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Data Driven Condition Based Maintenance Optimization

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Most studies on condition-based maintenance optimization consider the deterioration process of an industrial system to be known (De Jonge and Scarf, 2020). In this study, we make the often more realistic assumption of an unknown deterioration process and develop approaches for determining when to carry out maintenance based on limited condition data. Contrary to many existing studies that consider a certain parametric form for the deterioration process with uncertainty its parameters, e.g. in (Elwany et al., 2011; Flage et al., 2012; Si et al., 2018), we also assume that the parametric form of the deterioration process is unknown. Our approaches are therefore fully data-driven.

We consider a single-unit system whose deterioration level is observed periodically and refer to an interval between successive observations as a period. The deterioration process is denoted by $X(t)$ and starts from the as-good-as-new state with deterioration level $X(0) = 0$. We assume that the deterioration process and the failure behavior are unknown. We only assume that the deterioration process is non-decreasing and that it has the Markov property, i.e., the future only depends on the current deterioration level.

As long as the system has not failed, preventive maintenance can be carried out at cost c_{pm}. Upon failure of the system, corrective maintenance should be carried out immediately at cost c_{cm} with $c_{\text{cm}} > c_{\text{pm}}$. Both maintenance types bring the system back to the as-good-as-new state, require negligible time, and do not need to be planned in advance. We consider a threshold policy, in which preventive maintenance is carried out if the observed deterioration level of the system exceeds some threshold M.

We assume that there is data of K runs-to-failure available. We refer to a run-to-failure as one cycle from the system being as-good-as-new until its failure. If failure occurs, no deterioration level is observed, but the system is just identified as failed. Let us denote the total number of observations of all runs-to-failure together by n. We sort all observed deterioration levels in ascending order and let them be denoted by $x_1, x_2, \ldots, x_n$. Furthermore, we let the binary variables $y_1, y_2, \ldots, y_n$ indicate whether a deterioration observation has resulted in a failure in the next time step (1) or not (0).

As an example, let us assume that we have data for $K = 2$ runs-to-failure, namely '0 - 5.2 - 6.4 - Failure' and '0 - 4.6 - 6.8 - 7.2 - Failure'. This means that we have $n = 7$ observed deterioration levels, namely $x_1 = x_2 = 0$, $x_3 = 4.6$, $x_4 = 5.2$, $x_5 = 6.4$, $x_6 = 6.8$, $x_7 = 7.2$, and that we have failure indicators $y_1 = y_2 = y_3 = y_4 = y_6 = 0$ and $y_5 = y_7 = 1$.

The value y_i can be considered as the empirical estimate for the probability that the observed deterioration level x_i results in failure in the next time period. However, it is not reasonable that these probabilities are all either 0 or 1. Furthermore, it can be that $y_i = 1$, whereas $y_{i+1} = 0$, i.e., the sequence of failure probabilities does not need to be increasing in the deterioration level. Cai et al. (2023) have developed an approach for determining the sequence of estimated failure probabilities for the observed deterioration levels that is most likely given the data, under the natural restriction that this sequence should be non-decreasing in the deterioration level. Based on the analysis of De Jonge (2019, 2021) these estimated failure probabilities can be translated into a deterioration threshold M for carrying out preventive maintenance.

A drawback of this approach is that we only obtain estimated failure probabilities for deterioration levels that have been observed in the past. Furthermore, also only these deterioration levels can be selected as the preventive maintenance threshold M. Finally, the estimated failure probability is not gradually increasing in the deterioration level, but makes jumps from observed deterioration level to observed deterioration level.

Our aim is to improve the approach for data-driven condition-based maintenance optimization of Cai et al. (2023). We use logistic regression to obtain an estimated failure probability that is gradually increasing in the deterioration level. Furthermore, we extend the approach in such a way that any deterioration level can be selected as the preventive maintenance threshold M, rather than only deterioration levels that have been observed in the past. A numerical study shows that these refinements on average lead to better condition-based maintenance policies.

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