

Title: “Finding balance between corrective and preventative maintenance using predictive maintenance”

Authors: Anant Jain, Viral Patel

Introduction:

The technical meaning of maintenance involves operational and functional checks, servicing, repairing or replacing if necessary devices, equipment, machinery, building infrastructure, and supporting utilities in industrial, business, governmental, and residential installations. Over time, this has come to often include both corrective and preventive maintenance as cost-effective practices to keep equipment ready for operation at the utilization of system life cycle. Corrective maintenance can be defined as maintenance which is carried out after failure detection and is aimed at restoring an asset to a condition in which it can perform its intended function. Preventive maintenance can be described as following planned guidelines from time-to-time to prevent equipment and machinery breakdown using scheduled checks on machine.

Whereas, Predictive Maintenance can be defined as but not limited to predicting possibility of failure of an asset in the near future so that the assets can be monitored to proactively identify failures and take action before the failures occur. These solutions detect failure patterns to determine assets that are at the greatest risk of failure. This early identification of issues helps deploy limited maintenance resources in a more cost-effective way and enhance quality and supply chain processes. Such technologies enable easy development and deployment of end-to-end solutions with advanced analytics solutions, with predictive maintenance solutions providing arguably the largest benefit.

Business problems in the predictive maintenance domain range from high operational risk due to unexpected failures and limited insight into the root cause of problems in complex business environments.

The majority of these problems can be categorized to fall under the following business questions:

- What is the probability of failure of an equipment within a given interval of time?
- What will be the expected life cycle of an equipment?
- What preventive measures can help us reduce the cost and the number of failure occurrence and maintenance issues?

By utilizing predictive maintenance to answer these questions, businesses can:

- Develop aggregation of all mechanical faults detections in operations.
- Score mechanical default detection by their severity and potential impact for disrupting production and operational continuity.
- Reduce operational risk and increase rate of return on assets by spotting failures prior to their occurrence.
- Reduce unnecessary time-based maintenance operations and control cost of maintenance.
- Improve overall brand image, eliminate bad publicity and resulting lost sales from customer attrition.
- Lower inventory costs by reducing inventory levels by predicting the reorder point.

Proposed Project:

In the first stage of our project, we will be focusing on preparing the datasets for some preliminary data visualization. Our data consists of five different datasets which are real-time telemetry data (voltage, rotation, pressure, and vibration measurements) collected from 100 machines averaged over every hour, non-breaking error logs and messages which occur while the components are still operational and do not constitute as failures, historical maintenance records comprising of regular inspection of machines and breakdowns. Machine information such as type and age are included. Component replacement records with each record having a date, time, machine ID, and failed component type are included.

Once the data is well understood and cleaned, we are interested in feature engineering which requires bringing the datasets together to produce features that ideally describe a machine's health condition at any given hour. The timestamps in telemetry data make it suitable for calculating lagging features. A 24-hour window size for the lag features would be suitable for computing rolling aggregate measures. Errors also come with timestamps, but error IDs are categorical values, so we count the number of errors of each type in a lagging window. Possible features from maintenance records can be the calculation of duration since last replacement of a component as that might correlate better with component failures since the more used a component is, the more degradation it should have. The machine features about the type and age can be used as they are. Finally, we merge all the features to obtain the final feature matrix.

The next step would be the task of labelling. This is a multi-class classification procedure for predicting failure due to a fault, we will be taking an appropriate time window prior to the failure and label the feature records as "failure expected" if it falls in that window, while labelling the rest of the records as "normal." The time window can be picked according to the business's requirement as sometimes predicting failure hours is enough, but in other cases the business might require time for the arrival of replacement parts.

Finally, we would be experimenting with three different supervised machine learning models which we are supposed to learn in class, namely Naive Bayes, Neural Network and Random Forest Classifier to create predictive models which would be evaluated separately at the end.

References:

1. [https://en.wikipedia.org/wiki/Maintenance_\(technical\)#Corrective](https://en.wikipedia.org/wiki/Maintenance_(technical)#Corrective)
2. <https://docs.microsoft.com/en-us/azure/machine-learning/team-data-science-process/cortana-analytics-playbook-predictive-maintenance>