control
MANUAL
Optimal maintenance decisions for asset managers

BY ANDREW K.S. JARDINE AND NEIL MONTGOMERY
Most of us are familiar with the effort involved in purchasing a new car. You evaluated your vehicle needs and how much you can afford. But once you’ve made the purchase you have only made the first of many decisions about the life of that vehicle. How long should you keep it? Should you get it fixed only when there is a problem or should you take it to a mechanic for preventive maintenance? If the latter, how often should you get it serviced and what should be serviced? Is the manufacturer’s warranty sufficient to pay for these repairs? Will the manufacturer even exist for the duration of the warranty? Should you keep any spare parts for the car in case you need to perform emergency repairs yourself?

These are all familiar problems related to automobile ownership, and they are many of the same decisions that an engineering asset manager has to make about the myriad physical assets that make up any production process. In fact, the maintenance decisions made by the asset manager will have a substantial impact on the overall effectiveness and profitability of the entire organization. There are two key factors for the asset manager to consider. When making an optimal maintenance decision, what optimization criteria should be used? How can the available data collected on an asset be used in the most effective manner? These are the kinds of questions considered at the Center for Maintenance Optimization and Reliability Engineering (C-MORE) at the University of Toronto.

Optimal component replacement problem
To start with a basic example, consider the problem of replacing (or repairing) a component, such as a bearing on a shaker machine, in an optimal manner. The first question for the asset manager is: Optimal according to what criteria? Two possible answers include minimizing the cost per unit time or minimizing the downtime caused by bearing failure. Once the asset manager has selected the optimization criteria, the next two questions that must be answered are related to the data that has been collected related to the bearing: Is the impact of a failure more serious than the impact of a preventive replacement? Does the hazard of component failure increase with age?

If the answer to either of these two questions is no, the optimal maintenance strategy is to replace the bearing only on failure. If a failed bearing incurs no more cost or no more downtime than a preventive replacement, then the preventive replacement achieves nothing but to reduce the useful life of the bearing. If the hazard of component failure is constant (so that the conditional probability of failure does not depend on the age of the component), then preventively replacing the component will not affect the time to failure; replacement will be a waste of time and money.

The asset manager should use principled techniques to answer these two questions. Financial and operational data should be used to determine the total costs (or downtimes) of preventive versus failure replacement, while a statistical analysis of component histories should be used to estimate the probability distribution of the failure times. The key decision is to determine if the failures follow an exponential distribution in which failure times cannot be predicted and there would be no evidence that preventive maintenance is worthwhile. This decision can be made by performing a Weibull analysis of the failure time data, and if the shape parameter is greater than one, the optimal replacement time can be computed using appropriate software to minimize cost or maximize availability.

The basic concepts of time-based maintenance are well-understood, but the unwary asset manager is susceptible to a few common traps. The first trap is to mishandle historical data in which a component did not fail. Consider a simple example in which the bearing lifetimes are three, six and nine months. The best estimate of the average life would be six months. But suppose the bearing that was removed from service at six months had not failed; it was removed from service either preventively or for some other reason so that its lifetime was censored. The average bearing life is clearly greater than six months. Good software will allow the user to indicate which component histories end in failure and which were censored.

The second trap concerns repairable components, in which case the same component may have multiple histories. Suppose the times between failures of three components are as follows (recorded in the order in which they occurred):

Component A: 12, 25, 9, 13, 19
Component B: 9, 12, 13, 19, 25
Component C: 25, 19, 13, 12, 9

All three components have exactly the same times between failures, but in a different order. A Weibull analysis would give identical results in each case, but clearly the three components are behaving in substantially different ways. The lifetimes of Component B have an increasing trend, while those of Component C have a decreasing trend. The usual cost or downtime minimization models are based on having no such
trends in the data. A test such as a Laplace trend test that tests reliability growth must be performed on such data before proceeding to further analysis.

**Optimal critical spare part provisioning problem**

Once the asset manager has determined basic maintenance policies for some components, which may include some mix of time- and failure-based policies, the question arises of how many critical spare parts should be kept in stock to support these maintenance activities. The asset manager will want to stock the optimal number of spare parts. We have identified four criteria for this optimal state. Given the number of units in service, the number of spares in stock, the rate of demand for spare parts, and in the case of repairable spares, the repair rate, one can calculate:

**Instant reliability.** The probability that a spare will be available at a particular moment when it is needed. This probability is of interest to the maintenance technician, who wants to be able to complete a repair task using a spare part at the particular time it is needed.

**Interval reliability.** The probability that, over a specified planning horizon, there will never be a lack of a spare part when it is needed. This is a more stringent criterion than instant reliability, and would be of interest to the person managing the stock of spare parts and would not want to be caught out of spares at any time during the planning horizon.

**Cost.** The cost per unit time accounting for part purchase cost, depreciation, holding cost and the total cost of not having a spare part when it is needed. This quantity would be of interest to the finance department.

**Process availability.** The uptime of the production process support by the stock of spares, which would be of particular interest to the production or operations department.

Consider the example of a conveyor system in an oil sands processing facility operated by 62 repairable electric motors. The motors are highly reliable with a mean time to failure (MTTF) of eight years. It takes an average of 80 days to repair a failed motor. Where did these numbers come from? They came from historical data that can be subjected to a Weibull...
analysis just like in the previous section.

How many spare motors should the asset manager seek to stock? The answer depends on which of the four criteria is considered to be the most important. The asset manager should consider the point of view of the maintenance technician, spares manager, finance department and operations department. We will consider each case separately. The solutions were computed to be:

**Instant reliability.** If the asset manager wants to have a spare in stock when needed at any instant 95 percent of the time, the required number of spare motors is four.

**Interval reliability.** If the asset manager wants to never be out of stock when a spare is needed over the course of a five-year planning period, the required number of spare motors is seven.

**Cost.** The downtime cost is $1,000/day and the holding cost is $4.11/day. To minimize the cost per unit time, the asset manager should have six spares in stock.

**Process availability.** The asset manager might wish to stock the number of spares that will provide at least 99 percent uptime for the conveyor system. In this case, only two spare parts are needed.

The prudent asset manager might be concerned about the accuracy of these results in light of uncertainty of any of the inputs. A simple sensitivity analysis can be conducted by varying the inputs to see the impact on the answer. For example, seven spare parts were required for an interval reliability of 95 percent over five years. If the MTTF were in fact 6.5 years, the number of spares required only goes up to eight. If the MTTF were in fact 9.5 years, the answer is still seven spare parts required. We find the solution does tend to be quite robust against errors in the inputs. Good decisions based on solid techniques are therefore still possible even if the available data are not perfect.

**Optimizing condition-based maintenance decisions**

Recall from the section on optimizing component replacement decisions that it is not worthwhile to perform time- or age-based replacement if the hazard of component failure is not increasing. In cases where the hazard is constant, the age of the component provides no useful information at all. Even if the hazard is increasing, making maintenance decisions on highly critical assets using only the age of its components may not be precise enough. In such cases it might be possible to collect additional data on the asset that can provide an assessment of its health and perform maintenance when it appears failure may be imminent. This is the potential of condition-based maintenance (CBM).

Implementations of CBM vary widely in their complexity, with the simplest being a simple plot of a condition-monitoring (CM) variable against time. The asset manager would use this plot, perhaps along with pre-defined warning and action limits and some basic trending methods, to make maintenance decisions. We call this implementation the “control-chart technique.” While simple to implement and easy to understand, the technique suffers from several limitations.

There are often (if not almost always) many condition-monitoring variables. A large number of plots could prove difficult to interpret, and it is not obvious from the plots which variables, perhaps in combination, are the key predictors of failure, especially when there is more than one mode of failure to consider. The plot also does not take into account the possible effect of wear due to age over and above the wear information provided by the variables.

It is not obvious where the warning and action limits should be set. Manufacturer recommendations may not be optimized with respect to the costs of failure and preventive maintenance particular to that asset’s operating environment.

If an optimal maintenance decision is desired, or indeed any calculation related to the probability of failure given the current asset age and health as measured by the CM variables, it is necessary to predict future values of the key variables. It is not clear how this should be done from a simple plot.

There are many ways to overcome these deficiencies. One such methodology has been developed at C-MORE and implemented in a software tool called EXAKT. In a traditional Weibull analysis, the failure data is used to estimate the parameters of the Weibull distribution, giving a model that relates age and hazard of failure. This can be extended to include both a Weibull hazard model and a linear regression-style model for the CM variables. Standard statistical techniques are used to determine which key CM variables affect hazard and also if there is still an effect due to age over and above the information provided by the covariates. This model is called a Weibull proportional hazards model. In addition, the way in which the key variables change over time is estimated. This solves the first and third shortcomings of the control-chart technique.
The action limits are set depending on the ratio between the total cost of failure and the total cost of preventive maintenance supplied by the asset manager. Clearly, as this ratio grows larger and the risk of unplanned failure gets more severe, the asset manager should be more conservative and less tolerant of failure, so the action limit would be set lower and lower.

Consider the example of a set of critical bearings on a fleet of centrifugal pumps in a pulp and paper mill. Maintenance information is kept on these pumps, recording all bearing installations and failure times. In addition, vibration measurements are made on the pumps every month using a handheld device. The vibration data was examined using the classic control chart technique, but there were 56 variables to track and a more scientific approach was desired to address this maintenance problem. The data were given to C-MORE who blended the age, vibration and cost information provided by the reliability engineer to produce an updated control chart. Two key vibration variables were identified along with bearing age as the most significant predictors of failure. The cost of failure was about three times more than the cost of doing a preventive replacement. The new control chart is reproduced in Figure 1.

Notice that the vertical axis is the contribution to hazard of failure of the two key vibration measurements. The horizontal axis is the contribution of bearing age to the hazard of failure. Real data from a bearing history is shown on the chart. The white dots have exceeded the action limit and have moved into the red zone—indicating that preventive replacement is overdue. Maintenance should be performed once measurements enter the red zone in order to minimize the long run average maintenance cost per unit time. We determined that this optimal decision model had the potential to reduce this long run cost by more than 30 percent.

Long-term cost considerations are not the only criterion for determining a maintenance policy. The asset manager may also be interested in the remaining useful life of a piece of equipment given its current age and CM variable information. If a plant shutdown is imminent, it would be of considerable interest to calculate the probability of failure between today and when the shutdown occurs, at which time maintenance can be carried out opportunistically. The software is capable of performing these calculations.
EXAKT was installed on site and used while engineering modifications were made to the pumps to correct the actual problem that was causing so many bearing failures. Good data analysis and good engineering combined to prevent all bearing failures since the software was installed.

We have barely scratched the surface of the kinds of practical asset management problems we encounter at C-MORE stemming from our regular meetings with MORE Consortium industrial members. Optimizing asset management decisions covers the areas of component replacement, including the choice of optimal replacement time and the spare parts provisioning problem addressed above. It also addresses inspection decisions, which include optimizing CBM as well as the problems of optimizing inspection frequencies for a system and failure finding intervals for protective devices. The other main areas that we did not mention are capital equipment replacement decisions, maintenance resources requirements and maintenance shop scheduling.

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