DEGREE PROJECT IN MECHANICAL ENGINEERING,
SECOND CYCLE, 30 CREDITS
STOCKHOLM, SWEDEN 2019

Evaluation of a medium-sized entreprise’s performance by data analysis

Introducing innovative smart manufacturing perspectives

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Abstract

Small and medium-sized enterprises are highly limited on resources for the transformation into smart factories. Nytt AB, a new startup specialized in smart manufacturing solutions, is completely focused on taking down the barriers with a basic solution: implementing a machine vision system with the purpose to monitor the machines of the factories. The main aim of this thesis is to analyze the data collected from two different machines of a medium-sized factory by monitoring the color states of the stack lights.

First of all, some topics are analyzed in order to get a better understanding and knowledge of the main topic of this thesis: smart manufacturing. Secondly, the methodology used during the project is explained. Thirdly, the product developed by Nytt AB is described to get a better understanding. Together with this, the companies where the product is implemented are described. The next step is the presentation of the results by analyzing the data according to these parameters: (i), the availability of the machines, (ii), critical machine tool analysis; (iii), machine idling time; (iv), disruption events; and finally, (v), information transfer. In the results, some graphs and discussions are presented. In the following chapter the conclusions are presented, which allow the analyzed company to improve its current state. Lastly, the relocation of the product into the critical machine, the implementation of new sensors to detect temperature and vibration values of the machines and the implementation of the module *OpApp* within the factories are suggestions presented as future work at the end of this report.

Keywords

Smart manufacturing, SMEs, Industry 4.0, availability, machine vision system, waiting time, disruption events, breakdown.

Sammanfattning

Små och medelstora företag har mycket begränsade resurser för omvandling till smarta fabriker. Nytt AB, ett nystartat företag inom smart tillverkning, är helt fokuserad på att ta bort hinder med en enkel lösning: implementering av ett kamerasystem för övervakning av maskiner i fabriker. Huvudsyftet med detta examensarbete är att analysera data som samlats in från två olika maskiner i en medelstor fabrik genom att övervaka färgändringar i deras ljuspelare.

För det första analyseras några ämnesområden för att få en bättre förståelse och kunskap om huvudtemat i detta examensarbete: smart tillverkning. För det andra förklaras den metod som används under projektet. För det tredje beskrivs den produkt som utvecklats av Nytt AB för att få en bättre förståelse. Tillsammans med detta beskrivs de företag där produkten implementeras. Nästa steg är presentationen av resultatet genom att analysera data enligt följande parametrar: (i), maskinens tillgänglighet; (ii), kritisk verktygsmaskinanalys; (iii), maskinens tomgångstid; (iv), störningshändelser och slutligen; (v), informationsöverföring. I resultatet presenteras några grafer och diskussioner. Slutsatserna presenteras därefter. Dessa slutsatser gör att det analyserade företaget kan förbättra sitt nuvarande tillstånd. Som framtida arbete föreslås slutligen flytt av kamerasystemet till den kritiska maskinen, införande av nya sensorer för att övervaka temperaturer och vibrationsvärden för maskinerna och implementering av modulen *OpApp* i fabriker.

Nyckelord

Smart tillverkning, små och medelstora företag, industrin 4,0, tillgänglighet, maskinvisningssystem, väntetid, störningshändelser, uppdelning.

Acknowledgements

First of all, we would like to thank Sture Wikman for providing us this great master thesis and letting us work along with the company during the thesis period and his valuable inputs from manufacturing experience has helped us to approach the thesis in more realistic way. Secondly, we thank Thomas Lundholm, our supervisor from KTH , for all his valuable input, immense care he showed towards this topic, responding to our queries promplty and gave us good direction.

We would like to thank Praveen Natarajan and Bharat Sharma, employees at Nytt AB, for creating this potential thesis, being supportive through this 20 weeks, for being the best workmates and being our mentors. Moreover, we cannot forget about Praveen Palaniswamy, the IT lead, providing us all the data we used for analysis.

We would like to thank Laufey Benediktsdóttir, for being the best thesis co-woker. We could not have done better without the questioning and discussion on each of our findings.

Last but not least, the most special thank you is devoted to our families and close friends. You have been the support we needed during all these years, relying on us blindly and knowing that we will succeed. Finally, we could say that you were completely right. Thank you forever, families and friends, without you, absolutely none of this would have been possible.

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Nomenclature

2G	Second generation
3G	Third generation
4G	Fourth generation
5G	Fifth generation
AAA	Authentication, authorization and accounting
AI	Artificial intelligence
APT	Actual production time
CNC	Computer numerical control
CPMS	Cyber-physical manufacturing system
CPS	Cyber-physical system
ICT	Information and communications technology
IIoT	Industrial internet of things
IoT	Internet of things
IT	Information technology
KPI	Key performance indicator
M2M	Machine-to-machine
ML	Machine learning
OEE	Overall equipment effectiveness
PBT	Planned busy time

PdM	Predictive maintenance
PLC	Programmable logic controllers
PLM	Product Lifecycle Management
RFID	Radio-frequency identification
SME	Small and medium-sized enterprise

Chapter 1

Introduction

This chapter presents the context and the existing problems for which this master thesis has been developed. After explaining this, the business solution which came up and introducing the purpose and goal of this project, the final research questions are presented, pointing out which is the direction it should follow. Lastly, the limitations of the project have been introduced.

1.1 Introduction

Smart manufacturing is one of the most debated subjects in the manufacturing economy. The concept arises back by the term *Industry 4.0* from Germany in 2013. Later it was initiated research and development in areas such as sensors and beacon technology, Internet of things (IoT), cloud-enabled manufacturing, artificial intelligence (AI) and machine learning (ML), digital twin and so on. Industry 4.0 also focuses on reducing production to market lead time by identifying and eliminating non-value added process with the aid of smart machines and connected systems. The transition to a smart factory environment requires time as well as a high investment of money, which makes it difficult for small and medium-sized enterprises (SMEs) to take part in this evolution. This thesis focuses mainly on ways of making SMEs smart using brownfield technologies.

Stack lights are an integral part of machine tools. Valuable data can be retrieved by examining stack lights and several conclusions can be drawn from all this. This thesis discusses the data obtained by a machine vision system, a prototype which Nytt AB has developed, capturing the changes in the color states of the stack lights.

1.2 Problem

As it is aforementioned, the transformation from a normal factory into a smart one is complex due to the high investment and time required. However, this problem affects mostly to the SMEs since large-sized enterprises usually possess their own resources (the equipment, workforce and money) and they can afford to spend time on this process by creating their own department focused on this. These factors ease the transformation whilst SMEs do not have them.

Thus, reaching the next level (becoming smart factories) for SMEs sometimes means hiring third parties focused on this field. Although it could be a high investment, it is not in a short and medium-term compared to creating your own department within the factory focused on this purpose. These third parties obtain the data of the factories by connecting their own smart devices to the machines of the factories. Finally, the data are used intelligently to give some valuable conclusions to the factory.

However, although SMEs want to become smart factories, most of them are also worried about the security of their data: by installing a physical connection to the programmable logic controllers (PLCs) of the computer numerical control (CNC) machines, the data can be hacked and virus can be sent to these machines producing infinitive breakdowns. This fact scares the managers of the companies, being many of these quite skeptical about the overall performance of all this. Thereby, they want to find a new solution to start being smart but not compromising their security and data. So, *what could be done for SMEs to reach the next level solving all the aforementioned problems?*

1.3 Enforcement

Sture Wikman, a businessman with more than 30 years of experience, along with two postgraduate students, Praveen Natarajan and Bharat Sharma, both very eager to work on manufacturing field, were really aware of these problems. Together with the aid of Thomas Lundholm, a researcher at KTH Royal Institute of Technology, they decided to create a new company.

Nytt AB is a startup recently founded in August 2018 that has been created to actually provide a solution to the problems presented. The main aim of Nytt AB is to eliminate all the existing barriers that hinder SMEs to become smart factories by accessible brownfield technology used intelligently and efficiently without compromising the privacy of any SME.

Nytt AB provides a new and simple solution for SMEs, monitoring one of the most important assets in the factories: the machines. Hence, Nytt AB performs an assessment of the CNC machines through their stack lights through a machine vision system developed by the information technology (IT) department of Nytt AB. This evaluation gives a proper insight into how the factory is performing.

The current state of Nytt AB is the following one: at this moment, the product of Nytt AB is implemented in three SMEs in Sweden. For one of the companies the product is running in three machines since October 2018, whilst the product was implemented in the other two companies in March 2019. Currently there are eight monitored machines in total.

1.4 Purpose

The standstill or slow growth of the current state of most SMEs, together with their own limited resources, require new techniques to provide them with solutions to these problems. This will finally allow SMEs to cross borders and experience the fact of being a smart factory. Hence, this project pretends to illustrate the potential of Nytt AB within this market and demonstrate that its prototype system, which consists of three applications - *SetApp, OpApp* and *Admin panel* -, is a powerful tool which can make the difference between the current and future state of the SMEs. Furthermore, this project exposes the analytical results and conclusions that have been carried out in one of the three companies where the product is established.

1.4.1 Benefits

From the present project, there are three parts who will benifit:

- ***The project team:*** this project has been very useful to see and know how companies operate today and observe that there is a range of improvements where engineers can act. In addition, carrying out this project has served to investigate in the smart manufacturing field. Finally, thanks to the completion of this project, the academic stage is completed, so a new stage begins, giving way to new projects and challenges.
- ***Nytt AB:*** the startup will know the potential it has within this market. Moreover, some suggestions are given in the *Chapter 7 - Future work* in order to recommend to the company where it should start working on.
- ***Subject:*** the company from which the data has been analyzed. This report will be really helpful for this company in order to realize its performance regarding productivity and efficiency and the ways to improve them.

1.4.2 Ethics

The development of this project is largely thanks to the companies in which the product has been established. The gathered data have been used for analytics and to draw conclusions. Thus, the data used for the analysis have not been falsified in order to provide worse or better results. Furthermore, agreed in advance with the companies, their names are not displayed in this report in order to respect their privacy. Therefore, they are named as *company X*, where X is replaced by a letter of the alphabet. Last but not least, the content of this report is free of plagiarism.

1.4.3 Sustainability

Some of the conclusions of this report allow the selected company, in addition to becoming a smarter factory, to work efficiently and productively compared with the current performance. This means a reduction of wasting regarding time, material, equipment, workforce and energy. Thus, the companies, following what is stated in the conclusions, will be able to produce in a more sustainable way, maximizing the available resources within the factory without making any huge investments.

1.5 Research questions

The following research questions will be answered:

- ***First research question:***
  How can monitoring of shop floor assets, such as machine tools, help SMEs drawing conclusions, adapting to the product mix and improving key performance indicators (KPIs) like the availability of the machine?
- ***Second research question:***
  How SMEs can make the paradigm shift to smart manufacturing at an easier phase and method?

1.6 Limitations

First of all, at the beginning of the master thesis, the prototype system was not ready at all, producing a small delay in the schedule of the project. *SetApp* and *Admin panel* were ready to be implemented in the factories, although there were some aspects that could be improved in both of them, whilst *OppApp* was still in its design phase.

Secondly, the first data gathered from the first weeks are not reliable since the *SetApp*'s feature of color detection was not good enough, being necessary training to enhance this feature and to reach a proper accuracy level.

Last but not least, *SetApp* was frozen multiples times by the IT-technician. It was due to some technical issues which showed up during the implementation phase or due to some improvements which required its detention. This fact is translated in data missing and the uncertainty of some periods to know either if the machine was waiting or stopped for a really long time or if the *SetApp* was not capturing data due to the detection.

1.7 Outline

Once the problem and research questions have been defined in this chapter, this report presents the solution and answers respectively in the following ones.

Chapter 2 presents the topics chosen for the literature review regarding smart manufacturing and the final scope of the project. This chapter is devoted to providing a better understanding of the topic of the thesis: smart manufacturing.

Chapter 3 presents the methodology followed during the project, which has been divided into three parts: (i), literature review phase; (ii), implementation phase; and (iii), analysis phase. In the end, an overall schema of the methodology is presented.

Chapter 4 describes how the product works and introduces its components in detail. Moreover, it presents the companies where the product has been implemented and the use case of this project, which is company A. Lastly, a roadmap to smart manufacturing for SMEs is proposed.

Chapter 5 presents the results obtained by analyzing the data from company A. These results are accompanied by their respective discussion with the purpose to provide an insight into how the company is performing.

Chapter 6 presents the main conclusions drawn of the project considering the results from the previous chapter.

Last but not least, *Chapter 7* is devoted to presenting the recommendations of the future work.

*“We keep moving forward, opening new doors,
and doing new things, because we’re curious and
curiosity keeps leading us down new paths.”*

Walt Disney

Chapter 2

Literaure review

This chapter presents a detailed description of some of the significant topics which form the base of the smart manufacturing field, contributing considerably to the content of this master thesis project and to a better understanding. Finally, it also helps Nytt AB, suggesting which is the best direction it should drive to expand or in which it should invest.

2.1 Internet of things

Internet of things, IoT, at times known as *"machine-to-machine"* (M2M) communication technologies [1], is one of the buzzwords when Industry 4.0 comes up. It is not surprising since it is one of its fundamental bases. Kevin Ashton was the first person in introducing the concept with the idea of the information tracking using radio-frequency identification (RFID) in 1999 [2]. Although more than 15 years has been passed since then, it remains in its infancy and will offer new possibilities once it is completely developed.

IoT, as part of information and communications technology (ICT) solutions, is a worldwide network which allows the intercommunication between physical objects and the interconnectivity between people and *"things"*. It provides a new endless variety of unimaginable and improved ways of communication and interaction since it is reshaping and modifying the life of individuals, businesses and society in general [3].

According to [1], as it is shown in *Figure 2.1.1*, it is predicted to have around 19-40 billion of smart devices seamlessly connected by 2019. The significant difference is due to the multiple sources (Gartner, Harbor, Cisco, International Data Corporations...) considered into the analysis, being the average 28 billion connected devices at that time. Nevertheless, [4] predicts the number will reach up the amount of 125 billion smart devices in 2030 from the 27 billion ones in 2017.

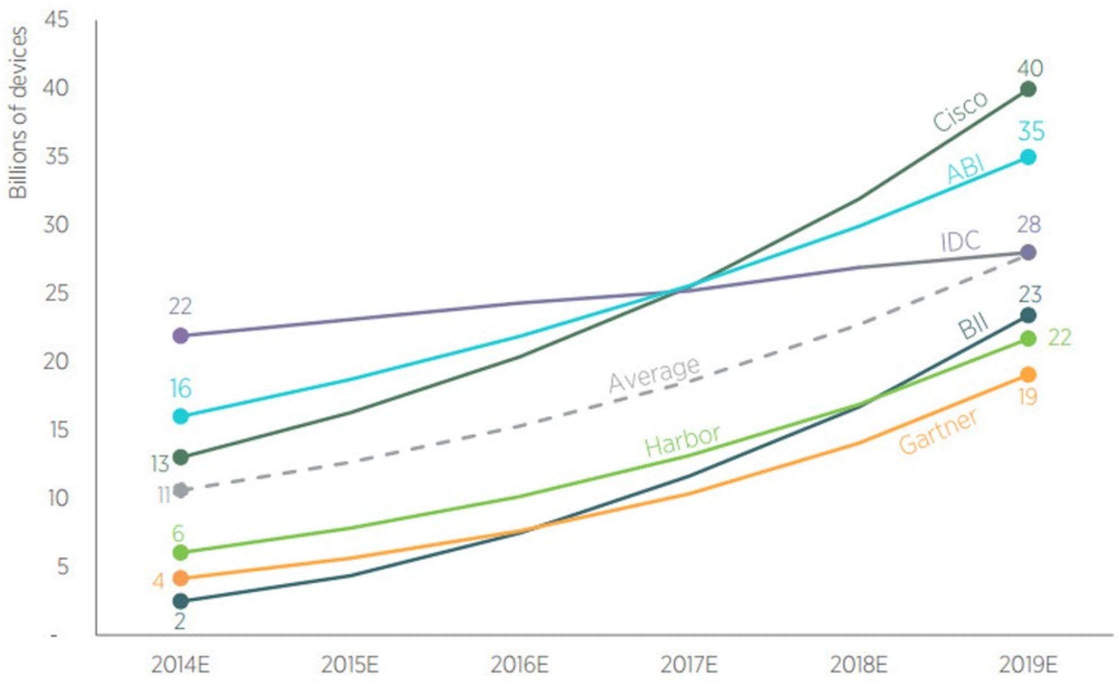


Figure 2.1.1: *Estimation of the IoT-devices connected by 2019 [1]*

This huge intercommunication permits to collect, share and exchange data created from the sensing behaviour and movement of the objects with the purpose to control and monitor the equipment in real-time with minimal human intervention. Thus, it is leading a better connectivity to the industrial systems since it is acting as a virtual neural network in which each smart object, which is playing the role of node, is conveying data about itself and its surroundings [5].

The current concept employed to refer the IoT used specifically in the manufacturing environment through smart assets for industrial applications is called industrial IoT (IIoT), also known as industrial internet. IIoT not only relies on cyber-physical systems (CPS), but also on embedded systems, cloud computing, edge computing and different technologies and software [6].

High-density and large-scale IoT enables industries enhance their current level to the next one, transforming them into smart industries [7]. Hereby, many industries have recently included this new technology in order to optimise their whole production value, which is translated in a reduction of energy consumption, better product or service delivery, better quality and so on.

The smart assets which could be found within an industry cover from engines, machine tools and sensors to simply smartphones. It is possible to find them at every stages of manufacturing floor since they are fully spread for specific applications. They are connected to the cloud over a network to monitor, gather, exchange, analyze and act on information to intelligently modify their demeanour without human intervention [6]. The connection between smart assets and the cloud is done through wired and/or wireless communication technology.

Wired communication technology such as ProfiBus, RS485 and Lonworks have been used to connect all kinds of devices during the last decades, but wireless communication technology showed up a few years ago and is in phase of development since then. The deployment of IoT has notably improved due to this wireless technology [8]. 2G, 3G, 4G, Wi-Fi and Bluetooth are only the basic and most common examples of wireless communication technology which have been and are still used in IoT applications.

However, the emerging fifth generation (5G) wireless network is bringing new opportunities for IoT. The IoT devices interaction within a smart environment will reach a new level through the 5G wireless network and the multiple intelligent sensors connected. This new level will allow the fastest communication and capacity due to the significantly enlarged scope and scale of the IoT coverage [8].

2.2 5G-enabled IoT

The evolution that the industrial world is experiencing is demanding new technologies and new ways of intercommunication within the factory in order to fulfil both the new requirements to evolve into a smart factory and with the new specifications demanded by the market to reach a desired increased flexibility in manufacturing: mass customization, better quality and improved productivity [9]. Although this fact brings multiple new possibilities, it requires a huge investment on the cutting-edge technologies, which will create and deliver a vast amount of data.

This data should be identified and clustered in a fast and effective way. Hence, an immediate communication between the smart assets and the cloud is required, which can be performed by wired and/or wireless communication technology. Although wired communication technology has been and is being used in multiple applications, the wireless one is the most used within this field and the one which is bringing infinitive chances and improvements due to its multiple advantages.

Wireless communication technology covers from small-area technology such as Wi-Fi, Bluetooth, 6LoWPAN and Zigbee to large-area one such as GPRS, GSM and 3G-5G [7]. As shown in *Figure 2.2.1*, the evolution from 1G to 5G has been done for about 40 years and the different applications and characteristics of each one have changed over time.

The most important eras within mobile communication technology have been three: first, the second generation (2G) due to the voice digitizing; secondly, the third generation (3G) due to the multimedia for voice and data; and finally, the fourth generation (4G) broadband internet experiences [7, 8].

Although the 3G and 4G are generally used for IoT, these are not fully optimized for its applications [11]. Furthermore, these two with other communication technologies do not achieve the requirements to meet the cyber-physical manufacturing systems (CPMS) demands, hindering its development and implementation [7]. Hence, the need of the emerging of 5G.

Figure 2.2.1: *Evolution of wireless communication technology [10]*

The 5G communication network will ease and allow seamless connectivity between a massive number of IoT devices, much bigger than the actual one. It is expected to be the promising generation that meets the required specifications such as high data rate, ultra-low latency, high scalability, security, etc., which are not currently satisfied by the actual communication technologies. The 5G will provide multiple improvements compared to the previous generations: current end-to-end latency of 20–100ms will be reduced at around 1ms; coverage, data transmission rate, security and reliability will have a 10-100-fold improvement over the current state; communication capacity will be 1000 times larger [7]; and transmission speed will reach up to 4-10 Gbps, whilst the 4G only provides 1 Gbps as maximum [8].

The main requirements of 5G-enabled IoT, which are shown in *Table 2.2.1*, are the following ones:

- ***High data rate:*** the vast amount of connected smart devices is generating a huge amount of data, which is demanding higher stable and uninterrupted data rates [7]. Besides, higher data rates increase the performance of the devices' applications.

Table 2.2.1: Key requirements for 5G-enabled IoT [12]

Requirements	**Specifications**	**Enabling solutions**
High data rates	10 Gbps peak data rate; 100 Mbps cell edge data rate; Enhancing mobile broadband services.	Millimeter wave communications; Massive MIMO; Ultra-densification.
Reduced latency	1 ms end-to-end latency	D2D communications; Big data and mobile cloud computing.
Low energy	1000 times decrease in energy constumption per bit; Enhacing massive machine type communications.	Ultra-densification; D2D communications; Green communications.
High scalability	Accommodating 50 billion devies	Massive MIMO; Wireless softwate-defined networking; Mobile cloud computing.
High connectivity	Improving connectivity for cell edge users	Ultra-densification; D2D communications; Wireless softwate-defined networking;
High security	Standardization on authentication, authorization and accounting	Wireless softwate-defined networking; Big data and mobile cloud computing.

- ***Very low latency:*** the term latency is referred to as the existed delay in the communication between devices. Hence, the lower the latency, the better. When the latency is reduced maximally, it is feasible to use this technology for real-time control applications since there will be prompt communications between devices [12].

- ***High scalability:*** it is a significant factor to support the vast number of IoT devices which will be increasing and increasing over time.

- ***High reliability:*** it is required a high reliability in order to provide an improved coverage and handover efficiency for IoT devices [8].

- ***High security:*** connectivity and user privacy are the main goals in the security strategy that the 5G must provide to have a whole secured network [8, 12]. Regarding IoT particularly, the processes of authentication, authorization and accounting (AAA) for interconnected devices should be warranted as secure and they must follow a standardization [12].

- ***Low energy:*** the 5G must support the continuous processes of the devices which require more energy, such as synchronization process with the base station. The greater the number of connected devices, the greater the number of base stations, which should be more energy efficient [12].

2.3 Artificial intelligence and machine learning

Artificial intelligence (AI) and machine learning (ML) are two concepts which have gained a lot of importance nowadays. It is frequently common to not distinguish the differences between their meanings. On the one hand, AI, also known as machine intelligence, is the intelligence of the machines which try to simulate the human mind by acting exactly like a human being would act regarding cognitive functions such as reasoning, perceiving or learning [13]. On the other hand, ML is a discipline within AI which allows computers to learn automatically by themselves and improve from the experience by using data and with no human intervention [14].

Regarding ML, [13] presents that ML algorithms can provide three types of analytics (descriptive, predictive and prescriptive), which are illustrated in *Figure 2.3.1* where their principal functions are exposed. Moreover, it also presents the three main major types (supervised, unsupervised and reinforcement learning) of ML. However, in [[15] is stated there are four types of ML: the previous ones together with semi-supervised learning. The difference between supervised ML and unsupervised ML is mainly that the first one uses classified (labeled) data meanwhile the second one uses unclassified (unlabeled) data; semi-supervised ML is a mix of the previous ones using much more unclassified data than classified in order to improve the learning accuracy; and finally, reinforcement ML which finds the best scenario with the greatest rewarded action [15].

Figure 2.3.1: *Types of ML analytics [13]*

It is a reality that these concepts have been and are being implemented in many sectors with the purpose to improve the performance and the purpose of using new techniques never used before. For example, [16] predicts that AI-based technologies will be integrated within the workplaces in the 70% of the current organizations in order to aid and enhance their employees' productivity. Regarding ML, although its implementation is still in the commencement within the manufacturing industry, its use is increasing in this environment since it is a very powerful tool [17].

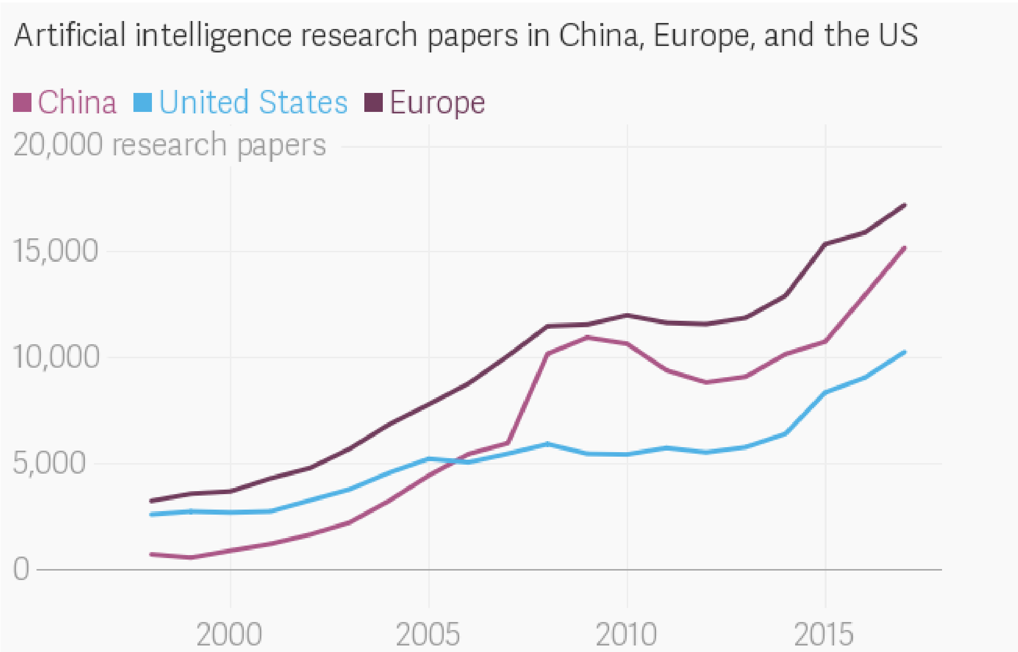


Figure 2.3.2: *Evolution of AI research papers in China, the US and Europe [18]*

It is a matter of time that these two terms will make a large revolution ever seen. This is the reason why Europe, United Stated and Chine are constantly investing in research in AI (therefore, also in ML) and the number of research papers has tremendously increased in such a short time as *Figure 2.3.2* [18] illustrates.

2.4 Maintenance

Industrial and manufacturing systems require different maintenance practices for the continuous smooth working of the equipment. Due to globalization and strong variations in customer demands, the manufacturing units are moving towards a dynamic production environment, where flexibility is the deciding factor [19]. The unplanned downtime due to ineffective maintenance strategies causes reduction in production capacity to 20% which costs around USD 50 billion each year [20]. Traditionally there are mainly four type of maintenance practices [21] which are illustrated in *Figure 2.4.1*.

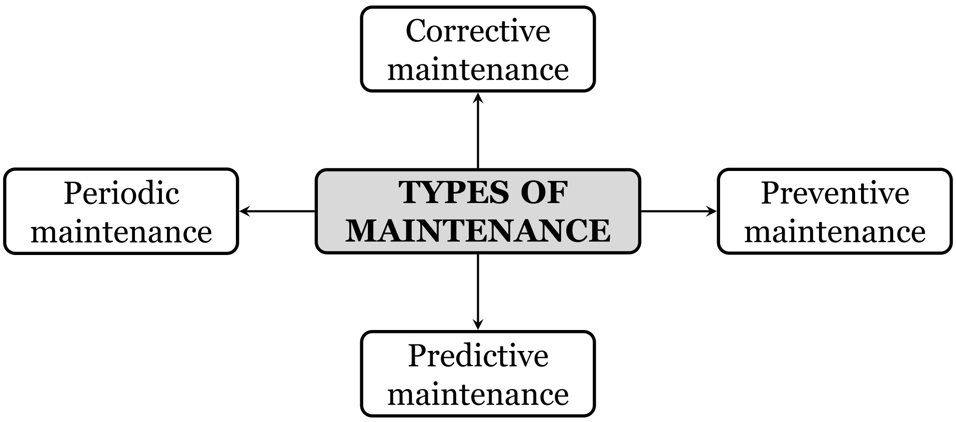


Figure 2.4.1: *Major types of maintenance strategies*

In the past, factories used corrective maintenance strategies (run to failure). Thus, by running the machine until a failure event, the utilization could be increased to an extent. However, the unplanned downtime caused by the same is not scalable. At present, preventive maintenance is the widely used strategy, where the machine tool/equipment are inspected and maintained periodically (planned downtime) to avoid unexpected breakdowns of machine [20]. While the major trade-off in this strategy is long machine suspension time as well as high maintenance cost.

Predictive maintenance (PdM) technique was originated from condition-based maintenance strategy [22]. In PdM, the condition of the machine tool or equipment is measured with assistance of sensors. Then, the failure event will be predicted with the help of data collected from sensors and AI algorithms [23]. The PdM technique gained more importance since the term Industry 4.0 was coined. It helps optimizing maintenance tasks to a great extent by reducing the unplanned machine downtime and maintenance cost, which in turn increase the useful production time.

The integration of sensors and the related software into the existing machines and production system is considered as the one of major limiting factor for large scale manufacturers to move ahead with a full-scale PdM system. Recently the term *Maintenance 4.0* was coined; however, research and development are still going on this topic [24].

2.5 Key performance indicators

The need for key performance indicators, KPIs, in smart manufacturing is increasing. Real-time data collection, analysis, and visualization are one of the aims of implementing a smart manufacturing system. By the development of various sensors tailored for measuring manufacturing process parameters, the data collection part becomes easy. The need for machine learning and deep learning system is inevitable for the analysis and drawing a useful conclusion from this data [25].

The KPIs give a detailed breakdown of the production process, it has a potential impact on giving out real-time process data and ways of maximizing the value adding time [26]. But in most SMEs, the product variety is high and mainly large investment are the main constraints for them. KPIs can be classified as two, fundamental and high level. Fundamental KPIs are obtained from the shop floor through direct data collection, whereas higher level KPIs are formed using fundamental KPIs.

This thesis uses the fundamental KPIs namely availability to analyze the machines. The availability is one of the fundamental KPIs to calculate the overall equipment effectiveness (OEE), which is the result of three factors: availability, quality, and performance. In addition to this, it discusses how SMEs can make improvement by analyzing simple fundamental KPIs.

As it is stated in [27], *”availability is the ratio that shows the relation between the actual production time (APT) and the planned busy time (PBT) for a work unit”*.

To have a better understanding of this factor, the definition of APT and PBT are:

- Actual production time: *"The APT shall be the actual time during which a work unit is producing. It includes only the value-adding functions"* [27].
- Planned busy time: *"The PBT shall be the planned operation time minus the planned downtime"* [27].

Chapter 3

Methodology

The methodology followed during the master thesis project is presented in this chapter. It is possible to differentiate three stages of the project, therefore this chapter is divided into three parts to explain each one. The first one is devoted to describing the steps taken to gather information for the literature review. The second one is devoted to explaining what has been done during the implementation phase of the project. Last but not least, the third part is devoted to describing how the data has been analyzed in order to get some valuable conclusion. Finally, the methodology structure is represented schematically.

3.1 Literature review phase

The main purpose of the literature review is, firstly, to gather as much information as possible in order to acquire good knowledge and understanding regarding the principal topic of the master thesis: smart manufacturing. Secondly, to select the best papers or any other reliable source with the most valuable information about the chosen topics. This phase lasted from the middle of January till the end of February.

To start this phase, a brainstorming was carried out with the purpose of selecting the most relevant topics respecting smart manufacturing. However, considering the scope of the project, another selection of topics was carried out in order to fulfill both criteria. The list of topics was: ERP system, big data, cloud computing, edge computing, IoT, artificial intelligence, machine learning, deep learning, neural networks, 5G, KPIs, Industry 4.0, maintenance, stack light, collaborative control and cyber-physical system.

Finally, these sixteen topics have been filtered and have been selected those ones which suit better with both criteria aforementioned: the smart manufacturing field and the project's scope. The *Figure* 3.1.1 illustrates the six topics finally chosen to develop in the previous *Chapter 2 - Literature Review* for the better understanding of the project.

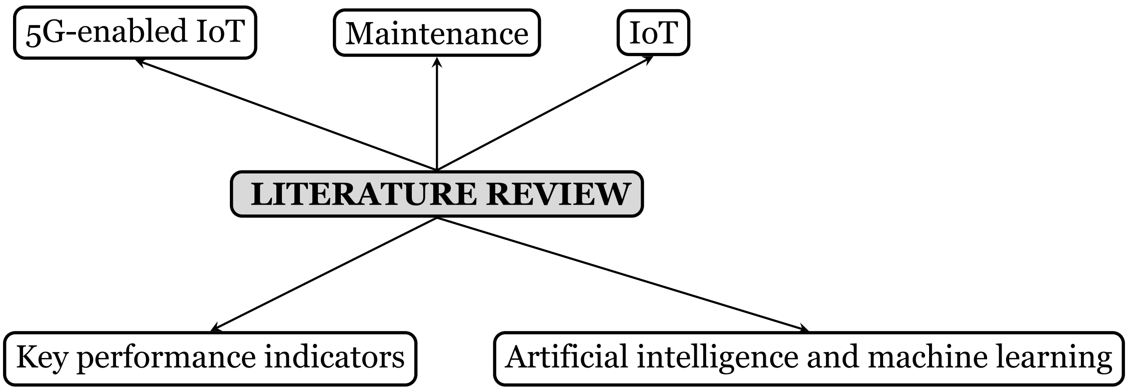


Figure 3.1.1: *Selected words after the filter*

In addition to this phase, two training were carried out through *Admin panel* and other software in order to improve the performance of the *SetApp*, which is described in the following *Chapter4 - Implementation* in more detail, before the implementation in the new two companies.

On the one hand, the first training was about enhancing the performance of the color detection feature by changing the wrong labels with the good ones. The system works automatically due to the ML algorithms, but if one color is wrongly labeled, it should be detected and corrected by human intervention. After this manual change, the ML algorithms will consider all this for the following labels.

On the other hand, the second training was about object recognition. The assigned task was to identify the stack light in a bunch of images with the purpose to train the future version of the system.

3.2 Implementation phase

The main purpose of this phase is the implementation of the product in the two new companies, whose detailed descriptions are presented in the following *Chapter 4*, in order to start gathering new data. It was decided in advance that the team project of this report would be responsible for only one of the companies: company A. Furthermore, the first training explained in the previous section was also carried out during this phase with the data gathered from the new machines. This phase lasted from the beggining of March till the end of April.

At the commencement of this phase, *SetApp* and *Admin panel* were ready to be implemented, meanwhile *OpApp* was not. Thus, it was decided to postpone the implementation of *OpApp* because the IT deparment was still developing it. Since *SetApp* is the tool dedicated to gathering data by detecting the color changes in the stack lights, this is the product implemented in the machines.

The implementation in both machines was established since the first day. The criteria to select the machines to monitor were two: (i) the machines had to be in different manufacturing cell, as it was established by company A; and (ii) the stack light of the machines had to work with three different states of operation (working, waiting and breakdown).

Once the machines were selected, the implementation of the smartphones, having the *SetApp* installed, was carried out in the two machines. These smartphones were placed facing at the stack lights in order to detect any change in the color state. To prevent the smartphones from turning off in order to gather data without interruptions, they were connected to the current through their charger. Moreover, a software called *AirDroid* was installed in the smartphones with the purpose to control and monitor them remotely with the purpose to review their proper functioning.

Lastly, it was agreed with company A to have a weekly visit to the factory during these two months to make different tests switching the location of the smartphones, updating their systems, connecting them again with *AirDroid*. In addion to this, some meeting with the managers were held to present the progression of the project.

3.3 Analysis phase

The main purpose of this phase is to analyze all the data gathered from both machines to start drawing conclusions. Although some data analysis were executed during the previous phase to present to the company's managers the progression of the project and some analytics of the performance of the machines, the significant analysis were executed when the implementation phase started. This phase lasted from the beginnings of May till the middle of May.

The data frame differs from one machine to the other one. The data of one of the machines, labeled as *machine 226*, is from week 11 till week 18, while the data from the other machine, labeled as *machine 230*, is from week 14 till week 18. The difference of the time frame is mainly due to some technical issues labeling data: the label blue was not working properly, even when it was changed manually. Thus, the data from week 11 till week 13 were rejected.

The methodology followed to analyze was simple. Firstly, the collection of the data. For this, it was necessary to talk to the IT department in order to get the data. Finally, it provided the data of the eight machines in an excel format. Secondly, the data was filtered with the purpose to cluster only the data from *machine 226* and *machine 230*.

Thirdly, once the data was clustered, an excel template was created in order to process the selected data aforementioned. Afterward, the data were reviewed in order to reject anomalies within the data . It is understood as an anomaly event that which does not follow the logic, e.g., if a machine is in the working state for 10 minutes when it is supposed to be around 2 minutes, this data is considered as an anomaly and therefore rejected.

In the fourth step, some analytics were carried out over the data to finally obtain different graphs, which appear in the *Chapter 5 - Results and discussion* and *Chapter 7 - Appendices*. For this, the data were also weekly clustered with the purpose to get a weekly overview of each machine. Finally, another software, *RStudio*, was used to obtain the weekly timelines of each machine.

In addition to this, during the commencement of the analysis phase, the project report was started to be written.

Lastly, the constraints made over the analytics are the following ones:

- The day starts and ends at 06:00am because of the working shifts.
- The events labeled as anomalies has been rejected and are the following ones: (i), working times longer and shorter than the average time of each machine, (ii), waiting times longer than 24 hours; and (iii), breakdowns longer than 24 hours.

3.4 Overall metodology

The *Figure* 3.4.1 presents the overall schema of the methodology followed in the project.

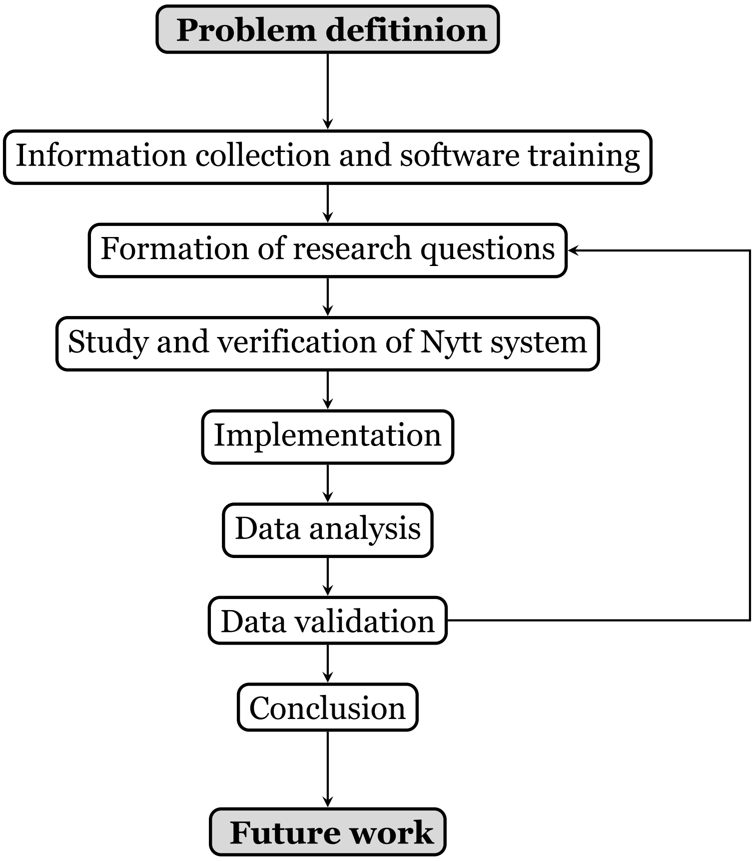


Figure 3.4.1: *Methodology structure*

Chapter 4

Implementation

This chapter presents the main content of the master thesis project. It presents a detailed description of the product developed by Nytt AB: the architecture of its system together with the description of the applications which make it. Moreover, it describes the three companies where the product is already implemented, followed by a section completely devoted to presenting the use case of this project, which is company A. Here, it is exposed the process and layout of each manufacturing cell, the machines where the product is implemented, how the product is placed facing the stack lights and so on. Finally, a roadmap to smart manufacturing for SMEs is presented.

4.1 System architecture

The machine vision system was developed from a master thesis by analyzing the shortcomings in small and medium-sized factory settings as well as the suggestions and inputs from the operators and managers from various companies. The *Figure 4.1.1* illustrates how the machine vision system and system architecture are. The system consists of mainly three units: *SetApp*, *OpApp*, and *Admin panel*. The data are transferred across these three units.

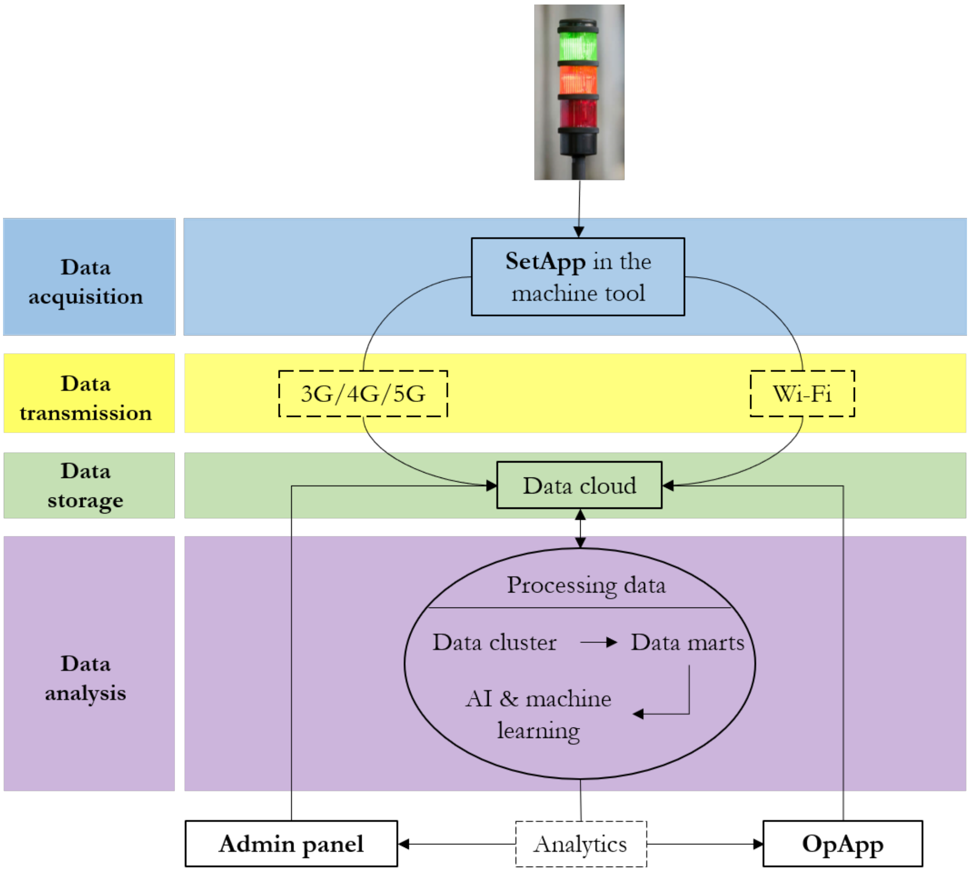


Figure 4.1.1: *Architecture of the system*

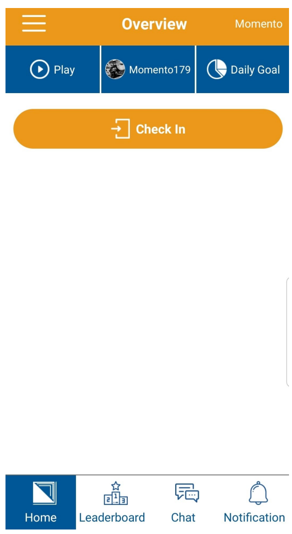
Firstly, *SetApp*, *Figure 4.1.2a*, is the data acquisition software, which is installed in a smartphone. The smartphone is placed facing the stack light and it captures the images of the stack light when it detects a change in the state, which is the color change of the stack light. The data are captured as images with timestamps. The acquired data are then stored in the data cloud which is being transmitted via Wi-Fi, 3G, 4G or 5G. Data analysis is carried out once the data reach the cloud, the processing is done as follows: from the data cluster, the data are differentiated as data mats according to the timestamps and machine number, which then directed to the AI and machine learning system. The machine learning then predicts the color status of the image. All the data analysis are carried out in the data cloud.

Secondly, *Admin panel*, *Figure 4.1.3*, acts as the overview page and as a dashboard. It illustrates the working status of all the machines connected with *SetApp*. The input to *Admin panel* is the processed data from the data cloud.

Various logics were defined inside *Admin panel* with respect to the factories. By the help of the pre-defined logic and processed data real-time value of the machines, the machines' availability and other manufacturing defining KPIs can be seen in the overview page. Furthermore, *Admin panel* is also connected to *SetApp* and *OpApp*. Some of the outputs to *SetApp* are the machine allocation to the operator and maintenance schedule assigning to the machine.

Lastly, *OpApp*, *Figure 4.1.2b*, is the assistant tool for the operator, which can installed in the operator's smartphone or tablet. The data from *Admin panel* go to *OpApp* as well. Thus, in addition to an overview of the data, it also illustrates the specific information of the machine/s in which the operator is assigned to. Furthermore, it will always notify the operator when a disruption/breakdown or a large waiting time occurred in the machine/s the operator is monitoring. The maintenance schedule is another important type of information communicated between the managers and operators. Besides, the operator can check which maintenance duties have been already done and which ones are left to complete. Finally, *OpApp* makes manufacturing factory more transparent and establish solid and easy communication between the operators, which are the most valuable assets of the factory together with the machines.

(a) *SetApp*



(b) *OpApp*

Figure 4.1.2: *Screen of SetApp and OpApp*

Figure 4.1.3: *Screen of Admin panel*

4.2 Presentation of companies

The product prototype was installed in three different medium-sized companies in Sweden. Each company has less than 100 employees in total.

1. Company A

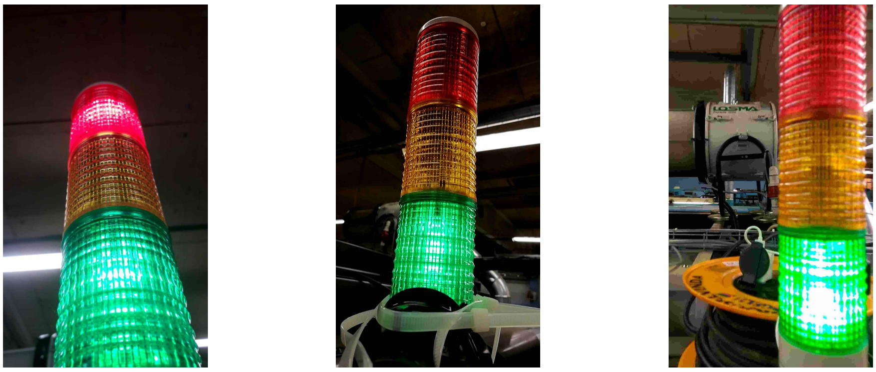
Company A is a medium-sized own equipment manufacturer which supplies its products to one of the largest companies in Sweden. The product variety is low. Two installations have been done in two different automated manufacturing cells. Each one produces the same product type throughout the year. The factory works on 3 shifts during the week. Major breakdowns in company A cause delays in the assembly line in the customer company. Hence, the efficiency of the process and the proper utilization of the machines are highly important for company A. *Figure 4.2.1a and Figure 4.2.1b* illustrate the stack lights in the installed machines.

(a) *Machine 226* (b) *Machine 230*

Figure 4.2.1: *Stack lights of company A*

2. Company B

Company B is a medium-sized firm which produces impact sockets. The product variety is high. The working shifts are planned according to the order received from the customer. Three installations have been done in Company B. One in a stand-alone machine with robotic loading and unloading. Two in the manufacturing cell of two machines. The *Figure 4.2.2a, Figure 4.2.2b and Figure 4.2.2c* illustrate the stack lights in the installed machines.



(a) *Machine 1* (b) *Machine 2* (c) *Machine 3*

Figure 4.2.2: *Stack lights of company B*

3. Company C

Company C is a small-sized precision component manufacturing firm which consists of fewer than 20 employees. The customers to company C are medium-sized manufacturing companies. The product variety is low. There are three shifts on weekdays, where two of them are manned and the night shifts are unmanned. Company C has stand-alone machines with robotic loading and unloading. The *Figure 4.2.3a, Figure 4.2.3b and Figure 4.2.3c* illustrate the stack lights in the installed machines.

(a) *Machine 1* (b) *Machine 2* (c) *Machine 3*

Figure 4.2.3: *Stack lights of company C*

The stack light color coding varies across the machine tool type, even though there is an ISO standard for the same. The *Table 4.2.1* describes the stack light color meaning associated with the eight machines from the three companies.

Table 4.2.1: The stack light color coding

MACHINES	WORKING	WAITING (IDLING)	DISRUPTION
Company A - Machine 226	🟢	🟢🔴	🔴
Company A - Machine 230	Off	🔵	🟡
Company B - Machine 1	🟢	🟡 / 🟡🟢	🔴 / 🔴🟡 / 🔴🟢
Company B - Machine 2	🟢	🟡 / 🟡🟢	🔴 / 🔴🟡 / 🔴🟢
Company B - Machine 3	🟢	Off	Off
Company C - Machine 1	🟢	🟡	🔴
Company C - Machine 2	🟢	🟡	🔴
Company C - Machine 3	🟢	🟡	🔴

4.3 Use case - Company A

This thesis discusses the implementation of the machine vision system in company A. The installations were made on two machines, which each one belongs in a different automated manufacturing cell.

Manufacturing cell 1

Cell 1 consists of four CNC milling machines. *Figure 4.3.1* illustrates the layout of cell 1. It is divided into three sub-cells, with three pick and place robots. The

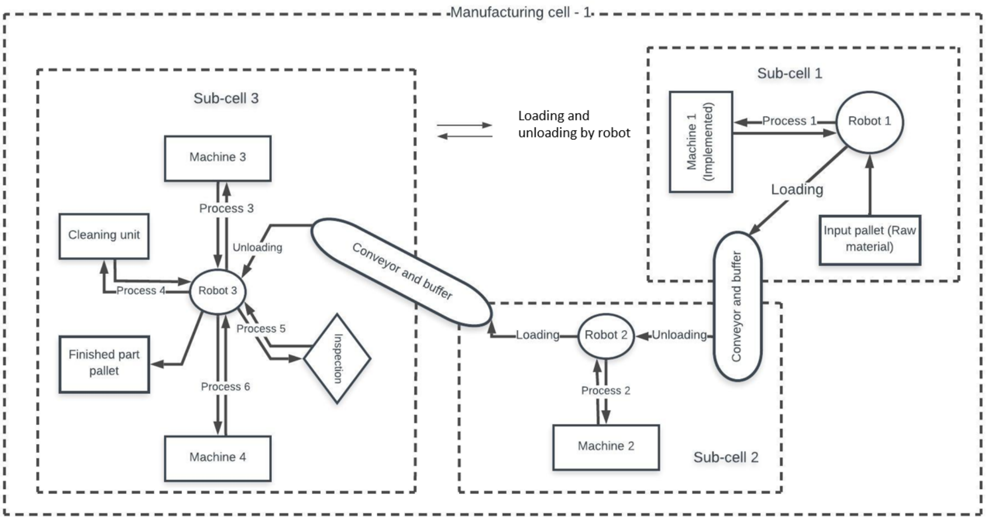


Figure 4.3.1: *Layout of manufacturing cell 1*

transfer of material between sub-cells is done through overhead conveyor which also acts as an intermediate buffer of 5 parts. The sub-cell 3 also has one cleaning unit and an inspection unit. The cells are separated and protected with grills.

Figure 4.3.2 shows the implementation of a smartphone, which has *SetApp* installed, facing the stack lights of the first machine, machine 230, of the sub-cell 1. In this process, the robot 1 loads the raw material to the machine from the input pallet. Facing and drilling are the machining operations carried out in this machine and the cycle time is around 3.5 mins per part, the shortest one in cell 1. As the machine has a turning table, meanwhile the machine is machining two parts at the same time, simultaneously the robot is placing two new raw parts in one side of the turning table. Thus, this machine would not have to wait unless a disruption occurs in this machine or in the following one, producing a product flow blockage.

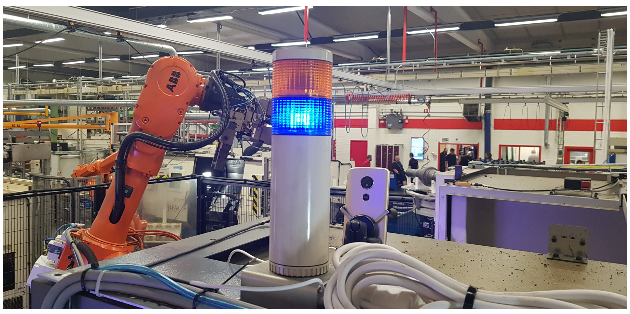


Figure 4.3.2: *Implementation of machine 230*

One operator is in charge of the whole manufacturing cell in each shift. The major operator tasks of the cell are:

- Changing the empty pallet with new raw material pallet.
- Changing the filled pallet and putting the empty pallet in sub-cell 3.
- Carry out tool change in the machines, when there is a disruption.
- Carry out the manual inspection on parts at alternate intervals.

Manufacturing cell 2

Manufacturing cell 2 consists of four coordinated CNC machines. *Figure 4.3.3* illustrates the layout of cell 2. The cell is divided into two sub-cells with two pick and place robots. The material transfer between these two sub-cells is also done through overhead conveyors, which also act as an intermediate buffer, having a capacity of 20 parts.

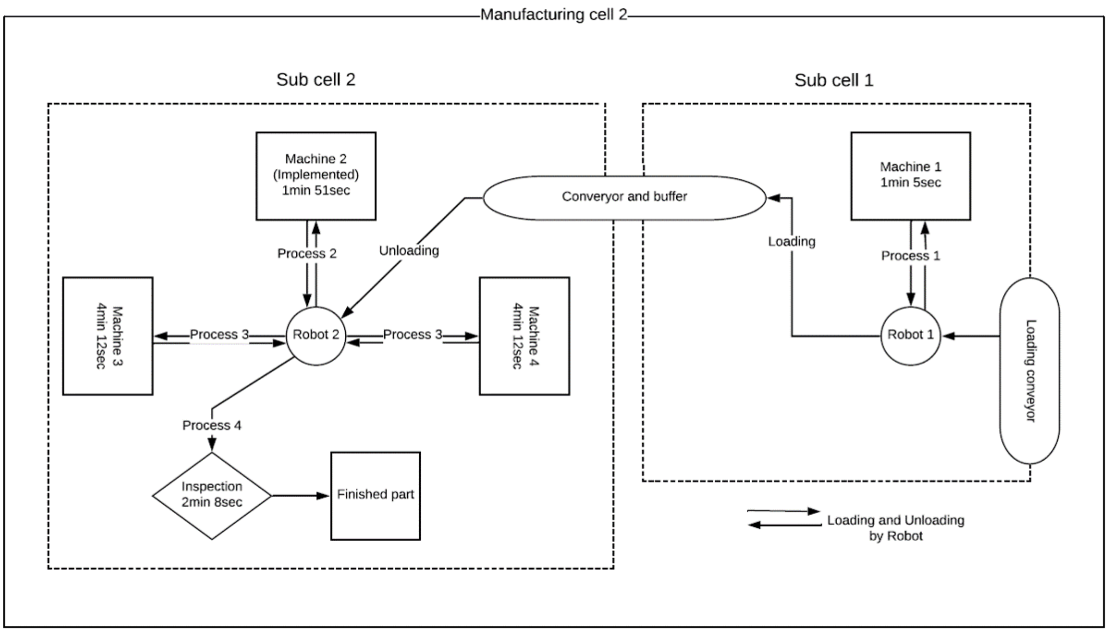


Figure 4.3.3: *Layout of manufacturing cell 2*

The smartphone with SetApp was installed in machine 226, the final machine of the manufacturing cell 2, which is the machine number 2 of the layout. *Figure 4.3.4* shows this installation. Finishing operations are done in this machine and the cycle time of the installed machine was 1 minute and 50 seconds at the time of the installation.

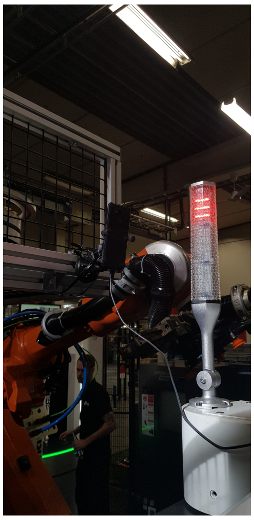


Figure 4.3.4: *Implementation of machine 226*

One operator is in charge of the whole manufacturing cell in each shift. The major operator tasks of the cell are:

- Loading the input conveyor with the raw material.
- Changing the filled finished part pallet and replace it with an empty one in sub-cell 2.
- Carry out tool change in the machines, when there is a disruption.
- Carry out the manual inspection on parts at alternate intervals.

In manufacturing cell 2, the data collection was carried out for 8 weeks, from week 11 to week 18. Over that time period, some processes have been changed by the company because multiple breakdowns started showing up in machine 226. These changes were done with the purpose to reduce the frequency of tool and machine failures and increase the production output through process optimization.

This thesis discusses if the change has improved the performance of company A in *Chapter 5 - Results and discussion*. This change in the production is analyzed as three scenarios:

1. **Before optimization:** Weeks 11-13.
2. **During breakdown:** Weeks 14 -15
3. **After optimization:** Weeks 16-18

4.4 Roadmap to smart manufacturing for SMEs

Nowadays, the flexibility in a production setting is necessary for all the companies regardless of the infrastructure. It is mainly due to variable demand and mass customization required by the customer. The integration of the IT system to lower level manufacturing system, which initiates the data collection from the shop floor and provide real-time performance visualization. The constraints for the implementation of sensors into shopfloor in SMEs are a lot more when compared with large scale manufacturers.

The full deployment of paradigm industry 4.0 is still in process. For SMEs, a roadmap to smart manufacturing through vertical integration is proposed. The roadmap is developed after analyzing the shortcomings in SMEs. Vertical integration is an integration strategy in which assistance/improvement is done in the critical areas of the production system [28]. In this case, it is a shop floor data collection. The roadmap suggests the effective way of reaching to smart factory concept with high effectiveness and at very low investment. The roadmap is breakdown five major criteria and the first three ones are successfully carried out in a medium-sized company and discussed in this thesis.

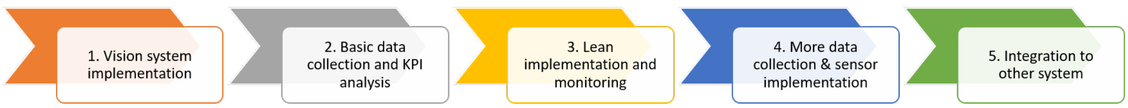


Figure 4.4.1: *Roadmap to smart factories*

Figure 4.4.1 illustrates the roadmap. The first step is the vision system implementation for basic data acquisition. The second step is the fundamental KPI analysis such as availability or OEE together with waiting and disruption events analysis in the machines. This will provide the managers and operators the information about the current performance of the machine tool. In this case, from all the installation and analysis, it is presented that the machines are being utilized less than 50%. A lot can be improved through lean methodologies, such as reducing the non-value adding processes. The changes made can be monitored through the system continuously. The following chapter, *Chapter 5 - Results and discussion*, more specifically in *section 5.1.1*, shows the change in availability before and after the optimization in the manufacturing cell 2.

In the fourth stage, the sensors can be implemented in the optimized production setting. By combining the initial data set from the vision system and sensor data, failure event prediction is possible and predictive maintenance methods can start carrying out in the factory. Finally, the last step is the integration to other higher level system such as maintenance and ERP or Product Lifecycle Management (PLM) systems. *Figure 4.4.2* shows the placement of the Nytt system in the production system architecture.

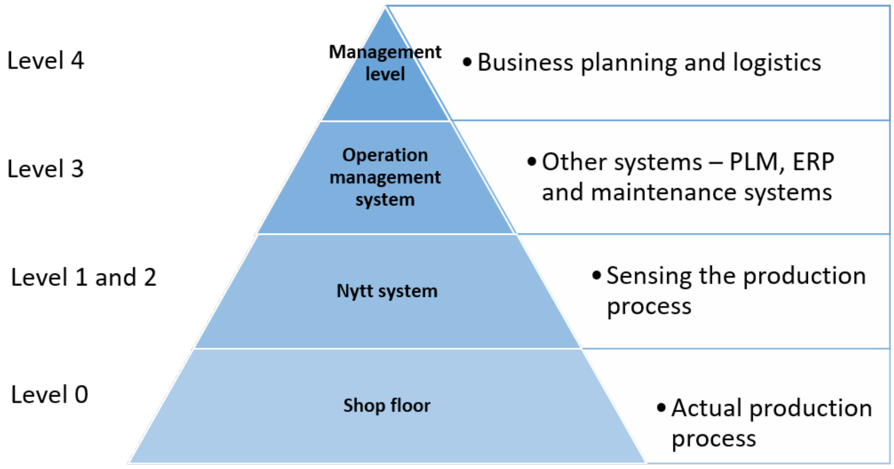


Figure 4.4.2: *Location of Nytt system in the overall system*

Chapter 5

Results and discussion

This chapter is divided into two part. On the one hand, the first part presents the results which have been obtained through the analysis carried out over the data of each machine. This part is also divided into five subsections in order to discuss the different factors considered to analyze both machines. These factors are the following ones: (i), availability; (ii), critical machine tool analysis; (iii), machine idling time; (iv), disruption events; and lastly, (v), information transfer. On the other hand, the second part is devoted to answering the research questions formulated in Chapter 1 - Introduction.

5.1 Implementation

5.1.1 Availability

The definition of this KPI is explained in *Chapter 2 - Literature Review*. The following figures, *Figure 5.1.1* and *Figure 5.1.2*, illustrate some of the graphs obtained during the analytic phase. As it has been aforementioned in *Chapter 4 - Implementation*, machine 226 is divided into three scenarios; therefore, there is one graph per scenario. However, machine 230 is analyzed without considering different scenarios since any change was carried out in the machine. Finally, the weekly graphs of each machine are in *Appendices*.

Machine 230

On the one hand, machine 230 has the availability of 63% as the average of the five weeks . This means that 63% of the time the machine was analyzed, it was working properly performing value-adding functions. However, the waiting time is 37% of the total, which means that the machine was waiting for more than a third of the total time analyzed because of different issues, excluding its own disruptions. Regarding this, machine 230 has a breakdown average of 0%, meaning that during these five weeks it was working almost perfectly without any disruptions produced in this machine.

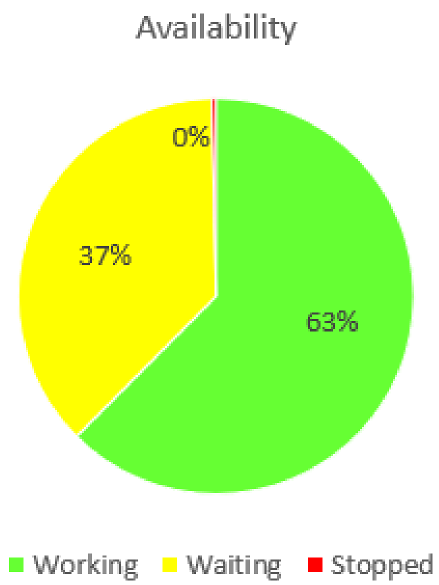
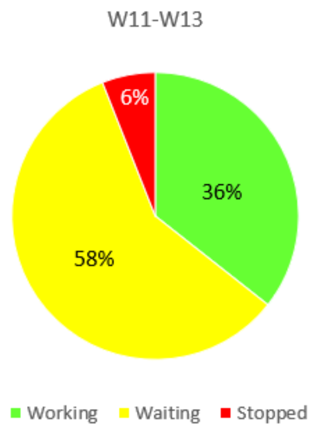


Figure 5.1.1: *Machine 230. Availability of W14-W18*

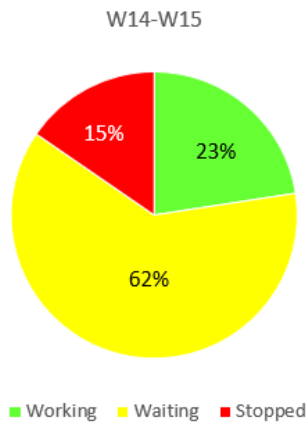
As it is aforementioned in *Chapter 4 - Implementation*, machine 230 is the first machine in the manufacturing cell 1 and its cycle time is the shortest. Thus, this machine should not have to wait 37% of the time with a proper conditions in the whole manufacturing cell. Moreover, this 37% is significant to be only produced by the delay of change of the pallet of the raw material. Thus, these waiting times are produced due to the disruptions or breakdowns occurred in the following machines of the manufacturing cell. Therefore, this machine is not considered a critical one.

Machine 226

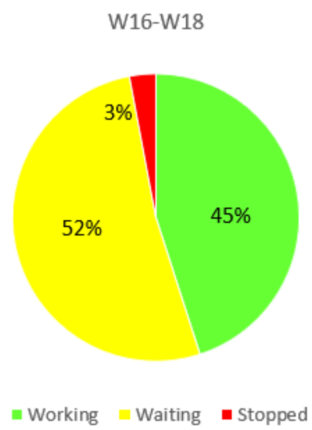
On the other hand, machine 226 and its three different scenarios are presented. *Figure 5.1.2a* illustrates the first scenario of three weeks, where the availability was 36%; *Figure 5.1.2b* illustrates the second scenario of two weeks, where the availability decreased until 23%; and finally, *Figure 5.1.2c* illustrates the last scenario of three weeks, where the availability arose until 45%.



(a) First scenario



(b) Second scenario



(c) Third scenario

Figure 5.1.2: *Machine 226. Availability of the three scenarios*

In terms of waiting times and breakdowns, the opposite logic is applied than in the working times. Their percentages increase from the first scenario to the second one, followed by a reduction in the third scenario, reaching these percentages the lowest values. Hence, the change implemented within the manufacturing cell has enhanced the performance of the machine and the manufacturing cell 2.

Although there is an improvement over time due to the change, the last results are not the ideal ones, especially due to the waiting times. The ideal solution would be reducing this yellow zone and increase the green one. However, as it was discussed with the production leader of company A, the production has improved a lot after the changes implemented in this manufacturing cell, performing more pieces than necessary (2500 pieces/week), even reaching around 3000 pieces the week 21.

Summarize

Machine 230

This machine was working perfectly for the 63% of the time analyzed, while the remaining 37% of the time was waiting largely to the breakdowns of the following machines. This machine barely had breakdowns. All this means that machine 230 is not a critical machine within its manufacturing cell.

Machine 226

This machine is analyzed by three scenarios. It is possible to observe a significant improvement in the availability of machine 226 from the first scenario to the third one. However, even though this, some measures would have to be taken in order to significantly reduce the waiting times (yellow zone in *Figure 5.1.2c*) in the third scenario.

Other graphs

There are two kind of graphs which illustrate the same information as the previous ones, but in a different weekly format. Furthermore, the graphs presented in this subsection belong to machine 226. The same graphs of the machine 230 are placed in *Appendices*.

On the one hand, the first graph, *Figure 5.1.3*, is a column bar where the weekly availability of machine 226 is displayed. The x-axis represents the analyzed weeks for the selected machine, whilst the y-axis represents the time in the fomat (hh:mm:ss), being h hours, m minutes and s seconds. Moreover, the horizontal black line in each column represents the total amount of hours *SetApp* was capturing data during the week. The gap between this line and the top of the column is the data missing produced by some anomaly events, e.g., *SetApp* was frozen several times to improve its performance, so it stopped capturing data and really long waiting times and disruption showed up that has not been considered in the analytics. Lastly, if the line does not reach the top of the y-axis is due to some breaks, e.g., the Easter break was during week 16 and 17, so the production was stopped for two and one day respectively. Regarding week 18, only two days are considered in this week.

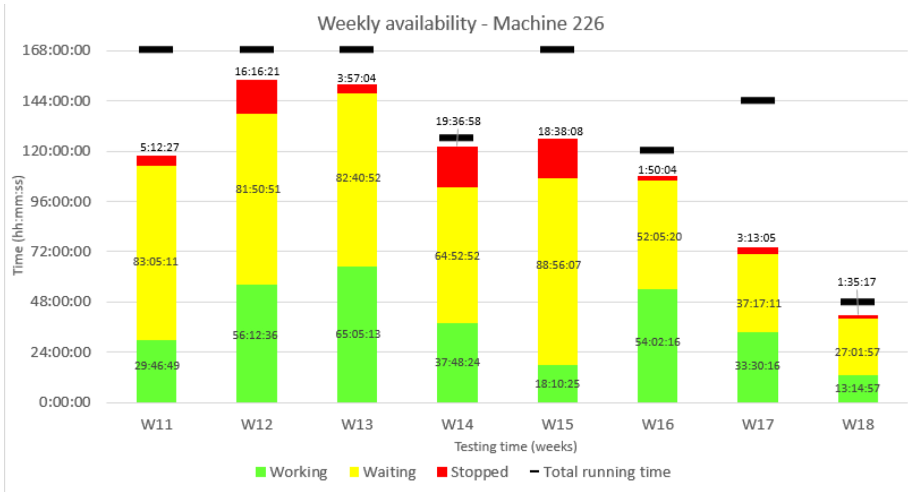


Figure 5.1.3: *Machine 226. Overall graph. W11-W18*

On the other hand, the second graph is a timeline which displays the same information as the first one, but chronologically in time. *Figure 5.1.4* illustrates the timeline of the week 16. There are only five days due to the Easter break during the weekend. The data missing is represented by gray color, while the other colors (red, yellow and green) represent the same states as before.

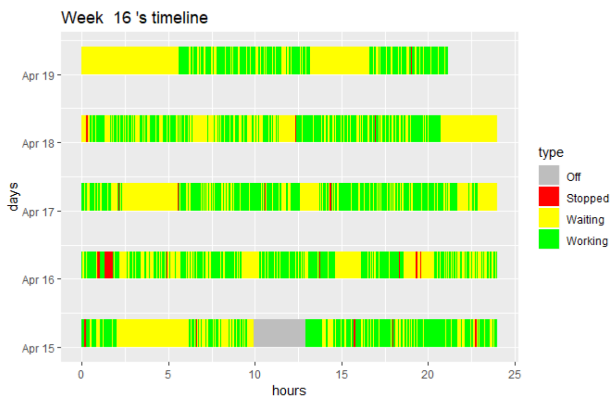


Figure 5.1.4: *Machine 226. Timeline. Week 16*

5.1.2 Critical machine tool analysis

There is always at least one critical machine tool in an automated machining cell. This means a failure of this critical machine has a great influence on the production flow of the cell. Monitoring these critical machines in a manufacturing setup helps the production system in many ways. Thus, some scenarios have been analyzed in order to identify the critical equipment within the manufacturing cells to know if they should be analyzed or not.

Manufacturing 1. Machine 230

Scenario 1: Breakdown of machine 1 (machine 230)

Its cycle time is 7 minutes for two pieces, being the cycle time for a single part of 3 minutes and 30 seconds. It is the first machine of the manufacturing cell with the lowest cycle time; therefore, it is supposed to work all the time until the moment the buffer is full, moment in which the machine will wait. The waiting times are produced because of the longer cycle times of the other machines or most likely due to the breakdowns of the other machines. Moreover, because of the delay changing the pallet of the raw material. Thus, it is stated again, this machine is not critical since it is working as it is supposed to do.

Scenario 2: Breakdown of robot 1, robot 2 or robot 3

Breakdown in any of the robots causes a stoppage of the whole manufacturing cell after the parts in the following conveyor-buffer are either full and empty. If robot 1 fails, robot 2 and 3 will work until the two conveyour-buffers are empty. If robot 2 fails, robot 1 will stop once the conveyour-buffer is full, meanwhile robot 3 will stop once the conveyor-buffer is empty. And finally, if robot 3 fails, robot 1 and robot 2 will stop once the respective conveyor-buffers are full, not existing any way to load and unload parts from the machines and inspection unit in the sub-cell 2. Thus, the robots in the cell are very critical elements, especially the second one.

Breakdown in the other machines

As it is aforementioned, machine 230 is not a critical machine. Thus, at least one of the following three machines is the critical ones. According to all the visits done to the company, the machine 2, which is the sub-cell 2, was always the critical machine which was stopping the whole manufacturing cell. Hence, it is possible to say that machine 2 is a critical machine.

Manufacturing 2. Machine 226

Scenario 1: Breakdown of machine 1

The cycle time of the machine is around 1min 5 sec and there is a conveyor combined with a buffer unit after the machine. There is always a minimum of 7 units in the buffer and the maximum capacity is 20 units. Therefore, if the machine 1 breakdowns suddenly because of tool breakage or any other reason, the rest of the sub-cell continues working until the buffer is empty; however, there is a time range to react before it happens. Thus, machine 1 is not critical.

Scenario 2: Breakdown of machine 3 or machine 4

These machines are carrying out the same operation and having a cycle time of approximately 4 minutes, which means one part is done at every 2 minutes. The breakdown in any of these machines stops the production in the whole sub-cell 2. Thus, these two machines are considered critical ones.

Scenario 3: Breakdown of robot 1 or robot 2

Breakdown in any of the robots causes the immediate stoppage of the whole manufacturing cell. If robot 1 fails, the sub-cell 2 keep working until the conveyor-buffer is empty. If robot 2 fails, there will not be any way to load and unload parts from the machines and inspection unit in the sub-cell 2. Thus, the robots in the cell are very critical elements, especially the second one.

Scenario 4: Breakdown of machine 2 (machine 226)

A breakdown here stops the whole sub-cell 2 since it is the final machining operation. Thus, this machine is also considered critical.

Examining this critical machine helps to draw several conclusions of the production process. Few of them are:

- Availability of the machine
- Waiting time: helps in finding the bottleneck of the manufacturing cell.
- Part counting.
- Failure events in the machine.
- Failure events in the other machines.

Summarize

After analyzing the different scenarios for both manufacturing cells, machine 230 is not identified as a critical machine, whilst machine 226 is identified as critical machine. Thus, from here in advance, machine 226 is the subject of the following results, more specifically for the weeks 16 and 17, which belong to the third scenario, since the machine 226 is currently working in this way.
Moreover, after analyzing these different scenarios in the manufacturing cell 2, a new layout for the sub-cell 2 would be highly recommended, since only one breakdown in any of the machines or robot produces the stoppage of the production in this sub-cell.

5.1.3 Machine idling time

Machine 226 has been analyzed during the week 16 and 17 to identify the long waiting times. *Figure 5.1.5* illustrates the total waiting events occured in these two weeks displayed only in a single day. The x-axis represents these 24 hours in the format (hh:mm:ss), whilst the y-axis represents the total amount of time the machine was waiting.

Analyzing this graph in detail, although there are a vast number of waiting events at the bottom, there are 14 waiting events above the horizontal line of 2:24:00 representing the 45% of the total waiting time. These long waiting times are mainly produced to the long breakdowns in the parallel machines within the

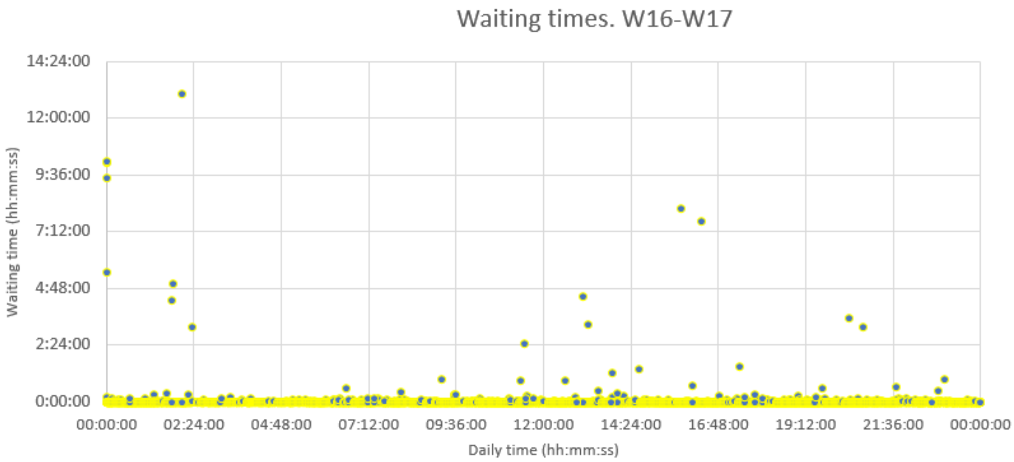


Figure 5.1.5: *Long waiting times of machine 226*

same sub-cell, supporting the idea that these two machines are also critical. Hence, reducing these waiting times, which also means reducing the time of the breakdowns of these two machines, the availability of all these three machines would highly improve.

Figure 5.1.6 illustrates the same information as *Figure 5.1.5*, but with different scale in the y-axis. It is possible to observe two horizontal "lines" at the bottom of the graph. The first one is due to a 1-second blinking light that appears in the middle of the production, and the second one is the ideal waiting time of the machine 226 for the robot to unload and load a new part in it. In this thesis, a waiting event is considered as short when its duration is between 30 seconds and 30 minutes. These short waiting times, which do not belong to these two trends aforementioned, represent the 20% of the total waiting time and can be produced for many reasons: breakdowns in the other machines or robots, the filled finished part pallet is not replaced in time, the operator cannot attend the machines of this manufacturing cell because is busy with other tasks and so on.

Finally, a strategy could be applied over these long and short waiting times with the purpose to reduce or even suppress them. Consequently, the availability of the machines would significantly improve.

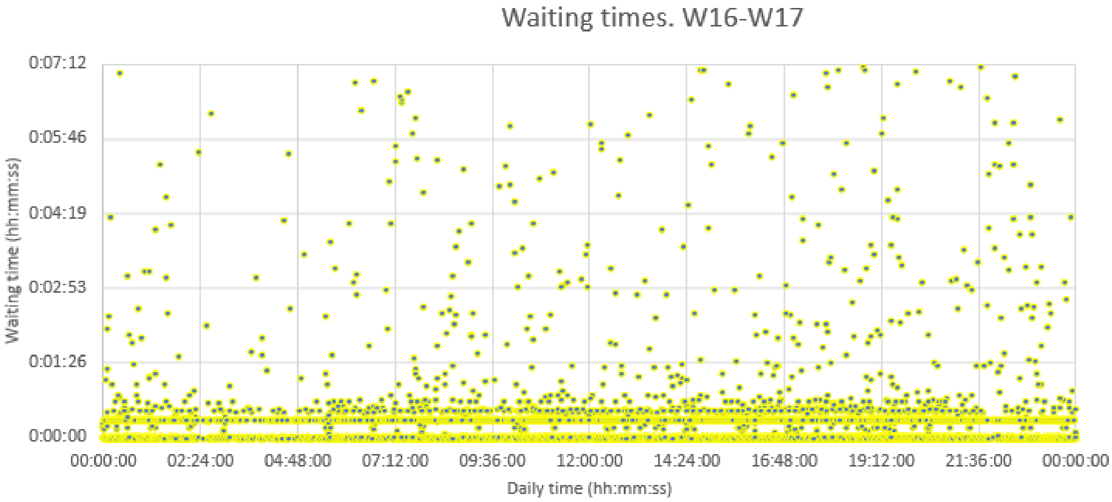


Figure 5.1.6: *Short waiting times of machine 226*

Summarize

The largest waiting times of machine 226 represents 45% of the total waiting time, meanwhile the short ones represent 20%. The first ones are mainly produced by the breakdowns of the previous parallel machines.
These large waiting times together with the short ones could be suppressed by implementing a strategy.

5.1.4 Disruption events

Figure 5.1.7 illustrates the disruption events produced during weeks 16 and 17 displayed in the format of 24 hours. The x-axis represents these 24 hours, whilst the y-axis represents the total amount of time the machine was stopped due to breakdowns or disruptions until it started working normally.

There are 5 events above 7 minutes which constitute the prolonged stop times. They account for 50% of the total stop time. A quick response of the operator over these disruptions would improve the availability of the machine. It could be achieved by the implementation of *OpApp*, which aids the operator by notifying him/her when a disruption event occurs. However, although the operator realises quickly about the disruption event, not always they are easy to fix and that is one of the reasons why these last much time.

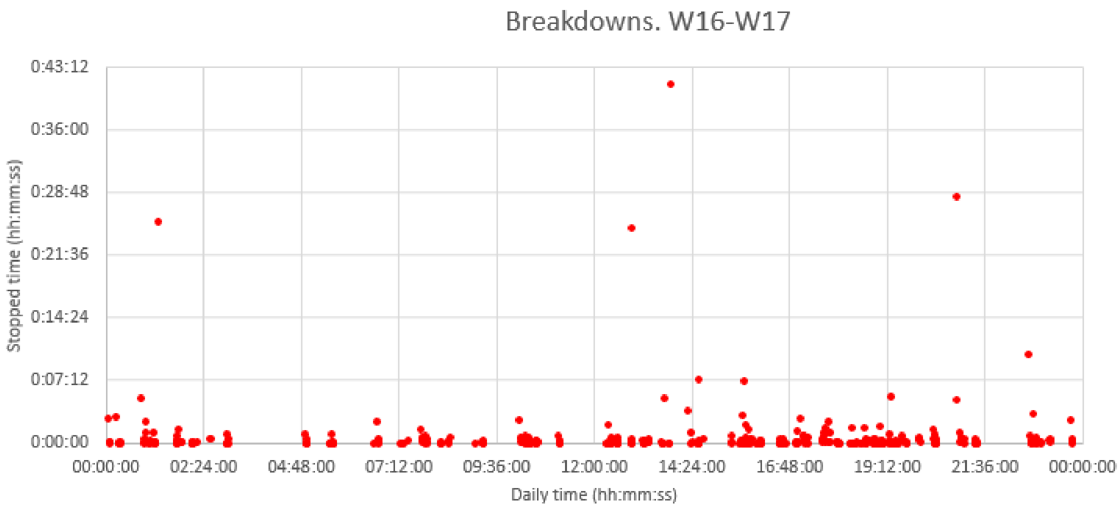


Figure 5.1.7: *Long breakdowns of machine 226*

Figure 5.1.8 illustrates the same information than *Figure 5.1.7*, but the y-axis has been scaled to analyze the disruption events below 7 minutes. This graph shows the quick response of the operators.

In addition to this, this scalability allows recognizing a pattern in the disruptions events. There are some time slots during these two weeks in which no interruption has occurred. However, the disruption events tend to happen during the afternoon and night shift. This could be mainly produced because the maintenance department stop working at 15:30.

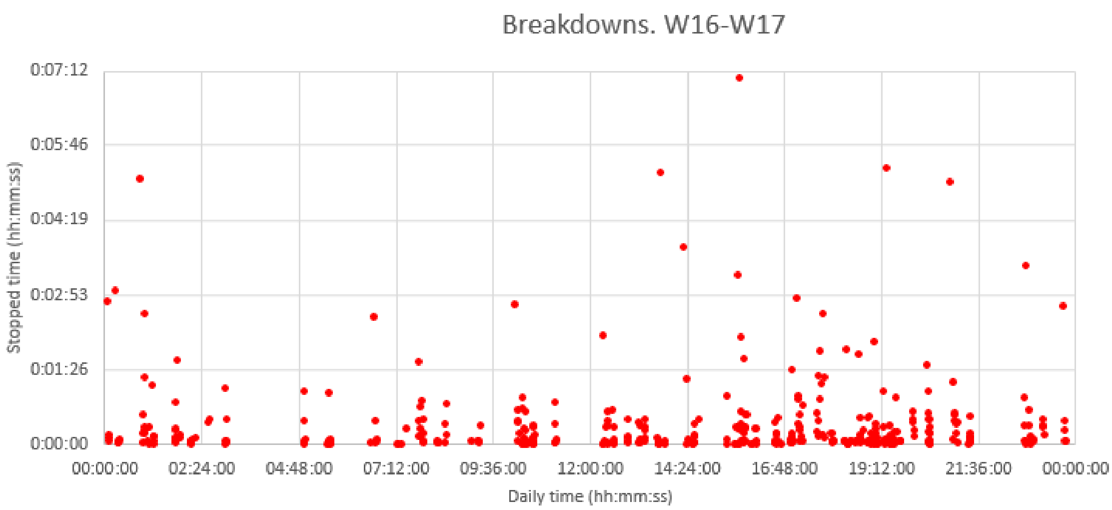


Figure 5.1.8: *Short breakdowns of machine 226*

Possible solutions to solve this problem could be:

- Implementation of pattern recognition with ML. However, more inputs of different factors are necessary for the ML algorithms to obtain proper and accurate results about it.
- The possibility to have the maintenance department available during the afternoon and night shifts.
- Provide more trainings with the purpose to have better-trained operators.
- Share this knowledge with the operators to make them be aware and be prepared for these disruptions.

Summarize

The long disruption events represent 50% of the total stop time. Moreover, the disruption events tend to happend during the afternoon and night shift. ML could be applied for pattern recogniton in order to predict these disruptions events. Another solution could be to have another maintenance department during the afternoon and night shifts.

5.1.5 Information transfer

The operators are the major assets of a manufacturing company. The information transfer between the operators and operator and manager is highly needed to create a transparent working environment. One of the major expected outcomes from a smart factory is also the smooth information transfer from the shop floor to the high-level management and it starts with operator decentralization.

A comparison between operator response time to disruptions events in two different manufacturing companies, company A and company C, is analyzed. The response time refers to the time taken by the operator to reach the machine at the time of a failure event in the machine and start working to rectify the machine breakdown. *Figure 5.1.9* shows the response time of the operators in company A to the disruption events. There were 21 disruptions in week 16, where 80% of the time the operator reacted to rectify the failure within 3-4 minutes. On the other hand, there were around 10 instances where the operator took more than the acceptable limit time to reach the machine. The highest one being 40 minutes in week 17, which translates to at least 40 minutes the machine was down. Finally, to mention that the horizontal green line represents the acceptable time of the operator to react to start fixing these disruptions. This acceptable time could be decided by the managers of the company.

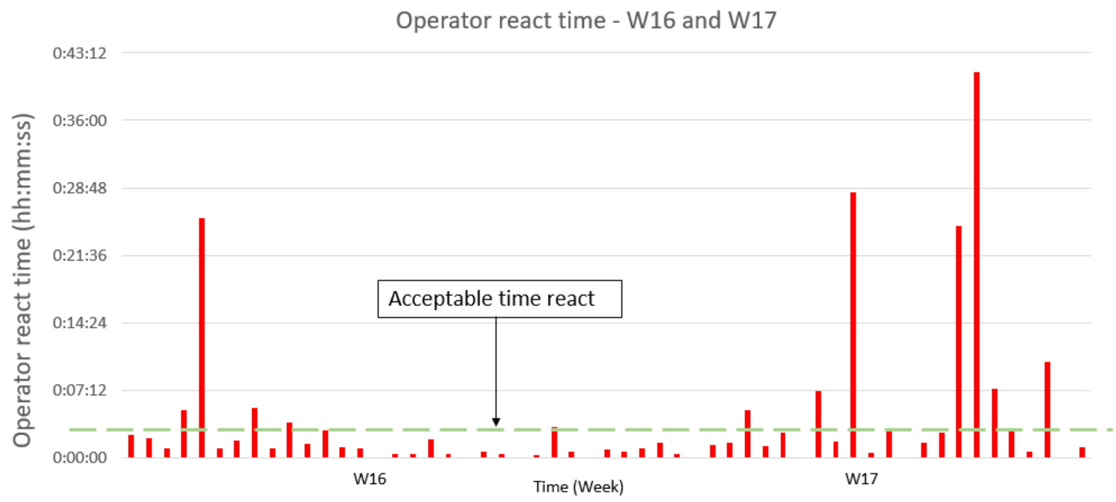


Figure 5.1.9: *Operator response time in machine 226*

Whereas in company C the operator response time together with the repair time was very lower compared with the ones in company A. Upon analyzing the data and monitoring the working environment, the following conclusion has been made. In company C, the better efficiency of the operator is firstly due to the effective information transfer. Both companies have a daily meeting between the operators and managers; however, the operator of company C usually has an important weekly meeting with top management, whereas it lacks in company A. This weekly communication helps to discuss the downtimes in the machine tools and how it got fixed, which helps everyone in the company to tackle such same failures at a faster phase future. However, the number of machines handled by one operator in company A is higher than company C, which provides more time to the operators in company C to prepare for the changeover, prepare the tools before the breakdown and load the raw material before it gets finished.

Summarize

The information transfer between operators and operators-managers is highly important for a proper perfomance of the factory.
Furthermore, the operator react time should be as low as possible in order to reduce the duration of the disruptions, but sometimes the operator has a lack of information, training or it has many responsibilities.

5.2 Research questions

This section is devoted to answering the research questions.

5.2.1 Research question 1

- How can monitoring of shop floor assets, such as machine tools, help SMEs drawing conclusions, adapting to the product mix and improving key performance indicartors (KPIs) like the availability of the machine? -

This research question is answered in this chapter by presenting the results obtained after analyzing the data collected from the two machines. Together with this, the conclusions presented in the following chapter are also a valid answer for this research question.

It is demonstrated the potential of monitoring shop floor assets such as machines, which are one of the most important assets of the factories together with the operators. Monitoring these assets allows companies to receive really valuable feedback information, since several parameters are analyzed in detail: (i), availability; (ii), critical machine tool analysis; (iii), machine idling time; (iv), disruption events; and (v), information transfer. The companies should apply solutions or strategies to the critical problems which do not allow the proper performance of the company. These solutions or strategies are presented in the following chapter, *Chapter 5 - Results and discussion*.

5.2.2 Research question 2

- How SMEs can make the paradigm shift to smart manufacturing at an easier phase and method? -

The second research question is answered with the roadmap presented in *section 4.4 - Roadmap to smart manufacturing for SMEs*. This roadmap has been created and proposed by the project team from the data gathered from SMEs during the thesis and considering the economic and production limitations of SMEs. Lean methodology is incorporated during the transformation which helps the companies to optimize their existing settings by reducing the non-value added processes and later moving to sensors integration.

Chapter 6

Conclusions

After discussing the results, the following conclusions were made.

No two machines can have the same performance characteristics. Certain information can be gathered by monitotring any machine in a manufacturing cell. However, in order to have a better insight into the production performance of the whole manufacturing cell, it is highly recommended to implement the product in the critical machine/s. Furthermore, the implementation of this product allows companies to realize if the machine performs properly, and later the behaviour of the whole manufacturing cell. In addition to this, the improvement in availability after any change implemented in some production parameters can also be monitored.

Regarding the machine idling time, firstly, it is concluded that it can be potentially reduced in terms of the number of events and duration by the implementation of *OpApp*. The operator would receive a notification when a waiting event remains more than a certain amount of time, which can be decided by the managers. In this case, the operator would have a faster response and thus the waiting times will be potentially reduced.

Secondly, a strategy can be implemented in the factory. Agreed in advance with the managers of the factory, the operator should first focus on the longest waiting times or the shortest ones. This decision will depend on the situation of the company. The total amount of short waiting times sometimes can represent the largest percentage of the total waiting time and vice versa. For this, before the decision, a study must be carried out in order to identify which one is the target of the strategy. In this specific case, the operator should focus first in the longest ones since they represent 45% of the total waiting time, while the shortest ones only represent 20%.

The operators are the most important assets in the factory. Thus, the operator must be properly trained and aware of any information about the manufacturing cell. The information flow between operators and operators-managers and vice versa should be transparent. This can also be solved by the implemention of *OpApp*, which can acts as a communication module. Moreover, it is highly recommended for company A to have the maintenance department available during the afternoon and night shifts, since it is the time when the disruptions events tend to happen.

Finally, two more conclusions which are related to each other. These two conclusions are derived from other ones. On the one hand, by reducing the duration of waiting and number of disruption events and their repare time, the machines will work more efficiently, leads to achieve a higher number of final parts per day. This is translated into a potential reduction of the number of shifts, allowing the company to have the weekends off. On the other hand, the production can be potentially increased without any change in the number of shifts. This is translated in an increase in inventory or even the initiation of new parts production for new or same customers.

Chapter 7

Future work

Machine 230 is identified as non-critical machine. Therefore, as future work, it is recommended to relocate the implementation into the critical machine in the same manufacturing cell. It is suggested to monitor the second and/or third machine in the manufacturing cell 1 since these machines are having high breakdown rates and repairing time.

OpApp is a powerful tool with a potential to ease out the communication flow between operator-manager and to other department managers. Although it is still in the development phase, its early implementation initiates the input from the operator, and along with data collected from the machines, helps the company and for Nytt AB to understand the reasons for waiting and disruption events.

Pattern recognition and predictive maintenance are also studied during the thesis. The collected data are weak in order to apply for these two concepts. Thus, it is recommended as a future work, to collect different kinds of data. Through the implementation of different sensors, such as beacons, in the monitored machines in order to get more information about the machine tool. Consequently, with this new data together with the previous one, the ML algorithms to recognize patterns in the data and allow the predictive maintenance will be more reliable.

As it is stated in *Chapter 2 - Literature review*, 5G is the best option to proceed this data transfer due to the innumerable advantages compared to 3G, 4G or Wi-Fi. Thus, once 5G is available, would be useful carring out data transfer.

Lastly, the integration of Nytt system with other systems of the companies such as ERP or PLM system would be possible. By this, the company becomes more transparent, smoothens the information and data flow from top to bottom and vice versa. So, it is suggested as future work to search about the compatibility of the integration between these systems.

Bibliography

[1] Thierer, Adam and Castillo, Andrea. *Projecting the growth and economic impact of the Internet of Things*. Tech. rep. Mercatus Center - George Mason University, 2015, p. 10. url: `https://www.mercatus.org/system/files/IoT-EP-v3.pdf`.

[2] Yen Ting, Ng, Yee Shee, Tan, and Sze Choong, Low Jonathan. "Internet of Things for Real-time Waste Monitoring and Benchmarking: Waste Reduction in Manufacturing Shop Floor". In: *Procedia CIRP* 61 (2017), pp. 382–386. issn: 22128271. doi: `10.1016/j.procir.2016.11.243`. url: `www.sciencedirect.com`.

[3] Aboul, Nilanjan Dey et al. *Internet of Things and Big Data Analytics Toward Next-Generation Intelligence*. Tech. rep. 2018. doi: `10.1007/978-3-319-60435-0`. url: `http://link.springer.com/10.1007/978-3-319-60435-0`.

[4] *The Internet of Things: a movement, not a market*. IHS Markit, 2017, p. 9. url: `https://cdn.ihs.com/www/pdf/IoT%7B%5C_%7Debook.pdf`.

[5] Satyavolu, Prasad et al. *Designing for Manufacturing's 'Internet of Things'*. Tech. rep. Technology Solutions, Cognizant, 2014, p. 15. url: `https://www.cognizant.com/InsightsWhitepapers/Designing-for-Manufacturings-Internet-of-Things.pdf`.

[6] Boyes, Hugh et al. "The industrial internet of things (IIoT): An analysis framework". In: *Computers in Industry* 101 (2018), pp. 1–12. issn: 01663615. doi: `10.1016/j.compind.2018.04.015`. url: `https://doi.org/10.1016/j.compind.2018.04.015`.

[7] Cheng, Jiangfeng et al. "Industrial IoT in 5G environment towards smart manufacturing". In: *Journal of Industrial Information Integration* 10 (2018), pp. 10–19. issn: 2452414X. doi: 10.1016/j.jii.2018.04.001. url: https://doi.org/10.1016/j.jii.2018.04.001.

[8] Li, Shancang, Xu, Li Da, and Zhao, Shanshan. "5G Internet of Things: A survey". In: *Journal of Industrial Information Integration* 10 (2018), pp. 1–9. issn: 2452414X. doi: 10.1016/j.jii.2018.01.005. arXiv: arXiv:1011.1669v3. url: https://doi.org/10.1016/j.jii.2018.01.005.

[9] Zhong, Ray Y. et al. "Intelligent Manufacturing in the Context of Industry 4.0: A Review". In: *Engineering* 3.5 (2017), pp. 616–630. issn: 20958099. doi: 10.1016/J.ENG.2017.05.015. arXiv: arXiv:1011.1669v3. url: http://dx.doi.org/10.1016/J.ENG.2017.05.015.

[10] Blyler, John. *Top 5 RF Technologies for 5G in the IoT | Microwaves & Radio Frequency*. 2017. url: https://www.mwrf.com/systems/top-5-rf-technologies-5g-iot.

[11] Akpakwu, Godfrey Anuga et al. "A Survey on 5G Networks for the Internet of Things: Communication Technologies and Challenges". In: *IEEE Access* 6 (2017), p. 29. issn: 21693536. doi: 10.1109/ACCESS.2017.2779844. arXiv: 1606.07360. url: https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=%7B%5C&%7Darnumber=8141874.

[12] Akyildiz, Ian F et al. "5G roadmap: 10 key enabling technologies". In: *Computer Networks* 106 (2016), pp. 17–48. doi: 10.1016/j.comnet.2016.06.010. url: http://dx.doi.org/10.1016/j.comnet.2016.06.010.

[13] Chui, Michael, Kamalnath, Vishnu, and McCarthy, Brian. *An executive's guide to AI | McKinsey*. url: https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/an-executives-guide-to-ai.

[14] *What is Machine Learning? A definition - Expert System*. url: https://www.expertsystem.com/machine-learning-definition/.

[15] Ansari, Fazel, Erol, Selim, and Sihn, Wilfried. "Rethinking Human-Machine Learning in Industry 4.0: How Does the Paradigm Shift Treat the Role of Human Learning?" In: *Procedia Manufacturing* 23 (2018), pp. 117–122. issn: 23519789. doi: 10.1016/j.promfg.2018.04.003. url: www.sciencedirect.comAvailableonlineatwww.sciencedirect.comwww.elsevier.com/locate/procedia.

[16] *Gartner Predicts 70 Percent of Organizations Will Integrate AI to Assist Employees' Productivity by 2021*. 2019. url: https://www.gartner.com/en/newsroom/press-releases/2019-01-24-gartner-predicts-70-percent-of-organizations-will-int.

[17] Stanula, Patrick, Ziegenbein, Amina, and Metternich, Joachim. "Machine learning algorithms in production: A guideline for efficient data source selection". In: *Procedia CIRP* 78 (2018), pp. 261–266. issn: 2212-8271. doi: 10.1016/J.PROCIR.2018.08.177. url: https://www.sciencedirect.com/science/article/pii/S2212827118310266.

[18] Gershgorn, Dave. *Europe publishes more AI papers than the US or China — Quartz*. 2018. url: https://qz.com/1490424/europe-publishes-more-ai-papers-than-the-us-or-china/.

[19] Wiendahl, H. P. et al. "Changeable Manufacturing-Classification, Design and Operation". In: *ELSEVIER* (2007), pp. 783–809. doi: 10.1016/j.cirp.2007.10.003. url: www.manufuture.org.

[20] Coleman, Chris, Damodaran, Satish, and Deuel, Ed. *Predictive maintenance and the smart factory | Deloitte*. Tech. rep. Deloitte, 2017, p. 8. url: https://www2.deloitte.com/content/dam/Deloitte/us/Documents/process-and-operations/us-cons-predictive-maintenance.pdf.

[21] *Types of Maintenance*. url: http://www.petrochemicalmaintenance.com/typesofmaintenance.html.

[22] Pawellek, Günther. *Integrierte Instandhaltung und Ersatzteillogistik: Vorgehensweisen, Methoden, Tools*. Berlin: Springer, 2013.

[23] Lee, Wo Jae et al. "Predictive Maintenance of Machine Tool Systems Using Artificial Intelligence Techniques Applied to Machine Condition Data". In: *Procedia CIRP* 80 (2019), pp. 506–511. doi: 10.1016/j.procir.2018.12.019. url: https://linkinghub.elsevier.com/retrieve/pii/S2212827118312988.

[24] Al-Najjar, B., Algabroun, H., and Jonsson, M. "Maintenance 4.0 to fulfill the demands of Industry 4.0 and Factory of the Future". In: *Journal of Engineering Research and Application www.ijera.com* 8.11 (2018), pp. 20–31. doi: 10.9790/9622-0811022031. url: http://urn.kb.se/resolve?urn=urn:nbn:se:lnu:diva-81915www.ijera.com.

[25] Brandl, Dennis L and Brandl, Douglas. "KPI Exchanges in Smart Manufacturing using KPI-ML". In: *IFAC-PapersOnLine* 51 (2018), pp. 31–35. doi: 10.1016/j.ifacol.2018.08.230. url: www.sciencedirect.com.

[26] Stricker, N. et al. "Considering Interdependencies of KPIs – Possible Resource Efficiency and Effectiveness Improvements". In: *Procedia Manufacturing* 8 (2017), pp. 300–307. doi: 10.1016/j.promfg.2017.02.038. url: https://linkinghub.elsevier.com/retrieve/pii/S2351978917300446.

[27] INTERNATIONAL STANDARD (ISO). *ISO 22400-2. Automation systems and integration — Key performance indicators (KPIs) for manufacturing operations management —*. 2014.

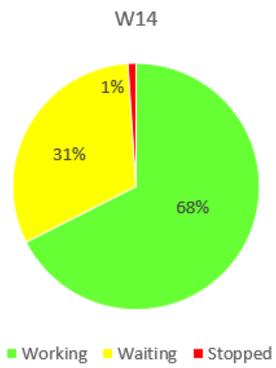
[28] Pérez-Lara, Magdiel et al. "Vertical and Horizontal Integration Systems in Industry 4.0". In: Springer, Cham, 2019, pp. 99–109. doi: 10.1007/978-3-030-03898-4_11. url: http://link.springer.com/10.1007/978-3-030-03898-4%7B%5C_%7D11.

Appendices

Appendix - Contents

A Weekly availability

A.1 Machine 230



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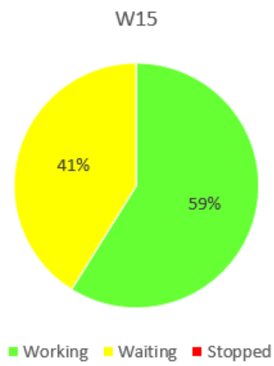

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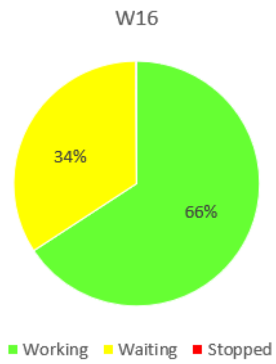

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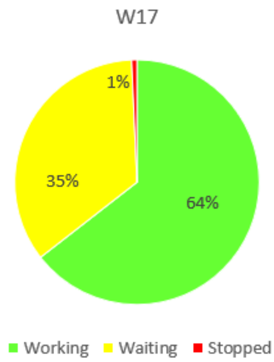

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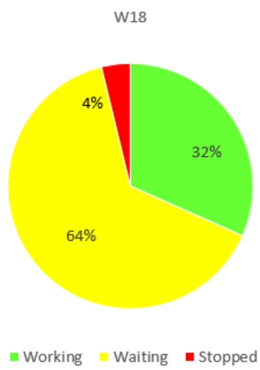
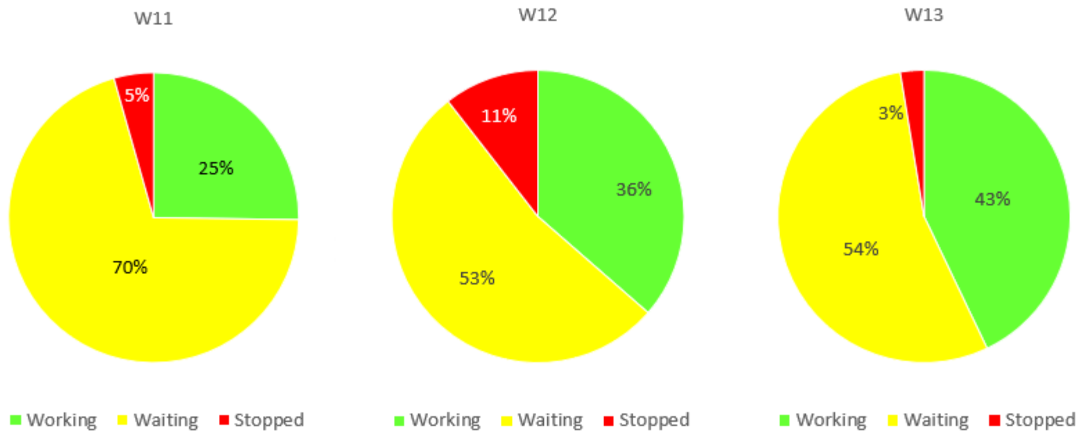


(e) Week 18

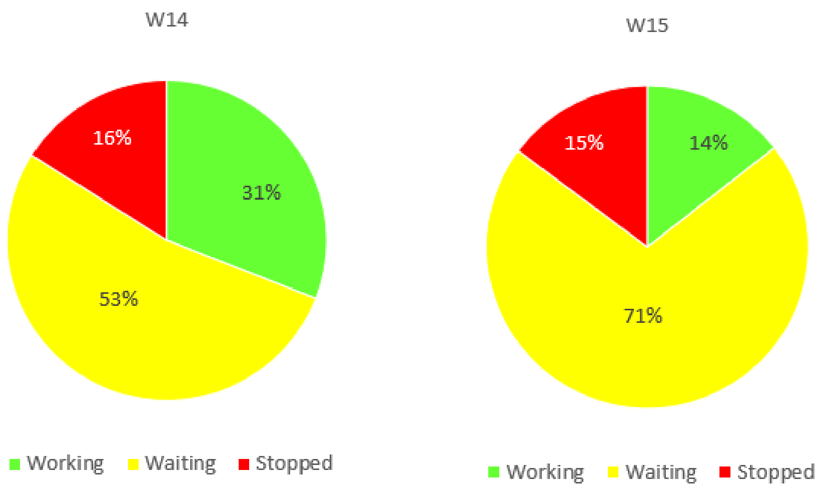
Figure A.1: *Machine 230. Weekly availability*

A.2 Machine 226



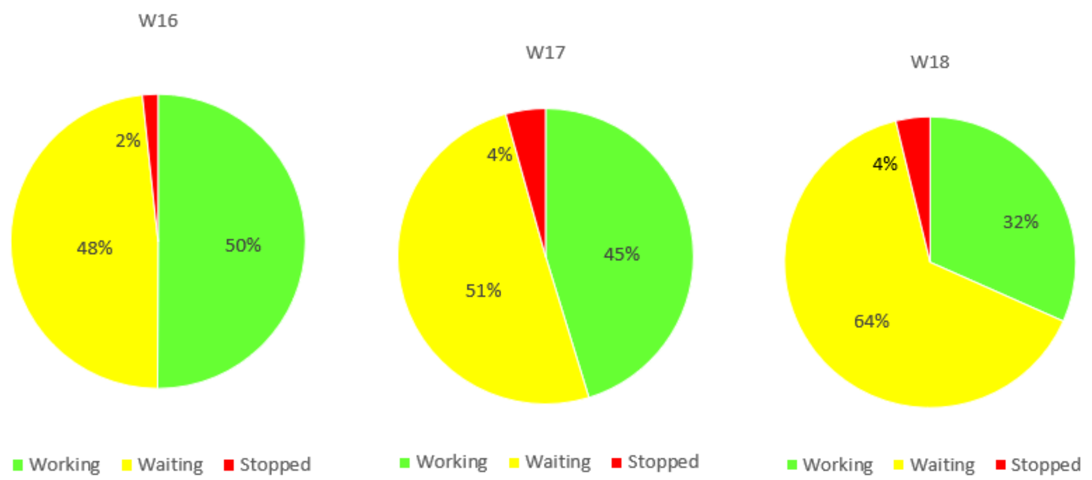
(a) Week 11 (b) Week 12 (c) Week 13

Figure A.2: *Machine 226. Weekly availability. First scenario*



(a) Week 14 (b) Week 15

Figure A.3: *Machine 226. Weekly availability. Second scenario*



(a) Week 16 (b) Week 17 (c) Week 18

Figure A.4: *Machine 226. Weekly availability. Third scenario*

B Overall graph

This figure represents the same information as *Figure 5.1.3*, but related to the machine 230.

B.1 Machine 230

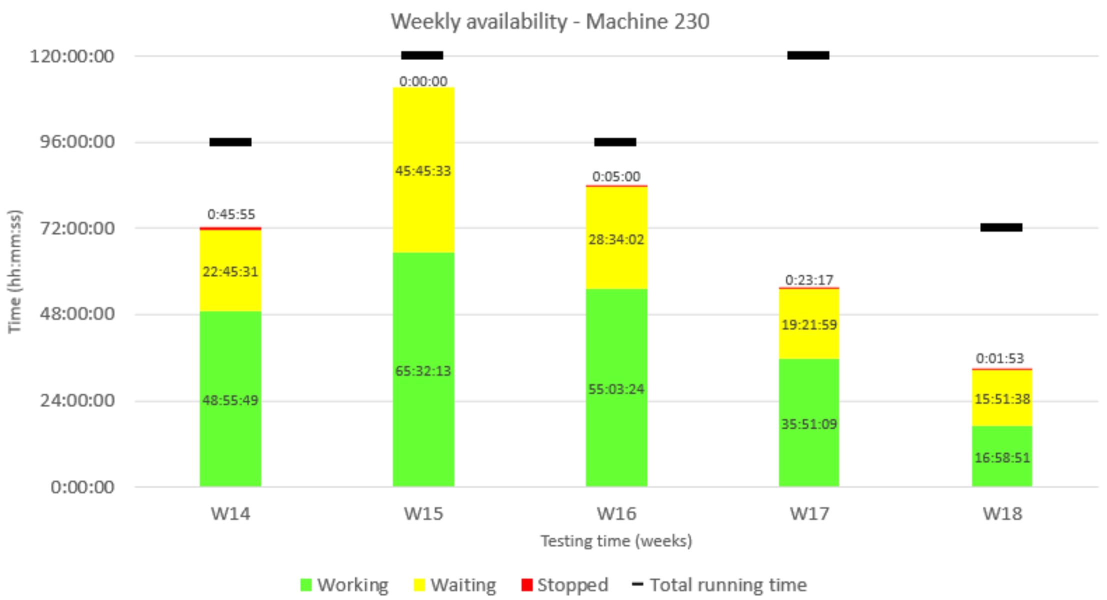


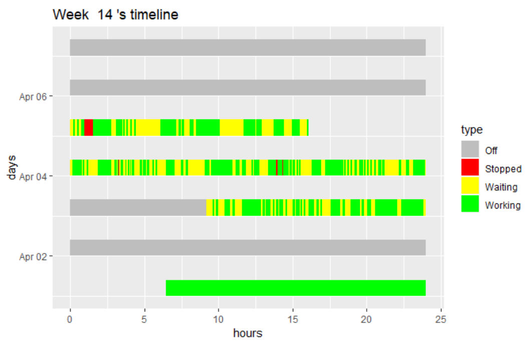
Figure B.1: *Machine 230. Overall graph. W11-W18*

C Timelines

The timelines provide an insight into the weekly availability of the machines.

C.1 Machine 230

Company A does not work in manufacturing cell 1 during weekends, which explains why there are only five days in these timelines.



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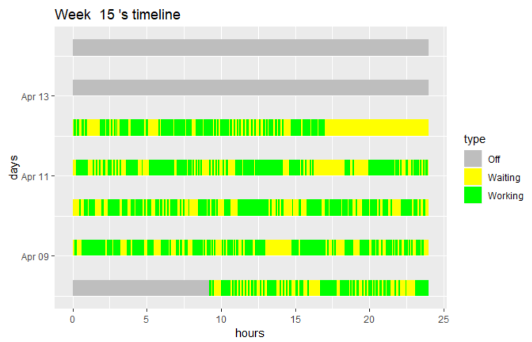

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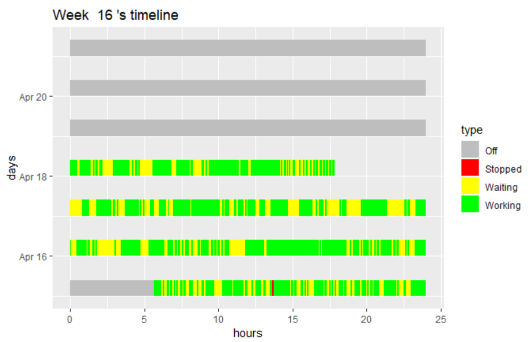

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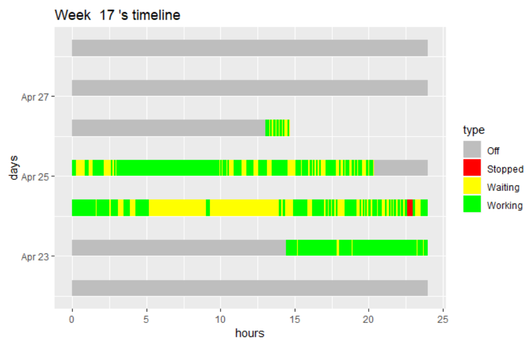
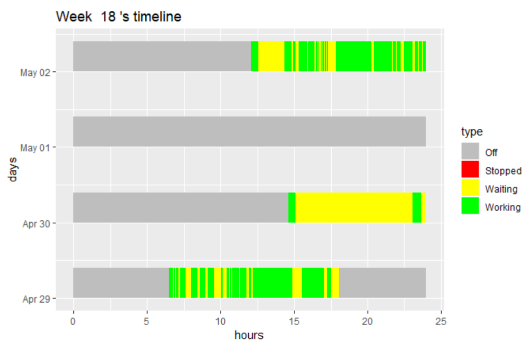


(d) Week 17

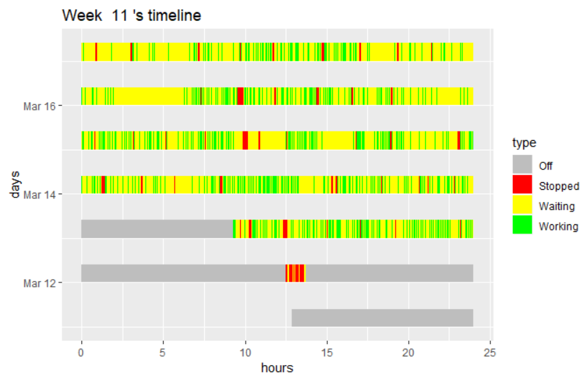


(e) Week 18

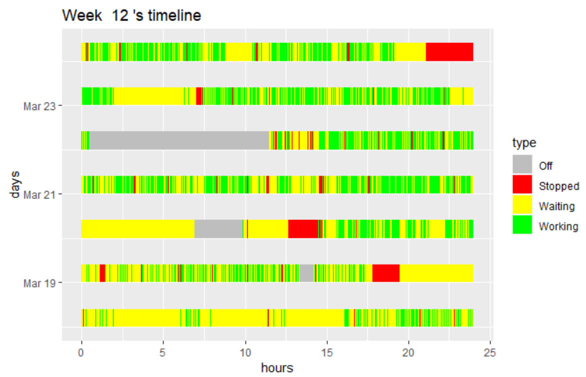
Figure C.1: *Machine 230. Weekly timelines*

C.2 Machine 226

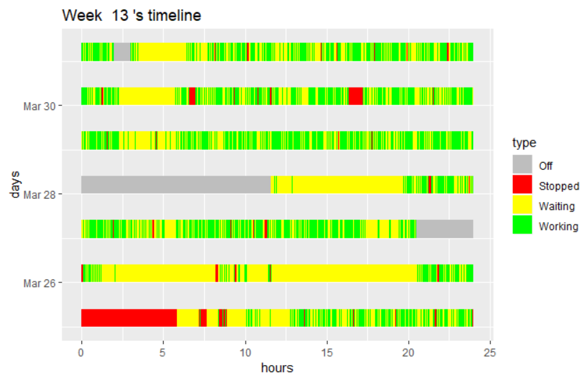
Company A here in this case works during the whole week.



(a) Week 11

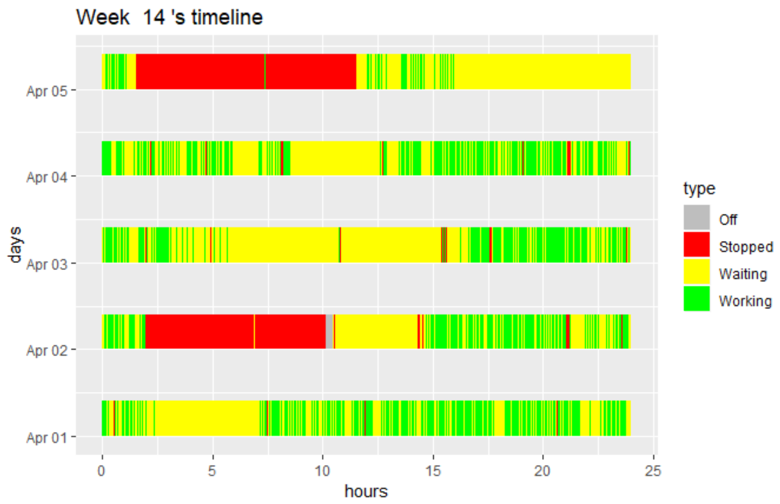


(b) Week 12

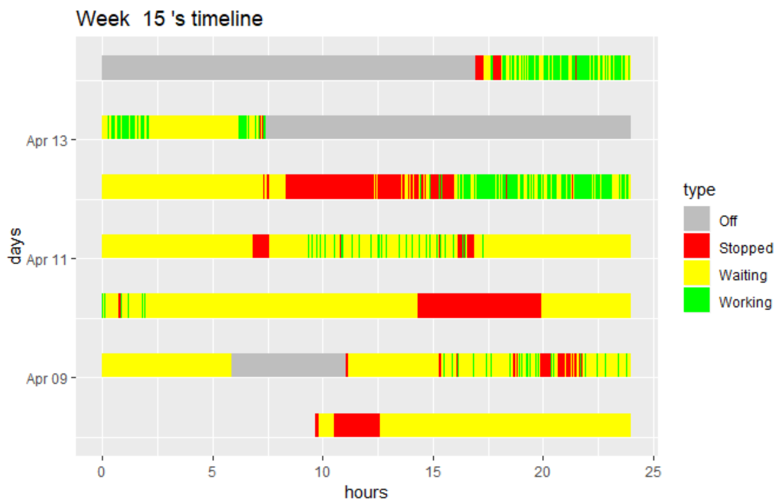


(c) Week 13

Figure C.2: *Machine 226. Timelines. First scenario*

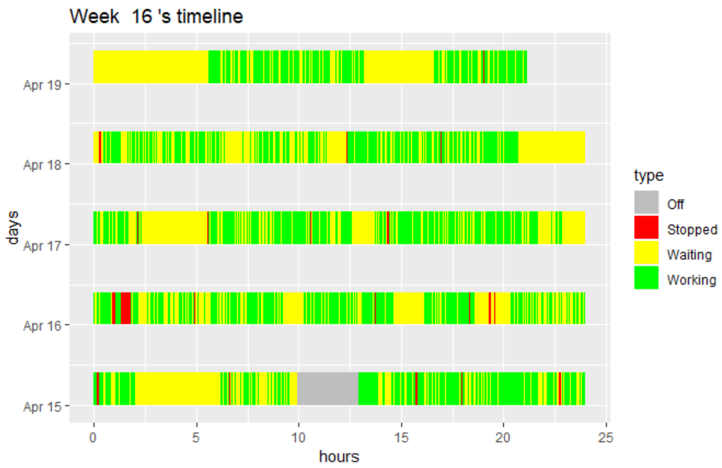


(a) Week 14

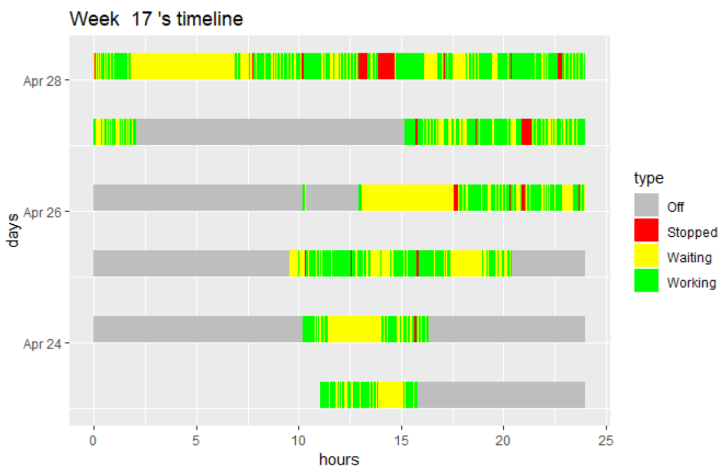


(b) Week 15

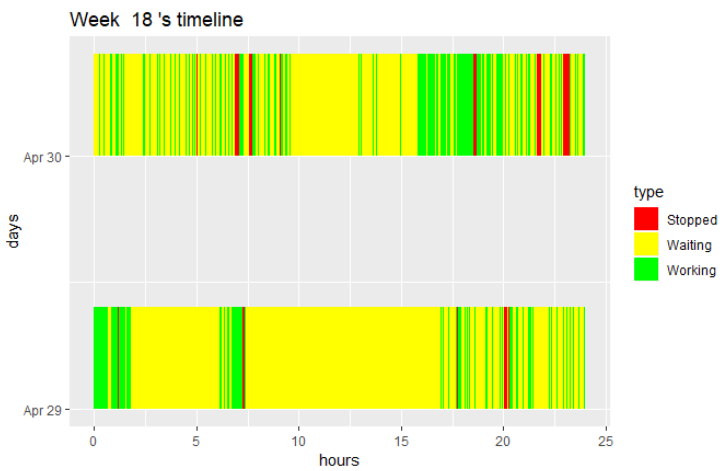
Figure C.3: *Machine 226. Timelines. Second scenario*



(a) Week 16



(b) Week 17



(c) Week 18

Figure C.4: *Machine 226. Timelines. Third scenario*