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Requirements & Enabled Improvements Related to the Implementation of Advanced Preventive Maintenance Methods

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Preface

This master's thesis was done in conjunction with ASSA ABLOY Entrance Systems during the spring of 2021. It is a representation of us finishing our Master of Science in Electrical Engineering at the Faculty of Engineering, Lund University.

Throughout the thesis, we have had the benefit of applying and analyzing much of what we have learned during our five years as students. We have gained valuable insights into how practice and theory are related and increased our knowledge within data science and operations strategies. The most valuable experience from the thesis has been learning how a large organization such as ASSA ABLOY Entrance Systems operates daily and what it is like to start our careers as engineers.

We are grateful that we were given the opportunity to carry out this thesis in collaboration with ASSA ABLOY Entrance Systems and would therefore like to thank them for a well-accomplish partnership. In particular, we would like to thank our two supervisors from ASSA ABLOY Entrance Systems, Anders Löfgren and Lars Halling, whose support and connections guided us throughout the entire thesis. We would also like to thank all ASSA ABLOY Entrance Systems employees who have taken part in various interviews and seminars during the work. Their expertise provided us with irreplaceable knowledge about the organization and the related IoT data.

Lastly, we would also like to thank our supervisor from the Faculty of Engineering at Lunds University, Ola Alexanderson, for his guidance through the entire thesis. As well as our opponent Sonja Kenari, who helped us ensure the quality of this master thesis.

Edvard Carlsson
Lund, June 2021

Simon Palmhager
Lund, June 2021

Abstract

Title	Requirements and Enabled Improvements Related to the Implementation of Advanced Preventive Maintenance Methods
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Problem Description	Currently well established technology-based manufacturing companies with a service business provides their markets with innovative and reliable products. Despite this, these companies often find their service delivery process to be inefficient, due to its time-based nature. Furthermore, the markets on which they operate are currently experiencing a shortage of qualified service personnel and thus sees a need to optimize the existing service delivery process. The collection of IoT data is an early step in the implementation of a more effective service delivery process. This data can be analysed in order to provide insight of the underling factors of machine breakdowns. If the company understands these factors they are also able to counteract the downtime related to failures and create new opportunities for the company.

Purpose The purpose of this thesis is to investigate the requirements and possible effects related to the implementation of preventive maintenance methods based on quantitative analysis of Internet of Things data, gathered from connected units in an industry environment, for a technology based manufacturing company with a service business.

Delimitations This thesis focuses on IoT data captured from devices operating in a industry environment, with the intentions of examining possible improvements of service offerings. The study focuses on the technological aspects of offering advanced preventive maintenance methods as a service, and disconnects itself from specific operating aspects.

Methodology The thesis is exploratory both with regard to the case company's opportunities on an organizational level and in the analysis of the IoT data. Initialized through an extensive research process, with a literature review of academic papers related to the subject, followed by an exploration of the case company. The research was followed by a data collection phase. This phase consisted of collecting the gathered IoT data as well as performing both qualitative interviews and quantitative seminars. Lastly, a benchmark study of established advanced maintenance practices.

Two analyses were conducted in parallel. One organizational analysis, focusing on the company, its market, and the possible implementation of outlined advanced preventive methods. The second analysis focused on the quantitative IoT data, and centralizes on exploring advanced preventive maintenance through established data analysis methods.

After constructing findings and answering the research questions, future research was suggested and academic contribution discussed.

Conclusion

This thesis found that predictive maintenance is the best suited advanced method for technological-based manufacturing companies with a service business and characteristics similar to the ones of the case company.

Through implementing advanced preventive maintenance methods the service delivery process will grow more technologically dependant. Furthermore, it will render the conventional pricing system useless and favour a new performance-based pricing system for service delivery. Additionally the implementing companies will experience a reduction in the need of educated service technicians. Which arises from a reduction of reactive service visits related to the implementation of advanced preventive maintenance methods.

This thesis was not able to construct a reliable failure prediction model for the case company, yet it identified several previous examples and methods where it has been done successfully. Apparent is that in order to archive sufficient results a considerable amount of domain knowledge is needed. Complementary data, which describes the setting of the predictions is also necessary. Further, there are heavy requirements on the data being analysed, both with regard to quality of measurements, sample size and in particular the length of the studied time interval.

Furthermore, this thesis found that customers lacks a strategic relationship with their device. The far majority of errors is caused by external factors inflicted by customers.

Keywords

Predictive Maintenance, Internet of Things, Service Delivery, Preventive Maintenance, Cycle-based Maintenance, Condition-based Maintenance, Predictive Modelling, IoT-Centric Business Model

Table of Contents

1 Introduction

1.1 Background

1.1.1 Context of Predictive Maintenance

Recent trends have resulted in increased availability of connected devices, collecting vast amounts of data from their everyday operations in the field. Parallel to these trends there have been significant developments within the area of data science, allowing companies to identify, analyze, interpret, and communicate insights recovered from the continuously increasing amount of growing data. This results in new innovative opportunities for companies to develop and innovate long-established parts of their business, such as after sales services (McKinsey & Company, 2019).

Hence it is now possible to analyze data collected from IoT sensors of devices active in the field and use this data to predict when in time breakdown or failures will occur. This is the concept of predictive maintenance and it enables companies to optimize their service process, generating lucrative attributes such as reduced downtime, improved customer experience and cost saving opportunities. The customer experience is increased by solving problems in the field much faster or before they occur, resulting in higher machine uptime and a significant reduction in service visits. The cost saving potential is significant, considering that the cost of service- and repair typically reach up to 70 percent of the operating cost for industry service companies. However, these opportunities are still relatively unestablished and will grow further as the 5G mobile networks and IoT matures (McKinsey & Company, 2019).

1.1.2 Relevance of Predictive Maintenance

Predictive maintenance is not a new topic, it has been a known industry concept for quite some time. However, it is not until recently in time that companies have started to adopt and implement predictive maintenance in their maintenance operations. As previously mentioned, ongoing trends within IoT and data science have just recently made the required technology for predictive maintenance available to such extent that companies are starting to implement it (McKinsey & Company, 2019).

The volume of data is doubling every three years as the information from wireless sensors, digital platforms and billions of phones are continuously growing. Simultaneously the data storage capacity has significantly increased during the last decade while the cost has plunged to record low levels (McKinsey & Company, 2019). Whilst the volume of data and the data storage capacity has been increasing the available computing power has also been exponentially increasing. According to Moore's Law, the computing power doubles every two years. Even though there has been a discussion whether or not it still applies, the industry has managed to keep pace with Moore's Law (Techrepublic, 2020). Recent breakthroughs in the area of data science have transformed the already sophisticated algorithms, making them of higher performance and complexity. As a result, data scientists now have unparalleled computing power, vast amounts of data, and data storage at their disposal with the ability to run more complex algorithms than ever seen before (McKinsey & Company, 2019).

1.1.3 Impact of Predictive Maintenance

According to McKinsey, a more analytical and data-driven approach to maintenance has the potential to impact both the operating model and the business model in several aspects. The most common incentive for companies to implement these types of analytics has been cost reduction. This can be achieved by reducing the need for field operations and remote-service centers when maintenance only is conducted when deemed necessary. But also by an improved allocation of resources when maintenance can be conducted in a more planned fashion compared to a reactive approach.

By being able to faster detect and diagnose failures as well as automate steps in the service process, companies could reduce waiting times and therefore present a faster and more reliable service experience for its customer. The perceived service quality could also be improved by solving issues before the customer notices them. Lastly, it can serve as differentiation from competitors and create additional revenue streams.

These may come both in the form of expanded service offerings and in an increase of the service level, for example, assurance of a higher uptime (McKinsey & Company, 2019).

Predictive maintenance has the prerequisite of large scale data analytics, which in itself also heavily may impact companies' offerings. One such use case is anomaly detection where underlying factors impacting performance may be detected. Another usage is as machine learning-based decision support (McKinsey & Company, 2019). Yan et al. (2017) also discuss the perspective of energy savings with improved management of idle machines. With this, potential savings can be made through switching off lights and optimizing usage conditions.

1.1.4 Definition of Internet of Things

The term Internet of Things (IoT), was first coined by Kevin Asthon in 1999, where he proposed the concept of connecting objects with radio-frequency identification (RFID) technology. Since then the definition has been evolving and still is. A common definition, held by the European Research Cluster on the Internet of Things (IERC), is as: "dynamic global network infrastructure with self-configuring capabilities based on standards and interoperable communication protocols; physical and virtual 'things' in an IoT have identities and attributes and are capable of using intelligent interfaces and being integrated as an information network" (Li et al. 2014). Because of IoTs wide range of applications both in regard to field and function, Sisinni et al. (2018) argue that the requirements and the purpose of IoT solutions greatly differ on a case-by-case basis. This then causes the definitions of the concept to differ since they try to capture different characteristics. They also propose the simple but effective description of a concept that turns common objects into connected devices, through the Internet.

However, what often is described when IoT is discussed today is the so-called Consumer IoT. Smart consumer electronics are connected with the purpose to improve efficiency and advance our awareness of our surroundings. When the application instead is in an industrial setting it is called Industrial Internet of Things (IIoT). In IIoT the objective is to connect and integrate the operational assets in the broader information system. The communication is therefore more towards machine-to-machine in order to achieve process automation compared to consumer IoT (Sisinni et al. 2018).

1.1.5 Different Maintenance Types

Maintenance is defined as the set of activities conducted in order to restore a device to a state in which it can perform its intended functions. Strategies for maintenance can be broadly classified into reactive maintenance strategies and preventive maintenance strategies (Rosmaini & Shahrul 2012).

1.1.5.1 Reactive Maintenance

Reactive maintenance (RcM) refers to service activities based on performance changes or breakdowns (Rastogi et al 2020). It is a method based on running a device until failure or critical state, to later replace or fix the component(s) which failed. It is the most fundamental and ineffective maintenance approach, since this method often results in additional cost related with excessive downtime and unscheduled service visits, which often also may require unscheduled deliveries of spare parts (Gęca, 2020).

1.1.5.2 Preventive Maintenance

The preventive maintenance (PvM) method refers to periodically performing maintenance activities to a planned schedule (Zoll et al. 2018). Hence the word preventive refers to planning service activities regardless of the device's current state (Rastogi et al. 2020). Typically the schedule is either time-based or based on process iterations, which approximately anticipates when in time a device or component will break down, given how many cycles a certain process is carried out (Carvalhoa et al. 2019). Therefore, the time between the service activities is based on one's limited knowledge about certain system components, resulting in limited use of their lifetime. The PvM method may therefore cause additional unnecessary costs due to performing unnecessary repairs (Gęca, 2020). This derives from that the actual condition of a device is unknown. As a result, the period between maintenance activities is often too long or too short, leading to either breakdown which results in unplanned maintenance activities or to an excessive maintenance frequency resulting in large operating costs. To counteract these unwanted consequences companies tend to carry out additional manual inspection of the state of the devices, resulting in further operation costs (McKinsey & Company, 2020). However, it is still a far more effective approach than the reactive based maintenance method when it comes to avoiding failures and maintaining uptime (Carvalhoa et al. 2019).

Time-based Maintenance

Time-based maintenance (TbM) is a subcategory of the preventive maintenance concept, where the maintenance planning activities are made upon a time-based schedule. Therefore, the maintenance activities are made periodically in time whether it is needed or not. This can result in unwanted operation costs through unnecessary service visits and last-minute visits when a breakdown occurs before the scheduled service visits (Carvalhoa et al. 2019). The intervals at which these maintenance activities are made are based on historical operating and maintenance data. Where insights have been found and implemented using probability theory models.

Cycle-based Maintenance

Cycle-based maintenance (CbM) is a more sophisticated subcategory of preventive maintenance, where the scheduling of maintenance activities is based on process iterations. The goal of cycle-based maintenance is to approximately anticipate when in time a certain device or component will break down based on the number of cycles a certain process is carried out within the device and plan the maintenance activities accordingly (Carvalhoa et al. 2019). The number of process iterations that are to be carried out between the maintenance activities is based on historical operating and maintenance data. Where, just as in time-based maintenance, insights have been found using probability theory models rather than machine learning.

Condition-based Maintenance

Condition-based maintenance (CbM) is a strategy where service activities are planned based on data analysis of the observed condition or working state of a connected device or its component. As the level of degradation of a machine or its component increases towards a threshold level a machine failure is more likely to occur. This is utilized in CbM by monitoring the condition and creating models of the degradation process. Conditioning data is gathered with the use of various types of sensors (Zhu et al. 2015). Examples of possibly useful parameters describing the operational condition are vibration, temperature, lubricating oil, contaminants, and noise levels. Rosmaini & Shahrul (2012) states that 99 percent of machine failures are preceded by observable indications. This further suggests that real-time monitoring and assessment of machine conditions would help in reducing maintenance related costs by optimizing service operations.

There is a debate regarding the definition and extent of CdM, where some argue that the notation can be used interchangeably with predictive maintenance (Shin & Jun 2015). However, in this study the terms are distinctly different in that of CbM not making any predictions regarding future failures or estimations of remaining useful lifetime. Instead CbM is defined as the strategy of performing maintenance service exactly when the measured parameters reach an unacceptable level.

Predictive Maintenance

The IoT paradigm shift has enabled organizations to connect their active devices into a large united system. This has allowed modern sensing devices to capture and transfer vast amounts of data on operating processes in real time (Liulys 2019). One of many consequences from this paradigm shift is the possibility of developing predictive maintenance systems. These systems uses the collected IoT data to detect breakdowns before they occur (Zoll et al. 2018).

Predictive maintenance (PdM) is a form of condition based maintenance. It is the concept of intelligent monitoring of connected devices with the intention to prevent future breakdowns before they occur. The concept is based on mathematical prediction models (Rahhal et al. 2020). The method was first derived from the primary method of visual monitoring of devices to later become an automated process using advanced signal processing technology based on machine learning, neural networks, etc. to predict with high accuracy when in time a given device will break down (Zoll et al. 2018). The predictions are typically based on historical service and IoT data, defined health factors, engineering approaches, and statistical inference methods (Gęca, 2020). The scope of PdM projects over the scope of PvM in the extent of planning future service activities in advance with the intention to avoid upcoming breakdowns. However, the activity of determining when the maintenance activity is done in a more sophisticated manner, which based on advanced analysis of collected machine data (Zoll et al. 2018).

PdM provides reliable maintenance solutions to a vast variety of different industry sectors, far more reliable than previous preventive maintenance solutions. It has shown to be reliable to such an extent that it enables businesses to avoid unnecessary equipment replacement and service visits, reduce device downtime, and find the main source of the breakdown. Resulting in many new ways to reduce costs and improve service efficiency (Zoll et al. 2018).

1.2 Purpose

The purpose of this thesis is to investigate the requirements and possible effects related to the implementation of preventive maintenance methods based on quantitative analysis of Internet of Things data, gathered from connected units in an industry environment, for a technology based manufacturing company with a service business.

1.3 Research Questions

In order to research the stated purpose, the study aims to provide clear and relevant answers to the following questions:

- RQ1: *Which advanced preventive maintenance method is best suited for a technology-based manufacturing company with a service business with a time-based service organization?*
- RQ2: *How will the service delivery process change with the implementation of advanced preventive maintenance on a time-based service organization?*
  - RQ2a: *Which economic implications does advanced preventive maintenance process have on a time-based service organization?*

- *RQ2b: Which operational implications does advanced preventive maintenance process have on a time-based service organization?*

- RQ3: *Is it today possible to predict future breakdowns based on IoT-data gathered from an industrial setting?*
  - RQ3a: *What IoT data is needed in order to make breakdown predictions?*
  - RQ3b: *What IoT data can be considered redundant in the case of breakdown prediction?*

- RQ4: *What is possible to learn about customer usage based on analysis of IoT data?*
  - RQ4a: *How can this knowledge be leveraged in the offering of service?*

1.4 Delimitations

The quantitative analysis is limited by the data being used. It is delivered in the form of log messages from IoT connected devices, provided by the case company only. No external tests are being conducted. This is the only dataset being analysed in this manner and is gathered from 51 devices over the time period 28 of September 2020 to 25 March 2021.

Furthermore, the following listed aspects are not further reviewed throughout the thesis.

- **Certificates**: Challenges related to certification for different types of performed maintenance are not reviewed within this thesis.
- **Patents**: The legal perspective regarding patents, namely if some solutions utilizes patented technologies, is not considered throughout this thesis.
- **Security**: The security perspective regarding proposed maintenance solutions for specific situations will not be discussed.

- **Emerging market**: This thesis solely focuses around current market structures and do not consider emerging markets and possible future markets within the industry and its service business.

2 Methodology

2.1 Work process

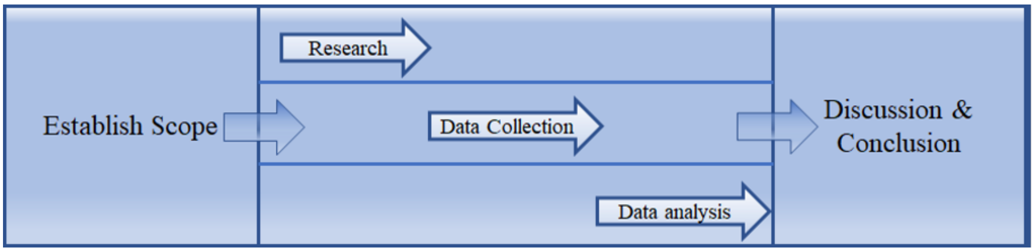


Figure 2.1: Work process of the project

2.1.1 Establishing scope

The first step of the project was to gain an overview of the problem, the subject at hand, and to better understand its context. This was made through introductory meetings with AAES representatives where the focus was on the simpler descriptions of AAES IDS products and service delivery processes. Along with this, the scope of the project was set, this was established through formulating the project's purpose, its research questions, and outlining some delimitations. Afterward, a detailed project plan with an associated time schedule was constructed. All of which were produced in collaboration with the supervisor at Lund University as well as supervisors at AAES. When finished these were communicated to the involved stakeholders.

Activity	Result
Introductory discussions with LU and AAES.	Defined purpose, RQs, delimitations, project plan, time schedule.
Determining Research Approach and Research Strategy	Research Approach & Research Strategy

Figure 2.2: Summary of the establishing of scope

Research Approach

Höst et al. (2006) describes four distinctive research approaches that are suitable for different types of academic reports. One chooses which approach to implement based on the purpose and context of the project. However, it is not required to exclusively use a single approach, hybrid approaches can be used depending on the nature of the project. The different approach is described by Höst et al. (2006) as the following:

- *Descriptive research: the purpose is to ascertain and describe a phenomenon.*
- *Exploratory research: the purpose is to comprehend the operation of a phenomenon.*
- *Explanatory research: the purpose is to interpret causations and explanations of the function of a phenomenon.*
- *Problem-solving research: the purpose is to solve an earlier observed problem. This approach is often used in combination with one of the other types.*

This thesis project is mainly exploratory in that the objective is to describe the current possibilities of implementing predictive maintenance within the case company, how predictive maintenance would impact the case company, and that of determining the possibilities of producing models for working predictive maintenance operations.

Research Strategy

In addition to approaches, Höst et al. (2006) propose four distinctive types of research strategies suitable for academic projects. A research strategy describes the approach by which empirical data is collected and analyzed. Höst et al. (2006) describe the different research strategies as the following:

- *Survey: The aggregation and description of the context of the studied object.*
- *Case study: The profound research of the study object.*

- *Experiment: The comparison of different configurations' impact on the study object.*
- *Action research: The study and documentation of a specific activity in order to solve a problem.*

This thesis focuses mainly on the case company AAES, where both the analysed IoT and organizational related data are solely gathered directly from AAES. Hence this thesis mainly implements the case study research strategies.

2.1.2 Research

The second block of the work process is the research. This is made both in order to gain a better understanding of the subject of preventive maintenance in general and predictive maintenance in particular, to later start building the frameworks and methodologies to apply to the case company. Therefore, further exploration of the case company and especially the current service delivery processes are conducted.

Activity	Result
Literature study	Industry landscape & usage Technical methodologies Theoretical organizational frameworks
Exploration of Case company	Insights in how the case company operates and general facts of sales etc. Better understanding of its operational characteristics, the different business segments, the service business and its strategic objectives and plans.

Figure 2.3: Summary of the research

Literature study

The literature study serves several reasons. First, it serves to gain a more in-depth knowledge of the state of maintenance services and the development of IoT. However, even though being the first research step, the literature review of general maintenance practice was conducted continuously over the project's earlier parts in order to achieve more expertise within the area. For this step of the research process various sources were used, academic publications, books, and consulting firms reports, the last one being especially useful to get the sought overview. For the more technical parts, academic publications were mostly used. Because predictive maintenance is a highly evolving subject with current advances in big data processing and machine learning, companies' current practices are not to a large extent publicly available. Because of this, the academic sources were deemed trustworthy. This part of the literature study resulted in several proposed methodologies, of different demanding levels, to solve the maintenance problem. Lastly, in order to establish a theoretical framework to compare the case company towards further studies within organizational management and business models were made. The literature consisted of the above-mentioned varieties.
As for literature searching of academic publications, the LUB Search and Google Scholar portals were used with keywords such as "predictive maintenance", "IoT", "service efficiency", and "Machine learning". Since the field is to a large extent currently being highly developed, preference was put towards newer publications. However, due to due to scarcity the literature search resulted in sources ranging from the last ten years being used.

Case study

In order to evaluate the potential improvements enabled by the use of predictive maintenance the case study of AAES is conducted. To do so an understanding of the current state of the company and its internal processes related to service delivery are required. This was mainly collected through AAES internal material, documentation and interviews with company representatives.

2.1.3 Data Collection

The process of data gathering can be divided into sections depending on the type of data. For the purpose of analysing types of maintenance solutions and building prediction models, quantitative historical data are used in the form of IoT logs. In regard to evaluating the potential efficiency improvements on an organisational level, qualitative data was gathered through readings of internal documents, qualitative interviews and quantitative seminars with different levels of AAES employees.

Activity	Result
Extracting IoT logs	IoT data
Reading of Internal Documents	Deeper understanding of specific internal processes and business segments
Qualitative Interviews	Insights in the service business internal processes Greater understanding of current service delivery process and the conceptual IoT based service delivery process Understanding of the common errors reported by customers and customer characteristics
Seminars	Quantified relative magnitudes of attributes related to different maintenance approaches

Figure 2.4: Summary of the data collection

Extracting IoT logs

This project is data-centric in that the analysis of IoT data constitutes a fundamental. This implies that the output in terms of the extent and performance of a working prediction model is highly dependent on the access to quality data. This access is, however, somewhat outside of the project's capabilities to influence, instead the current infrastructure of AAES connected devices will determine this. Since the objective is to explore different types of maintenance implementations and what data needed in order to successfully launch, these any data would suffice at some level. This data is being presented as a time series of logs consisting of information such as event happenings, error messages, and condition descriptions.

Reading of Internal Documents

The data collection was initialized through a thorough reading of internal documents from the case company. These documents complement the initial exploration of the case company well and give a deeper understanding of the different business segments and specific internal processes within the company. As well as the current state of the case company's market shares and strategic objectives. The information collected was proven to be valuable during the case study and provided a stable foundation for further analysis.

Qualitative Interviews

The data collection proceeded through a large number of qualitative interviews, discussions, and meetings with employees from different levels of AAES. These interviews resulted in a greater understanding of the current situation of the case company's service business. Furthermore, insights into the service business internal process were gained. Throughout these interviews, the focus was held on both the current service delivery process and the conceptual IoT-based service delivery process designed by the company. The interviews resulted in a greater understanding of the most common service activities requested by customers and customer characteristics for different types of customers. These characteristics were utilized throughout the analysis and enabled the customer segmentation analysis. Whereas the service delivery process and the most common activities yielded great insights into the current state of the company's maintenance situation and acted as a knowledge-base throughout the analysis.

Seminars

Several seminars with different management-level employees were conducted in order to quantify different identified relative magnitudes of attributes related to different maintenance approaches. The results of these seminars were utilized in later analysis to determine the best possible maintenance type for the case company's current situation.

2.1.4 Data analysis

The following section processes the methodology of the data analysis. However, two distinctive analyses are carried out parallel to each other through this thesis. The first analysis focuses on the organizational-related aspects of the project while the second focuses mainly on the analysis and mapping of the IoT data.

2.1.4.1 Analysis of Organizational Data

Activity	Result
Analysis of Customer Characteristics	Customer Segmentation
Identify Order Winners and Order Qualifiers	Order Winner Order Qualifiers
Deeper Analysis of Service Delivery Process	Deeper understanding of the current state of maintenance. As well as the service business strengths and weak points.
Implementation of IoT-Centric Business Model for Predictive Maintenance	Overview of a possible business model implementation for predictive maintenance
Benchmark Study of current predictive maintenance implementation in industry environments	Possible organizational impact of Predictive Maintenance
AHP analysis of different maintenance types	Best suited maintenance type for AAES current situation
Focusing Current Service Delivery Process	Interpretation of possible organizational changes predictive maintenance will entail

Figure 2.5: Summary of the Organizational data analysis

Analysis of Customer Characteristics

The customer characteristic-related insights from the qualitative interview were utilized through the customer characteristics analysis. The output of the analysis was four distinctive customer segments, all with different needs and requirements. These customer segments were utilized together with several other identified parameters in later analysis and were proven to be a valuable part of the empirical data. The intention of the segmentation was to identify the different customer segments in order to better specify how the value-proposition of predictive maintenance should be performed to better serve the different segments, and which of these the case company should focus on.

Identify Order Winning and Order Qualifying Criteria

By using the gathered data from the conducted qualitative interviews and the insights derived from the customer segmentation different order winning and order qualifying criteria were derived. Additionally through utilizing the customer segments and their characteristics several segment-specific order winning and order qualifying attributes were identified. This analysis provided value individually as well as in later analysis, for example when identifying the how-dimension of the IoT-centric business model.

Deeper Analysis of Service Delivery Process

A compilation of the data gathered from qualitative interviews and reading of internal documents was performed to gain a deeper understanding of the current service delivery process and the current state of the maintenance within the case company. Additionally, data from the literature study was carefully analyzed from a constructive and strategic point of view, with the intention of identifying possible weak points and points of improvement. Hence the analysis provided insights into the service business's strengths and weaknesses.

Implementation of IoT-Centric Business Model for Predictive Maintenance

The analysis continued by evaluating a possible implementation of the IoT-Centric business model identified in the literature study. This was made to gain a better understanding of how predictive maintenance may impact the structural, economic, and organizational dimensions of the current service business.

Benchmark study of current predictive maintenance implementation in industry environments

To assist the study of implementing the IoT-Centric business model a benchmarking study of current predictive implementations in industry examples was conducted. The study mainly focused on the organizational dimension in which gave a stable foundation for further analysis.

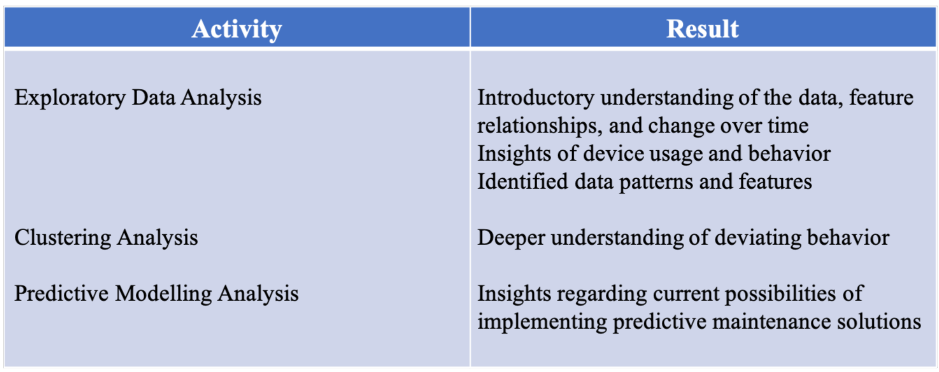
AHP Analysis of different maintenance types

In order to be able to provide the best conclusion of the case company's future actions within maintenance, an analytical hierarchy process (AHP) was carried out. The analysis thoroughly reviewed four different maintenance approaches to decide which one is best suited for the case company's current situation. The gathered data from the quantitative seminars was utilized during the analysis.

Apply Focusing on Current Service Delivery Process

The organizational data analysis was finalized by focusing the service delivery process through an established framework. This made it possible to identify possible improvements enabled by advanced preventive methods within the service delivery process in order to further discuss these and establish valid conclusions. The focusing resulted in a rearrangement of the infrastructure related to the service delivery process and actions needed to be performed throughout the maintenance transformation process.

2.1.4.2 Analysis of IoT Data



Activity	Result
Exploratory Data Analysis	Introductory understanding of the data, feature relationships, and change over time Insights of device usage and behavior Identified data patterns and features
Clustering Analysis	Deeper understanding of deviating behavior
Predictive Modelling Analysis	Insights regarding current possibilities of implementing predictive maintenance solutions

Figure 2.6: Summary of the IoT data analysis

Exploratory Data Analysis (EDA)

The first step of the quantitative analysis is to gain an introductory understanding of the data and in extension the connected devices and their usage. This is done in an exploratory manner, where first data distributions are studied and metrics compared across the devices. The second step is to identify patterns in the data. The reasoning behind this is that these patterns can be helpful in understanding the behavior of the devices. The hypothesis was that when these behaviors deviate or change it may provide insights about the machine's conditions and in that regard hold predictive power. The research is conducted in a broad sense since a general overview initially is desired. But because the final objective is to construct predictive models, features that show interesting relationships or prominent change during the studied period are prioritized. Insights from this analysis will serve as the groundwork for future analysis and influence the decision-making in these steps.

Clustering Analysis

From the EDA the knowledge of device behavior and the identified patterns a clustering analysis was conducted, with the objective to identify and group devices which show similar problematic features. The study wanted to determine whether these features can be useful in distinguishing between devices. After the clustering the constructed clusters are compared based on their other features and conclusions about this grouping discussed.

Predictive Modelling Analysis

Initially, the final step of the IoT-data analysis was to develop prediction models of varying complexity depending on which data being used. However, during the earlier steps of analysis, it was concluded that this would not be possible within the scope of the thesis. Therefore the central question of this step was instead shifted to analyzing and discussing the limitations with the current setup and what improvements were needed in order to achieve the desired performance.

2.1.5 Conclusion

Activity	Result
Discussion of results and their credibility	Summarizing findings and conclusions Answer to the research questions Recommendations and suggestions of potential future research

Figure 2.7: Summary of the conclusion

After finalizing the evaluation of the IoT data and its potential in the service organization a summarizing discussion of the results and their credibility are held. The objective of this step of the methodology is to try to answer the set research questions and conclude with a recommendation for AAES regarding future improvements of the service processes. The objective is however also to determine the academic contribution of the project and suggest potential future research.

2.2 Credibility

According to Höst et al, there are three important credibility parameters, these are reliability, validity, and representativeness. In the following paragraphs, these three are discussed in more detail. Their meaning will be defined and it will be explained how this report implements each of the different parameters. (Höst et al. 2006)

2.2.1 Reliability

According to Höst et al, reliability is the degree to which the analysis of the gathered data will result in consistent findings. It can be measured to which extent the analysis would have resulted in the same findings would it been carried out on other independent occasions. Another important parameter to consider for reliability is the transparency in the analysis, namely the transparency in how conclusions are based on the data. (Höst et al. 2006)

A large variety of actions have been taken during the thesis to ensure a high reliability level. Firstly during all of the several qualitative interviews and seminars both of the authors have been present to gain the deepest possible understanding of the presented information. Furthermore, the authors implemented a neutral approach when conducting the interviews, in order to eliminate possible subjectivity. Employees from different business areas have been consulted to further eliminate possible subjectivity from different branches. Lastly, to further ensure the thesis reliability a detailed description of the used methodology is presented, would others wish to conduct the same analysis.

One issue regarding the quantitative IoT data is that it is bound to the case company. Hence all the IoT-data analysis is based on internal data from the case company. However, the IoT data is considered to be reliable since it is based on the communication between the internal control unit within the entrance systems. Although some data deficiencies were discovered, they were considered throughout the analysis and discussed afterwards.

It is possible that the findings could deviate some if the same IoT data analysis was conducted, largely depending on the IoT data provider. Similar findings is considered to be found would the same case company provide the data. If another IoT data provider is utilized then the findings could deviate significantly.

2.2.2 Validity

According to Höst et al. (2006), validity is the extent to which a conclusion measures what it is supposed to measure, the more well-founded a conclusion is the higher validity it receives. Höst et al. (2006) claim that it is possible to increase the validity of a conclusion by using triangulation, namely to use a variety of data collection methods and base the conclusion on several different independent sources.

A variety of data collection methods has been used throughout the entire thesis. To gain a deeper understanding of the subject and its context methods such as literature review, qualitative interviews, quantitative data in the format of IoT data logs, and different websites were utilized. Furthermore, during the analysis a large variety of methods was utilized, the data collection base was extended by internal documents from the case company, quantitative seminars, qualitative discussions, and further benchmark studies through literature reviews. To summarize, a large variety of data collection methods and independent sources has been utilized throughout the entire thesis.

2.2.3 Representativeness

According to Höst et al. (2006), Representativeness refers to whether or not the findings are generalizable, namely if the findings can be applied to other study objects in other conditions. A proposed method of increasing representiveness is by including a detailed description of the case study and its context.

This thesis is a case study in nature, and in general case studies are not generalizable to a large extent, due to the data being highly related to the study object. Hence one should be aware of this fact when drawing conclusions. In order to increase the representiveness of the study, a detailed description of the study object ASSA ABLOY Entrance Systems and the context to which the thesis is conducted is included within the thesis. This enables others to gain an understanding of the study and context to perform a similar study in the future.

The results from the IoT data analysis should be applicable for other study objects in a similar context in that of AAES. Namely companies that are in the same phase of the development process regarding predictive maintenance. Relative should the findings from the organizational analysis be found for study objects in a similar context, i.e. with a similar service business, in the same development phase and industry as AAES.

3 Theory

3.1 Modelling for Preventive Maintenance

In this section prediction modeling based on IoT data is discussed. A few different approaches are outlined. These methods are supposed to serve as both as a knowledge base and in practise when the study attempts to answer Research Question 3 and 4, with their respective subquestions.

3.1.1 Modeling for Cycle-based Maintenance

In order to utilize a cycle-based maintenance approach data of historical machine failures needs to be gathered. This data should statistically be analysed to find possible the characteristics of these failures and in order to estimate a failure trend.

3.1.2 Modelling for Condition-based Maintenance

Since the used definition of CbM is purely diagnostic the method should aim to provide indications of failures in the form of abnormal operations. However, abnormal conditions do not mean immediate machine breakdown. Historical machine failure data should be studied in order to define limits for the measurements of interest and the machine as a complete system. The method then constitutes evaluating the current machine condition. If the condition level exceeds the set limit maintenance service is provided. If not, the machine is considered to be in sufficient condition.

3.1.3 Modelling for Predictive Maintenance

The objective of constructing efficient PdM models is highly dependent on the type and quality of the data (Gutschi et al. 2019). Gutschi et al. divide these model into three categories depending on which type of data they are based on:

- Log-based: Utilizes data in the form of historical logged events to train machine learning models in order to recognize irregular patterns. Remaining lifetime is predicted through the probability of failure on real-time log data as input.

- Sensor-based: Data is provided in the form of time-series signals from sensors and does not utilize physical models to assess the remaining lifetime. A common use case for this type of model is rotary machines and component tracking.

- Hybrid approaches: Approaches based on a mixture of the two earlier described methods.

3.1.3.1 Log-based Prediction Models

Many types of industrial equipment provide data in the form of event-based log messages. These record the time and state of the events happening for the machine as well as error messages when this occurs. These messages are critical for predicting failures since they are containing information about the machine's current condition. Examples of information may be system messages, alarm codes, numerical values, or keywords. However, since only a relatively small portion of these messages are relevant to failure predictions heavy data preprocessing like feature extraction might be needed (Wang et al. 2017).

Failure Prediction Method

In a case study Wang et al. proposes a problem construction method for failure prediction which they argue should be applicable to a wide variety of settings for which the model can be optimized. This generalizability is caused by the similarities many types of machines with error-logs exhibit in terms of failure behavior and solving processes. The method may also be extended to be implemented with real-time data. In the following two sections, their method is described. It should however be noted that even though this method serves as a possible course if action for this thesis it becomes quite specific at times and parts of it may therefore not be considered useful when implementing PdM at the case company.

Construction of Failure Prediction Model

1. **Description of Data**
   The data can be gathered from several sources and can describe different areas of operations, examples of types are, historical maintenance records, system logs, inventory data, environmental data, utilization data, and configuration information. The more available data the more reliable the analysis and prediction will be, however, maintenance records, system logs, and inventory data are deemed most useful. These various datasets are aggregated by their timestamps and will serve as input for building the predictive model (Wang et al. 2017).

2. **Description of Problem**
   In a reactive maintenance setting, when a device breaks down the operator files a maintenance service request and a service technician repairs the device. In the PdM setting the problem is defined as a binary classification problem, where the possible classes are: likely breakdown in the near future (Positive) and unlikely breakdown in the near future (Negative). More specifically the model will predict the creation of maintenance service requests, which is the outcome of a failure, rather than the error causing the failure (Wang et al. 2017).

3. **Defining Parameters and Performance Metrics**
   The model has five parameters, denoted X, Y, Z, M, and N. Below follows a visualisation of the problem, where some time intervals and important events are defined. From this description the five parameters are gathered (Wang et al. 2017).

   - **Prediction point (PP)**: Timestamp when the model makes the prediction.
   - **Observation window (OW)**: A list of the logged events occurring in the time interval before the PP.
   - **Measurement unit**: A subwindow of the OW, from each of which the features are extracted individually. In total X units each with the size of M days.
   - **Prediction window (PW)**: If a maintenance service request is created during the PW the instance is labeled positive, otherwise negative. The PW starts after the PP and is of Y length.

- **Prediction frequency (N)**: Also called sampling density, the parameter decides the number of learning instances generated.
- **Bonus time**: The time between PP and the earliest created maintenance service request. This is the time the service provider would be possible to save compared to a reactive maintenance setting.
- **Buffer window (BW)**: The buffer window is a set amount of time after the PP but before the PW. This in order to give the service provider sufficient time before conducting the maintenance service as well as ensure a considerable bonus time. The length of the BW is Z.

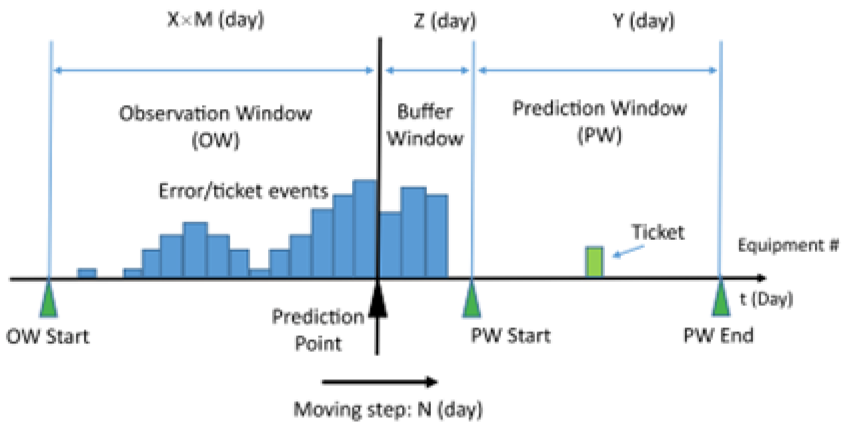


Figure 3.1: Visualisation of parameters and performance metrics (Wang et al. 2017)

The model applies X different performance metrics to validate its performance. Below follows a description where each of the performance metrics are defined.

The objective of predictive failure analytics is to anticipate all breakdowns before they happen. Therefore recall, also called sensitivity, is very central. Recall is defined as the fraction of relevant instances retrieved.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{3.1}$$

Another metric deemed central is precision, also called positive predicted value, this is derived from the costs related to false predictions. Precision is defined as the fraction of relevant instances among the retrieved.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{3.2}$$

Together with these two the receiver operating characteristic (ROC) curve and the area under the ROC-curve (AUC) is used to describe the descriptive ability of models with different parameters. In order to ensure that a balance between recall and precision is maintained and provide a flexibility in deemed importance between these the area under the precision-recall-curve (AUPRC) is studied. Because of this, the F1-score is also used which measures the balance between precision and recall.

$$\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3.3}$$

4. **Instance Generation**
   In order to generate different training and evaluation instances, each denoted as a vector S constructed by the instances specific features and its label, the PP is shifted along the time axis. The shifting is done in N steps. If a maintenance service request is present in the BW the instance is dropped from training. In testing, maintenance service requests in the BW or PW are labeled positive. This procedure is conducted for all machines and results in the generation of the training and test sets (Wang et al. 2017).

5. **Feature Extraction**
   Along the generation of instances the features are extracted. The features will make out the dataset for which the learning later is conducted on (Wang et al. 2017). Wang et al. describes four different types of features

   (a) Statistics-based features
   The distributions of error types in the observation window. The expectation is for the algorithm to learn the relationship between errors and machine failures. Statistics-based features are divided into two categories.

- **Basic statistic features**: The number of each error type in each measurement unit. Described in the vector **B**:

$$\mathbf{B} = \{c_{ij}, i \in [i, T], j \in [1, X]\}, \tag{3.4}$$

where T is the number of error types, X the number of subwindows, and cij the count of error instances of type i in the j-th subwindow.

- **Advanced statistical-based features**: These are details of the distributions, meaning the metrics extracted from observed distances among the points. The different advanced statistical-based features follows:
  - Distance between error instance and prediction point.

$$d = t_p - t_e \tag{3.5}$$

  - Error interval, v. Distance between two errors of the same type.

  From this the following feature vector is extracted:

$$\mathbf{A} = \{min(\mathbf{D}_i), mean(\mathbf{D}_i), mean(\mathbf{V}_i), stdDev(\mathbf{V}_i), i \in [1, T]\} \tag{3.6}$$

(b) Pattern-based Features
Patterns represent the association relationships among the error types and machine breakdowns. They are defined as a combination of error types that repeats in different observations. For example, the three error types e1, e2, e3, constitutes the patterns: (e1), (e2), (e3), (e1,e2), (e1,e3), (e2,e3), (e1,e2,e3), without any particular order of occurrence, if observed in the window. These patterns are then evaluated for their ability in predicting failures (Wang et al. 2017). Evaluation ability is defined as recall:

$$\text{Recall} = \frac{\text{Count of pattern occurrences in positive instances}}{\text{Count of pattern occurrences in all instances}} \tag{3.7}$$

Patterns which exhibit an evaluation ability exceeding a predefined threshold are set as features. Pattern-based features are collected in the vector **P**:

$$\mathbf{P} = \{p_i, \in [1, T]\}, \tag{3.8}$$

where T is the number of selected patterns and p_i either set to 0 or 1 depending on whether pattern i is found in the observation window.

(c) Failure Similarity Features
Because many failures of a given type often repeat themselves, and each failure is preceded by errors of similar types before it occurs, one can expect the prediction model to learn this relationship between repeat failures (Wang et al. 2017). The types of errors found in the observation window for the generated instance are collected in vector **G**. The types of errors found in the observation window for the maintenance service request are collected in vector **H**. The failure similarity, F, is defined as the Jaccard distance between **G** and **H**:

$$F = \frac{|\mathbf{G} \cap \mathbf{H}|}{\mathbf{G} \cup \mathbf{H}} \tag{3.9}$$

(d) Profile-based Features
Equipment-profile-related information, such as machine model and installation date. These are collected in the vector R. From this extraction the features of each instance S are generated. S are therefore defined as: **S** = (**B**, **A**, **P**, F, **R**, L), where L, the binary label, also is added. The set of generated instances create the dataset on which the learning is conducted (Wang et al. 2017).

Parameter Tuning, Feature Selection, and Algorithm Optimization

Wang et al. states that for optimized predictive performance experiments different configurations should be conducted. The optimization should be transacted in an automated evaluation process, this is done in the following seven steps: data preprocessing, pattern mining, instance generation, feature selection, model training, model testing, and model evaluation (Wang et al. 2017).

- **Parameter Tuning** The model's five parameters are used for pattern mining and instance generation. Different configurations will cause different datasets and should therefore be optimized for prediction performance (Wang et al. 2017).

- **Feature Selection** According to Wang et al, the selection of features aims to reduce redundancy and noise among the features which can be beneficially both from a computational perspective and a predictive performance perspective. The evaluation can be split into two parts. First the type of feature is evaluated, this can be done by studying the different performances achieved by different combinations of feature types. The second part studies the individual features and their predictive ability. This is done by applying feature ranking algorithms to find the features with the highest level of predictive ability. The features ranked as most important are selected and the model is trained and evaluated on these. More features are then added iteratively to the model to increase its complexity. This is continued until performance no longer is noticeably increased with the addition of more features (Wang et al. 2017).
- **Algorithm Optimization** Various classification algorithms should be compared and later the chosen algorithm's hyper-parameters tuned for optimal predictive performance (Wang et al. 2017).

3.1.3.2 Sensor-based Prediction Models

According to Rahhal & Abualnadi (2020), PdM is conducted through three key steps. The capturing of sensor data, which refers to the connected sensors within the machine which monitors operating conditions. The facilitating of data communications, which refers to the transmission process of the captured data from a device to a processing server. The processing servers will then build a mathematical model to estimate the remaining useful lifetime of the device. Lastly, the prediction-making process, which refers to the continuous monitoring of new data and the comparison of new data towards historical data. If the predictor predicts an upcoming failure or low health status, the prediction will trigger a maintenance action (Rahhal & Abualnadi 2020).

Framework for Sensor-based Prediction Models

Rahhal & Abualnadi presented a framework to implement an integrated system to perform PdM, with the assistance of IoT data. Through IoT, the system will gain access to the vast amount of data required to perform PdM. Furthermore, the large amount of data will enable the system to produce a more accurate model for the corresponding devices. The framework presented by Rahhal & Abualnadi is conducted in three steps: first, it requires a classification of the data into two categories. The data is later de-correlated in order to find a unified health model for the devices. Furthermore, a health function is defined, which is used to evaluate the remaining useful life for each device (Rahhal & Abualnadi 2020). Similarly to the approach described for Log-based Prediction. This method is an example of a possible course of action and parts of it may therefore not be considered useful for this thesis study of the case company. The proposed choice of algorithms is an example of such, both of which requires considerably larger datasets than what is used in this study.

1. **Classification of Data**: The data is divided into two categories, main information (**M**) and side information (**S**). Main information is data that is directly related to the device's operating condition, this can for example be input current, The difference between device temperature and inner temperature, and noise level. While the side data consists of parameters describing the settings or environment of the device, examples are machine configurations, humidity, and device altitude. Each of the parameters is to be normalized to 100% scale of the normal value to remove the individual differences between the parameters (Rahhal & Abualnadi 2020).

2. **De-correlation**: The parameters are fed into the de-correlator. The function of the de-correlator is used to remove any possible correlations between the main and side input data. Resulting in zero correlation between the side dataset and output of the de-correlator $\hat{\mathbf{M}}$ (Rahhal & Abualnadi 2020).

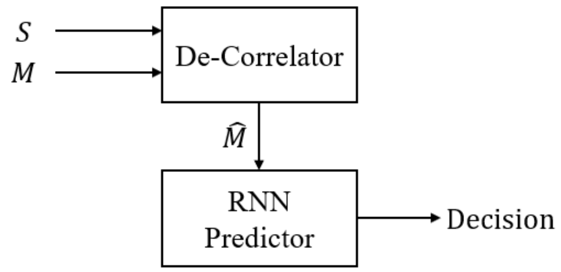


Figure 3.2: Visualisation of de-correlation process

The de-correlation matrix is derived as:

$$\hat{\mathbf{M}} = M - \alpha \mathbf{S} = [\hat{m}_1, \hat{m}_2, \hat{m}_2]^T \tag{3.10}$$

Where:

$$\mathbf{S} = \begin{vmatrix} s_1 \\ s_2 \\ s_3 \end{vmatrix}, \mathbf{M} = \begin{vmatrix} m_1 \\ m_2 \\ m_3 \end{vmatrix}, \hat{\mathbf{M}} = \begin{vmatrix} \hat{m}_1 \\ \hat{m}_2 \\ \hat{m}_3 \end{vmatrix} \tag{3.11}$$

Furthermore, the cross-correlation between the two is set to zero in order to solve for the de-correlation matrix α. Which will render the cross-correlation between zero between the normalized main and side datasets (Rahhal & Abualnadi 2020).

$$E\{\hat{M}S^T\} = 0 \tag{3.12}$$

Solving for α we find:

$$\alpha = \Delta^{-1} R \tag{3.13}$$

Where:

$$R = E\{MS^T\} \tag{3.14}$$

And:

$$\Delta = E\{SS^T\} \tag{3.15}$$

The uncorrelated is used as input for the prediction model which calculates the optimal maintenance time (t_{opt}) for each of the devices, which decides the optimal time in time-space to perform a service service activity (Rahhal & Abualnadi 2020).

3. **Defining a Health Function:** According to Rahhal and Abualnadi the optimal maintenance time (t_{opt}) is determined by the health function, which is exponential and follows:

$$H = H_{max}\left(1 - e^{-\beta^T \hat{M}(\frac{t_{max}-t}{t_{max}})^2}\right) \tag{3.16}$$

   The maximum health of the product is denoted with H_{max}, while the current health of the device is denoted with H, t_{max} is the maximum a device can be operational without maintenance (Rahhal & Abualnadi 2020). According to Rahhal and Abualnadi this is the designed lifetime of the device. The optimal maintenance time is derived by solving the health function for the minimum health value (H_{min}), resulting in:

$$t_f = t_{max}\left(1 - \sqrt{\frac{-ln(1 - H_{min})}{\beta^T \hat{M}}}\right) \tag{3.17}$$

   Where the weight vector is denoted by β^T

Implementation of the Prediction Model

Rahhal and Abualnadi suggests two different approaches to implementing the prediction model. The first approach is a prediction model based on a vanilla-RNN network, while the second approach is based on a LSTM-RNN. Rahhal and Abualnadi argue that RNN networks are a suitable implementation for the prediction model. While the LSTM-RNN produces a much lower prediction error, its complexity is of a much higher level than the one of the RNN network. This yields acceptable performance at a much lower complexity. Additionally, according to Rahhal and Abualnadi, the vanilla-RNN becomes more suitable as the size of the dataset grows, since the LSTM-RNN can only be used for critical devices. However, another aspect to consider is the cost-dimension. The average costs decrease as the prediction grows more accurate. Therefore, a trade-off is to be made between the two models. Either one implements a simpler prediction model (RNN) with acceptable performance, suitable for larger datasets or a more complex model (LSTM-RNN) of higher performance and therefore more cost-efficient, but suitable for smaller datasets (Rahhal & Abualnadi 2020).

3.2 Predictive-Maintenance as a Service Business Models

This section focuses on the organizational aspects of advanced preventive maintenance methods. The discussed literature is supposed to serve both as a knowledge base and a theoretical framework for answering Research Question 2 and 4, with their respective sub-questions.

3.2.1 IoT Architecture

According to Zoll et al., the IoT architecture consists of four layers that are built upon one another, where each layer is strongly dependent on its underlying layers. The first layer is the "Devices & Systems" layer which describes the information gathering process, which is typically made through capturing data from integrated sensing devices within the product, such as sensors. This data is then transferred to the "Data Integration & Transmission Layer" which uses standardized communication protocols such as Wi-Fi to further transfer the data to the "Data Storing Layer". Within the data storing layer, the data is accessible to the analytical layer. Where the data is prepared, analyzed, and consumed by the corresponding application such as analytical models for predictive maintenance (Zoll et al. 2018).

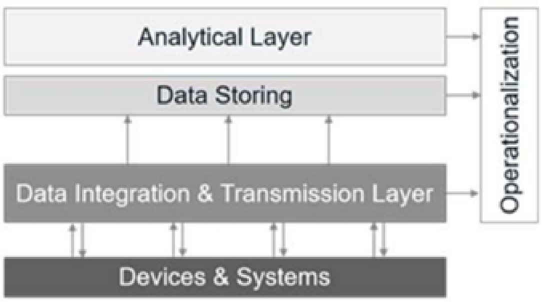


Figure 3.3: Visualisation of the IoT Architecture (Zoll et al. 2018).

Zoll et al. argues that the IoT architectural design constitutes a significant portion of the technical challenges related to offering PdM as a service. The architecture needs to be efficiently designed, highly scalable, and maintain a secure data exchange to be able to handle the vast amounts of requests from different users. Zoll et al. further argue that a poor architectural design is the main cause of failure when offering PdM as a service. Hence efforts should be made to maintain and optimize a highly functional architecture.

3.2.2 IoT-centric Business Model

Zoll et al. argue that the rapid development within IoT will drive a business model transformation, where business models transform from the traditional view of business model canvas to a more IoT-centric business model. According to Zoll et al., this new model will enrich the current product and service portfolio of manufacturing and engineering companies. While the classical business model typically focuses on an organization-centered approach, the IoT-centric approach focuses more on collaboration between partners, competitors, and industries instead of the organization itself (Zoll et al. 2018). Gassman et al. propose four fundamental elements to the IoT-centric business model, which are the Who, What, How, and Why, to the IoT-centric business model. The elements can be described as:

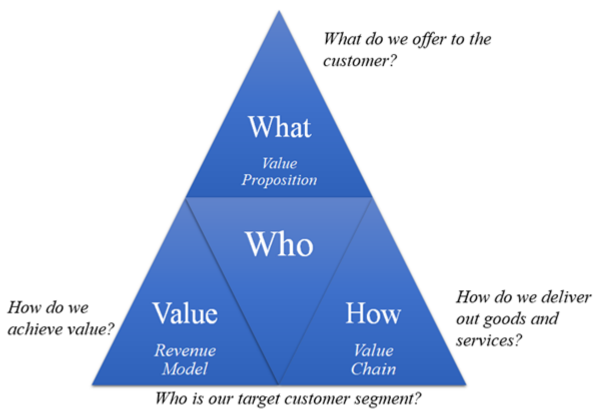


Figure 3.4: The IoT-centric business model

Who: Every business model serves a specific customer segment and the target customer must be clearly defined. Therefore, the who-aspect of the business model should provide clear answers to who the customer is. This is a central dimension in designing a new business model and is, therefore, the central aspect of this framework (Gassman et al. 2014).

What: The what-dimension describes what is offered to the customer, preferably the offer should resonate with what the customer values. This aspect of the business model is traditionally referred to as the value proposition (Gassman et al. 2014). Gassman et al. define the what-dimension as "a holistic view of a company's bundle of products and services that are of value to the customer".

How: The how-dimension refers to the activities and processes related to the building and distribution of the value proposition. A central aspect of the how-dimension is to integrate these activities within the company's internal value chain and the design of the new business model (Gassman et al. 2014). According to Gassman et al., these activities and processes need to be orchestrated together with the relevant resources and capabilities, to make the delivery of the value proposition as efficient as possible.

Value: The value-dimension relates to the revenue model of the business model canvas, by defining why a company's business model is financially practicable (Gassman et al. 2014). According to Gassman et al., it combines and clarifies the relation between certain aspects such as, the cost structure and the applied revenue model mechanism. Furthermore, it associates these aspects with the business models fundamental purpose; how to generate value.

Zoll et al. argue that the IoT-centric business model and the IoT architecture should resonate with one another. Thus, meaning that the value dimension should be analyzed and those valuable insights should drive the implementation of each level of the IoT architecture. Furthermore, Zoll et al. define a vast set of technical challenges related to the implementation of predictive maintenance, where the architectural design is defined as one of the main barriers. Which further emphasizes the relationship between the IoT architecture and the business model. Companies therefore need to take the architectural layout into account when developing and transforming business models (Zoll et al. 2018). Furthermore, as Zoll et al. imply that the rapid development within IoT drives the business model to a more IoT-centric approach, companies will need to establish incentives for collaboration with partners to ensure stable delivery of end-to-end solutions towards their customers. Additionally, the drive towards IoT-centric business models will affect the IoT-strategy of the companies. This will result in either of two strategies, the catch-up strategy, or the get-ahead strategies. Both somewhat intuitive, the get-ahead strategy refers to actions that enable the company to maintain a leading position within their industry sector and shape the IoT industry. Whereas the catch-up strategy refers to an action which enables the company to develop IoT businesses by following and learn from the industry leaders in their sector (Zoll et al. 2018).

3.2.3 Predictive Maintenance as a Service

According to Zoll et al., many companies were careful with their implementation of PdM due to the complexity of PdM systems and lack of technological experience. However, many still experience issues that PdM would resolve, such as unwanted machine downtime and unscheduled service visits. An effective way to resolve these matters is to offer PdM as a service towards one's customers. According to Zoll et al. literature review from 2018 there are two distinctive established cases of PdM as a service (PMaaS), these are:

- *PdM offered as a service by an IT vendor*
- *PdM offered as a service by an engineering or manufacturing company*

The first case is not considered to be of any interest to this thesis since the subject of study (ASSA ABLOY Entrance Systems) is strictly defined as an engineering or manufacturing company. Hence the first case will not be reviewed in this thesis.

3.2.3.1 PdM Offered as a Service by an Engineering or Manufacturing Company

For this case, the company in question has access to historical operation and service data and additionally possesses the product expertise to identify significant and irrelevant data for making a prediction (Zoll et al. 2018). Since the company develops and produces their own product, the implementation of necessary IoT devices within the products, such as sensors, are an easy task. A key requirement for implementing PdM as a service is extensive knowledge about the given product and its underlying processes. To ensure that only significant data is captured and used when making predictions (Zoll et al. 2016).

According to Zoll et al., the engineering company will create a standardized set of integrated sensors within their products. These connected sensors will collect, store and transfer the actual machine data, y after the installation and configuration are completed, which enables the automation of needed statistical analysis to be made. This analysis will act as a support when developing the initial statistical model, which is the foundation of the prediction model. The initial models will, based on their algorithm, make a prediction, . The stored machine data, y enables error calculation to be made after the introductory phase. The insights gained from error calculations are used to reevaluate the approach of the prediction and eventually improve the model. The error calculation is denoted as $|\hat{y} - y|$ (Zoll et al. 2018).

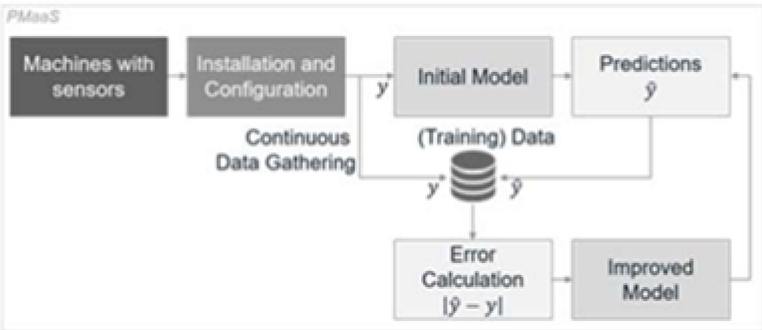


Figure 3.5: PMaaS offered by an engineering or manufacturing company (Zoll et al. 2018).

3.2.3.2 Business Challenges

According to Zoll et al., there are a significant amount of business challenges related to the implementation of PdM as a service. This derives from that IoT is a relatively new area of innovation, hence there are no well-established frameworks for developing the business model that will ensure a stable return of investment. Therefore, Zoll et al. have performed a literature review from which they have derived a list of common business challenges that manufacturing, and engineering companies face when implementing PdM as a service. Of which the four main challenges are the following:

- *Diversity of Objects*
  Diversity of objects refers to the vast amounts of different types of connected devices. Additionally, the area of IoT is relatively new; there are no defined standards considering the interfaces, resulting in a vast variety of different possible business model approaches. However, when considering a lone company, developing- and producing its own products, this is less of an issue. Since the company only can decide their own interface and tail their predictive algorithms accordingly (Zoll et al. 2018).

- *Immaturity of Innovation*
  This challenge refers to the immaturity of most IoT technologies, which are not yet standardized, resulting in a lack of trust from active industry players (Zoll et al. 2018). According to Zoll et al., approximately 90% of companies were still in the proof-of-concept stage in 2016 and were not ready to pursue expensive implementation of IoT solutions, such as PdM.

- *Unstructured Ecosystems*
  An area that also refers to the immaturity of the IoT focus area. Zoll et al. argue that since it is still very young, it lacks governance, stakeholder roles, and logic regarding value creations. Which results in a need for business model innovation and the creation of IoT-centric business model frameworks (Zoll et al. 2018).

- *Lack of Expertise*
  According to Zoll et al., the number of gigabytes handled per IT professional has increased by approximately 535% over a period of 6 years between 2014 and 2020. As of now, there is a significant storage burden per IT professional, resulting in a lack of IT personnel and an urgent need for advanced machine learning algorithms which do not need a human developer supervising (Zoll et al. 2018).

3.2.3.3 Technical Challenges

The IoT-architectural design is one of the main technical challenges related to PdM as a service, however Zoll et al. further argue there is a significant amount of other technical challenges related to PdM as a service, specific for manufacturing and engineering companies. The key challenges related to this case are the following:

- *Privacy*
  An issue with PdM is related to privacy, which derives from the openness of the IoT system. When a large amount of partners collaborates and ventures into PdM as a service, there occur lots of different interactions within the IoT architecture. Although it entails conveniences it may also create many data violation opportunities (Zoll et al. 2018). To counteract this Zoll et al. proposes that privacy policies for each domain have been specified and strictly maintained.

- *Security*
  As previously mentioned, PdM requires secure data transfer and storage. This is typically solved with security algorithms based on public and private keys, which are commonly used within the IT industry (Zoll et al. 2018).

- *Network Communication*
  IoT is currently lacking a standardized communication protocol. Therefore, it is essential to identify the most appropriate combination of different communication protocols within the IoT architecture. Wrong choices of protocols may have drastic consequences, such as a need to redesign the network communication architecture significantly (Zoll et al. 2018).

- *Data storing*
  Another challenge is regarding data storage, since enormous amounts of data have to be processed, transferred, and stored. According to Zoll et al., the order in which the data is processed and stored is a key component in creating a performing and sustainable system. Where data should be stored based on its future usage. Therefore, the storage layout requires a deep and profound understanding of the data, its future use, and its significance (Zoll et al. 2018).

- *Analysis*
  The main challenge in regard to analysis is the trade-off between the relevance of the analysis in regards to the time it requires. Zoll et al. further argue that one should rely on simplicity

when building the theory model, hence not make too many assumptions since they have a tendency to disrupt the outcome. Hence the data analysis aims to leverage the simplest and most effective methods (Zoll et al. 2018).

- *Machine Learning*
  Machine learning is a central aspect of building a PdM system. Although there are no standardized frameworks for model- and feature selection. PdM solutions systems are developed according to the specific problems. Hence the challenge of choosing the right model and features for each situation arises (Zoll et al. 2018).

To ensure safe delivery of PdM as a service one must first overcome the business and technical challenges stated above. Furthermore, a successful delivery of PdM services requires a deep and profound understanding and awareness of the advanced analytics needed in the prediction state. Additionally, the ability to separate hot and cold data is another underlying factor that needs to be considered during the development (Zoll et al. 2018). Therefore, Zoll et al. suggest an iterative and incremental development process for PdM as a service, supported by tests in a real-world environment to ensure its performance.

3.3 Frameworks for Operations Analysis

This section focuses solely on operations strategy frameworks. The discussed frameworks is considered to yield valuable insights for answering Research Question 1 and 2, with their respective sub-questions.

3.3.1 Service Profiling

Hill & Hill (2018) present a framework for service profiling, which reflects factors in different types of service delivery systems. Where typical characteristics for different types of service delivery systems are discussed for each of the different parameters. The model mainly separates service delivery systems based on the types of services which they deliver, scaling from non-repeat service repeat service. Non-repeat services are characterized by each service activity being distinctive, meaning that the same service activity will not be carried out multiple times. Relatives are repetitive services characterized through standardized service activities, where a given activity will be carried out multiple times (Hill & Hill 2018).

Factors reflected in service delivery system design		Non-repeat services	Repeat services Low volume	Repeat services High volume
Service variety		Wide	→	Narrow
Level of customization		High	→	Low
What does a company sell?		Expertise	→	Standard offering
How are orders won?	Typical order-winners	Unique skills Repeat business Recommendations	→	Price
	Typical qualifiers	Price On-time delivery and quality conformance*		
Prior knowledge of task		Not well defined	→	Well defined
Volumes		Low	→	High
Delivery system	Design	Unspecified system	→	Specified system
	Level of flexibility	High	→	Low
Level of system investment		Low	→	High
Ability of system to cope with change	New service	High	→	Low
	Service change	High	→	Low
Staff skill levels		High	→	Low
Operations key strategic task		Enhance skills/ respond to change	→	Reduce costs

Figure 3.6: Service Profiling (Hill & Hill 2018)

3.3.2 Focusing Operations

According to Hill & Hill, focus links operations to the right competitive factors of a business so that it can gain greater control of its competitive position. It is crucial that companies understand their business and market requirements when focusing operations. Hill & Hill recommends implementing the following approaches to ensure that the operations are successfully focused. Firstly, one should use a combination of approaches rather than a single approach in order to widen the scope of the focusing. When focusing operations it is important to understand business and market requirements to gain the highest competitive advantage possible. Hence one should not focus all processes, some processes function fine and have no need for improvement. Therefore one should not try to focus these. The drive of focusing is improving business performance and market support, hence these should be at the core of the focusing process (Hill & Hill 2018).

Hill & Hill presents a framework for focusing operations. The framework involves six main steps that are performed in an iterative manner. First, one must review the processes that need focusing. Thereafter market order winners and order qualifiers for the processes need to be identified. Based on the order winner and order qualifiers, the best approach is then selected for the affected products. The products are then grouped using the selected focus approach. Thereafter, the right processes and infrastructure are allocated to each unit to enable them to meet their requirements (Hill & Hill 2018).

3.3.2.1 The Six Steps

This section focuses on the six steps that are carried out when focusing operations. The six steps are visualized in figure 3.7, they are iterative in nature and require significant time to work through (Hill & Hill 2018)

Figure 3.7: The Six Steps

1. Review processes
   The first task is to review the existing operations and identify any processes that need improvements (Hill & Hill 2018).

2. Identify market order-winners and qualifiers
   The second step is to identify the operations related order qualifiers and winners for the affected products. These will be used to determine the optimal distribution of resources for the identified processes (Hill & Hill 2018).

3. Select focus approach
   The third step centralizes around identifying the approach that creates the best advantage and least disadvantages. To focus on the order winning criteria is typically a good approach, however sometimes the cost disadvantages related to these are too great and other approaches need to be identified (Hill & Hill 2018).

4. Group products and customer orders
   Products and customer orders should be grouped based on the selected focus approach from the previous step. Processes and infrastructures can be allocated once the split into products and customer order groups is determined (Hill & Hill 2018).

5. Allocate processes
   Once product and customer order groups have been determined, processes are correctly allocated to each unit to meet their requirements (Hill & Hill 2018).

6. Rearrange infrastructure
   The last step focuses on correctly allocating the required infrastructure. Significant benefits can be achieved during this step since overhead costs are typically constituting a large part of an organization's costs. Aligning them to aid the needs of the market will enable the organization to become more competitive. It is possible to reduce the total overhead costs across the business as the needs of the market is more clearly understood (Hill & Hill 2018).

3.3.3 Analytical Hierarchy Process

Forman and Gass describe the Analytical Hierarchy Process (AHP) as a structured method of analyzing and organizing complex decisions that need to be taken within an organization that is based on mathematics and psychology. The AHP approaches the decision by quantifying weights of different decision criteria. Where individual experts within the decision field are consulted to determine the relative magnitude between the different factors through pairwise comparisons (Forman & Gass). Furthermore, Saaty (2008) implies that it is an extensive framework for organizing a decision, for determining and quantifying relevant attributes, relating these attributes to an organization's goals and evaluating different solutions. According to Saracoglu (2013) it is a framework that can be used in a wide range of situations, and is commonly used in fields such as business, industry, government and healthcare. It is a psychological method that aims to find the best-suited decision for stakeholders' goals instead of finding the right decision.

4 Case Study: ASSA ABLOY Entrance Systems

This chapter processes the case company ASSA ABLOY Entrance Systems (AAES), it begins with an introduction of the ASSA ABLOY group and AAES. It then proceeds to describe their organizational structure, the different business segments, and the service business. Thereafter a detailed description of both the current and a conceptual service delivery process is presented.

4.1 ASSA ABLOY Entrance Systems

ASSA ABLOY Entrance Systems is a member of the ASSA ABLOY Group, which is the global leader in access solutions. Founded in 1994 and is now offering a wide product portfolio, consisting of opening solutions such as locks, doors, gates, and entrance automation solutions (ASSA ABLOY 2020)

AA strives to become the global leader in providing innovative access solutions that help people feel safe and secure so that they can experience a more open world. To ensure that the vision of AA is fulfilled, their operations are characterized by:

- Building sustainable shareholder value.
- Providing added value to customers, partners, and end-users.
- Being a world-leading organization where people succeed.
- Conducting business in an ethical, compliant, and sustainable manner (ASSA ABLOY 2020).

AA's strategic plan consists of the following four strategic objectives.

- Growth through customer relevance
  The growth within AA is characterized by providing relevant products and solutions. This is enabled by the ability to develop an in-depth understanding of the needs of customers and end-users.

- Product leadership through innovation
  Innovation is at the core of daily operations. The organic growth is accelerating through a constant flow of new, innovative, and sustainable products and solutions which optimizes customer value.

- Cost-efficiency in everything we do
  By focusing on cost-efficiency AA will further strengthen competitiveness and continuously improve operations

- Evolution through people
  AA deems it crucial for the Group's future growth and success that employees thrive and feel committed (ASSA ABLOY 2020).

The scope of this thesis is delimited to AAES, which is a division within AA. AAES focuses on delivering complete and automatic entrance systems. The offerings within AAES are divided into four different business segments. These are pedestrian, industrial, residential, and perimeter security business segments (ASSA ABLOY Entrance Systems 2020, b). This thesis is further limited to the industrial business segment, more specifically the Industrial Door Solutions (IDS) business area within the industrial segment. The main entrance system within the IDS business area is the overhead sectional doors, folding doors, and high-speed doors (ASSA ABLOY Entrance Systems 2020, c).

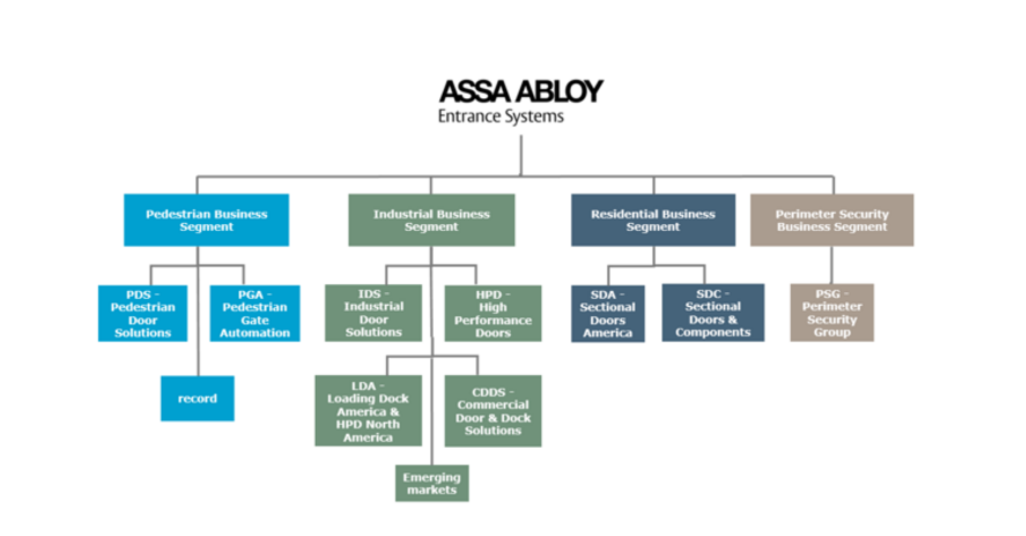


Figure 4.1: AAES Organizational structure (ASSA ABLOY Entrance Systems 2020)

AAES does not only provide entrance systems but also provides after-sales service and maintenance to their customers. Furthermore, AAES provides modernization kits that enhance a customer's device, improving the customer's profit or loss and helps them to obey their budgetary demands. After-sales service represents a significant portion of AAES revenue. Since AAES alone develops, produces, and provides service for their products, they are considered as an engineering or manufacturing company with a service process, as discussed in section 3.2.3.1 (ASSA ABLOY Entrance Systems 2020, d).

4.2 The Service Business

A detailed description of AAES service business will be presented in this chapter. Since the purpose of this thesis is to identify possible points of improvements enabled by the implementation of a predictive maintenance approach in the service process.

AAES service business is one of the most established on the market. AAES strives to always be the most strategic, professional, and innovative service partner in their industry as well as achieving a 10% annual growth. To achieve this do AAES combine local presence with global expertise to deliver both proactive and reactive service for the best customer experience (ASSA ABLOY Entrance Systems 2020, d). AAES possesses the majority of the Swedish after-sales service market. The closest competitor has a fleet of 62 service technicians, where AAES alone hired more service technicians during the year 2020 alone. Within the IDS-business segment, AAES currently dedicates approximately 185 service technicians for the IDS-business segment alone, where the majority of the annual revenue is generated for after-sales services (Service Manager IDS SE & Service Sales Manager, 2020 digital interview, 26 March).

Currently, do AAES to a large extent conduct a reactive-based service process. Meaning service actions will be taken once AAES has received information regarding breakdown of a certain device. The reactive service actions include equipment reparations once breakdowns or problems are observed, i.e. when the customers' entrance systems are no longer operative. However, AAES also carries out preventive maintenance (ASSA ABLOY Entrance Systems 2020, e). Preventive maintenance consists of service activities planned ahead of time. Service technicians visit customers at regular intervals to ensure the equipment is still operable or not in a critical state. It is stated by Swedish law that maintenance needs to be carried out at least once a year for industrial door solutions. However, the need for preventive maintenance significantly varies depending on which frequency the entrance system is used. Therefore, preventive maintenance for the industrial door solutions is usually carried out between one to four times per year depending on customer usage. The distribution between preventive and reactive service visits is approximately evenly divided (Service Manager IDS SE & Service Sales Manager, 2020 digital interview, 26 March). However, the reactive approach is considered by AAES to be cost-inefficient, since reactive service visits carry more costs compared to preventive visits. These are mainly derived from the large amounts of unscheduled visits. Therefore, AAES is currently transforming its service business approach, away from reactive and towards preventive. The purpose of the transformation is to work more proactively and minimizing the appearance of reactive service visits through the usage of preventive maintenance. This approach is more cost-efficient than the reactive approach. Since it allows to possibly identify and prevent breakdowns before they occur and strategically schedule each service technician's time in a more cost-efficient manner.

There are currently millions of IDS-devices worldwide, with these

AAES has started to build the foundation for the transformation ahead by connecting devices through IoT, allowing them to capture and transfer valuable data continuously. This is done by installing the monitoring 950 and 950D IoT control units within the entrance system. This data is essential for building preventive maintenance methods such as cycle-based, condition-based and predictive maintenance. The transformation is yet to be complemented. However, on completion, it will transform the current service business. Allowing AAES to more efficiently plan and perform their service and increase customer satisfaction by offering a more well-adapted service experience than before (Service Manager IDS SE & Service Sales Manager, 2020 digital interview, 26 March).

AAES provides a large product portfolio within the IDS business area, a total of 13 products family and a large variety of products within each family. The operation-process of these products highly differs (ASSA ABLOY Entrance Systems 2020). Hence the service visits performed are non-repetitive due to the large variety in products and product functionality. AAES, therefore, offers a wide range of service variety and a high level of service customization towards its customers. Due to this large variety, AAES service business focuses on expertise and aims of providing a functioning door with 100% uptime rather than the standard offerings related to reactive service (ASSA ABLOY Entrance Systems, 2020, d). This has manifested itself in their periodically preventive maintenance and in their intentions of moving their service business in the direction of predictive maintenance. The volume of service activities delivered is relatively low compared to other service industries, however, the variety of the performed services is high and requires the service technicians to be educated due to low prior knowledge of the task when dispatched (Service Manager IDS SE & Service Sales Manager, 2020 digital interview, 26 March). According to Hill & Hill, the key strategic tasks when improving such a service delivery system which AAES implements is to enhance the delivered skills and adapt to industrial changes rather than to reduce the cost of the provided service. Which indicates that AAES is transforming their service business in the right direction. Since the closer AAES gets to achieving their goal of developing a predictive maintenance algorithm, the greater knowledge they will gain regarding the behavior of their products and how breakdowns occur. Knowledge which should be utilized along the development process through educating technicians to be more experienced within their field.

Hill & Hill (2018) also discusses a service delivery system's ability to cope with change, where the non-repetitive system scores the highest due to its high flexibility and expertise. This indicates that AAES current service delivery system is well suited for a transformation in the direction of predictive maintenance. Furthermore, Hill & Hill (2018) discusses a service delivery system's ability to deliver new services and ability to change the current delivery process. Where the non-repetitive service delivery system maintains a high ability on both characteristics. However, the conversion into predictive-based maintenance will not require AAES to deliver new services but rather to change the delivery process of their current service portfolio. Which their current service business is well-suited to manage.

4.2.1 Service Contracts

AAES service offerings are divided into three different categories of contracts: Gold, Silver, and Bronze. The different contracts are described in more detail below. Although the contracts differ, there are still some features that are included in all contacts. All contracts include 1-4 scheduled service visits per year, 24/7 priority service hotline and fast response and safety, compliance and quality control checks. The contracts mainly differ from a cost-perspective, where some costs are covered in the high-end contracts and not in the low-end. However, all contracts only cover services related to machine error or breakdowns and not services related to damage caused by external factors, such as collisions between doors and forklifts (ASSA ABLOY Entrance Systems 2020, d).

Figure 4.2: AAES's different service contracts (ASSA ABLOY Entrance Systems 2020)

Gold

The gold contract covers all costs related to service and maintenance visits. It covers preventive maintenance visits, labor and transport costs related to reactive maintenance visits as well as the cost of any spare parts needed for the reactive maintenance visit. The gold contract is prepaid, meaning the customers will be charged fixed costs periodically. Therefore the costs of this contract need to be calculated in advance of a sale (ASSA ABLOY Entrance Systems 2020, d).

Silver

The silver contract is considered as the mid-range contract. It covers preventive maintenance visits and the labour and travel costs related to reactive maintenance. However, the costs for spare parts are not included, meaning the customer will need to pay for parts replaced in reactive maintenance visits (ASSA ABLOY Entrance Systems 2020, d). The silver contract is prepaid, meaning the customers will be charged fixed costs periodically. Therefore the costs of this contract need to be calculated in advance of a sale. The silver contract is designed to increase the perceived customer value of the gold offer rather than to act as an attractive contract, and therefore increase the sales of the gold contract (Service Manager IDS SE & Service Sales Manager, 2020 digital interview, 26 March).

Bronze

The bronze contract is the least covering contract. It only includes preventive maintenance visits but the cost of exchanging components is not included. Therefore, reactive service visits are not included in the price. Meaning the customer will be charged for all costs related to this kind of visit. Therefore, customers choosing the bronze contract have a tendency to use third-party service providers for their reactive service activities. Only using AAES for the preventive maintenance service offered in the contract (ASSA ABLOY Entrance Systems 2020, d). The bronze contract is post-paid, meaning the customers will be charged for the delivered services, after a service is carried out (Service Manager IDS SE & Service Sales Manager, 2020 digital interview, 26 March).

Currently, the majority of the customers are using the Bronze contract within the IDS-business segment. This distribution is partly related to AAES current enterprise resource planning (ERP) system. The system has supported AAES since startup and is now outdated. Therefore, AAES is motivated to replace it. Since both the gold and silver contract prices are prepaid, the outdated ERP system cannot handle the extensive calculations and data management required to support these contacts (Service Manager IDS SE & Service Sales Manager, 2020 digital interview, 26 March).

AAES wants to move in the direction of motivating customers to choose the gold contract, since it will result in a situation of stable revenue/cash flows on a periodic basis. The increased cash flow will increase the overall asset turnover and result in an increased return on investment. Whereas the current situation requires a service to be executed in advance. This ties up capital in account receivables which yields the opposite result as the example above. The tied-up capital will decrease the asset turnover rate and reduce the overall return of investment

4.3 Service Delivery Process

AAES's service process has been mapped in the figure below. It includes all activities made for a given breakdown, i.e. from the moment a breakdown is observed until the matter has been resolved and is, therefore, a reactive process. Currently, the service process differs between countries since there is no standardized process within AAES. However, the purpose of the thesis is to identify possible points of improvement for AAES Sweden service process. Therefore, this thesis is limited to AAES Sweden service process and it is considered to be of future research to map and analyze possible improvements for other countries' service processes. The service process has been simplified and broken down into individual activities, to be more intuitive and to leave out confidential information. The process has been broken down into five steps, which can be seen in Figure 4.3.

1. Order Creation
   A service order is created once AAES receives information about a breakdown. There are several different channels from which AAES receives this information. The majority of customers call AAES helpdesk. The employee at the help desk aims to

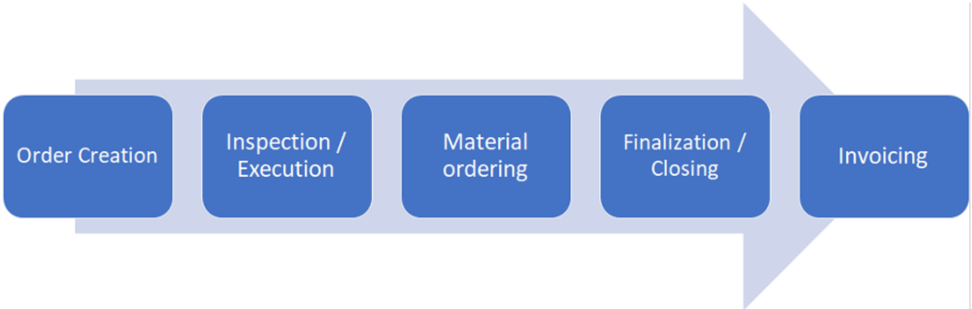


Figure 4.3: AAES's 5 step service process

extract as much information about the breakdown as possible, and evaluates if the matter can be resolved via phone (ASSA ABLOY Entrance Systems n.d, a). If the problem cannot be resolved via phone, a service order is created. The service will be performed the same day If the customer informs AAES before 12:00 AM. However, some customers choose to inform AAES via e-mail while others choose to call a service technician directly. A portion of the reactive service activities is discovered through preventive maintenance visits. Once AAES receives information regarding a breakdown, a service order is generated (Service Manager IDS SE & Service Sales Manager, 2020 digital interview, 26 March).

2. Inspection/Execution
   Once a service order is generated a service planner dispatches a service technician. The service technicians manage their orders through their individual work tablets. The technician receives the service order through the work tablet, where service order information and customer information are specified (Service Manager IDS SE & Service Sales Manager, 2020 digital interview, 26 March). Once the service technician is dispatched, the technician travels to the site and performs an inspection. Where the technician evaluates whether or not the breakdown is a warranty issue, in such case the customer will not be charged for the visit. The technician proceeds to perform the service if no material such as spare parts is needed (ASSA ABLOY Entrance Systems n.d, a).

3. Material Ordering
   If the service technician requires materials when performing the service. One of two scenarios will occur. Every service technician keeps a small stock of spare parts in the service truck. Therefore, either the required material is kept in the truck or it will have to be ordered. In a situation where material needs to be ordered the technician will fill out a material order form and the order needs to be approved. Once the order is approved the material will be ordered by the local service manager or material function and the order confirmation is sent to the customer. The follow-up visiting date will be aligned with the delivery date of the material (ASSA ABLOY Entrance Systems n.d, a).

4. Finalization/Closing
   Once the required material is delivered the service technician will revisit the customer on the follow-up date and perform the required service (ASSA ABLOY Entrance Systems n.d, a).

5. Invoicing
   Once the service order is complete the invoice will be performed. The customer's contract is checked to see which costs are included and which will be invoiced. Once the contract has been established, the material costs are also checked. If the service order was considered a warranty issue, no invoicing will be carried out (ASSA ABLOY Entrance Systems n.d, a).

According to Hill & Hill, a typical characteristic of the non-repetitive service delivery systems is a rather unspecified delivery system, which correlates with the AAES case. As seen in Figure 4.3. AAES current service delivery system is relatively simple to cope with the high flexibility required to perform all kinds of services to a vast variety of products. Which explains why AAES has kept their service delivery system uncomplex until this day. However, as discussed in chapter 4.2. AAES has all the attributes required to manage to transform the current service delivery process.

4.3.1 Common Errors

There is a small number of errors that are frequently recurring. These errors are typically characterized by a low degree of complexity and can therefore be resolved via phone, i.e. when the customer first calls the help desk (Service Manager IDS SE & Service Sales Manager, 2020 digital interview, 26 March). The three most frequently occurring cases are the following:

- **Blocked photocell**
  Blocked photocell is an error occurring when the machine operator blocks the entrance system with an external object. When a device photocell is blocked, the device will try to close itself six consecutive times. If all tries are unsuccessful the device will lock itself in a fully open position. Uneducated customers tend to gravitate towards this solution for keeping the device open for an extended duration of time. The error could easily be resolved by removing the object blocking the photocells and resetting the device (Service Manager IDS SE Service Sales Manager, 2020 digital interview, 26 March).

- **Disengaged engine**
  Disengaged engines are an error occurring when a machine operator disengages the port and does not engage it correctly. Resulting in a situation where the drive shaft of the device is disengaged from the motor which drives the port upwards or downwards. Uneducated machine operators also tend to gravitate towards this solution for keeping the device open for an extended duration of time. The error is easily resolved through a service technician pulling gently in the port to engage the driveshaft and the motor (Service Manager IDS SE Service Sales Manager, 2020 digital interview, 26 March).

- **Loss of power / current failure**
  The loss of power error occurs when a significant external power dip or power loss occurs. The device goes offline and will not be operational until the power is restored and the device is powered on. The error is therefore easily resolved by the service technician simply restoring the power for the device (Service Manager IDS SE Service Sales Manager, 2020 digital interview, 26 March).

The frequently occurring breakdowns are more exactly described as machine failures due to external factors. The frequency which they occur proves that the customers are missing a strategic relation towards the device. It is an entrance system, when it is operational the customer does not recognize its existence. However, when it's no longer operational it causes significant complications for the customers. Customers often lack the expertise to be able to resolve the issue themselves, and therefore contact AAES which are obliged to perform reactive service visits for this kind of failure. The urgency of the errors is often high and requires AAES to be agile and perform reactive service quickly. If the errors occur in inconvenient time periods such as mornings and nights, AAES loses profit resolving these, since the operational costs within these time periods are greater than the revenue generated (Service Manager IDS SE Service Sales Manager, 2020 digital interview, 26 March).

4.3.2 Remote Service Concept

AAES Netherlands has developed the concept of remote services to counteract the negative financial impact of the frequently recurring breakdowns. Remote service is a concept where the customer receives 24/7 support, the customer can call AAES and report a breakdown of any sort. However, if AAES deems it suitable for a remote service the customer will receive assistance within an hour. The customer receives support virtually and no service technician travels to the customer facility. Service technicians give the customer instructions on how to perform the service themselves. It is an efficient concept that enables AAES to be more agile and fix the minor breakdowns more efficiently (UX Interaction / UX Researcher & UX Writer / UX Interaction / UX Researcher, 2020 digital interview, 26 March). However, the concept comes with some flaws. It is not clearly defined who is responsible if an accident occurs and someone gets hurt when the customer performs the service under AAES instructions. There is also no clear definition of who is responsible if the device is damaged during the remote service. Furthermore, it is not clear how the invoicing process is carried out for these kinds of services. Due to these flaws and the lack of infrastructure to implement the concept, AAES Sweden does not deem it appropriate to implement within a short time horizon. However, it is a hot topic for a later time-horizon when greater insights can be derived from the IoT data (Service Manager IDS SE Service Sales Manager, 2020 digital interview, 26 March).

All flaws aside, the concept of remote service is an agile and efficient way to fix the commonly occurring errors discussed in section 4.3.1. It is these simple errors that require little to no service education to fix, that are most likely to be impacted the most from this concept. The perceived customer value will increase with this solution, customers do not want to be billed 10 000 Swedish crowns for AAES to simply pull the emergency brake or perform other similar simple actions. Therefore, the issue of invoicing must be clearly resolved and standardized for this concept to be financially viable (Service Manager IDS SE & Service Sales Manager, 2020 digital interview, 26 March).

Even though AAES will miss out on the revenue stream generated by these errors, the increased customer satisfaction the concept of remote service brings can be seen as a trade-off. It would strengthen the AAES brand and create greater long-term customer relationships which incentivize the customers to keep AAES as their preferred service provider (Technical Support Service, 2020 digital interview, 26 March).

4.4 Concept of IoT-based Service Delivery Process

Since the development and implementation of the connected devices have prolonged, departments within AAES have developed a concept for the IoT-centric service process. The concept has been mapped and visualized in Figure 4.4. It is currently not used and is continuously being developed and refined. However, it features the concept of remote service which is currently used in AAES Netherlands (UX Interaction / UX Researcher & UX Writer / UX Interaction / UX Researcher, 2020 digital interview, 26 March).

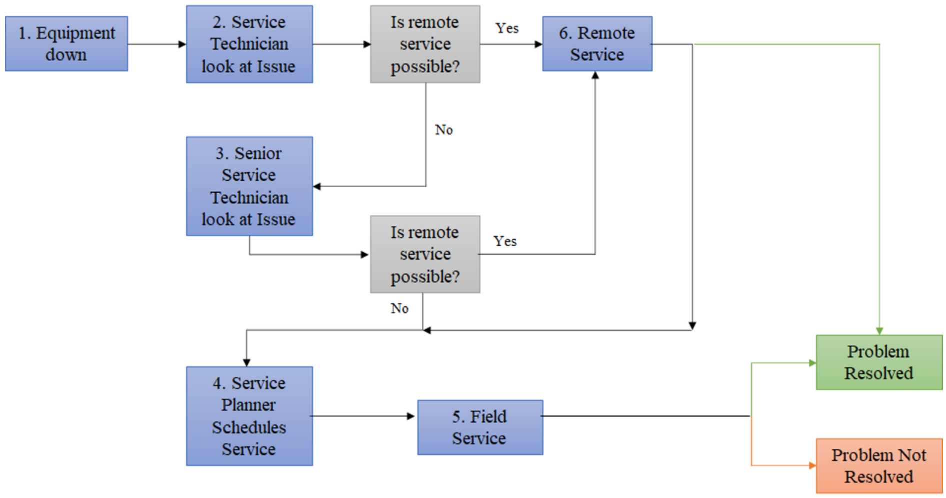


Figure 4.4: Visualization of the IoT-based Service Delivery Process

1. **Equipment down**
   The service process begins through AAES receiving information that a certain device no longer is operational. This information is received through different channels. Customers can call to AAES helpdesk and inform the service department that a device is down. However, some customers choose to inform AAES via email. While some customers use a door management system that automatically informs AAES when a breakdown has occurred (ASSA ABLOY Entrance Systems 2020, f).

2. **Service technician look at issue**
   After receiving information that a device requires service a ticket is created and a service technician is assigned to examine the issue. The technician first examines the possibility of resolving the problem remotely. It is common that service issues can be resolved remotely and it is therefore prioritized. it is not possible to resolve the issue remotely, the technician reviews the possibility of customer remote service (ASSA ABLOY Entrance Systems 2020, f).

3. **Senior service technician look at issue**
   If it is not possible to resolve the issue remotely, the case is transferred to a more experienced senior service technician. With more experience, the senior technician reviews the case once again to determine whether or not the issue can be resolved

remotely (ASSA ABLOY Entrance Systems 2020, f).

4. **Service planner schedules service**
   If the senior service technician determines that on-site service is required the matter is sent to a service planner. Who schedules when in time a field service technician will conduct the service, a time and a date is set for the maintenance activity (ASSA ABLOY Entrance Systems 2020, f).

5. **Remote service**
   When a service technician determines that an issue can be resolved remotely, remote service is performed (ASSA ABLOY Entrance Systems 2020, f).

6. **Field service**
   At the scheduled time a field service technician will travel to the facility and perform the needed service (ASSA ABLOY Entrance Systems 2020, f).

5 Analysis of Possible Service Solutions

This chapter focuses on analyzing AAES service business, the market on which it operates, and the possible improvements and changes predictive maintenance may bring. The chapter begins with a market analysis that thoroughly reviews the order-winner and qualifiers along with AAES current performance for each segment and what change predictive maintenance would bring. Thereafter follows a customer segmentation and an analytical hierarchy process to decide the best fitted maintenance type for AAES current situation. Later, focusing is applied to the current service delivery process to analyze how it can be improved. Lastly, the IoT-centric business model from the literature review is implemented from a predictive maintenance perspective to investigate its possibilities.

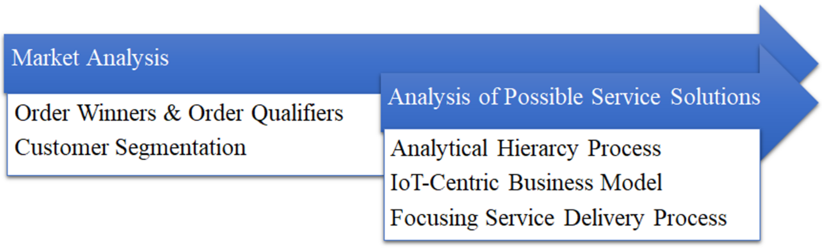


Figure 5.1: Workflow for the organizational analysis

5.1 Market Analysis

The following chapter focuses on the market on which AAES service business operates.

5.1.1 Order Qualifiers & Order Winners for After Sales Service of Entrance Systems

Hill & Hill's model for factors reflected in a service delivery system is well suited for identifying what the customers actually want and need from the service business, and to decide which factors should be at the core of the development of a predictive algorithm.

According to Hill & Hill, the order winner centralizes around unique skills and expertise while the order qualifiers centralize around price for these types of service delivery systems, namely systems based on non-repetitive services. A fact which also has been confirmed through qualitative interviews with AAES executives. Hence a predictive-based service process is well suited for AAES current position since it would allow AAES to offer these unique skills required to gain purchases. Furthermore, according to Hill & Hill the increase in expertise results in the price of the delivered service becoming less important for the offering. Allowing AAES to charge a higher price for the newfound services.

Further order qualifiers and order winners for AAES service business were identified through digital interviews (Technical Support Service, 2020 digital interview, 26 March), (Service Manager IDS SE & Service Sales Manager, 2020 digital interview, 26 March). These have been visualised on the following pages in Table 5.1. and Table 5.2. along with a review of AAES current performance in the different attributes, along with the possible changes a predictive service delivery system would yield in the different attributes.

Table 5.1: Review of AAES current performance, and changes a predictive service delivery system would yield within identified order qualifiers

Order Qualifier	Review of Current Performance	Predictive Maintenance Performance
Price	Offers a competitive price.	May yield a significant increase of price related to a new pricing system based on delivered uptime.
Expertise	27 years of service experience.	The amount of expertise will not change. However, the new product would showcase a higher perceived experience in the eye of the customers.
Brand & Products	Well-established brand as well as strong and stable products. Assa Abloy's strategy has been acquiring well-known- and established brands with strong products.	A predictive-based service business will strengthen the AAES brand and enhance the functionality of their products.
Commercial Factor	Currently owns the majority of the after-sales service market. Therefore AAES acts as the benchmark for after-sales services within the business.	A fully predictive service business will increase the overall market share since it correlates with customer needs.
Company Size	Currently the largest service providing company available on market by a significant margin. Customers tend to seek a service provider with a stable economic foundation.	AAES will remain the largest service provider.
Geographical Location	Covers the entire market.	The geographical covering will not change due to predictive maintenance.
Certification	Service technicians are certified to cover all possible breakdowns.	Due to the predictive algorithm, the need for educated and certified service technicians will decrease.

Table 5.2: Review of AAES current performance, and changes a predictive service delivery system would yield within identified order winners

Order Winner	Review of Current Performance	Predictive Maintenance Performance
Availability	The availability is high, there is a fleet of 185 technicians ready to be dispatched to a reactive service. Customers can digitally report breakdowns to AAES 24/7.	Increased availability, predictive-based maintenance allows for better disposal of technicians' time. Therefore, more technicians are available.
Service Delivery Reliability	High reliability, customers always receive service when reporting a breakdown.	Significantly increased reliability as a result of the predictive algorithm. AAES will preventively ensure a higher uptime towards customers. The need for reactive service visits will decline. Which correlates to the customers' need for a functional entrance system.
Service Delivery Speed	Medium to high delivery speed, usually resolves reactive services within 24 hours. Some cases may require more time.	Increased service delivery speed due to elimination of non-valuable adding activities and increased scheduling. Preventive service activities will increase, resulting in negative delivery speed. The devices need for reactive service visits will decline.
Relationship and Trust	High trust between service technicians and customers. Furthermore Assa Abloy's procuring strategy yields a high trust for the companies within the ASSA group.	Personal relationships between service technicians and customers will remain the same while the trust between the AAES brand and customers will increase, due to the innovative nature of the product.
Understanding of Customer Needs	High understanding of customer needs but fails to deliver on some points.	The perceived understanding will increase since implementing a predictive algorithm shows an understanding of customer needs.

5.1.2 Customer Segmentation

AAES is the leading service provider within the after-sales service market for entrance systems. Therefore, they provide service to a large variety of customer segments. Customer segment-specific order qualifiers and order winners have been identified. Four main customer segments were identified, where the chasm between the segments depends on the customer facility location and customer company size (Service Manager IDS SE Service Sales Manager, 2020 digital interview, 26 March). The following section focuses on the different customer segments and how the order winners and qualifiers differ between the two

5.1.2.1 Larger sized customers

For the larger-sized customers, the geographical coverage and the service provider company size tend to be weighted heavier. A typical characteristic for this segment is that large corporations tend to use a single service provider for their entire corporation. Hence they need a service provider that possesses the required geographical coverage to provide service to all of their facilities and a service provider of such a large size to manage all the facilities. Related to the company size of the service provider, these corporations need a service provider that is certified to execute all kinds of services, has the power of managing a large number of facilities and all the administrative work related to this (Service Manager IDS SE Service Sales Manager, 2020 digital interview, 26 March).

Relationship and trust tend to matter less for this customer segment, the customer only wants to ensure that their entrance systems are functioning properly. Furthermore, the price of the provided services tends to be less important since these customers are characterized by having a strong financial situation.

5.1.2.2 Smaller sized customers

For this segment, the relationship and trust between customer and service provider, the size of the service provider and price are important. The smaller customers tend to demand a service provider on which they can rely and are in some cases prepared to sacrifice the service delivery expertise for higher trust. This derives from the fact that the smaller customers only have a few entrance systems and are therefore more free to choose between different service providers. Since these customers are relatively small, their financial situation is not as strong as the larger customers. Therefore, the price of the service offering and the size of the service provider tend to be of larger importance. The size of the service provider is important since the customers want to establish a long-term relationship with the service provider and want to ensure that the service provider will not go bankrupt during this time period (Service Manager IDS SE Service Sales Manager, 2020 digital interview, 26 March).

5.1.2.3 Customers located in highly populated areas

For this segment, the security and service delivery speed is the most crucial feature. Since the devices are located in highly populated areas it is crucial that they do not remain broken for an extended time period, since unauthorized personnel can gain access to the customer facilities. Therefore the service delivery speed is the most important attribute for this segment (Service Manager IDS SE Service Sales Manager, 2020 digital interview, 26 March).

5.1.2.4 Customer located in less populated areas

For customers in less populated areas such as in the outskirts of cities or smaller districts, the relation and trust between customer and service provider are more important. Just as the smaller-sized customer segment, the customers want to build a long-term relationship with their service provider and therefore need a service provider on which they can trust (Service Manager IDS SE Service Sales Manager, 2020 digital interview, 26 March).

There are four different customer segments, all demanding different features from AAES. In the current situation, AAES provides all the segments with their desired attributes. However, in AAES current situation they are better suited to handle the larger cooperation rather than small. This derives from the fact that AAES currently is the largest actor in the after-sales service market and therefore they are the benchmark service provider within the business. This results in that AAES naturally becomes more suitable to handle the large customer segment rather than the smaller one. They are one of the few actors within the market who has reached the required size to deliver the geographical coverage required to handle these customers. However, this does not mean that AAES does not fulfill the order qualifiers and order winners of the other segments. Since their service business is better suited for larger customers, their needs should be at the core of the development of service business improvements.

5.2 Analysis of Service Delivery Processes

The following chapter focuses on analyzing the current maintenance situation of AAES, possible improvements and changes predictive maintenance may bring, and how predictive maintenance should be implemented within the organization.

5.2.1 Analytical Hierarchy Process of Different Maintenance Concepts

AAES currently stands at a pathway. They have implemented the IoT infrastructure needed to develop preventive maintenance algorithms such as: condition-based, cycle-based and preventive maintenance. AAES now needs to decide in which maintenance direction to move forward in, a decision that will highly impact the service business ahead of time. A complex decision has been organized and analyzed through the AHP model. The four different maintenance concepts which have been analyzed through AHP are time-based, cycle-based, condition-based, and predictive maintenance.

Time-based maintenance

The time-based approach is based on planning maintenance activities on a time-based schedule. Where the time-period between the maintenance activities is based on historical operating and maintenance data. Therefore, the maintenance activities are made periodically in time whether it is needed or not.

Cycle-based maintenance

The cycle-based approach schedules maintenance activities based on process iterations. The goal of cycle-based maintenance is to approximately anticipate when in time a certain device or component will break down based on the number of cycles a certain process is carried out within the device and plan the maintenance activities accordingly.

Condition-based maintenance

Condition-based maintenance is an approach where service activities are planned based on data analysis of the observed condition of a device or component. The degradation rate of a device or component increases towards a threshold level and the probability of a failure is greater the closer one gets to the threshold level. This is utilized in CbM by monitoring the condition and creating models of the degradation process. Conditioning data is gathered with the use of various types of sensors.

Predictive maintenance

Predictive maintenance is the concept of intelligent monitoring of connected devices with the intention to prevent future breakdowns before they occur. It is an automated process using advanced signal processing technology based on machine learning, neural networks, etc. to predict with high accuracy when in time a given device will break down.

There are several different decision criteria which impact the decision ahead. The following six decision criteria have been developed to gain maximum understanding of the current situation and to enable a thorough analysis of the decision.

- *Low Risk of False Negative*
- *Low Risk of False Positive*
- *Ability to Reduce Costs*
- *Simplicity of Development*
- *Ease of Implementation*
- *IoT Infrastructure Requirements*

Below follows an explanatory part of the different decision criteria, all criteria are individually explained.

Low Risk of False Negative

The parameter is defined as the risk that a maintenance algorithm predicts a false negative. The algorithm predicts that a breakdown will not occur in a case where a breakdown occurs, and therefore misses a breakdown. This results in a case where AAES will need to perform a reactive service visit for a no longer operational device. A high score for this parameter is defined as “the maintenance algorithm has a low risk of predicting false negatives”.

Low Risk of False Positive

The parameter is defined as risk that a maintenance algorithm predicts a false positive. The algorithm predicts a positive breakdown alert in a case where a breakdown does not occur, and therefore gives a false prediction of a breakdown. This results in a case where a reactive service visit is carried out for an operational device that is in no need of service. A high score for this parameter is defined as “the maintenance algorithm has a low risk of predicting false positives”.

Ability to Reduce Costs

Ability to reduce costs refers to a maintenance algorithm ability to reduce overall costs within the service business. There are several factors that impact the decision criteria. To what extent does the maintenance algorithm resonate with the customers’ needs and therefore their willingness to procuring the product? Will the volume of sales be sufficient enough to reduce the overall costs? The data-management costs will increase with more advanced maintenance algorithms, and therefore larger sales volume will be needed to succeed. A high score for this parameter is defined as “the maintenance algorithm possesses a high ability to reduce costs within the service business”.

Simplicity of Development

The parameters refers to the level of simplicity in developing the algorithm. How protracted will the process of developing the maintenance algorithm be given AAES current situation. How different is the maintenance algorithm compared to AAES current model and which development activities needed for this maintenance algorithm are already completed. A high score for this parameter is defined as “the maintenance algorithm is simple to develop”.

IoT Infrastructure Requirements

The parameter referes to the level of IoT Infrastructure required for developing and maintaining a maintenance algorithm. This includes all hardware and software technologies related to collecting, saving, transmitting and managing the necessary IoT data. A high score for this parameter is defined as “the maintenance algorithm has low IoT infrastructure requirements”.

Ease of Implementation

The parameter is refers to how difficult a maintenance algorithm is to implement and get operational within AAES current service process. What significant change of the current service business internal processes and information flow is needed to implement the maintenance algorithm. Will employees affected by this change require education on the new maintenance algorithm. A high score for this parameter is defined as “the algorithm requires little to no change on the current service business”

To quantify and find the relative weights between the decision attributes three different seminars were held, where different management- and development-level employees were asked to compare each criterion pairwise against all the others. The seminars were held to gain profound insights into AAES needs for the given technology at different levels of the organisation and to provide a deeper analysis of the decision. The management-level employees provide a better understanding of the organisation’s needs and goals with the technology while the development-level employees work with the technology on a daily basis and therefore provide deeper insights into what developers and service-technicians value within this technology. The respondents were asked to express the relative importance by the following expressions:

9 = "Extremely preferred"
7 = "Very strongly preferred"
5 = "Strongly preferred"
3 = "Moderately preferred"
1 = "Equally preferred"

The intermediate values (2,4,6,8) provided additional levels of discrimination.

5.2.1.1 Findings

Multiple digital workshops were held with individual experts in different fields, all employed by AAES. During the workshops, the individual experts within the decision field were consulted to determine the relative magnitude between the different factors through pairwise comparisons.

First Seminar

The first seminar was held in collaboration with AAES IoT Platform Manager and Senior Program Manager. Both are executive level employees with the intention of getting an organizational point of view when determining the relative magnitude of the decision criteria. From the first seminar the following relative magnitudes between the decision parameters were determined (Senior Program Manager IoT Platform Manager, 2020 digital workshop, 16 April).

Table 5.3: Matrix of the first seminars relative magnitude between the different decision parameters

Decision Criteria	False Negative	False Positive	Ability to Reduce Costs	Simplicity of Development	IoT Infrastructure Requirements	Ease of Implementation
False Negative	1	5	0,2	0,333	0,333	0,333
False Positive	0,2	1	0,2	0,333	0,2	0,333
Ability to Reduce Costs	5	5	1	5	5	3
Simplicity of Development	3	3	0,2	1	1	0,333
IoT Infrastructure Requirements	3	5	0,2	1	1	0,333
Ease of Implementation	3	3	0,333	3	3	1

As seen in the table above, the organizational related criteria such as Ability to Reduce Costs and Ease of Implementation were highly weighted. This due to the fact that they highly correlated with the underlying purpose of the transformation of the service delivery process, and due to the experts having executive level employment (Senior Program Manager IoT Platform Manager, 2020 digital workshop, 16 April). From the table of relative magnitudes an analytical hierarchy process was carried out, resulting in the following results.

Table 5.4: Matrix of the first seminars results

Maintenance Type	False Negative	False Positive	Ability to Reduce Costs	Simplicity of Development	IoT Infrastructure Requirements	Ease of Implementation	Sum (Σ)
Predictive	0,04763	0,02465	0,23533	0,00524	0,00651	0,00890	0,32825
Condition-based	0,02248	0,01164	0,11108	0,01237	0,01504	0,02412	0,19674
Cycle-based	0,01040	0,00538	0,05141	0,03033	0,03279	0,05661	0,18692
Time-based	0,00486	0,00251	0,02400	0,06518	0,07393	0,11762	0,28810
Sum (Σ)	0,09	0,04	0,42	0,11	0,13	0,21	1,00

Second Seminar

The second seminar was done in collaboration with AAES Software Developer and Technical Support Service. The attendees have deep knowledge of the current IoT implementation and service organization, which they work with on a daily basis. This seminar was held with the intention of widening the scope of the first seminar and gaining greater insights into the development and implementation phase of a maintenance transformation. From the second seminar the following relative magnitudes between the decision parameters were determined (Software Developer & Technical Support Service, 2020 digital workshop, 22 April)

Table 5.5: Matrix of the second seminar's relative magnitude between the different decision parameters

Decision Criteria	False Negative	False Positive	Ability to Reduce Costs	Simplicity of Development	IoT Infrastructure Requirements	Ease of Implementation
False Negative	1	0,1111	0,3333	0,5	9	1
False Positive	9	1	0,25	1	0,2	1
Ability to Reduce Costs	3	4	1	5	6	0,2
Simplicity of Development	2	1	0,2	1	3	1
IoT Infrastructure Requirements	0,1111	5	0,1667	0,3333	1	0,3333
Ease of Implementation	1	1	5	1	3	1

Even from a development and implementation perspective "Ability to Reduce Costs" was the decision criteria with the highest overall score. The relative magnitudes are overall similar compared to the first seminar. This implies that the two perspectives are relatively similar in nature. From the relative magnitude matrix an analytical hierarchy process was carried out, resulting in the following table.

Table 5.6: Matrix of the second seminar's results

Maintenance Type	False Negative	False Positive	Ability to Reduce Costs	Simplicity of Development	IoT Infrastructure Requirements	Ease of Implementation	Sum (Σ)
Predictive	0,07455	0,09484	0,14327	0,00544	0,00507	0,00954	0,33271
Condition-based	0,03519	0,04477	0,06763	0,01284	0,01172	0,02586	0,19801
Cycle-based	0,01629	0,02072	0,03130	0,03148	0,02556	0,06068	0,18602
Time-based	0,00760	0,00967	0,01461	0,06765	0,05764	0,12608	0,28326
Sum (Σ)	0,13	0,17	0,26	0,12	0,10	0,22	1,00

As seen in the result matrix, predictive maintenance is the favorable direction to move forward within given AAES current situation.

Third Seminar

The third seminar was held with Service Manager IDS SE and Service Sales Manager. The participants possess great knowledge within the areas and sales and complements. Hence their area of expertise well complemented the two previous seminars. The following relative magnitudes were derived from the third seminar.

Table 5.7: Matrix of the third seminar's relative magnitude between the different decision parameters

Decision Criteria	False Negative	False Positive	Ability to Reduce Costs	Simplicity of Develo-pment	IoT Infras-tructure Requirements	Ease of Impleme-ntation
False Negative	1	3	5	7	0,125	0,1111
False Positive	0,3333	1	5	7	0,1429	0,1111
Ability to Reduce Costs	0,2	0,2	1	5	0,1429	0,1429
Simplicity of Development	0,1429	0,1429	0,2	1	0,1111	0,1429
IoT Infrastructure Requirements	8	7	7	9	1	0,3333
Ease of Implementation	9	9	7	7	3	1

The result of this seminar deviated significantly compared to the other results. This is considered to be correlated with the expert's expertise solely within the area of service and sales. Hence the decision criteria related to service and infrastructure support were weighed significantly higher than other criteria. The following results were established from the seminar.

Table 5.8: Matrix of the third seminar's results

Maintenance Type	False Negative	False Positive	Ability to Reduce Costs	Simplicity of Develo- pment	IoT Infrastructure Requirements	Ease of Imple- mentation	Sum (Σ)
Predictive	0,06340	0,05131	0,02867	0,00118	0,01440	0,01864	0,17758
Condition-based	0,02993	0,02422	0,01353	0,00278	0,03327	0,05050	0,15422
Cycle-based	0,01385	0,01121	0,00626	0,00682	0,07253	0,11849	0,22916
Time-based	0,00647	0,00523	0,00292	0,01465	0,16354	0,24622	0,43903
Sum (Σ)	0,11	0,09	0,05	0,03	0,28	0,43	1,00

As seen in the table, the best direction to move forward within is time-based maintenance followed by cycle-based maintenance and later predictive maintenance.

5.2.1.2 Review of Results

There are a few parameters which impacts the result and credibility of the analysis. Firstly the fact that the selection of interview subjects was limited may impact the analysis. The subjects in this analysis consist of AAES employees which have been involved throughout the thesis. However, the subjects roles and areas of expertise are widely distributed and is considered to gain a fair understanding of the involved departments opinions regarding this decision.

Additionally, since the third results deviated to such an extent from the other two the results from the AHP became difficult to interpret. To better understand the results and establish which of the results are the better choice for AAES current situation further analysis has been performed.

Firstly the average score from each of the maintenance approaches has been calculated, a higher score correlates with the maintenance approach being better suited. As seen in Table 5.9. time-based maintenance is the approach with the highest score. However, this result is highly dependent on the high result from the third seminar, where bias was experienced when determining the relative magnitudes of the decision criterias. In which maintenance- and sale-oriented decision criteria such as ease of implementation and IoT infrastructure requirements were weighed significantly higher than in the previous seminars. This reduces the reliability of the analysis and makes it harder to interpret.

Table 5.9: Score from each seminar along with the calculated average

Seminar / Maintenance Approach	First Seminar	Second Seminar	Third Seminar	Average
Predictive Maintenance	0,32825	0,33271	0,17758	0,28
Condition-based Maintenance	0,19674	0,19801	0,15422	0,18
Cycle-based Maintenance	0,18692	0,18602	0,22916	0,20
Time-based Maintenance	0,2881	0,28326	0,43903	0,34

To neglect the effect of which the biased third seminar entails on the analysis, a ranking analysis was conducted. Where the overall score of the maintenance approaches from the different seminars were calculated. The score of the different maintenance approaches is summarized in Table 5.10.

Table 5.10: Visualization of the scores from each seminar along with the calculated total score

Seminar / Maintenance Approach	First Seminar	Second Seminar	Third Seminar	Total Points
Predictive Maintenance	1	1	3	5
Condition-based Maintenance	3	3	4	10
Cycle-based Maintenance	4	4	2	10
Time-based Maintenance	2	2	1	5

When one calculates the total score from the different seminars, predictive maintenance and time-based maintenance both become the best suited maintenance approach for AAES current situation. Before the calculation time-based maintenance had the overall highest average score of the different maintenance approaches. However, it is considered that the relative magnitudes of seminar three was influenced by bias and therefore valued too high. Resulting in a favourable situation for time-based maintenance. Therefore, the result is interpreted as predictive maintenance being the best maintenance approach for AAES current situation.

Additionally, the result could also imply that the best suited maintenance direction as visualized in Table 5.9 is the method which they are currently using, i.e. time-based maintenance. One can not further implement what they are currently using, hence the second best alternative, i.e. predictive maintenance, should be pursued. This could imply that time based maintenance is better suited for a short time-horizon while predictive maintenance will become more relevant for a longer time-horizon. Although it is clear from the AHP analysis that predictive maintenance is a good maintenance approach to consider moving forward.

5.2.2 IoT-Centric Business Model for Predictive Maintenance

This section aims to provide a thorough analysis of the IoT-centric business model presented in section 3.2.2. by Gassman et al. Each of the four categories defined within the model has been analysed individually, with the predictive-based service process as the core. The IoT-centric business model and the different categories are visualised on the following page in Figure 5.2.

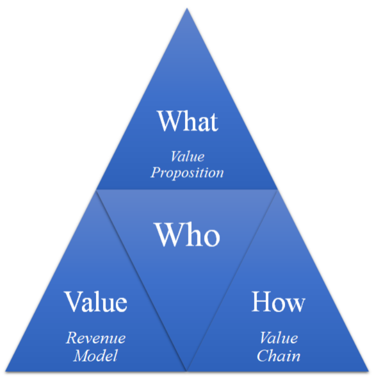


Figure 5.2: The IoT-centric business model

5.2.2.1 What

In this case, the product offered is predictive maintenance as a service offering, i.e. the theoretical predictive maintenance algorithm developed from the generated IoT data from AAES connected devices.

5.2.2.2 Who

The scope of this thesis is delimited to the IDS business area within the industrial business segment. AAES current IoT infrastructure within IDS is limited, where the connected doors consist of the devices with either the 950, 950D or the MCC control unit. Furthermore, AAES offers three different service types of service contracts, namely: Gold, Silver and Bronze.

Gold contract includes all the expenses related to service and maintenance visits. However, due to the current ERP system, the majority of the customers within the IDS business segment use the bronze contact. Another aspect to consider is whether or not customers are prepared to change service contracts because of the new service process. The chasm between the Gold and Silver contract is small relative to the chasm between Gold and Bronze. Hence, the added value the PdM service model brings may incentivize customers to upgrade their current service contract. Therefore, the targeted customer segment is further reduced to customers within IDS that own a 950, 950D, or a MCC control unit regardless of their service contract.

The main customers targeted are the customers with a bronze contract and use AAES as their only service provider, since they represent the majority of the customers. However, some of these customers are using third-party service providers rather than AAES. The added value from the PdM service model may also incentivize these customers to upgrade their contracts and use AAES as their only service provider. The third-party service provider may be cheaper, but they will not be able to offer the same expertise and service efficiency as AAES new PdM service model.

Furthermore, AAES has a large base of legacy products installed within various industries. Legacy products are devices installed before the development and implementation of the IoT control units that are compatible with the developed control units. Hence, customers who own these products can also be targeted by a predictive service delivery model. Therefore the targeted customer segment is extended by customers who currently own and use any of these legacy products. The final targeted customer segment is compiled as the following:

Customers within the IDS business area that owns a device with either a 950, 950D or a MCC control unit and possibly customers who own any of the legacy products that are upgrade compatible. Furthermore, customers are targeted regardless of service contracts. The targeted customers mainly use AAES as their only service provider. Furthermore, customers with a Bronze service contract that uses a third-party service provider will also be targeted.

5.2.2.3 How

In the case of offering predictive maintenance as a service offering, the how dimension is defined as the activities and processes that are related to the building and distribution of the predictive-based service process. To make the delivery of the new predictive-based service process as efficient as possible, it is important that these activities and services are orchestrated together with relevant resources and capabilities.

The how-dimension is divided into sections of activities that are intended to be executed in chronological order. The sections contain the identified activities and processes required to build and deliver the predictive-based service process.

Complete predictive based algorithm

The first step of the how-dimension is centralized around continuing and completing the development of the predictive-based algorithm. Activities related to this section is to define and implement valuable data attributes missing within the IoT-infrastructure. According to Lee et al., Hyundai Motors has developed a predictive maintenance system called AI Car Diagnosis Systems, which through AI diagnose vehicle faults based on noise and vibration analysis to determine engine abnormalities. The algorithm is deemed to be of high performance and has an accuracy of 87.6% when predicting breakdowns. This state-of-the-art algorithm is based on noise and vibrations, two vital data attributes that AAES current IoT control unit could benefit from. Lee et al. argues that it may be possible to further improve the system's accuracy by combining sound, vibration, temperature, and other factors. Furthermore, Lee et al. states that a system analyzing these features could be applied to all mechanical things, not just cars. Therefore it should be a conceideration of AAES to extend their current IoT control unit to capture both sound and vibration data.

Furthermore, it is crucial for AAES to deliver the features that the customers actually need and demand. Therefore, AAES needs to ensure that the predictive-maintenance algorithm assists AAES service business in fulfilling the identified order winning criteria from Section 5.1.1. This is achieved by centralizing the development of the predictive algorithm around these criteria. The order winners follow:

- *Availability*
- *Service Delivery Reliability*
- *Service Delivery Speed*
- *Relationship and Trust*
- *Understanding of Customer Needs*

The algorithm needs to establish a fine balance between functionality and innovation. AAES needs to acknowledge and emphasize that it is the delivered products and services that sell, not the innovation. Hence it is crucial to implement the order winning attributes and not innovate and digitalize just for the cause of innovation. The purpose of the innovation is to ensure that AAES delivers 100% uptime to their customers and that the devices are functioning properly, not to develop a highly technological and complex product since it's not required by customers.

Completing the development of the predictive algorithm is a large and complex activity. Therefore, it is favorably broken down into smaller activities. The proposed method is to first finish the development for the 950, 950d, and MCC devices, since these are the product categories where the IoT implementation has come the furthest. Once an arbitrary algorithm with significant performance is developed for these products, the same model can be tweaked and reversed engineered to better fit the other product categories.

Make the predictive algorithm interface intuitive and easy to interact with for customers

Once the predictive algorithm is implemented within the service business the algorithm needs to be communicated to customers in an intuitive manner. Three approaches are identified for executing this.

The first approach is based on integrating the interface of the predictive algorithm within the customers' own facility management system. Customers will then be able to easily interpret the state of a device and identify when the next service is scheduled. The integration can increase the efficiency of the customer's own facility by more easily informing customers of devices in a critical state. If the integration is done well, the new system will motivate customers to use AAES as their one and only service provider. However, this approach is highly complex since customers rarely use the same facility management systems. Customers tend to use an on-site solution tailored for their specific needs. Hence a large number of resources and time will be spent executing this implementation for a large variety of systems.

The second method is based on a more standardized approach, that is AAES develops their current IoT API in such a way that customers easily can interpret the state of their device and identify when the next service is scheduled. Since all affected customers will use the same API all customers will use the same solution. Resulting in the integration between the customer and AAES system will only be carried out once. Hence not as much resources and time will be needed for the approach. However, the customer level of motivation to use AAES as their only service provider will not be as high. Customers in general tend to have a low motivation for learning to use a new application. A rule which also applies to service-delivering organizations, since they are obligated to educate the customers on how to properly use the new system.

The third approach requires the least amount of time and resources. This approach is based on utilizing AAES current IoT dashboard with no further development. The customers will gain access to interfaces where they can see the state of their own devices to the extent that the dashboard currently allows them to. This approach will be the fastest of the three and is recommended to use in a short time-horizon, preferably when the predictive algorithm is initialized.

As the product becomes more established and gains a greater customer base AAES should move in the direction of the second approach since it correlates better with the customers' needs and entails greater customer experience and satisfaction.

Digitalize internal processes to be more efficient

To maximize the use of the predictive algorithm, AAES needs to increase the digitalization of their internal processes. The majority of the service technicians' administrative work is carried out through long internal processes, work such as material order and invoicing management. The service technicians already possess the required technology to digitize these tasks. The majority of the administrative tasks could easily be made through fingerprint approval from their individual tablet (Service Manager IDS SE Service Sales Manager, 2020 digital interview, 26 March).

Service technicians focus more on sales

Once the predictive algorithm is developed and implemented the need for educated service technicians will decline as in section 5.2.2.4. The service technicians will only need to be educated on the specific service technique that is required for the breakdowns to which they are dispatched. Hence there is more time for the technicians to focus their time on sales. A portion of the time that originally would be disposed of on service education can now be spent focusing on selling techniques. Thereafter, once a service has been carried out the service technicians shall communicate the newfound algorithm and service improvements towards their customers, regardless of customer service contract. In the cases of smaller towns, the customers have a fixed service technician who solves all their service activities. Therefore, the technicians maintain a valuable relationship with the customers. This relationship can be utilized through the service technicians by communicating the new possibility of delivering higher uptime through predictive maintenance from a sales point of view. Since the trust between customer and service technician is high a simple sales pitch can highly motivate the customers into buying the new service. However, this can be utilized for other customer segments as well. In larger cities, there is a fleet of service technicians who are dispatched to a pool of customers. Where the experienced technicians will have established a relationship with a large number of customers, since they have been dispatched to a large number of cases. This relationship can be utilized in the same way.

Other value-adding activities such as seminars and workshops can also be used to motivate customers into upgrading service contracts. The value-adding activities should be performed by an employee from AAES with a good relationship towards the receivers, such as the service technicians described above. The seminars and workshops should centralize around the increased perceived customer values and added benefits the predictive algorithm brings. As well as how to properly use the devices provided by AAES, and how unsuitable behavior leads to breakdowns. The workshop leader can also inform customers on deviating behavior which the algorithm studies, for them to gain a deeper understanding of the state of the devices.

Align marketing and service business

Once the service business is transformed to be predictive based it is crucial that AAES align their marketing division with their new service delivery system. Their current service delivery system is mainly reactive with some preventive cases and the marketing is designed accordingly, focusing mainly on price and their experience within after-sales services. Therefore the marketing and service are aligned. However, once the delivery system is transformed they are not. The service delivery system is now predictive while the marketing is designed for a reactive service delivery process. Worst case scenario the customer perception of AAES will be incorrect and their new innovative product is not communicated. Therefore, it is important for AAES to align its marketing division with the new service delivery system. For the predictive service delivery system AAES should focus their marketing efforts on communicating their unique skills in the form of the predictive delivery system and their expertise within the service business. They should focus on rebranding their service business. Branding themselves as an innovative service provider with strong products, where IoT and machine learning should be at the core. Both the current situation and desired situation, along with the required alignment have been mapped in Figure 5.3.

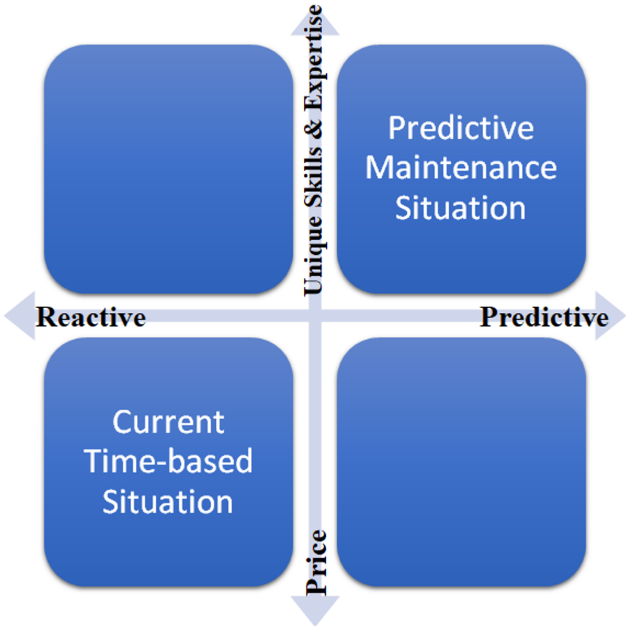


Figure 5.3: Proposed alignment of marketing and the transformed service business

5.2.2.4 Value

The value-aspect describes why the business model is financially viable and how it generates value. This chapter explains why the predictive-based service delivery system is financially viable through four different approaches. The first approach is based upon the fact that the new service-model will enable AAES service business to reduce its operating costs by reducing the number of reactive service visits. The second approach focuses on the possibility of reducing personnel- and material costs due to the need for educated service technicians will decrease as the predictive algorithm performance grows higher. As well as the predictions that indicates an approximate understanding of the needed material for a service visit, allowing for better material planning. The third approach centralizes around introducing a new financially viable pricing system. Where the price is based on the delivered uptime for each customer. The fourth approach centralizes around the fact that a predictive-based service model will increase perceived customer value in a variety of different ways. The added value will encourage AAES customers to pay a higher price for the newly established service-process, which will increase the revenue of the service business.

Reduction of Reactive Service Visits and Operating Costs

A fact which advocates for the first approach is that the predictive algorithm can significantly reduce the number of reactive service visits. The reactive service visits make up for the majority of the operating costs within AAES service-business. The fact that all reactive service visits are unplanned results in a short scheduling time, often resulting in a poor disposition of the service technicians' time.

The predictive algorithm will send an alert of devices that are in a critical state, devices that are soon to break down but are still operational. As mentioned in section 3.1.3.1 this results in bonus time (see Figure 3.1), the time between prediction point and the earliest created maintenance service request, which is the maximum time AAES can save compared to the current reactive maintenance approach. Therefore, the prediction model's performance is to some extent dependent on the service planner. The faster a service-ticket is created after a prediction point, the more time AAES will save. The bonus time will allow AAES to more efficiently allocate their service technicians' time. Furthermore, the enhanced time-management will result in a decrease in operational costs, since less time is required to execute the same amount of service activities. Resulting in AAES achieving a significant reduction in operational costs while maintaining the same amount of revenue, hence the predictive service model is financially viable.

Canzio et al. describe that approximately 30% of all industrial equipment currently does not benefit from any sort of predictive maintenance techniques. Instead, these devices utilize periodic maintenance, namely preventive maintenance visits to detect any form of malfunctions or deviations in operating behavior for these devices (Canzio et al. 2017). More specifically, these are made through visual and physical inspections, which is highly similar to AAES current preventive maintenance approach. Furthermore, Canzio et al. clearly state a large chasm in performance between periodical and predictive maintenance. A benchmark study of industry examples states that there were no problems found in the device's daily operations in approximately 70% of the periodic maintenance visits. While this number reached up towards 90% for industries using predictive maintenance techniques

(Canzio et al. 2017). This emphasizes that predictive maintenance techniques significantly can increase the maintenance efficiency of a service delivery system and reduce the total number of failures.

Canzio et al. means that predictive maintenance approaches can increase the number of preventive maintenance visits by 20 percentage points. Before the transformation from preventive to predictive maintenance techniques, periodically represented approximately 70% of all carried out service visits, resulting in reactive service visits representing approximately 30% of all service visits. While using predictive maintenance techniques, preventive maintenance visits represented approximately 90% of all carried out service visits, respectively reactive service visits represented 10% (Canzio et al. 2017). Thus predictive maintenance has the potential to reduce reactive maintenance visits upwards to 66%.

However, for this kind of reduction the algorithm's performance needs to be high. Canzio et al. do not specify the performance of the predictive algorithms within their paper, but to gain a greater understanding of what kind of performance is needed other papers were studied (Canzio et al. 2017).

Lee et al. have done a thorough analysis and mapping of different industry cases that implement predictive maintenance and quality management in their daily operations. One of these cases focuses on Hyundai Motors, which 2017 was the eighth largest car manufacturer. Hyundai has developed a version of predictive maintenance called AI Car Diagnosis Systems, which utilizes AI to diagnose vehicle faults based on noise and vibration analysis to determine engine abnormalities. In an experiment conducted in 2017, the predictive algorithm was benchmarked against 10 noise analysis experts. The noise analyse experts managed to determine breakdowns at an 8.6% accuracy while the predictive algorithm reached an accuracy of 87.6% (Lee et al. 2019).

Furthermore, Durbhaka and Selvaraj implemented a predictive maintenance algorithm for wind turbine diagnostics based on vibration signal analysis. Durbhaka and Selvaraj delimit themselves to focus exclusively on bearings of the rotating machinery within the turbines. Within the paper several machine learning was utilized, however, the best results were found using the Collaborative Recommendation Approach method. Which yielded an accuracy of 93% when detecting machine faults (Durbhaka & Barani 2018).

The predictive techniques reviewed by Canzio et al. were implemented within industries and used on a daily basis (Canzio et al. 2017). Hence, the predictive algorithms used are assumed to be based on state of the art techniques. For AAES to be able to achieve the same results in regards to reactive service visit reduction, the performance of the developed predictive algorithm should be in the range of that of Lee et al. and Durbhaka and Selvaraj. Thus reach an accuracy in the range of 87.6% to 93% or above for determining machine failures.

Personnel- and Material Costs Savings

With a predictive maintenance algorithm AAES need for more extensively educated service technicians will be reduced. The algorithm would provide an indicator of which component within the device is failing. Therefore the dispatches service technician will know their work tasks and the material needed in advance. Meaning the service technician does not need to be prepared for a vast variety of breakdowns as in the current approach. Hence, the predictive maintenance algorithm allows AAES to work with more simple personnel. Since an educated service technician costs AAES 72 000 Swedish crowns more per year than a maintenance technician, a reduction in educated service personnel would yield significant cost savings for AAES service business annually (Service Manager IDS SE Service Sales Manager, 2020 digital interview, 26 March). The potential personnel costs savings from the reduction in reactive service technicians have been summarized in Table 5.11.

As stated in Table 5.11. there is a significant personnel-cost savings potential related to the reduction in need of educated service technicians. The three possible scenarios visualises the savings potentials related to a transformation in the distribution between uneducated and educated service technicians. When redistributing the technicians to a state of 70/30, a 4% reduction in personal costs is observed, that is 30% educated technicians and 70% uneducated technicians. However, the greatest saving potential arises when the total number of service technicians is reduced. A savings potential of 13.7% was observed from a 25% reduction of the educated service technicians, which is visualised in scenario three. Since Canzio et al. means that predict-

Table 5.11: Potential personnel costs savings due to reduction in the need for educated service technicians

Cost	Current Situation	Possible Scenario #1	Possible Scenario #2	Possible Scenario #3
Amount of Service Technicians [SEK]	185	185	163	123
Distribution Preventive vs Reactive	50/50	70/30	57/43	76/24
Preventive Service Technicians [#]	93	129,5	93	93
Reactive Service Technicians [#]	92	55,5	69	30
Cost of Preventive Service Technician [SEK/year]	312000	312000	312000	312000
Cost of Reactive Service Technician [SEK/year]	384000	384000	384000	384000
Total Cost [SEK/year]	64344000	61716000	55512000	40674240
Potential Savings [SEK/year]	-	2628000	8832000	23669760
Potential Savings [%]	-	4,084%	13,726%	36,786%

ive maintenance has the potential of reducing reactive service visits by approximately 66%, the 25% reduction in the need for educated service technicians becomes a plausible scenario (Canzio et al. 2017). Although, the greatest saving potential of 36.8% arises when assuming that the number of educated service technicians can be reduced as heavily as the reactive service visits, namely by 66%.

An advanced predictive algorithm indicates which component of a device has reached a critical state. The indication of which component within the device is failing will yield an perception of the material needed to perform the service. Hence, the service technicians will not need to carry the same amount of spare parts in their vehicles. Resulting in less tied-up capital in spare parts, which increases the asset turnover rate and therefore increases the return of investment accordingly. Furthermore, the algorithm will allow for planning of the technicians' routes since it knows where the devices in need of service are located. Since the vehicles will no longer act as a mobile component safety stock and better possibilities of route planning, the need for cars will be reduced.

New pricing system

One approach in order to make PdM financially viable is to transform the pricing system of the services. Instead of the conventional approach where customers are charged with a fixed price for each delivered service activity or a fixed monthly price for all services, the price should be based on delivered uptime rather than costs. This will imply that the customer is paying for what they are actually using, rather than paying for each delivered service and spare parts.

The how-dimension, regarding how the pricing system should work is a difficult issue. Although a simple and intuitive way of solving this problem would be to charge a monthly price for the delivered maintenance activities. Where the price fluctuates between different price brackets based on the delivered uptime for the past month. The goal of AAES service business is to develop the highest possible uptime.

AAES could offer their PdM in different service-packages based on the priority the customer will get within the service business. If the packages are offered similar to the current service-contracts, the gold contract customers would receive the highest priority and hence the highest uptime for the highest price. Relative the bronze-contracts would receive the lowest priority and the lowest uptime but benefit from lower costs. However there needs to be some kind of cost related to choosing the higher priority contracts since all customers want the highest possible uptime. Without the related costs all customers would choose the best contracts and hence no customer would be prioritized since all customers would be prioritized.

Note that AAES should base the price on the delivered uptime regardless of the priority contract of the customer. If a customer with a gold contract receives the same uptime as a bronze contract the costs of the services would be the same. However, the gold contract customer should receive some kind of compensation for not receiving the targeted uptime related to their contract.

The concept of basing the price on delivered services is not a new concept and has proven to be financially viable. An industry example of why this is financially viable is Rolls-Royce with their outcome-based approach the "TotalCare" program. Under this model Rolls-Royce gets paid for continuous uptime rather than performing reactive service activities during the downtime of an aircraft. The new pricing system not only increased its revenue but also incentivized Rolls-Royce to increase their engines reliability and maintenance techniques to reduce the overall downtime (Efficient Planet, 2012).

Since the goal of AAES service business is to deliver a high uptime as possible, the new pricing system would incentivize AAES to develop and implement the best possible predictive algorithm as well as increase the reliability of their entrance systems.

Increase Perceived Customer Value

This approach focuses on the added customer value a predictive service-process would enable, and how these attributes incentivize customers' willingness to pay an increased price for the newfound service.

Since the underlying purpose of the entrance systems is to assist customers in their need of experiencing a more open world. As defined in section 5.1.1, a portion of the order winning criteria for after-sales services consist of delivery reliability, service speed and understanding customer needs. The predictive algorithm will enable AAES to proactively service and fix devices to which the algorithm has alerted to. By doing so AAES can offer a significant reduction or possibly completely eliminate product downtime. Which entails a reduction in service speed and showing a deeper understanding of their customers' needs. One can not offer a reduction in machine downtime without decreasing the service speed, i.e. the time it takes to discover and counteract/fix a breakdown. A predictive service-process would enable AAES to offer a negative service speed compared to their current reactive service-process. Since the customer needs to experience a more open world, by offering a higher machine uptime AAES acknowledges their customers' needs. Hence, by significantly reducing or totally eliminating machine downtime, the perceived customer value is significantly increased. The price of a service is considered an order qualifier, and it is therefore weighted less valuable from a customer perspective than the order winners. Therefore, by increasing the perceived customer value of their service business, through a reduction in machine downtime, AAES increases the customer's willingness to pay an increased price for their services. Through increasing the price of after-sales services AAES increases their revenue of their service-business, hence the predictive service model is financially viable.

5.2.3 Focusing Service Delivery Process from a Predictive Maintenance Perspective

Hill & Hill (2018) provides an established framework for focusing and improving processes called “The Six Steps”. The framework focuses mainly on focusing and improving manufacturing and operation processes. However, it is easily tweaked to adapt to other processes such as a service delivery process.

The first step centralizes around identifying and reviewing the processes that are to be optimized. The process that is to be focused on is AAES current service delivery process. The process has been thoroughly reviewed in chapter 4.3.

The second step focuses on identifying order winners and order qualifiers for the affected process, and possible changes the desired improvement can yield in all attributes. For the identified processes, namely the service delivery process, the following were identified in chapter 5.1.1:

Table 5.12: Order winners and qualifiers

Order Qualifiers	Order Winners
Price	Availability
Expertise	Service Delivery Reliability
Brand & Products	Service Delivery Speed
Commercial Factors	Relationship and Trust
Company Size	Understanding of Customer Needs
Geographical Location	
Certification	

The third step focuses on selecting a focused approach. For this case study the different focus approaches consist of different maintenance concepts. The different maintenance concept reviewed was time-based, cycle-based, condition-based and predictive maintenance. In order to decide the best suited approach for AAES current situation three different analytical hierarchy processes were carried out. The three different analytical hierarchy processes were made in conjunction with different employees from AAES in order to gain a deep and profound understanding of which maintenance direction is best suited for AAES current situation. The three different analytical hierarchy processes yielded the same results, namely that predictive maintenance is the best suited alternative for AAES current situation.

The fourth step centralized around segmenting product groups and customer orders. Since only one product is related to the service delivery process the thesis is delimited to grouping customer orders. This has been done thoroughly in chapter 5.1.2. Where four different customer segments are identified, these being:

- *Customers of smaller size*
- *Customers of larger size*
- *Customers located in highly populated areas*
- *Customers located in less populated areas*

The framework's fifth step focuses on allocating the right resources to each of the identified segments in the previous step in order to gain a greater competitive advantage. For the four segments described in the previous step, three different allocations of resources and processes have been identified.

Customers of larger size are already willing to choose the gold service contract (Service Manager IDS SE & Service Sales Manager, 2020 digital interview, 26 March). However, the current enterprise resource planning system cannot manage the required calculations to support large customers using the gold contract. Therefore, to better be able to sell the gold service contract and gain a higher cash flow from its pre-paid system, AAES needs to update or replace their current enterprise resource planning system.

For both the smaller and larger size customers the first and foremost goal is to communicate the new product towards the customers. The new product, i,e, the new service delivery process can possibly make up the required motivation for customers to switch from their current bronze service-contract to the more desired gold contract. To successfully communicate the new product AAES should focus on aligning their marketing division with their new service delivery process. As described in section 5.2.2.3, their current marketing division focuses on communicating the current reactive/preventive service approach where the focus lies on delivering a reliable service for a competitive price. After the transition to a predictive maintenance approach, the marketing department should focus on communicating the new maintenance method where the focus lies on delivering a competitive service based on unique skills and expertise. Furthermore, the competitive advantages the new service approach could bring to customers should also be communicated.

Furthermore, AAES service technicians should utilize their strong relationship between the service provider and customer to communicate the new product mainly towards the smaller sized customers. As described in section 5.2.2.3, the relationship and trust between service technicians and customers are significantly higher in less populated areas since every customer has a fixed service technician. However, this measure could be proven efficient in higher populated areas as well, if there are experienced technicians which have established good relationships with several of their many customers.

The sixth and last step focuses on correctly allocating the required infrastructure to enable the selected focus approach from previous steps. In this case when the required infrastructure is considered to be the service delivery system, and its included components such as the connected devices, the predictive algorithm, and the involved service technicians. The following rearrangement of the infrastructure is proposed in the format of a conceptual service delivery system. The system has carefully been developed after considering the current service delivery process, the conceptual service delivery process developed by the user experience team and quantitative interviews with experienced personnel. The proposal is visualized by Figure 5.4 below, with a description of the different parts following.

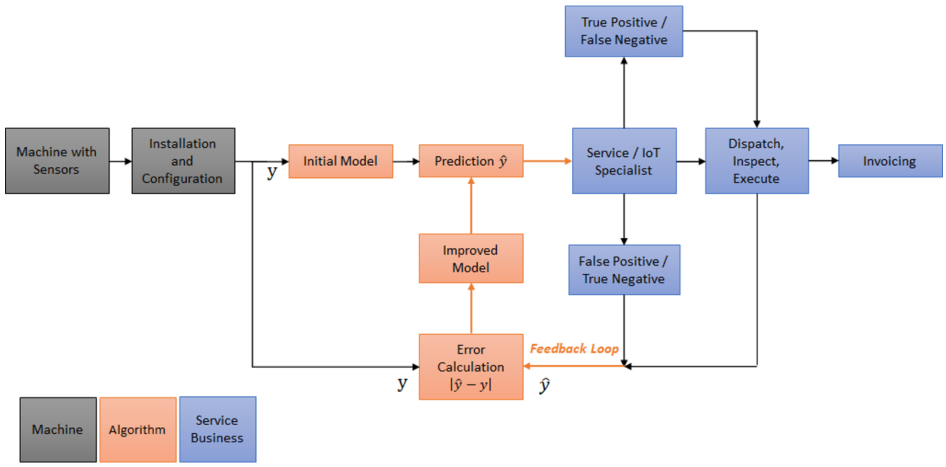


Figure 5.4: The proposed rearrangement of the service delivery system

Connected Machines

Smart IDS devices installed with sensors and either the 950, 950D, or MCC control unit operating in an industrial environment. The devices continuously gather data of their daily operations (denoted y), which they transmit to the initial prediction model on fixed time periods. Both the 950 and 950D control units transmit sensor data every fourth hour and event data is transmitted continuously, similar time periods are recommended for future use.

Predictive Algorithm

The initial model produces a prediction based on the data gathered from the connected devices. The gathered data is transferred to the internal feedback loop, where the unlabeled data from the devices is used together with the labeled data from later stages of the service process to perform error calculations and continuously improve the prediction model.

Service Business

Firstly a service/IoT specialist evaluates the predictions from the predictive algorithm to determine the state of the prediction, i.e. determine if the prediction is a true positive, a true negative, a false positive, or a false negative. This person is considered to be an educated individual with experience in AAES service business, the IoT data gathered from the machines and the predictive algorithm.

The evaluation is based on individual expertise within the area and typical prediction patterns.

Once the predictions have been determined, the label of the prediction becomes known. If it is deemed a true positive or a true negative the prediction was right, relative false positive and false negative represents a wrong prediction. These labels will be fed via the feedback loop and be used for continuous improvement of the predictive algorithm through error calculations.

If the prediction is determined to be a true positive a service order will be generated within the prediction window for the given device in the same manner as the current service delivery process. A service technician will be dispatched to the customer facility to inspect and execute service on the given device. Note that the severity of the prediction can be identified by the service/IoT specialist and therefore it is possible to dispatch educated technicians on more complex issues and uneducated technicians on the more standardized issues. From the prediction the specialist will receive some indication of which component or parts within the device are failing, hence the technicians can prepare the materials needed for the service beforehand. However, if the needed material is not available in stock it will have to be ordered in the same manner as before.

Once the service activity is performed and the customer is satisfied, the ticket will be closed and be prepared for invoicing in the same manner as the current process. However, the pricing system may change towards being based more on the delivered uptime rather than standardized prices for different activities.

6 Analysis of IoT data

This chapter covers the quantitative data analysis segment of the study which aims to provide an understanding of today's available IoT data and to discuss the future possible development of the IoT processes.

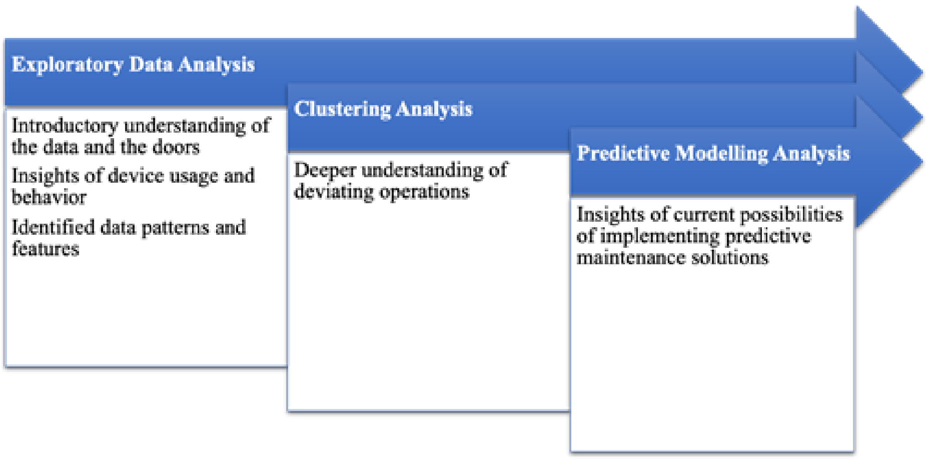


Figure 6.1: Workflow of the quantitative analysis.

6.1 Context and Objectives

AAESs concept of IoT-connected devices at customer sites is a newly started initiative and for now, there are only a few installed IoT devices in Sweden. Because of this, the study examines doors placed in the Netherlands rather than the Swedish market. The analysis is delimited to one type of control unit, the 950, because this type of unit has additional sensors to the 950D and the MCC. In total, this results in a sample of 51 doors. The doors are mainly from the product category "Overhead sectional doors", and spread out over four different models which may and have variations in regard to size as well as mounted accessories. However, there is also a possibility that other product categories and models are connected in this way and therefore may occur in the dataset. The reason for this is that there can be legacy models that have been upgraded with IoT connectivity. To what extent the data consist of these is to the study unknown.

Figure 6.2: Two types of overhead sectional doors (ASSA ABLOY Entrance Systems 2020, g)

6.2 Description of Data

The data used in this study is the communication messages sent between the CPUs located in the control unit. The information is saved as a stream and accessed by us in the form of JSON files. The data consists of measurements from sensors, cycle counters, error messages, event messages as well as various configuration and version settings. In total data is gathered from 51 doors, 39 of which includes event data and 50 includes sensor data. The data ranges from the 28 of September 2020 to 25 March 2021. Below follows an excerpt of the data.

[{"doorIdmsgId": "111713472OpCy", "msgid": "OpCy", "deviceId": "FT762", "timestamp": 1601124043752, "tot": 1521, "timestamp_aws": 1601124043752, "did": "111713472"},
{"doorIdmsgId": "111713472Cmax", "msgid": "Cmax", "val": 418, "deviceId": "FT762", "timestamp": 1601124044139, "timestamp_aws": 1601124044139, "did": "111713472"},
{"doorIdmsgId": "111713472Tmax", "msgid": "Tmax", "val": 485, "deviceId": "FT762", "timestamp": 1601124045955, "timestamp_aws": 1601124045955, "did": "111713472"},
{"doorIdmsgId": "111713472Tmean", "msgid": "Tmean", "val": 484, "deviceId": "FT762", "timestamp": 1601124046219, "timestamp_aws": 1601124046219, "did": "111713472"},
{"doorIdmsgId": "111713472ErIn", "msgid": "ErIn", "b31_16": 0, "deviceId": "FT762", "b15_0": 0, "timestamp": 1601124048474, "timestamp_aws": 1601124048474, "did": "111713472"},
{"doorIdmsgId": "111713472ErIn_v2", "msgid": "ErIn_v2", "deviceId": "FT762", "timestamp": 1601124048836, "id": [], "timestamp_aws": 1601124048836, "did": "111713472"},
{"doorIdmsgId": "111713472OpTi", "msgid": "OpTi", "deviceId": "FT762", "dy": 537, "timestamp": 1601129015677, "timestamp_aws": 1601129015677, "did": "111713472"},
{"doorIdmsgId": "111713472OpCy", "msgid": "OpCy", "deviceId": "FT762", "timestamp": 1601138443681, "tot": 1521, "timestamp_aws": 1601138443681, "did": "111713472"},
{"doorIdmsgId": "111713472Cmax", "msgid": "Cmax", "val": 418, "deviceId": "FT762", "timestamp": 1601138444021, "timestamp_aws": 1601138444021, "did": "111713472"}]

Figure 6.3: Excerpt of the analysed IoT-data.

6.3 Exploratory Data Analysis

In order to gain an initial understanding of the data and gain insights into what further examinations will be possible and desirable the exploratory data analysis is conducted. The process can be divided into five categories depending on the data being studied, this division is visualized in Figure 6.4. However, cross-examination of different types of data was also conducted.

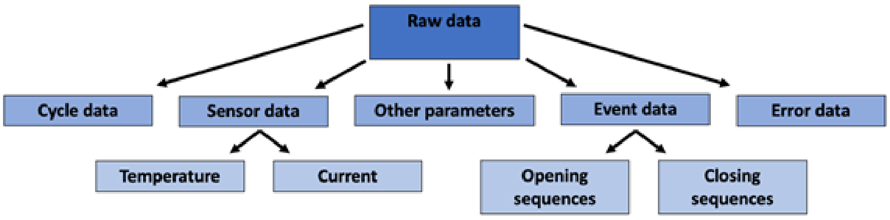


Figure 6.4: The different types of data

6.3.1 Descriptive basics

A majority of doors have data from the full studied period, while a few have shorter due to them being installed at a later date. The devices with 129 operating days have been running for longer but due to the limitations of the datasets, this served as the start of the study.

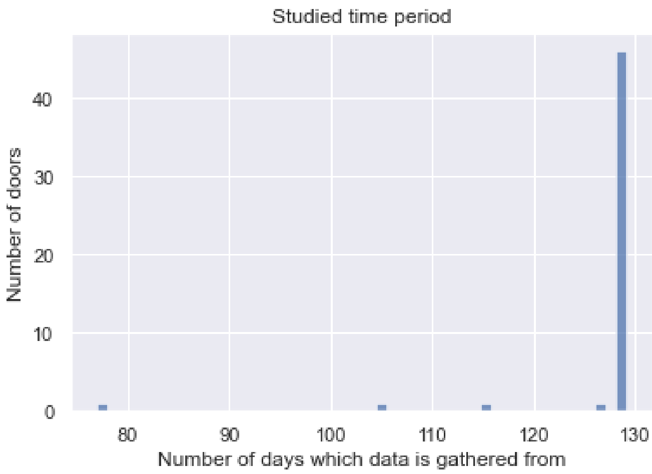


Figure 6.5: Visualisation of the number of included days

The amount of data varies heavily between doors, this is to a large extent caused by event frequency, but also by irregularities in device behavior that cause a large number of messages to be sent. At first glance, this might seem like a rich dataset but as the data deemed useful is isolated it becomes apparent that many of these data points do not hold useful information in regard to understanding or predicting machine behavior.

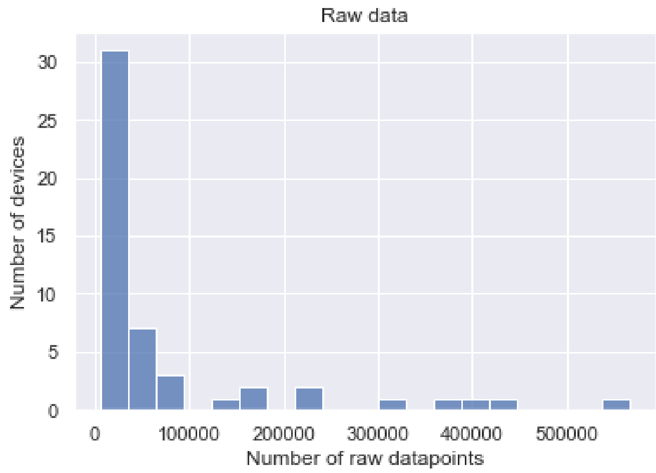


Figure 6.6: Number of raw datapoints across devices

6.3.2 Cycle Data

The cycle data was the first type of data to be evaluated in this study. All the studied doors have counters measuring the number of conducted opening cycles. There are two types of counters, one which tracks cycles since the installation of the control unit and one counter since the last reset. A reset is made when the door is repaired or maintained, specifics about the repairs in question are to this study unknown.

The total number of cycles is updated through a log message every fourth hour, while the number since the last reset is updated after 100 cycles. Because of this, the dataset contains considerably more updates of the total number of cycles, 36140 compared to 1068. Eleven of the 51 devices have undergone resets during the studied period. The number of cycles at the time of reset is visualized in figure 6.6 below. The color indicating which device the data is gathered from is the same across all graphs in this section 6.3.

Overall one can observe that there is a significant dispersion among the cycles, both in regard to their counters and in their usage, with very different daily frequencies.

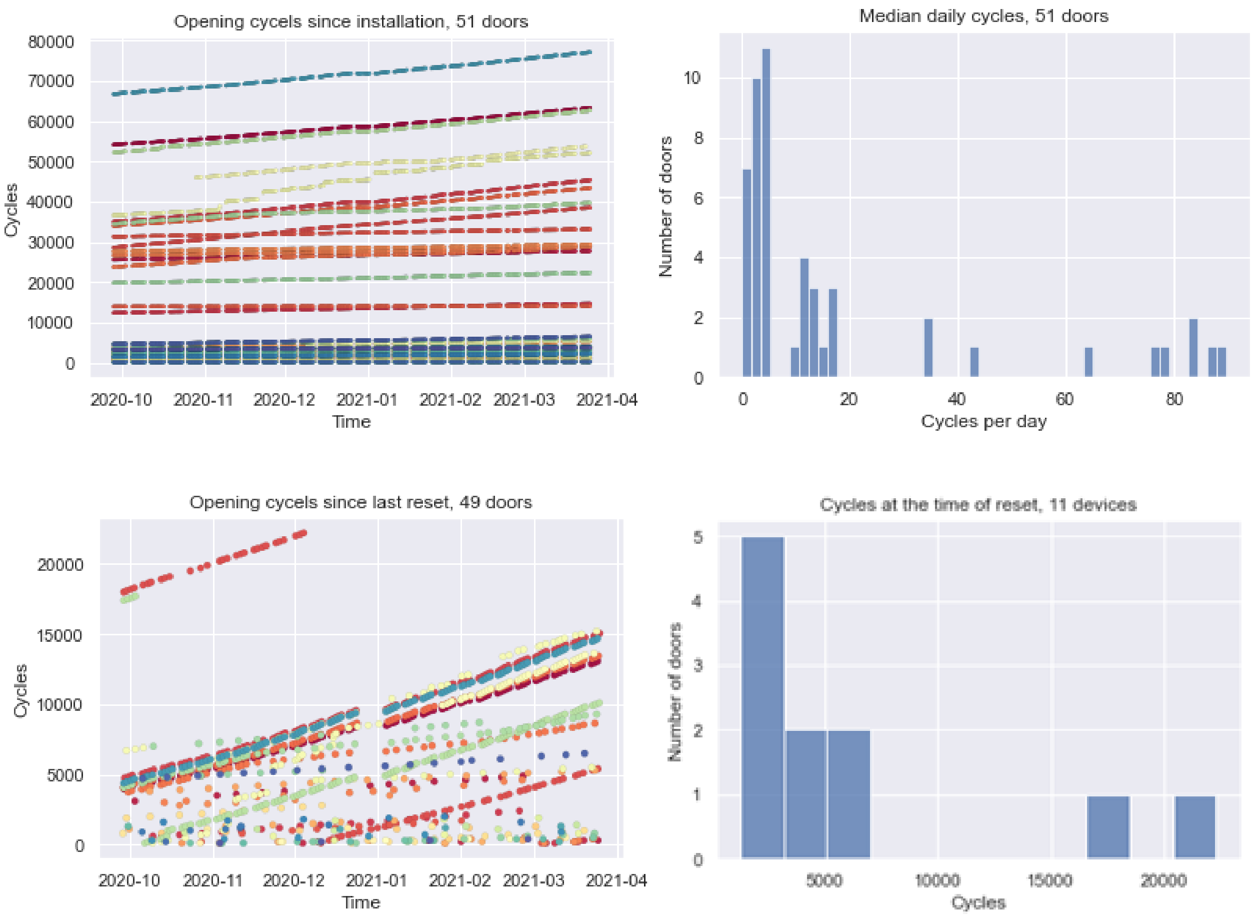


Figure 6.7: Cycle data

6.3.3 Sensor Data

The sensor data is based on two types of sensors: temperature and current. Both are measured during each opening cycle. Every fourth hour the mean of the last four-hour period is calculated and recorded in the logs together with the period's highest measured value. These metrics will later in this study be called T_{max} and T_{mean} respectively C_{max} and C_{mean}, as this is how they are reported in the logs. In both temperature and current, the mean exhibits some strange values. In some instances, the mean is even higher than the max which of course should not be possible. There are also a lot of measurements missing, meaning that only one of the metrics was saved in the logs for a specific 4-hour period. The metrics are being reported in the unit of raw A/D value which makes them difficult to transfer outside of this domain or translated into degrees or amperes. 50 of the 51 available doors are used for this exploration, the reason one was excluded is that it contained unreasonable values in all four metrics. In total the dataset contains 138866 data points considered sensor data.

6.3.3.1 Temperature

In the figures below, showing T_{max} over the studied period, one can see the considerable dispersion between doors, this indicates that the entrance systems' have individual characteristics that may be large contributing factors. One could be the earlier discussed number of opening cycles or frequency of cycles, another possible influential factor is the weight of the door, since it would be reasonable that a heavier door requires more power hence develops more heat during the cycle. However, it also becomes apparent that the values often deviate, sometimes heavily, from their respective median. This could be caused by uneven cycle frequencies, where periods of more movement cause higher temperature, but also by inaccurate sensors.

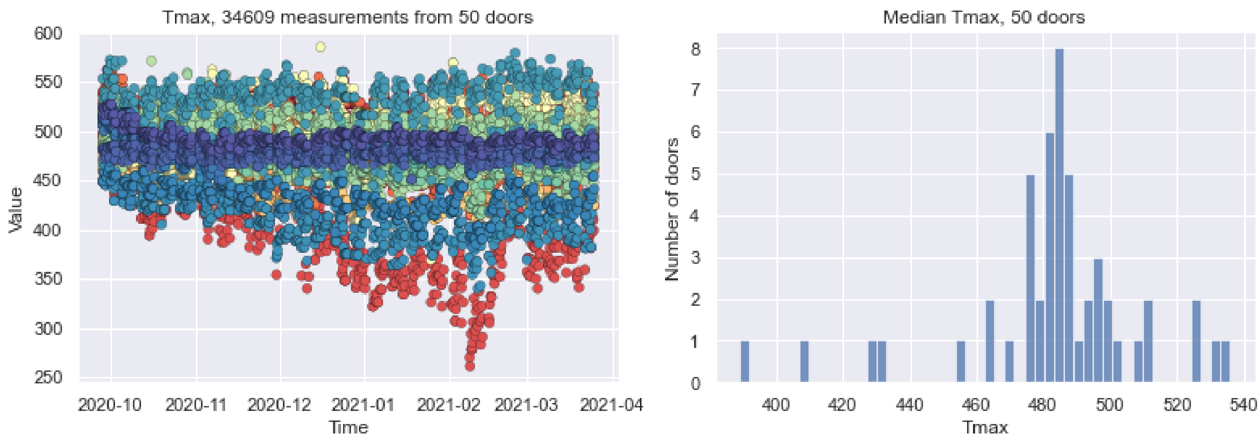


Figure 6.8: T_{max}

T_{mean} exhibits similar behavior to that of T_{max} but with higher variance, especially in an upward direction. Some measurements are extremely high, even higher than the highest value found in T_{max} (585), therefore T_{mean} values above this are not reasonable. The third figure below visualizes the measurements without the ones deemed unreasonable. It is still remarkable to see that there are many measurements at the top around 585, even though the 585 is a quite isolated instance in the T_{max} chart. Overall, this inconsistency becomes a difficulty when evaluating device behavior. More knowledge about the sensors, their operations, and accuracy would be greatly beneficial in the future development of IoT solutions.

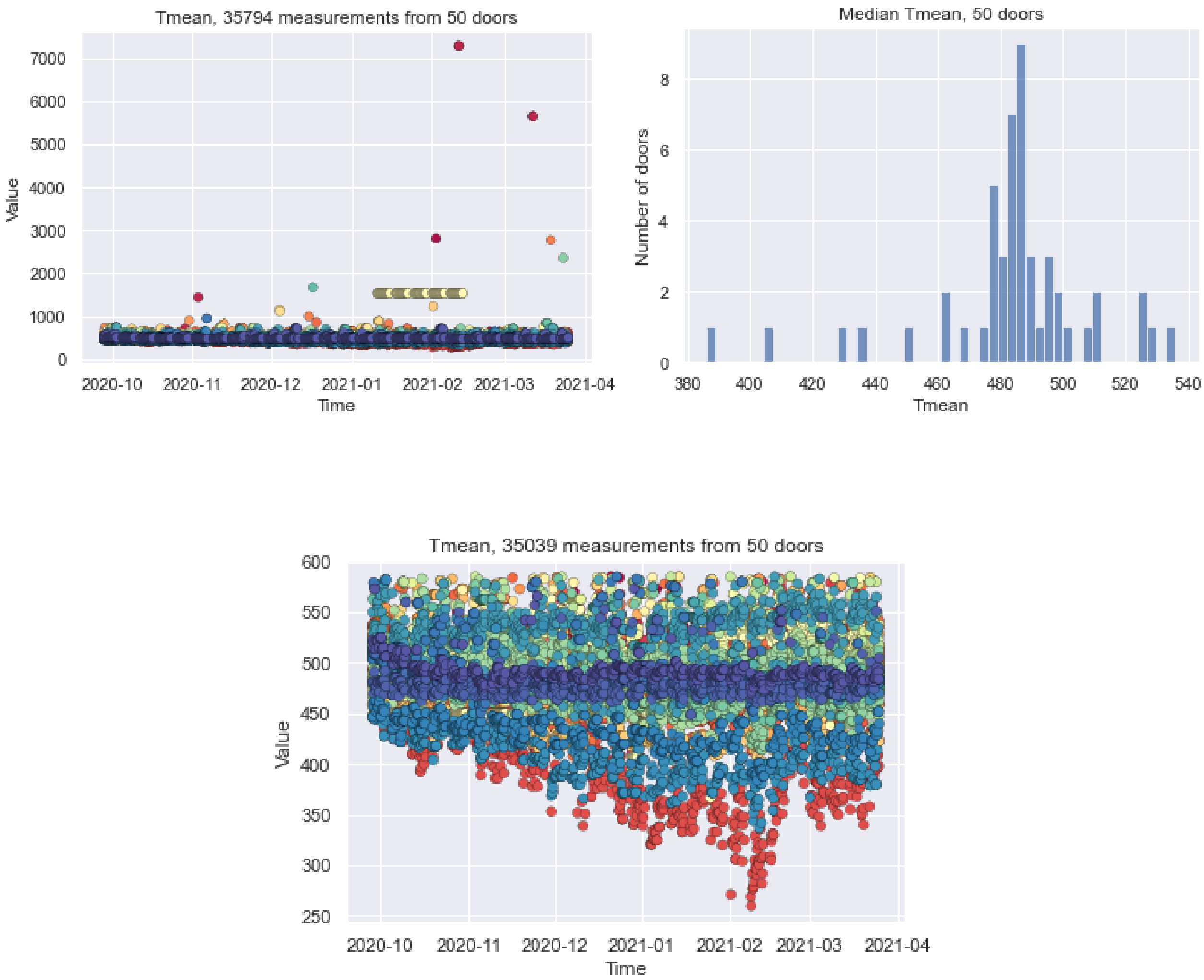


Figure 6.9: T_{mean}

6.3.3.2 Current

The current measurements are in general even more spread than those of temperature. Deviating values are more common to be part of a larger trend than an alone outlier, as was the case with temperature. Once again there is a large difference among the devices, which further strengthens the case for the devices different characteristics and therefore different needs. These features are visualized on the following page.

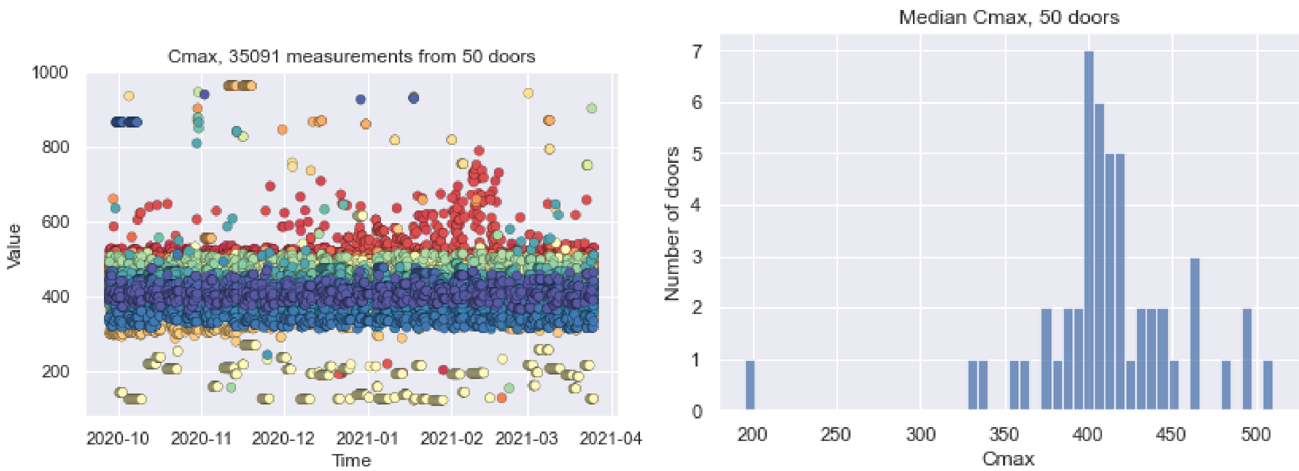


Figure 6.10: C_{max}

C_{mean} also contains some unreasonable values in those exceeding the maximum of C_{mean} (961). Unlike temperature where the max and mean metrics often were similar, C_{max} and C_{mean} are clearly separated. This indicates that current has a more spiky behavior with short periods of high supply, compared to the more even level of temperature.

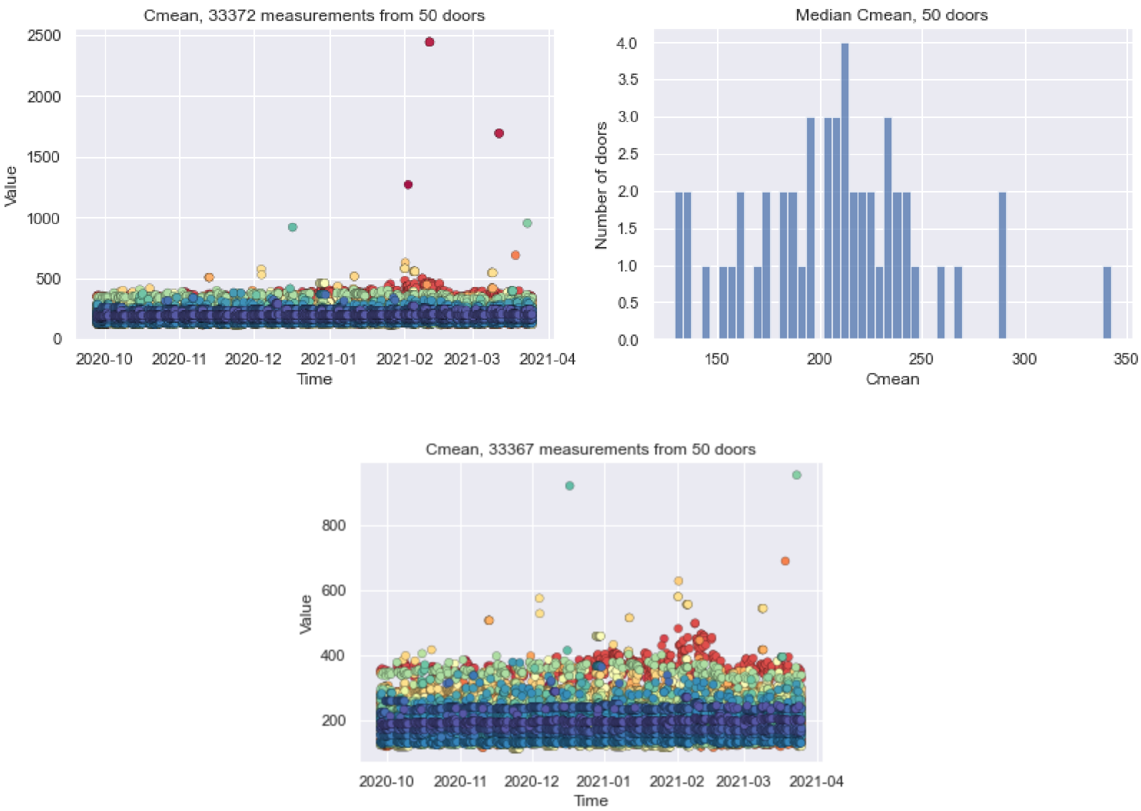


Figure 6.11: C_{mean}

6.3.4 Comparing Sensor Data and Opening Cycles

In order to search for relationships between the different types of sensor data as well as the cycle counter, various mappings and linear regressions were made. Below follows charts of the data points divided based on their type, and then summarizing tables of the regression results. The data were first processed to remove any outliers. This was made according to each individual device's robust three-sigma interval, mathematically:

$$x_i \in X_{j,k} \text{ is an anomaly if:} \tag{6.1}$$

$$\begin{aligned} x_i \notin \Big[& median(X_{j,k}) - 3 \times median\Big(|x_i - median(X_{j,k})|\Big), \\ & median(X_{j,k}) + 3 \times median\Big(|x_i - median(X_{j,k})|\Big), \Big] \end{aligned} \tag{6.2}$$

Since the limiting number of doors is set by the sensor data a maximum of 50 doors is used. However, for some timestamps and doors, there are missing values of one or both of the measured features of the pair. This causes some of the charts to not have any values for some specific door. Due to this one should also note that in Table 6.1 there is a difference between the number of measurements for the pairs. In the case of opening frequency, the metrics are grouped as daily instead of by four hours. The reason for this is that some doors have a too low frequency to give useful information on the 4-hour timeframe, the compared metric is in these cases the daily median of the collected 4-hour values.

6.3.4.1 Total Cycles

The number of opening cycles differs heavily between the different devices. A higher number of total cycles indicates a higher overall temperature level. This seems reasonable since a more heavily used machine is more likely to develop defects or tears that impair movement hence through friction develops a higher temperature. It is also more likely that devices with a high number of total cycles also have a higher opening frequency, which should increase the temperature of the engine. This knowledge of correlation between temperature and cycles may be useful in CbM and PdM processes. In the case of current, the results are more ambiguous, with C_{max} showing a positive correlation with a strong center at 400, while C_{mean} has an even stronger negative correlation and a large number of data points located around 175. However, since there are several deviating devices, both above and below these centers, the study's hypothesis is that there are other characteristics that affect these values more than the number of cycles conducted.

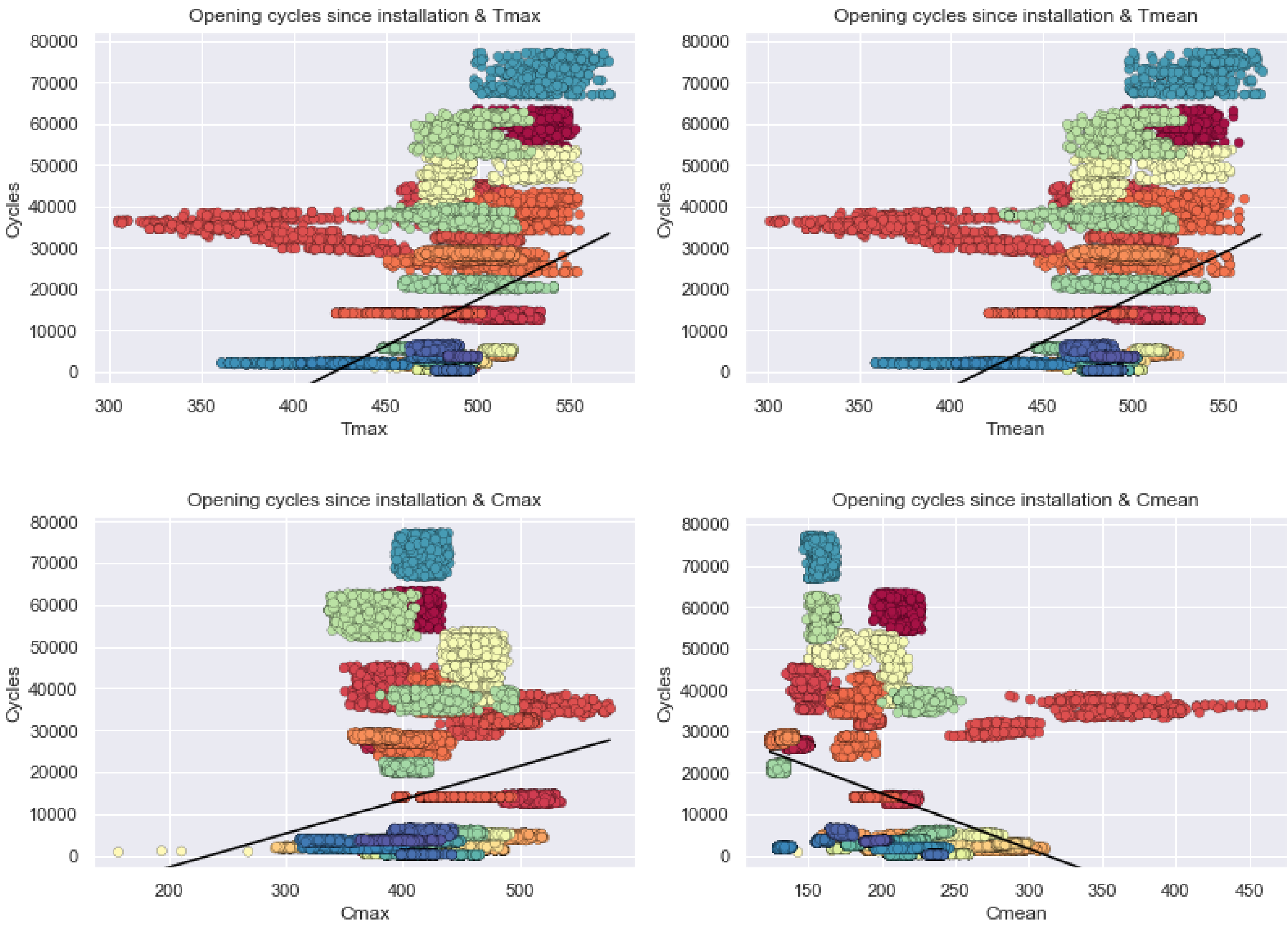


Figure 6.12: Total cycles & sensor data

Table 6.1: Regression Results: Total cycles & sensor data

Metric	Number of measurements	Slope	Standard error of slope	Correlation	Two-tailed p-value
Tmax	29001	224.86	3.5	0.35	0
Tmean	28892	217.64	3.47	0.35	0
Cmax	29508	80.88	2.64	0.176	$5.64 * 10^{-203}$
Cmean	25684	-133.115	2.47748	-0.317884	0

6.3.4.2 Frequency

Since opening frequency is a derivative of total cycles, its comparison with sensor data should look similar to the one from the last section. Yet the study deems it interesting to examine this closer as it would be reasonable that usage is linked to operating condition. The vast majority of opening frequencies are below 20 cycles per day. The charts of data points do not show this distribution well, however, the regression line indicates that the relationships between the variables are not as unilateral as they first may be perceived. Otherwise, the results are similar to those of section 6.3.4.1.

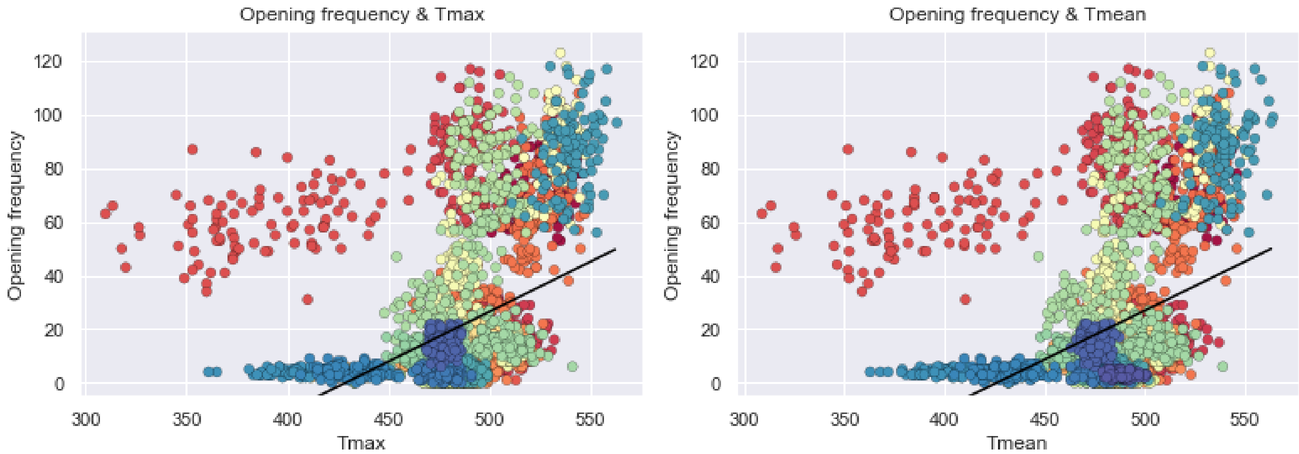


Figure 6.13: Correlation between opening cycles and T_{max}, and T_{mean}

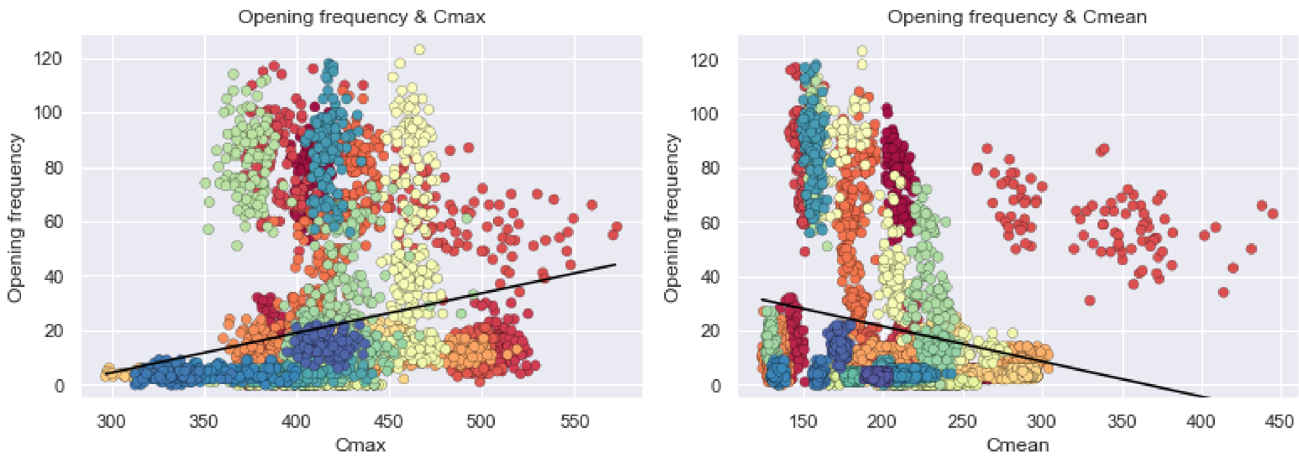


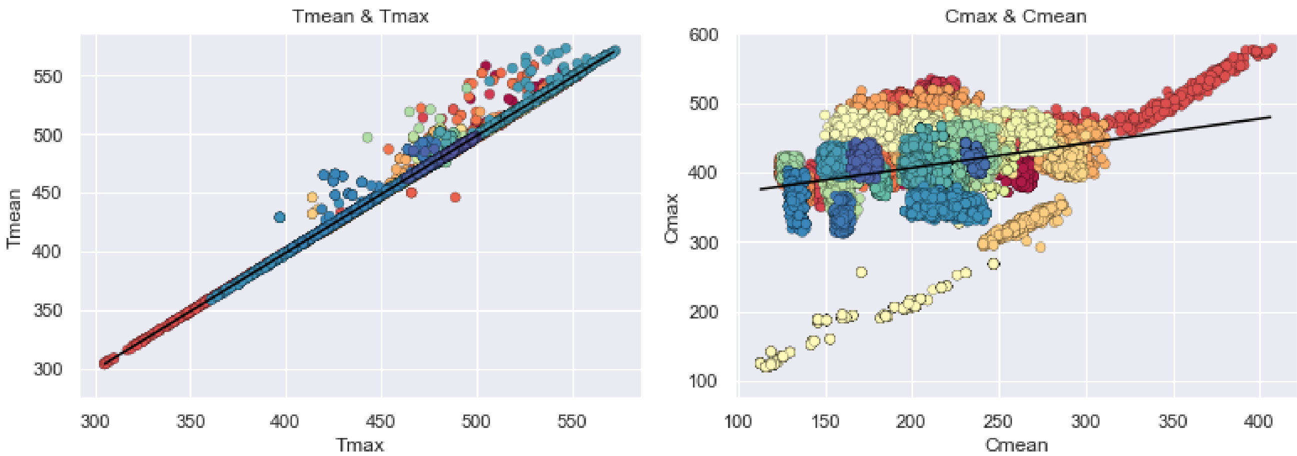
Figure 6.14: Daily cycle frequency sensor data

Table 6.2: Regression Result: Daily cycle frequency & sensor data

Metric	Number of measurements	Slope	Standard error of slope	Correlation	Two-tailed p-value
Tmax	4473	0.37	0.014	0.37	$4.09 * 10^{-151}$
Tmean	4479	0.36	0.014	0.37	$1.43 * 10^{-144}$
Cmax	4596	0.15	0.010	0.20	$1.31 * 10^{-43}$
Cmean	4490	-0.13	0.093	-0.20	$4.61 * 10^{-43}$

6.3.4.3 Sensor Data

When comparing the sensor data it becomes apparent that the temperature measurements correlate with each other almost perfectly while the current does not. This could be due to the fact that T_{max} is more stable than C_{max} and that spikes in current may to a larger extent be affected by external factors. However, as seen in the C_{max}-C_{mean} chart there are a few of the devices that do correlate well. The study has not been able to find an explanation for this deviating behavior, but do note the importance of understanding it in order to develop reliable advanced preventive maintenance methods. In the charts describing C_{max} with respect to temperature a large amount of data is missing, more specifically the entire device with the lowest overall C_{max} values. Yet the overall trend indicates that a high temperature corresponds with the need for a higher power supply, whereas discussed earlier the weight of the door could be an influential factor. Contrary to this do C_{mean} seems to indicate the opposite, where the devices with lower C_{mean} values exhibit higher temperature metrics.



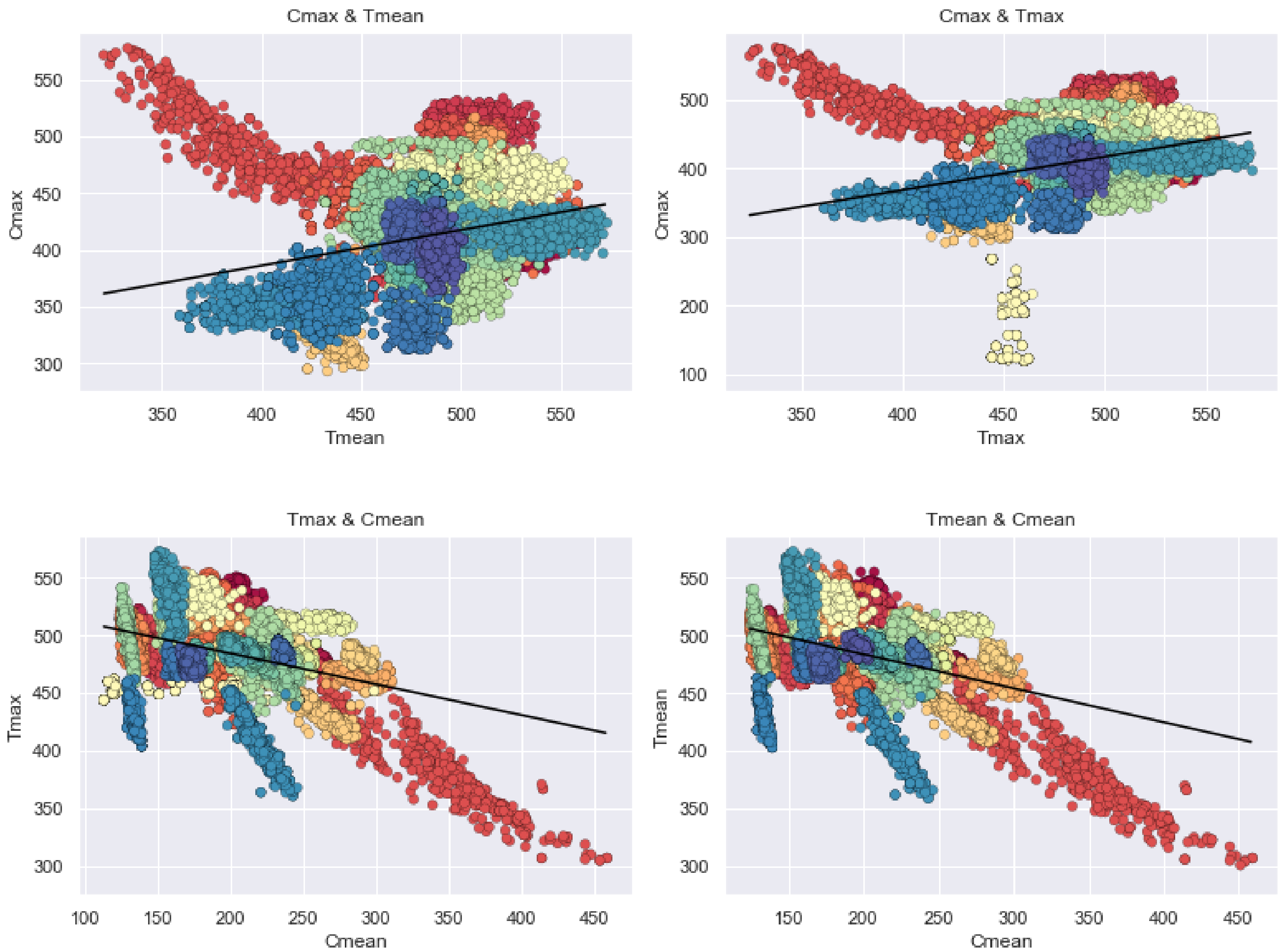


Figure 6.15: Sensor data

Table 6.3: Regression Result: Sensor data

Metric-pair	Number of measurements	Slope	Standard error of slope	Correlation	Two-tailed p-value
Tmean-Tmax	27385	0.996	0.0006	0.996	0
Cmax-Cmean	23999	0.35	0.0077	0.28	0
Cmax-Tmean	26471	0.31	0.0084	0.22	$1.2 * 10^{-295}$
Cmax-Tmax	26477	0.48	0.011	0.27	0
Tmax-Cmean	23247	-0.27	0.0040	-0.41	0
Tmean-Cmean	24047	-0.29	0.0039	-0.44	0

6.3.5 Other Parameters

The parameter of torque (trq) was examined but showed to be the same (9) across all studied doors, therefore no further studies on this parameter were made. Parameters regarding software versions and configurations were also examined without any significant findings and are therefore not being reported on further.

6.3.6 Event Logs

A large extent of the logs is constituted by the event logs. These describe the movement of the door and make notes whenever unexpected events occur. The reason only 39 doors are part of the study is that the 12 others only logged a few of the events, specifically they did not log the events describing the movement of the door. In total there are 25 different types of events found in the dataset, a shorter description of the most frequent ones can be found in Table 6.4.

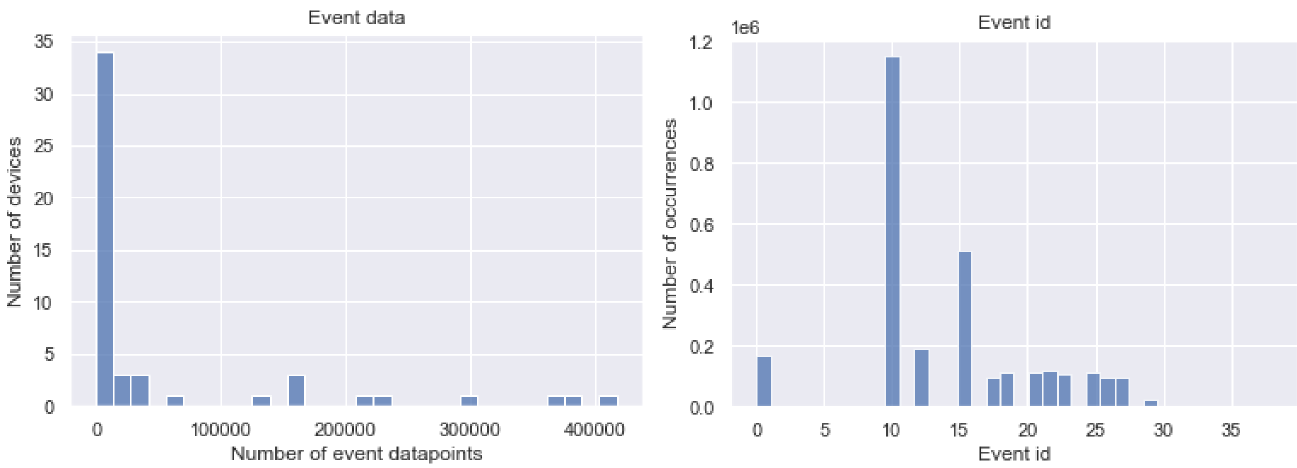


Figure 6.16: Event logs

Table 6.4: The ten most frequently occurring events

Event Id	Occurrences	Description
10	1131526	Photo sensor sending a 1 if the sensor is blocked, 0 if not. If blocked a close is not possible
15	515045	Request for opening
12	169421	Squeeze list activated
1	163622	A stop in what the door is currently doing
22	117043	Request for closing
25	113360	Indicates closing movement
18	112698	Indicates opening movement
21	112141	Fully open
23	109519	Start closing movement
17	96421	Passing F50 position during open movement

6.3.6.1 Opening Sequences

From the event data certain patterns of event sequences could be identified, one of which is the opening sequence. Beginning with an open request (Event Id: 15) and ending with a message stating that the device is fully open (Event Id: 21). In between these events, other events may be found, for example, new open requests, apparent due to their frequent usage as seen in the table above.

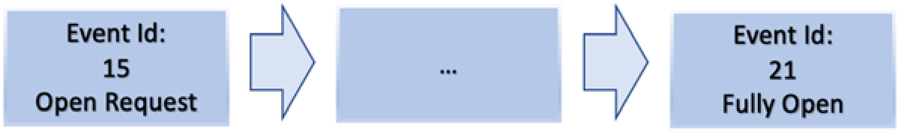


Figure 6.17: Opening Sequence pattern

The "regular" opening sequence is defined as, in between these two, to also include a message stating that the door is passing the F50 position (Event Id: 17) and a message stating opening movement (Event Id: 18).

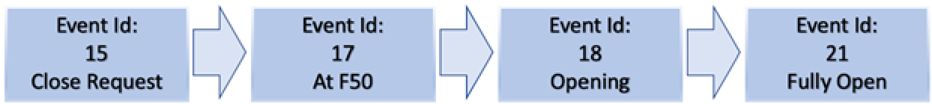


Figure 6.18: Regular opening Sequence pattern

Sequences that do not follow this schema, yet begin with a request (15) and end with a fully open (21), are marked as irregular opening sequences. A few devices exhibit a very large proportion of irregular sequences, this is caused when the device stops sending the F50-message (17) during the studied time period. The reason for this change is for the study unknown.

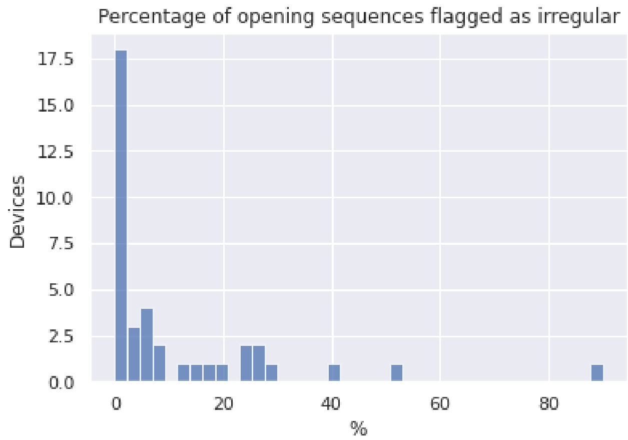


Figure 6.19: Visualisation of distribution of irregular opening sequences

Another notable type of opening sequence is the ones that are not being completed, i.e. missing the fully open message (21). These sequences are labeled "Canceled" and may be caused by expected events such as a sudden call for closing or a blockade. However, when these sequences make up a large portion of the total opening sequences questions of the device's condition may be raised.

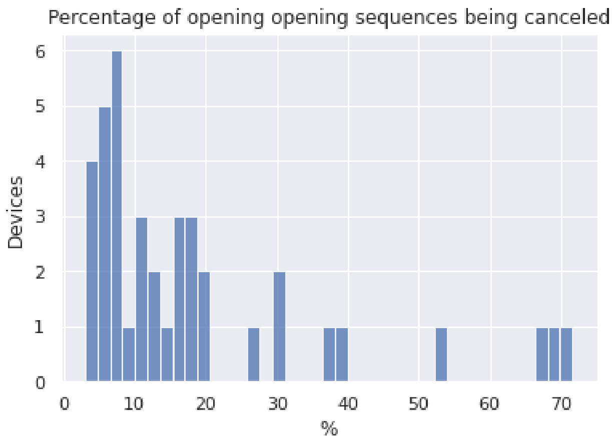


Figure 6.20: Visualisation of distribution of canceled opening sequences

The third type of "wrongful" opening sequence is the faulty ones. These are opening sequences that include the fully closed message (Event Id: 27). The reason they are labeled "Faulty" is that this type of sequence should not exist. The fully closed event should follow in a sequence starting with a close request (Event Id: 22) and that request would break the opening sequence labeling it as canceled.

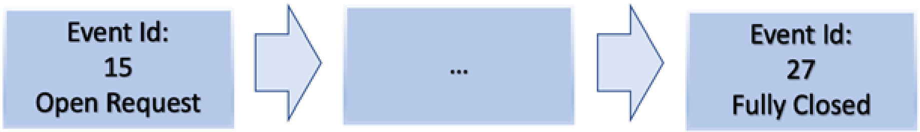


Figure 6.21: Faulty opening sequence pattern.

However, in most cases these types of sequences only make up a small fraction.

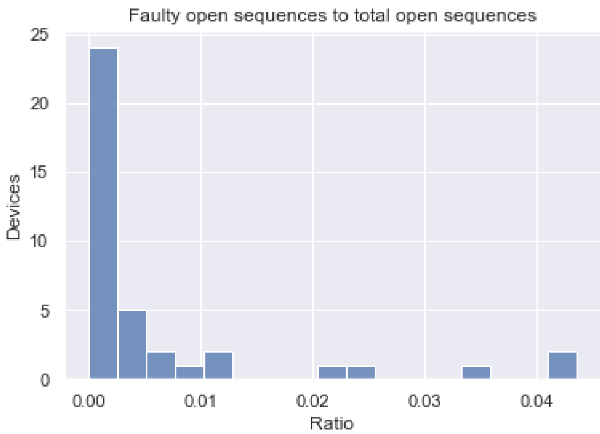


Figure 6.22: Visualisation of distribution of faulty opening sequences.

Opening Times

With the opening sequences mapped, it is possible to calculate the time intervals within the sequences. This is done both from the initial open request to the fully open state, to the F50 position and in between these two states.

Starting with the full sequence. The 39 studied devices together contain 105486, all of these are visualized in Appendix C. However, because of the sequences' irregularities, a visualization without abnormal times is preferred for readability purposes. The abnormal sequence times are defined according to each individual device's robust three-sigma interval, mathematically the same as Equation 6.2.

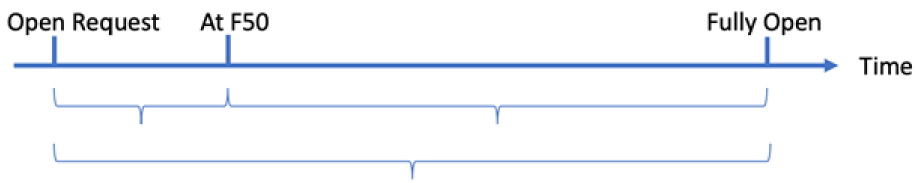


Figure 6.23: Different time intervals studied

The extent to which these abnormal times occur differs widely between different devices. In order to account for the devices' different usage, this metric is reported as the percentage of the device's total opening sequences. To be noted here is that only 4 of the 39 studied devices have results below 10%. This further shows that the time deviation for each device is heavy, and this lack of standardization may make future analysis more difficult.

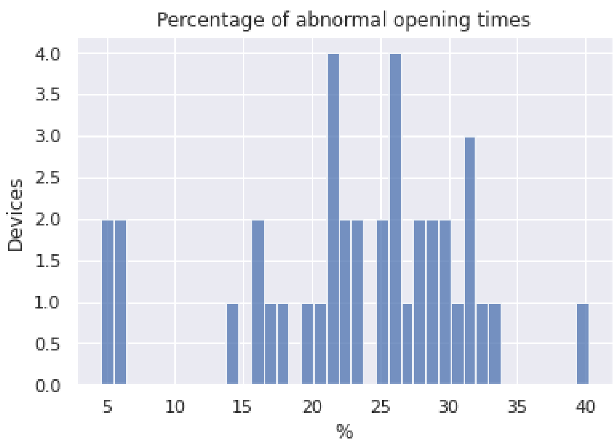


Figure 6.24: Visualisation of distribution of abnormal opening times

The removal of anomalies results in 78265 opening sequences, seen in figure 6.28 below. In the figure, it becomes apparent that the opening time varies heavily between different devices, both in regard to the devices' mean and median time and to the deviation in the doors individually, indicating that sequence times often differ between cycles. It is eye-catching in the chart that the yellow device exhibits some extremely low times. The validity of these results may be questioned, yet after closer inception of the event logs it was concluded that the times are correctly calculated according to what is being reported.

However, these opening times, some being less than 1 second long, does seem unlikely compared to the results from the other devices.

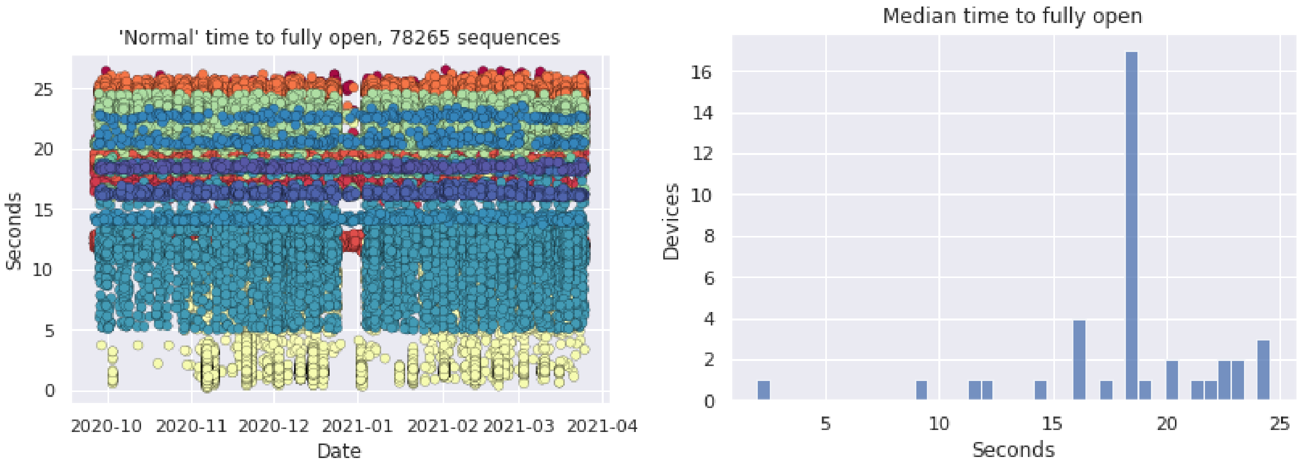


Figure 6.25: Normal opening time

The full opening time was then studied together with some of the features described in the earlier sections, namely T_{max} and cycle frequency. None of which indicated any stronger relationship linking the features together. The small upward regression lines are instead thought to be caused simply by the fact that higher values are more frequent within the datasets. Once again the individuality of the devices seems to have a too large impact for any causal conclusions to be drawn. In the first figure below the opening times are linked to their corresponding four-hour period since T_{max} is being reported at this interval. One could argue that this is quite inaccurate since T_{max}, in most cases, is not measured during the specific sequence.

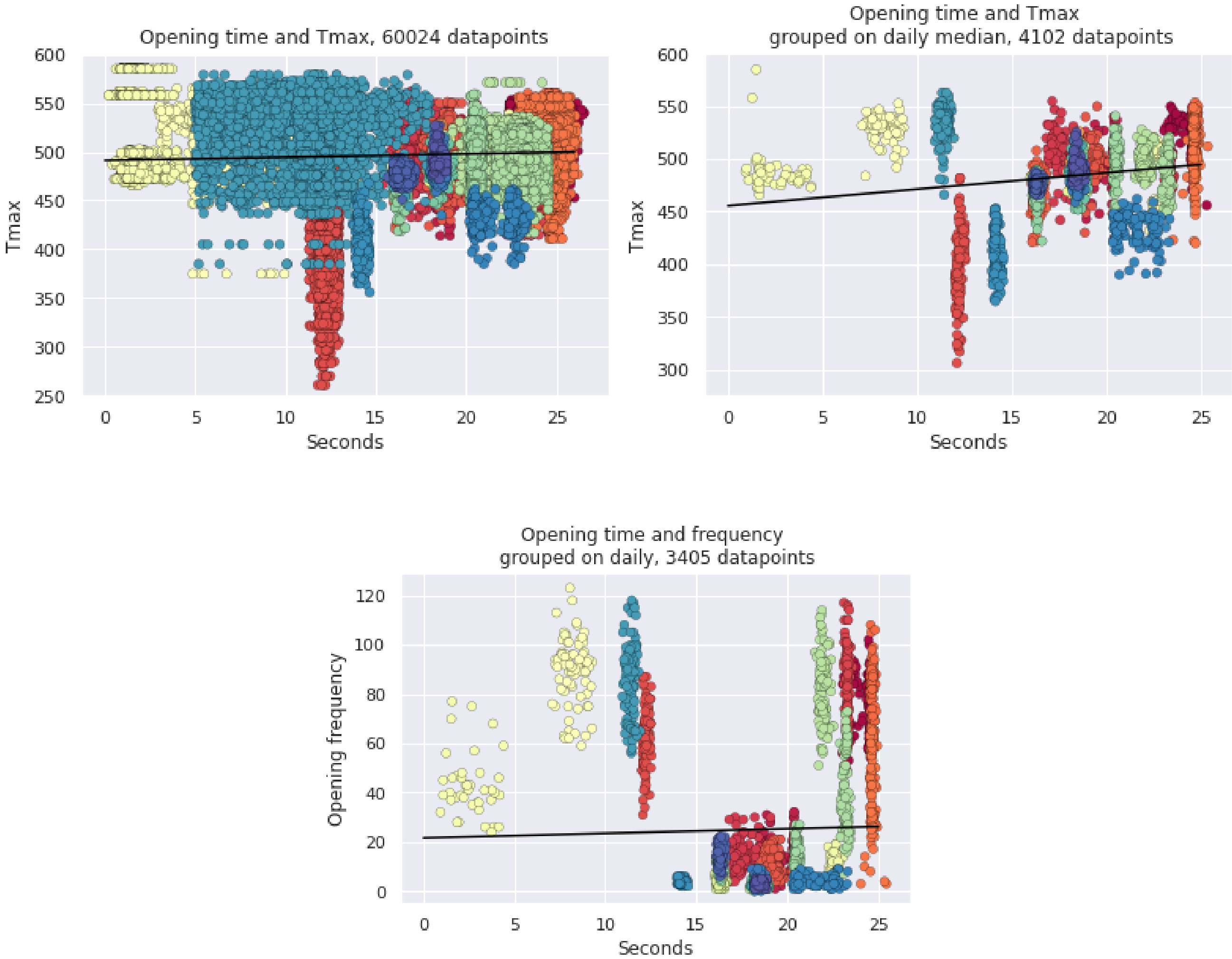


Figure 6.26: Opening time compared to device measurements

F50 Position

As previously mentioned the logs contain event messages indicating that the device passes the F50 position during its path to fully open. This sequence time was also calculated similarly to the fully open state. To be noted here is that, in the graph, the yellow device exhibits the slowest F50 time yet the fastest time to fully open, further strengthening the case that the devices have different characteristics influencing their performance. As seen in Figure 6.27 this study includes a higher number of sequences compared to the last section when full sequences were studied, this of course is partly caused by the canceled sequences which may appear here if they pass the F50 before being interrupted. However, in two of the devices, there are close to three times more sequences that do not include an F50 event yet a Fully open one compared to sequences including both, as seen in Figure 6.28. Closer inspection shows that some devices stop sending these messages during the studied period. The reason for this is unknown. Lastly, the time interval from F50 to Fully open was looked at. These results followed the earlier seen with high variance between devices and no noticeable change of trend across time.

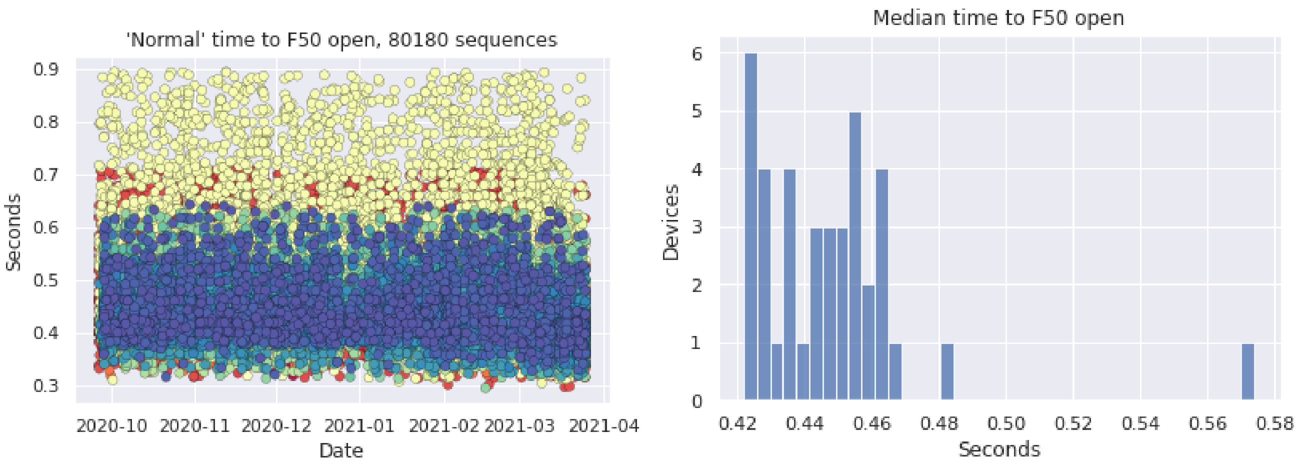


Figure 6.27: From closed to F50 position

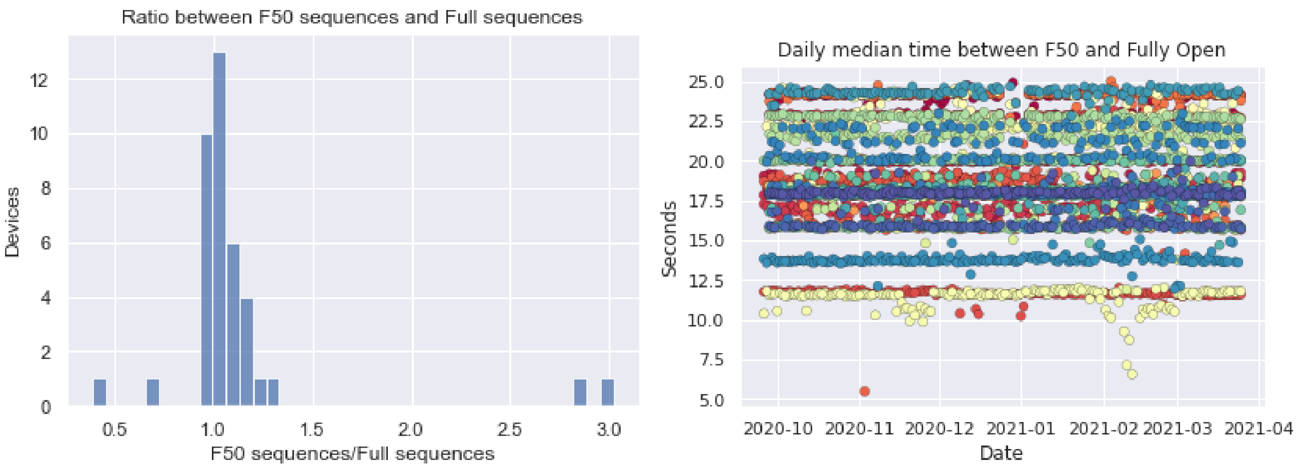


Figure 6.28: From F50 position to Fully open

6.3.6.2 Closing Sequences

In a very similar manner to the study conducted in the previous section the closing sequences also were identified and examined. Unsurprisingly the results of this analysis were very uniform with the last one. Therefore, this chapter only includes the definitions made and a broad description of the results. For a more in-depth look, all charts are found in Appendix C.

Closing sequences start with a closing request (Event Id: 22) and end with a fully closed message (Event Id: 27). As with opening sequences, other types of events often occur in between the request and end messages. One of which is the message indicating that the closing movement has begun (Event Id: 23). There is a corresponding message for the opening sequences (Event Id: 16), however, it is not being used and therefore not found in the logs. Squeeze List Activated (Event Id: 12) is another frequently occurring event within the closing sequences. It indicates that the squeeze list, at the bottom of the door, is being triggered, oftentimes as the door touches the floor.

Figure 6.29: Closing Sequence pattern.

The "regular" closing sequence, in addition to the mentioned events, also includes a message stating closing movement (Event Id: 25) and an F50 position message (Event Id: 26).

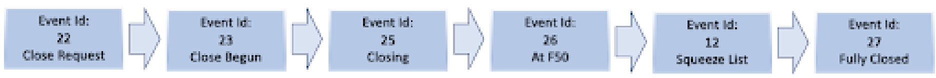


Figure 6.30: Regular closing Sequence pattern

Overall closing sequences follow a similar behavior to that of the opening sequences. Mostly low percentages of irregular, canceled, and faulty sequences and a relatively high percentage of abnormal times. The dispersion of closing times are both found when studying abnormal and normal ones. With high variance between devices, as well as for individual devices along the studied period. Notable, opening is, in general, a little slower than closing, on average 4.25% slower. Yet in 6 out of the 39 devices, the opposite is true.

6.3.7 Error Logs

The last defined type of log data is the Error logs. These are similar to the event logs but have their own Ids. The errors are categorized into three levels of severity: 1, 2, and 3. Today only severity level 1 and level 3 are used. In total 6289 errors are found in the dataset, the distribution is visualized in Figure 6.31 the far most frequently occurring error is a communication error between the two processors on the device (Error Id: 3), followed by the error indicating problems with the safety edge (Event Id: 4). However, since it is only severity level 3 that requires immediate action the study further focuses on these, the implications of some of these are also discussed in section 4.3.1. Errors were gathered from all 51 doors, yet only 48 of these had errors of any level, 80% of which had fewer than 50 errors and a majority of devices had less than 8 errors during the studied time period. There are 739 data points showing errors of severity level 3, these are spread out over 42 devices.

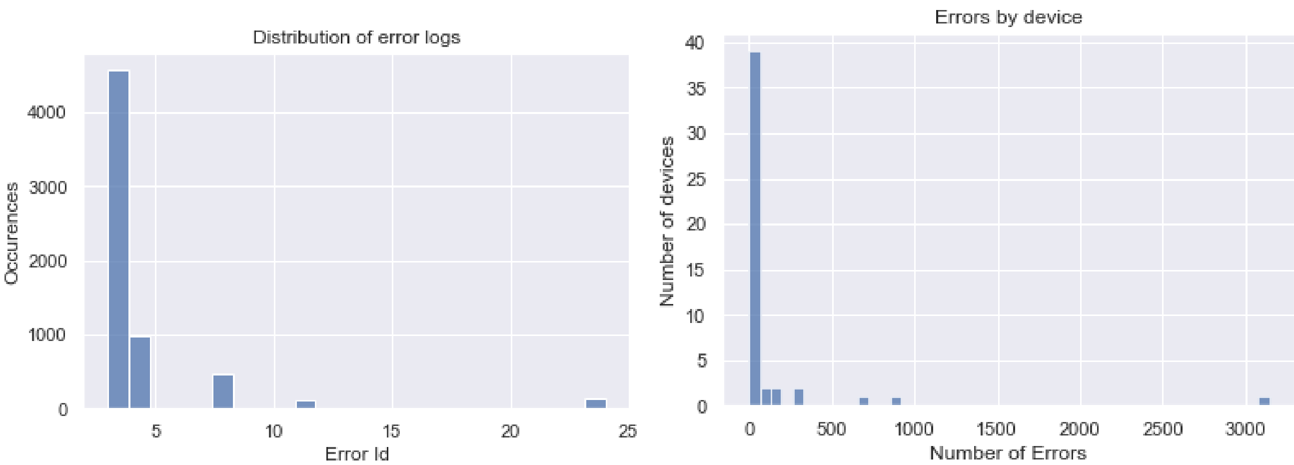


Figure 6.31: Distribution of errors

Table 6.5: The four most frequently occurring errors

Error Id	Occurrences	Description
5	10	Automation system off line
8	470	Stop circuits open (emergency button)
11	111	Engine disengaged
24	148	Power failure (Power supply shut off)

6.3.7.1 Cycle Resets

Considering that the devices' service history is not accessible to study one could use the "counter since last reset" as a proxy for the maintenance work, with the caveat that a reset may indicate any type of service. Since the counter is recorded every 100 cycles, the lowest possible value for the counter also is 100. Separating the devices containing logs with the counter value 100 without it being its first value, if it is the first value it would not be possible to conclude if the maintenance had been conducted before the logs recording. This showcases eleven devices from our sample. Four of which do not include any error messages and seem to operate as usual through the reset, a behavior which the study is not able to explain. In these cases, it is not possible to determine exactly when the reset took place these doors are not being focused on. The remaining seven devices can be divided into two groups: those with a few errors during a short specific period of non-functionality and those with error messages leading up to a non-operational period.

- **Group 1**: Consisting of 3 doors which have the similarity of sending the error messages 11 and 24, meaning that the motor is being disengaged and the power shut off. This period where the device is not operational lasts for two of the devices approximately 20 minutes, and in the third about 20 seconds, which seems strange. In the two longer ones, an error message 8 respective 5 is also sent in during the period.

- **Group 2**: The devices in this group have either a continuous flow of error messages, for example, a message warning of the safety list (Error Id: 4), or only a few messages, for example, "low main voltage" (Error Id: 9) or communication problems between the CPUs (Error Id: 3) leading up to a non-operational period. The non-operational period is very similar to the one described for the other group, consisting of error messages 11 and 24 over a time period ranging from five minutes to half an hour.

This further strengthens the thesis that the data's irregularities are problematic. It is clear that the maintenance work is being made during the non-operational period outlined above, but from this, it is difficult to draw too general conclusions. The very small sample size is of course also an important factor in this. However, problems with the squeeze list seem to be frequently occurring and very much detected and reported by the current implementation (Service Manager IDS SE Service Sales Manager, 2020 digital interview, 26 Mars).

Further, the study examined the characteristics of the individual devices more closely, divided into their separate groups. In regard to the number of cycles conveyed at the time of the reset (maintenance work), there does not seem to be a difference among the groups

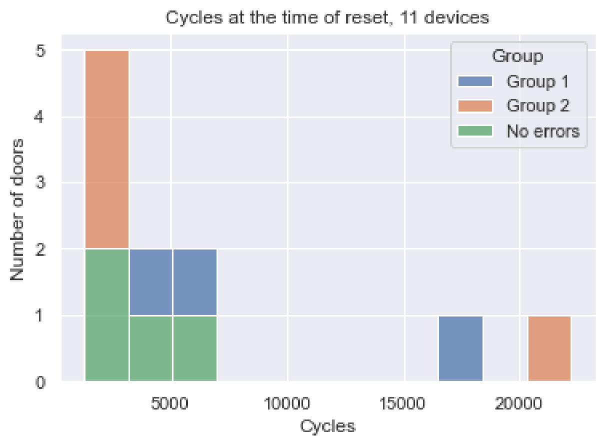


Figure 6.32: Number of cycles since last reset at the time of service

As earlier outlined is a hypothesis of the study that the sensor data and the sequence times could be utilized as a helpful indicator for determining the condition of the connected machine. In order to test this and gain a more comprehensive understanding of the device and its maintenance, the earlier identified reseted doors are looked at separately. In the following section the figures of each door's different types of measurements and features are plotted as time series, the found errors are also marked as a cross at the bottom. The idea is therefore to study the possible change of pattern in the data before and after the service is performed.

Starting with the first group, the devices that are presumed to have undergone the routine time-based maintenance process and therefore are not expected to indicate a major difference in condition. Worth mentioning is that the figure to the left has had a few strange values (above 1000) removed from the plot, for readability purposes. These values are, as earlier discussed, only occurring in the mean measurements and considered unreasonable. An ocular inspection of the figures does not indicate any considerable change in values. In order to examine these closer, each metrics' means and standard deviations are calculated both before and after the maintenance is performed. The period used for counting is set to be 30 days but as some devices are limited in this regard the longest possible period is used instead in these cases. As expected it is difficult to use these results for making any causal claims. The mean values seem unaffected of the work done and the deviation is high both before and after. All these results can be found in Appendix D together with more examples of device performance before and after maintenance work was conducted.

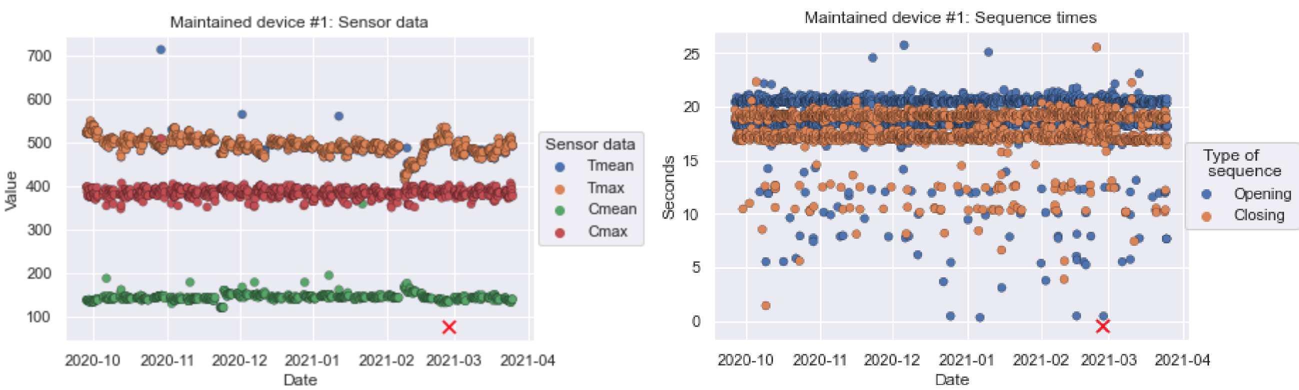


Figure 6.33: Device measurements before and after reset: Group 1

The second group consists of the devices where errors were observed and connected by maintenance work. The smaller red crosses leading up to the larger indicate these error messages, the larger then shows the maintenance work. This group is of particular interest since it may give insights into how consecutive errors affect the devices' condition. However, the study did not find deviating results compared to the previous group. Both the sensor data and sequence times seem unaffected by the work done. As with Group 1 specific device results can be found in Appendix D.

Figure 6.34: Device measurements before and after reset: Group 2

6.4 Clustering Analysis

As outlined in section 2.1.4.2 a hypothesis is that more frequent irregularities among the operating sequences could indicate possible future breakdowns or misuse of the machine. The objective of the clustering analysis is therefore to group the devices according to their relative value of these irregularities and study if this clustering can give useful information about the devices operating conditions. The analysis was based on the same 39 devices which were used in the event data section, since the constructed features are based on the event data. This is a quite small sample which could limit the ability to draw conclusions and credibility of them, especially more general statements regarding machine behavior. Yet the intention of the study is to evaluate the possibilities and therefore chooses to explore this concept to screen potential insights and whether it could be a useful tool in future development in order to categorize and understand machine behavior.

6.4.1 Features

In order to show unusual behavior among the operating devices, several features were produced. These are features that have either come up in discussions with AAES employees or through insights gained during the exploratory data analysis. In sections, 6.3.6 the patterns of opening and the closing sequences were identified, within these four types of unusual sequences were discussed: faulty, irregular, canceled, and those with abnormal times. As for features to base, the clustering analysis on canceled and faulty sequences was excluded. The reason for this is that canceled sequences often occur by natural causes. Therefore, even though a high number of canceled sequences are strange it many times does not indicate any problem with the devices' operating condition. The reason for excluding faulty sequences is because the frequency of these are extremely low and does not differ much between devices. A correlation analysis between all these features can be found in Appendix E but did not lead to any stronger conclusions. In the following sections, the features which were deemed to contain some descriptive or predictive power are more closely described. Since the features are taken from the open-/closing-sequence analysis the cluster was made separately on both the two types of sequences. The idea was that this could give a broader view of the behaviors and to see if the same traits can be found in both types of patterns.

Irregular Sequences

In section 6.3 irregular sequences are defined as those that do not follow the outlined pattern. The extent of this phenomenon varies heavily among the devices, one reason which was discussed earlier is that a few devices stopped sending F50 messages midway through the studied period. These are the devices with extremely high percentages in the histograms below. In order for these outliers to not affect the results of the small sample, they were dropped for the analysis. For the clustering, the feature was scaled to have zero mean and unit variance.

Abnormal Sequence Times

The second feature to base the clustering on is the percentage of abnormal sequence times. This feature is more evenly spread out over the distributions compared to the previous, but also includes a wide range of values. For the clustering, this feature was also scaled to have zero mean and unit variance.

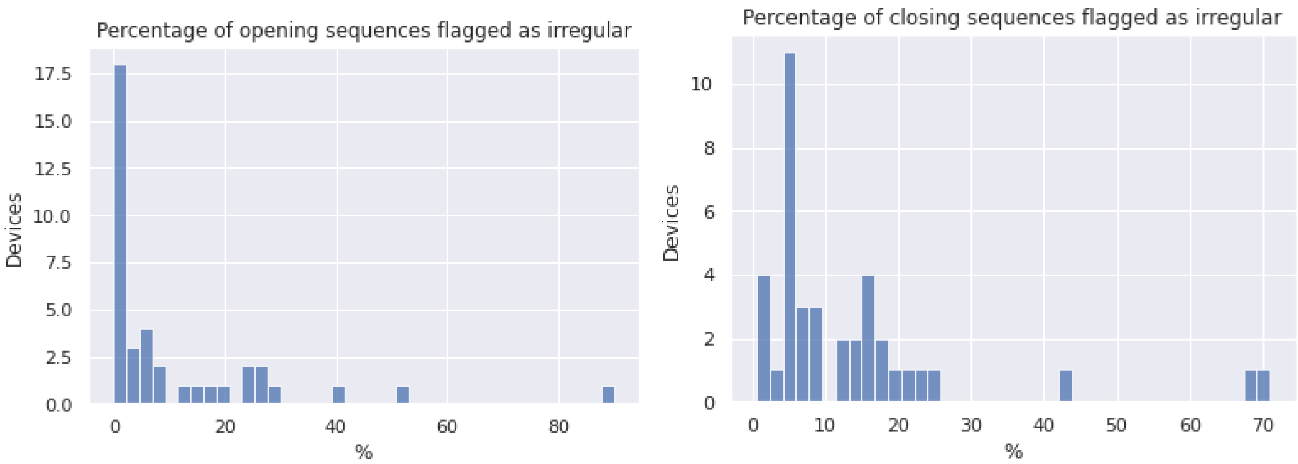


Figure 6.35: Percentage of irregular sequences

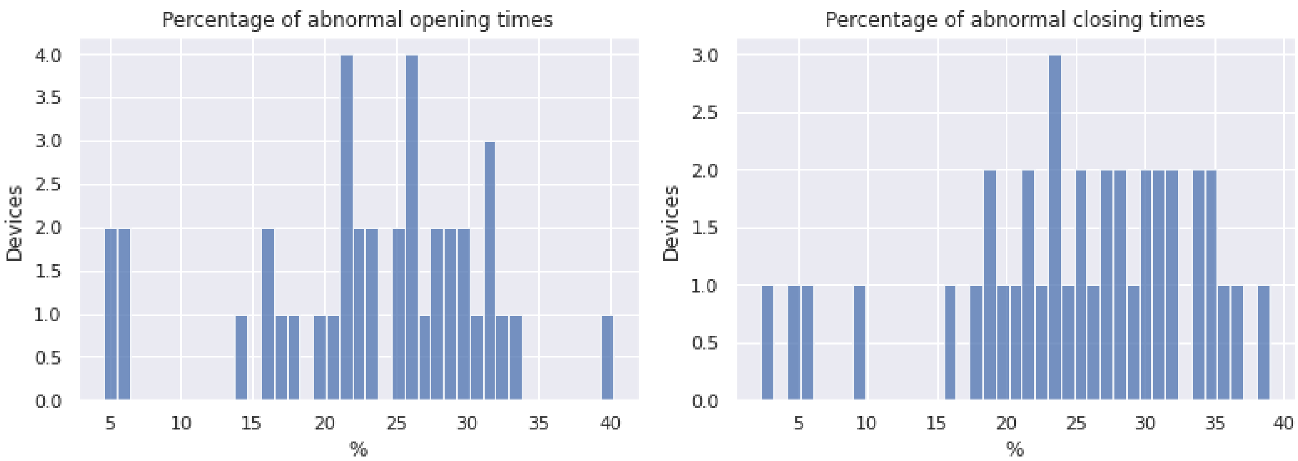


Figure 6.36: Percentage of abnormal sequence times

6.4.2 Clustering Based on Opening Sequences

For clustering, the common K-Means algorithm (MacQueen 1967) was used. In order to decide on the appropriate number of clusters to be used an Elbow study of 1 to 10 clusters was conducted. After 5 clusters the gradient of the graph below flattened out and therefore four clusters were deemed fit for the task. (Agnihotri et al. 2015)

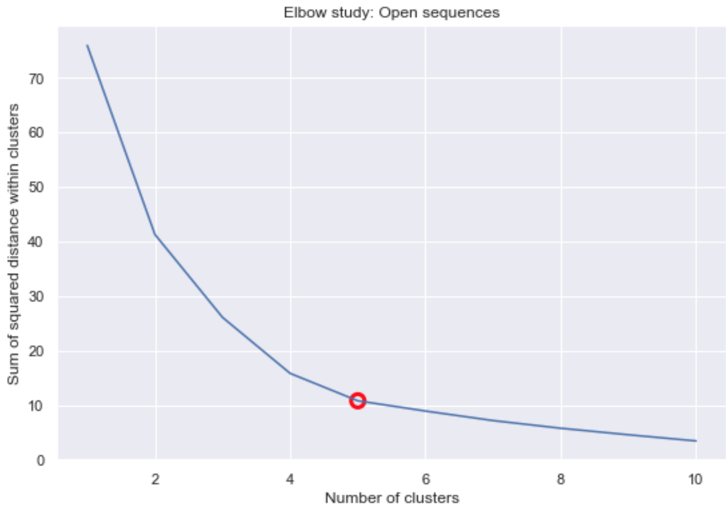


Figure 6.37: Elbow study for closing sequences

The clustering results in a few somewhat distinct clusters. For example Cluster 1 and 3, the by far largest groups with about 35% of the studied sample each. Both clusters consist of the devices with a low percentage of irregular openings which, as seen in Figure 6.42, is the majority of devices. The groups are then split based on their level of abnormal times. The other clusters look more like outliers but due to their extremely limited size possible future conclusions should be drawn with cautiousness.

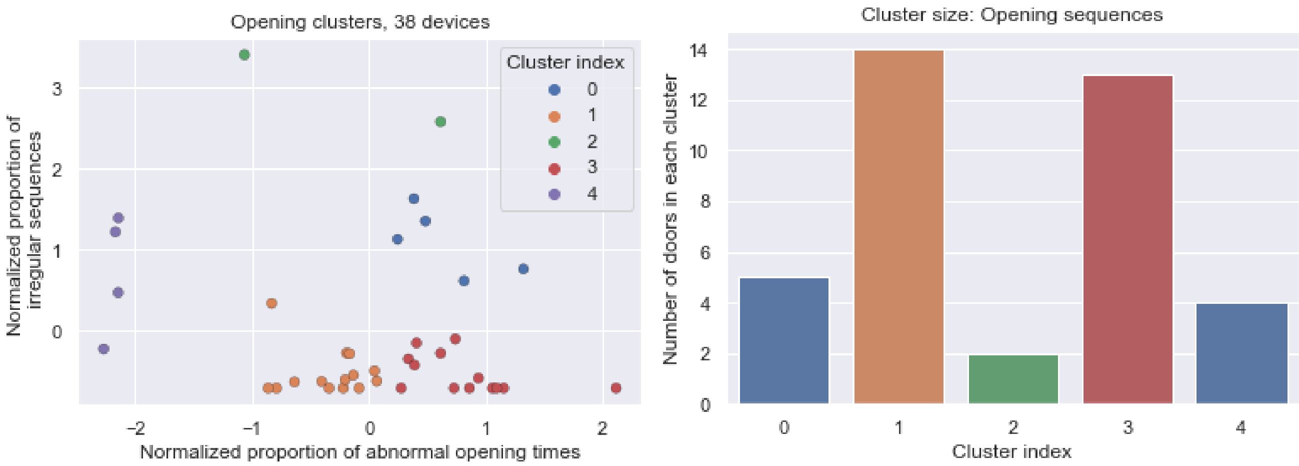


Figure 6.38: Identified opening clusters

To gain more knowledge of the devices' behavior or condition the clusters are compared through their other features. First, by opening frequency, it becomes clear that there is a wide dispersion with the clusters. However, the largest clusters, Cluster 1 and 3, exhibit relatively low frequencies. But then as stated in section 6.3.2 the vast majority of devices in the entire sample do have frequencies below 20 as well. Looking at sensor data the dispersion is even greater and no real relationships can be concluded from this analysis.

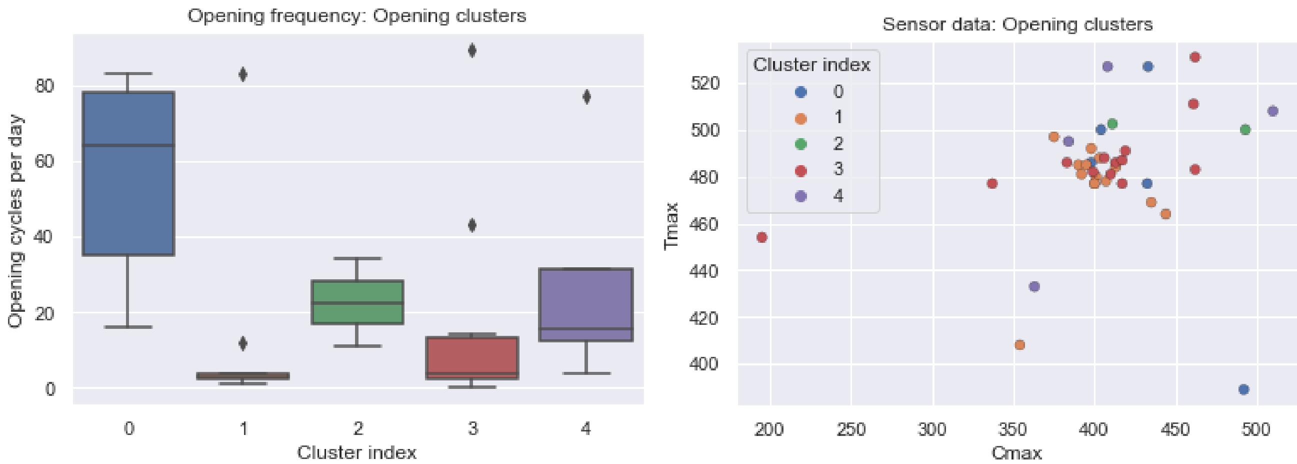


Figure 6.39: Features of the opening clusters

6.4.3 Clustering Based on Closing Sequences

In this section the features gathered from the closing sequences are used. The method used is the same as that of the previous clustering. Four clusters were also in this case deemed fitting for the task.

Compared to the opening sequences irregular sequences are a bit more spread out for closing sequences. Therefore the clusters do not get as distinctly separated on this metric, with that said Cluster 0 distinguishes as the group with the higher percentages of irregularities. As for the previous clustering is Cluster 2 somewhat of an outlier consisting of the devices with a very low percentage of abnormal times.

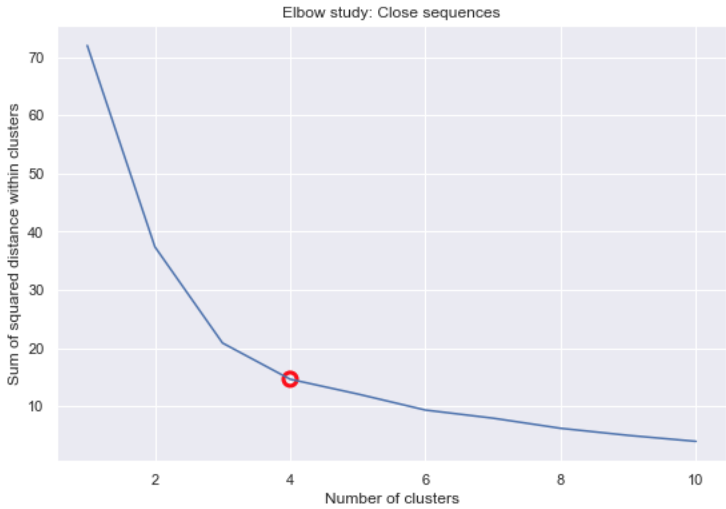


Figure 6.40: Elbow study for closing sequences

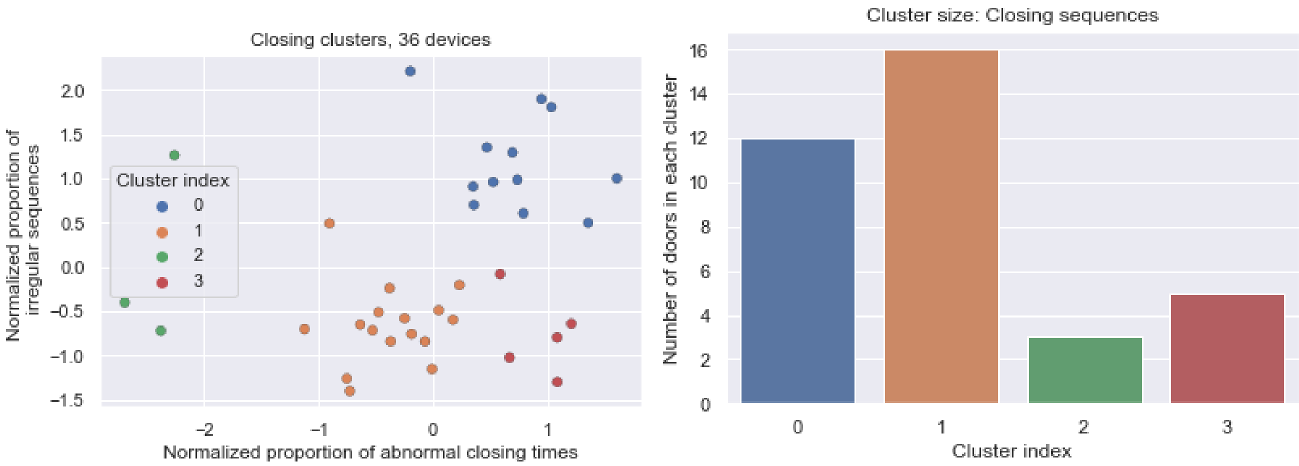


Figure 6.41: Identified closing clusters

Also the comparison to other features show similar results as earlier examinations, with no clear relationships to be concluded.

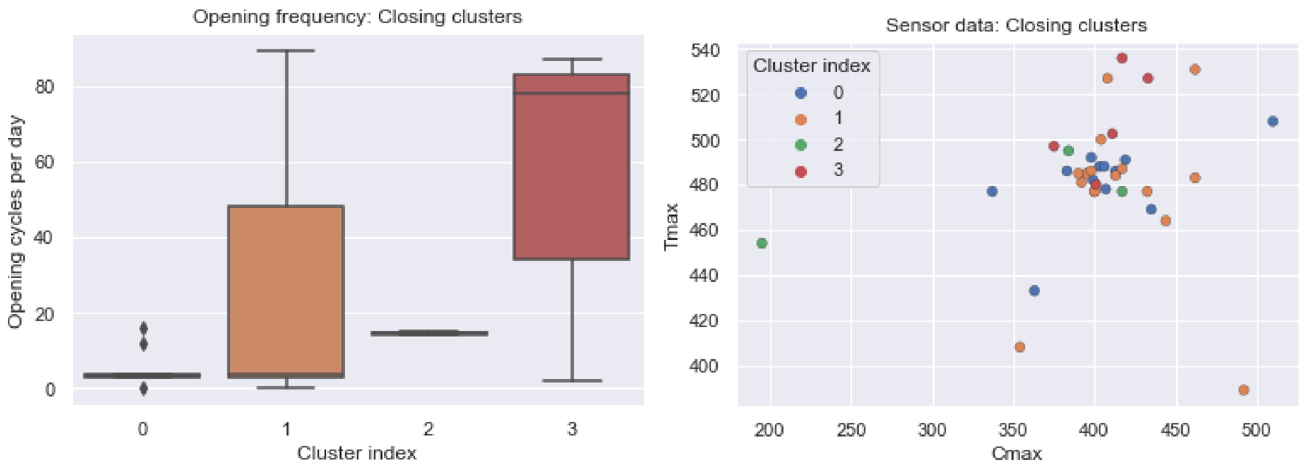


Figure 6.42: Features of the closing clusters

6.4.4 Comparing the Clusters

Combining the nine clusters identified from the previous sections the groupings become very dispersed, with most containing only one or two devices. This indicates that the clusters' characteristics in ways do not translate well between the two types of sequences. It may also be influenced by the fact that some of the identified clusters are already small due to the limited sample size. However, it can also be concluded that the majority of devices are found in a combination of at least one cluster indexed 1. For both types of sequences, Cluster 1 contains devices with a low proportion of irregular sequences. Showing that this characteristic is applicable to devices on a more general level. Further studying these groups one could draw the conclusion that these combinations, with the exception of Group 31, have a low operating frequency, yet this might be a cause of the group containing the majority of doors and most doors of the entire sample fall in the lower end of the frequency range. Studying the groups' relationships with the result from the sensor data no significant correlation could be extracted. In part, the smaller sample size could constitute the problem, but more likely is that the features constructed for the clustering have little or no impact on the condition of the machine.

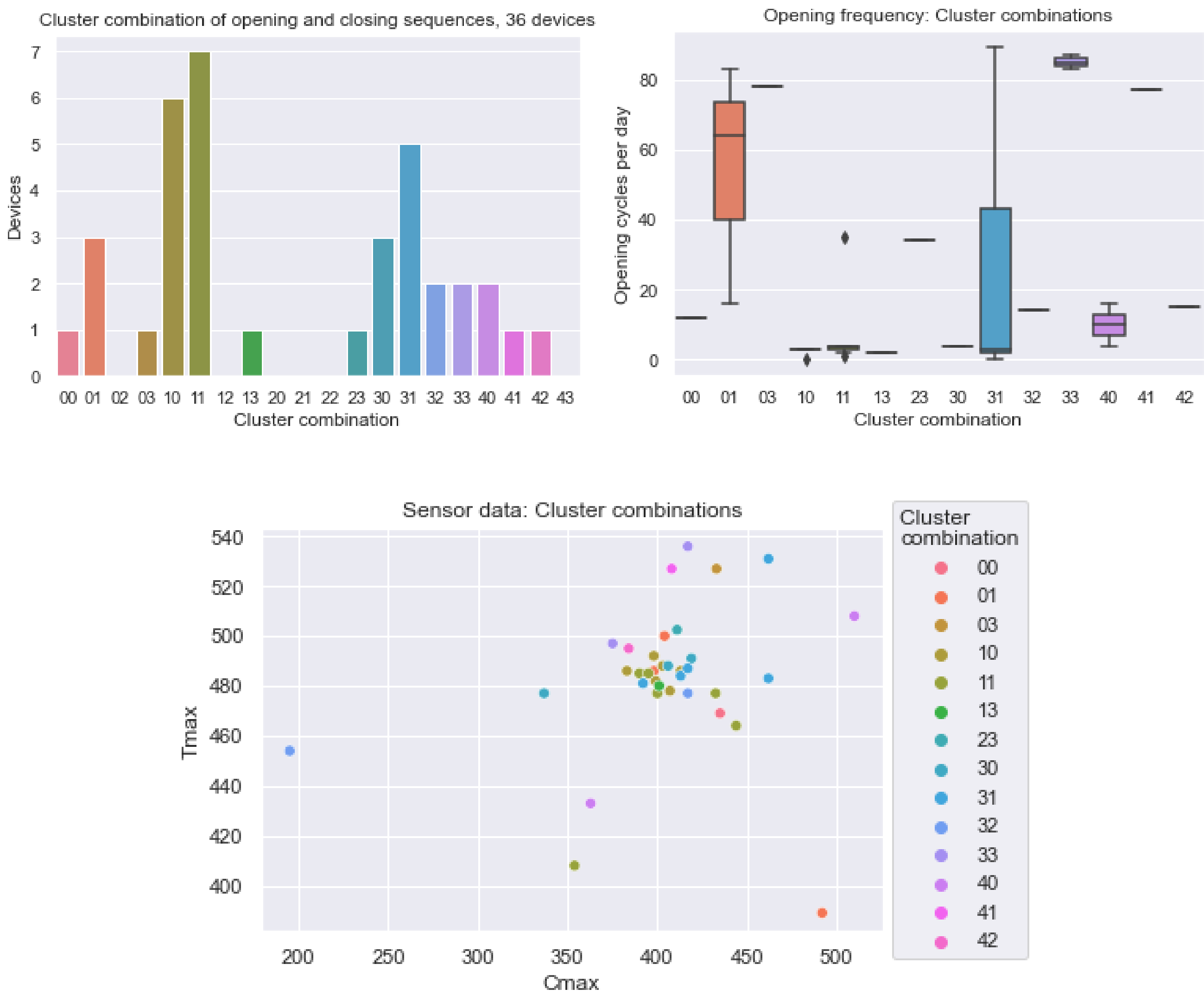


Figure 6.43: Devices indexed by both their opening and closing clusters

6.5 Predictive Modeling Analysis

The third research question of this study was to determine whether or not it is the current situation where possible to predict the breakdowns of the devices based on the accessible IoT data. As the project prolonged it became apparent that this would not be the case. On neither level of the outlined approaches: cycle-based, condition-based, or predictive. Some broader problems, affecting all three methods, became apparent during the analysis. Firstly, the lack of data regarding previous device breakdowns or service history, secondly the short time interval studied, and thirdly the high level of device-individuality and absence of clear causal relationships among the different features. These factors, among others, are elaborated on in chapter 7.

7 Discussion

AAES currently stands at a pathway crossing. They have started implementing the IoT infrastructure required to develop more sophisticated maintenance solutions and are now to decide in which direction the development of the service business will move forward. A complex decision analyzed through an AHP. The analysis established that time-based maintenance is better suited for a short time horizon while predictive maintenance will become more relevant for a longer time horizon. However, it is established that predictive maintenance is a good maintenance approach to consider moving forward.

The initial literature study showed that companies are to change their current business model in order to better exploit the possibilities enabled by IoT. Therefore, the IoT-centric business model was implemented for AAES from a PdM perspective. It resulted in insights into what changes PdM will bring to their current service business. Four distinctive approaches to why the IoT-centric business model is financially viable are identified, a few of which are discussed below.

Reduction of reactive service visit and operation costs

Through a benchmark study, it is identified that PdM has the potential to reduce reactive service visits by a maximum of 66%. However, this highly depends on the accuracy of the predictive algorithm. The reviewed prediction models are considered state of the art, achieving an accuracy level of between 87%-93%. Therefore, for AAES to achieve the same reduction results, the accuracy of the predictive model must be within the identified range.

Personnel and material costs savings

The concept centralizes around the fact that the need for educated service technicians will be reduced along with reduction in reactive service visits. The reactive service visits are more complex and require service technicians of higher experience. Currently there is a lack of available educated service personnel to hire. However, if the total number of reactive service visits is reduced upwards to 66% then the need for the experienced personnel will be reduced. Several possible scenarios were analyzed, where just reducing the percentage of educated service technicians by 30% resulted in an approximate 11% personnel cost reduction.

New Pricing System

AAES should transform their service business pricing system once a reliable predictive model has been developed. Rather than using the current conventional pricing model, the price should be based on delivered uptime rather than costs. A financially viable and established approach which has the potential of increasing the generated revenue, depending on the performance of the product. Hence incentivizing AAES to increase the reliability of their products, develop the best possible prediction model. The approach is considered to increase the relationship and trust between service provider and customer, due to the high mutual benefits. Where customers receive a higher delivered uptime while the service provider increases its revenue.

Furthermore, several different actions related to the building and distribution of the predictive model have been identified, the main actions are further discussed below. Firstly the development of the predictive algorithm has to be finalized. The market analysis established both order qualifying and order winning criteria for the after-sales service industry and four different customer segments. However, due to AAES characteristics, their service business is currently better suited to handle the larger corporations rather than small ones. Yet, this does not entail that they are lacking in fulfilling the needs of the other segments. Since their service business is better suited for larger customers while not lacking in satisfying the other segments, AAES should focus the development of service business improvements towards the larger customers' needs. The identified order winning attributes should be at the core of the predictive model development, where the main focus should be on the order winning attributes specific to the segment "larger sized customers".

As it was concluded during the quantitative analysis it was not, for the study, possible to build reliable prediction models with today's setup, the more interesting issue became identifying the problems and what was missing to be able to deliver the sought maintenance process. The most notable missing piece is complementary data to the IoT logs, such as service history of machine breakdowns and the maintenance that has been conducted as well as data describing the doors and their characteristics. Service data would have a central role in any preventive maintenance process. Firstly by providing insights of the breakdown landscape during development, both in regard to frequency and severity. Secondly to be used as the actual labels during training of an advanced supervised prediction algorithm. The study discusses an alternative solution with cycle resets. But because of the limited sample this method currently becomes considerably inaccurate, a reason to prefer service history. Door descriptions could include weight, size, mounted accessories, model, and environment the device is located in. This could be useful in order to, before any log data processing, categorize and in that way make more relevant comparisons and get better conditions for understanding behaviors and finding patterns. For this to work to its best potential it would also require more data.

All types of data analysis become more accurate the more data that is accessible and in the assignment of understanding door behavior both a longer studied time period, as well as a higher number of connected devices, could improve the analysis. The data used in this study ranged over about six months. However, it became apparent, due to the low frequency of resets and errors in the dataset, that this period is shorter than the average time between breakdowns. A longer timespan is therefore assumed to provide a better understanding of device behavior and if/how it changes over time. This change was something that the study failed to demonstrate, both in regard to the sensor data and to the identified patterns. A larger set of devices could also improve this, both in learning the “normal” operations and in having more deviating situations. A larger sample size could especially benefit the clustering analysis, which today with the used setup could not identify any deeper findings. More devices are thought to provide a more complete view which may show new relationships.

An issue that has been noted several times during the project is the high variance among measurements. Both between devices, which seem to have a lower level of standardization, but also within the measurements for individual doors. This first became apparent when studying the sensor data and made it difficult to conclude strong relationships between the different features. One possible explanation for this is the presumed inaccuracy of sensors, based on the occurrence of missing or unreasonable measurements. However, there is no guarantee that increasing the quality of data would improve the ability to find causal relationships, one concern in this regard is the assessed high level of natural variance between the doors. In such situations it becomes critical that the correct type of sensors are used based on the characteristics of the errors. In order to utilize the sensor data to its fullest much understanding of the sensors is needed. This becomes especially evident with regards to the current sensor, whose results and relationships with other features are difficult to interpret. In extension to this, the results from the data analysis in general, become more reliable when conducted by people with high domain knowledge.

The issues outlined above are all in some degree important in the process of offering solid preventive maintenance solutions and improvements in all of these accepts should therefore be pursued. However, since the development in many ways is in the earlier stages the preferred method forward should be guided by simplicity with a focus on what the customer deems most valuable.

The study concluded that preventive maintenance methods, either based on cycle data, sensor data, event data, or a combination, can provide substantial value both for customers and the organization. Even though the conducted analysis did not find any considerably strong relationship of sensor or sequence data, it is still considered highly possible that there are, which might be found during continuous evaluations with different circumstances.

Once a new preventive maintenance model has been established, the right resources need to be allocated to assist the service delivery process in order to gain the best competitive advantage. Firstly the ERP system should be updated in order to enable the willing customers to utilize the prepaid gold contract, which will increase AAES return of investment. Secondly, an intuitive API for the predictive model has to be developed, three different approaches were identified for this action. However, the best way of action is to start by letting customers utilize the current API with no further development when the predictive model is initialized, since it requires the least amount of effort. As the product becomes more established and gains a greater customer base AAES should put more effort into developing the API into a more standardized product, where customers more easily can interpret the state of their devices.

8 Conclusion & Recommendation

8.1 Findings

The findings of the master thesis are summarized below by answering the formulated research questions.

- RQ1: *Which advanced preventive maintenance method is best suited for a technology-based manufacturing company with a service business?*

  This study found predictive maintenance to be the best suited alternative for technology-based manufacturing companies with a service business. Manufacturing companies characterized by underlying conditions similar to the ones of the studied case company. Conditions such as similar market positioning, customer expectations and sufficiently technological advanced products, with significant technical differences between product variants.

- RQ2: *How will the service delivery process change with the implementation of advanced preventive maintenance on a time-based service organization?*

  The service delivery process will see a significant increase in its technological dependence. Connected devices, gathered IoT data, labeled historical service data, and complementary data will become a central part of the service infrastructure. Furthermore, the service related infrastructure will assist the service delivery process in its continuous improvement of the prediction model.

  - RQ2a: *Which economic implications does advanced preventive maintenance process have on a time-based service organization?*

Offering advanced preventive maintenance, in particular predictive maintenance, as a service will have significant economic implications on a time-based service organization. The main implication is that it will render the conventional pricing system which a time-based service organization uses obsolete. Both the service organization and its customers better benefit from a performance-based pricing system, where the prices are based on the delivered performance. Which in the case of entrance systems are defined as delivered uptime. Further economical implications consist of reducing different expenses related to reactive maintenance. Where a cost saving potential in the range of 13.7 % - 36.7 % arises from a reduction in the need of experienced service technicians.

- RQ2b: *Which operational implications does advanced preventive maintenance process have on a time-based service organization?*

  Offering advanced preventive maintenance, in particular predictive maintenance, as a service will have a significant impact on a time-based service organization's daily operations. Firstly, the organization will experience a reduction of redundant service visits. As identified in through literature review, advanced methods such as predictive maintenance possesses the ability to reduce a time-based service organization reactive service visits by upwards of 66%. Furthermore, this reduction allows for more efficient allocations of service technicians' time and reduces the organization's need for educated service technicians. Hence the daily operations of the service technicians will focus more on simple preventive activities, allowing them to focus on and perform other value-adding activities for the organization.

• RQ3: *Is it today possible to predict future breakdowns based on IoT-data gathered from an industrial setting?*

This thesis found, though the initial literature review, that breakdown prediction has been implemented successfully in several previous cases. However, based on the IoT data gathered from the case company the study was not able to achieve similar results using any of the outlined preventive methods at the current moment in time. The study points to the importance of having complementary data to the analysis of IoT data in order to better understand the setting in which the analysis takes place. In concussion, the study argues that IoT data alone is not enough to make predictions. Yet models for making predictions for standardized devices can exhibit successful results when developed with a high level of knowledge regarding domain and context.

- RQ3a: *What IoT data is needed in order to make breakdown predictions?*

  Through the study's literature review of predictive maintenance solutions, it became apparent that a common approach was to rely on various sensors in order to describe the operating condition of the machine. This approach requires reliable sensors of types appropriate both to the studied devices and to the type of breakdowns that are being predicted. It is also important to have a firm understanding of the measurements. Sensors linked with machine deterioration such as produced heat or vibrations have shown favorable results on a case basis. Another, somewhat more advanced approach, is to gather the IoT data describing movements or states in order to learn the operational sequences and in this way recognize deviations. An issue related to the study's failure to produce prediction models in regard to IoT data needed is the timespan and sample size the data is gathered from. The study concludes that the dataset should be considerable longer and advantageously include more samples, compared to that used in this thesis.
- RQ3b: *What IoT data can be considered redundant in the case of breakdown prediction?*

  Since the study's failure of producing prediction models was in large part caused by factors outside of the IoT data. Therefore, none of the studied data is considered redundant. More available data helps in understanding the setting of the prediction, an understanding that is vital in order to produce reliable results. When this setting has been sufficiently mapped the issue of redundancy can be further considered.

- RQ4: *What is possible to learn about customer usage based on analysis of IoT data?*

  From the IoT data the considerable difference in frequency of which the devices are used became apparent. However no stronger concussions could be drawn from this knowledge. On a broader level this study found that the examined customer segments lacks a strategic relationship with their connected devices. External factors inflicted by customers causes the far majority of all the reactive service visits. These manifest themselves as what is referred to as common errors, i.e. machine failures due to external factors. These are frequently occurring, shown in the IoT data, easily resolved and, generate revenue. However, they force the service delivery company to be both agile and flexible since the urgency of the reactive service is high and customers want the possibility of receiving support during a large portion of the day.

  - RQ4a: *How can this knowledge be leveraged in the offering of service?*

    The findings identified from the IoT data can be utilized through offering customers individual service packages based on the frequency of which their devices are used. Additionally can the broader findings identified in RQ4 can be utilized through the concept of remote service due to the simple nature of the related reactive service activities. However two main parameters must be defined for this to be a viable alternative. Firstly, the issues of responsibility must be strictly defined. Secondly, a standardized pricing framework must be established, a framework that does not reduce the revenue streams generated from these errors.

8.2 Credibility Discussion

AAES is a large organization with a wide variety of different branches that all possess valuable information for this master thesis. Therefore, because of the nature of the organisation, there is a large risk that not all accessible and valuable information have been collected. However, to counteract this effect and increase the chances of collecting this information, a wide range of interviews has been conducted throughout the thesis. Where employees of different management-level from different branches have been consulted. In larger organisations there is a greater risk that some departments have eventual biases for certain subjects. The wide range of interviews reduces the risk of these biases influencing the analysis. To further reduce the risk of bias influencing the results, the authors maintained a neutral position throughout all interviews. Furthermore, all interviews were conducted in the native language of the interviewees to eliminate the risk of possible misinterpretation.

Regarding the analysis of IoT data, the examination is naturally very closely tied to the study object. The analysis has mainly evaluated the case company's current abilities to implement new preventive maintenance methods. This limits the representativness of the findings significantly. Yet the study attempts to widen the scope by a thorough literature review with industry examples.

Several other factors concerning the IoT data also question the certainty of the conclusions drawn. The small sample of devices is such a factor. This especially affected the clustering analysis and caused very small groups to be formed. This is thought to be part of the reason to why no notable relationships were found. A larger sample could exhibit a wider view of devices and in that way indicate stronger relationships. Another problematic part is the short time horizon of which data is gathered, on which it was difficult to display a change in behavior. It is to the study probable that an examination of the devices during a longer time period would present more clear changes, due to the hypothesis that deterioration shows in operations and machine condition. Yet the study was unable to exhibit this. Even during the analysis of cycle reset, in which the short time horizon was not considered a problem, was no clear change of performance found. Further suggesting that large portions of knowledge are still missing and that the results include a high degree of uncertainty.

Furthermore, the overall inaccuracy of data constitute a considerable defect to the credibility of the findings. Examples of this are the inconstancy of sensor data and the sequence tagging. Both of which can be improved to be more accurate. In order to limit the impact of these did the study remove outliers, both based on domain knowledge and on what was considered statically reasonable.

The representativness of the value-dimension related to offering predictive maintenance as a service, namely whether or not the value-dimension analysis can be applied to other technology-based manufacturing companies with a service business, varies depending on a number of parameters. However, the underlying drive of change for the value-dimension is based on benchmark studies and is considered to be the same across different study objects. It is the magnitude of the driving forces which varies heavily between study objects.

Offering predictive maintenance as a service has the possibility to reduce the amount of reactive service visits significantly, while the exact figure varies heavily depending on the prerequisites of the study object. However, the underlying drive, i.e. the possibility of reducing reactive visits, is considered to be the same across all study objects. Although it requires the predictive algorithm to fulfill a variety of requirements. The concept of the possible personnel-and material cost reduction is based on this reduction. It centralizes around rearranging the distribution of educated personnel, and saving costs from utilizing less educated personnel. These possibilities may vary significantly depending on the geographical location of the study object. Where in some regions it is more culturally acceptable to utilize this approach, while in other regions it is not acceptable. Therefore, the representativeness of these concepts is relative and will fluctuate depending on the study object.

The representativeness of the increased perceived customer value and new pricing system is considered to be significantly higher than previous approaches. These are considered to be applicable for all technology-based manufacturing companies with a service business which products value are based on its performance. Just as the value of AAES' entrance systems are based on their functionality, i.e. the delivered uptime.

Lastly, both the how and the who-dimension will vary significantly depending on the study object. The study objects prerequisites for developing and implementing predictive maintenance as a service highly influence the outcome of these parameters. Therefore, the representative will also fluctuate depending on the study object.

8.3 Academic Contribution

The Internet of Things is an established subject in which there is a substantial research base. However, the concept of predictive maintenance is relatively new with a lack of academic research conducted regarding how predictive maintenance should be developed and implemented within a technological-based manufacturing company with a service business. The research mainly focused on how it should be conducted internally, mainly in a manufacturing environment, and on the effects of well-established market-leading predictive systems. From a service perspective, the research is lacking.

This master thesis has contributed with a detailed description and mapping of the requirements to implement predictive maintenance within a technological-based manufacturing company with a service business. Additionally, how predictive maintenance is to impact the service business of a technological-based manufacturing company with a service business.

The contribution gives a holistic overview of the actions related to developing predictive maintenance, what challenges are related to the development, and the changes required within the organisation. Furthermore, once the development is completed the thesis contributes with an overview of how to implement predictive maintenance within the service business, and deals with the organisational and economical changes it may enable.

Lastly, the thesis contribution is summarized as acting as a guide and assisting technological-based manufacturing companies with a service business to understand their limitations and abilities related to developing and implementing predictive maintenance based on analysis of IoT data.

8.4 Suggestions for Future Research

As concluded in previous sections, the thesis lacks generalizability since large portions of the analysis are solely based on the case company. To broaden the view it would be beneficial to include comparisons with other companies, both within and outside the own sector, in similar situations with resembling business models as the chosen case company. This could give insights into what issues are unique and which are more commonly occurring. An important realization in order to optimize the strategic path forward.

The thesis takes an initial look at the IoT data from the case company which as a suggestion could be extended. An extended analysis could include some or several of the denoted “missing pieces”, such as complementary data or a longer timespan, in order to evaluate the possibilities of producing prediction models. An addition to the clustering analysis is also preferable, with the investigation of other features that could indicate problematic behaviors.

Further research with regards to the described new pricing system is also interesting. A broader benchmarking, both within and outside the current sector, and mapping of best practices by established actors in how to deliver uptime instead of solely a product is desirable and currently not found within academic research.

References

Agnihotri, L., Aghababyan, A., Mojarad, S., Riedesel, M. & Ess, A. (2015). *Mining Login Data for Actionable Student Insight.*

ASSA ABLOY (2020). *Annual Report 2020.* Available at `https://www.assaabloy.com/group/en/investors` [2021-03-25]

ASSA ABLOY Entrance Systems (AAES) (2020 a). *Our Division*

ASSA ABLOY Entrance Systems (AAES) (2020 b). *Business Segments*

ASSA ABLOY Entrance Systems (AAES) (2020 c). *Industrial Business Segment*

ASSA ABLOY Entrance Systems (AAES) (2020 d). *Service*

ASSA ABLOY Entrance Systems (AAES) (2020 e). *Preventive Maintenance*

ASSA ABLOY Entrance Systems (AAES) (2020 f). *Service Information Flow*

ASSA ABLOY Entrance Systems (AAES) (2020 g). *IDS Product Documentation*

ASSA ABLOY Entrance Systems (AAES) (n.d. a). Service Delivery Process IDS (PowerPoint Presentation)

ASSA ABLOY Entrance Systems (AAES) (n.d. b). ASSA ABLOY Insight (PowerPoint Presentation)

Canizo, M., Onieva, E., Conde, A., Charramendieta, S., & Trujillo, S. (2017). *Real-time predictive maintenance for wind turbines using Big Data frameworks.* IEEE International Conference on Prognostics and Health Management (ICPHM). pp. 70-77.

Carvalho, T., Soares, F., Vita, R., Francisco, R., Basto, J., & G. Soares Alcalá, S. (2019). *A systematic literature review of machine learning* *methods applied to predictive maintenance.* Computers & Industrial Engineering.

Durbhaka, G. K. & Selvaraj, B. (2016). *Predictive maintenance for wind turbine diagnostics using vibration signal analysis based on collaborative recommendation approach.* International Conference on Advances in Computing, Communications and Informatics (ICACCI). pp. 1839-1842.

Efficient Planet. (2012). *The Rolls-Royce Of Effective Performance-Based Collaboration.* Available at `https://www.efficientplantmag.com/2012/06/the-rolls-royce-of-effective-performance-based-collaboration/?fbclid=IwAR2qGF5jm4oDupcu1yJy4zO-LOOhi8iDldHZSscwNsRKsxoaktYzqWeXb8Y` [2021-05-21]

Forman, E., Gass, S., (2001). *The Analytic Hierarchy Process—An Exposition.* Operations Research. Vol. 49, pp 469-486.

Gassmann, O., Frankenberger, K. & Csik, M. (2014). *Revolutionizing the Business Model.* Management of the Fuzzy Front End of Innovation. pp 89-97

Gęca, J. (2020). *Performance Comparison of Machine Learning Algorithms for Predictive Maintenance.* Informatyka, Automatyka, Pomiary W Gospodarce I Ochronie Środowiska. Vol. 10, Iss. 3, pp. 32-35

Gutschi, C., Furian, N., Suschnigg, J., Neubacher, D. & Voessner, S. (2019). *Log-based predictive maintenance in discrete parts manufacturing.*

Hill, T. & Hill, A. (2018). Operations strategy : design, implementation and delivery. London: Palgrave.

Höst, M., Regnell, B. Runeson, P. (2006). Att genomföra examensarbete. 1st edition. Lund: Studentlitteratur.

Lee, S.M., Lee, D. & Kim, Y.S. (2019). *The quality management ecosystem for predictive maintenance in the Industry 4.0 era.* Int J Qual Innov. Vol. 5, Iss. 4.

Li, S., Xu, L.D. & Zhao, S. (2015). *The internet of things: a survey.*

Information Systems Frontiers. Vol, 17 pp 243–259.

Liulys, K. (2019). *Machine Learning Application in Predictive Maintenance.* Open Conference of Electrical, Electronic and Information Sciences. pp. 1-4.

MacQueen, J. (1967). *Some methods for classification and analysis of multivariate observations.* Berkeley Symposium on Mathematical Statistics and Probability. Vol. 5, pp: 281-297.

McKinsey & Company. (2019). *Cracking the code of repair analytics.* Available at `https://www.mckinsey.com/business-functions/operations/our-insights/cracking-the-code-of-repair-analytics` [2021-02-11]

McKinsey & Company. (2020). *The future of maintenance for distributed fixed assets.* Available at `https://www.mckinsey.com/business-functions/operations/our-insights/the-future-of-maintenance-for-distributed-fixed-assets` [2021-02-11]

Rahhal, J. S., & Abualnadi, D. (2020). *IOT Based Predictive Maintenance Using LSTM RNN Estimator.* International Conference on Electrical, Communication, and Computer Engineering (ICECCE). pp. 1-5.

Rastogi, V., Srivastava, S., Mishra, M., & Thukral, R. (2020). *Predictive Maintenance for SME in Industry 4.0.* 2020 Global Smart Industry Conference (GloSIC). pp. 382-390.

Rosmaini, A., Shahrul, K. (2012). *An overview of time-based and condition-based maintenance in industrial application.* Computers & Industrial Engineering. Vol. 63, Iss. 1, pp 135-149.

Saaty, T. (2008). *Relative Measurement and its Generalization in Decision Making: Why Pairwise Comparisons are Central in Mathematics for the Measurement of Intangible Factors – The Analytic Hierarchy/Network Process.* Review of the Royal Academy of Exact, Physical and Natural Sciences, Series A: Mathematics (RACSAM). Vol. 102, Iss. 2, pp. 251–318.

Saracoglu, B.O. (2013). *Selecting industrial investment locations in master plans of countries.* European Journal of Industrial Engineering.

Vol. 7, Iss. 4, pp 416–441.

Shin, J-H., Jun, H-B. (2015). *On condition based maintenance policy.* Journal of Computational Design and Engineering, Vol. 2, Iss. 2, pp 119–127.

Sisinni, E., Saifullah, A., Han, S., Jennehag, U. & Gidlund, M. (2018). *Industrial Internet of Things: Challenges, Opportunities, and Directions.* IEEE Transactions on Industrial Informatics. Vol. 14, pp. 4724-4734.

Techrepublic. (2020). *Moore's Law turns 55: Is it still relevant?* Available at `https://www.techrepublic.com/article/moores-law-turns-55-is-it-still-relevant/` [2021-02-16]

Wang, J., Li, C., Han, S., Sarkar, S. & Zhou, X. (2017). *Predictive maintenance based on event-log analysis: A case study.* IBM Journal of Research and Development, Vol. 61, Iss. 1, pp. 11:121-11:132.

Yan, J., Meng, Y., Lu, L. & Li, L. (2017). *Industrial Big Data in an Industry 4.0 Environment: Challenges, Schemes, and Applications for Predictive Maintenance.* IEEE Access, Vol. 5, pp. 23484-23491.

Zhu, Q., Peng, H. & van Houtum, GJ. (2015). *A condition-based maintenance policy for multi-component systems with a high maintenance setup cost.* OR Spectrum. Vol. 37, pp. 1007–1035.

Zoll, M., Jack, D., & Vogt, M. (2018). *Evaluation of Predictive-Maintenance-as-a-Service Business Models in the Internet of Things.* pp. 1-9.

Appendices

A. Interview Guide (Swedish)

Organisatoriska

1. Vilka entrance systems är det som säljer bäst inom IDS?
2. Inom vilken av kategorierna ovan är 950, 950D som vi undersöker?
3. Vilka kategorier av dörrar är nu uppkopplade?

Personliga frågor

1. Vilken tjänst har du?
2. Vilken erfarenhet har du inom AAES Service?
   (a) Hur länge har du arbetat inom AAES?

Service Business

1. Hur stor del av era service activities är preventive vs reactive service?
2. Kan kunderna använda sig av en tredje part-service?
   (a) Hur ofta sker detta?
3. Hur stor del av AAES intäkter består av service?
4. Finns det statistik på hur många av kunderna som tillhör de olika service kontrakten?
   (a) Guld
   (b) Silver
   (c) Brons

5. Vilka kundtyper väljer typiskt de olika kontrakten? Finns det någon kundtyp som brukar välja t.ex. guld kontraktet snarare än bronze? Ex.vis. Större bolag drar sig åt guld kontraktet.
    (a) Guld
    (b) Silver
    (c) Brons
6. För er service Business, vad anser du är Order Qualifiers och Order Winners.
    (a) Order qualifiers
    (b) Order winners

Service Process och Service Aktiviteter

1. Vi har mappat serviceprocessen enligt ovan [], Skulle du kunna definiera de olika stegen mer i detalj.
2. Hur får ni reda på equipment breakdowns?
3. Hur ser arbetsuppgifterna ut för en:
    (a) Service Technician
    (b) Senior Service Technician
    (c) Field Service Technician
4. Field Service Technician
5. Hur tror Du att serviceteknikers arbetsuppgifter kommer att förändras vid implementering av en predictive maintenance algoritm?
6. Vilka förbättringar i serviceprocessen anser Du att en predictive maintenance algoritm hade medfört?
7. Vilka fel/breakdowns anser Du man borde kunna prediktera med en sådan algorithm?
8. På vilka parametrar baseras beslutet om remote service är lämpligt?

    Om en service technician inte anser att remote service är lämpligt, skickas ärendet vidare till en senior technician.

9. Vilka aspekter är det vanligen som en senior technician ser men inte en “junior”?
10. Hur fungerar en remote service?
    (a) Service via cloud?
    (b) Instruerar kund?
11. Hur fungerar en customer remote service
    (a) Reparerar kunden själv enheten?
12. Vad är skillnaden mellan customer remote service och remote service?

B. Analytical Hierarchy Process

The first AHP was made in collaboration with the Iot Platform Manager and the Senior Program Manager. The entire AHP is visualised below.

Step 1: Consult individual experts within the decision field were consulted to determine the relative magnitude between the different factors through pairwise comparisons.

Decision Criteria	**False Negative**	**False Positive**	**Ability to Reduce Costs**	**Simplicity of Development**	**IoT Infrastructure Requirements**	**Ease of Implementation**
False Negative	1	5	0,2	0,3333	0,3333	0,3333
False Positive	0,2	1	0,2	0,3333	0,2	0,3333
Ability to Reduce Costs	5	5	1	5	5	3
Simplicity of Development	3	3	0,2	1	1	0,3333
IoT Infrastructure Requirements	3	5	0,2	1	1	0,3333
Ease of Implementation	3	3	0,3333	3	3	1

Step 2: Calculate the values of different decision parameters

Decision Criteria	False Negative	False Positive	Ability to Reduce Costs	Simplicity of Develop-ment	IoT Infrastr-ucture Requirements	Ease of Impleme-ntaion	Average
False Negative	0,065789	0,227272	0,09375	0,03125	0,03164557	0,0625	0,085367
False Positive	0,013157	0,045454	0,09375	0,03125	0,018987342	0,0625	0,044183
Ability to Reduce Costs	0,328947	0,227272	0,46875	0,46875	0,474683544	0,5625	0,421817
Simplicity of Development	0,197368	0,136363	0,09375	0,09375	0,094936709	0,0625	0,113111
IoT Infrastructure Requirements	0,197368	0,227272	0,09375	0,09375	0,094936709	0,0625	0,128262
Ease of Implementa-tion	0,197368	0,136363	0,15625	0,28125	0,284810127	0,1875	0,207257
Sum	1	1	1	1	1	1	1

Step 3: Evaluate the different maintenance approaches based on the decision criteria

False Negative

Maintenance Type	Predictive	Condition-based	Cycle-based	Time-based
Predictive	1,00	3,00	5,00	7,00
Condition-based	0,33	1,00	3,00	5,00
Cycle-based	0,20	0,33	1,00	3,00
Time-based	0,14	0,20	0,33	1,00
Sum	1,68	4,53	9,33	16,00

Maintenance Type	Predictive	Condition-based	Cycle-based	Time-based	Average
Predictive	0,60	0,66	0,54	0,44	0,56
Condition-based	0,20	0,22	0,32	0,31	0,26
Cycle-based	0,12	0,07	0,11	0,19	0,12
Time-based	0,09	0,04	0,04	0,06	0,06
Sum	1,00	1,00	1,00	1,00	1,00

False Positive

Maintenance Type	Predictive	Condition-based	Cycle-based	Time-based
Predictive	1,00	3,00	5,00	7,00
Condition-based	0,33	1,00	3,00	5,00
Cycle-based	0,20	0,33	1,00	3,00
Time-based	0,14	0,20	0,33	1,00
Sum	1,68	4,53	9,33	16,00

Maintenance Type	Predictive	Condition-based	Cycle-based	Time-based	Average
Predictive	0,60	0,66	0,54	0,44	0,56
Condition-based	0,20	0,22	0,32	0,31	0,26
Cycle-based	0,12	0,07	0,11	0,19	0,12
Time-based	0,09	0,04	0,04	0,06	0,06
Sum	1,00	1,00	1,00	1,00	1,00

Ability to Reduce Costs

Maintenance Type	Predictive	Condition-based	Cycle-based	Time-based
Predictive	1,00	3,00	5,00	7,00
Condition-based	0,33	1,00	3,00	5,00
Cycle-based	0,20	0,33	1,00	3,00
Time-based	0,14	0,20	0,33	1,00
Sum	1,68	4,53	9,33	16,00

Maintenance Type	Predictive	Condition-based	Cycle-based	Time-based	Average
Predictive	0,60	0,66	0,54	0,44	0,56
Condition-based	0,20	0,22	0,32	0,31	0,26
Cycle-based	0,12	0,07	0,11	0,19	0,12
Time-based	0,09	0,04	0,04	0,06	0,06
Sum	1,00	1,00	1,00	1,00	1,00

Simplicity of Development

Maintenance Type	Predictive	Condition-based	Cycle-based	Time-based
Predictive	1,00	0,25	0,17	0,13
Condition-based	4,00	1,00	0,20	0,17
Cycle-based	6,00	5,00	1,00	0,25
Time-based	8,00	6,00	4,00	1,00
Sum	19,00	12,25	5,37	1,54

Maintenance Type	Predictive	Condition-based	Cycle-based	Time-based	Average
Predictive	0,05	0,02	0,03	0,08	0,05
Condition-based	0,21	0,08	0,04	0,11	0,11
Cycle-based	0,32	0,41	0,19	0,16	0,27
Time-based	0,42	0,49	0,75	0,65	0,58
Sum	1,00	1,00	1,00	1,00	1,00

IoT Infrastructure Requirements

Maintenance Type	Predictive	Condition-based	Cycle-based	Time-based
Predictive	1,00	0,33	0,20	0,11
Condition-based	3,00	1,00	0,33	0,20
Cycle-based	5,00	3,00	1,00	0,33
Time-based	9,00	5,00	3,00	1,00
Sum	18,00	9,33	4,53	1,64

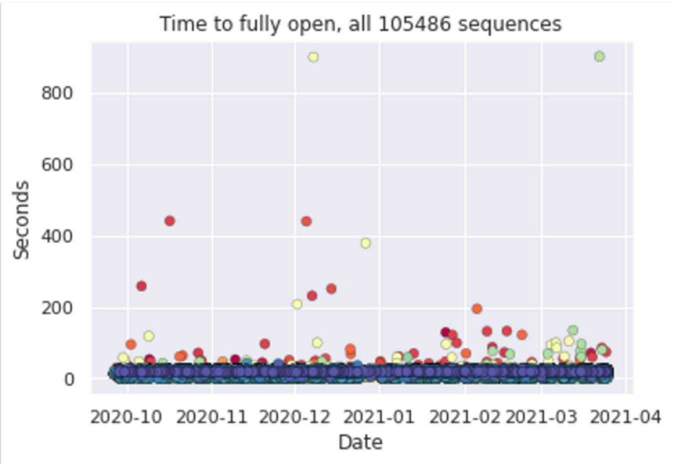
Maintenance Type	Predictive	Condition-based	Cycle-based	Time-based	Average
Predictive	0,06	0,04	0,04	0,07	0,05
Condition-based	0,17	0,11	0,07	0,12	0,12
Cycle-based	0,28	0,32	0,22	0,20	0,26
Time-based	0,50	0,54	0,66	0,61	0,58
Sum	1,00	1,00	1,00	1,00	1,00

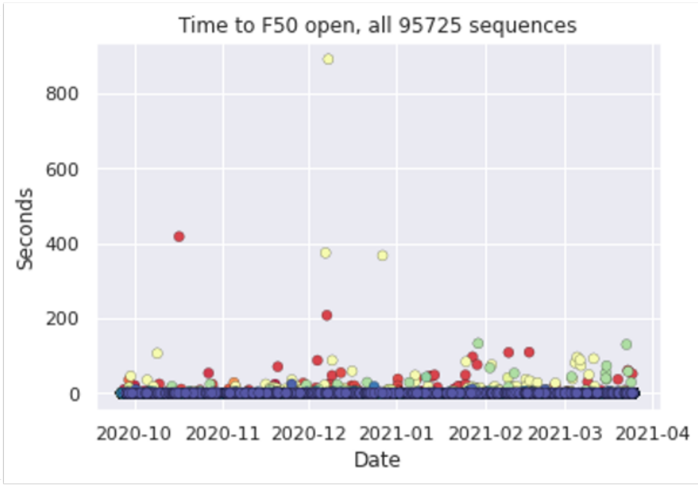
Step 4: Summarize the analysis and draw conclusion

Maintenance Type	False Negative	False Positive	Ability to Reduce Costs	Simplicity of Develo-pment	IoT Infrastructure Requirements	Ease of Imple-mentation	Sum
Predictive	0,04763	0,02465	0,23533	0,00524	0,00651	0,00890	0,32825
Condition-based	0,02248	0,01164	0,11108	0,01237	0,01504	0,02412	0,19674
Cycle-based	0,01040	0,00538	0,05141	0,03033	0,03279	0,05661	0,18692
Time-based	0,00486	0,00251	0,02400	0,06518	0,07393	0,11762	0,28810
Sum ()	0,09	0,04	0,42	0,11	0,13	0,21	1,00

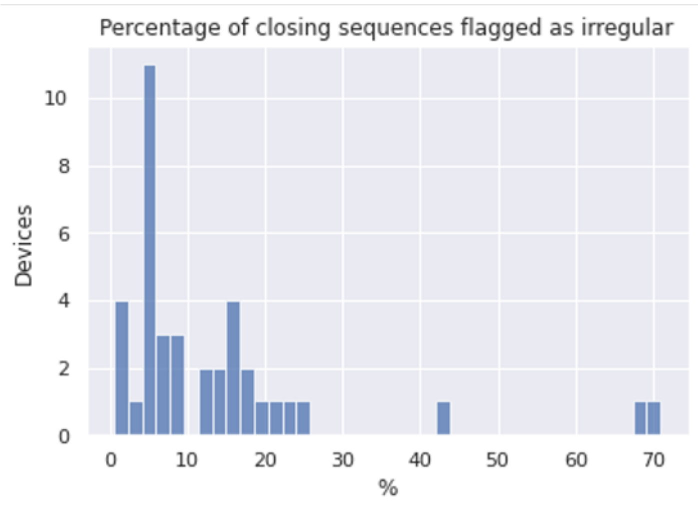
C. Opening and Closing Sequences

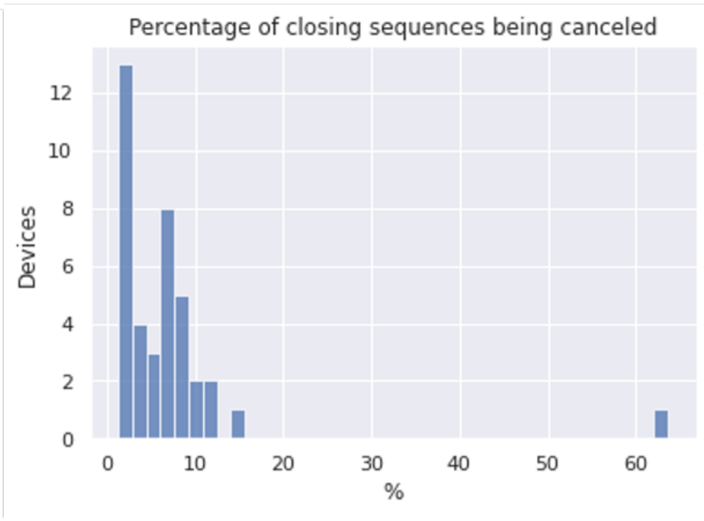
Opening sequences



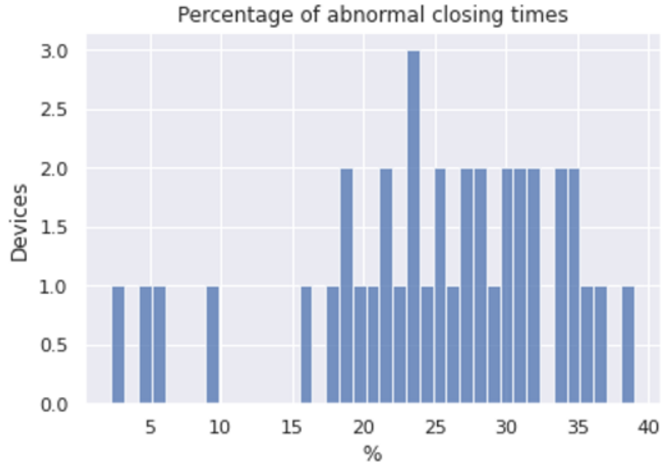


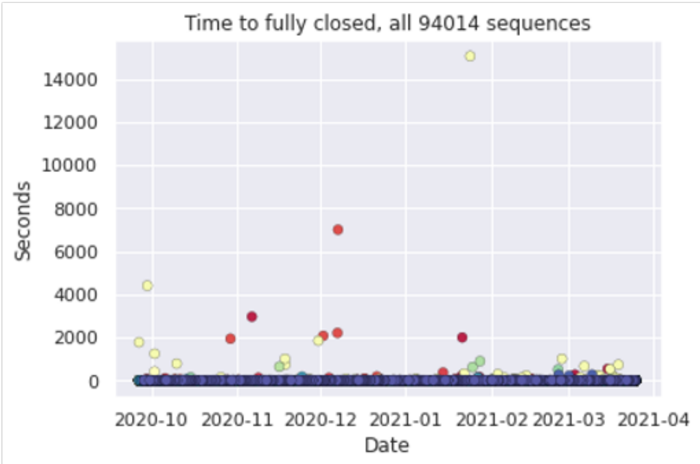
Closing sequences

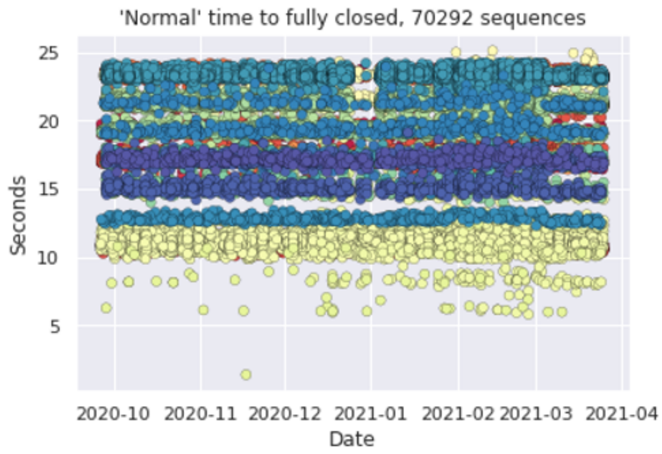


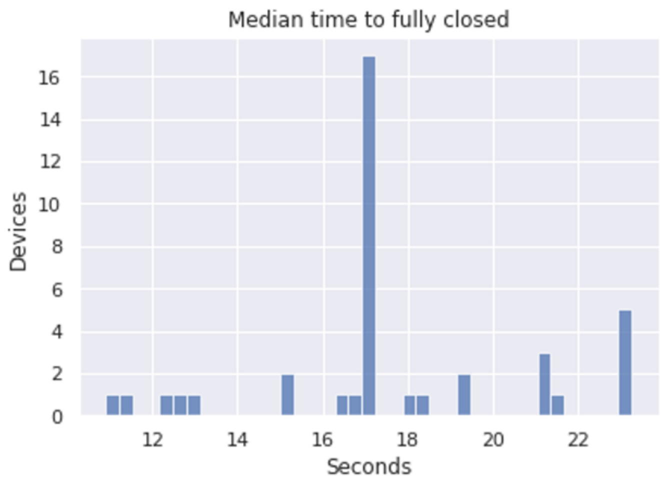


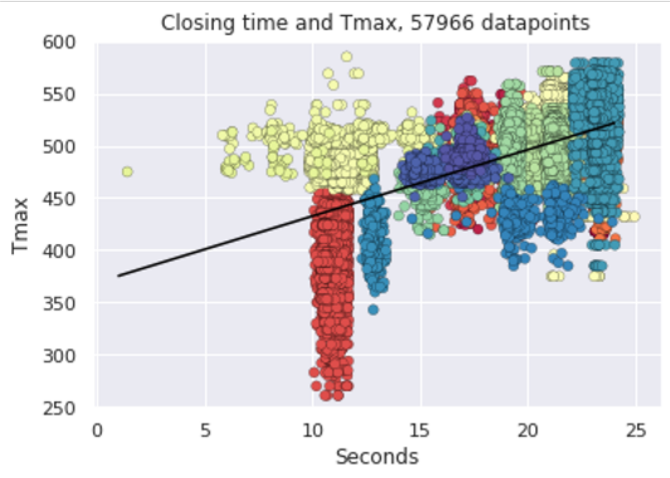

Faulty close sequences to total close sequences
Devices
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
Ratio

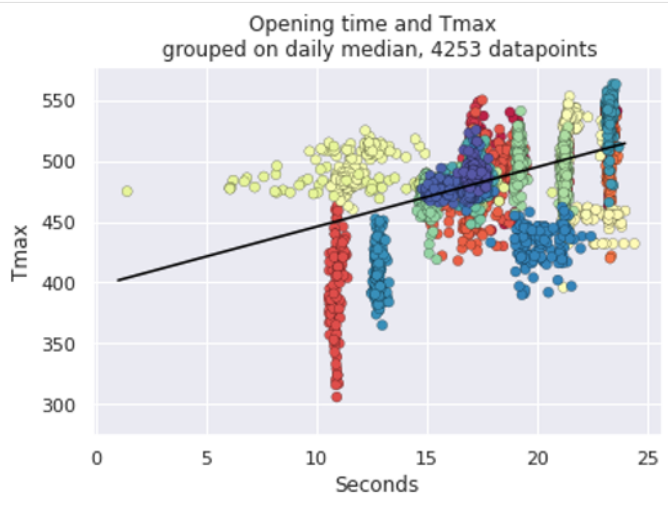

Percentage of abnormal closing times
Devices
3.0
2.5
2.0
1.5
1.0
0.5
0.0
5
10
15
20
25
30
35
40
%

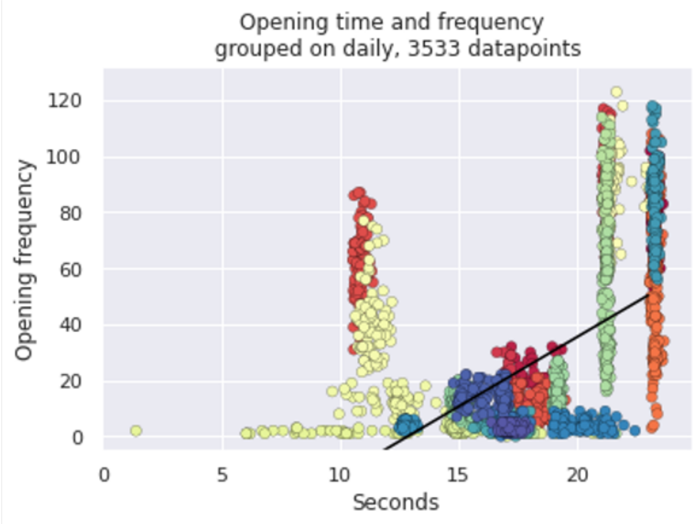

Time to fully closed, all 94014 sequences
Seconds
14000
12000
10000
8000
6000
4000
2000
0
2020-10
2020-11
2020-12
2021-01
2021-02
2021-03
2021-04
Date

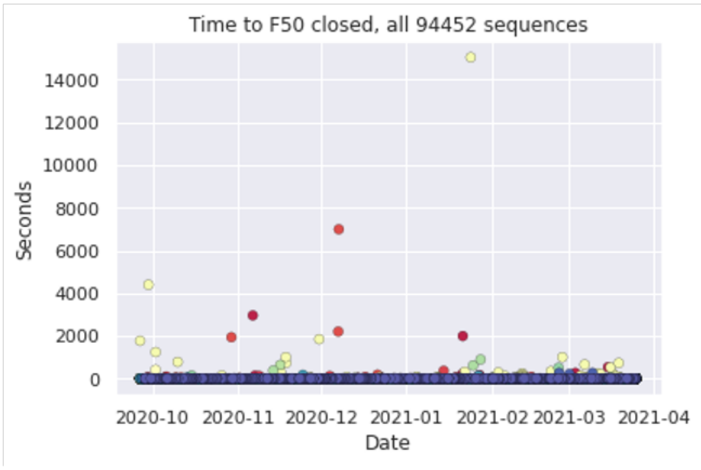

'Normal' time to fully closed, 70292 sequences
Seconds
Date
2020-10 2020-11 2020-12 2021-01 2021-02 2021-03 2021-04

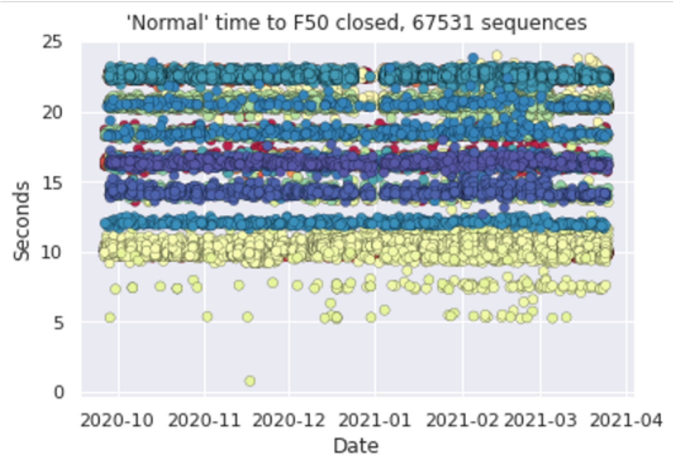

Median time to fully closed
Devices
Seconds

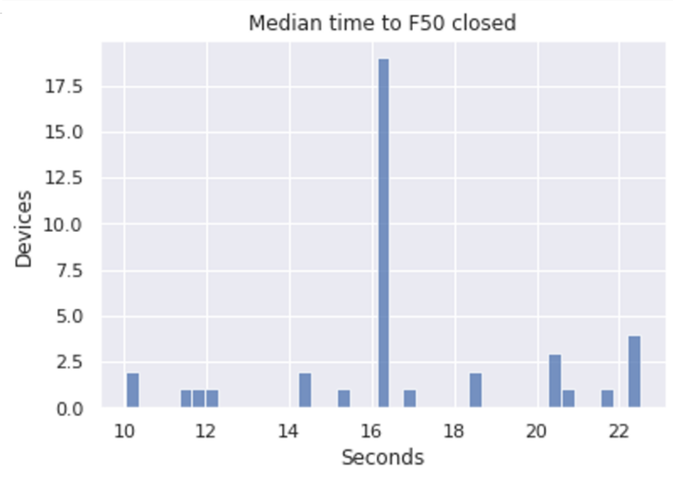

Closing time and Tmax, 57966 datapoints
Tmax
Seconds

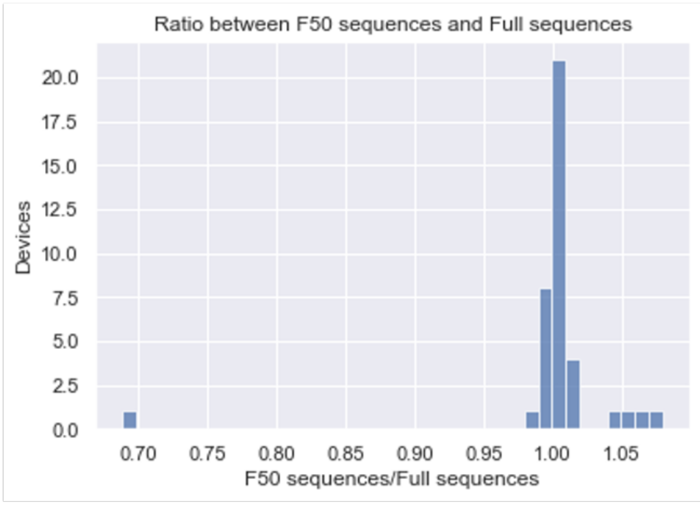

Opening time and Tmax
grouped on daily median, 4253 datapoints
Tmax
Seconds

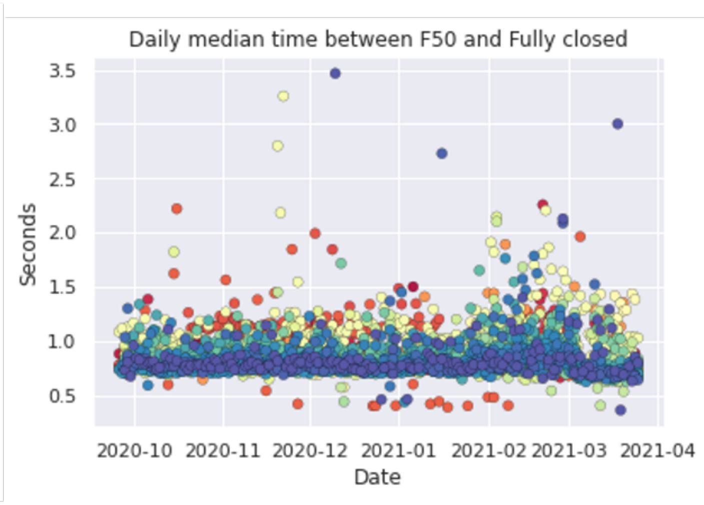

Opening time and frequency
grouped on daily, 3533 datapoints
Opening frequency
Seconds
0
20
40
60
80
100
120
0
5
10
15
20


Time to F50 closed, all 94452 sequences
Seconds
Date
0
2000
4000
6000
8000
10000
12000
14000
2020-10
2020-11
2020-12
2021-01
2021-02
2021-03
2021-04


'Normal' time to F50 closed, 67531 sequences
Seconds
Date
0
5
10
15
20
25
2020-10
2020-11
2020-12
2021-01
2021-02
2021-03
2021-04

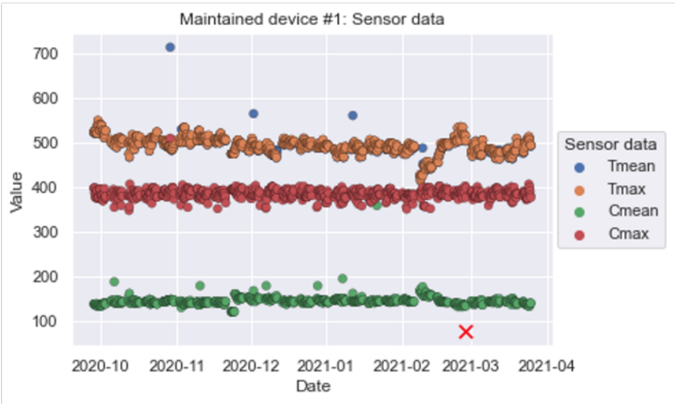

Median time to F50 closed
Devices
Seconds
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
10
12
14
16
18
20
22

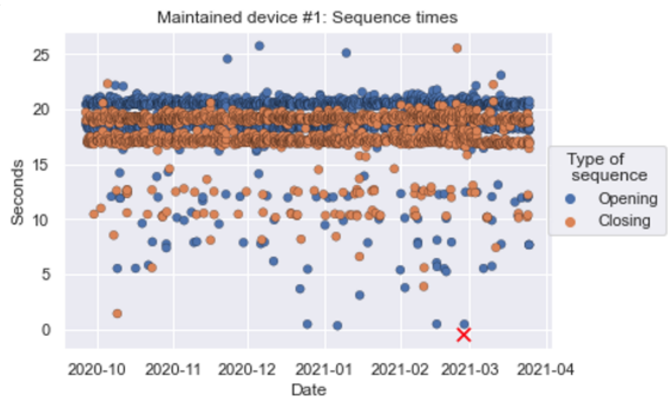

Ratio between F50 sequences and Full sequences
Devices
F50 sequences/Full sequences
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
0.70
0.75
0.80
0.85
0.90
0.95
1.00
1.05

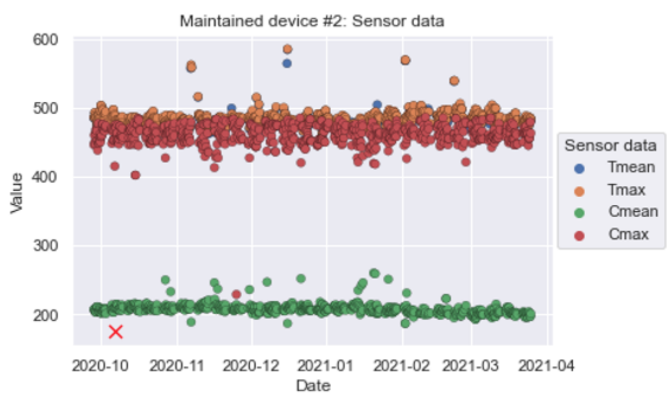

Daily median time between F50 and Fully closed
Seconds
Date
0.5
1.0
1.5
2.0
2.5
3.0
3.5
2020-10
2020-11
2020-12
2021-01
2021-02
2021-03
2021-04

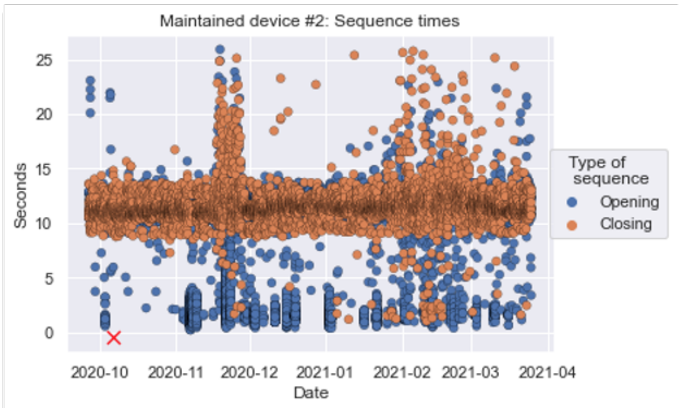
D. Analysis of Cycle Resets

Analysis of device conditions before and after maintenance was conducted. Results Part 1. Corresponds to "Group 1".



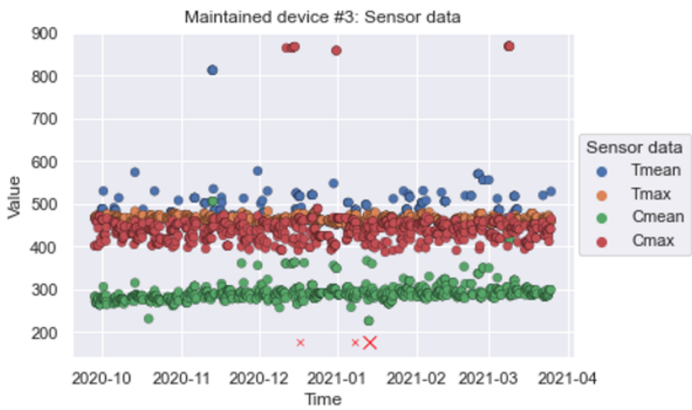


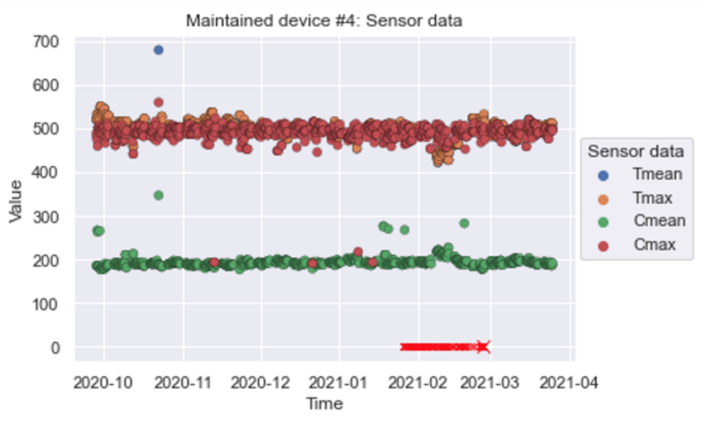


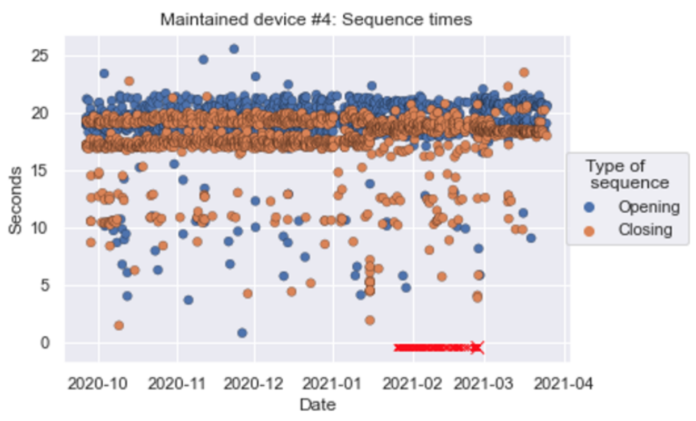


Metric	Statistic	Device 1 before (28 days)	Device 1 after (28 days)	Device 2 before (7 days)	Device 2 after (7 days)
Tmax	Mean	481	484	478	479
	Standard dev.	28	12	7	5
Tmean	Mean	480	483	487	478
	Standard dev.	27	12	7	5
Cmax	Mean	383	384	461	461
	Standard dev.	11	9	10	9
Cmean	Mean	145	141	206	210
	Standard dev.	15	4	3	3
Open	Mean	19.0	19.2	10.7	11.7
	Standard dev.	2.87	2.50	3.53	1.16
Close	Mean	18.0	17.7	11.2	0.85
	Standard dev.	2.02	2.01	11.1	1.09

Analysis of device conditions before and after maintenance was conducted. Results Part 2. Corresponds to "Group 2". Note that device 3 is missing values regarding sequence times. This is caused by the device only sending a few of the possible event messages during the studied period, none of which were in regard to opening and closing sequences.

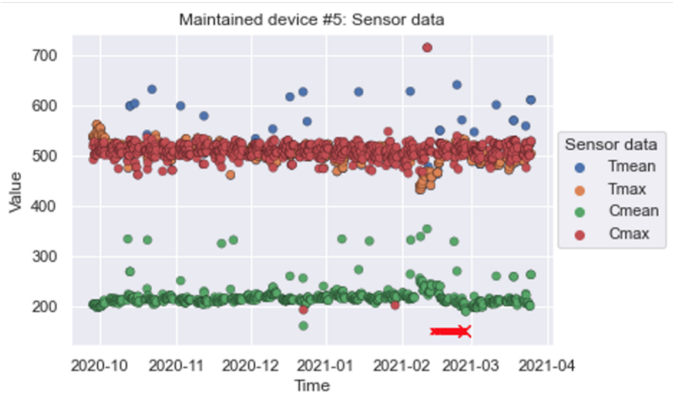


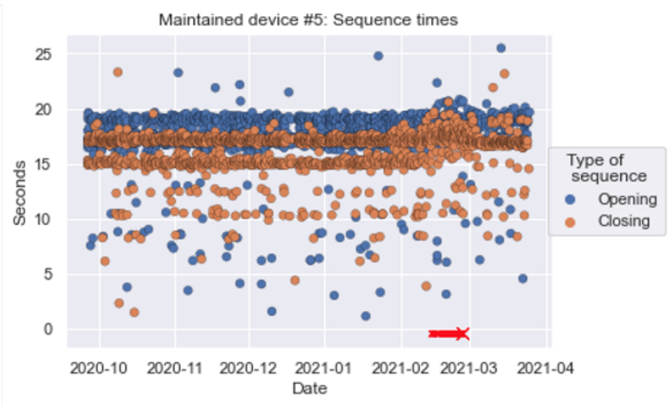


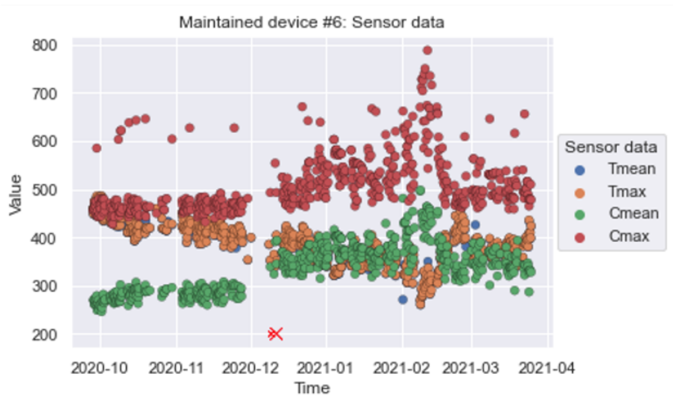


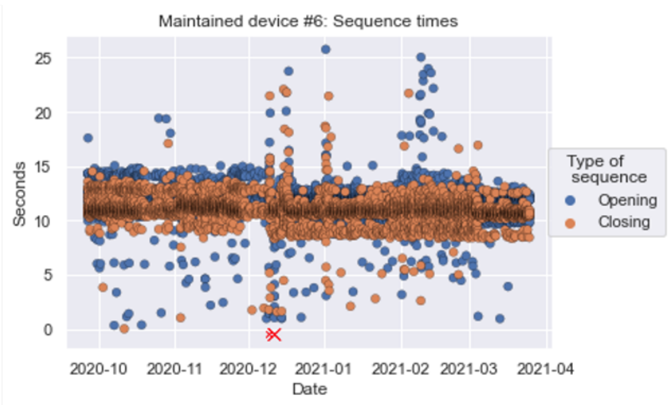
Metric	Statistic	Device #3 before (30 days)	Device #3 after (30 days)	Device #4 before (30 days)	Device #4 after (30 days)
Tmax	Mean	463	462	485	494
	Standard dev.	6.66	8.09	25.7	9.08
Tmean	Mean	469	469	470	467
	Standard dev.	20.6	20.2	27.0	17.9
Cmax	Mean	458	440	488	495
	Standard dev.	94.7	19.3	14.0	11.3
Cmean	Mean	295	293	199	194
	Standard dev.	21.1	14.3	14.1	3.95
Open	Mean	-	-	19.1	19.7
	Std	-	-	2.11	1.63
Close	Mean	-	-	17.8	2.52
	Std	-	-	18.3	1.45

Analysis of device condition before and after maintenance were conducted. Results Part 3. Corresponds to "Group 2"









Metric	**Statistic**	**Device #5 before (30 days)**	**Device #5 after (30 days)**	**Device #6 before (30 days)**	**Device #6 after (30 days)**
Tmax	Mean	497	498	410	371
	Standard dev.	23.3	11.2	18.5	25.1
Tmean	Mean	497	503	408	369
	Standard dev.	30.6	24.5	18.1	25.0
Cmax	Mean	507	510	468	523
	Standard dev.	40.6	12.7	22.9	41.4
Cmean	Mean	226	211	288	364
	Standard dev.	24.4	13.0	14.7	24.1
Open	Mean	17.8	18.1	12.3	12.2
	Std	2.06	2.14	0.98	1.4
Close	Mean	16.4	16.8	11.2	11.2
	Std	2.03	1.60	0.87	0.94

E. Clustering Analysis

Correlation between occurrence of unusual patterns

Feature pair	Correlation
Open features	
Abnormal times - Canceled	0.201
Abnormal times - Irregular	-0.048
Abnormal times - Faulty	0.120
Canceled - Irregular	0.142
Canceled - Faulty	-0.085
Irregular - Faulty	-0.106
Close features	
Abnormal times - Canceled	-0.103
Abnormal times - Irregular	0.025
Abnormal times - Faulty	0.033
Canceled - Irregular	-0.045
Canceled - Faulty	0.166
Irregular - Faulty	-0.042

F. Interviews with AAES Employees

Title	Date of Interview	Interview Method
Service Manager IDS SE	2021-03-26	Digital Interview
Service Sales Manager	2021-03-26	Digital Interview
Technical Support Service	2021-03-23	Digital Interview
UX Interaction / UX Researcher	2021-03-26	Digital Interview
UX Writer / UX Interaction / UX Researcher	2021-03-26	Digital Interview
SW Developer	2021-02-17	Digital Conversation
UX Interaction / UX Researcher	2021-01-27	Digital Conversation
Senior Program Manager	2021-01-26	Digital Conversation
IoT Platform Manager	2021-04-16	Digital Workshop
Senior Program Manager	2021-04-16	Digital Workshop
Technical Support Service	2021-04-22	Digital Workshop
SW Developer	2021-04-23	Digital Workshop
Service Manager IDS SE	2021-04-29	Digital Workshop
Service Sales Manager	2021-04-29	Digital Workshop