

# **Evidence of realization**

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# Contents

1	INTRODUCTION	4
2	DATA CLEANING	5
3	DATA VISUALIZATION	6
3.1	Power BI	6
3.2	Correlation matrixes	
3.3	Scatter plots	
3.4		
4	CONCLUSION	10

## 1 INTRODUCTION

This document serves as evidence or realization for my internship at Duracell, where I worked on the analysis of a machine responsible for manufacturing rings used in battery composition. The manufacturing process involves harsh materials that put a strain on the equipment, necessitating regular equipment maintenance and replacement. The objective of the project was to analyse the machine's behaviour, identify influential measures and conditions, and develop machine learning models to predict optimal equipment maintenance timing. During my internship, I actively participated in data cleaning, data visualization, and drawing meaningful conclusions to lay the groundwork for model development.

The project involved working with datasets obtained from iHistorian and a SQL server, aiming to gain valuable insights into machine performance and identify critical factors for further analysis. This document provides a comprehensive overview of the data cleaning techniques employed, the visualizations created, and the conclusions derived from the analysis. By presenting this evidence, I aim to demonstrate my understanding of data analysis methodologies, visualization techniques, and the ability to draw meaningful insights to support the development of machine learning models for predictive maintenance.

## 2 DATA CLEANING

The initial dataset was obtained from iHistorian. This dataset is updated only when a value is changed, with the updated measure entered and other measures filled with NA. To clean this dataset using Python, I created a pandas data frame, standardized the measure names to English, and removed any duplicate entries, if present.

K1.DosingStation1 K1.DosingStation2 K1.DosingStation3 K1.AvgValueM+Station1 K1.AvgValueM+Station2 K1.Av

0.0	0.00	0.000000	0.0	0.0
21.6	23.74	19.620001	27.0	27.0
NaN	NaN	NaN	NaN	NaN
NaN	NaN	NaN	NaN	NaN
NaN	NaN	NaN	NaN	NaN
	21.6 NaN NaN	21.6 23.74  NaN NaN  NaN NaN	21.6 23.74 19.620001 NaN NaN NaN NaN NaN NaN	21.6       23.74       19.620001       27.0         NaN       NaN       NaN       NaN         NaN       NaN       NaN       NaN

5 rows × 270 columns

To ensure data accuracy during calculations and analysis, I proceeded to adjust the intervals between entries to be consistent at one second. Additionally, I filled all NA values with the corresponding values from the preceding rows.

Another dataset was obtained from a SQL server, which provides information about machine status, including downtime, uptime, and the material present in the machine at specific time periods. While most of this data is irrelevant to the project, the line of the machine, material, downtime, and date with time are of interest. During machine downtime, the data related to it is not significant. Hence, the first dataset was filtered based on downtime, material name, and the machine's line, and this information was added to the first dataset.

In order to filter out downtime and merge the necessary values, it was necessary to identify the rows in the first dataset that fell within the time period covered by the second dataset and match the required values. Once the datasets were connected, the rows with non-zero downtime could be removed.

K1.DosingStation1 K1.DosingStation2 K1.DosingStation3 K1.AvgValueM+Station1 K1.AvgValueM+Station2 K1.AvgValueM+Station2 K1.AvgValueM+Station3 K1.AvgValueM

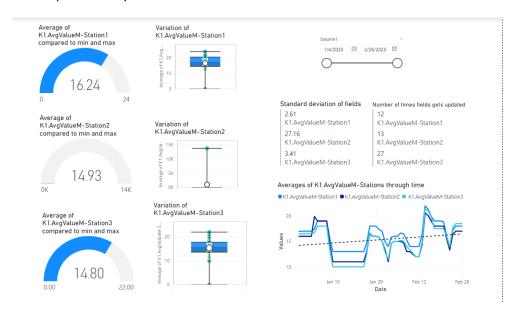
timestamp					
2023-03-06 23:59:55+00:00	19.950001	20.889999	18.92	29.0	28.0
2023-03-06 23:59:56+00:00	19.950001	20.889999	18.92	29.0	28.0
2023-03-06 23:59:57+00:00	19.950001	20.889999	18.92	29.0	28.0
2023-03-06 23:59:58+00:00	19.950001	20.889999	18.92	29.0	28.0
2023-03-06 23:59:59+00:00	19.950001	20.889999	18.92	29.0	28.0

# 3 DATA VISUALIZATION

The subsequent phase involved examining the behaviour of the machines, necessitating the creation of visualizations. I will present a range of graphs from each group and explain their significance to the project or noteworthy aspects. I will also share the findings and challenges encountered during the visualization process.

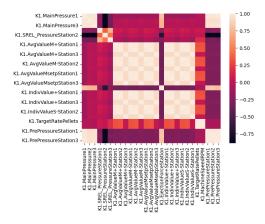
#### 3.1 Power BI

Initially, I utilized Power BI to create graphs that focused on a longer time period, specifically from the beginning of January to the middle of March. During this phase, it was crucial to explore the data further and determine the key factors for future analysis. Graphs were generated for each measure to observe their changes over time, frequency of updates, and key performance indicators such as minimum, maximum, average values, and standard deviations. These insights helped in better understanding the measures. After several meetings, specific measures were selected for long-term importance, and certain daily trends were identified, such as spikes at the beginning of the day. Consequently, the decision was made to focus on shorter time periods for subsequent analysis.



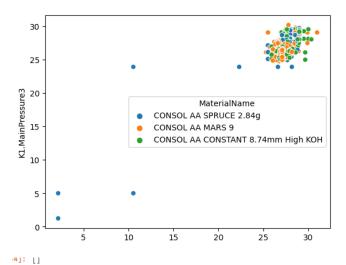
#### 3.2 Correlation matrixes

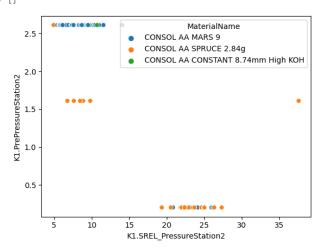
To address memory limitations, I transitioned to using Python and a virtual environment with a Jupyter server that had been set up earlier. The analysis continued by examining correlations between measures to determine which ones could potentially be eliminated and which ones were crucial to retain. Any changes in correlation indicated potential issues. Following a meeting with the production team, it was concluded that all stations of main pressure and SREL pressure should be retained, as consistent correlations among the stations were crucial. Deviations in these correlations could indicate faults in the machine.



# 3.3 Scatter plots

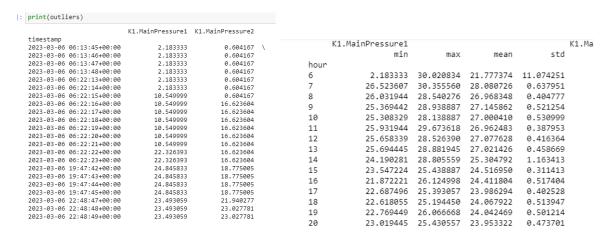
The next step involved creating scatter plots for multiple measures, using different colours to represent the material in the machine. This analysis aimed to assess the impact of different materials on the measures. Certain materials exhibited distinct trends and had more outliers compared to others. These observations were noted and considered during the model development.

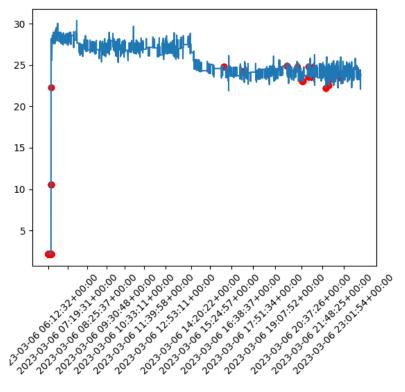


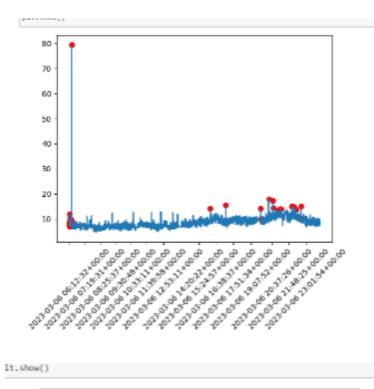


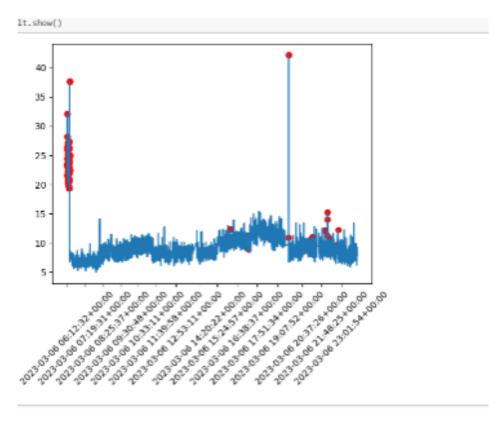
## 3.4 Over time analysis

Finally, line graphs were generated to visualize the changes in values over time. This time, only a short 24-hour period was considered, focusing solely on the most important measures affecting the machine. Outliers were plotted on top of the line graphs, and calculations were performed to determine minimum, maximum and average values, and standard deviations for each hour. Moving averages were also calculated with a window size of 1 minute to smooth the line graphs and facilitate comparison. These calculations and graphs provided additional insights, such as the incorrect values observed at the beginning of the day when the machine was just being turned on, the decreasing trend in most measures with occasional exceptions, and more. All these observations were taken into account when deciding which measures to retain for the model, which measures to combine, and which trends, materials, and times should be considered.









## 4 CONCLUSION

In conclusion, this document not only demonstrates the successful application of data cleaning techniques and data visualization processes for machine behaviour analysis but also highlights the valuable skills I have acquired during my internship experience. By leveraging tools such as Power BI and Python, I have gained a comprehensive understanding of data analysis, including measures, trends, and correlations, which has enhanced my abilities as an IT specialist.

Throughout this project, I have learned how to set up a virtual environment and conduct in-depth data analysis, providing me with a solid foundation for future endeavours. These acquired skills will undoubtedly contribute to my professional growth and serve as a strong starting point for my career upon graduating.

Moreover, this internship experience has provided me with invaluable opportunities to work with data, Python, perform a thorough analysis, and draw meaningful conclusions. Through these tasks, I have gained practical insights into machine performance and identified potential faults, equipping me with the ability to make informed decisions regarding equipment maintenance. The knowledge and skills I have acquired through this internship will undoubtedly serve me well in my future career. The ability to effectively work with data, perform analysis, and draw insightful conclusions is a strong foundation for continued growth and a career in the field of data analysis and machine learning.

In addition to technical skills, this internship has enhanced my time management abilities as I worked on various tasks within specified deadlines. The experience has also fostered adaptability as I navigated through different datasets, software tools, and analysis techniques. Moreover, I have sharpened my problem-solving skills by identifying and addressing challenges encountered during the data cleaning and visualization processes.

In summary, this project has not only provided valuable experience during my internship but has also equipped me with the necessary skills and knowledge to excel in my future endeavours. The groundwork established through the virtual environment setup and the thorough analysis conducted will undoubtedly contribute to ongoing analysis and future advancements to work with data.