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How Lean Six Sigma can improve predictability in an Industry 4.0 perspective

A case study of lead times in manual operations at GKN Aerospace

Master thesis in industrial engineering and management

Quality management

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Abstract

Industry 4.0 is a concept that is being widely discussed in the manufacturing industry. However, Industry 4.0 is often related to highly automated processes that has a low human machine interaction. Manual operations are something that normally is not seen as a part of Industry 4.0 but Industry 2.0 where manual operations are going to be widely decreased in the near future. Although, when it comes to a high-complexity product that has very low production volume it might not be economical feasible to change the operations from manual to machines. Also, material variation of high-complexity products makes it difficult for machines to handle the variation with today's technology. The unclear technical requirements in some of the manual operations makes it impossible to have a machine instead if you cannot tell the machine exactly what it is supposed to do.

Predictability in time for machine operations are predictive because of a standard program that is executed. Robots cannot understand if they are missing something which makes them predictable in time. Manual operations on the other hand, are not as predictable because if the human discovers a deviation it needs to be handled, either in the current step or later in the process flow. This creates variation in manual operations when the variation should have been handled in the machine operation instead. The purpose of this thesis was to investigate how predictability in manual operations (in lead times) can be enhanced by a Lean Six Sigma project in an Industry 4.0 perspective.

The Lean Six Sigma project resulted in breaking down a manual operation into smaller steps increases the measurement accuracy. With increased measuring points statistical tools can be used to analyze and find the source of variation. For this project, manual deburring was chosen to conduct an improvement work on. The MSA-study that was conducted within the manual deburring resulted in that the data that has been registered into SAP/R3 is correct. The results from the Lean Six Sigma project showed that it was not only the operator variation that has effects in the predictability. It could not be confirmed but indications of that the robot from previous operations can't handle variation in material that is the main factor. Because, a robot is not able to deburr on all the areas which gives the operators at manual deburring more work. The five different phases in Lean Six Sigma influences and have been combined with Industry 4.0 technologies as a conclusion of how improvements can be executed:

- Define phase
    - Defines the industrial problem – are we solving the right problem?
- Measure phase
    - Measure the industrial problem – can we trust the data?
    - Industry 4.0 increases the amount and reliability of data – including sensors (IoT)
- Analyze phase
    - Breaking down of a process layout in more detailed steps helps to find to sources of variation and enhance predictability
- Improve phase
    - Efficient use of Industry 4.0 technologies -> smartphones, tablets, VR etc.
    - Machine Learning (AI) to improve production processes
- Control phase
    - Control by sensor data and implement specification limits
    - Machine learning (AI) to control production

Keywords: Lean Six Sigma, Industry 4.0, predictability, manual operations, high complexity products, lead times, aerospace industry.

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If you as a reader have any questions you can send me a mail at: chrjo1400@student.liu.se

Abbreviations

CAD = Computer Aided Design

GUI = Graphical User Interface

Q3 = Deviation from CAD-model (handles internally)

Q4 = Deviation from CAD-model (externals need to be involved)

SAP/R3 = Systems Applications Products

QSYS = Quality (SPC) systems

R3 = Real-time data processing, 3-tier (multitier architecture; database, application server & client SAPgui)

MSA = Measurement System Analysis

AIM = Affinity Interrelationship method

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1 Introduction

Boone et al. (2019) argue that Industry 4.0 is a concept that is binding automation and computers into new frameworks. This concept can be used to develop computer system where robots can be connected in a manufacturing line and minimizes the need of an operator. Gorecky et al. (2014) claim that most work in the future will be “mental work”. In the industry 4.0 context, this proposes solving many different problems that mostly will be attached to planning activities (Gorecky et al. 2014).

According to Ranta (2019) three different steps should be taken into consideration when implementing Industry 4.0, the first one (1) is what transformation the company wants to achieve with this technology, what is the goal? The second one (2) is where to prioritize the resources, on what operation or product flow. The third step (3) is about what type Industry 4.0 technology suits the companies need best. Dennis et al. (2017) states that the business uncertainty of financial benefits when it comes to justifying an investment in Industry 4.0 technology. Also, Industry 4.0 is a new concept where there is not enough business that has fully developed for this technology. The threat of cyberattacks is also something that concerns providers from the third party since the third party wants to protect its technology (Dennis et al. 2017).

A concept that is widely discussed when it comes to total autonomous and predictability in manufacturing is industry 4.0. According to Schwab (2016), Industry 4.0 is a concept that is built on the third industrial revolution where automatic production was used with the help of electric information systems. Industry 4.0 is a concept that is advancing and is often discussed how to implement industry 4.0 in machine but not often in manual operation where human labor is a critical factor. With this new technology the human work will have another meaning and the demand for humans will be changed within the factory (Gorecky et al., 2014). Liao (2011) states that predictability of operations will indirectly affect the customer satisfaction because the customers know what they are getting as reliability, trust and safety makes the customer increases the credibility of the supplier. Also, the lack of trust between provider and customer can appear when there is unpredictability.

According to Richards (2018), manual work is a type of work that is going to decrease in the near future as it will be replaced by robots. Although, customers don’t always go for the cheapest commodity where customer instead of low prices value hand-made commodities higher, even if the hand-made are more expensive (Richards, 2018). Richards (2018) predicts that the uniqueness of the human work will increase which will enhance the demand for the human touch in a product at the same time. Gorecky et al. (2014) claims that for the worker there will be more data driven work which proposes the production processes are self-organizing and the worker will supervise and steer the strategy of the production.

Chiabert et al. (2018) discusses the possibilities about using Lean Six Sigma as a maintenance service process for industry 4.0, where both analyses and improvements can be included. Rastogi (2018) states that Lean Six Sigma is a problem-solving methodology that bases the improvements on facts and aims to identity and eliminate root causes. When the root causes have been identified the variation of a process can be controlled, where variation exist a Lean Six Sigma methodology can be used (Rastogi, 2018).

Previous research focuses more on Lean Six Sigma as an approach to improve the quality of products but doesn´t consider how the data in lead time is gathered in manual operations and what useful areas this can be used in. In this report a case study at GKN Aerospace Trollhättan (now called GKN) was conducted where interviews and an improvement project were conducted to investigate how a Six Sigma project can enhance the predictability in lead time at the manual operations. GKN is an aerospace manufacturing company with low volume and a high complexity production flow.

1.1 Background

According to a GKN employee, most companies aim for a total autonomous manufacturing where the human factor has as low as possible impact on the process. However, in terms of high complexity products which cannot be handled by machine a human touch is necessarily to execute the operation. For GKN, this proposes that when it comes to aerospace products where the severity is high there is no space for mistakes, which puts a high pressure on the manufacturing companies not to send any defect products away for usage. This is a problematic issue for GKN since manual operation with a high human factor is involved causing a high variation between the different operators. Where working method, experience and how the manual data is gathering varies. This makes the lead times in the product flow unstable and difficult to measure.

GKN is an aerospace manufacturing company with low volume and a high complexity production flow. Based on the experience from a GKN employee, it is suspected that operators tend to report the standard time as the actual time. Based on the experience from a GKN employee, it is suspected that when there is a standard time (goal time) given for a specific production sequence (see table 8) strengthen this argument. The operators tend to report the standard time as the lead time instead of the actual time. In the aerospace industry there is a high severity if a component is defect which puts the manufacturing companies on a high-quality demand where no defected hardware can be cleared from the factory.

1.2 Problem description

When it comes to implementing Industry 4.0, Ranta (2019) claims that there are three steps that needs to be taken into consideration:

- What kinds of transformation the company wants to achieve
- Where to prioritize the resources
- What industry 4.0 technology should be used?

Therefore, the company needs to have a clear structure of how to implement Industry 4.0. According to Dennis et al. (2017), Industry 4.0 is a new technology and there are no clear frameworks of how much it costs to implement certain technologies. This proposes that the three steps from Ranta (2019) is of high importance when it comes to be cost beneficial. According to Ansari et al. (2018), when it comes to manual work there is a high individual difference between the operators compared to a machine. Also, the variation between operators is high when it comes to problem-solving abilities and experiences. In the decision-making context an operator can be affected of the complexity and risk of the decision which a robot wouldn’t consider (Ansari et al., 2018).

GKN wants to improve the predictability in lead times within manual operations where disturbance free processes and the concept zero-defect is outlined as visions. In manual operations the data is measured manually by operators. This can have a variation if the data registration doesn’t have a clear method. For example, one operator starts the time at a certain point and the other operator starts the time at another point which can depend on the variation in experience of the operators (see table 7). There are many different factors influencing the cycle time in manual operations which is something that has been investigated. With the help of Industry 4.0 assistance with different tools can help the operator to conducts its work. GKN strives to have an enhanced use of industry 4.0 technology. Where focus lays on improved measurement systems. Also, improved operator’s support, data handling systems, working method etc.

1.3 Aim and research questions

The aim of this master thesis was to enhance the use of Lean Six Sigma in improving predictability of manual operations in a way that exploit new opportunities connected to Industry 4.0. This research has also evaluated how predictability can affect a large sized company. Also, investigate how predictability can be enhanced in manual operations. To achieve the aim of this study three research questions have been established:

> *RQ 1: Why should a company with low volume and high complexity products enhance predictability (in lead time) in manual operations?*

The first research question gives a motivation why there is a need for predictability within manual operations. This question was answered by conducting interviews to see how different roles are affected of an uncertain predictability in the production flow and how are the different roles within a company taking into consideration the predictability. The importance of predictability is something that can an affect on all the different roles and indirectly affect the customer satisfaction. To know why there is a need for enhanced predictability is important for all the roles. Because, a motivation of why there is a need can help to motivate people to work proactively within this area.

> *RQ 2: How can predictability be handled in manual operations and how can manual operations be enhanced with Industry 4.0?*

The second research question is developed to investigate how predictability is going be handled in manual operations when it comes to Industry 4.0 techniques. To answer this question the author needs to investigate into how the data gathering is handled in certain operations that have a big variation. Also, to get an understanding of how the operators work. Manual operations are going to be investigated how these operations can be enhanced with industry 4.0. In the high-complexity manufacturing area, some of the manual operations will remain for a long time which proposes that to be able to keep up with the market these manual operations also need to be developed and adjusted for the future.

> *RQ 3: How can a Lean Six Sigma (Problem solving) project enhance the predictability in manual operations connected to industry 4.0?*

To get an understanding of how an improvement project can be to effectively implement Industry 4.0 techniques a Lean Six Sigma project was conducted. As an improvement project a Lean Six Sigma project were conducted to enhance the predictability in manual operations connected to industry 4.0. To keep up with the competitors, the latest technology is needed but also to maintain the costs within competitive limits which proposes that the need for effective use of techniques that is needed. An increased knowledge of how to conduct an improvement project in order to efficiently implement Industry 4.0 is needed in order to be competitive in the future.

1.4 Research scope and delimitations

Due to the time limit of this master thesis it will not be possible to implement any findings into the production, this proposes that from the DMAIC phases in the Lean Six Sigma project only the first three phases were conducted (DMA). This study focus on analyses of how the lead times are measured and gathered and will not focus on the quality of the products or the quality of the operations. A case study with interviews and an improvement project were conducted within one large sized company. This case study only covers high complexity products with low volume production within GKN aerospace Trollhättan.

1.5 Disposition of thesis

Table 1 shows the disposition of the thesis. The introduction chapter gives an overview of the purpose of the thesis. Therefore, problems and opportunities of predictability, the reason for embedding Industry 4.0 and Lean Six Sigma within predictability.

The method chapter discusses the research approach embedding the theory of a case study as well as primary and secondary data collection methods. Finally, Reliability and validity are discussed on the method chapter.

In the theoretical framework Industry 4.0 was discussed and different technologies embedded in the Industry 4.0 concept. The theory gives an overview of Lean Six Sigma and key things to implement Lean Six Sigma. A comparison between Industry 4.0 technologies and Lean Six Sigma methodology in the last chapter in the theoretical framework.

The empirical findings and analysis present the findings from the Lean Six Sigma project and results from the interviews. The discussion is a compilation between interviews, literature review and improvement project. Also, a discussion about research credibility, research method and proposal for further research. Finally, conclusions and recommendations for the master thesis of how the

Table 1. Disposition of thesis.

Disposition
1. Introduction
2. Method
3. Theoretical framework
4. Empirical findings and analysis
5. Discussion
6. Conclusions and recommendations

2 Method

The method chapter explains how the author approach the problem, what types of data that was collected and analyzed. Also, reliability and validity are discussed.

2.1 Research methodology

Based on Chalmers (1999) paper, this master thesis will use both a deductive and inductive reasoning. Induction proposes data will be gathered through observations based on hypothesis, in this research a case study with interviews and an improvement project was conducted to receive new theories (Chalmers, 1999). Deduction reasoning is used through a literature review where theory was used to be derived into predictions for further investigations (Chalmers, 1999). According to Douven (2017) a combination between inductive and deductive reasoning is called abductive reasoning. This proposes that the thesis is taking the approach from two directions with both qualitative and quantitative data to get a broader perspective. Svennevig (2001) claims that abductive reasoning is a functional explanation. Meaning that that there is a function that is linked to a social phenomenon that gains new knowledge as a development process. Interviews and improvement project have been conducted alongside a literature study.

An explanatory research was conducted which according to Yin (2009) is a case study research where you collaborate with a company to study their processes and then generalize based on previous research. A single case study was used for this master thesis. Voss et al. (2002) claims that a single case study gives a greater depth in the problem that is going to be investigated but with only one case it makes it difficult to generalize the conclusions. Because a single case study only focuses at one company and instead of multiple companies that is easier to generalize.

According to Yin (2003) there are two different types of single case designs, holistic and embedded. Holistic proposes that there is only one unit that is going to be analyzed and embedded proposes that multiple unit within the case study is analyzed (Yin, 2003). A holistic case study gives a broader perspective and is not limited to multiple units of analysis on the other hand an embedded case study gives deeper knowledge in the analysis of issue (Yin, 2003). For this thesis embedded design was used to get a deeper knowledge of the problem where multiple research questions was used.

2.1 Data collection

There is no best practice of how data collection should be executed (Denscombe, 2010). Denscombe claims that when conducting research, the data collection theory should be used throughout the project which proposes that the theories should be based on empirical research. Because, to confirm that the theory works and after that generalize with theories that are similar with the other data (Denscombe, 2010). According to Denscombe (2010), primary data is what the author gather from the research Secondary data is data that has been developed for purposes that is not the exact same as for the research (Denscombe, 2010). Primary data was collected from interviews and improvement project. Secondary data was used for the literature review which has been collected through scientific papers.

The aim of this master thesis is to enhance the use of Lean Six Sigma in improving predictability of manual operations in a way that exploit new opportunities connected to Industry 4.0. Figure 1 shows a map of how this master thesis has been approached. The literature review was developed based on the findings from the improvement project and vice versa. Interviews were conducted in parallel with the improvement project and interacted with the literature review. Later, the interviews, improvement project and literature review were combined into conclusions and recommendations.

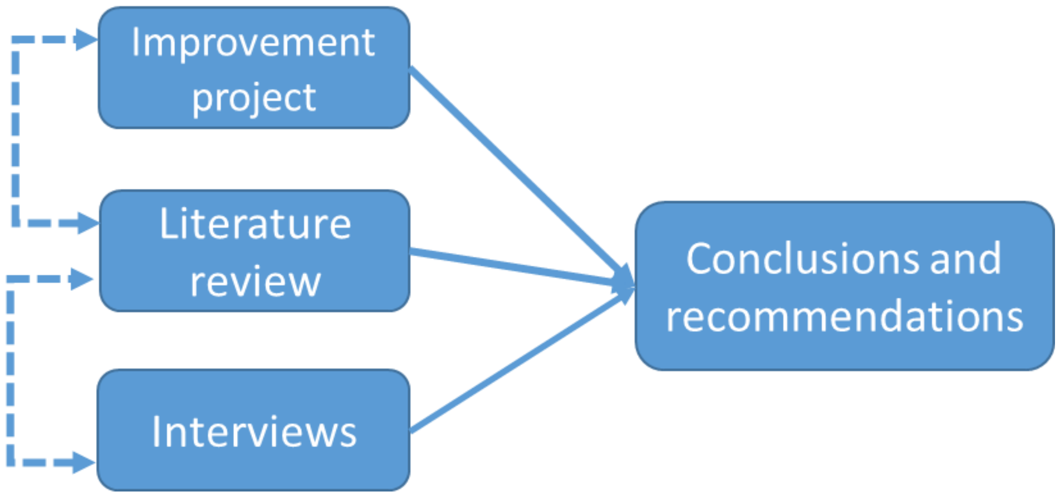


Figure 1. Research approach.

Interviews

Interviews were used to get an understanding of the views and challenges about improvement projects and an understanding of how the interviewee opinions of manual operations. More in-depth interviews were conducted to get an understanding of the problem and get answers that are needed for further research in this project. According to Sreejesh et al. (2014), semi-structured interviews was used because this strategy gives a more structured way follow through the interview compared to the unstructured strategy. Berg (2009) argues that semi structured interviews give a flexible interview in case that problems were not addressed. However, it can be explored throughout the interview by using open-ended questions (Berg, 2009).

Semi structured interviews can explore new paths during the interview but also gives the opportunity to develop the conversational style during the interview that focuses on the topic (Patton 2002). The author started the interviews with showing graphs of variation in different operation steps and had a discussion with the interviewee. All interviews were recorded and transcribed later, so the author did not miss anything and could focus on the interview instead of taking notes. 12 people were interviewed, 11 internal within the company and one external, see table 2. The interviews took approximately 45-60 minutes.

Table 2. Different roles that were interviewed.

Questionnaire form	Roles
Appendix A	Integrated logistic support engineer - Human factors
Appendix A	Quality manager within engineering
Appendix A	CAM office manager
Appendix A	Engineering management & support
Appendix A	Industrial manager
Appendix A	Manager shared product engineering
Appendix A	Production technican
Appendix B	CNC operator - commercial
Appendix B	Manual operator - military
Appendix A	Head of operations
Appendix A	Value stream manager for cases
Appendix A	**External;** industry- and material science, design human factors Professor

Literature review

A literature review where different studies of manual operations connected to Industry 4.0 and investigate how predictability can affect the outcome of a process and how can it be improved was used. The information was gathered by a systematic approach based on Tranfield et al. (2003) strategy which include three steps, (1) Planning the review where the theories on the ground level are clarified before the project starts. (2) Conducting a review is about determine previous research that is relevant for this topic. (3) Findings from the literature review, is about present what has been found from the literature review.

Improvement project

An improvement project within a Lean Six Sigma project was conducted to investigate how a problem-solving tool can be used to enhance the predictability in lead times at manual operations. According to Brook (2017,) a Lean Six Sigma project is a problem-solving methodology that aims to decrease variation as well as decrease the number of defected products. The Lean Six Sigma project was conducted in collaboration with Chalmers University with the help of two students with the implementation of the Lean Six Sigma project. The structure for the Lean Six Sigma project is based on Brook´s (2017) structured approach DMAIC cycle.

Conclusions and recommendations

From the previous step’s findings can be derived into conclusions and recommendations for this master thesis.

2.3 Data type

Based on Kelle (2006), the pattern of the used qualitative and quantitative data can help to address certain aspects to each other. For instance, interview helps to address aspects in quantitative data. When combining these two research approaches the validity of a quantitative research can be increased with the help of a qualitative complement (Kelle, 2006). This master thesis is based on qualitative data from semi structured interviews, which proposes textual observations with more in-depth study (Wienclaw, 2013). Kelle (2006) claims that quantitative data gives an overview of the data on a described macro-level, in this research to scope the problem a quantitative numerical data analysis has been made to map the areas that are going to be investigated. David & Sutter (2016) claims that qualitative data is used when a more in-depth study is needed, as it helps to explore new problems. The quantitative data that was gathered for this project was gathered from SAP/R3 where R3-data has been used for this project, see figure 1. With R3-data that gives flow times of operations it´s possible to conduct a quantitative analysis.

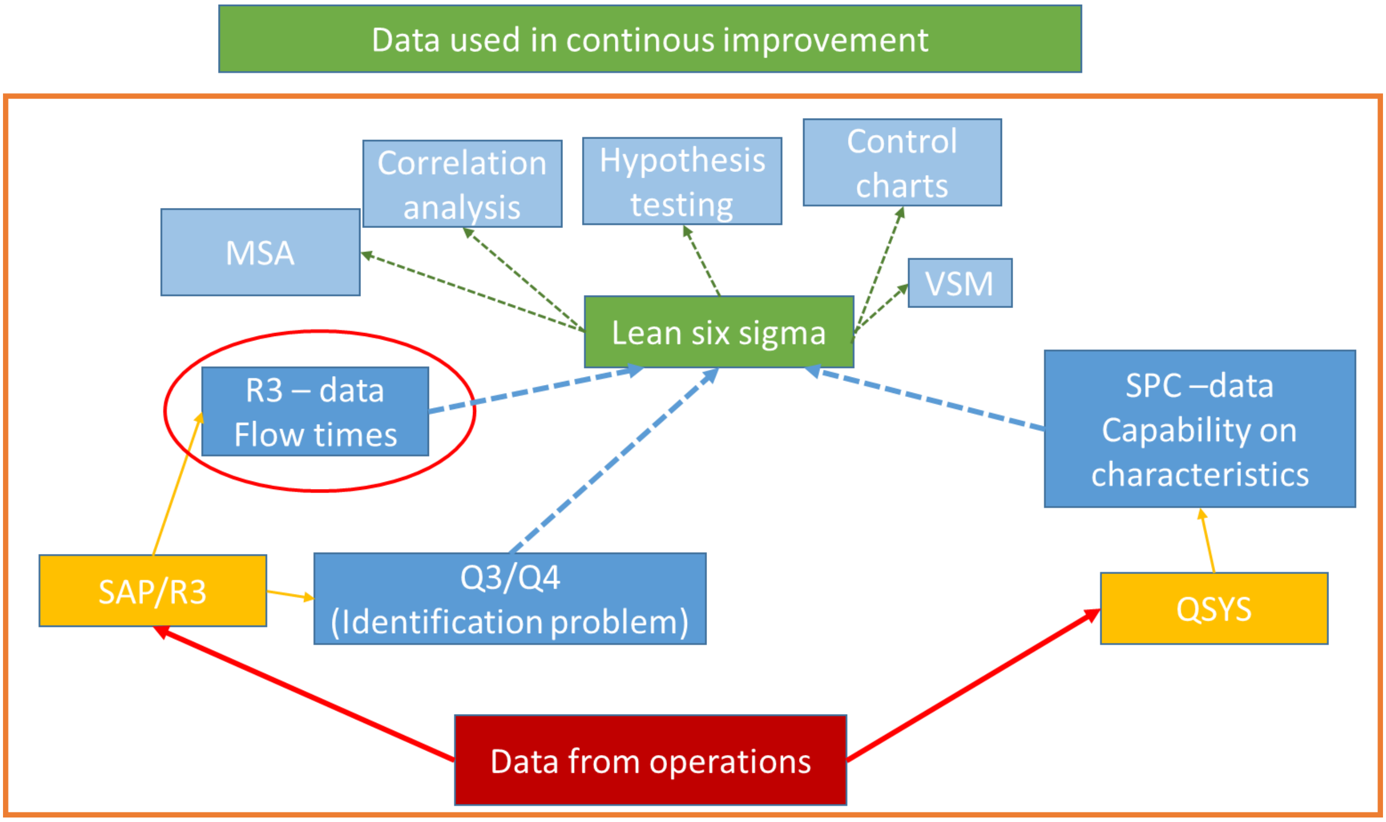


Figure 2. Data gathering systems at GKN Aerospace, where R3-flow time data has been used for this project.

2.4 Data analysis

In the data analysis an Affinity Interrelationship Method (AIM) was used, which according to Alänge (2009) is used as a method on complex problems to get an understanding and an analysis. To get an overall view of the problem that was going be investigated within the improvement project, an AIM was conducted that discusses problems that might occur when enhancing the predictability in manual operations. Correlation analysis was conducted to investigate the relationship between the different operations in a flow and the total time to see if there was any correlation between manual operations and automatic operations. Hypothesis testing was used between different data sets. Root cause analysis was conducted to investigate what the source of variation could be.

2.5 Reliability and validity

2.5.1 Reliability

According to Golafshani (2003) reliability defines if the study can be replicated with the same results when using the same approach. To get a reliable result the study needs to have consistent result over time and the total population should be represented in the quantitative research. In Krueger et al. (as cited by Merriam, 1988) reliability in case studies can be addressed in three steps:

(1) The first step is about being able to explain why this is happening and what the underlying theories that strengthen this argument are. In this step the improvement project has been used to explain how predictability within manual operations can be enhanced. Theories about Lean Six Sigma has been reviewed to strengthen the reliability of this thesis.

(2) The second step is triangulation, which proposes that multiple methods of data are going to be used when data is collected. Three different methods of data have been collected; a literature review, interviews and an improvement project were conducted where these methods have been triangulated in the discussion.

(3) The third step is to have an “audit trail” which proposes that independent sources are going to verify the results of the study and how the researcher’s approach should be visualized so it can be used if someone else wants to replicate the study. A literature study was conducted where theory from Industry 4.0 and Lean Six Sigma was compared to look for patterns in terms of method focus and the data to drive improvements.

Golafshani (2003) meaning that reliability refers to how the results are consistent over time and accurate representation of the total population under study is referred to as reliability. If the study can be reproduced under a similar methodology, then the research instrument is considered to be reliable. According to Golafshani (2003), when conducting interviews reliability can be achieved by asking the same questions to each group and asking about the same topic for all the different roles that are going to be involved. If the respondents give similar answers for the different roles it can be considered reliable (Golafshani, 2003).

2.5.2 Validity

According to Sreejesh et al. (2014) there are two types of validity, internal validity and external validity. Sreejesh et al. (2014) states that validity proposes that the research approach is free from any errors that can occur during the research process. External validity presents the idea how the research can be generalized outside the experimental area (Sreejesh et al., 2014). Yin (2003) states that internal validity is about finding relationships in the case study and to use models that are relevant for this research. To create validity to this master thesis, different product flows was investigated in effective scoping at GKN for the improvement project to get a more overall view of how the different manual operations are performing. The interviewees were conducted between different roles to get a general view of the desired area. For increased validity, an AIM was developed in the improvement project which later was revised and reviewed by a fifth employee at GKN that had not been involved in the AIM workshop to strengthen the validity.

3 Theoretical framework

This chapter gives an understanding of different topics that been used to analyze the results from the empirical findings. Industry 4.0 is a topic that will be discussed including big data and cyber physical system. The theoretical framework also gives a view of how different Industry 4.0 studies is connected to the Lean Six Sigma methodology. This gives a perspective on how implementation of Industry 4.0 can be enhanced with an improvement project. Lean Six Sigma is being discussed to give an overall view of Lean Six Sigma as a methodology to effectively implement an improvement project. Finally, a chapter of how to increase the predictability of planning and measuring an operation is included to give an understanding of how an operation can be broken down into operation steps.

3.1 Industry 4.0

Crandall (2017) claims that so far there has been four different industrial revolutions which are called “the first industrial revolution”, “the second industrial revolution”, “The third industrial revolution” and the “The fourth industrial revolution” which is the latest revolution.

Crandall (2017) describes that, in the eighteenth century the first revolution began where power in the factories was mainly water and steam. Crandall (2017) claims that during the first industrial revolution the workers were doing “easier” jobs where mechanical products were developed, and transportation of goods had been improved by steam engines and the development of transportation. The second revolution took place between the late 1800s till the early 1900s. The electricity was the driving factor for this revolution, which influenced production in a way where efficiency and speed were increased (Crandall, 2017). During this time the assembly lines were introduced and made it possible to implement mass production (Crandall, 2017).

Crandall (2017) mention that the third revolution was more of a digital revolution since the computers were developed and had an impact on the industry. In the 1960s computing was developed and in the 1990s the internet was developed, which had an impact of how products were manufactured. The latest industrial revolution is the fourth industrial revolution that started in Germany but is now widely spread throughout the world (Crandall, 2017). Crandall (2017) claims that Industry 4.0 is about real time data and advanced computers that are affecting manufacturing.

Gilchrist (2016) states that Industry 4.0 is a concept that is combining different technologies in the same category of value-chain organizations such as big data, cyber physical system and internet of things. Industry 4.0 is a concept based on that production in the whole value chain of a certain product gives feedback directly to the worker of how the process is going (Gilchrist, 2016). Cyber physical system (CPS) is a technology that is included within Industry 4.0. This is a type of monitoring that measure the physical process and makes decisions based on a created virtual copy of the chosen process (Gilchrist, 2016). According to Gilchrist (2016), the vision of Industry 4.0 is that factories will convert into smart factories that is controlled by smart systems that are sharing information. By sharing information, decentralized decisions will be made based on the physical world that has been made into virtual copy and can trigger actions in the system if something is wrong (Gilchrist, 2016).

Ustundag & Emre (2018) claims that attention has been drawn to Industry 4.0 in the past years both from service systems and manufacturing companies. According to Ustundag & Emre (2018) Industry 4.0 does not have a clear definition and there is not a clear method of how to integrate current technologies into Industry 4.0. To implement these futuristic technologies, Ustundag & Emre (2018) claims that technologies like autonomous robots, cyber physical infrastructure, additive manufacturing etc. is needed for an adaption to be successful. Also, a cyber-physical system that is connected to adaptive robots and the real time decision making where different coordination tools are needed to effectively use Industry 4.0 (Ustundag & Emre, 2018).

Rojko (2017) discuss about the Industry 4.0 smart factory where the connection between the key component is the conversion between the physical world into the digital world (see figure 3). Figure 3 explains how data is sampled by the physical world and uploaded into the big data cloud storage. When the data has been analyzed it can go to the IT support if there is something that need to be handled. Big data has cooperation with the customer to keep track on the production tact or if the customer wants customized products. The big data cloud passes the information back to the smart factory and the factory adjusts to the changes.

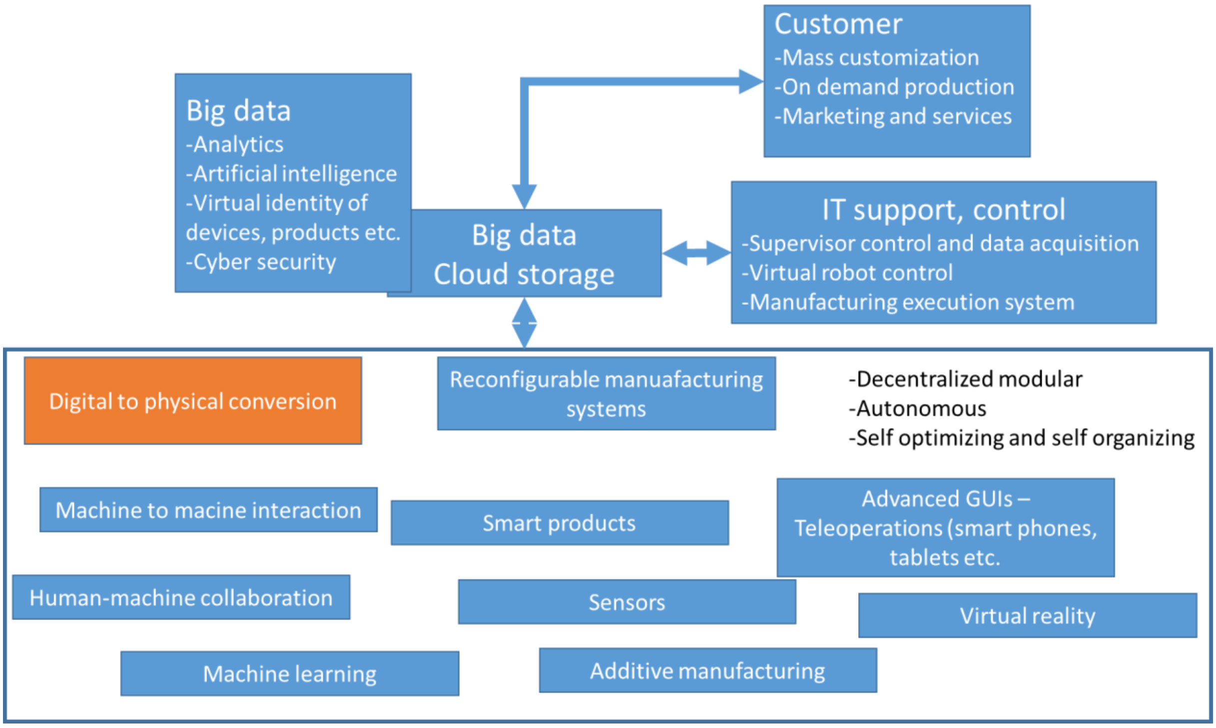


Figure 3. Industry 4.0 smart factor (adapted from Rojko, 2017).

3.1.1 Internet of things

According to Madakam et al. (2015) Internet of Things is a concept that has changed the IT sector where Internet of things is developed from two words, the “internet” and the “things”. The “internet” has billions of users that receives assistance from the computer networks, using standard inter protocol where networks are built on networks from different sectors such as government, business and academic networks (Madakam et al., 2015). The “things” can be defined in the real world such as an object or a human being (Madakam et al., 2015). However, “things” does not just include electronics or technological products, and “things” can also include food and clothing.

Madakam et al. (2015) stated that Internet of Things is a technology with intelligent virtual objects used as a simulation for the real-world, the purpose for Internet of Things is about the state of keeping us informed and to control the things around us. When it comes to defining Internet of Things there is not a precise definition that is common accepted by the users in this community (Madakam et al., 2015). This includes many different groups such as developers, innovators, practitioners, academics and corporate people that have their own definition of Internet of Things (Madakam et al., 2015). Something that these different job categories can agree upon is that earlier the internet was about data created by people and now data is created by things. An accepted definition of Internet of Things is: “An open and comprehensive network of intelligent objects that have capacity to auto-organize, share information, data and resources, reacting and acting in face of situations and changes in the environment” (Madakam et al., 2015, pp.165). When it comes to the manufacturing ecosystem, Internet of Things is defined as “all machinery and products are equipped with embedded computing devices connecting them to the internet” (Cemernek et al., 217, pp.240).

3.1.2 Cyber physical system

Almada-Lobo (2015) claims that Cyber physical system (CPS) is a system that is built into a physical system which includes computing power and a software that can make it possible for adaption within a process. In an Industry 4.0 perspective the number of smart products is going to increase in manufacturing the production flow to be able to handle itself; for example, if a hardware is stiffer than the usual the robot will be able to handle this without any help from a human (Almada-Lobo, 2015).

CPS was initiated in 2006 in the United States where the importance between the physical world and interconnected computing systems was something that got more important. Cemernek et al. (2017) claims that the Cyber-Physical system is build up on five different levels of how the data is processed. First the sensors in the machines are sending data to the CPS where the data is being processed and after that a new plan of how the machines shall operate will be sent out (see figure 4). Chiabert et al. (2018) discuss about the challenges of implementing future solutions such as CPS since today's technology is not there yet and for a company it can take 3 to 10 years to have this functionality up and running where maturity degree is a factor needs to decent.

Almada-Lobo (2015) states that collaboration between a human and a machine can be done in a cyber-cloud manufacturing environment where for example robots can be controlled from another location, which will affect the speed of changes directly and indirectly the economy. This depends on that costs will decrease if there is a quality problem or something wrong in the process, which can be corrected faster from distance and don't require a visit to the manufacturing. Gorecky et al. (2014) discuss in a CPS perspective that virtual reality can be a help to simulate how the operator is going to conduct his/her work.

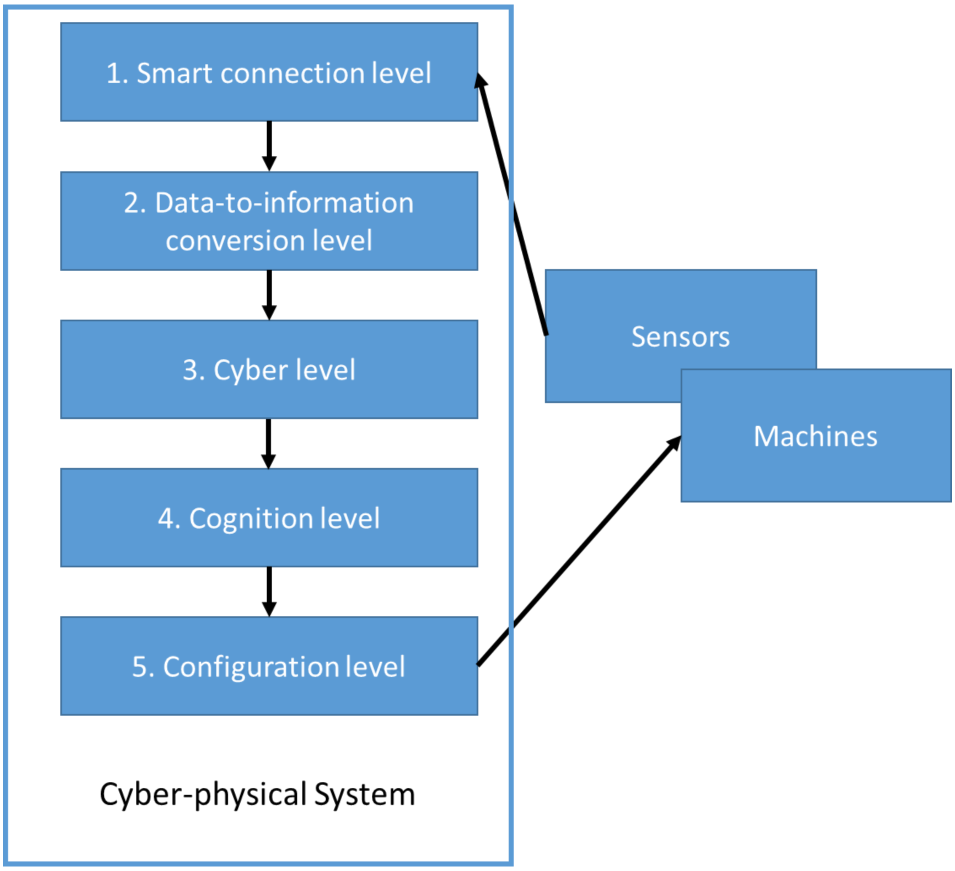


Figure 4. Cyber-Physical System process. (Adapted from Cemernek et al., 2017)

3.1.3 Big data

Chen & Mao (2014) claims that big data can be explained as “massive data” or “very big data”, which is an abstract concept where not only the amount of data matters but also other features such as quality. Chen & Mao (2014, pp.173) claims that there is a general definition for big data: “big data shall mean that datasets that could not be perceived, acquired, managed, and processed by traditional IT and software/hardware tools within a tolerable time”.

Big data is about how the decision making can increase the insight in an innovative way that is cost effective, where high-velocity, high volume and high variety is different measurements within the big data concept which shows how the data can be handled (Cemernek et al., 2017). According to Cemernek et al. (2017) big data can help to improve the process activity in a production plant which generates services for the production system that are more data-driven. Cemernek et al. (2017) claims that there are five dimensions (5v´s) that need to be considered to evaluate if the data that has been collected is relevant, see table 3.

Table 3. Five types of data – big data.

Volume	The size of the data
Velocity	Time it takes for the data to be created
Variety	Different types of data, sensor data, XML data etc.
Veracity	Stands for how reliable the data is, e.g. data quality
Value	Defines the value of the data, at the beginning the data has a low value but after data analysis that reveals information the data has a high value

To describe the method and best practice of the big data process through generating knowledge from data, Cemernek et al. (2017) claims that the data can be divided into two sub-processes, Data management and analytics. Data management starts from recording and acquisition data, then the data is being extracted and cleaned for integrations and be able to be representative data for the later process step in the big data process (Cemernek et al., 2017). Cemernek et al. (2017) states that when it comes to data analytics techniques, predictive analytics where correlation analysis is used to detect patterns which is important in a big data perspective. The results from these data analysis will produce knowledge from the process that has been analyzed so that the management can make decisions based on facts (Cemernek et al., 2017). Cemernek et al. (2017) further outline how the big data process and the Cyber-Physical systems is connected including the decision making from the humans in the process, see figure 5 for the process map. The big data process shows how data is gathered by sensors which is sampled into the cyber-physical system and has a continuous interaction with the big data process. The human interaction comes when the big data process has finished the analytics part and is going to be configured in the cyber physical system. The CPS send signals to the machines of how they are going to interact.

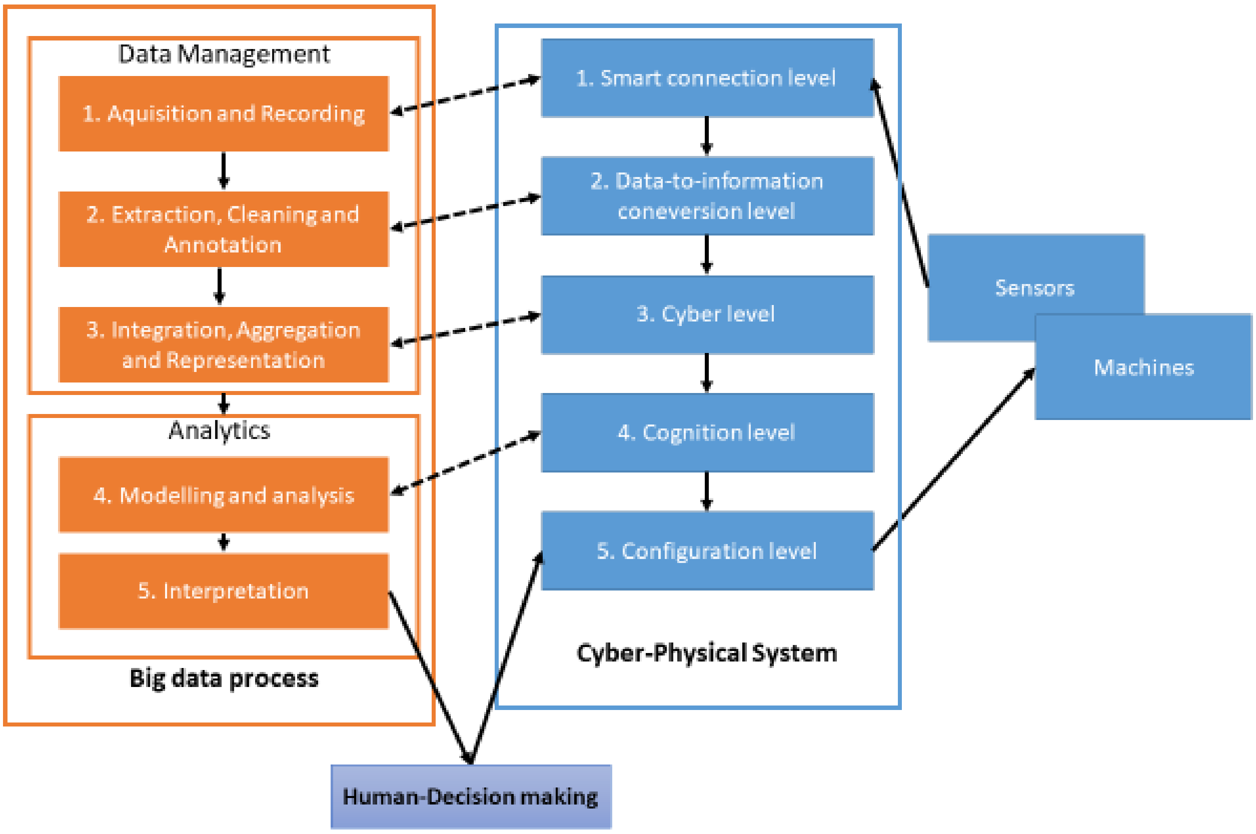


Figure 5. Process map for the big data process (Adapted from Cemernek et al., 2017).

3.1.4 Machine learning

According to De Mello & Ponti (2018), machine learning is how a software that can be programmed into conducting specific tasks such as make decisions and support specialist on a daily problem. Machine learning can be used to separate material based on the quality such as hardness or geometry, it can also be used to diagnose people that have a disease (De Mello & Ponti, 2018). Machine learning has connection with statistics, artificial intelligence and pattern recognition (De Mello & Ponti, 2018).

According to Madakam et al. (2015) artificial intelligence (AI) is something that is connected to Internet of Things where AI is a high technology and specialized intelligence in machines. The everyday life of people is something that AI can help with support in a way where intelligence and information is used within devices that are connected in the network. According to Madakam et al. (2015) AI is characterized by five different characteristics:

- Embedded, the environment is integrated by net-worked devices.
- Context aware: The situation you are in you can be recognized by a device.
- Personalized: your requirements can be customized.
- Adaptive: What you are telling the machines can make them change.
- Anticipatory: Machines can without you giving any information to AI satisfy your needs.

Chiabert et al. (2018) discuss how a simplified process map for Industry 4.0 can look like. They claims that there are different phases of how the data is managed, where the first phase is about how the data is collected with an Internet of Things layer where the data is stored in a cloud which is connected to a network. After the data has been shared in a cloud the big data layer is used to clean the process and make sure the data is valid (Chiabert et al., 2018). Later, the data is being processed by machine learning which is analyzed in a structured way with four different phases, Descriptive, Diagnostic, Predictive and Prescriptive (Chiabert et al., 2018). Descriptive is about the current state of the data, Predictive describes why the problem appeared, Diagnostic describes the prediction of the data what is about to happened if there are any outliers or something else in the manufacturing that deviates (Chiabert et al.,2018). The fourth step is about deciding what action that needs to be considered and improve the problems, figure 6 describes the Industry 4.0 process.

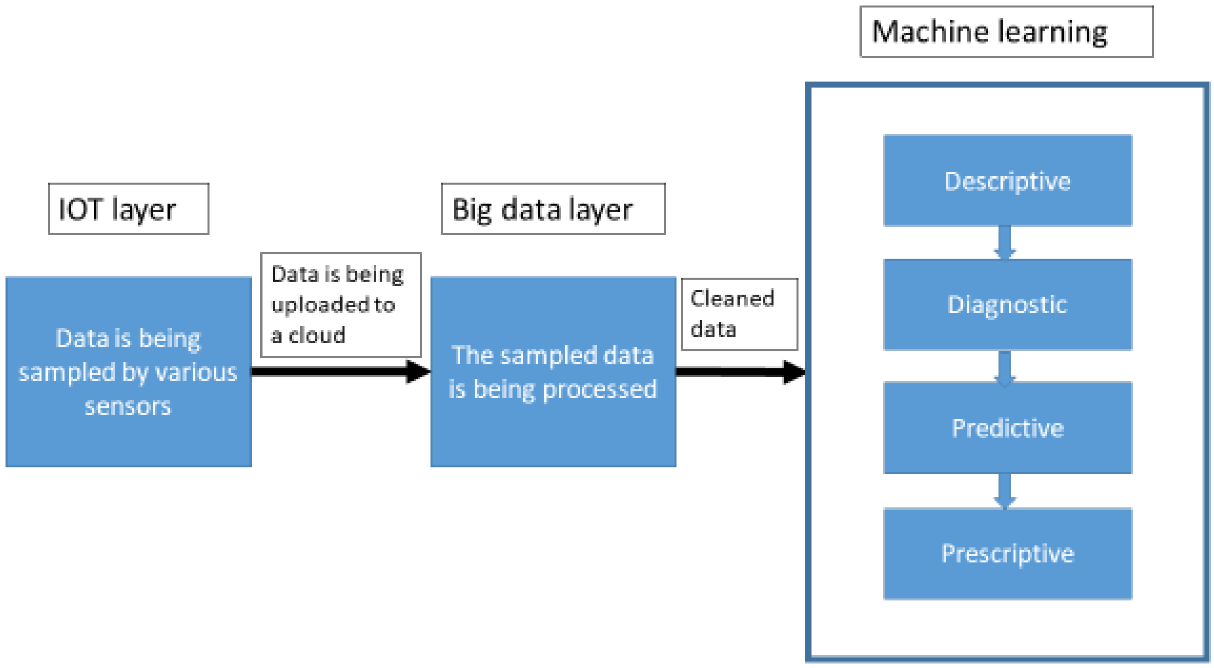


Figure 6. Simplified Industry 4.0 process map. (Adapted from Chiabert et al., 2018)

3.2 Lean Six Sigma

According to Boslaugh (2019) Six Sigma is a methodology that focus on quality improvements with the help of statistical tools. Boslaugh (2019) claims that the reason to conduct a Six Sigma project is to identify and decrease the variation in processes which in the long run will decrease the defects of the products. Brook (2017) claims that Six Sigma is a methodology where problem solving, and data is compiled into “data driven problem solving”. A Six Sigma project is divided into five different phases (DMAIC) which are; Define, Measure, Analyze, Improve and Control. Further the Six Sigma methodology can be used as a Lean Six Sigma application in which Six Sigma is connected to Lean manufacturing processes, and the focus is on the reduction of waste.

Schroeder et al. (2007) claims that Six Sigma has similarities to quality management as it has been used before Six Sigma was introduced. Six Sigma helps to identify problems between different members in the organization and gives a structured process for improvement (Schroeder et al. 2007). Also, Six Sigma is a methodology that helps to act more as an organically organization when it comes to generating new ideas such as fishbone diagrams and affinity interrelationship model. Further, when implementing the ideas generated in the Six Sigma project the management is the ones who is making the decision which proposes that the organization is switching over the a mechanistically organization (Schroeder et al. 2007).

Antony & Banuelas (2002) claims that Six Sigma can be defined both as statistical and business methodology, the business method is the focus on eliminating defects such as quality costs, eliminate waste and to improve the efficiency in different operations. Six Sigma in a statistical term is about reducing the process average variation where the term Six Sigma is referring to 3.4 defects per million opportunities (DPMO) (Antony & Banuelas. 2002). Antony & Banuelas (2002) discuss the key ingredients of how to optimize and manage the outputs of a process and put forth 11 key ingredients that influence the result of a Six Sigma project. (Table 4).

Table 4. Key ingredients for implementing Six Sigma. (Based on Antony & Banuelas, 2002)

Management involvement and commitment	The management needs to be involved to provide the necessary training and resources, the management needs to have an underlying understanding of Six Sigma as it can have a great impact on the structure and attitude of the organization.
Cultural change	When it comes to the cultural change the motivation of having an increased responsibility over the quality processes for the employees is something the employees need to accept. The fear of change is something that is a problem in cultural change where employees are afraid of a change and might not be able to meet the new standards that have been set. To deal with this problem the need for change needs to be understood by the employees, a communication plan can be used to motivate why Six Sigma should to be used.
Organization infrastructure	The need of top-management support is important since the organizational infrastructure support is needed for the efficiency of the Six Sigma development within an organization. The CEO is described as the champion in a Six Sigma project which is the highest in the hierarchy where the next levels are in the order: master black belts, black belts, green belts and the rest of the team.
Training	When it comes to training, the improvement of the employee’s knowledge about Six Sigma can be used to improve the comfort level of the employees which “why” and “how “needs to be communicated as early as possible for the employees about the Six Sigma methodology

Project management skills	To have good project management skills is needed to comply the milestones or deadlines that need to be met, Six Sigma project often fails due to bad project management skills.
Project prioritization and selection, reviews and tracking.	Selection of what kind of projects that is going to be conducted needs to be based on proper criteria, delayed results is something that can depend on the definition or selection of the problem. Three categories of what needs be included in the project selection, (1) business benefit criteria, (2) feasibility criteria and (3) organizational impact criteria.
Understanding the Six Sigma methodology, tools and techniques.	DMAIC is the Six Sigma project model that is used when it comes to training in Six Sigma. Three different techniques are often used to get an understanding of Six Sigma which process improvement tools and techniques, leadership tools and team tools. Also, the measurements of the customer requirements need to be clear of how it's going to be measured.
Linking Six Sigma to business strategy	The customer requirements are something that the project should start to identify where the link between customer and the Six Sigma project is vital for a project to succeed. The identification of the customer requirements in Six Sigma can be divided into two different steps, (1) identifying the core processes where the identification of the key customers and the outputs of the chosen processes and (2) customer needs and requirements needs to be identified and defined.
Linking Six Sigma to customer	The first thing in a project should be to define the customer requirements, two steps have been developed: 1. What kind of key outputs does apply for the key customer. 2. The customer needs and requirement need to be identified and defined.
Linking Six Sigma to human resources	To attain the desired behavior and result human resources actions need to be executed; e.g. 61 per cent of the companies that have a good business strategy can correlate it with rewards such as promotions.
Linking Six Sigma to suppliers	When it comes to implement Six Sigma in an organization, advantages have been found if the Six Sigma methodology is being expanded to the organizations supply chain. Top management in the supplier's organization is important.

3.2.1 DMAIC

DMAIC is an acronym for five different phases, Define, Measure, Analyze, Improve and Control (see Table 5) (Brook, 2017). These different phases are used as a structured way to define and solve problems where solutions will be implemented to underlying causes, and to make sure that the solutions that has been implemented will be sustained (Brook, 2017). Brook (2017) claims that the DMAIC approach is one of the key factors for success in Six Sigma projects because of its structured way to approach a problem.

Table 5. Definitions of DMAIC-phases (Brook, 2017).

Define	The define phase is about defining the business case. To understand the customer what they want and how the project will be linked to the customer. The understanding of the problem in a process needs to be defined since we need to know what is going to be measured and to know if we are solving the right problem.
Measure	The measure phase is about developing process measurements and investigating how the project can be measured. Collection of data will be conducted in the measure phase where the quality of the data will be analyzed, and conclusions drawn on how good the data is and on the capability of the process status.
Analyze	The analyze phase is about identifying root causes and critical factors that affect the process. There is no clear structure of how to conduct the analyze phase, this phase is more of providing tools and techniques to support various analyses.
Improve	The improve phase is about counteracting the root causes that was found in the analyze phase and develop it into the best solutions. The developed KPI from the measure phase is used as a measurement for evaluation of the developed solutions.
Control	The control phase is about maintaining the improvements that have been mad and make sure that they have been implemented.

Tools for Lean Six Sigma

Lean Six Sigma have a big toolbox of different tools that can be used when conducting a project. According to Brook (2017), table 6 shows a compilation of different tools that can be applied in a Lean Six Sigma project.

Table 6. Tools for Lean Six Sigma (based on Brook, 2017 & Arlänge (2009).

Tools	Description
Project charter	The findings from the define phase is summarized in a project charter.
Effective scoping (SIPOC)	Helps to identify what the focus for this project is.
Affinity Interrelationship Method (AIM)	An AIM is used as method on complex problems to get an understanding and an analysis of the problem.
Process mapping	Gives an understanding of how the process works.
Measurement System Analysis (MSA)	A method of how to analyze the quality of a measurement system.
Control chart	Show graphical deviations that deviates from the normal deviation.
Hypothesis Testing	A tool that refers to how certain one can be if it´s true or not by making a specific decision.
Scatterplot Matrix	Helps to identify correlations between two factors.
Fishbone diagram	Breaks down a problem into smaller branches to find root causes.
Box plot	Summarizes data into boxes and whiskers to compare between data sets.

Design of Experiments (DOE)	Is an experimental technique that experiments in a process within a specified areas which later on is observed and analyzed.
Failure Mode and Effect Analysis (FMEA)	Is a tool that is used to make risk analysis such as severity, Occurrence and how to detect when a problem occurs.
Quality Control plan	Measurements details for each process step are developed into a process management document.

3.3 Implementing Industry 4.0 in a Lean Six Sigma context

According to Gorecky et al. (2014), the analysis of the data that comes from manual work stations has a structured way to be analyzed. First there is the structuring of the result where the data is being converted into compressed and structured result which could be seen as the measure phase in the Six Sigma methodology. This data is taking into further analysis which can be seen as the analyze phase. The realization of the results from the data is visualized in tangible models that are being changed into goals. In manual operations Gorecky et al. (2014) claims that when to develop an optimal model of how to conduct the work for an operator, the objects movements should be tracked. Movements with real-time adjustments can be made where the operator can get help if errors are made. Gorecky et al. (2014) claims that the data can be collected through GPS, Wi-Fi access points or indoor positioning systems where virtual reality can be used as a tool to help the worker to do their job in an optimal way. Gorecky et al. (2014) claims that the different methods that are used should produce data that is easy to record so it can be shared with other operators to get the optimal route of how to do the work.

Herrmann et al. (2016) discuss metrics that can be used to evaluate what kind of improvements that should be prioritized. Herrmann et al. (2016) states that there are three different principles that can be used to implement Industry 4.0 solutions. According to Herrmann et al. (2016) one principle is “interconnection” which is about having stable measurement system where sensors, devices, machines and humans are connected to each other. This proposes that an important factor is that communication is standardized. In this case it proposes the communication between machines and humans are necessarily. Information transparency is also discussed as a principle where analysis of data is made with sensor data linked with virtual reality. Drawings and simulation models are examples of information sources virtual reality can gather (Herrmann et al., 2016). According to Herrmann et al. (2016) the third principle is decentralized decisions which presents the idea that decisions that are based on information from both inside and outside the production plant needs to be transparent since the people that are taking the decisions need to have an interconnection with the objects. Herrmann et al. (2016) claims that an increased overall productivity can be achieved by decentralized decisions. The fourth principle which is discussed is technical assistance. Technical assistance is about decreasing the human touch on the machines and shift to the machines. The operator’s roles will shift to become a problem solver and a decision maker.

3.4 Improving measuring accuracy

Lichtenberg (1984) discuss how to improve the accuracy in project planning where the amount of different time measurements is affecting the security of the outcome. To get a more reliable result and measurement, operations can be broken down into smaller sequence to get a more reliable result. This proposes that breaking down an operation into smaller sequences will increase the predictability of the time measurements (Lichtenberg, 1984). Lichtenberg (1984) claims that there are seven principles that can be used for breaking down operations into smaller measurement posts:

1. Early start- a serious start should be planned early, the most vital decisions should be made early in the planning phase.

2. Uncertainty – The uncertainty in the data needs to be taken into consideration and manage in the project in a consistent way to eliminate results that is unrealistic.

3. Detailing - the detail grade needs to be adjusted and limited to the relevant areas. A clear detail planning is always needed so there is no resource waste in the later phase of the project, also it can affect by hiding the real factors of the critical circumstances.

4. Overview and control. It is vital that the project planner and the ones making decisions have overview and control of the project instead of putting all responsibility into a project planner software. It is good to use as help, but it should not be taking over the control of the project.

5. Assessment criterions. The assessment criteria's needs to be chosen carefully and be balanced in a way that the criteria's is wide and easy to evaluate.

6. Walkthrough and semi-intuitive work flow. Proposes that there is a structured base on how to work and there is an iterative method that can be used for changes that can be made easily.

7. Pictures and models. Which helps to visualize the result for the stakeholders and it confirms the results of the project.

Lichtenberg (1984) claims that based on these seven solving principles the successive principle is integrated in the solving principle. The successive principle builds the systematic limitations of the level of detail which helps to increase the accuracy of predictability (see figure 7). Lichtenberg (1984) states that there are four common principles that can be describe by the successive principle:

1. Only the most important data should be used.

2. The collected plan should be divided into smaller parts to increase the measurement posts and get a higher security of the project planning.

3. Investigate with the help of the variance to visualize different measurement post to get an overall view of the project plan.

4. This plan keeps on going until the plan's precision and accuracy is good enough or if one of the measurement posts have an unavoidable variance.

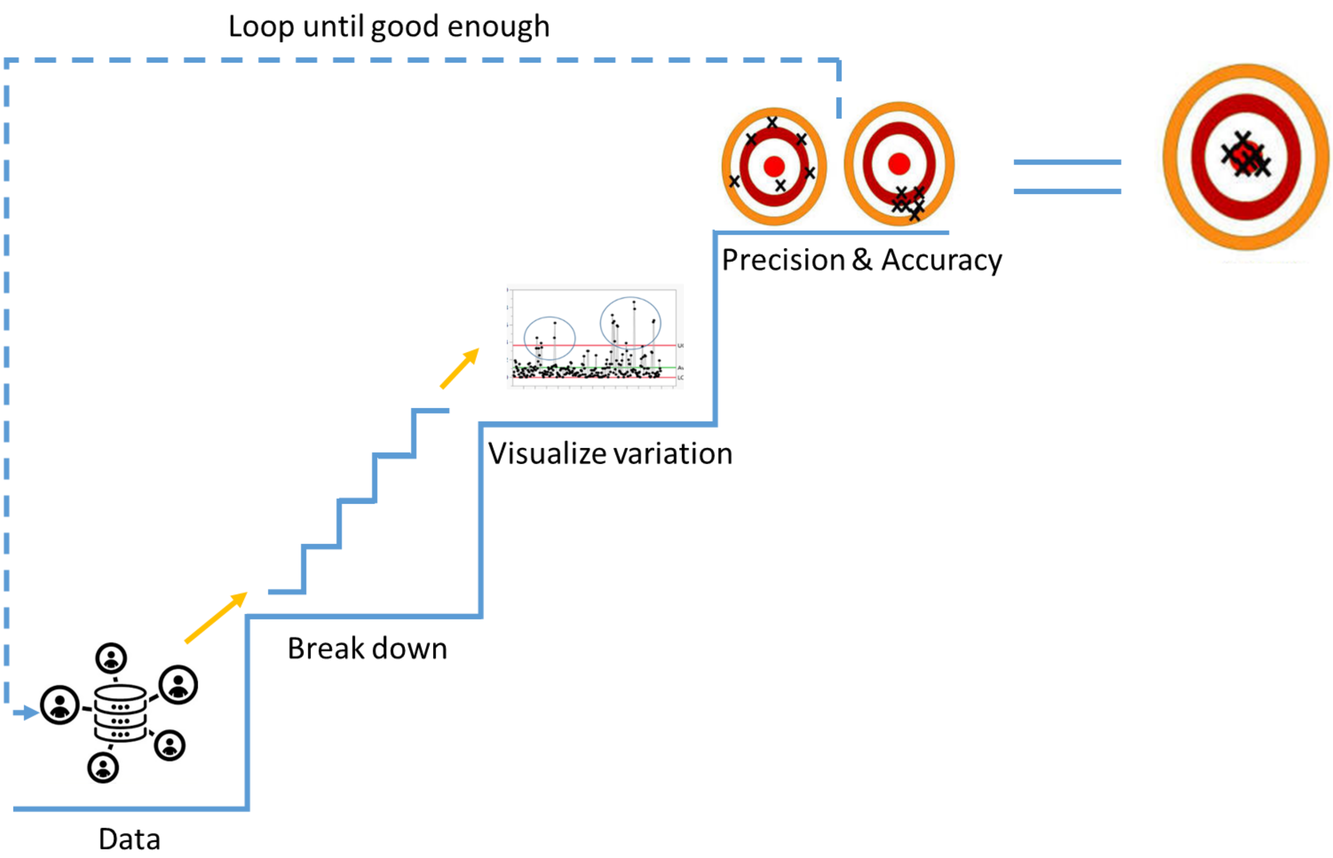


Figure 7. The successive principle (adapted from Lichtenberg, 1984).

3.5 Studies on Industry 4.0 and Lean Six Sigma

A summary of important factors of how Industry 4.0 studies can relate to the Lean Six Sigma methodology have been summarized in table 7.

Table 7. Comparison between different studies on Lean Six Sigma in relation to Industry 4.0, in terms of method focus and the data to drive improvements.

		Author			
Comparison between different studies		Cemernek et al. (2017)	Gorecky et al. (2014)	Herrmann et al. (2016)	Chiabert et al. (2018)
Method	Clear structure of how the problem is defined	x			x
	Clear structure of how the data is measure and analyzed	x	x	x	x
	Clear structure of how to implement and prioritize solutions			x	
	Clear method of how to control the process	x	x		x
	Takes economical feasability into consideration			x	
Metrics	Sensor data	x	x	x	x
	XML -data	x	x	x	x
	Photo	x	x	x	x
	Automatic optical inspection (AOI)	x			
	CAD-models	x			x

What can be seen in table 6 is that all the studies that was analyzed have a clear structure of how the data is measured and analyzed which indicates that the inherent focus on data-driven improvement from Six Sigma is taken into consideration in Industry 4.0. Something that was only taking into consideration in one study (Herrmann et al., 2016) is the economic perspective when implementing various techniques. Also, when it comes to having a clear structure of how to implement and prioritize solutions there is only one of the studies that takes this into consideration. When it comes to the metrics sensors, XML and photo data is something that was discussed in all of the studies. This indicates that these three metrics might be more relevant for measuring how the operators are working with the machines.

4 Empirical findings and analysis

In this chapter the findings from the empirical study with the improvement project and the interviews will be presented and analyzed. The first chapter (4.1) gives an introduction of why predictability is needed within a company and a pre-study of why the investigation in manual operations is needed. The second chapter (4.2) is about identifying factors that can influence predictability in manual operations based on the interviews. The third chapter (4.3) is about how trustworthy the data that has been sampled is and to investigate how to improve the causes that has been identified as problems within manual deburring, the improvement project will be presented. The fourth chapter (4.4) is based on the interviews how different roles sees on manual operations in an Industry 4.0 perspective.

4.1 Predictability in manual operations

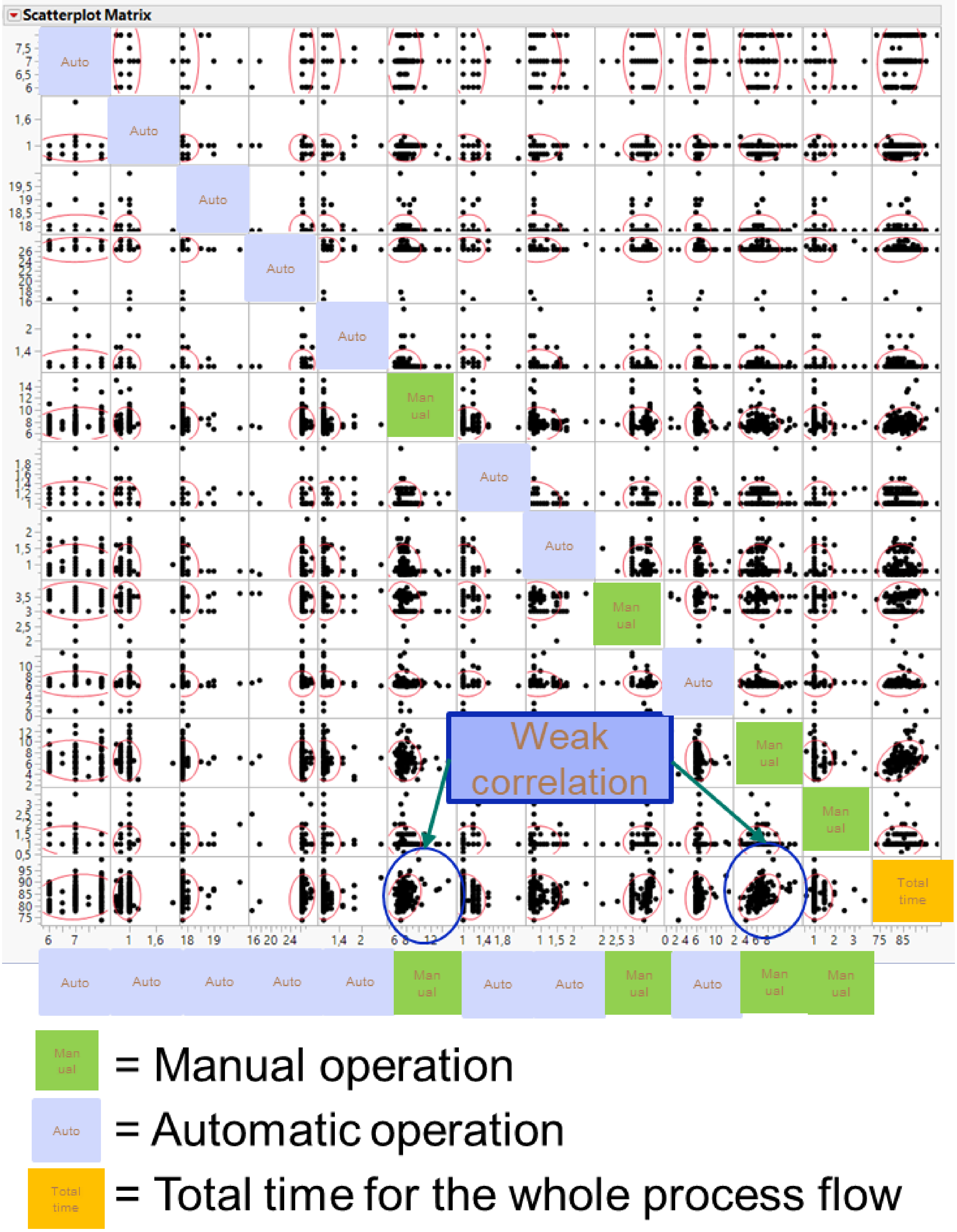
Predictability within GKN is a vital component for the company to operate because you need to know how long time a certain operation will take. Both from a manager and an operator perspective predictability is needed, from the manager's perspective you need to know how much it will cost to produce a certain number of hardware and how many that can be promise to the customer in a certain time period. For example, there is a five-week delivery plan to the customer and you have a deviation on two weeks where the customer can receive the hardware within three up to seven week which will not make the customer satisfied if they are not certain when to receive the hardware. When it comes to the operator there is a need for a high predictability, to know when the next hardware is coming into their station is an important factor for the operators. The operators need to be able to plan what their working schedule looks like and be able to set up the fixtures that is needed for the incoming hardware to save time and to have a smoother flow. The predictability affects calculations of the safety buffer and the capacity analysis in a way where the safety buffer needs to be decreased. When having a big safety buffer, the lead time is increased which increases the capital that is locked into the flow that could have been invested in something else.

Another interviewee stated that if the company wants to be competitive in the future, predictability is vital both in the current production but also when it comes to starting up new products. The changing speed is an important factor and you need to know that there is a high probability that the production flow will work before you start to produce. It is very expensive to start over or do reworks, you should be able to say with a high probability that before we start we know this is going to work based on previous data, how the good the equipment is and how good it performs and how the manual operations are performing. From the interviews it was also discussed about that the operators feel that measuring time is difficult to keep track on when conducting their work. Because of external disturbances might disturb the operators when conducting their work and should it be added into the time when operator is talking to a manager during their work. Also, the operators don't have any watch or tool that can help them keep track of the time.

Pre-study

A pre-study was conducted where a scatterplot matrix (see table 8) was used to map correlations between manual operations and automatic operations to see if any connections in the process flow could be found. It can be seen that there is no correlation between the automatic operations and the total time which indicates that there is a predictability for these operations. This depends on that, the automatic operations have a given time where the operator press start, and then the machine does their program. However, it can be seen that there is no straight line where some variation for these operations exist, which is most likely how the different operators is measuring the time since the time is registered manually by the operators. The machines are predictable when it comes to how long time it takes to conduct an operation. Although, the cycle times in this graph doesn't show the whole picture of what comes out after the hardware's are finished. If one machine is missing something on the hardware it will not be able to tell what happened or what has been missing. Instead the next manual operation will have to deal with this problem which can affect the time in the manual operations. When it comes to the manual operations it can be seen in table 8 that there is a weak linear correlation between manual operations and the total time which indicates that manual operations are not as predicable in time as machine operations are. For the multivariate correlation see appendix C.

Table 8. Scatterplot matrix for a production process flow.



4.2 Identifying factors affecting predictability in manual operations

Enhanced predictability in manual operations was discussed in the interviews. There are many factors that affects the predictability in manual operations, arising from the drawing table where error proofing is considered, all the way to the design and use of production processes. Critical factors that were identified from the interviews:

- Robust system – proactive system to detect deviation from nominal
- Design at the drawing table –design for manual operations optimized
- Human factor – experienced operators tend to work faster
- Working methods – Operators have different strategies
- Technical requirements
- Material variation
- Identification of hardware that deviates from a standard norm
- Standard time

Robust system

From the interviews it was discussed that to have a high predictability in the processes you need to have a robust system which proposes that the processes are monitored and reacts before something has happened. Further, it proposes that there are clear control limits on the products in case if there is an outlier it should be possible to react before it goes outside measured tolerances. Another person that was interviewed discussed about that robustness is about that you get the same output where you have a stable process that correlates with each other, the process is in statistical control. If you have the process in control you can predict how long time it will take based on the historical data. When new programs are about to start up and there is no experience from that product but parts of that product. If you break down the product flow into different processes there is higher and lower predictability on different work moments and builds up business case. One of managers discusses about when it comes to predict how long time a manual operations will take doesn't correlate with how long the lead times is. It is more of the quality of the product that is correlating with the lead time for the whole process. Because when it comes to controlling the hardware to see if the quality is good enough there is no clear manual of what defines the certain control points in the checklist. For example, when it comes to defining what is brown and what is not, at the moment at GKN operations the technology is not there yet to be able to define what is a pass or a fail. Another manager discusses about the need of working with the whole methodology for manual work and how we are preparing and steering but also how GKN should verify hardware's.

Design at the drawing table

The design from the drawing table is of high importance when it comes to making it predictable. The operators that is going to conduct the operation needs to be taking into consideration both in ergonomic and executing perspective. Since GKN have products that are from the 90´s which proposes that back in the days there was no measurement machines and only manual measurements. Therefore, these products cannot be used for machines which proposes that there are long cycle times on these products and the operators were not taken into consideration when designing the product such as how the control for a certain hardware be executed.

The human factor

The human factor was discussed as the variation between different operators will always be there, where the most experienced workers execute their work faster than an operator that doesn't have the same experience do their work slower. Height, strength and personality are also factors that can have an effect on predictability. A stronger person might be able to use a heavier tool than someone who isn't as strong. Also, the feeling of using different tool also matters, one operator maybe like one specific tool and another one likes another tool, and this makes it difficult to be able to predict time as everyone is performing the operations differently.

Working methods

In most of GKNs manual operations there is no standardized methods of how to conduct their work, some of the manual operations have job training documents but they are more of guidelines of how the operators are going to do their work. If not all the operators are doing the exact same thing it will decrease the predictability and it makes it more difficult to measure an operation of not everyone is doing the same thing.

Technical requirements

One of the biggest problems when it comes to manual operations is how to define if a hardware is finished or not. For example; if a hardware is at the inspection operation and the operator is going to look at the hardware and tell if a stain is brown or not, is it good enough? One of the reasons why it will be manual operations in the future is the technical requirements, it is not possible to tell a machine to do something when there is not clear instruction of the technical requirements.

Material variation

Material variation came up in the interviews, both from the operators and from the managers. One of the operators discussed about how sheet metal has a big variation and is almost never predictable since it´s always a different shape of the material. Also, some of the manager discussed about how the material differs from the supplier since these hardware has a high complexity and there is only a low number of suppliers that can deliver these hardware.

Identification of hardware that deviates from a standard norm

When a hardware deviates from its standard norm it is difficult to know when this happens or how to measure when something deviates.

Standard time

Standard time was discussed in all of the interviews where some of the interviewee were sceptic about the data that has been measured and uploaded to SAP/R3, the data could not completely be trusted but it could be used as indication of how an operation is doing. Standard time is something that is given for all the operation step, this time is what the management is expecting from the operators to. The cost of a product is based on the standard time which gives this a high importance for the operators to do it this fast. When asking different roles how the standard time is set, different answers were given but the most common was that the standard time was based on the average from the historical data. Other answers were that it was based on historical data and adjusted based the operators experience when it comes to the variation.

The operators register the time of the operation manually. However, if one operator is doing an operation faster than the given standard time the operator writes down the standard time instead of the actual time. The reason for noting down the standard time is that if the operators writes a shorter time, the standard time in which the operators have to conduct their operation will be decreased. Another manager proposes that a certified operator should normally be within 5% of the given standard time.

4.3 Data handling/reliability in manual operations – a Lean Six Sigma project

Based on the pre-study a Lean Six Sigma project was initiated with the structure of Define-Measure-Analyze-Improve-Control.

4.3.1 Define phase –D

In the define phase problems occurred of what needs to be solved and where it needs to be solved.

Affinity interrelationship model - AIM

Four employees from GKN was participating from different departments to give their opinion in the AIM session (see figure 8) and later the diagram was revised by a fifth employee. The employees that was involved in the AIM was asked rank what they believed that had the highest effect on making manual operations predictable. The employees got one of each number, 3 (red) is the one with the highest effect, 2 (blue) is the one with the second highest effect and 1 (green) is the one with the lowest effect. The arrows show how the different categories are correlated with each other.

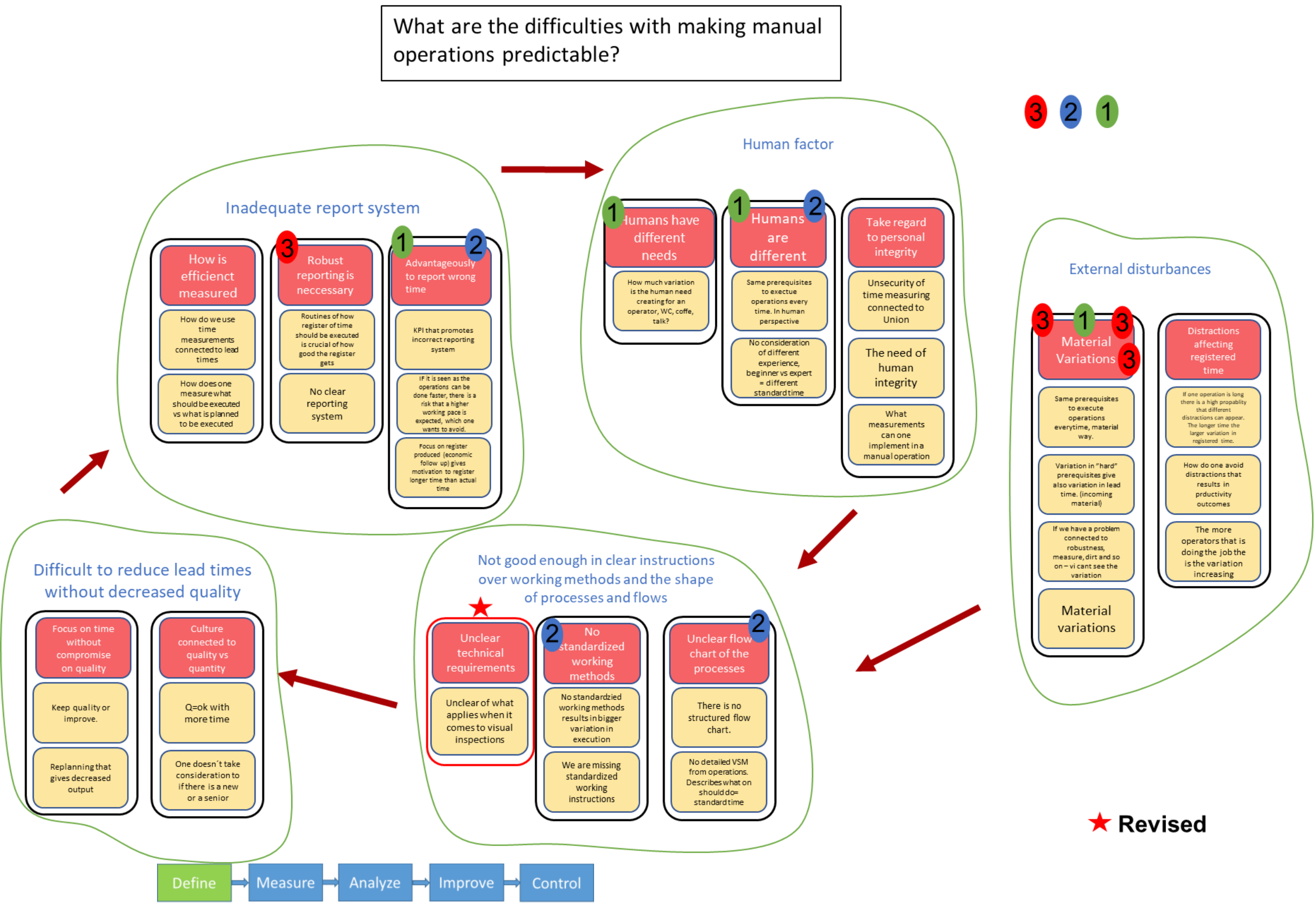


Figure 8. AIM – create predictability in manual operations.

Five different areas came up as the main challenges in enhancing predictability in manual operations:

- External disturbing problems - was the subgroup that got the highest point (10). Material variation is seen something that affects the predictability where the difference between a hardware to another can make a big difference on the time. Also, problems connected to robustness such as dirt, dimensions or such that is not able to see in the variation.
- Automatic reporting system – got the second highest score (5) where robust reporting is seen as a problem where difficulties of how the time reporting is being handled since there is no clear structure of how time is supposed to be measure and there is no clear report system.
- The human factor – is seen as one of the groups that is a problem from creating predictability in manual operations. When it comes to the human factor there is a variation between an experienced and an unexperienced operator which is a factor that was seen as a problem.
- Clear instructions over work methods and the shape of the processes and flows – discusses about that there are no standardized working methods which increases the uncertainty of how long time it takes to finish an operation. An interview that was conducted with the industrial manager said that before you can measure everyone needs to do the same method with the same tools otherwise you will get incorrect results.
- Decrease the lead time without decreasing the quality – is about time reduction without affecting the quality. There is no consideration if the operator has experience or not which also influences the predictability since the cost throughout the process flow is based on a goal time that is the same for all the operators.

Effective scoping

Analyzing the variation in the different production flow operations gave an overview of how the different operations were performing. From the interviews it could be said that one should not trust the data completely and use it more as indicators to see if there are any trends. One of the reasons for the lack of trust in the data is that the operators tend to report the standard time instead of the actual time it took to execute an operation. Also, from an operator's perspective it is not easy to keep on track how long time everything takes which also affects the reported time.

Manual deburring is included in one of the product flows (see figure 9,) which had variation in its operation time and due to the availability in the other product flows and operations this was the best suitable operations to conduct an improvement project on.

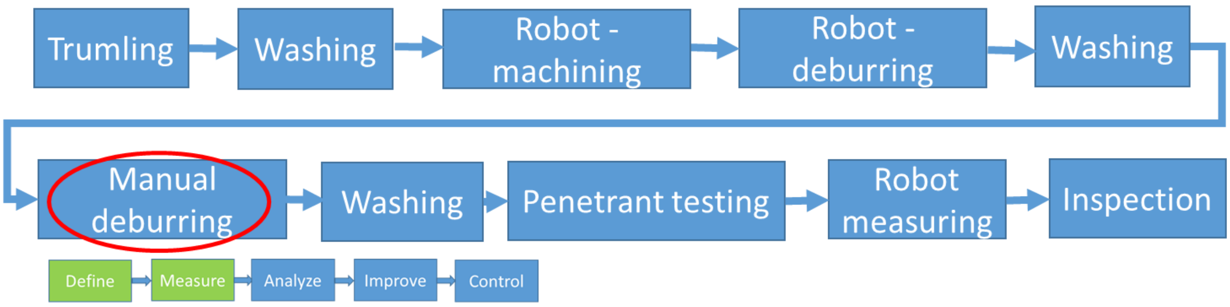


Figure 9. Process flow for chosen operation.

What can be seen in figure 10, the individual measurement for the cycle time in manual deburring is not in control but there are only a few outliers. Although it can be seen in the moving range chart (see figure 10.) that more outliers can be identified, this proposes that the variation in manual deburring is not in control.

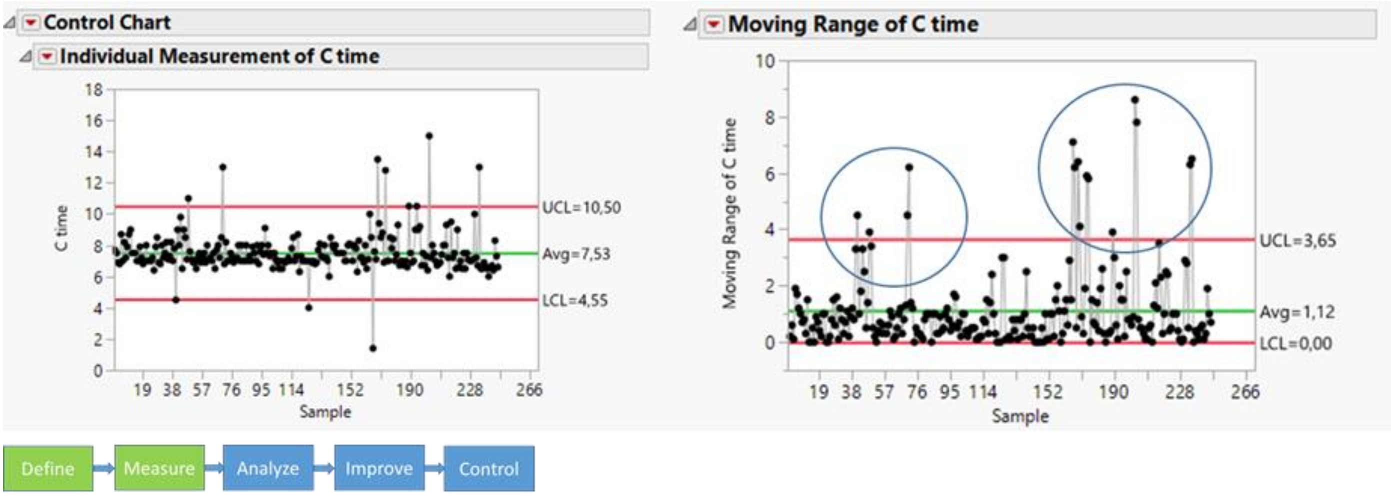


Figure 10. Control charts historical data – manual deburring.

4.3.2 Measure phase - M

The measure phase shows the results of the process map that was conducted at manual deburring which was a given process of how the operators works. The MSA shows variation

Process map

A process map was developed for manual deburring to get an understanding of the operation is executed (see figure 11.). Figure 11 show how the operation steps has been divided into different "tempo" which is a specific area on the hardware that needs to be executed.

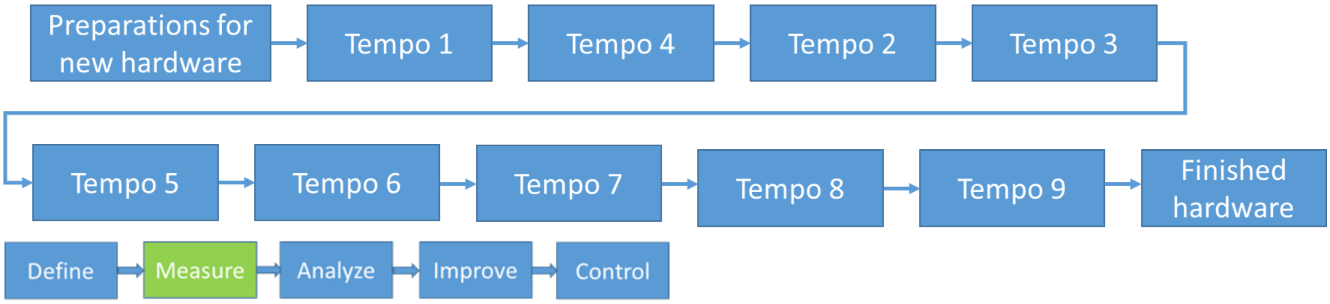


Figure 11. Process map – manual deburring.

Measurement system analysis –MSA

For further analysis a time study was conducted at the manual deburring to verify the historical data. The operations were broken down into smaller steps to increase the number of measuring posts and to see if there was only difference in the different steps. The nine different tempo was used as measurement points. Twenty samples were gathered but one of samples had known problems from the previous operations which gave this hardware more edges to deburr (see appendix D). Hence, this isn't a representative value for the study, see appendix E for example form. The second sample that was eliminated from result was excluded as someone had registered the wrong numbers.

The control chart (see figure 12.) shows that there is variation in the manual deburring operation although all the values that have been gathered is within the 3σ limit which proposes the process is in control. However, it can be seen that there is some variation within the control limits.

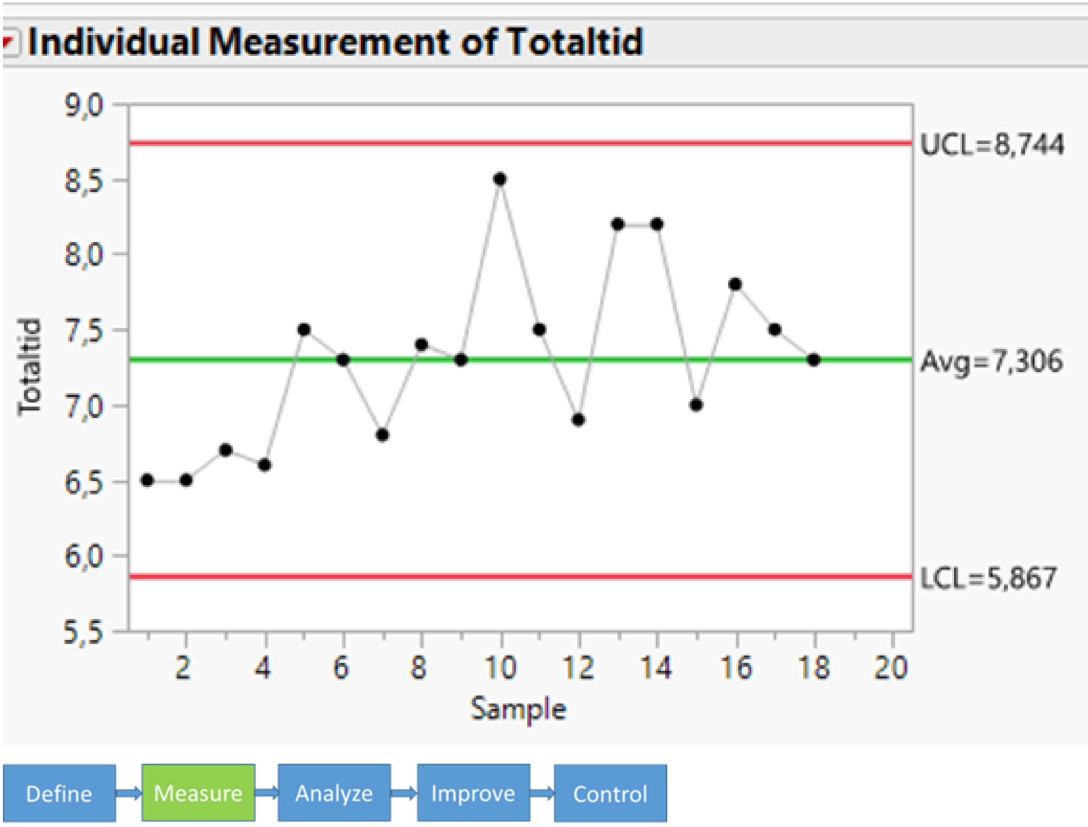


Figure 12. Control chart MSA – manual deburring

To investigate if the gathered data corresponds to the historical data a hypothesis testing between the historical mean and the mean from the MSA was conducted, see figure 13. H_0: there is no difference in mean between historical data and MSA data. The p-value is >0.05 which proposes that H_0 cannot be rejected. This proposes that the data is representative, the historical data and the MSA-data can be used for further analysis.

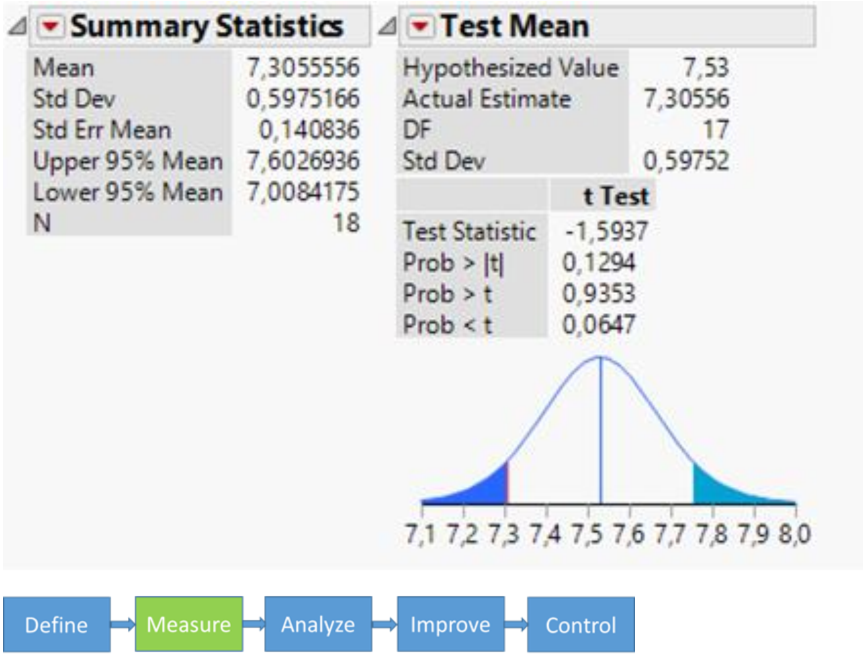


Figure 13. Hypothesis testing in mean between MSA and historical data.

A one-way ANOVA was conducted between the different tempo to investigate if there was any difference between averages and variations. In figure 14 it can be seen that four different tempo was sticking out; tempo 2, 3, 5, & 8. These tempos have a higher standard deviation than the other tempos which gives an understanding of where the variation within an operation is. Although, since the values of these tempos differ in averages it can be misleading to compare the actual standard deviation since the ones with a higher standard deviation doesn’t necessarily have a big variation in its own step compared to another tempo that has the same standard deviation but with a lover average.

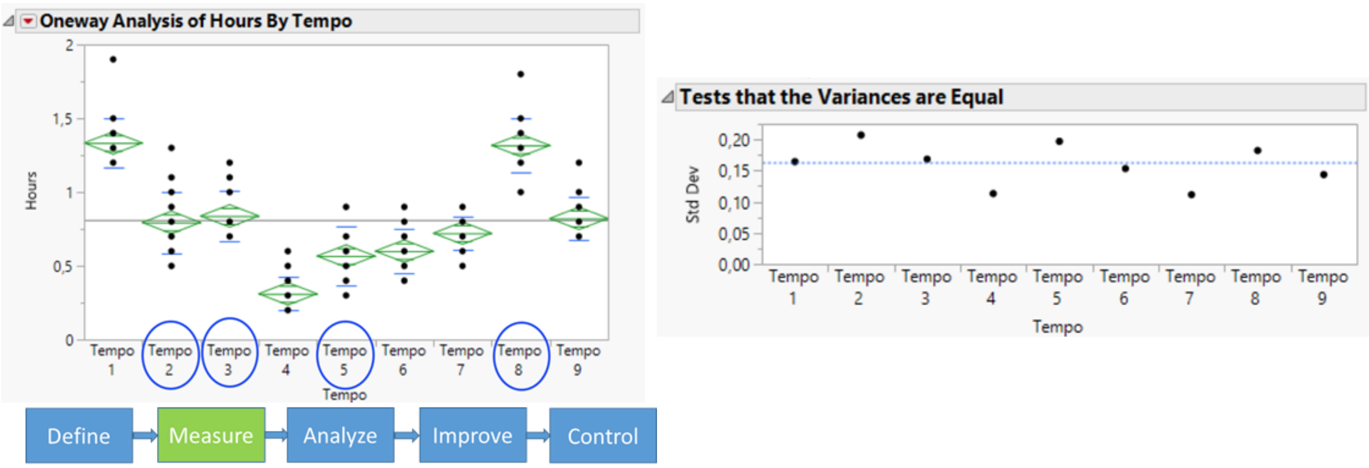


Figure 14. One-way ANOVA of the different tempos.

Instead of a one-way ANOVA, a compilation from the MSA and input from operators at the manual deburring was put together (see table 9) to get a deeper knowledge of the different tempo´s. The second column describes how the tempo have been going through at the previous operations which gives an indication if the previous operation has an effect on a specific tempo. The third column describes the how the operators see on the different tempo which they think have the largest variation or who they think works fine. This is a subjective opinion from the operators, but it gives and understanding of which tempo they think are having problems in. The fourth columns are the % deviation which gives a correct picture of how the actual variation is within the manual deburring operations. Complexity is also visualized in the table that is based on which tempo the operator finds more difficult than the others.

In table 9, it can be seen that there is a connection between the type of deburring and the % deviation which indicates that there is most likely something wrong with the previous operations. It can be seen that tempo 1 have a low % deviation which indicates that the previous operation can handle this area good compared to the other tempo that has been robot deburred. Tempo 4 is the one with the highest % deviation. Although, this tempo has the lowest mean time and the operators write down time manually so the rounding´s can have an effect on this tempo.

One thing that could be seen in table 9 is that tempo 3 that was fully deburred, and the operators found this tempo the most difficult area to work in where the % deviation is the largest which can indicate that there is most likely a larger variation between the operators compared to the other tempo that has been fully deburred.

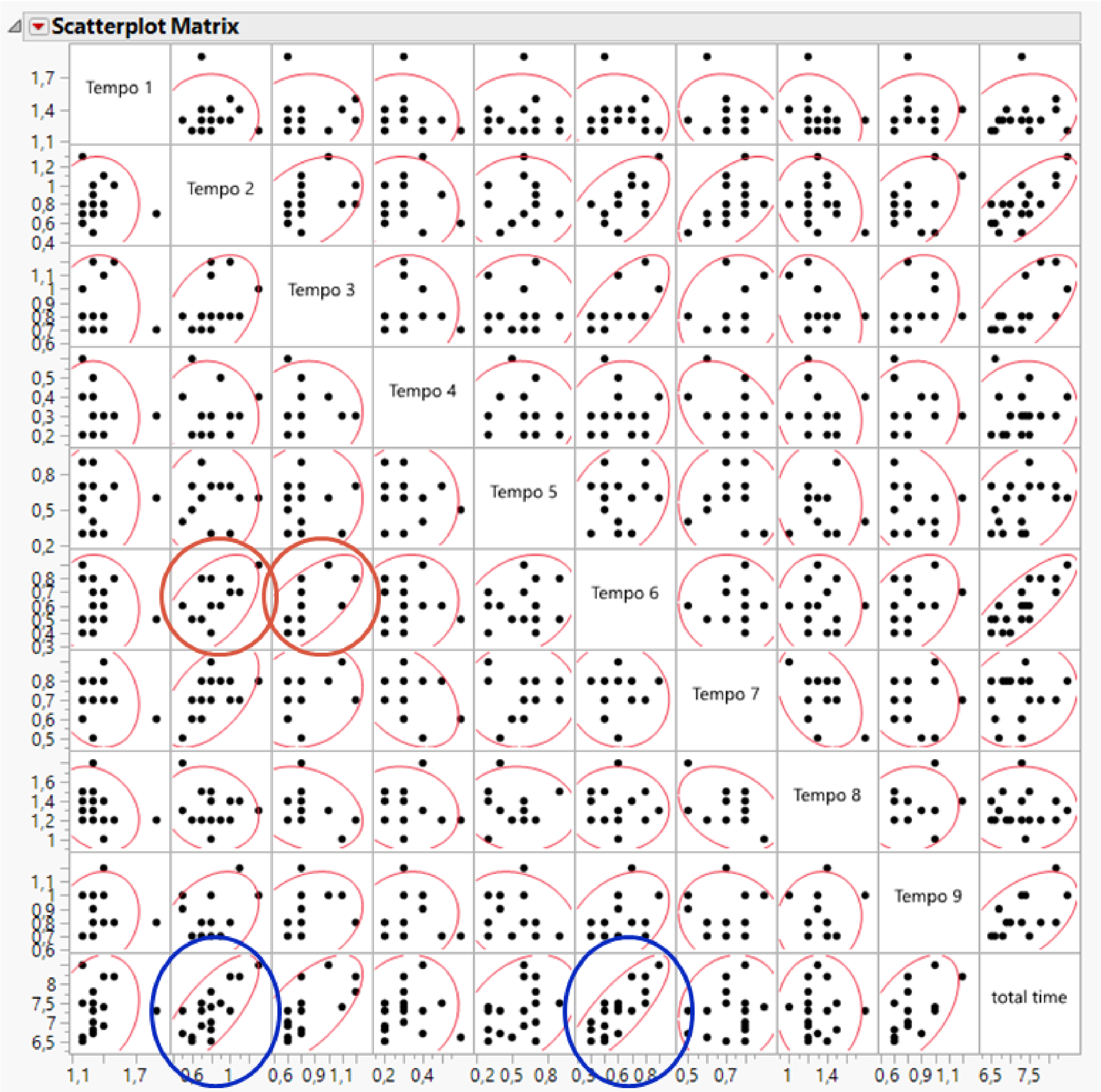
Table 9. Compilation MSA – manual deburring.

Tempo	Type of deburring	Comment from operators	% deviation	mean time (h)	Complexity	Comments
Tempo 1	Robot deburred	Largest variations according to operators	12%	1,3	Easy OP	Low variation, few/only errors from the robot
Tempo 2	Robot deburred	Almost all robot miss, similar quality	26%	0,8	Easy OP	Can be the human factor
Tempo 3	Fully deburred	More sensitive area to work in	20%	0,8	Difficult OP	Can be the human factor
Tempo 4	Robot deburred	Milling can affect the material if it´s hard, similar quality	36%	0,3	Easy OP	Most likely problems with previous OP
Tempo 5	Robot deburred	Largest variations according to operators	35%	0,6	Easy OP	Most likely problems with previous OP
Tempo 6	Robot deburred	Similar quality	26%	0,6	Easy OP	Can be the human factor
Tempo 7	Fully deburred	Works fine	15%	0,7	Easy OP	Can be the human factor
Tempo 8	Inside robot deburred	Largest variations according to operators	14%	1,3	Inside difficult	Low variation, previous op is most likely doing well
Tempo 9	Fully deburred	Works fine	17%	0,8	Easy OP	Can be the human factor

Definition "type of deburring"
Robot deburred = pre-deburred by robot
Fully deburred = Only manual deburring

A multivariate correlation analysis was conducted to investigate if there are any correlations between the different tempos (see table 10). Tempo 2 that was outlined as complex area to work in is seen as having a high correlation with the total time for the operation. This indicates that this correlation is because of operator variation. Although, since the only factor that is analyzed is time it´s not possible to conclude that there is an operator variation. Tempo 6 have correlation with tempo 2 which also might indicate on operator variation. However, Tempo 6 is correlated with tempo 2 and 3 but the team members with the help of the operators tried to figure out why there was a correlation here, but no one knew what this depends on, only speculations. For multivariate correlation see Appendix F.

Table 10. Scatterplot matrix for the different tempo.



4.3.3 Analyze phase - A

The analyze phase generated causes that can have an effect on the variation in manual deburring.

Fishbone diagram

A fishbone diagram (see figure 15) was conducted in manual deburring to investigate what kind of factors that the operators see that can have an effect on the time where the starting question was about what factors affects the time in manual deburring. Two operators from the manual deburring operation participate and the diagram was later on revised by a former operator from the manual deburring operation. The fishbone diagram confirmed factors that were brought up in the AIM.

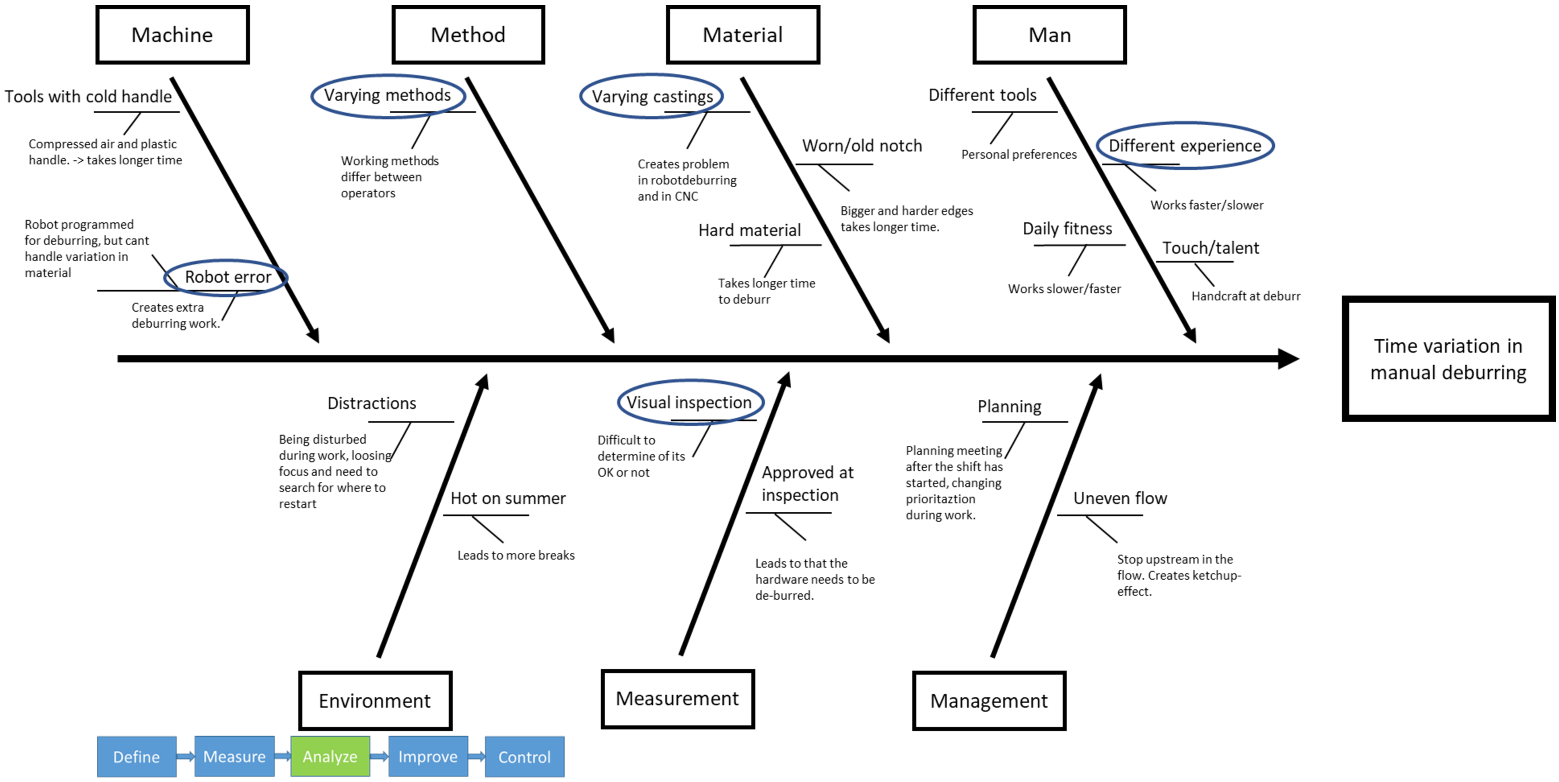


Figure 15. Fishbone diagram – time variation in manual deburring.

The operators came up with five different factors that they predicted hade the largest effect on the time:

- Varying methods – the operators don't have the same working methods which can affect the time.
- Varying castings – the hardware's that are coming in have a variation in hardness and in the geometry, which proposes that the previous operations, the robot can't handle the variation, this proposes that the operators in manual deburring needs to do extra work
- Robot error – the robot is stupid, it can only do what is told and when there is variation in the material the robot cannot take all the areas that it´s supposed to do. This proposes the operators at manual deburring needs to fix what the robot can't handle.
- Different experience levels – has an effect of have fast an operator can work, a more experienced operator tend to do the operation fast than one who doesn't have the same experience.
- Visual inspection – when a hardware is seen as finished by the operators, they do a visual inspection by themselves and feel with their hands. This can have a variation between the operators, if one sees if something is finished and another operator sees that it is not finished.

Also, if someone sends away a hardware that is not finished it needs to be re-deburred later in the process which leads to more work the operators.

Analysis of supplier

For this product flow there are two different suppliers, an analysis was conducted to investigate if there was any difference between these two suppliers in time. The analysis was investigated by the cycle time at manual deburring and the other factor was supplier. Figure 16 shows that the average is similar but one of the supplier has more outliers which indicates that there is a larger variation between the two suppliers.

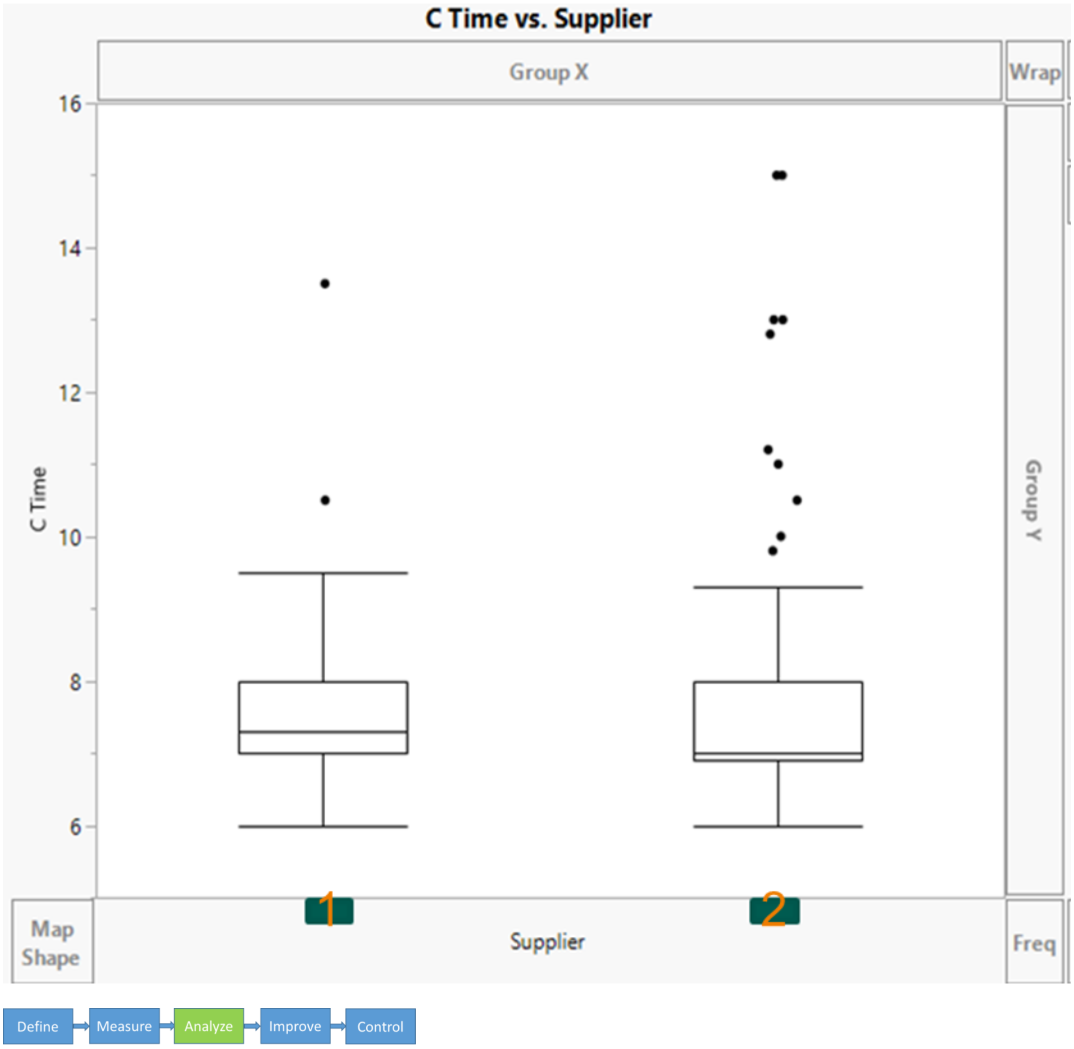


Figure 16. Box plot – supplier.

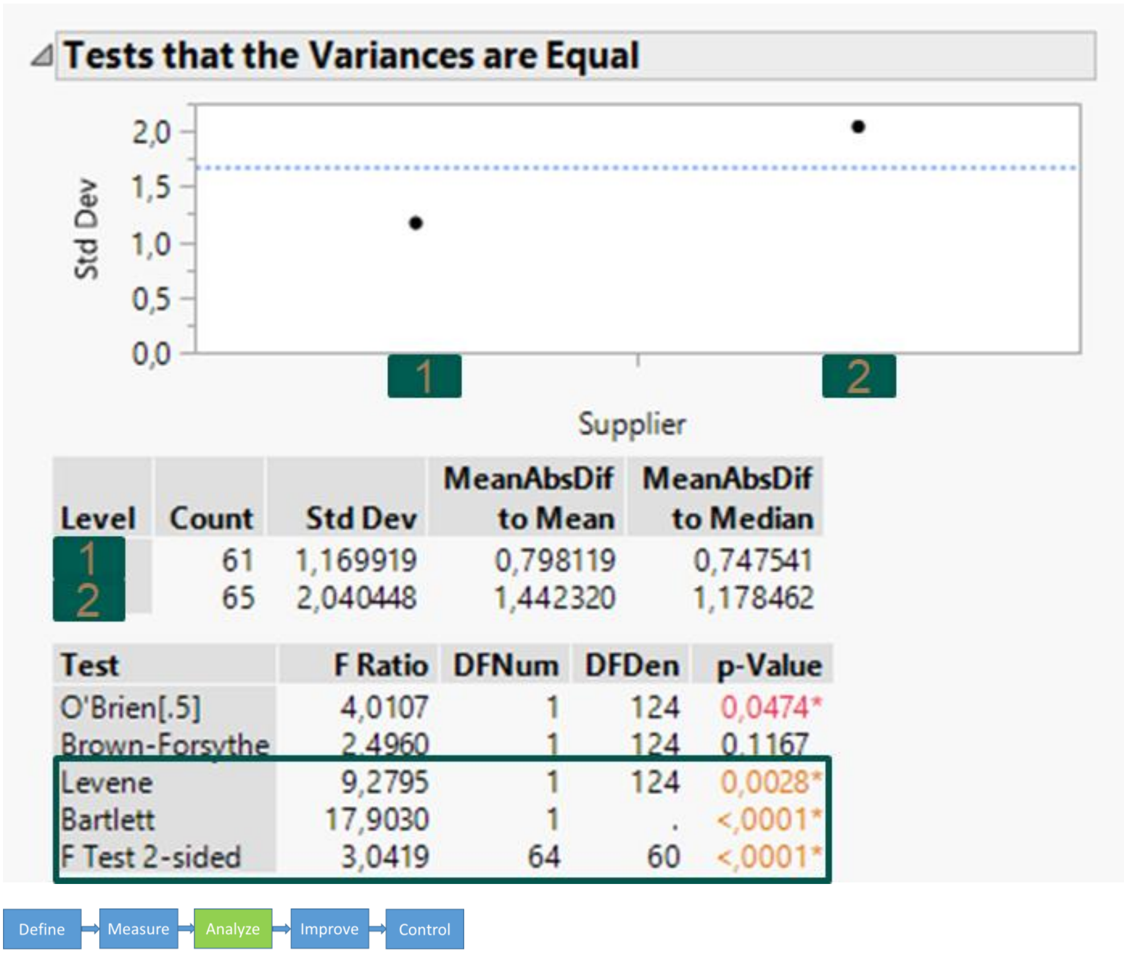
A hypothesis test was conducted (see figure 17) to test if the variances are equal between the suppliers:

H_0: there is no difference in standard deviation between the suppliers.

H_a: There is a difference in standard deviation between the suppliers.

$P<0.05$ – based on the data that has been analyzed Ho can be rejected.

This proposes that there is a significant difference in standard deviation between the different suppliers. The variation between the two suppliers indicates that there is most likely material variation that is the reason for variation, because when an operation takes longer time in the manual deburring it is often because of the robot that is in the process steps before (see figure 9). The robot cannot handle variation in material which leads to that the operators needs to do more work in manual deburring to deburr the areas that robot wasn't able to handle.



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
1	61	1,169919	0,798119	0,747541
2	65	2,040448	1,442320	1,178462

Test	F Ratio	DFNum	DFDen	p-Value
O'Brien[.5]	4,0107	1	124	0,0474*
Brown-Forsythe	2,4960	1	124	0,1167
Levene	9,2795	1	124	0,0028*
Bartlett	17,9030	1	.	<,0001*
F Test 2-sided	3,0419	64	60	<,0001*

Figure 17. Hypothesis testing between suppliers.

To investigate if there is any difference in average between the two suppliers, a hypothesis testing was conducted (see figure 18).

H_0: There is no difference in averages between the suppliers.

$P>0.05$ – based on the data that has been analyzed there is not enough evidence that H_0 can be rejected.

Inconclusive.

This proposes that there is no significant difference in averages between the suppliers.

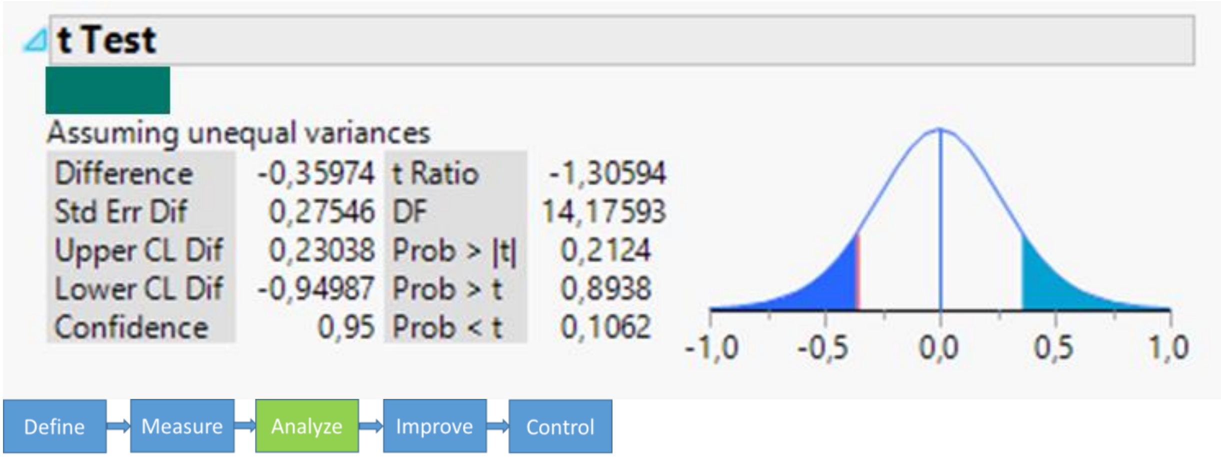


Figure 18. Two sample t-Test between suppliers.

Improvement suggestions

From the Lean Six Sigma project, improvement suggestions were developed in the context of Industry 4.0:

- Varying methods, different experience
  - VR-googles can be used to assist operators to execute their work that shows exactly how to do the operation.
- Varying castings
  - Increase availability of material data and certificate from supplier (material variation etc.), analysis of casting data before manufacturing.
- Visual inspection
  - CAD models & automatic optical inspection (AOI), use of AI to identify defects or deviations.
- Robot error due to variation in material.
  - Be able to measure the problem in the operation later if one measure on multiple steps
- Variation in material
  - Be able to predict how long time a hardware will take before it´s entering the product flow based on material.
- Manual registration of actual time
  - Measure time with smartphone to make it easier for the operators to keep track of the time and increase the number of data points.

Varying methods, different experience

Varying methods and different experience came up in both the AIM, fishbone diagram and in the interviews. This proposes that from three different sources confirmed that this is a problem. The reason why there is different methods in some of the manual operation is that there no clear method of how the operator should execute their work. In the chosen operation for this project (manual deburring) there was similar methods of how to execute the operation but not completely similar. There was some difference of how the execution of the operation within the different tempo. In an industry 4.0 perspective VR-glasses could be helpful to assist the operator to execute the optimal road for deburring. Also, for an unexperienced worker it can be helpful to have instruction of how to execute the work and what tools to use.

Varying castings

Because of the high complexity of the products and only a few suppliers are able to produce these kinds of hardware proposes that a variation in the castings can exist. The AIM, fishbone diagram and the analysis of the supplier shows that material variation exist and most likely comes from the supplier. To increase the awareness of the material variation, increased availability of material data and certificate form the supplier can be used to analyze and see if a certain hardness of the material will take longer time than a hardware with a lower hardness.

Visual inspection

When a hardware is finished in the manual deburring operation there is a visual inspection to see if there is something more that is needed to deburr, if not the hardware is pushed to the next operation in the process flow. If there is something that is wrong with the hardware the inspection in the end of the process flow will find is something is wrong and then re-deburr the hardware. Instead of not knowing if the products are finished or not can cost a lot of money. With Industry 4.0 techniques such as automatic optical inspection (AOI) & CAD models can be used to scan the product to see if its finished or not. AI can be used to identify defects or deviations on the hardware.

Robot error due to variation in material

In the fishbone diagram, the robot came up as a factor that affects the manual deburring in time. The reason why it that the robot can handle variation in the material. When there is variation in the material the robot won't be able to detect the variation and execute what it's told. When this problem appears there nothing in the robot that says something is wrong. Instead the operation after the robot operation, manual deburring has to handle this variation. With the help of manual deburring the errors from the robot can appear.

Variation in material

When a hardware arrives at the product flow, it should be possible to predict how long time that specific hardware will take to be finished. Different standard times for different hardware can increase the predictability of manual deburring. For example, if one hardware has a higher hardness that the average hardware hardness it should be possible to adjust the standard time based on this. Also, if that specific hardware needs to be prioritized in order to be able to meet the scheduled transport to the customer.

Manual registration of actual time

Currently the time that is registered is manually registered by the operator. Measure the time with smartphone will make it easier for the operator to keep track of the time and increase the number of data points to measure on.

4.4 Manual operations in an Industry 4.0 perspective

Based on the interviews one person discussed about how Industry 4.0 is an ecosystem where many companies see Industry 4.0 as something they need to implement without any concrete goal of why it is needed. This can create a lot of waste to introduce industry 4.0 techniques at places where it´s not needed or should have been prioritized somewhere else.

When it comes to what types of barriers that can come up when implementing Industry 4.0 in manual operations the personal integrity issue came up in this study. It was brought up in the AIM (see figure 8) and in the interviews where time measuring is a parameter that is something that is sensitive. Since Industry 4.0 is a technology that demands a lot of data and therefor the amount of data on an individual will increase. Measuring with the help of video is also something that is critical when it comes the personal integrity. Developing a fully predictive manual operation in Industry 4.0 way requires that the operators to do the exact same thing over and over again. This proposes that there are no individual differences i.e. to be equally strong, the same height and do the exact same movements. This is not realistic with any manual operation, where you have to accept individual difference.

Industry 4.0 technologies comes with opportunities not only in automated operations but also in manual operations. In one of the interviews it was discussed about the possibilities to optimize a manual operation in CAD-modeling where it´s possible to get the best practice for a manual operation. Another technique that was discussed was a scanning system that scans what you have been doing and gives you feed if it´s good or bad what, if there is a need to do some extra on one part or something that has to be changed. With a scanning system it can help to reduce the loops of hardware coming back to the operation step which increases the lead time for a product. Also, when it comes to sending away a defected product to the customer, this is also an expensive outcome and the customer will be dissatisfied. When it comes to zero defect a scanning system can be a useful tool for inspections and in other manual operations to know when “it´s good enough”.

5 Discussion

The discussion chapter discusses the research questions, the choice of method and future research proposal.

5.1 Purposed fulfilled

The purpose of this thesis was to investigate how a Lean Six Sigma project can enhance the predictability in manual operations in an Industry 4.0 perspective. The three research questions that has been studied are discussed below.

RQ 1: Why should a company with low volume and high complexity products enhance predictability (in lead time) in manual operations?

When it comes to run a business, the demand of products and accuracy has increased and components such as safety stock and capacity analysis calculations are vital for a company. The customer wants to know how long time it will take for a certain product to be delivered and the company wants to make the customer satisfied. Also, when it comes to winning a business case there is a need for high predictability when it comes to calculating how much it will cost to produce a product in order to give a reliable cost estimation for the customer. Also, the need to know how long time it will take for a product in lead time which is an important factor when calculation the cost. As Mentioned by Liao (2011), predictability will indirectly affect the customer satisfaction because the customers will know when and what they are receiving. Also, the lack of trust can decrease between the customer and the supplier if the supplier's delivery is unpredictable.

When it comes to workshop-floor the importance of be able to predict when the next hardware will arrive to the next operations step. As an operator you want to know which hardware is arriving and when it is arriving, so the operators can start planning by setting up the correct fixtures, have the right tools available and be sure to be available when the hardware arrives.

When starting a new product there is a high importance of knowing even before the product flow has started how the different process steps perform. The opportunities to know how an operations goes based on previous products that has been using this process step such as how stable the process is and in what condition the tools are. Also, predictability will help creating a situation in which you with a high probability can be sure that this will work and not do a lot of rework for the hardware which costs a lot of money. Cemernek et al (2017) discuss about that every machine should be have embedded computer systems and connect theses to the internet, with the help of these data systems use big data for

RQ 2: How can predictability be handled in manual operations and how can manual operations be enhanced with Industry 4.0?

The successive principle developed by Lichtenberg (1984) increases the measurement points in operation to study variability in a process which helps to identify causes of variation and to improve the predictability. Industry 4.0 is a technology that increases the amount of data which gives more data. Also, prediction of how long time a hardware will take before it has started the process, e.g. if material variation effects the time, a longer time should be predicted for this hardware. This could help to know which hardware to prioritize in the process step if one hardware is falling behind.

Industry 4.0 techniques can be used when it comes to assist the operator to efficiently perform an operation, e.g. smart phones, tablets, VR-glasses etc. With smart phones, time measuring can be made with the help of the successive principle, to break down one process operation in many steps (tempo) and use an application to measure the time for each tempo where the data is reported to the cloud.

Also, if one step in an operation takes longer time be able in an easy way to report why it took longer time than expected. Tablets can be used to look at instructions of how to conduct the operation or if it has been any changes in the drawing. VR-glasses can give an instruction of how to conduct an operation and guide through an operations best practice. Gorecky et al. (2014) discuss that in order to develop an optimal model of how to conduct the work for an operator, the operator and the hardware movement should be tracked. Also, the movements from the operator with real-time data can provide adjustments if the operator has done something wrong or additional steps are needed in the operation the operator can get help by virtual reality to do their work in an optimal way.

RQ 3: How can a Lean Six Sigma (problem solving) project enhance the predictability in manual operations connected to Industry 4.0?

Industry 4.0 is a technology that increases the access of data where the technology enhances the use of more data that can be analyzed by techniques such as big data and AI, where Lean Six Sigma is a data driven methodology for solving problems. Jayaram (2016) discuss about how Industry 4.0 and Lean Six Sigma goes hand in hand where both concepts aim for the "ideal process" which proposes that a process that is free from defects. Industry 4.0 is a combination of different technologies that can be used to enhance the predictability, and a Lean Six Sigma project provides problem solving and identification of source of variation with its toolbox to improve predictability.

Lean Six Sigma has a structured way of solving problems with DMAIC. In the define phase the industrial problem is being defined where the question arises, "are we solving the right problem?" which could be seen in chapter 3.5 (table 6) that when it comes to defining the problem there were only two out of four studies that had a clear structure of how to define the problem, namely the studies by (Cemenek et al., 2017 & Chiabert et al., 2018). With the DMAIC- structure the define phase is used for defining the problem. But also, as mentioned by Antony & Banuelas (2002) a key ingredient for implementing Six Sigma is "project prioritization and selection, reviews and tracking". This proposes the selection of what kind of projects that is going to be conducted needs to be based on proper criteria, delayed results are something that can depend on the definition or selection of the problem. Three categories of what needs to be included in the project selection are: (1) business benefit criteria, (2) feasibility criteria and (3) organizational impact criteria (Antony & Banuelas, 2002). This is something that is not taken into consideration in all of the studies that has been reviewed, which is something that can help to increase the use and reliability of Industry 4.0 when it comes to improvement projects.

The measure phase is about to measure on the industrial problem with the help of Internet of Things where sensors are involved. All four studies that was reviewed in chapter 3.5 (table 7) have a structured method of how to measure the problem, which indicates that in this case Industry 4.0 technologies can be help for the Six Sigma problem solving method. When it comes to measure the problem, "can we trust the data?" With more reliable technologies that can assist the operator, for example automated measurements or VR-glasses that gives the operator instructions of how to conduct an operation. This helps to standardize a manual operation and increases predictability if everyone is using doing the same method.

The analyze phase is about Analyzing the industrial problem where breaking down of the process layout into more detailed steps to identify the sources of variation and enhanced predictability. With the help of the analyze phase identification of what causes the variation can be identified (Brook, 2017). With more data and more measurement points to analyze the chances to find the source of variation increase.

The improve phase helps to identify what, and how, Industry 4.0 techniques can be used to identify the root causes. Instead of just trying to implement Industry 4.0 on everything, the improve phase helps to identify what improvement area to prioritize.

The control phase is about controlling the processes with sensor data, the same as in the measure phase but in this case, there are control limits applied to signal if operations goes outside the control limits. Artificial intelligence can be embedded with a control plan to get real time response if a hardware goes outside the control limits.

As mentioned by Ranta (2019) about the three different steps that should be taken into consideration, the first step is what transformation the company wants to achieve, what is the goal? The second where to prioritize the resources. The third step is how and what of Industry 4.0 technology suits the companies needs best. The use of a Lean Six Sigma project defines the problem that investigate if we are solving the right problem which can be correlated with the first step from Ranta (2019). The second and third step from Ranta (2019) was developed in the measure phase where the MSA increased the number of measurement points to find source of variation within an operation. With the help Industry 4.0 technologies such as sensors and smartphones the data handling and reliability would increase because the operators don't need to keep track of the time by themselves.

Improvement suggestions was developed where VR-glasses can be used to make it easier for an operator to conduct its work which was also discussed in Goreck et al. (2014) about how this technique can assist the operator to conduct its work. Smartphones came up also as an improvement suggestion from the Lean Six Sigma project to increase the amount of data.

5.2 Choice of method

The Lean Six Sigma project was a big help to fulfill the purpose, with a given structure of how to approach the problem and a toolbox where many different tools that can be used. A given structure was used for the improvement project, DMAIC which increases the reliability. Continuously meetings were arranged with operators and managers that were involved in the project to discuss the findings from the project and to their point of view. The result could thereafter be changed or revised if a GKN employee disagree or have additional feedback on the results.

All of the managers that was interviewed have participated in a Six Sigma project which helped the author to conduct the improvement project since the ones involved knew what Six Sigma is about. Also, some of the managers have Six Sigma black belt or green belt which also indicates that the managers have knowledge and expressed their gratitude to perform such a project. From this, based on Antony & Banuelas (2002) 11 key ingredients 9 of these were fulfilled in the project, see key ingredients in table 4.

- Management involvement and commitment
- Training
- Organization infrastructure
- Project prioritization and selection, reviews and tracking
- Project management skills
- Understanding the Six Sigma methodology, tools and techniques
- Linking Six Sigma to business strategy
- Linking Six Sigma to customer
- Linking Six Sigma to suppliers

“Cultural change” from Antony & Banuelas (2002) key ingredients was not taken into consideration since this thesis was aim was not the implemented any solutions only describe the possibilities of the Industry 4.0 concept. Also, “linking Six Sigma to human resources” was not taken into consideration in this thesis since the author doesn’t have the authority to give rewards or promotions to the employees.

If the improvement project would have been conducted again it doesn’t have to give the same outcome since the manual deburring that was chosen for the project was mainly chosen because the choice of manual operations was based on the availability for the author to execute an improvement project. The interviews are dependent on what people that has been interviewed the answers could differ if other managers would be interviewed instead, for this thesis same questions were asked to the managers and similar answers was given for most of the questions. When it comes to the Industry 4.0 concept which is continuously improved and might be something completely different in just some years can influence the whole thesis if new technologies are implemented.

5.3 Future research

This thesis enhances the use of Lean Six Sigma when it comes to implement Industry 4.0 of where and what to implement and prioritize implementation of Industry 4.0 technologies. The Lean Six Sigma ended at improvement suggestions that needs to be developed further and investigate if it’s technical and economical feasible to implement Industry 4.0 technologies in manual operations. This study has only been investigating the possibilities of Industry 4.0 in manual operations and not taken the technical economic perspective into consideration. This project doesn’t cover all the phases from DMAIC but what could have further investigated is how Lean Six Sigma can enhance machine learning (AI).

Video surveillance, GPS-tracking and sensors on operators is something this thesis not have done any deeper study on but needs to take into consideration in further research in the Industry 4.0 perspective. However, having collaboration with the union is an important factor for continuously improvement. To keep up in the business area, improvement work and the latest technology is needed but also the company should provide “a great place to work” for the employees.

6 Conclusion and recommendation

This chapter concludes the results for the thesis. First the effect of having high predictability. Later on, conclusions about how predictability can be enhanced in manual operations is being concluded. Last but not least, this chapter concludes how Lean Six Sigma can be used in improving predictability in an Industry 4.0 perspective.

Predictability is vital within a high complexity and low-production rate company. The key drivers for the need to have high predictability are:

- Calculations of safety stock and capacity analysis
- Delivery time
- Winning business case – cost of product
- Satisfied customers
- Well-managed ramp-up of new product
- Ability to predict when the next hardware arrives to an operation step

Breaking down an operation helps to identify the source of variation. An overview of the operations does not give the same picture as breaking it down into smaller measurement steps. With Industry 4.0 comes the possibilities of increasing the amount of data enable deeper analysis of manual operations and the possibility to report reliable data.

From the Lean Six Sigma project, material variation was the main factor for variation in manual deburring, operator variation also existed but was difficult to fully explore as a list of operators was not accessible. Correlations between different tempo could be identified but the team members and employees were not able explain these correlation. Further investigation of how the material hardness is affecting the manual deburring needs to be further analyzed.

A Lean Six Sigma project helps to implement Industry 4.0 technologies in a way where identification of root causes shows where to prioritize the implementations of these technologies. Industry 4.0 can make the manual work more predictable. For example. VR-glasses can be used to instruct the best practice of an operation. Further, smartphones can be used to increase accuracy of reporting the correct time into SAP/R3 and increase the number of measurement points in a process step. This allows for a quantitative analysis of finding source of variation in a process step. Only looking at the cycle time at a process step doesn't give the whole picture just indicators of what is happening, if there are any patterns that needs to be further investigated. The five different phases in Lean Six Sigma influences and have been combined with Industry 4.0 technologies as a conclusion of how improvements can be executed:

- Define phase
  - Defines the industrial problem – are we solving the right problem?
- Measure phase
  - Measure the industrial problem – can we trust the data?
  - Industry 4.0 increases the amount and reliability of data – including sensors (IoT)
- Analyze phase
  - Breaking down of a process layout in more detailed steps helps to find to sources of variation and enhance predictability
- Improve phase
  - Efficient use of Industry 4.0 technologies -> smartphones, tablets, VR etc.
  - Machine Learning (AI) to improve production processes
- Control phase

- Control by sensor data and implement specification limits
- Machine learning (AI) to control production

Lean Six Sigma and Industry 4.0 goes hand in hand, Lean Six Sigma is a methodology that requires a lot of data for the quantitative part and Industry 4.0 is a technology that generates a big amount of data. Figure 19 show how the different phases from the Lean Six Sigma methodology can be combined with Industry 4.0 technologies.

When it comes to the personal integrity in the Industry 4.0 perspective further investigations needs to be done. What can be said from the findings of this study is that currently there is not a problem with conducting improvement projects if the purpose is made explicit to all affected by the project.

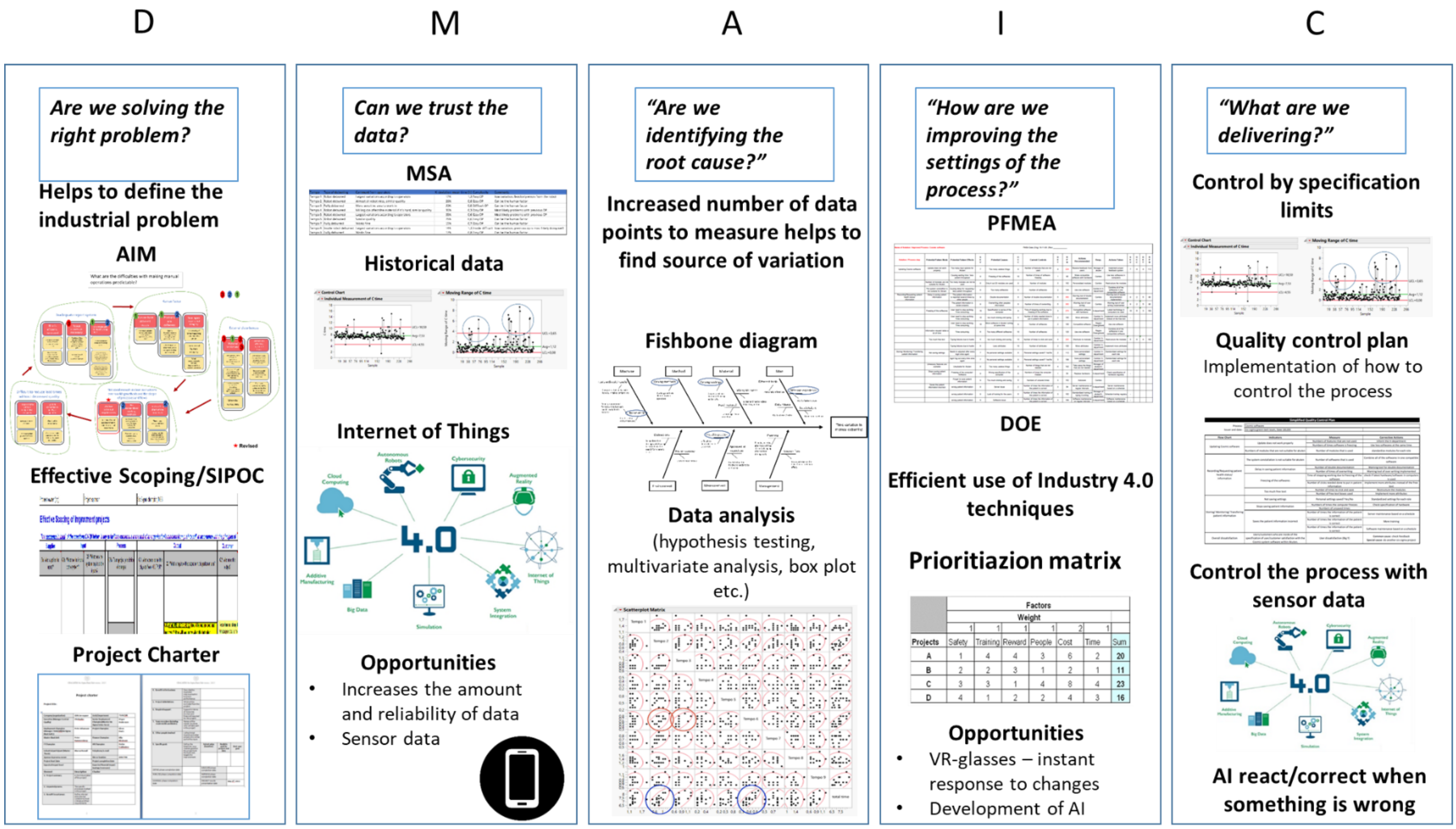


Figure 19. Lean Six Sigma combined with Industry 4.0.

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Appendix

Appendix A – Interviews managers and engineers

Bakgrund

Vad är din roll i företaget?

Vad är ditt ansvarsområde?

Hur länge har du haft det här ansvarsområdet?

Hur länge har du jobbat på GKN?

Vilka erfarenheter har du från tidigare förbättringsarbeten?

Förbättringsverktyg

Vilka olika förbättringsverktyg använder du dig utav?

Finns det något förbättringsverktyg utöver PPL och 8D som du skulle vilja använda mer men inte har tillräckligt med kunskap om?

Vilka faktorer är det som avgör vilken förbättringsmetodologi som ni ska använda er utav?

Har du använt dig utav Lean six sigma som förbättringsmetod kopplat till robusthet?

Om ja, hur påverkade det ditt arbete?

Varför använde du dig utav Lean six sigma som förbättringsmetod och inte någon annan förbättringsmetod?

Om nej, varför inte?

Hur viktigt skulle du säga att det är det med kunskap om Lean six sigma när det gäller förbättringsarbeten?

Hur viktigt tycker du det är med mätdata kopplat till ett problem?

Hur mycket tror du ledtiden säger om hur bra en operation går?

Hur jobbar du med operationer som har stor variation i cykeltid?

Har du initierat ett problemlösningsprojekt/förbättringsarbete baserat på ledtider?

Om ja, Varför?

Om inte, varför inte?

Industri 4.0 (robusthet)

Robusthet är viktigt när vi går mot högt automatiserade processer som man kan tänka sig för Industri 4.0, kan du kort formulera dig vad Industri 4.0 innebär för dig?

Vad är robusthet för dig?

Hur viktigt skulle du säga att robusthet är för företaget?

Vilka utmaningar ser du på robusthet kopplat till manuella operationer?

Hur ser du på manuella operationer kopplat till Industri 4.0?

Predikterbarhet

Vad är predikterbarhet för dig?

Varför behövs predikterbarhet?

Hur förhåller ni er till variationen i manuella operationer kopplat till ledtider?

Vilka typer av problem ser du relaterat till predikterbarhet i GKN´s manuella processer?

Hur påverkas ditt arbete utav stor variation i processerna?

På vilket sätt skulle du säga det påverkar andras arbete?

Hur hanterar du variationen i era processer?

Hur viktigt anser du att det är att ha en hög predikterbarhet?

Kopplat till robusthet vilka faktorer är det som avgör vilken förbättringsmetod som ska användas?

Vilka är dina tillvägagångssätt på hur ni implementerar robusthet i manuella operationer (kopplat till industri 4.0)?

Har du några konkreta exempel?

Hur arbetar du för att göra det möjligt att implementera Industri 4.0?

Vilka barriärer anser du finns det för att kunna implementera industri 4.0 i manuella operationer?

Hur tror du att mätsystemen i manuella operation ser ut om 10 år kopplat till Industri 4.0?

Facklig aspekt (endast head of operations)

Vilka fackliga regler är det som påverkar ditt arbete kopplat till manuella operationer?

Hur påverkar de fackliga reglerna ditt arbete i robusta manuella operationer kopplat till industri 4.0?

Vilka fackliga problem ser du på tidssättning kopplat till manuella operationer?

Appendix B – Interviews operators

Bakgrund

Vad är din roll i företaget?

Vad är ditt ansvarsområde?

Hur länge har du haft det här ansvarsområdet?

Hur länge har du jobbat på GKN?

Vilka erfarenheter har du från tidigare förbättringsarbeten?

Syfte

Hur viktigt tycker du det är med mätdata kopplat till en process?

Hur mycket tror du ledtiden säger om hur bra en operation går?

Hur jobbar du med operationer som har stor variation i cykeltid?

Hur registrerar du tiden det tar att utföra en operation?

Ser du att det finns några svårigheter att mäta tiden?

Vilka möjligheter ser du på att mäta tiden?

Manual operations

Vad är en manuell operation för dig?

Vad är robusthet för dig?

Vilka möjligheter ser du kopplat till robusthet i manuella operationer?

Industri 4.0 (robusthet)

Har du hört talas om industri 4.0?

Robusthet är viktigt när vi går mot högt automatiserade processer som man kan tänka sig för Industri 4.0, kan du kort formulera dig vad Industri 4.0 innebär för dig?

Vilka möjligheter/konflikter ser du i manuella operationer kopplat till industri 4.0?

Hur skulle det kunna underlätta ditt arbete?

Predikterbarhet

Vad är predikterbarhet för dig?

Hur påverkar predikterbarheten ditt arbete i manuella operationer?

Vilka typer av möjligheter ser du relaterat till predikterbarhet i GKN´s manuella processer?

Hur påverkas ditt arbete vid stor variation i processerna?

På vilket sätt påverkar det andras arbete?

Hur hanterar du variationen i era processer?

Hur viktigt anser du att det är att ha en hög predikterbarhet?

Förbättringsverktyg

Vilka olika förbättringsverktyg använder du dig utav?

Om ett problem uppstår i en operation, hur hanterar du det?

Hur rapporterar du ett problem som måste åtgärdas kopplat till själva operationen?

Finns det något strukturerat arbetssätt på hur ni ska åtgärda problem i en operation?

Finns det något förbättringsverktyg du skulle vilja använda mer men inte har tillräckligt med kunskap om?

Skulle du vilja mer involverad i förbättringsarbeten?

Vad är det som avgör vilket förbättringsverktyg som ni ska använda er utav?

Appendix C – Correlation matrix. Multivariate

Multivariate

Correlations

	Auto	Auto	Auto	Auto	Auto	Manual	Auto	Auto	Manual	Auto	Manual	Manual	Total time
Auto	1,0000	-0,0347	-0,0039	0,0620	-0,0025	0,0218	-0,1619	-0,0770	-0,0614	-0,0136	-0,1210	-0,2187	0,1134
Auto	-0,0347	1,0000	0,0229	-0,0392	0,0120	-0,0819	-0,1246	0,0141	-0,0670	0,0214	-0,0374	0,0817	0,0174
Auto	-0,0039	0,0229	1,0000	0,0130	-0,0108	0,0085	0,0761	-0,0681	0,0036	-0,0053	0,0328	0,1344	0,1155
Auto	0,0620	-0,0392	0,0130	1,0000	0,0638	0,0330	0,0188	0,0680	-0,0726	-0,0170	-0,0128	-0,1588	0,1307
Auto	-0,0025	0,0120	-0,0108	0,0638	1,0000	-0,0263	0,0936	0,0306	0,0179	-0,0161	-0,0579	-0,0569	0,0617
Manual	0,0218	-0,0819	0,0085	0,0330	-0,0263	1,0000	0,0114	-0,0444	-0,1526	-0,0531	-0,0474	-0,0238	0,2728
Auto	-0,1619	-0,1246	0,0761	0,0188	0,0936	0,0114	1,0000	-0,1988	-0,0615	0,0380	-0,0106	0,1575	-0,1588
Auto	-0,0770	0,0141	-0,0681	0,0680	0,0306	-0,0444	-0,1988	1,0000	-0,0550	-0,0023	0,0109	-0,0197	0,0591
Manual	0,0614	-0,0670	0,0036	-0,0726	0,0179	-0,1526	-0,0615	-0,0550	1,0000	-0,1239	0,0323	0,0189	0,1626
Auto	-0,0136	0,0214	-0,0053	-0,0170	-0,0161	-0,0531	0,0380	-0,0023	-0,1239	1,0000	-0,0850	0,0243	0,0739
Manual	-0,1210	-0,0374	0,0328	-0,0128	-0,0579	-0,0474	-0,0106	0,0109	0,0323	-0,0850	1,0000	-0,0459	0,4273
Manual	-0,2187	0,0817	0,1344	-0,1588	-0,0569	-0,0238	0,1575	-0,0197	0,0189	0,0243	-0,0459	1,0000	0,0430
Total time	0,1134	0,0174	0,1155	0,1307	0,0617	0,2728	0,1588	0,0591	0,1626	0,0739	0,4273	0,0430	1,0000

Appendix D – compilation of data sampled from MSA-study

Robot error | Q3 | No robot deburr

Övrigt	Ordernum	Tempo 1	Tempo 2	Tempo 3	Tempo 4	Tempo 5	Tempo 6	Tempo 7	Tempo 8	Tempo 9	Totaltid
Tid		1,3	0,5	0,8	0,4	0,4	0,6	0,5	1,3	0,9	**6,7**
~~Tid~~		~~2,5~~	~~0,5~~	~~1~~	~~0,2~~	~~2~~	~~1,5~~	~~1~~	~~2~~	~~0,5~~	~~**11,2**~~
Tid		1,3	0,9	0,8	0,5	0,7	0,6	0,8	1,2	0,7	**7,5**
Tid		1,2	0,6	0,7	0,2	0,7	0,5	0,7	1,2	0,7	**6,5**
Tid		1,2	0,6	0,7	0,6	0,5	0,5	0,6	1,2	0,7	**6,6**
Tid		1,3	0,5	0,8	0,4	0,4	0,6	0,5	1,8	1	**7,3**
Tid		1,2	0,8	0,7	0,2	0,3	0,4	0,8	1,4	0,7	**6,5**
Tid		1,3	0,8	1,2	0,3	0,7	0,8	0,7	1,2	0,8	**7,8**
Tid		1,3	0,8	0,8	0,2	0,3	0,4	0,8	1,5	0,7	**6,8**
Tid		1,4	0,8	1,1	0,3	0,3	0,6	0,9	1	1	**7,4**
Tid		1,3	1	0,8	0,2	0,3	0,7	0,8	1,4	0,8	**7,3**
~~Tid~~		~~1,5~~	~~1,2~~	~~0,7~~	~~0,7~~	~~0,7~~	~~0,7~~	~~0,7~~	~~0,7~~	~~0,7~~	~~**7,6**~~
Tid		1,2	1,3	1	0,4	0,6	0,9	0,8	1,3	1	**8,5**
Tid		1,3	0,7	0,8	0,3	0,9	0,5	0,8	1,5	0,7	**7,5**
Tid		1,5	1	1,2	0,3	0,7	0,8	0,7	1,2	0,8	**8,2**
Tid		1,4	0,7	0,7	0,2	0,6	0,5	0,8	1,2	0,8	**6,9**
Tid		1,4	1,1	0,8	0,3	0,6	0,7	0,7	1,4	1,2	**8,2**
Tid		1,3	0,8	0,7	0,3	0,7	0,4	0,8	1,2	0,8	**7**
Tid		1,2	0,7	0,8	0,2	0,9	0,8	0,7	1,5	0,7	**7,5**
Tid		1,9	0,7	0,7	0,3	0,6	0,5	0,6	1,2	0,8	**7,3**

Appendix E - MSA form

Mätsystemanalys på manuell gradning [redacted]

Namn & anställningsnummer:________________________ Ordernummer: [redacted]

Startdatum & starttid: 2019-04-04________ Totaltid (ex. 7,8 h 8,9 h): 6.5

Information

Operationssteg – Visar de olika stegen som innefattar gradoperationen.
Tid – Den faktiska tiden det tar att utföra just det operationssteget i timmar (ex. 1,3 h, 2,7 h).
Verktyg – Namnet på verktyget som användes för att genomföra operationssteget.
Ordning – Vilken ordning tog ni steget i. ex Tempo 1 utfördes först och då ska "1" skrivas in i kolumnen, om Tempo 4 utfördes efter Tempo 1 då ska "2" skrivas in i kolumnen.
Kommentar – kan innefatta varför operationen tog längre/kortare tid än vanligt eller om det var skiftbyte. Vid skiftbyte ange då namn och anställningsnummer.

Op-steg	Tid	Verktyg	Ordning	Kommentar
Tempo 1	1,2		1	
Tempo 2	0,8		3	
Tempo 3	0,7		4	
Tempo 4	0.2		2	
Tempo 5	0.3		5	
Tempo 6	0.4		6	
Tempo 7	0.8		7	
Tempo 8	1,4		8	
Tempo 9	0,7		9	

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Appendix F – Multivariate correlations between tempos

Multivariate

Correlations

	Tempo 1	Tempo 2	Tempo 3	Tempo 4	Tempo 5	Tempo 6	Tempo 7	Tempo 8	Tempo 9	total time
Tempo 1	1,0000	0,0058	0,0566	-0,0843	0,0181	-0,0699	-0,1711	-0,2550	0,1659	0,1955
Tempo 2	0,0058	1,0000	0,4110	-0,0725	0,0384	0,5369	0,5408	-0,1687	0,3601	0,7369
Tempo 3	0,0566	0,4110	1,0000	0,0377	0,0591	0,6827	0,1705	-0,2713	0,2780	0,6579
Tempo 4	-0,0843	-0,0725	0,0377	1,0000	0,0176	0,1016	-0,3938	-0,1235	0,1286	0,1034
Tempo 5	0,0181	0,0384	0,0591	0,0176	1,0000	0,2725	0,0089	-0,0655	-0,2424	0,3614
Tempo 6	-0,0699	0,5369	0,6827	0,1016	0,2725	1,0000	-0,0688	0,0000	0,4003	0,8087
Tempo 7	-0,1711	0,5408	0,1705	-0,3938	0,0089	-0,0688	1,0000	-0,3378	-0,1428	0,1482
Tempo 8	-0,2550	-0,1687	-0,2713	-0,1235	-0,0655	0,0000	-0,3378	1,0000	0,0748	0,0099
Tempo 9	0,1659	0,3601	0,2780	0,1286	-0,2424	0,4003	-0,1428	0,0748	1,0000	0,5328
total time	0,1955	0,7369	0,6579	0,1034	0,3614	0,8087	0,1482	0,0099	0,5328	1,0000