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Procedia CIRP 59 (2017) 95 – 101

www.elsevier.com/locate/procedia

The 5th International Conference on Through-life Engineering Services (TESConf 2016)

Modelling of predictive maintenance for a periodically inspected system

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Abstract

Predictive maintenance includes condition monitoring and prognosis of future system condition where maintenance decision-making is based on the results of prediction. In this paper, the modelling of predictive maintenance is conducted. It is assumed that the system is periodically checked by using imperfect measuring equipment. The decision rule for the predictive checking is formulated and the probabilities of correct and incorrect decisions are derived. The effectiveness of the predictive maintenance is evaluated by the average availability and downtime cost per unit time. The mathematical models are proposed to calculate the maintenance indicators for an arbitrary distribution of time to failure. The proposed approach is illustrated by determining the optimal number of predictive checks for a specific stochastic deterioration process. Numerical example illustrates the advantage of the predictive maintenance compared to the corrective maintenance.

Peer-review under responsibility of the scientific committee of the The 5th International Conference on Through-life Engineering Services (TESConf 2016)

Keywords: Availability; Corrective maintenance; Decision rule; False failure; Predictive checking; Prognostics; Remaining useful life; Undetective failure

1. Introduction

Currently, the most promising strategy of maintenance for various technical systems and production lines is the predictive maintenance (PM), which can be applied to any system if there is a deteriorating physical parameter like vibration, pressure, voltage, or current that can be measured. This allows to recognize approaching troubles, to predict wear or accelerating aging and to prevent failure through the repair or replacement of the affected component. Predictive maintenance is based on the prognostic and health management technology, which supposes that the remaining useful life of equipment can be predicted. However, due to uncertainty of prognostics there could be wrong decisions regarding the remaining time to failure. The growing interest to PM is evident from the large number of publications related to various mathematical models and implementation techniques. Let us consider some references related to the modelling of the PM.

In [1], a PM policy for a continuously deteriorating system subject to stress is developed. Condition-based maintenance policy is used to inspect and replace the system according to the observed deterioration level. A mathematical model for the maintained system cost is derived. In [2], the predictable reactive maintenance policies are studied based on a fatigue crack propagation model of the wind turbine blade considering random shocks and dynamic covariates. In [3], a PM method is developed to determine the most effective time to apply maintenance to equipment and study its application to a real semiconductor etching chamber. The PM decision is based on the likelihood of the predicted health condition, which exceeds a certain maintenance threshold. In [4], the costs model is analysed where the costs include small repair cost, PM cost and productive loss. An optimal model of PM strategy is further proposed to overcome the shortcoming of PM model with identical period. In [5], a PM structure for a gradually deteriorating single-unit system is considered. The decision model enables optimal inspection and replacement decision in order to balance the cost engaged by failure and unavailability on an infinite horizon. In [6], a data-driven machine prognostics approach is considered to predict machine's health condition and describe machine degradation. A PM model is constructed to decide machine's optimal maintenance threshold and

Peer-review under responsibility of the scientific committee of the The 5th International Conference on Through-life Engineering Services (TESConf 2016)
doi:10.1016/j.procir.2016.09.032

maintenance cycles. In [7], a PM model for the deteriorating system with semi-Markov process is proposed. A method to determine the best inspection and maintenance policy is developed. In [8], a discriminant function is developed on the basis of the representation of the observed system degradation process as a discrete parameter Markov chain. In [9], a multiple classifier machine learning methodology for PM is considered. The proposed PM methodology applies dynamical decision rules to maintenance management.

It should be noted that all considered models of PM do not take into account the probabilities of the correct and incorrect decisions made by the results of the predictive checks (PCs).

In this paper, a new PM model is developed for determining optimal periodicity of PCs. A decision rule is proposed for inspecting the system condition, which is based on the evaluation of the remaining time to failure. Based on this decision rule, general expressions are derived for calculating the probabilities of correct and incorrect decisions made by the results of the PCs. The effectiveness of the PM is evaluated by such indicators as average availability and average downtime cost per unit time.

Nomenclature

PC	predictive check
PDF	probability distribution function
PM	predictive maintenance

2. Decision rule

Assume that the state of a system is completely determined by the value of the parameter $X(t)$, which is a non-stationary random process with continuous time. The system should operate over a finite horizon T and is checked with prediction of condition at discrete time $k\tau$ ($k = \overline{1,N}$). When the system state parameter exceeds threshold FF, the system passes into the failed state. The measured value of $X(t)$ at time $k\tau$ is expressed as follows:

$$Z(k\tau) = X(k\tau) + Y(k\tau), \tag{1}$$

where $Y(k\tau)$ is the measurement error of the system state parameter at time $k\tau$.

Assume that random variable Ξ ($\Xi \geq 0$) denotes the failure time of a system with probability distribution function (PDF) $\omega(\xi)$. Let Ξ_k be a random assessment of Ξ based on the results of the PC at time $k\tau$.

Random variables Ξ and Ξ_k are the smallest roots of the following stochastic equations:

$$X(t) - FF = 0 \tag{2}$$

$$Z(k\tau) - FF = 0 \tag{3}$$

Let $\xi_{j,k}$ be the realisation of Ξ_k for the j-th system. Then, when carrying out the PC at the instant $k\tau$ the following decision rule is used: if $\xi_{j,k} \geq (k+1)\tau$, the system is judged to be suitable for operation in the time interval $[k\tau, (k+1)\tau]$; if $\xi_{j,k} < (k+1)\tau$, the system is judged as unsuitable for operation in the time interval $[k\tau, (k+1)\tau]$.

By the results of the PC at time $k\tau$ the following decisions are made: to allow the j-th system to be used until the next PC at the instant $(k + 1)\tau$ if $\xi_{j,k} \geq (k+1)\tau$; to restore the j-th system if $\xi_{j,k} < (k+1)\tau$.

The mismatch between the solutions of (2) and (3) results in the appearance of one of the following mutually exclusive events by the results of the PC at the instant $k\tau$:

$$h_1(k\tau) = \left\{ \Xi > (k+1)\tau \bigcap \left(\bigcap_{i=1}^{k} \Xi_i > (i+1)\tau \right) \right\} \tag{4}$$

$$h_2(k\tau) = \left\{ \Xi > (k+1)\tau \bigcap \Xi_k \leq (k+1)\tau \bigcap \left[\bigcap_{i=1}^{k-1} \Xi_i > (i+1)\tau \right] \right\} \tag{5}$$

$$h_3(k\tau) = \left\{ k\tau < \Xi \leq (k+1)\tau \bigcap \left(\bigcap_{i=1}^{k} \Xi_i > (i+1)\tau \right) \right\} \tag{6}$$

$$h_4(k\tau) = \left\{ k\tau < \Xi \leq (k+1)\tau \bigcap \Xi_k \leq (k+1)\tau \bigcap \left[\bigcap_{i=1}^{k-1} \Xi_i > (i+1)\tau \right] \right\} \tag{7}$$

$$h_5(k\tau) = \left\{ \Xi \leq k\tau \bigcap \left[\bigcap_{i=1}^{k} \Xi_i > (i+1)\tau \right] \right\} \tag{8}$$

$$h_6(k\tau) = \left\{ \Xi \leq k\tau \bigcap \Xi_k \leq (k+1)\tau \bigcap \left[\bigcap_{i=1}^{k-1} \Xi_i > (i+1)\tau \right] \right\} \tag{9}$$

Events $h_1(k\tau)$, $h_4(k\tau)$ and $h_6(k\tau)$ correspond to the correct decisions by the results of the PC at time $k\tau$. Event $h_2(k\tau)$ is the joint occurrence of two events: the system is suitable for use over the interval $[k\tau, (k+1)\tau]$ and by the results of the PC it is judged as unsuitable. We define event $h_2(k\tau)$ as a 'false failure'. Events $h_3(k\tau)$ and $h_5(k\tau)$ we define as 'undetected failure 1' and 'undetected failure 2', respectively.

3. System states

Let us consider the stochastic process $S(t)$, which characterizes the state of the system at an arbitrary instant of time t: S_1, if at time t, the system is used as intended and is in the operable state; S_2, if at time t, the system is used as intended and is in an inoperable state (unrevealed failure); S_3, if at time t, the system is not used for its intended purpose because the PC is carried out; S_4, if at time t, the system is not used for its intended purpose because event h_2 has occurred and a 'false corrective repair' is performed; S_5, if at time t, the system is not used for its intended purpose because either h_3 or h_6 event has occurred and a 'true corrective repair' is performed.

Further we assume that process $S(t)$ is the regenerative stochastic process. When determining maintenance efficiency indicators we use a well-known property of the regenerative stochastic processes [10], which is based on the fact that the