A discrete event simulation design for block-based maintenance planning under random machine usage

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A discrete event simulation design for block-based maintenance planning under random machine usage

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ABSTRACT: Existing research on block-based preventive maintenance planning generally assumes that machines are either used continuously, or that times until failure do not depend on the actual usage of machines. In practice, however, it is often more realistic to assume that machines are not used continuously and that they only deteriorate when they are used. In this paper, we present a discrete event simulation design for optimizing block-based preventive maintenance under random machine usage. Furthermore, we will deliver some preliminary results that indicate that the optimal preventive maintenance interval not only depends on the utilization rate of the machine, but also on the usage pattern.

1 INTRODUCTION

Due to an ongoing automation of production processes and a very competitive marketplace, effectively scheduled preventive maintenance activities become more and more important. Two types of preventive maintenance policies can be distinguished; condition-based maintenance and time-based maintenance (Ahmad and Kamaruddin 2012).

Condition-based maintenance has the advantage that it leads to more effectively planned maintenance actions, because the condition of machines is taken into account. However, condition monitoring is not always technically feasible and the benefits may not outweigh the costs of implementing condition-based maintenance (e.g. monitoring equipment and software to analyze deterioration data). Therefore, many preventive maintenance actions in practice are still scheduled based on time. In this paper we also consider time-based preventive maintenance.

A further distinction can be made between age-based maintenance and block-based maintenance (Barlow and Hunter 1960). Under the age-based maintenance strategy, preventive maintenance is performed when the unit reaches a specified age T. The age is set back to zero at failure. The block-based maintenance strategy performs preventive maintenance at fixed times T, $2T$, $3T$, $\ldots$. This schedule is not updated when a failure occurs. The disadvantage of block-based maintenance is that preventive maintenance is sometimes performed shortly after a failure. However, it has the advantage that it allows for easier planning as it is exactly known in advance when preventive maintenance will be performed. Furthermore, when multi-unit systems are considered, it allows for clustering preventive maintenance actions by choosing the same maintenance interval for each machine or component. In this paper, block-based maintenance for single-unit systems is considered. Other recent studies on block-based maintenance for single-unit systems include Zhao et al. 2015, Zhang et al. 2014, Khojandi et al. 2014, and Borrero and Akhavan-Tabatabaei 2013.

Existing studies on block-based maintenance optimization generally assume that machines are either used continuously, or that the times until failure do not depend on the actual usage of the machines. Recent examples of such studies are Coria et al. 2015, Godoy et al. 2014, Khojandi et al. 2014, and Park and Pham 2012. In many practical situations, however, these assumptions are doubtful. Machines are often not used continuously and it is often not known in advance when a machine will be used. Furthermore, it is reasonable to assume that machines only deteriorate and are only subject to failure when they are in use. This has to be taken into account when determining a block-based maintenance strategy.

The current paper presents a discrete event simulation design to analyze and optimize block-based maintenance for a single machine under random usage. Furthermore, preliminary results will be presented that indicate how the optimal block-based maintenance strategy is affected by the usage pattern of the machine. It turns out that not only the fraction of time that the unit is used is relevant, but also the switching frequency.

The remainder of this paper is organized as follows. In Section 2, we describe the problem formulation. In Section 3, we present the simulation design. Section 4 is devoted to preliminary results. Section 5 ends the paper with some concluding remarks.

2 PROBLEM FORMULATION

We consider block-based preventive maintenance for a single machine under random usage. The machine is alternately turned on and off. The durations that the unit is turned on have exponentially distributed lengths with parameter α_{on}, the durations that the unit is turned off have exponentially distributed lengths with parameter α_{off}. All durations are independent of each other. As a consequence, both the likelihood that the machine will be turned on when its off and the likelihood that it will be turned off when it is on are constant over time.

The lifetime of the machine is assumed to follow a Weibull distribution. This is the most commonly used distribution to model times until failure and provides a good description for many types of lifetimes (Rinne 2008, Lawless 2002). The Weibull distribution has two parameters, a shape parameter k and a scale parameter λ. Only shape parameters $k > 1$ correspond to an increasing failure rate, implying that preventive maintenance can be beneficial. We will therefore not consider cases with $k \leq 1$. Recent studies that adopt a Weibull lifetime distribution include Xia et al. 2015, Zhou et al. 2015, and Xu and Cao 2015.

If the unit fails, a corrective maintenance action will be carried out. Furthermore, according to the block-based preventive maintenance strategy, preventive maintenance will be performed at fixed times T, $2T$, $3T$, ... The preventive maintenance interval T is the only decision variable of the problem. Both corrective and preventive maintenance are assumed to make the unit as-good-as-new. Furthermore, preventive maintenance is expected to be less expensive than corrective maintenance. These assumptions are often made, see for example De Jonge et al. 2015, Jiang and Jardine 2007, Sheu and Zhang 2013, and Zitrou et al. 2013. The cost of a corrective maintenance action is normalized to 1, and the cost of a preventive maintenance action is denoted by $c < 1$. Both types of maintenance actions are assumed to require a negligible amount of time. We are interested in the maintenance interval T that minimizes the long-run cost rate.

Because we believe that it is not possible to derive analytical results on the distribution of the time the machine is turned on between two consequetive maintenance actions, we propose to use discrete event simulations to evaluate the block-based maintenance policy. Simulation is a commonly used method in the area of maintenance optimization, see for example the recent studies of Coolen and Coolen-Maturi 2015, Yin et al. 2015, and Zhong and Jin 2014. By using a sufficiently large amount of iterations, the results of such simulations become virtually equal to the exact results. A description of the simulation design is described in the next section.

3 SIMULATION DESIGN

In this section we present a discrete event simulation design that can be used to analyze the performance of the block-based maintenance strategy for a specified value of the maintenance interval T, and specified values of the parameters of the problem. These parameters are the length of the time horizon of the simulation S, the parameters α_{on} and α_{off} of the exponential durations that the machine is respectively turned on or off, the parameters λ and k of the Weibull lifetime distribution, and the relative cost c of performing preventive maintenance.

By executing the simulation for various values of the maintenance interval T, and by comparing the resulting long-run cost rates, the optimal maintenance interval T_{opt} can be determined. The selected time horizon is sufficiently long if a smooth graph of the long-run cost rate as a function of the maintenance interval T is obtained.

We will first state the simulation algorithm, after which a detailed explanation follows.

Simulation script

Initialization
$n = \text{ceil}(1.5 \times S/(1/\alpha_{on} + 1/\alpha_{off}))$
$dur_{on}[i] = \text{ExpRand}(\alpha_{on})$ for $i = 1, \ldots, n$
$dur_{off}[i] = \text{ExpRand}(\alpha_{off})$ for $i = 1, \ldots, n$

For $i = 1, 2, \ldots, n$:
  If $i = 1$ then
    $t_{switch}[1] = 0$
    $t_{switch}[2] = dur_{on}[1]$
  else
    $t_{switch}[2i-1] = t_{switch}[2i-2] + dur_{off}[i-1]$
    $t_{switch}[2i] = t_{switch}[2i-1] + dur_{on}[i]$

  $period_{type}[2i-1] = 1$
  $period_{type}[2i] = 0$

$period_{cum\_on}[1] = 0$
$period_{cum\_on}[2] = dur_{on}[1]$

For $i = 2, 3, \ldots, n$:
  $period_{cum\_on}[2i-1] = period_{cum\_on}[2i-2]$
  $period_{cum\_on}[2i] = period_{cum\_on}[2i-1]$
    $+dur_{on}[i]$

t = 0
t_pm = T
totalcost = 0

Actual simulation
While $t < S$:

$period_{cur} = \max\{i : t_{switch}[i] \leq t\}$
$TotalTimeOn = period_{cum\_on}[period_{cur}]$
$\quad +period_{type}[period_{cur}]$
$\quad\quad \times(t - t_{switch}[period_{cur}])$

$X =$ WeibullRand(k,λ)
$TotalTimeOnFailure = TotalTimeOn + X$
$period_{fail} = \max\{i : period_{cum\_on}[i]$
$\quad <$ TotalTimeOnFailure$\}$
$t_{fail} = t_{switch}[period_{fail}]$
$\quad +(TotalTimeOnFailure$
$\quad\quad -period_{cum\_on}[period_{fail}])$

If $t_{fail} < t_{pm}$ then
$\quad totalcost = totalcost + 1$
$\quad t = t_{fail}$
else
$\quad totalcost = totalcost + c$
$\quad t = t_{pm}$
$\quad t_{pm} = t_{pm} + T$

$mcut = totalcost/S$

Two sets of events have to be simulated; the switching times of the machine, i.e. the times at which the machine will be turned on and off, and the times at which preventive maintenance and failure occurs. Because the switching times of the machine do not depend on the preventive maintenance actions and failures of the machine, they will be generated during the initialization phase of the simulation. The total duration of a period that the machine is on and a period that the machine is off has length $1/\alpha_{on} + 1/\alpha_{off}$ on average, implying that $S/(1/\alpha_{on} + 1/\alpha_{off})$ of such periods are on average required for a simulation over a time horizon with length S. To make sure that the switching process has been generated for the entire time horizon, this number is multiplied by 1.5. It is assumed that the machine is turned on and is as-good-as-new at time 0. The effect of these assumptions are negligible of the entire simulation horizon with length S.

First, n random exponential durations with parameter α_{on} and n random exponential durations with parameter α_{off} are generated to model the respective times that the machine is on and off. Based on these durations, the vector t_{switch} is determined with switching times of the machine. For each period i, the ith element of the vector $period_{type}$ has value 1 if the machine is on during this period, and has value 0 if it is off. The vector $period_{cum\_on}$ indicates the total time that the machine has been turned on at the start of each period.

At the end of the initialization phase, the current time t is set to 0, the time t_{pm} of the next preventive maintenance action is set to T, and the total costs are set to 0. Thereafter, the actual simulation of the occurence of failures and preventive maintenance actions starts until the end of the time horizon with length S is reached.

Each iteration starts with determining the index $period_{cur}$ of the current period, and, based on that, the total time $TotalTimeOn$ the machine has been on since time 0. The latter equals the total time the machine has been on at the start of the current period, increased by the amount of time the current period is running in case the machine is currently turned on.

Thereafter, a random time until failure X from the Weibull lifetime distribution is drawn, and the total time $TotalTimeOnFailure$ the machine has been turned on at the moment of failure is determined (would this failure occur). Based on this, the index $period_{fail}$ of the period at which failure occurs is determined, which can be used to determine the time t_{fail} at which the machine fails.

If this time t_{fail} comes earlier than the time t_{pm} of the next preventive maintenance action, failure indeed occurs at time t_{fail} and the failure cost of 1 will be incurred. In this case, the current time t will be set to t_{fail}, and the time t_{pm} of the next preventive maintenance action is not affected. If, on the other hand, $t_{pm} < t_{fail}$, the failure will be prevented, and the lower cost c of preventive maintenance will be incurred. The current time t is then set to t_{pm}, and the time of the next preventive maintenance action is increased by T. Note that, in both cases, we start again with a machine that is as-good-as-new at the new current time t. These iterations are continued until the end of the simulation horizon is reached. Finally, the long-run cost rate is approximated as the total costs incurred divided by the length S of the simulation horizon.

4 PRELIMINARY RESULTS

In this section we will present some preliminary results obtained by performing the discrete event simulation described in the previous section. We consider a machine with a Weibull lifetime distribution with shape parameter $k = 5$ and scale parameter $\lambda = 1$. Furthermore, we will assume that the relative cost of preventive maintenance is $c = 0.1$, i.e., that failure is ten times as expensive as preventive maintenance. For all simulations performed in this section, we use a simulation horizon with length $S = 100,000$. This is sufficiently long to guarantee stable results: the obtained long-run cost rates are smooth graphs as functions of the maintenance interval T.

We will first investigate the situation in which the machine is always turned on, which is equivalent to $\alpha_{off} = \infty$. Figure 1 shows the long-run cost rate for this case as a function of the maintenance interval T. It can easily be seen that T should not be choosen too small, because preventive maintenance is then performed too often, and that is should also not be choosen to large, because that results in too many expensive failures. The optimum maintenance interval is approximately $T_{opt} = 0.5$ with a long-run cost rate of approximately 0.26. If the maintenance interval T increases further, failure almost always occurs between preventive maintenance actions, but the timing of the subsequent preventive maintenance action after this failure becomes better, resulting in a slight decrease in costs.

We will now assume that the same machine is only turned on half of the time. First, we will consider a very high switching frequency, i.e., the respective durations that the machine is on or off are very short. We choose parameter values $\alpha_{on} = \alpha_{off} = 100$, implying that all durations have mean length 0.01. As a consequence of this high switching frequency, there is not much variation in the total time the machine is turned on in between two preventive maintenance actions. It easily follows that the optimal maintenance interval is twice as high as the optimal maintenance interval in the case the machine is always turned on. This is confirmed by Figure 2, which shows the long-run cost rate as a function of the maintenance interval T. The optimal maintenance interval T_{opt} is approximately 1, which is indeed twice the optimal maintenance interval of approximately 0.5 under constant machine usage. Furthermore, because time is basically slowed down with factor 2, the long-run cost rate is halved compared with the case in which the machine is always turned on.

The results become less obvious if the swithcing frequency decreases, i.e., if the mean durations that the machine is turned on or off become longer. In such cases, the variation in the total time the machine is turned on in between two preventive maintenance actions is much larger. Doubling the maintenance interval if the usage rate is halved is then no longer optimal. Sometimes, the actual usage rate will be much larger than 0.5 within such an interval, resulting in a high risk of failure; whereas, on other occasions, the usage rate is much lower, and preventive maintenance is performed too early. The first effect turns out to have the largest impact on the optimal maintenance interval. Figure 3 shows the long-run cost rate as a function of the maintenance interval T for the case with $\lambda_{on} = \lambda_{off} = 2$, i.e., the mean time the machine is turned on or off is 0.5 each time. The optimal maintenance interval of approximately 0.7 is obviously higher than the optimal maintenance interval under constant usage because the machine is only used half of the time. However, because the actual usage between preventive maintenance actions is less predictable, preventive maintenance is performed more frequently compared to the situation with frequent switches. This also involves a higher long-run cost rate.

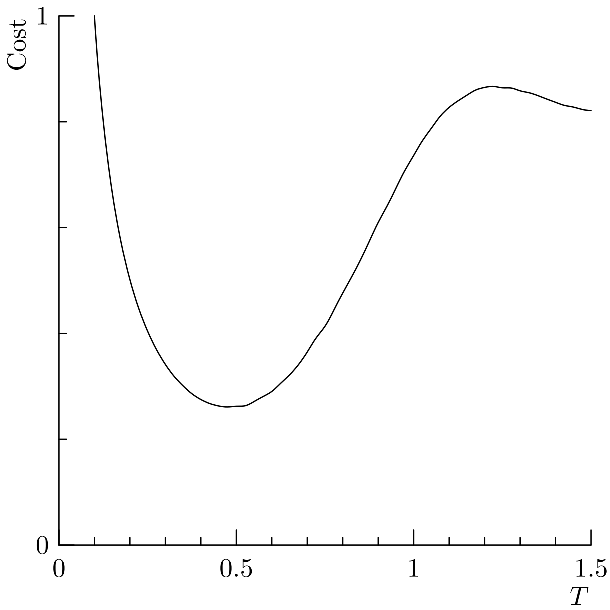

Figure 1. Mean cost per unit of time if the machine is always turned on.

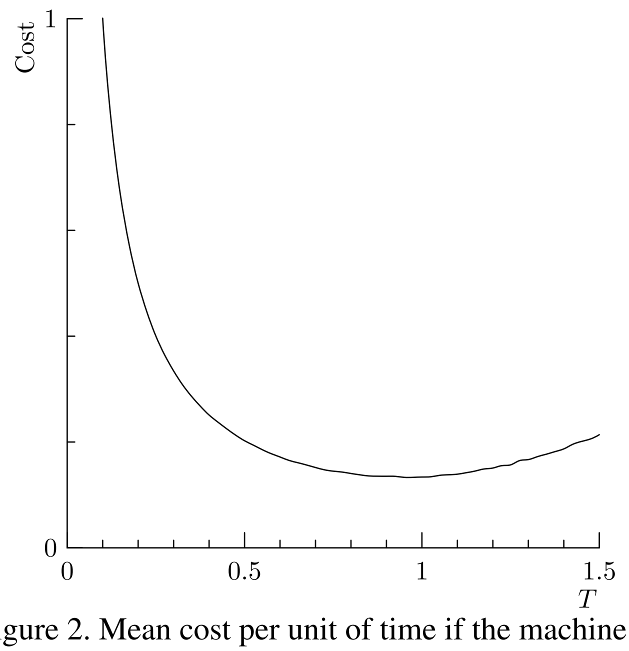

Figure 2. Mean cost per unit of time if the machine is frequently switched and turned on half of the time.

5 CONCLUDING REMARKS

This paper has developed a discrete event simulation design for block-based maintenance optimization for a single machine that is not used continuously. Instead, it is assumed that the usage pattern is random,

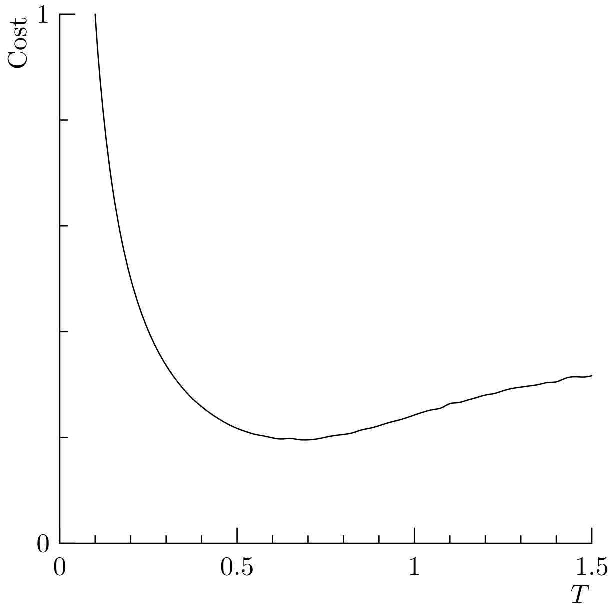

Figure 3. Mean cost per unit of time if the machine is infrequently switched and turned on half of the time.

whereas the block-based maintenance strategy has to be determined in advance.

Preliminary results have been presented based on the implementation and application of the simulation design. It turned out that the optimal block-based maintenance strategy does not only depend on the fraction of time that the machine is turned on, but also on the switching frequency. A more extensive analysis on the effects of the various characteristics of the setting on the optimal block-based maintenance strategy is required and will be the topic of future research.

Furthermore, future research could be devoted to multi-unit systems for which a common block-based maintenance strategy has to be determined. If all machines are identical and have the same distributions for the times they are switched on and off, the optimal block-based maintenance strategy for a single machine is also optimal for the entire system. However, if the machines are different or have a different usage patterns, the optimal block-based maintenance strategy at the system level is not straightforward. In such cases, simulations are required that include the multiple machines. For such studies, the simulation design presented in this paper should be extended.

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