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A model for online failure prognosis subject to two failure modes based on belief rule base and semi-quantitative information

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ABSTRACT

As one of most important aspects in condition-based maintenance (CBM), failure prognosis has attracted an increasing attention with the growing demand for higher operational efficiency and safety in complex engineering systems. Currently there are no effective methods for predicting the failure of a system in real-time by using both expert knowledge and quantitative information (i.e., semi-quantitative information) when degradation failure and shock failure are dependent and competitive. Since belief rule base (BRB) can model the complex system when semi-quantitative information is available, this paper focuses on developing a new BRB based method for online failure prognosis that can deal with this problem. Although it is difficult to obtain accurate and complete quantitative information, some expert knowledge can be collected and represented by a BRB which is an expert system essentially. As such, a new BRB based prognosis model is proposed to predict the system failure in real-time when two failure modes are dependent and competitive. Moreover, a recursive algorithm for online updating the parameters of the failure prognosis model is developed. Equipped with the recursive algorithm, the proposed prognosis model can predict the failure in real-time when two failure modes are dependent and competitive. An experimental case study is examined to demonstrate the implementation and potential applications of the proposed online failure prognosis method.

1. Introduction

With a growing demand for higher operational efficiency and safety in industry, failure prognosis, as a key technology in condition-based maintenance (CBM), has attracted considerable attention world-wide in the past three decades [5,8,14–17].

In the engineering practice, some complex systems may be subject to two failure modes that are degradation failure and shock failure. The system failure may occur due to the competition of these two failure modes [6,7,30]. For example, the rocket control system is a complex system that is composed of inertial platform, electronic equipment, servomechanism and other equipment. For the electronic equipment, the failure may occur suddenly. This type of failure is named as shock failure. Due to the existence of wear, the performance of mechanical device will degrade slowly in the servomechanism. When the performance degradation exceeds the given threshold, the failure may also occur. This type of failure is named as degradation failure. As a result, the failure of the rocket control system is the competitive result of two failure modes. Therefore, these two modes need to be considered when the system failure is predicted. On one hand, if the two modes do not affect each other in some systems, two failure modes are independent. On the other hand, for some systems, with the development of performance degradation, the probability of shock failure may increase. In other words, two failure modes are dependent and the system failure is the competitive result of the two failure modes.

1.1. Failure prognosis when two failure modes are independent

When the degradation failure and shock failure are assumed to be independent, failure prognosis and optimal maintenance can be solved once the system availability is maximized [30]. If it is assumed that two failure modes are independent, the problems of performance degradation modeling and failure prognosis are formulated and solved under multi-failure modes and the random attacks [12]. Based on the assumption that k_1 shock failure modes

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and k_2 degradation failure modes are independent, Huang et al. proposed a method to calculate the failure rate of a complex system [6,7]. Bocchetti et al. studied the failure prognosis model of diesel engine. In this study, the failure modes include the degradation failure of wear and the shock failure of thermal cracking. These two failure modes are assumed to be independent. Moreover, the non-homogeneous compound Poisson process is adopted to model the degradation process, and the Weibull distribution is used to describe the shock failure. Then a competitive failure model is established and the model parameters are estimated by using the observable data [2]. At present, a lot of research works are focused on the performance degradation modeling when the two failure modes are independent [2,6,7,12].

1.2. Failure prognosis when two failure modes are dependent and competitive

Combining the distribution density function of degradation with the probability of shock failure, the mixed mathematical formulation of performance degradation is developed [22]. Under the degradation failure and multiple shock failures, the problem of competitive failure is solved using the Wiener model when the degradation process is assumed to be linear [2–4]. Based on the assumption that the shock failure is considered as the external attack whose strength is the function of performance degradation and stress, a competitive failure model is proposed [9,10,13]. This paper focuses on failure prognosis when two failure processes are dependent and competitive.

In the above methods for predicting the system failure, the quantitative information which includes the model mechanism of system and observable data are mainly used. However, for some complex systems, the complete quantitative information may not be available. For example, due to the fact that the price of rocket control system is extremely high and the useful life is short, it is difficult to obtain enough complete and accurate observable data which can reflect the system performance. Fortunately, some knowledge can be obtained by analyzing the system mechanism. Moreover, the other knowledge, especially in qualitative form and partially historical observable data about system behavior, may be given by experts. In this paper, the combination of expert knowledge and quantitative information is named as semi-quantitative information. Then the question is how the semi-quantitative information can be used to predict the system failure in real-time when two failure modes are dependent and competitive. Based on the belief rule base (BRB) which has been developed recently in [20,21], a new model is proposed for online failure prognosis when two failure modes are dependent and competitive. We propose to adopt BRB for the following reason.

The BRB is described as being capable of capturing the relationships between system inputs and outputs that could be discrete or continuous, complete or incomplete, linear or nonlinear, nonsmooth, or their mixture [19–21]. It can also process incomplete or vague information. Some offline optimization models and recursive algorithms for training the BRB parameters have been proposed [18,20,21,23,24,27]. Moreover, a sequential learning algorithm for updating the BRB structure and parameters at the same time has also been developed [26].

This paper is organized as follows. In Section 2, the problem of failure prognosis is formulated and defined. In Section 3, a new BRB based model is proposed to predict the performance degradation of system in real-time when the two failure modes are dependent and competitive. Section 4 presents a BRB based algorithm for online failure prognosis. An experimental case study is presented to verify the proposed algorithm in Section 5. The paper is concluded in Section 6.

2. Problem formulation

2.1. Notations

The notations that will be used in this paper are listed as follows:

x: a key parameter that is used to describe the performance degradation;
t: discrete time index;
$P_{SF}(t)$: the probability of shock failure at time instant t;
$P_{DF}(t)$: the probability of degradation failure at time instant t;
$P_F(t)$: the failure probability of the whole system at time instant t;
P_{th}: failure threshold;
$\mathbf{\Omega}(t-1)$: all the available information about the system up to time instant $(t-1)$;
D_N: the state of degradation failure
λ_{r0}: initial value of failure rate;
$\boldsymbol{\psi}$: the parameter vector included in function $q(\hat{x}(t), \boldsymbol{\psi})$;
A_i^k: referential value of the ith antecedent attribute in the kth rule of BRB;
$A_i = \{A_{i,j}, j = 1, \ldots, J_i\}$: a set of referential values for the ith antecedent attribute of BRB;
θ_k: relative weight of the kth rule of BRB;
$\delta_1, \ldots, \delta_{p+1}$: relative weights of $(p+1)$ antecedent attributes in the kth belief rule of BRB;
D_j: jth consequent of BRB;
$\beta_{j,k}$: belief degree assessed to the jth consequent D_j in the kth belief rule of BRB;
$\mathbf{V}$: parameter vector in BRB;
$\beta_j(t)$: belief degree in D_j at time instant t;
$f(\bullet \mid \bullet)$: conditional probability density;
$\mathbf{Q}$: parameter vector in conditional probability density;
H: constraint set that is composed of the constraints of the parameters.

2.2. Problem formulation of online failure prognosis

Suppose that the system may be subject to two failure modes. The first mode is degradation failure and the second one is shock failure. These two failure modes are dependent and competitive. For example, the failure modes of pulse xenon lamp mainly include degradation failure that is induced by melting of electrode material and shock failure that is induced by blow lamp. The probability of shock failure caused by blow lamp may increase when the probability of degradation failure becomes large.

Firstly, the following assumptions are given:

(1) There is only one degradation failure mode and one shock failure mode. These two failures can both lead to the failure of the whole system. If the degradation failure happens firstly, then the system failure is mainly caused by the degradation failure. Otherwise, the system failure is mainly caused by the shock failure. In other words, the system failure is induced by the competition of two failure modes.
(2) If the shock failure happens, the system cannot work.
(3) A key parameter x can be chosen to reflect the performance degradation of system. In other words, the performance degradation can be reflected by x. It is assumed that there are N states that are used to denote the performance degradation. For example, three states $D_1, \ldots, D_3$ can be chosen, i.e., $N = 3$. Then meanings of these three states are as follows:
D_1: The system is operating normally and the degradation failure does not occur.