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On the use of on-line detection for maintenance of gradually deteriorating systems

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ABSTRACT

This paper deals with condition-based maintenance and non-stationary degradation process due to sudden changes. This is an attempt to propose an adaptive maintenance policy based on the on-line change detection procedure which can help to detect switches from a nominal mode to an accelerated mode in a non-informative context about the change mode time.

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1. Introduction

This paper deals with a non-stationary deteriorating system where the mean deterioration rate can change during a life cycle. The system begins to deteriorate according to a nominal mode and the mean deteriorating rate increases suddenly, e.g. due to a change of its environment [1]. The main aim of this work is to propose a preventive maintenance policy which relies on the monitoring of the measurable system state. A maintenance decision criterion is given, based on the observed deterioration level of the system for a system which undergoes a continuous random deterioration [2,3]. The system state is monitored through periodic inspections and when it exceeds a threshold L the system is considered as subject to non-obvious failures. Therefore, in the presence of a non-obvious failure, the system is not known to be failed until it is revealed by inspections. When a failure is detected upon inspections, a corrective maintenance operation replaces the failed system by a new one. Moreover, a preventive replacement takes place when the system state exceeds a threshold in order to avoid a failure occurrence and a resulting period of inactivity of the system (duration between the instant of failure and the following inspection).

The choice of the inter-inspection times and the value of the preventive threshold both influence the economic performance of the maintenance policy. For example, when the inspections are costly it is not worthwhile to often inspect the system, but decreasing the number of inspections leads to increase in the risk of missing a failure occurrence. For a single mode deteriorating system, condition-based inspection/replacement (e.g. see [4–6]) and continuous monitoring replacement policies (e.g. see [7]) have been proposed. In previous works, a maintenance cost model is proposed which quantifies the costs and benefits of the maintenance strategy and permits to find the optimum balance between monitoring and maintenance efficiency. For systems subject to sudden change of mode of deterioration it is natural to adapt the maintenance decision rule according to the on-line information available about the system. An adaptive maintenance policy has been proposed in [8] for a continuously monitored system provided that the time of change of mode is immediately and perfectly detected.

In a context of total lack of a priori information about the time of change of mode, the main aim of this paper is to propose an adaptive maintenance policy based on an embedded optimal on-line change detection algorithm. The detection of every change in the deteriorating system rate is based on the degradation levels successively observed and takes into account the delay for detection.

In Section 2 the deteriorating system is described. After a brief presentation of the on-line change detection in Section 3, an adequate change detection algorithm with a short detection delay is introduced. Section 4 is devoted to the description of an appropriate maintenance policy. In Section 5, results from numerical experiments illustrate and analyze the behavior of the proposed preventive maintenance policy.

2. Model of deterioration

Consider a stochastically deteriorating system, for which the state at time t can be summarized by a random aging variable X_t. In absence of repair or replacement, $(X_t)_{t\geqslant 0}$ is an increasing stochastic process such that:

- the initial state is $X_0 = 0$,
- the deterioration process after a time t_0 is independent of the deterioration before t_0.

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In this paper, it is assumed that $(X_t)_{t\geqslant 0}$ is a gamma process and for all $0\leqslant s\leqslant t$, the increment of $(X_t)_{t\geqslant 0}$ between s and t, $Y_{t-s}=X_t-X_s$, follows a gamma probability distribution function with shape parameter $\alpha(t-s)$ and scale parameter β. This probability distribution function can be presented as follows:

$$f_{\alpha(t-s),\beta}(x)=\frac{1}{\Gamma(\alpha(t-s))\beta^{\alpha(t-s)}}x^{\alpha(t-s)-1}\,\mathrm{e}^{-x/\beta}\mathbf{1}_{\{x\geqslant 0\}}. \tag{1}$$

The two parameters α and β can be estimated from deterioration data with classical statistical methods. The average deterioration speed rate is $\alpha.\beta$ and its variance is $\alpha.\beta^2$. The choice of α and β allows to model various deterioration behaviors from almost deterministic to highly variable. Note that the gamma process is a positive process with independent increments. It implies frequent occurrences of tiny increments which makes it relevant to describe gradual deterioration due to continuous use such as erosion, corrosion, concrete creep, crack growth, wear of structural components [9–12]. Another interest of the gamma process is the existence of an explicit probability distribution function which permits feasible mathematical developments. It has been widely applied to model condition-based maintenance (see Ref. [13]).

The system fails when the aging variable is greater than a predetermined threshold L which depends on the properties of the considered system. In this paper, we consider systems whose failures are not obvious to the user and cannot be easily characterized and identified. The system can be declared as "failed" as soon as a defect or an important deterioration is present, even if the system is still functioning. In this situation, its high level of deterioration is unacceptable either for economic reasons (poor products quality, high consumption of raw material, etc.) or for safety reasons (high risk of hazardous breakdowns). An example is given by van Noortwijk in [14], where the problem of maintaining coastal flood barriers is modeled. The sea gradually erodes the flood barrier and the barrier is deemed to have failed when it is no longer able to withstand the pressure of the sea.

The parameters of the deteriorating system can change during a life cycle (e.g. according to the operating environment) at an unknown time T_0. The variable T_0 can be random but the fundamental hypothesis in this paper is that its probability distribution and mean remain unknown. The system can evolve according to two degradation modes denoted by M_1 and M_2. The first mode M_1 corresponds to the nominal evolution of the system and the second mode M_2 corresponds to an accelerated deterioration. These two modes can be modeled by two gamma processes with different parameters. According to the characteristic of the system, it is supposed that the mean values of the increments in the accelerated mode M_2 are greater than those corresponding to the nominal mode M_1. In each mode M_i, $i=1,2$, the process $(X_t)_{t\geqslant 0}$ has independent increments and for any $\Delta t>0$ the increment $Y_{\Delta t}=X_{t+\Delta t}-X_t$ follows a gamma law with a probability density function $f_{\alpha_i\Delta t,\beta_i}(x)$ defined by (1). Such a situation can occur, e.g. in the oil and gas industry [15]. Pipelines are often thermally insulated, buried or submerged and subject to corrosion which has to be controlled. Protection against corrosion can be provided by coatings that are able to cope with bad environmental conditions. The system state is then represented by the level X_t of corrosion at time t. The continuous monitoring of hidden systems being too costly the amount of deterioration is revealed by inspections. The existence of a protective coating leads to a slow nominal deterioration rate (mode M_1). But as soon as the lining resistance decreases the deterioration of the pipeline suddenly switches to an accelerated rate (mode M_2). The pipeline has then to be quickly maintained. In this case T_0 represents the lifetime of the coating which provides protection to the pipeline.

3. Detection method

3.1. CUSUM algorithm and mean detection delay

The problem of quick detection of abrupt changes in a stochastic system on basis of sequential observations from the system and with low false alarm rate has many important applications including industrial quality control, automated fault detection in controlled dynamical systems. As it is noted in [16], there is a large literature on the detection algorithms in complex systems but the application of these methods to a maintenance policy is never discussed. The main aim of this paper is to apply, in the context of condition-based maintenance, an adequate change detection algorithm to a stochastically deteriorating system described by a scalar aging variable $(X_t)_{t\geqslant 0}$ which summarizes its condition. As it is introduced in Section 2 the parameters of the deterioration process $(X_t)_{t\geqslant 0}$ can change (e.g. according to the systems environment) at an unknown time T_0 (possibly random with an unknown probability distribution and mean). The system can then evolve according to two modes of deterioration M_1 and M_2.

The two main classes of quickest detection problems are the Bayesian and non-Bayesian approaches. When the observations are independent, Shiryaev [17] has formulated the problem of optimal sequential detection of the change time T_0 in a Bayesian framework by putting a geometric prior distribution on T_0 and assuming a loss of c for each observation taken after T_0 and a loss of 1 for a false alarm before T_0. From optimal stopping theory it can be shown that the Bayes rule triggers an alarm when the posterior probability change occurred exceeds some fixed level. The method has been developed for more general prior distributions, random process and loss functions [18,19].

The framework of the paper in a non-informative context about the change mode time deals with the non-Bayesian approach. The first algorithm in the non-Bayesian framework, suggested by Page in [20], is the cumulative sum algorithm (CUSUM). The asymptotic minimax ("worst case") optimality of CUSUM has been proved by [21]. A lower bound for the worst mean delay to detection is given and the CUSUM algorithm has been proved to reach this lower bound when the mean time before false alarm is large. The non-asymptotic optimality of the non-Bayesian algorithm is given in [22,23].

In this paper the non-Bayesian algorithm CUSUM is applied to the gradually deteriorating process and the asymptotic optimality of this algorithm is used to propose an adapted condition-based maintenance policy. Let us recall that in the nominal mode M_1 the elementary random deterioration increment in a time interval Δt, i.e. $Y_{\Delta t}=X_{t+\Delta t}-X_t$ for $t\geqslant 0$, follows a gamma law with shape parameter $\alpha_1\Delta t$ and scale parameter β_1. In the accelerated deterioration mode M_2, $Y_{\Delta t}=X_{t+\Delta t}-X_t$ $(t\geqslant 0)$ follows a gamma law with respective shape and scale parameters $\alpha_2\Delta t$ and β_2. We shall use $f_{\alpha_i\Delta t,\beta_i}$ to denote the density function of the gamma law in mode M_i, $i=1,2$.

Let $Y_1,\dots,Y_n$ be a sequence of n observed deterioration increments. Define the CUSUM stopping rule

$$N=\min\left\{n\geqslant 1,\ \max_{1\leqslant k\leqslant n}\sum_{i=k}^{n}\log\frac{f_{(\alpha_2\Delta t,\beta_2)}(Y_i)}{f_{(\alpha_1\Delta t,\beta_1)}(Y_i)}\geqslant h\right\}. \tag{2}$$

It is decided that the system is in mode M_2 as soon as the cumulative sum of the log-likelihoods exceeds a given threshold h. According to this decision rule the detection time of a change of mode is $t_N=N\Delta t$. The constant h is chosen such that $\Pr_{M_1}(N<\infty)\leqslant a$ or equivalently $\mathbb{E}_{M_1}(N)\geqslant\gamma$. $\Pr_{M_1}(N<\infty)$ is the probability of false alarm (probability to detect a change given

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