How predictive analytics can optimise asset maintenance

BADRINATH SETLUR explains how to use data to address key strategic objectives.

Collecting and distilling digital information and extracting meaning from it holds great potential to enhance customer satisfaction, reduce total cost of ownership, optimise resources and improve compliance.

Little wonder then that predictive analytics – a process of using statistical and data mining techniques to analyse historic and current data sets, create rules and predictive models, and predict future events – is fast becoming a vital instrument to realise asset life cycle cost reduction and improve the speed and accuracy of decision-making.

Predictive analytics for assets

Assets are seldom standalone. They exist as a system of assets where they feed off each other. Between asset procurement/commissioning and decommissioning/salvage lies the productive life of an asset. Regular upkeep or maintenance is needed to maximise this life. There are two perspectives on how predictive analytics can help optimise asset maintenance:

- **Individual equipment perspective:** Typically, maintenance frequency is defined based on various parameters such as asset age, asset criticality, operating environments, risk of failure and so forth. As a result, more frequent maintenance would mean higher maintenance expenses. Often the risk of failure forces over-maintenance of assets. Over-maintaining can mean replacing lubricants or bearings that still have life left. The ability to predict a failure can help move maintenance activities closer to the real need for maintenance and reduce over-maintenance.
- **Productivity perspective:** As can be imagined, a system of assets, designed and scheduled for maximum productivity, can benefit immensely if a failure of an event requiring maintenance is known in advance. Alternative schedules or plans can be prepared to ensure maintaining productivity levels.

Ironically, in almost all common maintenance scenarios, the ability to predict failures and move maintenance procedures closer to failure exists. It is just that the risk of failure keeps many organisations from taking those steps.

Let us consider a multi-stage centrifugal air compressor. Some of the typical maintenance procedures carried out today on centrifugal equipment include:

- **Oil change:** This involves oil replacement at a fixed schedule because real-time oil quality analysis is not possible.
- **Intercooler cleaning:** This involves intercooler cleaning at a fixed schedule because real-time analysis of coolant and intercooler efficiency is not available, even though inlet and outlet temperatures are measured.
- **Bearing replacement:** This involves bearing replacement at a fixed frequency because no scientific way to determine bearing life left is deployed even though lubrication oil temperature, viscosity and bearing vibrations are measured regularly.
- **Major overhaul:** This involves a major overhaul of the equipment at a fixed frequency, usually more than that of the aforementioned procedures, because the manufacturer has prescribed it, even if all vital parameters look all right.

All this entails avoidable downtimes, unnecessary maintenance expenses, lots of collected yet unutilised data, additional Capex (capital expenditure) for back-up equipment and complexity of operations due to the need to accommodate multiple downtimes, coordinate with downstream and upstream customers, and so on.

That can cost a lot of money; however, the maintenance requirements are real. Operating equipment close to failure thresholds may be riskier than we think. Why then are we talking about predictive analytics? Primarily, predictive analytics can help to determine failure thresholds, identify buffer zones and quantify risks in operating equipment within known buffer zones. That's also how predictive analytics can help optimise equipment maintenance.

Power of predictive analytics

Let us reimagine the same scenario with predictive analytics capability. Predictability does not mean the maintenance software will tell you to replace a certain bearing on a certain piece of equipment in a certain process on a certain date at a certain time.

But it would indicate the probability (for example, there is 89 percent chance) of a bearing failing at a given time. Business rules can be built to instruct a bearing replacement above a certain threshold (for example, when there is a more than 70 percent probability of failure). Evidently, this allows risks one is willing to take to be quantified (for example, 70 percent is the risk threshold).

- **Oil change:** Oil quality over a period of time can be plotted to predict with a degree of confidence what the oil quality (oil viscosity or decomposition) will be at a given time. This can then help to answer the question: is there a significant difference in the quality of oil supplied by different vendors?
- **Intercooler cleaning:** Temperature delta between inlet and outlet for coolant water and air is a good way to measure efficiency. A lower delta would mean less heat taken away and lower efficiency, assuming everything else is intact. This delta over a period of time can be plotted to determine statistically what the value will be at a given point of time and whether or not there is a need for maintenance. This can help figure a trend.
- **Bearing replacement:** Predicting bearing life can be tricky, as identical bearings tend to display different endurance lives. Reliability of bearings has to be predicted based on the installed population of bearings and analysing failure data to identify patterns.
- **Major overhaul:** Something like this will be difficult to predict statistically (or there may not be a need). But if individual components – such as intercoolers and bearings – are working fine, making a judgement or qualitative decision on the need for a major overhaul should be straightforward.

All this can help widen maintenance intervals, push maintenance activities closer to when needed and consequently, optimise asset operations.

It's not difficult or expensive

Does building predictive analytics capability cost lots of time, money and effort? The answer to this big question is an emphatic 'no'. There is always a sweet spot where savings from predictive capabilities (reduction in maintenance expenses, Capex, spares utilisation and so on) outweigh the cost of building those capabilities (software, human resources etc). Once done, the benefits through direct asset-related saving (fewer maintenance dollars, fewer spares, longer life span), and organisational saving (optimal teams, increased operational efficiencies) are immense.

KPIs to monitor assets

KPIs (key performance indicators) are different for different asset types, operating conditions, criticality and so forth. Due consideration needs to be given to the role of statistics and the related process changes and change management, among others, required to build a predictive maintenance culture. Data and statistics will provide quantification, but will need to be applied with business insights to derive benefits (for example, the 70 percent risk quantification mentioned earlier).

Here are a few commonly used KPIs:

- **Reliability given time:** This indicates the probability that a unit will operate successfully at a particular point in time. For example, there is an 88 percent chance that the product will operate successfully after three years of operation.
- **Probability of failure given time:** This indicates the probability that a unit will fail at a particular point in time. This is also known as 'unreliability'. For example, a 12 percent chance that the unit could potentially fail after three years of operation (probability of failure or unreliability) is the same as an 88 percent chance that it will operate successfully (reliability).
- **Mean life:** This indicates the average time that the units in the population are expected to operate before failure. This metric is often referred to as 'mean time to failure' (MTTF) or 'mean time before failure' (MTBF).
- **B(X) life:** This indicates the estimated time when the probability of failure will reach a specified point (X percent). For example, if 10 percent of the products are expected to fail by four years of operation, then the B(10) life is four years.

Predictive analytics and maintenance practices

Traditionally, maintenance practices are classified as reactive, preventive, predictive and reliability-centred maintenance (RCM). However, predictive and RCM approaches are the ones that best leverage predictive capabilities.

- **Reactive maintenance:** In this, practice equipment is allowed to run until it breaks. No actions or efforts are taken to maintain the equipment.
- **Preventive maintenance:** This involves activities carried out for the purpose of maintaining equipment in satisfactory operating condition by systematic inspection, detection and correction of failures either before they occur or before they develop into major defects.
- **Predictive maintenance:** In this, practice statistical techniques are used to determine the condition of in-service equipment in order to predict when maintenance should be performed. This approach promises cost-savings over routine, time-based preventive maintenance, because the tasks are performed only when warranted.
- **RCM:** This emphasises the use of predictive maintenance techniques in addition to traditional preventive measures. When properly implemented, RCM provides companies with a tool to achieve lowest asset Net Present Costs (NPC) for a given level of performance and risk.

Predictive analytics is the process of moving from hindsight to insight. While data and distilling data are the key, equally important is the way in which organisations instrument, capture, create and use data to address their strategic objectives. ●

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