# Machine Predictive Maintenance

**Maintenance** it is functional checks, servicing, repairing or replacing of necessary devices, equipment, machinery, building infrastructure, and supporting utilities in industrial, business, and residential installations.

The different types of maintenance are:

**Predictive maintenance** use sensor data to monitor a system, then continuously evaluates it against historical trends to predict failure before it occurs.

**Preventive maintenance** which consists of intervening on a piece of equipment before it is faulty, in order to try to prevent any breakdown

Corrective maintenance which consists of intervening on a piece of equipment when it is faulty.

In this project, I am interested to build a machine learning model that predicts machine failure. This model will reduce the down time for the machine, spare parts inventory strategy and optimize Maintenace cost by predicting the failures.

This is really interested in the results and outcome for this project since I am working in the industrial field and may such techniques can help improving current maintenance and inspection strategy for machinery equipment.

### **Data Description**

The dataset consists of 10 000 data points stored as rows with 14 columns:

- 1. UID: unique identifier ranging from 1 to 10000
- **2. Product ID**: consisting of a letter L, M, or H as product quality variants and a variant-specific serial number
- **3. Type:** a letter L, M, or H for low (50% of all products), medium (30%) and high (20%) as product quality variants and a variant-specific serial number
- **4. air temperature [K]:** generated using a random walk process later normalized to a standard deviation of 2 K around 300 K
- **5. process temperature [K]:** generated using a random walk process normalized to a standard deviation of 1 K, added to the air temperature plus 10 K.
- **6. rotational speed [rpm]:** calculated from power of 2860 W, overlaid with a normally distributed noise
- 7. **torque [Nm]:** torque values are normally distributed around 40 Nm with an if = 10 Nm and no negative values.
- **8. tool wear [min]:** The quality variants H/M/L add 5/3/2 minutes of tool wear to the used tool in the process.
- 9. **Machine failure:** label that indicates, whether the machine has failed in this particular data point for any of the following failure modes are true.
- **10. tool wear failure (TWF)**: the tool will be replaced of fail at a randomly selected tool wear time between 200 and 240 mins (120 times in our dataset). At this point in time, the tool is replaced 69 times, and fails 51 times (randomly assigned).

- **11.** heat dissipation failure (HDF): heat dissipation causes a process failure, if the difference between air- and process temperature is below 8.6 K and the tool's rotational speed is below 1380 rpm. This is the case for 115 data points.
- **12. power failure (PWF)**: the product of torque and rotational speed (in rad/s) equals the power required for the process. If this power is below 3500 W or above 9000 W, the process fails, which is the case 95 times in our dataset.
- **13. overstrain failure (OSF)**: if the product of tool wear and torque exceeds 11,000 minNm for the L product variant (12,000 M, 13,000 H), the process fails due to overstrain. This is true for 98 datapoints.
- **14.** random failures (RNF): each process has a chance of 0,1 % to fail regardless of its process parameters. This is the case for only 5 datapoints, less than could be expected for 10,000 datapoints in our dataset.

Feature engineering may be required as since may end up taking out all failure modes columns for features to prevents any leakage.

## **Acknowledgements**

UCI: https://archive.ics.uci.edu/ml/datasets/AI4I+2020+Predictive+Maintenance+Dataset

Dua, D. and Graff, C. (2019). UCI Machine Learning Repository [http://archive.ics.uci.edu/ml]. Irvine, CA: University of California, School of Information and Computer Science.

### Tools:

- Numpy, statsmodels and Pandas for data preparation
- Scikit-learn, keras & pycaret for modeling
- Matplotlib and Seaborn for plotting
- imblearn to perform over-sampling if needed

### **MVP Goal:**

- Target: predicate the failure for given tool and operations conditions.
- Failure Type: Type of Failure.