 = \{t_2, f_2\}$, then $\Omega_X = \{(t_1, t_2), (t_1, f_2), (f_1, t_2), (f_1, f_2)\}$.

A valuation m^{Ω_i} represents the knowledge about the possible values of x_i. A valuation m^{Ω_L} represents the knowledge about the possible values of a subset of variables L. $\mathcal{M}_X = \{m^{\Omega_L} : L \subseteq X\}$ is the set of valuations. A graphical representation of the VBS is called a valuation network.

In this paper, uncertain knowledge is represented using belief functions theory, and valuations are expressed by basic probability assignment (bpa, also called mass). A bpa is a mapping function $m^{\Omega} : 2^{\Omega} \to [0,1]$ that assigns values to elements of the power set 2^{Ω} in the interval [0,1] such that $\sum_{A \subseteq \Omega} m^{\Omega}(A) = 1$. Every subset $A \subset \Omega$ such that $m^{\Omega}(A) > 0$ is called a focal set.

The degree of belief $Bel(A)$ is defined as the sum of all bpas of subsets contained in A as follows Shafer (1976)

$$Bel(A) = \sum_{B|B \subseteq A} m^{\Omega}(B) \quad A, B \subseteq \Omega. \tag{1}$$

The degree of plausibility $Pl(A)$ is defined as the sum of all bpas of subsets having non-empty intersection with A as follows Shafer (1976)

$$Pl(A) = \sum_{B|B \cap A \neq \emptyset} m^{\Omega}(B) \quad A, B \subseteq \Omega. \tag{2}$$

For example, if an expert gives the bpas of the state of a binary component as follows: $m^{\Omega}(working) = 0.7, m^{\Omega}(failed) = 0.2, m^{\Omega}(\{working, failed\}) = 0.1$, then the probability of the component being working is included in $[Bel(working), Pl(working)] = [m^{\Omega}(working), m^{\Omega}(working) + m^{\Omega}(\{working, failed\})] = [0.7, 0.8]$. The uncertainty of the component being working is measured by the length of the interval.

2.1.2. Combination and marginalization

Combination rules are used to successively aggregate all bpas in order to obtain a joint bpa representing all available evidence. Let m_1^{Ω} and m_2^{Ω} be normalized bpas induced by distinct pieces of evidence which are defined on the same frame of discernment Ω. The joint bpa $m_{1,2}^{\Omega} = m_1^{\Omega} \oplus m_2^{\Omega}$ is obtained using Dempster's rule of combination as follows Dempster (1967)

$$\begin{aligned} m_{1,2}^{\Omega}(H) &= \frac{\sum_{A \cap B = H} m_1^{\Omega}(A) m_2^{\Omega}(B)}{1-k}, \quad \forall A, B, H \subseteq \Omega, H \neq \emptyset \\ m_{1,2}^{\Omega}(\emptyset) &= 0 \end{aligned} \tag{3}$$

with $k = \sum_{A \cap B = \emptyset} m_1^{\Omega}(A) m_2^{\Omega}(B),\ \forall A, B \subseteq \Omega$. k is the conflict factor between combined bpas. In this rule, it is assumed that all bpas related to the variables stem from independent sources (i.e. the experts' opinions are not based on overlapping experiences).

Let $m_{1,2}^{\Omega_1 \times \Omega_2}$ be a joint bpa defined on $\Omega_1 \times \Omega_2$. The marginal bpas $m_{1,2}^{\Omega_1 \times \Omega_2 \downarrow \Omega_1}$ and $m_{1,2}^{\Omega_1 \times \Omega_2 \downarrow \Omega_2}$ defined respectively on Ω_1 and Ω_2 are (Dempster, 1967)

$$m_{1,2}^{\Omega_1 \times \Omega_2 \downarrow \Omega_1}(A) = \sum_{B \subseteq \Omega_2} m_{1,2}^{\Omega_1 \times \Omega_2}(A \times B), \quad \forall A \subseteq \Omega_1 \tag{4}$$