Complete Predictive Maintenance Workflow in 100 hours

Credit: https://en.wikipedia.org/wiki/Steam_turbine

The Challenge

The accumulation of salt deposits on turbine blades can significantly impair turbine efficiency, to the extent that a process bottleneck occurs. It is difficult to determine when this will happen, hence a suboptimal turbine washing schedule is applied causing efficiency losses.

What We Did

Turbine sensor data was analysed to identify features indicative of fouling. A model was developed to estimate the remaining useful life i.e. to predict the optimal time of the next wash. A web user interface was created such that decision makers have easy and fast access to up-to-date data to define more optimal wash schedules.

The Results

Significant cost saving due to turbines running more efficiently given the implementation of optimal turbine wash schedules.

As steam drives the turbines, salt deposits accumulate on the blades changing the blade profile which impairs the efficiency of the turbine. A point is often reached where the expected throughput cannot be maintained due to pressure limits which cut back the steam flow into the turbine for safety and operational limits, which then causes the driven compressor to become a production bottleneck. The concept of “Remaining Useful Life”[1] (RUL) can be used to determine the optimal time to wash in order to prevent bottlenecking.

Sasol and Opti-Num Solutions collaborated on an end-to-end implementation of a predictive maintenance algorithm that forecasts the optimal time to perform turbine washing. The optimal time to wash is at the point where availability is maximised while no bottlenecks occur as a result of unchecked fouling.

Previous maintenance interventions (turbine washes) were analysed in order to establish a RUL prediction for a turbine, with the goal of integrating this analysis with future turbine monitoring. Sensor data was analysed, and a predictive model was developed using MATLAB® software. The entire project lifecycle was executed in less than 100 hours.

Products used:

MATLAB

Request a trial | **Contact** sales

Database Toolbox

Request a trial | **Contact** sales

MATLAB Compiler

Request a trial | **Contact** sales

Services used:

Consulting

Contact sales | **Visit** Tech corner blog

[1] How to Estimate Remaining Useful Life with MATLAB

The challenge

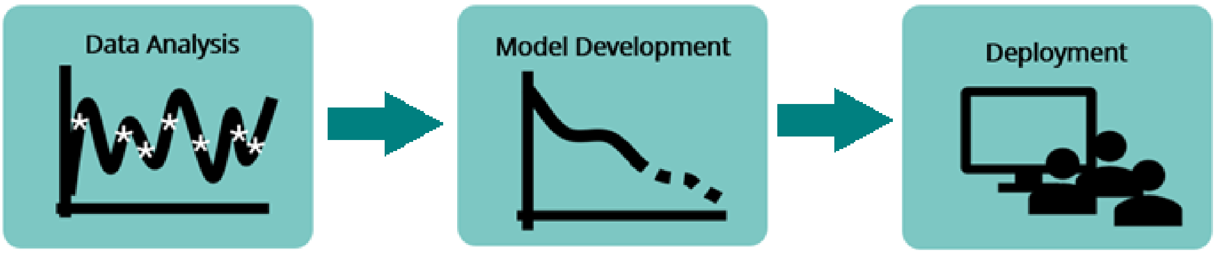
The rate at which salt deposits accumulate on a turbine blade is dependent on the quality of steam. The steam quality varies over time which makes it challenging for maintenance to be applied at the most appropriate time. As a result, maintenance was based on a sub-optimal tool, resulting in the following scenarios occurring frequently:

- Turbines washed too *late*, resulting in **bottlenecks**.
- Turbines washed too *early*, resulting in unnecessary **downtime**.

In order to solve the problem analyses of 6 years' worth of data, sampled at 20-minute intervals, from numerous sensors installed on several turbines must be performed. Condition indicators had to be identified and generalised across this large dataset in order to predict the RUL accurately. Working with this sheer volume of data can be challenging on its own without the right tools and approach.

What we did

Opti-Num developed an application that can be applied to both new and historic data to support the creation of an efficient maintenance schedule, as well as review previous maintenance performance. The following workflow was applied, using MATLAB® and consulting services to develop the end-to-end predictive maintenance application to enhance the operation – from initial analysis of the underlying data through to the deployment of the algorithm in production.

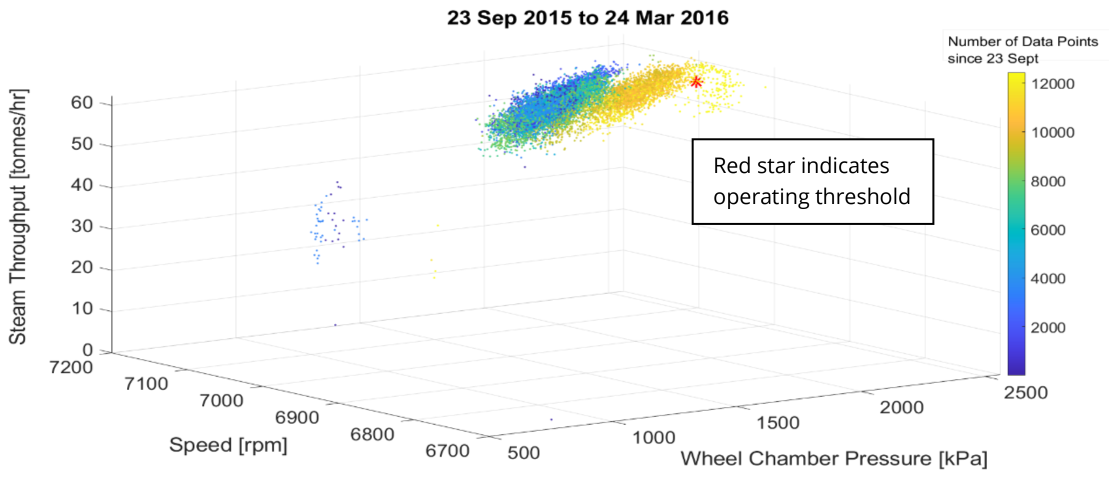


Data analysis

Sensor data captured in Excel spreadsheets was imported into MATLAB for pre-processing and analysis. Pre-processing the data entailed the filtering of outliers. All data points outside of specified operating ranges were removed prior to analysis to prevent the results from being skewed. Examples of these operating outliers include data captured during ramp-up or maintenance periods.

Since the wash dates were not available in logs, an algorithm was developed to automatically identify them using wash-procedure knowledge supplied by Sasol. This creative capability increased both the robustness and accuracy of the solution developed for Sasol as it removed the dependence on washing schedules that are logged manually. Manually logged information is subject to challenges such as limited availability (stored physically on paper or in an unstructured, varying format) and human error (the planned schedule may not always have been followed).

Once wash dates were identified, data for various turbine lifecycles were superimposed in order to analyse and extract consistent features indicative of fouling. After various visualisations of the data (3D and 4D plots of different sensor combinations and ratios thereof) the team was able to identify the key features that correlates fouling over time, as shown in the figure below.



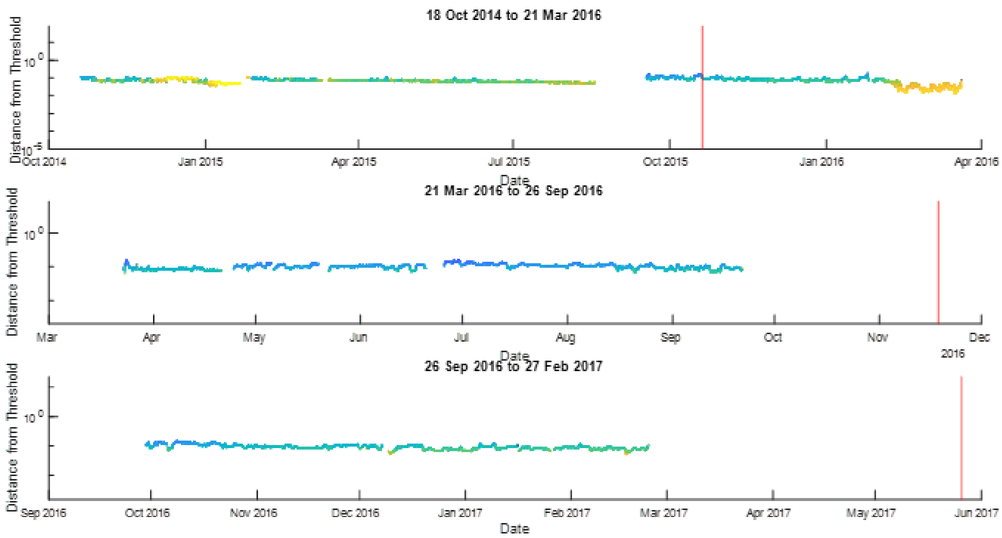
4D plot of different combinations and ratios of four different sensors visualised between a Wash Cycle

The colour bar represents time. Blue and yellow signifies the time straight after the first and right before the next wash, respectively. The red marker represents the time at which the turbine fouled to the extent at which it was bottlenecking the process. Any operation past the red marker should be avoided and was therefore used as the threshold for RUL estimations.

Model Development

Leveraging Sasol's domain knowledge together with Opti-Num's expertise in data science, the team was able to create a statistical model that can predict the RUL of a turbine based on observations of efficient and inefficient (bottlenecked) regions of operation.

The model works by fitting a linear function to the distance of historic data points from the threshold. This distance is indicative of the RUL. A rolling window is applied to the data to ensure that the model adjusts the predicted date according to the latest information. The final model was validated using unseen data, shown in the figure below.



Plot indicating distance to threshold

For each turbine lifecycle, the distance between each data point and the threshold is shown over time. Each data point is coloured according to the wheel chamber pressure (WCP) with blue indicating a low pressure and yellow a high pressure. The red line indicates when the turbine should have been washed according to the algorithm. By extrapolating to where the distance from the threshold will be zero along with the indicated WCP, the team could confirm that a reasonable wash date is suggested by the algorithm. It should be noted that predictive models are not meant to be used in isolation but as an additional tool to assist expert decision making in a holistic maintenance plan.

For the first period of the initial lifecycle shown, there was an overhaul which is why the WCP appears to improve without starting a new lifecycle due to a wash. Overhauls were added to the wash detection later in the project. In the latter part of this operation cycle the steam quality was worsened by plant factors and resulted in a sudden increase in the WCP as noted by the very rapid deterioration, however the model was predicting a wash in the operating region shortly after the overhaul had the rotor not been replaced with a spare. While in the last two lifecycles, maintenance occurred too early.

Deployment

A Graphical User Interface (GUI) was built to present model predictions to end users without the need to interact with the code. A summary of the data was provided in the GUI which enables operators to monitor RUL as well as visualise the performance of past maintenance. Sasol went on to integrate the GUI with their database to allow quick and easy access and visualization of up-to-date operational data. The GUI was deployed as a web application, thus allowing managers, engineers and operators to access the GUI through a URL internal to their network.

The Results

A practical predictive maintenance solution was developed by Opti-Num which allowed Sasol to deploy a system which achieved the following:

- The ability to process large data sets – 6 years' worth of 20-minute data – in support of developing a robust RUL algorithm.
- The occurrence of historical washing events was determined algorithmically, thereby removing the need to access manually logged historical wash schedules which were not consistently available and subject to human error.
- The application of creative visualisation techniques enabled the selection of a single feature most suitable as a proxy for blade fouling.
- The team was able to create a statistical model that can predict the RUL of a turbine – this was successful as a result of leveraging both Sasol's domain knowledge and Opti-Num's expertise in data science.
- An improved maintenance schedule was achieved which was based on observations of efficient and inefficient regions of operation, thus avoiding washes that are too early or too late.
- A GUI was built to present turbine wash predictions to end users without the need to interact with the code.
- The application was successfully integrated into Sasol's operations within 100 hours.

Sasol can effectively use the application during operation review meetings to analyse the performance of past maintenance schedules and optimise future maintenance based on the current model predictions, thereby improving the bottom line of the operation through enhanced efficiency.