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Reliability assessment of multi-state phased-mission systems by fusing observation data from multiple phases of operation

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ABSTRACT

Multi-state phased-mission systems (MS-PMSs) are multi-state systems that intend to complete multiple, consecutive, and non-overlapping phases of operation with different functional requirements. Even though many computationally efficient tools have been developed to facilitate reliability modeling of MS-PMSs in the past few decades, reliability assessment of an MS-PMS by observation data is still a difficulty because of the state and phase dependencies. This paper devotes to addressing this challenge by putting forth a new method that can assess reliability of an MS-PMS by fusing observation data collected from multiple phases of operation. A dynamic Bayesian network (DBN) model is constructed to characterize the state dependence between an MS-PMS and its units as well as the phase dependence of each unit across consecutive phases. By putting observation data into the DBN model, the joint probability distributions of the nodes of the MS-PMS at any time slice can be updated, and with which the unknown parameters associated with the state transitions of all the units can be furtherly estimated by a tailored Expectation-Maximization (EM) algorithm. The reliability function of the MS-PMS can be, then, assessed by these estimates of all the units. Two illustrative examples, including a numerical case and a data collection robot are exemplified to demonstrate the effectiveness of the proposed method.

1. Introduction

Nowadays, reliability, as a crucial characteristic of engineered systems, has been even more concerned for advanced engineering systems because failures of these systems may be catastrophic and/or cause a huge amount of economic losses [1]. It, therefore, necessitates accurate reliability assessment for these systems, so as to predict system failures and facilitate maintenance planning. In the fields of aviation, aerospace, manufacturing, and nuclear industry, some systems are required to perform a sequence of tasks in multiple, consecutive, and non-overlapping phases of operation, and the system configuration and/or functional requirements may vary from phase to phase. These systems are called phased-mission systems (PMSs). A typical example of PMSs is the manned spacecraft mission system that experiences four distinct phases during a mission, i.e., lifting off, on-orbit operation, leaving orbit, and landing phases, and each of these four phases executes different tasks and requires respective system configuration [2]. The state dependence of components across multiple phases and the dynamic

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configuration of system structure pose challenges to the existing reliability modeling and assessment methods [3]. Hence, PMSs have been intensively studied by the reliability community in the past few decades [4–7].

Since the reliability of PMSs was studied by Esary and Ziehms in [8], many methods and tools have been developed to facilitate reliability modeling and assessment of PMSs on the premise that all the parameters associated with the deterioration of a PMS are exactly known. For example, Band et al. [9] determined the minimal cut sets for each phase and assessed the performance of non-repairable PMSs within all the phases by a fault tree. Several binary decision diagram (BDD)-based algorithms were developed to evaluate the reliability of PMSs [10,11]. Recently, Mo et al. [12] proposed a novel multiple-valued decision diagram to analyze the reliability of binary-state PMSs with a lower computational complexity. For many engineering systems, both a system and its units can exhibit more than one intermediate state between perfectly functioning and completely failed during their deterioration processes [13]. A PMS with the multi-state nature is termed as a multi-state phased-mission system (MS-PMS) [14]. For MS-PMS reliability analysis, a hierarchical modeling method and an integrated modeling approach to the reliability analysis of repairable MS-PMSs were developed by Wang et al. [15] and Shrestha et al. [16], respectively. However, the integrated models still suffer from the "state-explosion" problem. To overcome this downside, the Bayesian network (BN), as introduced in [17,18], is a feasible and promising way to analyze reliability of PMSs due to its ability of characterizing dependencies within a phase and across multiple phases.

Nonetheless, the parameters that characterize the deteriorating behaviors of an MS-PMS and its units may not always be known before the system is put into use. The reliability measures of an MS-PMS can, therefore, only be assessed by collecting a sufficient amount of observation data over time. To the best of our knowledge, the study on the reliability assessment of PMSs and MS-PMSs by observation data has not been fully explored yet. Rani et al. [19] used the maximum likelihood estimation method to assess the reliability of PMSs by deriving the distribution function of system operational time when the operational times of all the subsystems are observed. In their work, components in different subsystems are connected in parallel and the lifetimes of components are assumed to be independent, identical, and exponentially distributed random variables. By taking account of condition monitoring information and degradation data, He et al. [20] introduced the stochastic filtering model to achieve reliability estimation of an individual PMS. Si et al. [21] presented a novel condition-based approach to dynamically estimate reliability of a specific individual PMS. The stochastic filtering model was first used in their study to model the phase duration, and the mission time and lifetime distribution of the PMS were updated in a real-time manner to assess the mission reliability. However, the PMS in their studies was treated as a simple single-unit system, and these methods cannot be straightforwardly implemented to an MS-PMS composed of a number of units. On the other hand, in many engineering cases, observation data of an MS-PMS can be collected from multiple physical levels of the system. Due to the state dependence between a system and its units, that is, the system state is dependent on the states of its units, observation data from different physical levels of a system cannot be treated statistically independent. In the context of binary-state systems, Hamada et al. [22] estimated the posterior distributions of basic and top events by a fully Bayesian approach, which can simultaneously combined non-overlapping data of basic and higher-level events in a fault tree. By incorporating both prior knowledge from experts and multi-level observation data, the reliability of a binary-state system consisting of multiple binary-state units was estimated in a Bayesian inference framework [23,24]. Pan and Yontay [25] introduced a Bayesian network model to assess the reliability of a hierarchical system, and the mixed data types, i.e., both pass/fail data and lifetime data, combined with prior beliefs from different physical levels of the system were used to infer the posterior distributions of lifetime parameters. In the context of multi-state systems, Jackson and Mosleh [26,27] incorporated multiple overlapping datasets, drawn from the same process or system at the same time instants, to conduct a Bayesian reliability inference for multi-state on-demand systems. Li et al. [28] developed a Bayesian multi-level information aggregation approach to analyze the reliability of a multi-state electro-mechanical actuator system by utilizing imbalance reliability data from multiple physical levels of the system. By using dynamic Bayesian networks and a tailored least squares algorithm, Jiang and Liu [29] proposed a new method to estimate the reliability of multi-state systems by aggregating multi-level observation sequences. Guo et al. [30] investigated the Bayesian melding method for multi-state system reliability assessment by integrating various available sources of experts' knowledge and data from both subsystem and system levels. However, the aforementioned methods are only applicable to the cases where both the system configuration cannot change over time. Because of the system reconfiguration and the phase dependence of each unit across consecutive phases, the state dependence and deteriorating behaviors of an MS-PMS alter from phase to phase. Additionally, the structure of observation data may also change as some units and/or subsystems become observable in some phases and unobservable in other phases. It, therefore, necessitates the development of a new method for reliability assessment of MS-PMSs that can tackle both the state and phase dependencies involved in observation data.

To advance the-state-of-art of reliability assessment for complex systems, this study devotes to introducing a new reliability assessment method for MS-PMSs, enabling fusing observation data from multiple phases of operation. By the proposed method, the state and phase dependencies of MS-PMSs are characterized by constructing a dynamic Bayesian network (DBN) model. The structure of the DBN model, representing the configuration of an MS-PMS, can vary from phase to phase. By inputting observation data, the joint probability distributions of the nodes of the MS-PMS at any time slice can be updated by the DBN model, with which the unknown parameters associated with state transitions of all units can be furtherly estimated by a tailored Expectation-Maximization (EM) algorithm. The reliability function of the MS-PMS can be, then, assessed by these estimates of the state transitions of all the units. The confidence interval of the reliability function is also estimated by the bootstrap method. The effectiveness of the proposed method is exemplified via an illustrative case and a data collection robot.