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Condition-based spares ordering for critical components

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ABSTRACT

It is widely accepted that one of the potential benefits of condition-based maintenance (CBM) is the expected decrease in inventory as the procurement of parts can be triggered by the identification of a potential failure. For this to be possible, the interval between the identification of the potential failure and the occurrence of a functional failure (P-F interval) needs to be longer than the lead time for the required part. In this paper we present a model directed to the determination of the ordering decision for a spare part when the component in operation is subject to a condition monitoring program. In our model the ordering decision depends on the remaining useful life (RUL) estimation obtained through (i) the assessment of component age and (ii) condition indicators (covariates) that are indicative of the state of health of the component, at every inspection time. We consider a random lead time for spares, and a single-component, single-spare configuration that is not uncommon for very expensive and highly critical equipment.

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1. Introduction

The main principle behind the use of condition monitoring techniques for the maintenance of industrial equipment is that of anticipating the occurrence of failures. When condition-based maintenance programs are in place, the removal of a component from operation is ideally triggered by the detection of a degradation process within the equipment (when resistance to failure has started to decrease). If we are able to detect the start of this failure process (i.e. the occurrence of a potential failure) early enough so that the expected lead time to receive a spare part on-site is less than the expected time to failure, then there is no need to stock a spare component. Using reliability-centered maintenance (RCM) terminology (see Ref. [1]), when the P-F interval is longer than the lead time there is no need to stock a spare. This idea constitutes a widely accepted potential benefit of condition-based maintenance (CBM) policies (see e.g. [2,3]), and creates an opportunity for the optimization of the ordering time of spares when demand can be anticipated. Gains can be important as in several industries, spare related holding costs are huge. For example, the commercial aviation industry has more than 40 billion dollars worth of spare parts on stock [4].

The use of condition monitoring techniques in industry has largely increased over the last few years [5]. The use of the condition information collected in the determination of optimal spare parts ordering could therefore generate significant savings in stockholding related costs. The latter statement is of particular importance to the case of expensive, complex components. However, the incorporation of condition information in the spare parts stockholding decision (i.e. the impact of condition-based maintenance policies in spare parts inventories) has seldom been approached in the literature. In fact,

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our literature survey only identified recent efforts by Ghodrati and Kumar [6], which are based on the use of *external* conditions to adjust demand estimations for spare parts (a more detailed account of these works is given in Section 6). The latter might be explained by the little integration between the areas of maintenance and reliability engineering and that of inventory and logistics, as examples of stockholding decisions with respect to maintainability or reliability parameters are, in general, scarce.

The opportunity to reduce inventory levels via the implementation of condition-based decision programs (based on the *internal* state of health of the equipment) has not been addressed in the literature, to the best of our knowledge.

In this article, we present a model resulting in the decision to order a spare or to continue to operate without ordering until the next inspection, based on estimations of the remaining life of the item given its age and internal condition. We concentrate on a single-system, single-spare configuration, which is not unreasonable for very expensive, highly critical components.

The remainder of the article is structured as follows. In the following section we review the concepts of conditional reliability function and remaining useful life of a component. Then we discuss methods for the calculation of these functions, taking into account condition monitoring information. Next we present an original decision model for spares ordering, which results in the decision to order a spare and the optimal ordering time, so that costs are minimized. We then present a case study from a mining application. We conclude the article, identifying areas for further development and providing some final remarks.

2. Conditional reliability and remaining useful life

The reliability function of an item is defined as the probability of survival of the item over an interval of time, say t. Typically, two cases for this function have concentrated interest in reliability analysis: the *unconditional* case (which assumes that the item has not yet been put into operation) and the *conditional* case (which assumes that the item has been operated for some time, say x). That is, for the unconditional case the figure of interest is $P(T>t)$, whereas for the conditional case it is $P(T>t|T>x)$, where T is the lifetime of the item.

In the case of condition-based maintenance decisions, we are interested in the conditional reliability of the item, given that it has been in operation up until the moment of inspection. In addition, since condition of the item is being monitored via different measurements (e.g. vibration levels, concentration of metals in the oil, noise levels, temperatures), these measurements should be included in the calculation of the conditional reliability.

In order for the reliability function to be calculated, an appropriate model for the hazard rate (or alternatively for the probability density function of the time to failure) should be constructed. In particular, we are interested in a model capable of representing the hazard rate of the equipment, combining usage information (age) with condition information (through condition indicators or covariates). Such a model would help to provide better prediction of the remaining life of the item, thus improving the anticipation of demand for spare parts.

In general, covariates can be classified as *internal* and *external*. Internal covariates relate to the internal state of the equipment. External covariates can be observed independently of the failure process (e.g. variables indicating conditions of the environment where components operate). In addition, covariates can be fixed (i.e. time-independent) or time-varying (i.e. time-dependent).

A widely accepted method to incorporate condition monitoring information in lifetime analysis is the proportional hazards model (PHM, see Ref. [7]). Kumar and Klefsjö [8] provide a comprehensive review of applications of the PHM in the reliability field.

The PHM models the hazard rate function, $\lambda(t)$, as

$$\lambda(t)=h_0(t)\exp\left(\sum_i \gamma_i Z_i(t)\right), \tag{1}$$

where $h_0(t)$ is a deterministic baseline hazard function (which depends on the age of the item only) and $Z(t)=(Z_1(t), Z_2(t),\ldots)$ is a vector of time-dependent covariates, which can be internal or external.

The model in Eq. (1) implies that the hazard rate function is conditioned on a stochastic process that is related to the condition (state of health) of the item. A common model used to represent the state of a system is the discrete Markov process (see e.g. [28]).

Banjevic and Jardine [9] indicated that in condition-based maintenance applications, the use of a non-homogeneous Markov process (NHMP) is of particular interest, as it allows for the rate of change of the system state to be dependent on the system's age. In their paper, they present theoretical and numerical methods for the calculation of the reliability function of an item under the assumption of a Markov process model. They use a PHM to model the hazard rate of the equipment, and introduce a reliability function model for the case of time-dependent, internal covariates (which is the case of our interest in this article). Furthermore, they consider the case of a NHMP, allowing for the transition rates of the condition process to change in different periods within the life of the item (e.g. early life, normal-life, wear-out). We will use their results for the calculation of the reliability function.

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