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Extended composite importance measures for multi-state systems with epistemic uncertainty of state assignment

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ABSTRACT

Importance measures of multi-state systems have been intensively investigated from different perspectives in the past few years as the results are able to provide a valuable guidance for effective reliability improvement and enhancement. The state assignment is oftentimes conducted to identify the state of a multi-state system when features and/or knowledge related to the health condition of the particular system are collected. However, due to the scarcity of sensor data, limited accuracy of sensing techniques, and vague/conflicting judgments from experts, conducting the state assignment is imprecise and inevitably produces epistemic uncertainty. In this paper, some composite importance measures of multi-state systems are extended by considering the epistemic uncertainty associated with component state assignment. To take account of such epistemic uncertainty, the proposed method contains three basic steps: (1) propagate the epistemic uncertainty associated with component state assignment to the reliability function of a multi-state system by dynamic evidential network models, (2) evaluate the intervals of the conditional reliability by inputting hard evidences and/or vacuous evidence into the tailored dynamic evidential network models, and (3) compute the extended composite importance measures by constructing a pair of optimization problems and properly handling the dependency among input intervals. A numerical example of a multi-state bridge system together with an engineering example of a feeding control system of CNC lathes is exemplified to demonstrate the impact of the epistemic uncertainty on the importance measures of components and their rankings.

1. Introduction

Importance measures are effective tools to identify the weak components of an engineered system from the reliability and/or structure perspectives [1]. The results gained from importance measures can provide valuable insights to reliability

Abbreviations: MSS, Multi-State System; ET, Evidence Theory; TBM, Transferable Belief Model; EMC, Evidential Markov Chain; EN, Evidential Network; DEN, Dynamic Evidential Network; CIM, Composite Importance Measure; CBIM, Composite Birnbaum Importance Measure; MRAW, Multi-state Reliability Achievement Worth; MRRW, Multi-state Reliability Reduction Worth; MFV, Multi-state Fussel-Vesely; E-CIM, Extended Composite Importance Measure; E-CBIM, Extended Composite Birnbaum Importance Measure; E-MRAW, Extended Multi-state Reliability Achievement Worth; E-MRRW, Extended Multi-state Reliability Reduction Worth; E-MFV, Extended Multi-state Fussel-Vesely.

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Nomenclature

$\mathbf{C}(t)$	the state combination of all the components at time instant t
$\phi(\bullet)$	system structure function
$A_j^{C_l}$	component C_l in state j
$A_j^{C_l(t)}$	component C_l in state j at time instant t
$\mathbf{S}_{C_l}$	state space of component C_l
$m(A_j^{C_l} \mid A_i^{C_l})$	transition mass of component C_l transiting from state i to state j within a basic time interval
$\mathbf{m}^{C_l}(t)$	mass distribution of component C_l at time instant t
$Con(A_j^{C_l(t)})$	conditional reliability at time instant t on condition that component C_l in state j
$R(t)$	system reliability at time instant t
$PR(A_j^{C_l(t)})$	partial reliability of a system at time instant t
$PD\{a > b\}$	the degree of preference of the interval a over the interval b

improvement and maintenance planning of a system [1,2]. Many importance measures have been developed from various angles [1], and they have been successfully implemented to complex engineered systems, such as nuclear power plant [3], mechanism models [4], reconfigurable systems [5], and so forth.

Among the existing reliability importance measures, the Birnbaum importance measure was the most popular one used for system reliability design [6]. The Birnbaum importance measure quantifies the most critical component to the system reliability. Other reliability importance measures, such as the Risk Reduction Worth (RRW), Risk Achievement Worth (RAW), and the Fussell-Vesely importance measure (FV) [7], were also studied from different implications of reliability improvement or decrease. More recently, Natvig et al. [8] presented a new importance for repairable and non-repairable systems. Zio et al. [9] studied a joint importance measure based on the partial derivative on the reliability of a group of components. Peng et al. [10] introduced a criticality measure for degrading components. Alieea et al. [11] proposed a new Birnbaum importance to non-coherent systems. Kuo and Zhu [1,12] summarized the importance measures into c-types and p-types, and they applied importance measures to the component assignment problem (CAP). Nevertheless, the traditional importance measures were based on the premise that a system and its components can only be in one of only two possible states, either fully functioning or completely failed.

As engineered systems become more sophisticated, the traditional reliability methods for binary-state systems, however, fail to characterize the complicated deteriorating process of systems with multi-state nature. By introducing more than two states, from completely functioning down to completely failed, multi-state system (MSS) models are able to more accurately characterize the complicated behaviors of a system [13–15]. In the context of MSSs, many novel approaches, such as the simulation-based method [3,16,17], the multi-valued decision diagram method [18,19], the stochastic processes [15], the universal generating function [20], and the recursive algorithm [21], have been developed to facilitate the reliability assessment of MSSs. The importance measures of MSSs have also received considerable concerns, and a set of new importance measures of MSSs have been defined from various perspectives. Griffith [22] firstly introduced the concept of multi-state system performance, and studied an importance measure to quantify the MSS performance improvement due to the component performance improvement. Levitin and Lisnianski [23] proposed a partial derivative method to examine how a component performance may influence the availability of an MSS. Levitin et al. [24] introduced a new MSS importance measure based on the performance restriction. Zio and Podofillini [3] presented Birnbaum, Fussell-Vesely, RAW, RRW unavailability measures for MSSs. In their study, the Monte-Carlo simulation (MC) was used to emulate the stochastic behaviors of multi-state components. Ramirez-Marquez and Coit [2] proposed composite importance measures (CIMs) to analyze how a specific multi-state component may affect the reliability of an MSS. Lisnianski et al. [25] studied a new sensitivity measure for aging components based on the definition of importance measures. Si et al. [26] put forth an integrated importance measure of multi-state systems to study how the transition intensities of components affect the loss of system performance. Dui et al. [27] proposed a cost-based integrated importance measure for the preventive maintenance of MSSs. Among all the existing importance measures of MSSs, CIMs proposed by Coit [2] have received the most widespread applications, such as the network allocation [4], network resilience [28], power industry [29], and so forth, because they are capable of evaluating the influence of all the states of a particular component, not a single state, on the reliability of an MSS. Our focus on this work is placed on the CIMs due to their popularity in a sizable amount of engineering applications.

Nevertheless, epistemic uncertainty, caused by lack of sufficient data and vague/conflicting knowledge, is inevitable in engineering practices, and manipulating epistemic uncertainty is a challenging task to reliability assessment of complex systems [30,31]. Some non-probabilistic methods were used to represent epistemic uncertainty, such as the evidence theory (ET) [32,33], the fuzzy set theory [34], the interval theory [35], and the imprecise probability theory [36]. Generally, the ET, as one of the representations of epistemic uncertainty, have received considerable attentions in the field of information fusion [37], fault diagnosis [38,39], decision making [40] and so forth. Some attempts have been made to study the influence of epistemic uncertainty on the reliability analysis of MSSs in the context of the ET. Sallak [41] generalized the universal