Maintenance Optimization based on Mathematical Modeling

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Chapter 6

Summary and conclusions

Due to an increasingly competitive marketplace and an ongoing shift from labor intensive to technology intensive industries, effectively scheduled maintenance activities become more and more important. In this thesis, we consider the effect of uncertainty in the lifetime distribution on the optimal age-based maintenance strategy, and point out the importance of taking this uncertainty into account under various circumstances. We also investigate the potential benefits of initially postponing preventive maintenance in order to reduce the uncertainty in the lifetime distribution faster. This reduced uncertainty can leads to better maintenance decisions during the second phase of the lifespan of equipment. Furthermore, we review studies that compare condition-based maintenance with time-based maintenance, and perform an extensive numerical investigation on the relative benefit of condition-based maintenance. In this analysis, we take various practical factors that influence this benefit into account. Finally, we consider systems with multiple critical units and study the benefits that can be obtained by clustering maintenance actions based on condition information of the units.

Existing studies on time-based maintenance optimization typically assume that the lifetime distribution of equipment is known with certainty. In practice, however, there is often substantial uncertainty in the lifetime distribution. In Chapter 2 of this thesis, we consider the optimal age-based maintenance strategy under uncertainty in the parameters of the lifetime distribution. We start with an algebraic analysis on the effect of uniformly distributed uncertainty in the right-end point of a uniform lifetime distribution. Thereafter, we numerically evaluate more realistic settings with
a Weibull lifetime distribution with a known shape parameter and with uncertainty in its scale parameter, and show that the results of the uniformly distributed case carry over.

Both for the uniform and for the Weibull lifetime distribution, and for various preventive maintenance costs relative to the cost of corrective maintenance, the effect of parameter uncertainty on the optimal maintenance age reveals a similar pattern. The optimal maintenance age first decreases as the level of parameter uncertainty increases. Thus, some uncertainty leads to a higher maintenance frequency. However, when the level of uncertainty exceeds a certain threshold, the optimal maintenance age starts to increase in the level of uncertainty. This effect is explained by the fact that the increased likelihood of a large remaining lifetime starts to outweigh the risk of an imminent failure.

Taking the uncertainty in the lifetime distribution into account is most important when the additional costs that result from ignoring the uncertainty is highest. This is the case when the cost of preventive maintenance is relatively low compared to that of failures, and for lifetime distributions with a relatively low variance. In the first case, when the uncertainty is neglected, preventive maintenance is often performed too late, resulting in too many costly failures. When the lifetime distribution itself has a low variance, the relative effect of the additional variance in the times until failure caused by the parameter uncertainty is much larger. Taking the parameter uncertainty into account is therefore most important when the variance in the lifetime distribution, given the value of that parameter, is smallest.

The maintenance policies considered in Chapter 2 are static, long-run policies. They are not updated when more information becomes available, and they ignore that the choice of a maintenance age influences the information that becomes available. In Chapter 3 we do update the uncertainty in the lifetime distribution when more data becomes available. Furthermore, we acknowledge that event durations resulting from failures and long censored durations resulting from choosing a high preventive maintenance age are more informative than short censored durations. Thus, the uncertainty in the lifetime distribution is reduced much faster if preventive maintenance actions are initially postponed. Although this will increase the expected costs during the first phase of the lifespan of a unit, the reduced uncertainty also enables more effectively scheduled maintenance actions during the second phase of the lifespan.
In Chapter 3 we investigate the potential cost benefits of initially postponing preventive maintenance actions, and perform a numerical study to identify under what circumstances these benefits are largest. We again consider Weibull lifetime distributions with a known shape parameter and with uncertainty in the scale parameter. Because there are no existing studies that recognize that the choice of a maintenance policy influences the information that becomes available, we consider a simple setting with two unit types, respectively referred to as weak and strong units. A discrete distribution with two mass points is thus used to model the uncertainty in the scale parameter, this distribution is updated in a Bayesian manner. We use a threshold policy that postpones preventive maintenance as long as the estimated probability that the unit is strong exceeds a certain threshold; and we compare its performance with a so-called myopic policy. This policy also updates the maintenance age over time, but it only uses the information that is currently available.

It turns out that substantial cost savings can be obtained by initially postponing preventive maintenance actions. The circumstances under which this is the case show similarities with the circumstances obtained in Chapter 2 under which taking the uncertainty into account is important when making static maintenance decisions. The threshold policy offers substantial cost savings over the myopic policy when the cost of preventive maintenance is relatively low compared to that of failures, and when the variances of the lifetime distributions of the separate unit types are small. In these cases, the myopic policy selects a conservative maintenance age that is likely to prevent failures arising from both unit types. As a consequence, almost no information about the true unit type becomes available. Meanwhile, by postponing preventive maintenance, it is quite likely that we are able to identify whether the unit is weak or strong. Finally, the lifespan of the unit should be sufficiently long to ensure that the long-run benefits outweigh the initial additional costs.

In Chapter 4 we broaden our perspective and compare the performance of condition-based maintenance with that of time-based maintenance. We start with an extensive literature review of studies that compare these two maintenance policies. Furthermore, we recognize that the relative benefit of condition-based maintenance depends on the behavior of the deterioration process, the severity of failures, the required setup time, the accuracy of condition measurements, and the amount of randomness in the deterioration level at which failure occurs. In the second part of our review, we consider studies that take these practical factors into account.
Our literature review reveals that, although a lot of research has been done both on condition-based and on time-based maintenance, few studies compare them. Furthermore, existing comparative studies confine themselves to a few examples. Insights on how the various characteristics influence the performance of condition-based and time-based maintenance are lacking. Therefore, we continue Chapter 4 with a simulation study to derive insights on the effects of the various characteristics on the relative benefit of condition-based maintenance. Based on a simple system with a single unit we start with the effects of the behavior of the deterioration process and the severity of failures. Thereafter, we extend our model and analyze the effects of a required setup time, imperfect condition monitoring, and randomness in the deterioration level at which failure occurs.

The behavior of the deterioration process turns out to be more important for the relative cost benefit of condition-based maintenance than the severity of failures. The cost difference is substantial for a small level of variation in the deterioration process, but diminishes quite rapidly if this variation increases. The preventive maintenance cost as a fraction of the corrective maintenance cost is less important for the magnitude of the relative cost saving of condition-based maintenance; the cost benefit is substantial for a wide range of preventive maintenance costs. Only if preventive maintenance is very cheap or if it is almost as expensive as corrective maintenance, the potential cost benefit is limited.

From the practical factors that we take into account in our extended model, a required planning time and imperfect condition information do not influence the lifetime distribution and therefore only influence the performance of condition-based maintenance. Uncertainty in the failure level does affect the lifetime distribution. Furthermore, because it makes the condition information less informative, it has a negative effect on the performance of both condition-based and time-based maintenance. However, because the effect on condition-based maintenance is stronger, uncertainty in the failure level also worsens the relative performance of condition-based maintenance. The cost benefit of condition-based maintenance turns out to decrease linearly in the planning time, and is negated completely when the planning time equals the maintenance age of the optimal time-based maintenance policy. The effect of a planning time is thus substantial if it is large compared to the optimal maintenance age.

Both imperfect condition information and uncertainty in the failure level only
have a minor effect on the relative cost benefit of condition-based maintenance if the respective uncertainties are small. The marginal effects become stronger and significantly impact the cost benefit of condition-based maintenance if the uncertainties increase further. A notable difference between these two effects is that the cost benefit gradually decreases but continues to be positive if the uncertainty in the failure level increases; whereas a large level of uncertainty in the obtained deterioration information might make condition-based maintenance perform worse than time-based maintenance.

In Chapter 5 of this thesis we switch from single-unit to multi-unit systems. Whereas existing studies on condition-based maintenance for multi-unit systems focus on rather complex models and policies, we consider simple settings and policies that are easy to implement. Our approach is to consider a system that consists of a number of identical critical units with economic dependence. Each unit contains a sensor that provides either one signal (alarm) or two signals (alert, alarm). In our systems, maintenance should be performed within a period with constant length after an alarm signal. Because of the criticality of the units, the length of this period is chosen such that maintenance is always performed before failure occurs. This property also highlights our focus on the benefits of clustering maintenance actions instead of optimizing preventive maintenance frequencies.

Two clustering policies are proposed based on the occurrence of alert and alarm signals. The first policy maintains all units that have given an alarm signal if some unit must be maintained; whereas the second policy also maintains units that have only given an alert signal. The latter policy can obviously only be applied to the system with two signals. We compare the performance of these clustering policies with the policy that maintains all units separately when required, i.e., that does not cluster any maintenance actions.

For systems with constant alert and alarm rates, i.e., exponential times until signals, we derive analytical results on the cost savings that result from using clustering and on the optimal degree of clustering, i.e., after an alarm or after an alert. It turns out that clustering offers considerable benefits for a wide range of realistic settings and of about 28% for a real-life case of equipment maintenance at the Groningen gas field in the north of the Netherlands. Furthermore, if the fixed maintenance cost is above a certain threshold, then the higher degree of clustering (after an alert) is preferred. A particular insightful result is that this threshold increases with the number
of units. This is explained by the fact that more units imply more clustering opportunities for highly deteriorated units, and so there is less additional benefit of opportunistically maintaining somewhat deteriorated units as well, relative to the reduction in lifespan that results.

Discussion, limitations and future research directions

Our study on age-based maintenance optimization in Chapter 2 has shown that uncertainty in the lifetime distribution of a unit often implies a higher maintenance frequency. As a consequence, hardly any failures occur and the uncertainty is, to a large extent, retained. The solution to this dilemma that we consider in Chapter 3 is to initially postpone preventive maintenance actions until the level of uncertainty is reduced to a specified level. Because there might be cases where this is too expensive or where it is undesirable to induce failures, future research could be devoted to performing (accelerated life) tests in controlled settings to reduce the uncertainty. Mathematical modeling could facilitate the decision making in such settings.

Because the amount of existing research on time-based maintenance optimization under uncertainty in the lifetime distribution is limited, in Chapters 2 and 3 we consider quite simple settings with a Weibull lifetime distribution with uncertainty only in the scale parameter. In addition, in Chapter 3 we use a distribution with only two mass points to model this uncertainty. Possible extensions are (i) to consider continuous uncertainty in the scale parameter in Chapter 3, (ii) to consider uncertainty in both parameters of the Weibull distribution, and (iii) to assume that the distribution family itself is also not known with certainty. Furthermore, in Chapter 3, we use a simple threshold policy to make decisions on postponing preventive maintenance actions. Improvements of this policy offer interesting opportunities for future research. Finally, we consider the age-based maintenance policy, which is a specific time-based maintenance policy. The other well-known time-based maintenance policy is block-based maintenance. The effect of lifetime distribution uncertainty on this policy is also of interest.

In Chapter 4 we study the benefits of condition-based maintenance over time-based maintenance, and in Chapter 5 we consider cost-effective condition-based maintenance in multi-unit settings with economic dependence between the units. Although we assume the model parameters to be known in these two chapters, we
note that in practice model uncertainties are also likely to emerge in condition-based maintenance settings. This offers interesting future research opportunities as well.

We consider gradual deterioration according to a continuous stochastic process in Chapter 4. In practice, such a process often has to be estimated based on a limited amount of data, implying that there is generally substantial uncertainty in the estimated model parameters. Furthermore, we take randomness in the deterioration level at which failure occurs into account, but we do assume that we know the stochastic distribution of this random failure level. This assumption is often also doubtful, particularly because the preventive maintenance policies that have been applied in the past are often quite conservative. As a result, only limited failure data is commonly available.

It is of interest to investigate how these uncertainties influence condition-based maintenance decisions. A suitable approach could be to minimize the expected costs under the uncertainty, as in Chapter 2. However, related to the exploration-exploitation dilemma encountered in Chapter 3, one could also opt to reduce the uncertainty at a higher cost in the first phase of the lifespan of equipment, and to exploit this reduced uncertainty during the second phase. When, for instance, the behavior of the deterioration process has to be determined based on inspections, one might choose to initially perform more frequent inspections. If, on the other hand, the distribution of the deterioration level at which failure occurs is not known with certainty, it might be beneficial to elicit some failures to reduce the uncertainty.

In addition to adding uncertainty, other interesting research avenues on the benefit of condition-based maintenance over time-based maintenance exist. Future studies could for instance consider (i) a wider range of deterioration processes, (ii) stochasticity in the planning time that is required to perform preventive maintenance, and (iii) alternative modeling choices regarding the measurement errors and the randomness in the failure level. Studying these extensions is useful in determining the extent to which our results are generalizable. Furthermore, we have considered the effects of various single factors on the benefit of condition-based maintenance. The manner in which these factors interact with each other also constitutes interesting research opportunities.

The simple multi-unit settings and policies that we consider in Chapter 5 also allow for several extensions. The mean times until alert and alarm signals in the real-life case in Chapter 5 are for instance based on estimates from reliability en-
engineers. The extent to which the performance of the policies deviate when the real averages differ from the point estimates obtained from the reliability engineers is of interest. Furthermore, systems with non-identical units can be analyzed, the deterioration process can be modeled in more detail by using more than two deterioration states/signals, imperfect signaling (i.e., false positives and false negatives) could be added to the model, the time between an alarm signal and maintenance can be modeled as a decision variable, and the deterioration levels that trigger a signal and the type of clustering policy used could be optimized simultaneously.

To conclude, our studies reveal several interesting insights on maintenance optimization, but also make clear that ample interesting research opportunities exist in this area. A final note is that we have studied maintenance scheduling in isolation, whereas in practice it often interacts with processes as production planning, spare parts ordering, and repairmen routing. Joint optimization of maintenance scheduling and these related processes also constitute interesting future research avenues.