

97% Preventive Failure Detection without modeling

The two key problems in implementing predictive modeling for Condition Based Maintenance (CBM) are its cost and the accuracy of the results. Traditional machine learning and statistical approaches require highly trained data scientists who are both expensive and in short supply. For CBM, the data scientists need time to familiarize themselves with all the nuances of the specific business cases and to understand them. Hence, they have to discuss these with the subject matter experts (SMEs). Furthermore, all traditional approaches require long histories of equipment failures in order to build accurate models. As a result, money, time and accuracy frequently deter the implementation of CBM.



Imagine that the engineers responsible for maintenance could conduct the analysis themselves. Imagine that they do not need any historical data but instead they can use any suspicious pattern they detect to track and recover other equipment. Imagine that can be done with over 90% accuracy. This is exactly what our innovative motif discovery approach offers. It is easy to use because it works like Google search. However, instead of searching for words, engineers can search for data patterns leading to failure that they have previously identified, or, for patterns specified by the equipment manufacturer. The engineers can monitor, modify and find variants of the patterns, thus enriching the knowledge of the motives leading to failure. The benefit to organizations is that they can deploy CBM and save money and time by democratizing the analytics, i.e., by putting it in the hands of the engineers who operate the equipment who know how to use the case best.

The best way to validate an approach is to take historical data on machine failure and compare the percentage of cases identified by each method. This gives a direct comparison of the accuracy of the different analytical approaches. The more engines are identified, the bigger the savings, and the higher the ROI.

Lockheed Martin presented us with a historical data set of 100 engines. This data set was used to build statistical models to predict which engines were going to fail and when. The objective was to identify an engine near the point of failure that maximizes the utilization of the engine (i.e. it works for as long as it can, and at the same time minimizes the cost of maintenance as it is less costly to repair an engine before it shuts down completely).

In implementing our approach, we discovered the first failed engine. We then identified the pattern leading to the failure on a time series chart - this is the downward

trending pattern at the end of the time series data monitoring the performance of the engine. We selected this motif and searched for similar patterns across the entire data set. Similar to Google, we wanted the user to see the top 100 search results. Then we investigated how many of the top 100 search results correctly identified the patterns leading to failure. In other words, was the match result occurring exactly where we expected it to occur, i.e., at the end of the time series sequence for each engine? In 97% of the cases, the match was exactly there. In three of the cases, the match occurred prior to the end, which would be considered a false positive, i.e., a match that might have caused a failure but did not.

We compared our approach to the Pearson correlation which identified only 14 matches. It is obvious that increasing the accuracy of the search results is of great importance and many statistical approaches will deploy data transformation and other techniques in order to achieve that. However, it requires the involvement of data scientists and becomes expensive as well as time consuming.

We looked for a solution that could improve the accuracy without escalation of costs and realized it could be achieved by empowering engineers to do it themselves. Our belief is that by offering a more straightforward the approach, the benefits of CBM can be reaped faster.

