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A predictive maintenance policy with imperfect monitoring

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ABSTRACT

For many systems, failure is a very dangerous or costly event. To reduce the occurrence of this event, it is necessary to implement a preventive maintenance policy to replace the critical elements before failure. Since elements do not often exhibit incipient faults, they are replaced before a complete exploiting of their useful life. To conjugate the objective of exploiting elements for almost all their useful life with the objective to avoid failure, condition based and, more recently, predictive maintenance policies have been proposed. This paper deals with this topic and proposes a procedure for the computation of the maintenance time that minimizes the global maintenance cost. By adopting a stochastic model for the degradation process and by hypothesizing the use of an imperfect monitoring system, the procedure updates by a Bayesian approach, the a-priori information, using the data coming from the monitoring system. The convenience in adopting the proposed policy, with respect to the classical preventive one, is explored by simulation, showing how it depends on some parameters characterizing the problem.

1. Introduction

For many systems, failure is a dangerous or costly event. The available information on the failure time is often not very accurate because of the great variability among elements belonging to the same population. By adopting the classical preventive maintenance policy, elements are replaced before a complete exploiting of their useful life. This approach reduces, of course, significantly the failure risk, but increases costs for spare parts, for people managing maintenance activities and for the unavailability of the system during the maintenance operations.

During the designing phase, system reliability could be increased by redundancy of critical elements. However, this solution is not always possible or convenient. Therefore, the implementation of condition-based maintenance is more suitable. In particular, by employing a monitoring system that follows in real-time the degradation process, it is possible to intervene only when it is strictly necessary.

Generally, a maintenance activity must be programmed in advance to make possible both the supplies of costly spare parts, that are not stored for evident economic reasons, and the availability of the maintenance team. This necessity has favoured the transition to the predictive maintenance policy. In fact, on the basis of the information coming from a monitoring system and by employing a stochastic model, describing the evolution of the degradation process, it is possible to predict the failure time and consequently to schedule the maintenance activity in time.

However, the great industrial interest for this approach, it has been not much faced in literature, differs from the previous preventive and condition-based approaches.

Some authors have proposed maintenance policies based on the observation of the effective degradation level of the component by periodic inspections. Among the first authors dealing with this topic, it is possible to mention the paper of Christer and Wang [1] and the paper of Chu et al. [2], while more recently the paper of Crowder and Lawless [3]. In the last one, the authors, by a periodical measurement of the degradation level and by a comparison of the observed value with a prefixed threshold, proceed to the scheduling of the maintenance activities. The corrective action is also considered if failure occurs before the scheduled time, but only for the critical elements whose failure causes the stop of the system. The determination of the maintenance times is obtained by minimizing the expected total cost that includes also the inspection costs. In [4], authors apply a stochastic degradation model to repairable multi-component systems, providing a maintenance optimization scheme. In the model, failure is not only a consequence of an excessive degradation level but also a consequence of random shocks.

Deloux et al. [5] propose a maintenance policy based on a degradation model and on two inspection actions for a single-unit system subject to two failure mechanisms: a progressive deterioration and a lethal shock due, for example, to a stressful working environment. The first failure mechanism can be observed by the measurement of a correlated variable through costly inspections (X-inspections). The second inspection action (Z-inspection) consists of continuous monitoring of the stress variable. With the employment of a classical control chart, it is

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possible to detect drifts in the observed variable. This minimal inspection, less expensive, reveals only if the system is failed or not, but delivers no information on the *X*-variable. Both inspections address the decision maker to a corrective replacement, when the component is failed, or to a preventive replacement, if the fixed threshold is reached.

In the same maintenance context, Wang [6] proposes the development of a model for the determination of the critical level and the monitoring intervals. These two parameters are decision variables that influence the scheduling of the maintenance activities. With such policy, the monitoring checks are undertaken when necessary in order to minimize a cost function.

In the previous works, the maintenance actions are considered perfect. After each maintenance cycle, in fact, the element is considered as good as new. Some authors [7,8] do not accept this hypothesis and in particular Zhou et. al. [9] propose a reliability-centered predictive maintenance policy for a system whose wear is not completely removed by the maintenance activity. By monitoring the system, the evolution of the hazard rate function is determined in order to predict the system reliability in subsequent maintenance cycles.

Inspections can be sometimes replaced by the information coming continuously from sensors and the development of adequate technologies has simplified this monitoring activity.

The transition from the condition-based maintenance (CBM) to the predictive CBM (PCBM) is focused in [10]. The authors propose a state-space model and Kalman filtering methods for recursively forecasting the future deterioration state, which is converted to the failure probability in the subsequent step. Maintenance decisions are made according to the predicted failure probability. In [11], by taking into account the technological, organizational and control issues, an evaluation system for the set up of a predictive maintenance programme is proposed. In [12], a practical framework for the extension of the predictive maintenance policy to a multi-state system is developed. In this work, authors study the impact of the quality of a maintenance work on system performance by introducing a "Restoration factor" that represents the percentage recovery of a system's mean performance.

In order to implement a sensor-driven predictive policy, it is necessary to model the degradation process. Many types of stochastic models for degradation processes have been proposed in the literature.

Lu and Meeker [13] develop general statistical models and data analysis methods for using degradation measures to estimate a time-to-failure distribution.

Gebrael et al. [14] propose an exponential model in which the deterministic parameters represent a constant physical phenomenon common to all the components of a given population, while the stochastic ones follow a specific distribution and capture variations among individual components, nominally identical. The distributions of the stochastic parameters across the population of components (a-priori distributions) together with the monitoring information collected for each component (a-posteriori distribution) are used to compute the residual life distribution for the individual component. A Bayesian approach is employed to update the prior information of each individual component at any instant.

In [15], the same author proposes and validates two sensory updating procedures using the real-world vibration signal coming from sensors installed on rolling bearings. The results are compared with two benchmark policies.

Lu et al. [16] extend the problem of reliability estimation to a component operating in real-time changing environments.

In the present paper, a sensor-driven predictive maintenance policy is proposed. Since the organization of the maintenance activities requires an adequate interval of time, the proposed methodology determines the time at which the decision must be taken and the date for the starting of the maintenance activity. Assuming a first order autoregressive model with drift as representative of the stochastic degradation process [17], the a-priori information on the population which the element belongs to is updated by a Bayesian approach. Different from other previous works, the monitoring system is considered imperfect [18] and the influence of this uncertainty on the performance of the proposed policy is analyzed.

A comparison between the proposed policy and the classical preventive one is performed by simulation. Varying some parameters characterizing the problem, it is shown that the predictive policy reduces the maintenance cost with respect to the preventive one, excluding those cases in which the quality of the monitoring system is poor, and hence the system cannot be followed correctly in its degradation process.

2. Degradation model and monitoring system

To apply the predictive maintenance policy, it is necessary to have reliable observations on the parameters of interest and a statistical model for the degradation process.

A Markovian degradation process, described by a first order autoregressive model with drift [17], is here assumed:

$$y(t+dt)=y(t)+\gamma' dt+\eta(t)dt \tag{1}$$

where y is the parameter characterizing the wear, γ' is the mean value of the increment rate and $\eta(t)$ has $E[\eta(t)]=0$ and $cov[\eta(t), \eta(t-\tau)]=\sigma_\eta^2\,\delta(\tau)$, where $\delta(\tau)$ denotes the Dirac's delta.

The assumed model is intentionally simple because the main focus of the paper is the maintenance policy presented in Section 6.

Generally the degradation process is observed at regular time intervals Δt. For this reason, the discrete form of the model (1) will be considered.

In this case $\gamma=\int_t^{t+\Delta t}\gamma' dt=\gamma'\Delta t$ while $\varepsilon_i=\int_{t_i}^{t_i+\Delta t}\eta(t)dt$ results independently normal distributed with mean zero and variance $\sigma_\varepsilon^2=\sigma_\eta^2\Delta t$.

Considering Δt as the unit of time, the model becomes

$$y_i=y_{i-1}+\gamma+\varepsilon_i \tag{2}$$

The assumption of normality for ε is justified when the acquisition interval of the monitoring system is not very small. On the other hand, this assumption could generate decrements of the parameter y. Since this is unrealistic in engineering applications, as the wear process, the quantity $y_i-y_{i-1}=\gamma+\varepsilon_i$ must not be negative, i.e. $\gamma-3\sigma_\varepsilon$ must be far from 0. The last condition implies that the probability of a negative wear increment is negligible. Considering that $\gamma=\gamma'\Delta t$ increases with Δt more rapidly than $\sigma_\varepsilon=\sigma_\eta\sqrt{\Delta t}$, the previous condition is assured when Δt is sufficiently large.

In many real situations, the degradation path of y cannot be observed directly. The monitoring system supplies a parameter m correlated with the real degradation parameter y. Let m_i be the value of such parameter at time t_i. If the monitoring system is affected by a reading error, assuming a linear response, the relation between m_i and y_i can be expressed as follows:

$$m_i=a+by_i+\Delta_i \tag{3}$$

where a and b are the coefficients of the linear transformation and δ_i represents the monitoring system error. Let δ_i be normal distributed with mean 0 and constant variance σ_δ^2, independent of δ_j and ε_i.