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System dynamic reliability assessment and failure prognostics

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ABSTRACT

Traditionally, equipment reliability assessment is based on failure data from a population of similar equipment, somewhat giving an average description of the reliability performance of an equipment, not capturing the specificity of the individual equipment. Monitored degradation data of the equipment can be used to specify its behavior, rendering dynamic the reliability assessment and the failure prognostics of the equipment, as shown in some recent literature. In this paper, dynamic reliability assessment and failure prognostics with noisy monitored data are developed for a system composed of dependent components. Parallel Monte Carlo simulation and recursive Bayesian method are integrated in the proposed modelling framework to assess the reliability and to predict the Remaining Useful Life (RUL) of the system. The main contribution of the paper is to propose a framework to estimate the degradation state of a system composed of dependent degradation components whose conditions are monitored (even without knowing the initial system degradation state) and to dynamically assess the system risk and RUL. As case study, a subsystem of the residual heat removal system of a nuclear power plant is considered. The results shows the significance of the proposed method for tailored reliability assessment and failure prognostics.

1. Introduction

Traditional reliability assessment computes the reliability of an equipment based on failure data from a (large) number of similar equipment [1,10,17,19,9]. This provides the reliability for the somewhat average equipment, without taking into account the specificity of the physical process of degradation and the related monitored data of the individual equipment under assessment.

Recently, dynamic reliability assessment and failure prognostics have been investigated. Following Liu et al. [12], dynamic reliability assessment in this paper is interpreted as the dynamic updating or modification of the reliability model of a specific equipment, when additional information becomes available, related to the state and degradation process of the equipment. The failure prognostics of the equipment can also be dynamic, within the reliability assessment framework.

Dynamic reliability assessment and failure prognostics have been investigated with reference to single components. The works of Dong and He [2], Ghasemi et al. [4], Ye et al. [23] and Si et al. [20] are some examples.

The dynamic reliability assessment and failure prognostics of a system of multiple components have not yet been explored in depth, because of the complications due to the interactions and dependences of behavior of the components constituting the system. The work of Liu et al. [12] and Moghaddass et al. [14] represent recent efforts in developing methods for the dynamic reliability assessment and failure prognostics of a system, where the observations on the system state are considered (although without noise).

In this paper, the dynamic reliability assessment and failure prognostics of a system with dependent multi-state/continuous degrading components is addressed. To the authors' knowledge, this is the first time that such type of system is considered for dynamic risk assessment and prognostics. Some main practical considerations are:

i) Degradation is usually described as a continuous process by physics-based or data-driven models [11,18,5,6,8]. In this paper, the authors propose a framework for dynamic reliability assessment and prognostics of a system composed of a pump and a valve, whose degradation processes are multi-state and continuous, respectively. The degradation model for each component is given.
ii) As the system can be operated in different conditions and environments, uncertainties affect the degradation models.

Acronyms: AE, Absolute Error; MC simulation, Monte Carlo simulation; PDF, Probability Density function; PDMP, Piecewise Deterministic Markov Process; RUL, Remaining Useful Life

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Symbols

t	time
C	number of components in a system
$s_{i,t}$	state of component i at time t
$M_{i,j}$	j-th degradation state of component i
$s_{i,t,M_{i,j}}$	degradation state of component i at time t is $M_{i,j}$
$\boldsymbol{s}_{s,t}$	state of the system at time t
x_t	measured value of the system state at time t
Δs_i	difference between two consequent states of component i
$\Delta \boldsymbol{s}_{s,t}$	difference between two consequent discrete system states at time t
N_i	number of possible degradation states of component i
N_{all}	number of possible degradation states of the system
N_{MC}	replication times of Monte Carlo simulation
Th_i	threshold for failure of component i
$g_i(\bullet)$	degradation function of component i
$h(\bullet)$	relation between the system state and the measured value
$\boldsymbol{\delta}_t$ and γ_t	uncertainty in the degradation function at time t
$\boldsymbol{X}_{1:t}$	vector including the values monitored from inspection time 1 to inspection time t
$p(A\|B)$	conditional probability of A given B
$p(A, B\|C)$	conditional probability of A and B given C
$p(A\|B, C)$	conditional probability of A given B and C
$p(A)$	unconditional probability of A
RUL_s	true RUL of the system
$\hat{RUL}_s$	estimated RUL of the system
$R(t)$	estimated reliability of the system at time t
λ_{mn}	transition rate from state m to state n
$N(\mu, \sigma)$	Gaussian distribution with a mean of μ and a standard deviation of σ
$\boldsymbol{\varepsilon}_t$	noise in the measured value at time t

iii) As the system can be operated in different conditions and environments, uncertainties are included in the degradation model of each component.
iv) The data monitored by the sensors is noisy.

To the authors' knowledge, this is the first time that such a system is considered for dynamic risk assessment and prognostics.

In Lin et al. [10], the simulation of a Piecewise Deterministic Markov Process (PDMP) model is performed for the reliability assessment of multiple dependent components with multi-state and continuous degradation processes, where the system degradation state is supposed to be precisely known and no uncertainty is considered. PDMP gives a same average result for different systems, without considering information on the specific system. If the precise system degradation state is not available, how can one assess the system reliability and predict the Remaining Useful Life (RUL) of the system with monitored noisy data? If the system degradation state is available for some time instances, how can one update the results on the reliability assessment and prognostics with the monitored value? This paper proposes a modelling framework to answer these questions.

Given a known system degradation state, PDMP can update the reliability and RUL of a multi-component system based on data monitored on the system. To exploit the information in the monitored data, especially in the case that the true system state is not known, a modelling framework combining recursive Bayesian method and parallel Monte Carlo simulation is proposed in this paper.

Specifically, the general recursive Bayesian method for system degradation state estimation with monitored data is firstly established for the considered system. As in Tombuyses and Aldemir [21], the system degradation state is discretized into a finite number of states. The recursive Bayesian method for the considered system with a finite number of degradation states is derived. The strategy for numerically implementing the established Bayesian framework for dynamic reliability assessment and failure prognostics is a parallel Monte Carlo simulation: one Monte-Carlo simulation is carried out for each possible system degradation state. The reliability and RUL of the considered system are calculated based on the results of the parallel Monte Carlo simulation. The dynamic reliability assessment and failure prognostics of an illustrative system with two dependent components are carried out to show the application of the proposed modelling framework. The case study in this paper concerns the degradation of a subsystem, composed of a pneumatic valve and a centrifugal pump, belonging to the residual heat removal system of a nuclear power plant.

The remainder of the paper is organized as follows. The generic formulation of the modelling problem considered is presented in Section 2. Section 3 details the framework for the proposed dynamic

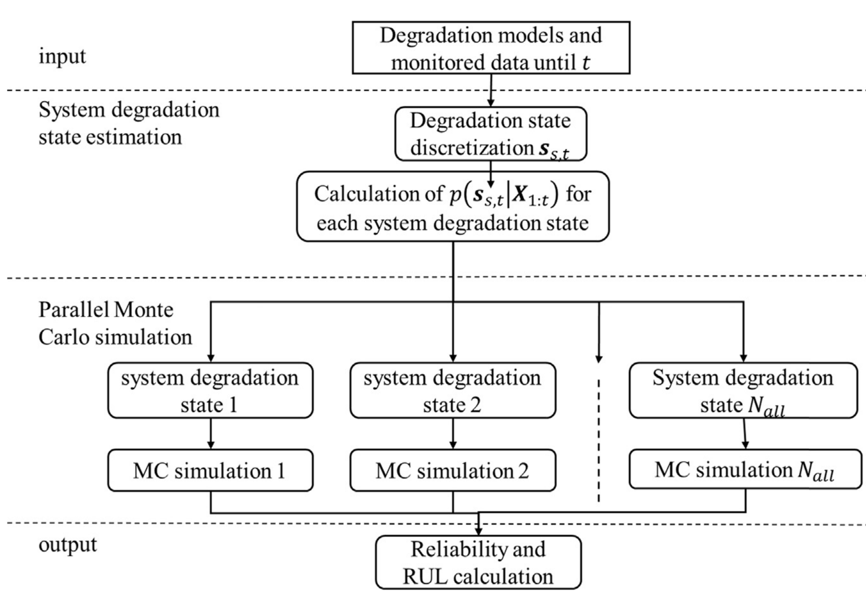

Fig. 1. Flowchart of the proposed modelling framework for dynamic reliability assessment and failure prognostics.