Investigating Robustness to Variation for Increased Net Output in Production Flow

A Statistical Approach to Transitioning from Mass Inspection to Robust Process Control for Improved Cycle Times

Master's Thesis at the Department of Industrial and Materials Science

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Abstract

In modern industrial manufacturing processes, a deep understanding of process variation and the system's inherent robustness is crucial for maintaining high product quality and at the same time improving the process performance. This master thesis project which has been performed in collaboration with SKF Sverige AB aims to systematically analyze and identify the factors that affect robustness, in one of the company's production flows for producing rollers.

The primary objective of the project is to enhance machine utilization and solve a specific cycle time problem within the existing production line, with a clear requirement that the optimization performed should not result in sub-optimization in other parts of the system. In order to approach the problem systematically and with a data-driven approach, the study is structured around Six Sigma, and its proven DMAIC- framework (Define, Measure, Analyze, Improve, Control). In the project's early phase, a combination of qualitative and quantitative tools were applied, including Affinity-Interrelationship Method (AIM), detailed process mapping, and Cause & Effect- Matrix. These methods were applied to systematically break down the problem, filter out irrelevant variables, and determine the current state of knowledge. Following this, the reliability of the current measuring equipment was assessed using a Measurement System Analysis (MSA) to evaluate whether the existing system was to actually detect the upcoming variation. To then isolate and analyze how key parameters such as tool wear, cycle time variations, and the choice of machine affect the process's outcome, Design of Experiments were applied. The experimental design was then complemented by Bayesian optimization to find the optimal process parameters, in an efficient way.

The results from the statistical analyses highlight the measurement equipment's actual ability to detect real product variation. Furthermore, the study identifies which of the tested parameters have a statistically significant impact on the process outcome, and separates them from what can be defined as process noise. Based on these insights, the study serves as the foundation for improvements that will enhance the resource efficiency in the bottleneck machine and increase the net output of the production flow.

Keywords: Process Variation, Six Sigma, DMAIC, MSA, DOE, Bayesian Optimization

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Conducting this research required information and knowledge from different departments within the production site. A significant part of the project is owed to the process operators on the shop floor. The commitment and curiosity from you regarding data gathering, experimental testing, and willingness to share information about the process was crucial for the outcome of this thesis. Also thank you to Michael Jacobson from process development for providing valuable insights about Six Sigma, and useful tools for conducting the research.

Finally, I would like to thank my academic examiner and supervisor at Chalmers, Peter Hammersberg, for his commitment, valuable insights, and expertise in how a research like this should be conducted.

Hugo Ringeby, Gothenburg, May 2026

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

AIC	Akaike Information Criterion
AICc	Akaike Information Criterion correction
AIM	Affinity-Interrelationship Method
ANOVA	Analysis of Variance
BO	Bayesian Optimization
C&E	Cause and Effect
DMAIC	Define, Measure, Analyze, Improve, Control
DOE	Design of Experiments
EI	Expected Improvement
EMP	Evaluating the Measurement Process
EWMA	Exponentially Weighted Moving Average
GP	Gaussian processes
ICC	Intraclass Correlation
MES	Manufacturing Execution System
MSA	Measurement System Analysis
ndc	Number of Distinct Categories
NDT	Non-Destructive testing
OFAT	One-Factor-At-a-Time
PLC	Programmable Logic Controller
QMS	Quality Management System
TQM	Total Quality Management

Nomenclature

Below is the nomenclature of indices, sets, parameters, and variables that have been used throughout this thesis.

Indices

i	Index for experiment
j	Index for factor

Parameters

λ	Smoothing coefficient for the EWMA chart
L	Amount of levels for each factor in a full factorial design
M	Amount of investigated factors in a full factorial design
N	Total experimental runs

Variables

β	Parameter vector / coefficients
$\hat{\beta}$	Estimated coefficients
β_0	The intercept
β_j	The coefficient for each factor j
ϵ	The error term of the model
H_0	Null hypothesis
p	Probability / p-value used for assessing statistical significance
X	Process inputs or variables / The model matrix
x_{ij}	Set value for factor j in experiment i
Y	Key Process Output or response

y	The dependent variable that is measured
$\hat{y}$	The predicted response.

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1 Introduction

In a process or a product, variation is the contrast between expected and achieved outcome, it defines the uncertainty of a process or a system [1]. In an industrial perspective, variation affects both the production itself, and also the final product. To understand a system's sensitivity to variation is essential to be able to improve the performance of the production. Variation is often a result of so called noise factors, and control factors. Noise factors are expensive or impossible to control and are often defined as the main reason why variation arises in production [2], while control factors also affect but are easier to control and manage.

To handle and understand variation, the concept of robustness has become central within quality management [3]. A process that is non sensitive to variation, is defined as a robust process. Dr. Genichi Taguchi, who developed the concept during the 1950s, defined robustness as a condition where the technology, product, or the process is minimally sensitive to factors that cause variability, regardless if it is occur in the manufacturing- or user environment [1].

There are two approaches that can be applied to handle variation, and improve quality performance. Either redesign a whole process which is expensive and often not considerable. Instead, a "robust engineering approach" can be applied, making existing processes more patient against different factors.

The strategy behind robust design is based on identifying settings for design factors that neutralizes the effect of noise factors [3]. Experimenting on this comes with challenges as the values of noise factors are randomized in reality. As a solution to this, simulation based data models can be used together with industrial data. By combining simulation, regression modeling, and robust design methodology, robustness within a production flow can be studied without disturbing the production.

1.1 Background

1.1.1 SKF

The presented master thesis is performed at SKF AB Sverige, in Gothenburg, Sweden. SKF is a world leading global manufacturer of bearings, seals, lubrication systems, condition monitoring, and related services [4]. Founded in 1907, the company has a strong history of performing technological development to reduce friction and optimize motion. Today, SKF operates in around 130 countries, with 38 000 employees and serves around 20 different industries.

The specific study in this thesis investigates the robustness to variation in a roller manufacturing department, where large size rollers are hard machined before getting assembled together with cages and rings in other departments. The process transforms already heat treated, soft machined rollers into fully functional rollers that meet all quality standards that SKF promises and requires to be delivered to customers. Produced rollers are both delivered to assembly departments internal within SKF Gothenburg, but also external to other SKF sites around the world.

1.1.2 About the production flow

The investigated production flow has a cellular layout with different machines located in three different sub-cells. Three industrial robots are used to transport the material between machines and cells. The process involves 1 infeed station, 2 turning machines performing the same operation, 1 honing machine, 1 measuring machine, 1 Non-Destructive testing (NDT) machine, 2 visual control stations and one pallet station for finished products. The flow requires two operators to be able to produce at 100% speed. Incoming material is defined as RQ rollers and finished products as RS.

Incoming RQ rollers are manually transported to the infeed station in sub-cell 1, where the industrial robot 1:1 picks them and moves to a buffer place. The same robot move rollers from buffer station to the turning machines. After turning operation, rollers are moved with robot 1:1 to measurement station before industrial robot 1:2 moves them to sub-cell 2 and the honing station. Rollers are moved from honing station to NDT machine with conveyor belt, and after NDT operation, robot 1:2 moves finished rollers to measurement station, before being moved to manual inspection 1. Industrial robot 2 moves rollers to sub-cell 3 and manual inspection 2, before being packed into finished pallets.

1.1.2.1 Quality assurance

RQ rollers are delivered from distributor with a certain addition on the diameter and length dimension. This addition ensures that the turning machine cut across the whole roller, as the machine has parametric numerical controlled programming that moves the cutting tool over the same coordinates for each roller.

To deliver final rollers with nominal measurement, an offset value is used to determine the required measurement value from the turning operation, before the product is machined in the honing machine. This offset value is first programmed by the operator and is then automatically controlled i turning machine, based on the results from the measurement station. When rollers have been measured in the stage between turning and honing, the system compensates the turning machine, to meet the determined offset value.

When the rollers have been machined in the honing machine and checked by the NDT machine, the final measurement of the product is determined by the same measurement station that is used between turning and honing operation. The measurement station is therefor used for two reasons, first control the turning machine, and second verify and determine the final measurement of the product.

Before being packed into pallets, a manual visual inspection is performed on all rollers on two different stations to ensure that the whole product have been controlled. The first station has a maximum level of three rollers and the second 28, operators choose by themselves when to approve the rollers.

1.1.2.2 Product variants

As the production flow is capable of producing a lot of different roller types with different dimensions, constant variation affects the flow regularly. The varying size determines the cycle times for the different machines. For the turning the machine, the same program and tools are used for all types, only the coordinates controlling the numerical programming are changed. For the honing machine, certain tools need to be changed for each type, and the machine setting differs regarding pressure, time, and length. The measurement station has an adjustable height scale that can be changed depending on the length of the roller, to save time during measurement. For the NDT machine, some tools are changed and the program updates itself when the new type is being registered.

Regarding the material handling for the different product variants, the industrial robots have different tools for certain dimensions that needs to be changed manually by operators during set ups. There is a bypass function that can be activated, which causes some rollers being transported directly from the turning machine to the honing machine. This function can be activated manually by operators and the value of how many rollers that can be bypassed can also be set manually. However, there is no standard or instruction on which types or how many rollers that should be bypassed.

1.1.3 About the problem

The production flow experiences inefficiencies that affects the cycle time for one produced unit negatively. Numbers from the Manufacturing Execution System (MES) system shows that the cycle time for one produced unit is clearly greater than the cycle time in the bottleneck machine, which should control the final cycle time [5]. In combination with numbers from MES system, visual observations supports that the bottleneck machine suffer an inefficient resource efficiency, meaning that it has to much idle time, waiting for material to be moved and delivered.

As the production flow is capable to produce a lot of different roller dimensions, certain types with different dimensions has been investigated. Figure 1.1 shows the actual cycle time gathered from the MES with the red staples, and the cycle time in bottleneck machine with the blue staples. Each letter on X-axis represent a certain product type, and all produced types over 2025 have been included. The cycle time for bottleneck machine has been calculated with a formula, and verified by comparing it in reality. The reported cycle time in the MES system is based on when the flow runs optimally, meaning that tool changes, down times, resetting, breakages, and other disturbances is separated and not investigated.

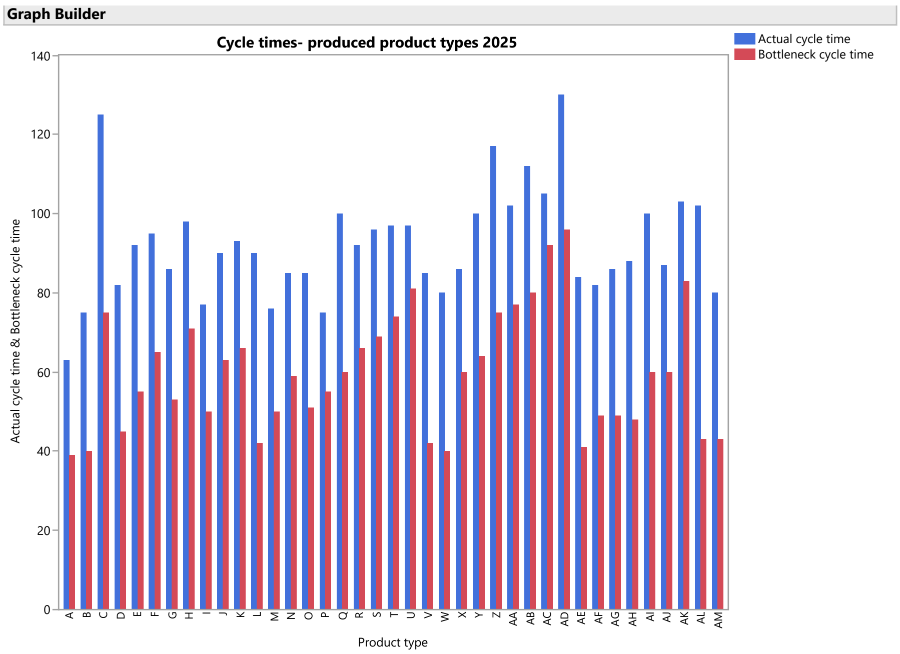


Figure 1.1: Cycle time in Bottleneck machine Vs. Actual cycle time

Figure 1.1 display that there is a varying difference between actual cycle time and cycle time in the bottleneck machine for different roller types. For some types, the actual cycle time is up to 100% greater, while for some other it is 40% greater. Figure 1.2 presents an Individual & Moving Range chart over the difference between the two cycle times.

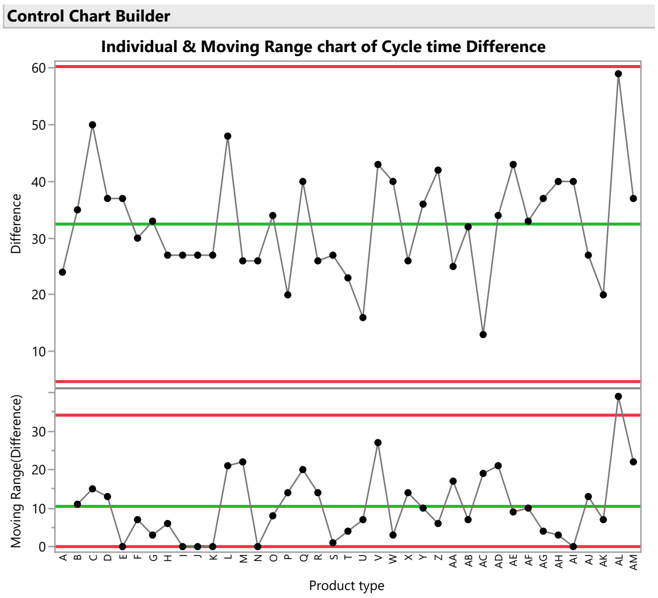


Figure 1.2: Individual & Moving Range chart over cycle time difference

1.1.4 Purpose

The purpose is to analyze and identify which factors that affects the production flow's robustness, to push the frontier of knowledge forward. An increased knowledge in understanding the robustness to variation will help the company to increase efficiency and the problem at the given production flow, without doing sub-optimizations. The purpose involves research in both process related factors and external factors, where the aim is to separate controls and noise from each other. Example of process related factor can be cycle times, while an external factor can be dimension of raw material.

The project will first evaluate the general research questions, with the purpose of developing more specific research questions that will gain the valuable information for the company. The first formulated questions will set the direction and goal, to later be able to aim for that goal and formulate more specific research questions. The purpose of this is to follow an upstream process, ensuring that all improvements will be based on facts and an understanding of how it is connected to the system, answering the question why it is important and interesting for the company.

1.1.5 Delimitation

As a big part of the projects purpose is to avoid sub-optimizations, no delimitation in input factors can be defined in the early stages. The effective scoping and identification of current state is performed with the certain process flow in center. In that case, it is limited to the process flow itself and not involving support functions or outside processes during the first analyzes. However, as the first step of the project will set the direction, it can end up with an investigation in a support function despite being limited to the process flow in the beginning.

As the time is limited to 20 weeks and to fulfill the purpose to avoid sub-optimizations, focus will be on analyzing and identifying the factors that affects the robustness, rather then running into quick improvements that can end up becoming a sub-optimization. Focus will be to develop a study that can be beneficial for SKF in future projects.

1.1.6 Research Questions

To fulfill the purpose of the project, which is to analyze and identify which factors that affects the production flow's robustness, to push the frontier of knowledge forward, the report will address two research questions. To be able to push the frontier of knowledge forward, the first step is to analyze and evaluate were the actual knowledge regarding variation is located today. Therefore the first research question is:

- Where is the frontier of knowledge today, regarding understanding of variation?

  When the frontier of knowledge is identified, the next step is to identify which factors that affects the robustness the most, and how different they, or the correlation between them can impact the researched (Y) of the project. An important step to understand how different factors affect the robustness, is to define which factors that are noise, and which are controllable. The second research question is:

- Which factors affects the robustness the most?

As these two formulated question more serve as investigation question rather than actual research question, the final research question, based on the findings presented in the report is formulated as:

- Can mass inspection be eliminated in order to optimize the material handling between machines, to increase the resource efficiency in bottleneck machine?

1.2 Structure of the report

Chapter one, *Introduction*, provides the concept of robustness to variation which is the basis of the project. It also presents the background of SKF and the problem given from a company perspective. Followed by a definition of the project, consisting of purpose, delimitation, and research questions.

Chapter two, *Theory*, describes the different concepts and theoretical frameworks that the project covers and are using. It provides the reader with a deeper understanding of how different theoretical concepts are defined by theory, to facilitate the understanding when they are applied later in the report.

Chapter three, *Method*, covers the different tools and methods that are used during the project to conduct the research. It describes how they are used in relation to the given research.

Chapter four, *Problem Definition and Current State*, presents results from the early findings, describing the state of the given production flow when the project started. An essential step for providing the reader what actual problem that the final analysis will focus on evaluating.

Chapter five, *Analysis* presents the analysis performed on the defined problem, with the tools presented in the theoretical framework and method chapter. The chapter answers the defined research questions.

Chapter six, *Discussion & Conclusion* discusses the used methods and final result, it covers how the company can use the study, and finally the conclusion is presented.

2

Theory

In the following chapter, all theories, methods, concepts, and definition that the project covers, is presented. These form fundamental parts throughout the project, and are essential to be able to investigate and analyze the given problem.

2.1 Quality Management

Quality can be defined as a level of goodness or value, and is one of the most common tools an organization trusts to reach its goals [6]. Historically, the view on quality has developed a lot. In the early 1900's, the main focus of quality was to reduce cost. During the 70's to the 80's, the Japanese shifted focus into a more quality assurance perspective. In the late 80's, the western world realized that quality can be a strategic competitive advantage and a broader view of quality grew up, which is called Quality Management.

In today's organizations, quality management is a management philosophy that is driven by continuous improvements and responsiveness to customer needs and expectations. The focus of organizations has broadened to encompass not only the final product or service, but also resources, materials, personnel, procedures, and relations with stakeholders.

2.1.1 Total quality management

The concept of Total Quality Management (TQM) grew up as a quality revolution during the 1980's to 1990's [6]. The philosophy was inspired by quality experts as W. Edward Deming and Joseph M. Juran from the 1950's, but was later developed by Japanese companies, with Toyota as an example.

TQM describes the culture and attitude of the organization, where the continuous aspiration is to offer products and services that satisfies customer's needs. It can be described as a business philosophy that is related to the organization's management system. With the aim to improve the results and financial performance, ensure long-term survival through a consistent focus on increased customer satisfaction, meet the needs of all stakeholders, including customers, employees, owners, and suppliers. It also aims for fostering an environment that facilitates a never-ending process of continuous improvement, and works to eliminate waste and rework.

2.1.2 Quality Management Systems

Quality Management System (QMS) is built on TQM and is a collection of processes that aims to fulfill customer's expectations, and continuously enhance their satisfaction in a reliable way [6], [7]. The system is defined to align with the organization's overall goals and strategic direction. It describes and formulates objectives, strategies, procedures, documented information, and resources that are required. The most common standard for QMS globally is the ISO 9000 family, where ISO 9001 consist of specific criteria that organizations must fulfill to be certified.

2.1.3 Deming's 14 points of quality management

Deming established that quality is funded in humans, and that an organization's most important asset is their employees [8]. Total quality management is a philosophy that empowers the whole organization and encourages each individual to contribute with improvements [9]. To help people understand and to implement this mindset, Deming made a list of 14 points that are vital for employees to feel satisfied in their daily work.

Create constancy of purpose, the first principle. The board needs to create a constant purpose of continuously improving products and services. Resources should be allocated for long term needs, and for the survival of the company, rather than only focusing on short term profitability [9].

Adopt to the new philosophy. Mistakes, defect, and delays can not be accepted in the current age. A total conversion of the western leadership style is necessary to avoid an industrial decline [9].

Stop depending on inspection. The need for mass inspection to achieve top quality should be eliminated, quality of the product should be an outcome from built in quality in the process [9].

Focus on Total cost, Not Price Tag. Do not only choose distributor based on price, focus on requirements that can ensure quality. Reduce the amount of distributors and strive to minimize the total cost instead of the initial cost [9].

Improve constantly and forever. Work continuously with identifying problems that can improve the process or product. This increases the quality and productivity, which leads to constantly reduced costs [9].

Institute on the job training. Implement modern methods for education in and for the workplace. This should be done for all roles over the organization, so that the organization can better benefit from all employees [9].

Institute leadership. Implement modern methods for work management with the focus on helping people and machines to perform a better job. Managers should move focus from numbers and volume, to quality [9].

Drive out fear. Encourage efficient two way communication to drive out fear from the whole organization. This is crucial to make everyone work more efficiently and productivity [9].

Break Down Barriers. Break down the barriers between different departments. People within research, design, retailing, administration, and production must act as a team to handle products and services [9].

Eliminate unclear slogans. Avoid the usage of slogans that encourages the manpower to "zero defect" and new production volumes, without providing methods on how to get there. This only creates contradictory relation with the manpower, as common causes to decreased quality often is out of the worker's control [9].

Eliminate Management by Objective. Eliminate working standards that prescribes numerical targets and quotas. Replace this with a supporting leadership and use statistical methods for continuous improvement [9].

Remove Barriers to Work Pride. Remove barriers that deprives worker and managers right to feel pride over the work. It means, among other things to abolish annual merit ratings and management by objective [9].

Implement Education & Self-Improvement. Implement a powerful program for education and retraining. New skills is required all the time to keep even steps with changes in material, methods, technology, and product design [9].

Make Transformation Everyone's Job. Clarify the top management's permanent commitments for continuous improved quality. Create a structure in top management that daily pushes to implement the previous 13 points [9].

2.2 Statistic process control and system variation

2.2.1 Common Cause vs. Special Cause

To be able to control and improve a process in an efficient way, a deep understanding regarding which type of variation affecting the system is required. Defined by established statistical theory, variation is divided into two main categories; common cause and special cause variation [10] [11]. Common cause is built in to the system's design. It represent the common measurement noise and the combined effects of many small, non investigated factors that constantly exist in the process [10]. A process that only indicates common variation, is defined to be in statistic control and predictable within its control limits.

Special variation is instead caused by specific, identifiable causes outside of the system. Such as, machine breakdown, defect raw material, or measurement errors due to environmental factors [11]. A common mistake within quality management is to confuse these two types of variation. To act or adjust a machine based on data that is only based on common cause variation, is defined as *"tampering"* [10]. This acting, does not stabilize the process, instead it introduces more variation to the system.

2.2.2 The Pitfalls of Mass Inspection

Within the frame of Deming's quality philosophy, more specific the third point regarding to eliminate the need for mass inspection, It is emphasized that 100% inspection of products is an ineffective strategy for quality assurance [11]. Mass inspection means that quality is achieved by trying to control it, rather than create it in the actual process. When a process is located within its statistic control and have high capability, a continuous measuring procedure is does not contribute to any value adding performance.

Mass inspection is therefore more defined as a contribution factor to waste of time and resources, leading to unnecessary bottlenecks of the system [11]. Moving from mass inspection to a data driven, sample based measurement interval, reduces the lead times without compromising on the quality, provided that the underlying stability of the process has been statistically verified [11] [12].

2.2.3 Process Behavior and the Flaw of Averages

When analyzing data gathered from production, it is common to trust mean values when evaluating performance, which can lead to misinterpretations. This phenomena is called *"The Flaw of Averages"* [13]. Performing operational decisions only based on average conditions, hides the actual variation and the outliers in a distribution, which means that bottlenecks can be missed [13]. To facilitate a robust analysis, it is essential to study the whole distribution and variation in a system, rather than only looking at the average.

2.2.4 Exponentially Weighted Moving Average (EWMA)

Traditional Shewhart control charts, such as XmR- or X-bar charts are well proven tools for assessing process behavior. However, they are primarily designed to detect relative large and sudden deviations in a process. While monitoring high capable processes where the common variation is remarkable small, these diagrams tends to be insensitive to smaller, incremental changes [14].

To handle this, *Exponentially Weighted Moving Average* (EWMA) charts is often used. EWMA is a statistical method that calculates a weighted average of a time-ordered sequence of measurement data. Unlike traditional charts that primarily evaluate the latest measurement value against control limits, EWMA includes all historical data to its calculation. The model applies a weight factor where he latest gathered observations are given the largest weight, while the older data is given an exponential decreasing weight [14].

The sensitivity of the EWMA chart is controlled by a smoothing coefficient, λ. A small value of λ is chosen when slower or more frequent changes in the process average wants to be detected [14]. This smoothing effect filter out the short term noise, and visualizes small, systematical trends, such as gradually machine- and tool wear, long before the process is at risk to generate products outside of the tolerance limits.

2.3 Six Sigma

Six Sigma is a business strategy and quality methodology that focuses on continuously improving processes, minimizing waste, and eliminating causes of defects [15]. The concept was originally introduced by Bill Smith at Motorola in 1986 [16]. Today, the method is applied for reducing cost, cycle times, and to a greater degree to meet customers expectations. The starting point is that a systematic way of working leads to a more efficient resource utilization and increased customer satisfaction [15].

From a statistical perspective, Six Sigma is the definition of a process when the distance between the process mean value and the closest tolerance limit is at least six times the standard deviation . The main objective is to centralize the process exactly around its target value and reduce the process variation [17]. In practice it means that a process that has reached a six sigma level, performs at its highest state with 99,99966 percent of its products or services delivered without any defects. This corresponds to only 3,4 defects on one million possibilities [17].

Six Sigma differs from many other initiatives, by its rigorous and disciplinary way of working. Problem solving and decisions are always based on collected data and objective facts, instead of assumptions . To thrive and structure the improvement work in existing processes, the method trusts the standard procedure of DMAIC (Define, Measure, Analyze, Improve, Control) [15], [16], [17]. The implementation of Six Sigma requires a strong “top-down”- perspective, which means that the initiative and engagement needs support from the top management [15]. The work is structured in project form and should be led by individuals who have performed certain training in the methodology, responsibility should be divided in hierarchy of roles.

One central principle of Six Sigma is the integration of proven quality management tools, and how they play a central part of the framework. In the early phases of a project, the tools facilitate the transformation of qualitative data into quantitative data that is measurable. This ensures that the organization has the correct definition and requirements of the problems, which makes it easier to utilize resources in a correct way.

2.3.1 DMAIC

Within Six Sigma, DMAIC is the central method for systematically improving existing processes [18]. The structure reminds of Deming's Plan-Do-Check-Act cycle, but differs with its strong emphasis in statistical analysis and data driven decisions. The core of DMAIC is to methodically convert a diffuse organizational problem to a specific measurable statistic problem, to be able to identify and solve the root causes.

Define- In the early stages, focus is to understand the problem and establish clear definitions for the project. The goal is to identify what causes deviations from the customer's expectations, and break down these to measurable goals [18]. To map the process and create consensus among the stakeholders, tools as flow charts and SIPOC-diagram can be used [15].

Measure- When the problem is defined, the work moves further to gather reliable data, making sure the current state of the process is established, which creates the baseline for future comparisons. In this state, the problem is translated to a measurable condition [18].

Analyze-In the analysis phase, the collected data is examined in depth to identify the relationships between variables and determine the true root causes of the problem. Often, several potential causes are found, and these must be prioritized. Common tools in this phase include Pareto charts (to see which errors are most common), Ishikawa diagrams (cause-and-effect diagrams), and logical hypothesis testing. By analyzing data, an organization can find critical bottlenecks [18].

Improve- With root causes identified and verified, the purpose with the improvement phase is to develop and implement solutions that can eliminate the losses. The solutions are analyzed carefully to ensure that they solve the actual root causes, and not only is a sub-optimization [18].

Control- The ending phase aims to ensure that the reached improvements are maintained over time, so that the process does not returns to its earlier, defect condition. To achieve a sustain solution, the working methods should be standardized. Control charts and monitoring diagrams is often used here [18].

2.4 Effective scoping

Effective scoping is a tool used in the define phase of a six sigma project [19]. It can be used to characterize the problem, not just by defining the problem but also how the problem can be quantified, and how progress can be measured. The tool is built on pull-thinking and starts with looking at what comes out of the process before looking at the actual process or resources. A central concept of the tool is to define the primary cause and understand the correlation between the small “y’s” and big “Y’s”, which can be defined as what process step (small y), should be improved to increase the customer satisfaction (big Y).

Common mistakes when running a project is to run into quick improvements because data is easy to gather in some areas. Effective scoping facilitates a thinking that helps to avoid these sub-optimizations and a mindset that is locked in too early in the improvement phase. The method also clarifies who is responsible and accessible for each process, which is beneficial later in the project.

2.5 Affinity Interrelationship Method

Affinity-Interrelationship Method (AIM) is a problem solving tool designed for gathering, structuring, and analyzing qualitative data [20]. The method is built on a systematic approach of two of the so-called “7 management tools”, which are affinity diagram and interrelationship diagraph. The purpose with AIM is to create a common understanding of complex problems by processing verbal data, as words and sentences, more than numerical data. This method is used in the early stages of a Six Sigma project to identify and clarify where the frontier of knowledge is today, where the organization stands when it comes to knowledge regarding the investigated problem.

AIM is described by Alänge as a “bottom-up” process that transforms concrete facts and experiences from the participants, into more overall describing headings [20]. The process starts with gathering data from all the participants, regarding the chosen topic. It is described as a “brainwriting” process to ensure that all participants contribute regardless of personality and that the participants can inspire each other.

After each participant has written their thoughts on post it papers, the team together clarifies the meaning of each paper, ensuring that everyone has understood and that the statement is accurate. When all of the papers are gone through, they are grouped together based on affinity. The team decides together which topics are connected to each other and creates a heading for each grouping. Grouping can be done from 1 up to 3 levels, depending on how easy it is to separate them from each other.

To build on the affinity phase and the different created groups, interrelationship between them is analyzed by the team. The purpose is to identify cause and effect relations or contradiction, between the groups. In the end, the final goal with the AIM is to prioritize which factors that have the most impact on the investigated problem. This is done by a voting process where each participant gives different scores to the different topics analyzed. By following this procedure and selecting a winner, simple words and thoughts from different workers can transform into useful data about where the organization is located today, and where to start with improvement work. This is an essential step in the Define (D) phase.

2.6 Process map

A process map is fundamental tool within Quality Management and Six Sigma that aims to identify, understand and illustrate how input- and output signal in a system are connected [21]. The foundation of the tool rests on the mathematical concept $Y = f(X)$, meaning that process output after result (Y) is a straight function of its gathered input variables (X) [22]. Process map forms the basis for continuous improvements and is used to generate a gross list over all potential factors that affects the variation in a process [21].

Process map is often confused with Value Stream Mapping (VSM), but a process map gives deeper insight. VSM is primarily used for illustrate the flow of the process with the aim to identify and eliminate waste [21]. A process map focuses instead on studying in detail the input and output variables for each process step to find root causes of variation. Where VSM gives an overview, the process map works as a tool that defines that the cause of variation sits in the details. Both tools aims to stabilize processes, but the process map thrives reduction of variation, and VSM thrives reduction of waste.

A process map illustrates transformation where input variables (X) is put in to a process and transforms to one or more desired output signals (Y) [22]. By aesthetic reasons, the input variables is often placed below the process line och output variables above. The actual process is defined by geometrical symbols depending on the characteristics of the process.

A critical phase in the mapping of a process map is the classification of all identified input variables (X). By classify all inputs in a correct way, the project can focus on factors that is possible to control [22]. Input variables are defined in the following categories [21]:

- **C - Controllable:** Variables that are easy to control and adjust, to observe the effect on the output (Y), for example feed rate in a machine.

- **N - Noise:** Input variables that affects the (Y) but are uncontrollable, difficult, or expensive to control, for example ambient temperature.

- **S - Standard Operating Procedure:** Procedures that describes how the process is run and identifies factors that continuously is monitored and maintained.

In addition to these basic categories, **Critical parameters (!)** is also identified [21]. These are variables that have been proven through process knowledge and tools to have a decisive impact on the output signal (Y). Any of the input variables (C, N or S) can be classified as a critical input.

2.7 Measurement system analysis

A measurement system consists of many different factors, both hardware and software related to the machine or equipment itself. Beyond that, there are also factors such as operators, environment, or procedure that can affect the measurement process [23]. Measurement system analysis (MSA) is a method used for quantifying the system's accuracy, precision, and stability. That is done by assessing and quantifying both the randomized and systematic errors in the system [24]. The goal is to estimate the accuracy and precision in the measured products, to ensure that both the measurement system and the products maintain high quality.

A MSA is used to understand how much of the total observed variation is caused by the measurement equipment, and how much that comes from the process itself [24]. Before analyzing the variation from the process, it is essential to understand if the current measurement system is accurate and precise enough to handle the researched variation. During a MSA, variation is analyzed in variation between different parts (part-to-part variation), variation that depends on the actual equipment (gauge), or variation that is caused by human variation (operator).

2.8 Cause and effect matrix

Cause and effect matrix (C&E Matrix) is an analytical tool that is used within the framework of six sigma [25]. The tool constitutes an essential link in the problem solving methodology which is applied in the early phases, after the process mapping. The primary function of the tool is to be used as a prioritization tool before entering more detailed analyses. The main purpose is to objectify and prioritize different inputs, based on how much they affect the outputs.

The matrix is designed to evaluate different customer requirements or other outputs, which are defined as "Y". When all Y's are identified, they are ordered on a scale 1 to 10. All process steps are analyzed to be able to define all inputs that possibly can affect the output, these inputs are defined as "x". Every x is judged in correlation to the Y's, to determine a point depending how much they correlate.

2.9 Design of Experiments

Design of experiments (DOE) is an established method that aims to plan and conduct experiment in a structured way, to draw scientific and economically efficient conclusions [26]. The theoretical fundaments for DOE was funded in the 1920's by the statistician R.A. Fisher, and the methodology has then further developed. For industrial and business related practices, the method was to a large extent developed by G. Taguchi. The method was integrated in the modern framework for Quality management.

The purpose of DOE is to replace inefficient and non systematically methods as trial-and-error, or One-Factor-At-a-Time (OFAT) [27]. By exploiting mathematical and statistical connections, the test is forced to gather the data from the experimental space that result in the highest possible information gain. The utilization of DOE enhance the speed of reaching desired quality requirements, reducing undesired variation in a process, determine which parameters that is the most critical, and at the same time keep cost for experiments as low as possible [26].

Within the frame for DOE, a special terminology is used describe the constituents of the experiments, two common terms is factor and response [26]. One factor is an independent variable (example time or temperature) that actively is changed to study its effect, while a response is the dependent variable that is measured to quantify the result.

2.9.1 Factorial design

In the first screening phase of an experiment, there are many different factors that has to be evaluated, to get an understanding of how and which different factors affect the response [27]. A full factorial would therefore be both very time consuming and expensive. Instead, a fractional factor design can be used as it only tests a small amount of the different combinations, but still deliver an accurate assessment of the factors direct effect on the response.

In a full factorial design, a formula is used to determine how many runs that is required. The formula is:

$$N = L^M \tag{2.1}$$

Where N is the total experimental runs, L the amount of levels for each factor, and M the amount of investigated factors [27]. In the fractional design, the amount of N is decreased by only running a fraction of all possible combinations, for example with the help of orthogonal systems [26] [27].

Statistical DOE is built on mathematical linear empiric models and the main model for predict the response $\hat{y}$, is defined mathematically by:

$$\hat{y} = \beta_0 + \sum_{j=1}^{M} \beta_j x_{ij} \tag{2.2}$$

Where β_0 is the intercept, β_j the coefficient for each factor, and x_{ij} the set value for factor j in experiment i [27].

To facilitate the actual impact of each factor, all experimental settings are gathered in a design matrix D, which then is built to a model matrix X. The mathematical equation is then written in matrix form as:

$$y = X\beta + \epsilon \tag{2.3}$$

Where ϵ is the error term of the model. To find the best settings of parameter β, an optimization problem is solved with the help of the least square fitting model. The exact mathematical solution for estimate the coefficients is then:

$$\hat{\beta} = (X^T X)^{-1} X^T y \tag{2.4}$$

By this calculation, the effect of each fractional chosen parameter is isolated.

2.9.2 Bayesian Optimization

Bayesian optimization (BO) is a sequential and probabilistic optimization method that is specially designed to handle "black-box"- functions. These functions are recognizable by their non convexity, that they miss accessible gradient information, and by large cost for calculation. The purpose of BO is to find the global optimal value with as few function evaluations as possible. The method has had a huge impact in recent years and is widely used in modern machine learning, scientific research, and complex engineer design [28].

The fundament in Bayesian optimization is built on Bayes theorem. It constitutes a mathematic and probabilistic framework to handle uncertainty, where prior beliefs is updated as new observation data is added. By continuously and iterative adapt an underlying model, the algorithm can understand the behavior of the function and draw intelligent conclusion on where the next investigation should be performed.

As the true target function is to resource demanding to be evaluated frequently, the algorithm constructs a statistical approximation that is called surrogate model, or meta model. Gaussian processes (GP) is the most established and used type of surrogate modeling within Bayesian optimization.

A GP is a non parametric model that offers a flexible way of working to estimate underlying functions and simultaneously quantify the prediction uncertainty for data points which has not yet been observed. The mathematic fundament of a Gaussian process is primary defined by a mean function, combined with covariance function, often called "kernel". The covariance function is used to for modeling the spatial correlations and connections between different observation points [28].

In real systems where observation can be affected by noise, GP-models can be expanded with a "nugget-effect" to handle homogeneous noise. Alternative, methods for stochastic kriging can be applied for measurements affected by heterogeneous noise. For optimization problem in high-dimensional search spaces, where traditional GP-models becomes computationally too heavy, some other networks can be used as a more scalable alternative [29] [28].

To methodically navigate the search space and make decisions about where to evaluate the function next, Bayesian optimization uses an acquisition function. This function exploits the gathered information from the surrogate model, to mathematically evaluate how attractive or rewarding a potential data point is to investigate

[28].

The most difficult task for an acquisition function is to constantly balance the optimization process between exploitation and exploration. Exploitation means that the algorithm actively searches in spaces where the target function is expected to have very favorable values based on existing data. Exploration aims for prioritize spaces that is characterized by high uncertainty in order to not risk missing the global optimum. Common occurring mathematical acquisition functions to manage this critical trade-off, includes Expected Improvement (EI), Upper Confidence Bound (UCB), and Probability of Improvement (PI) [29] [28].

The actual Bayesian optimization process runs through a clear and cyclical workflow. The cycle is often initiated by collecting a few initial data points, often created using space-filling design strategies. In the next stage, the surrogate model is built and adopted based on these initial observations [29].

The algorithm then maximizes the acquisition function to localize the most theoretical optimal to evaluate next. The resource demanding black box function is then run at this specific point, where the new result is fed back into the system to update the belief about the appearance of the function. This iterative course is repeated until desired performance has been achieved [29].

2.9.3 Statistical Evaluation Criteria

2.9.3.1 P value

In statistical analysis, the p-value is the most common tool for assessing whether an experimental result is statistically significant [30]. The core of the method is based on a null hypothesis (H_0), which is an assumption that there is no real effect or difference between the factors being investigated.

The P-value is mathematically defined as the probability of obtaining the observed measurement result, under the strict assumption that the null hypothesis is true [30]. To make a decision, the calculated p-value is compared with a predetermined margin of error, which in scientific research is usually set at 0.05 (5 percent). This limit represents the maximum acceptable risk of a so-called Type I error – that is, the risk of incorrectly rejecting the null hypothesis and claiming that a relationship exists, when the result is actually just due to random noise. If the p-value is less than ($p < 0.05$), the result is considered statistically significant, and the null hypothesis can be safely rejected.

2.9.3.2 Confidence interval

Confidence interval is a statistic method used to describe the uncertainty in an estimate of a measured data. Instead of giving one certain value, the confidence interval provides a range of possible values, which within the true parameter is excepted to be located with a certain grade of level [31].

The concept is built on the idea that data which is gathered from certain samples varies depending on which observations that happens to be included. To handle this variation, confidence intervals are used to quantify the difference the difference between the observed value in the sample, and the unknown true value in the population [31].

Practically, a confidence interval is constructed by starting from the sample mean and adding and subtracting a so-called margin of error. This margin of error, is dependent on how large the variation in the data is, and how large the sample is. When the variation in data is larger or the sample becomes smaller, the interval is getting larger, which indicates a larger uncertainty in the estimate [31].

2.9.3.3 AICc

Within data studies and analytics, statistical modeling and the selection of predicative variables are fundamental steps, to be able to describe the data correct and predict future results. An important and efficient tool evaluate and choose the best model among different candidates is Akaike Information Criterion (AIC) [32]. Theoretically, the AIC works as an estimator of the expected Kullback-Leibler information (K-L). The K-L information works as distance measure between the true, often unknown process that has generated the data and the specific mathematical candidate model that is being evaluated. When different models are evaluated, the one with lowest AIC value is chosen, as it theoretically has the lowest deviation from reality.

As the AIC tends to wrongly favor models that contain an unnecessarily large number of parameters, which leads to overfitting, Akaike Information Criterion correction (AICc) were developed [32]. AICc was developed by mathematically applying a deeper approximation of the K-L information than the original AIC model does. In practice, this means that AICc requires greater demands on keeping the model simple, it subtracts more points than regular AIC for each additional parameter added. It is a correction that helps to avoid overfitting.

3
Methods

This study is designed as a quantitative case study with qualitative elements, conducted at SKF. Initially, the project was driven as a broad investigation of the robustness to variation. However, through the systematic application of scoping frameworks (such as AIM and Effective Scoping), the core bottleneck was identified, and the study progressively narrowed its focus. Followed by this, the study developed to investigate a specific phenomena in its real context, which was the role of a measurement station.

To structure the problem solving process and ensure a systematic methodology, the study has been followed by the Six Sigma framework DMAIC (Define, Measure, Analyze, Improve, Control). In the *Measure* phase, AIM and Effective Scoping was used to determine and define the industrial project. In the *Measure* phase, a Measurement System Analysis (MSA) was conducted to evaluate the measurement system's reliability. Finally, in the *Analyze* and *Improve* phases, Design of Experiments (DOE) and Bayesian Optimization was used to evaluate how different process parameters affect the variation.

3.1 Affinity Interrelationship Method

An Affinity-Interrelationship Method (AIM) was performed in the early stages of the project to clarify and identify the current state of knowledge regarding understanding of variation's impact to the production flow. The theme of the AIM was defined as; "What have been the biggest problems with working in the production flow?". The question was formulated in a past tense perspective to facilitate a mindset where the participants reflect back in the time and based their reflection on facts and experiences [20].

The session involved four process operators that have been working in the flow in the past 15 years, and before starting with the "brainwriting" step, a presentation about why and how this workshop is performed was presented. The next step was to let the participants write their thoughts and experiences as concrete as possible on post it paper. After that, each paper was analyzed together in the group to make sure that everything was clear, before grouping them into different levels. When the grouping was performed, cause and effect relations was defined before giving scores to different groups.

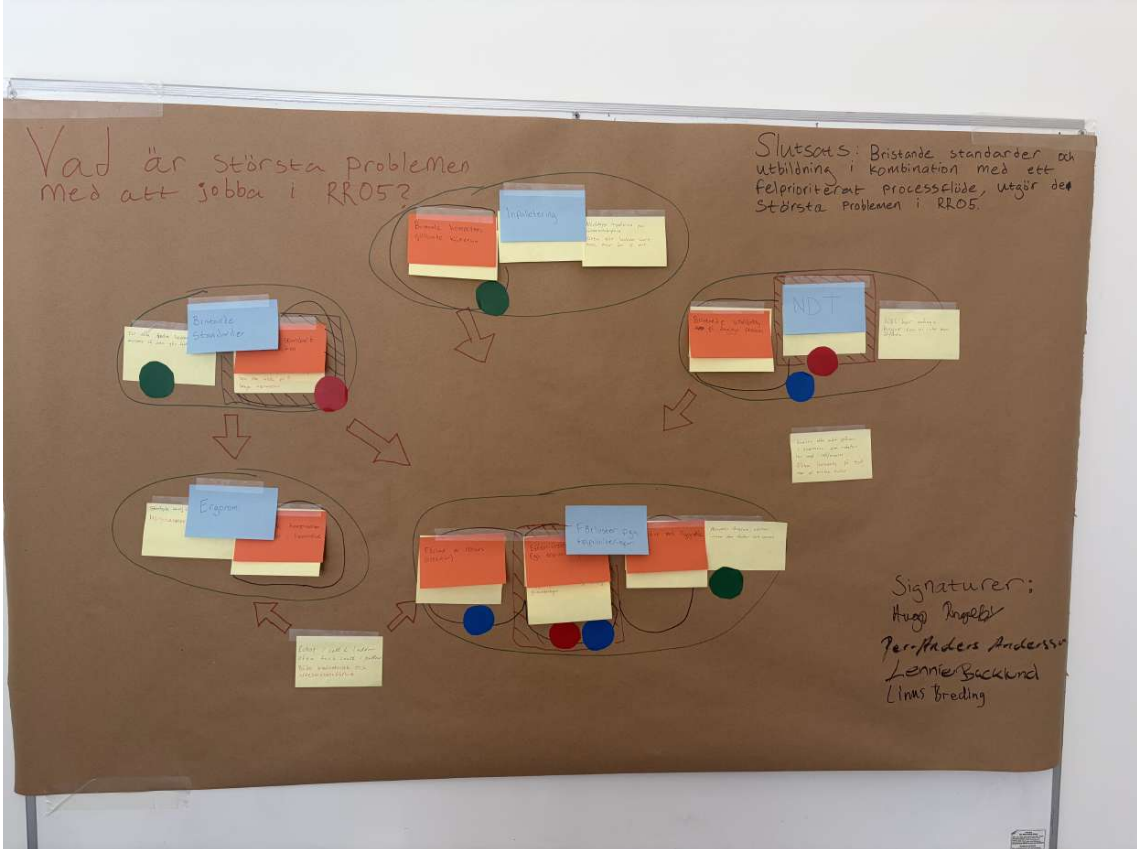


Figure 3.1: Affinity Interrelationship Method

3.2 Effective Scoping

To ensure that the project addressed the correct underlying problem and to create early consensus about the projects aim, Effective scoping was used in the study's initial "Define" phase. The method is built on a framework consisting of nine sequential questions divided into three main steps (3x3) [19]. By following this order, a "Pull-thinking" was ensured, where the process output and customer requirements were defined before the physical process and its output was mapped. In this project, two effective scoping was performed as a result of the define phase, both exhibits of the scoping is presented in Appendix..

The application of the framework were performed in three steps. In the first step, focus shifted towards what the process actually delivers [33]. The first question answered what comes out of the process, the performance of a product, or result of an operation.

The next question focused on in which context the actual output is being used, who uses the output? It could be a manager receiving monthly updates about production rates, a customer receiving ordered products, or an industrial robot receiving a product from a conveyor belt.

The third question in step one, answered the question about what is required from the output, the big Y. Focused on which requirements need to be fulfilled, what makes the receiver satisfied with the delivered output.

The second step was dedicated to define which one measure the project should focus on [33]. The work was based on the insight that initial project goals are often formulated based on the desire to address a visible symptom rather than understanding the hidden root cause. Each customer requirements can be measured in several ways, and each measure (small y) is affected by different sets of hidden underlying factors, despite belonging to the same physical process. To avoid an unmanageable complexity search, the method required a strict delimitation where only one measure was chosen for improvement.

Question four that was involved in step two, focused on the baseline of the y. What facts supports the measure y to be improved, is there any methods for measuring y today [19] [33]. Have any improvements been done before, with the purpose of improve y. It also involved the question about how data could be gathered, and if previous data could be used.

The last part of step two was to evaluate what other Y that not can be lost in the process, the constraints of the project scope. The constraints was defined as factors that were not allowed to be deteriorated as a result of the improvement work [33].

When the measure (y) and the system was defined, the project's framework and staffing were determined. The first question in this step involved where in the process the project had mandate to do improve and perform changes [33]. This was performed to avoid later conflicts in the project regarding authority and ability to change, which was crucial to determine in which direction focus should be shifted. It answered the question if the project should be shifted upstream, or shifting focus from eliminating variation, to mitigating it [19]. The question also involved what competences that are needed to perform the tasks for the project.

The two ending parts of the last step was to evaluate the inputs. What are the inputs who supports the input, and what does the system require from the input [33]. This step was crucial to get an understanding of where incoming variation occur and what possible factors that can affect the incoming variation.

3.3 Process Map

To map the actual process and create a deep understanding for the underlying reason to variation, a process map was designed for the actual production flow. The mapping was performed in close cooperation with a process operator and a reliability engineer, to gather necessary practical experience from daily work and a deeper perspective from the Skf production system.

The mapping was based actual observations in the physical production environment, a methodology that within the frame is defined as "walk the process" [21]. By physically follow the flow in reality, step by step, the actual way of working was identified, and not only the theoretical way of how it is assumed to work. This practical way of working was necessary because the level of detail is necessary to understand the root causes of the variations.

During mapping, the process was broken down into its specific components to illustrate the connection $Y = f(X)$, where each input impact (X) on the output (Y) was evaluated. To ensure a structured evaluation and avoid missing parameters, 7M-categories (Man, Machine, Method, Material, Measurement, Management, Mother Nature) was used as support during the discussions [21]. The result of the process map is visualized in Figure 3.2.

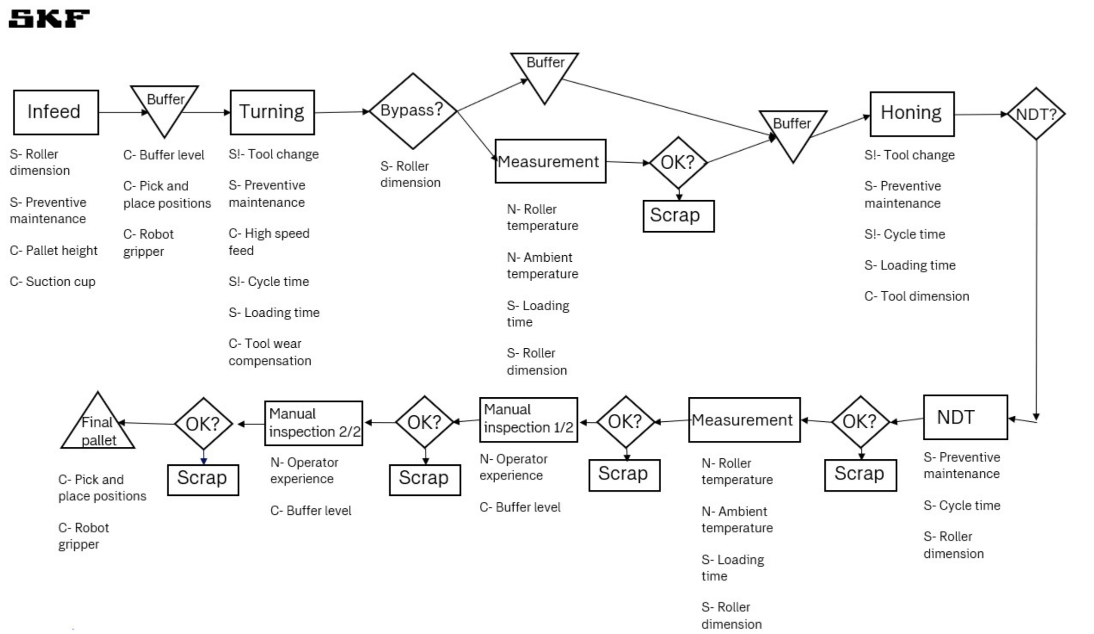


Figure 3.2: Process Map

3.4 Cause and Effect Matrix

As an extension to the process map where all potential process factors where identified, a Cause and Effect- matrix (C&E-matrix) were applied. This was done to systematically evaluate and prioritize the different factors. .

As this project's primary customer requirement is defined as "cycle time for one produced unit" and no other $(Y's)$ were identified yet, it was defined as the only "Key Process Output" with the highest possible weight score. [25]. To then assess how much each individual process input (X) affected the (Y), all identified factors from the process map were transferred and listed into the matrix.

A correlation assessment was then conducted, where each correlation was scored based on its specific impact on cycle time. To ensure an objective and structured assessment, an established correlation scoring scale was applied: 0 indicated no correlation, 1 meant a remote or weak impact, 3 represented a moderate impact, and 9 was used when the process had a direct and strong effect on cycle time [25].

When all different (X) had been evaluated, the individual correlation values were multiplied with weight score for the (Y), which was summed in a total score for each (X). This quantitative calculation resulted in a clear ranking, which made it possible to identify and sort the most important process steps.

3.5 Measurement System Analysis

An MSA was performed to evaluate the capability of the existing measurement equipment. As the equipment is 100% automatic, the MSA differed compared to a traditional one. Reproducibility could not be evaluated with different operators, instead different sizes of produced rollers. Repeatability was evaluated by measuring the same detail four times, from three different grouping sizes. The grouping sizes were +5, Nominal, and -5, meaning that there were 12 replicates (4x3) for each size of produced rollers. Four different sizes of rollers were analyzed, meaning that 48 runs were performed in total, (12x4).

In order to facilitate the MSA and to avoid manually heavy calculations, JMP software were used to perform the MSA [34]. In JMP, a certain tool aimed for just MSA was used and the first step was to define the response, the Y. This was defined as "Diameter variation". The next step was to define the factors, which were "Grouping and the size of the roller, "Roller diameter". After that, both a Gauge R&R and an EMP analysis was run in the software.

3.6 Design of Experiments

To evaluate how different parameters affect the stability of the diameter measurement in the turning machine, Design of Experiments (DOE) was used. Instead of using inefficient trial-and-error methods, or varying one machine setting at a time, DOE provided maximum information from a limited number of experiments [27]. The method made is possible to perform experiments that would have been financially and timewise impossible if it not had been used. The method also made it possible to try the different parameters combined, rather then isolated, which facilitated the mapping of correlational and interaction between the different parameters.

Followed by the general way of performing a DOE, the experiment was divided into sequential phases, where the first step was to set up what should be measured and how [26]. The whole experiment plan was performed digitally with the help of JMP software, and the plan followed the built in structural way of performing a custom design DOE [35].

The response, which is the dependent variable, and the factors, which are the independent variables was defined in the software. For each specific factor, the data type was defined as either continuous or categorical and they were given values depending on their category. When the response and factors were given, the effects between them were defined following the custom design structure in the software. In the next step, the software automatically created a complete data table, which facilitated the runs and worked as timetable. It included which settings on the different factors that should be tested and then an empty column were the results from the different experiments later could be added.

3.6.1 Bayesian Optimization

To detect optimal process parameters and support the DOE with accurate data points, Bayesian Optimization was applied to the DOE design. In this study, it was also performed with the JMP software [36], to navigate in the experimental space in an efficient way. Instead of guessing and trust resource demanding methods as "grid search" or "trial and error", the Bayesian model build a surrogate model of the process [29]. This facilitated an iterative and efficient identification of settings that minimized the variation, without performing a large amount of physical experiments in the production flow.

4

Problem Definition and Current State

The following chapter will present the a description of the current state, with the help of using different methods and tools. It includes, observations, time studies, and quantitative Six Sigma methods. These steps are essential to evaluate and form the *define* and *measure* phase, and facilitates the whole starting point of the project.

4.1 Affinity Interrelationship Method

The AIM session that were performed with different operators, highlighted the deviations that observed during the first observation and time studies. The operators mentioned some concrete problems directly related to some machines, but the most disturbing problem and one of the winner of the election phase, was the frustration of the inefficient and wrong prioritized move pattern of the industrial robots in the cell.

As all data gathered during the session is qualitative, no certain times or precise data were mentioned, but in general it went clear that there was a common knowledge about that both robot 1:1 and 1:2 was not working optimally. The arguments was that robot 1:1 often had to wait before entering measurement station, that robot 1:2 had wrong prioritization order, and that measurement station had to wait for robot 1:2 to come and get measured rollers. Another frustrating moment mentioned was the uncertainty about the bypass setting in the measurement station, that is controlled by the operators. They are allowed to activate a bypass function that sends roller straight from the turning operation to the honing station, via a buffer place without going in to the measurement station. However, there is no standard on when the bypass function should be activated, some are never using it, some are only using it on small rollers, and some are not aware of it at all.

4.2 Effective scoping 1

A first effective scoping based on standard template was performed to facilitate the identification of small y's affecting the big Y. The scoping showed that no previous research in robustness to variation had been performed in relation to improve the cycle time. However, previous projects in certain machines, and common knowledge from operators and reliability engineers could be used to exclude some small y's from the problem.

4.3 Cause and Effect Matrix

Based on the process map, the (C&E- Matrix) were formed. The matrix presents that four different process steps in correlation with certain inputs were calculated to have the biggest impact on the cycle time for one produced unit (Y). The first one was in the turning machine, were the cycle time for the turning operation were rated with the highest score, as it is the bottleneck machine of the process. The cycle time were defined as a Critical Standard Operating Procedure (**S!**)

The second one was the bypass station for the measurement machine, as the process input defined as roller dimension could determine to activate the bypass function, meaning that 66% of all produced rollers skip the whole measurement procedure before the honing operation. The given input factor roller dimension was described as a Standard Operating Procedure (**S**) at that stage. However, based on the MSA, there was no standard or regulation controlling when the bypass should be activated. Meaning it could also be defined as a controllable (**C**).

The third step with the biggest impact was calculated to be at the manual visual inspection with buffer level as the process input. The buffer level of this station has a maximum of three rollers and one operator need to approve each roller before the robot picks them up. The operator can choose to approve whenever they want, regardless the current buffer level. If the buffer level is full and no approval is performed, the cell stops and wait for the operator. As a result of the big impact from the human factor, this correlation between the visual inspection station and the buffer level determined by the operator were given the highest score.

4.4 Observations

As an important step of the define phase, observations at the production flow were conducted. This was performed to get a brief overview of how the flow is oriented, how machines cooperate, and to better understand the results and data gathered from the AIM, Process Map, and the C&E- Matrix. As the production flow runs as three shifts, during night, morning, and afternoon, together with different types of roller with different dimensions, the observations were spread out through different times to maximize the input of variation.

First, the whole flow was observed without any respect to human factors. During the observation it was noted that the industrial robots handling the material were interrupted almost all the time. Robot 1:1 had a straight working flow, doing its task in the same order all the time. The turning machine which is the bottleneck machine was not working all the time, often waiting for the robot to get finished material and feed it with new. However, robot 1:1 also had some waiting time, when it correlated with the measurement station.

The measurement station was observed to play a critical role as it distinguishes sub-cell 1 with 2, by being a part of them both. Sub-cell 2 with robot 1:2 did not work in straight flow as it has a flexible movement pattern depending on what is happening in the cell. When the flow was observed with human factors in mind, it became clear that the manual inspection has a big impact on robot 1:2 movement as it always prioritizes reaching and grabbing approved rollers from the inspection station, regardless of buffer level in the inspection station. The buffer level in the inspection is maximum 3, and operator can choose by themselves when they want to approve or decline rollers.

4.5 Time studies

A time study for different roller types were performed in sub-cell 1, to measure the time of material handling. One cycle for the 1:1 robot was measured several times, which is the time from delivering one roller to turning machine until doing it the next time. Figure 4.1 and 4.2 display the measured cycle time for one cycle, including the different steps for the robot within one cycle. The two diagrams are results based on the exact same measurement procedure, but for different roller types with different dimensions.

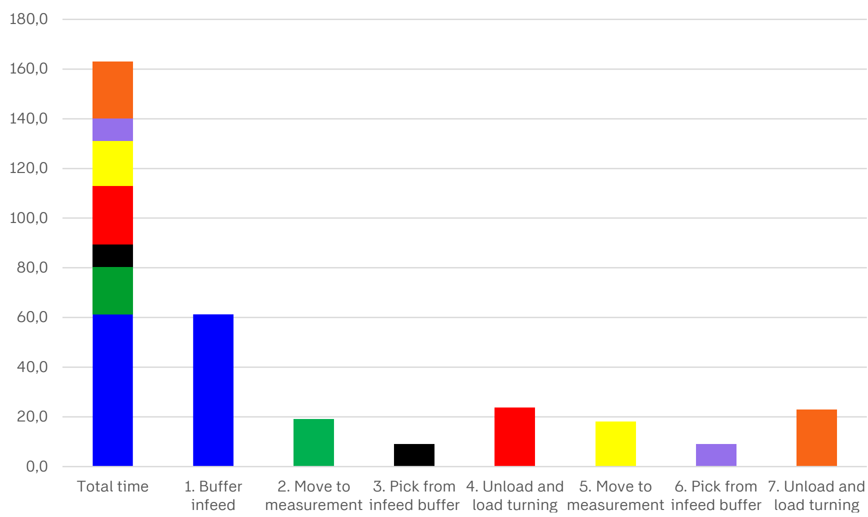


Figure 4.1: One cycle Robot 1:1

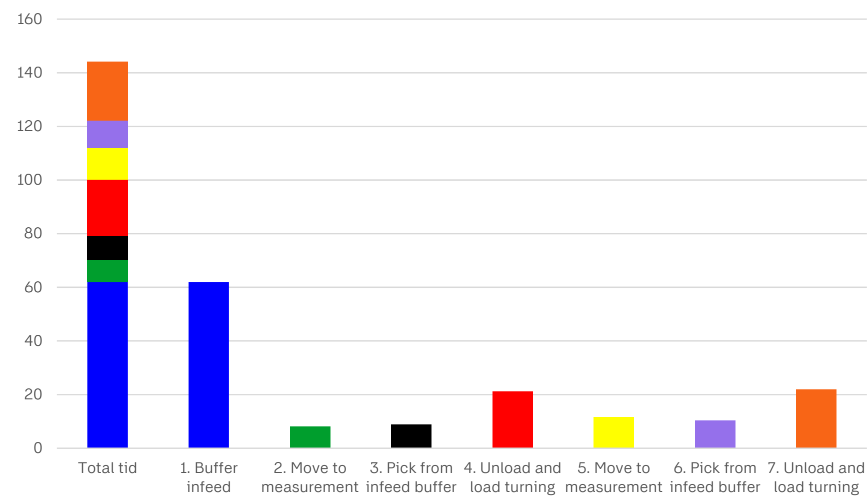


Figure 4.2: One cycle Robot 1:1

The time study showed that robot 1:1 was not capable to do all its task within the time frame for one cycle time in the bottleneck machine, leading to decreased resource efficiency in bottleneck machine while its waiting for material. Depending on roller type, the time for one robot cycle varied between 10-20% higher than the cycle time in the bottleneck machine.

Each task within the robots working cycle were break downed. It showed that some of the steps within the robot cycle were more robust to variation compared to some other. The infeed step with is belonging buffer did not get affected of variation caused by different roller types, which is displayed in the blue staples in Figure 4.1 and 4.2. The step including picking rollers from the buffer, followed by unload and load the turning machine did also show robustness to the variation caused by different roller types, which also is presented in the figures with the black, red, purple, and orange staples.

The task of moving rollers to the measurement station was heavily affected by variation, which is presented by the difference between Figure 4.1 and 4.2 regarding the green and yellow staples. As the measurement station distinguishes sub-cell 1 with 2, all variation from sub-cell 2 affected the robot 1:1's delivery of rollers to the measurement station. That in correlation with the variation and uncertainty regarding the bypass function in the measurement station, indicated that the measurement station showed lack in robustness to variation.

4.6 Reformulation of research questions

As a result of the current state and the previous described findings from the AIM, Process map, C&E- Matrix, observation, and the time studies, the project went back to the define phase. This was done as the result showed that the lack of knowledge regarding robustness to variation in the measurement station had a big impact on the previous defined (Y), the cycle time for one produced unit.

The setting of the bypass function in the measurement station were shown to play a a vital role, as the time studies and the observation indicates that the measurement station more or less controls the work pattern for the two industrial robots 1:1 and 1:2, due to the fact that it distinguishes the both sub-cells from each other. The AIM also showed that there was a big frustration regarding the lack of standard of when the function should be activated.

Looking at the C&E- Matrix, the bypass problem was given the highest score together with the cycle time in turning machine and the buffer level at visual inspection station 1. The cycle time was not further investigated due to early findings about what could possibly be changed. It was defined as **Standard Operating Procedure (S)**, and that it was judged to have a good robustness to variation due to its standardized numerical control programming that changes coordinates depending on roller type. During the observations, no noise factors were identified to interrupt the cycle time.

The visual inspection step were defined to have **Controllable (C)** factors that could be further analyzed and investigated as it indicated lack of robustness and could have a negative impact on the previous defined (Y). However, as the problem with the bypass function comes earlier in the process flow, and that a more robust setting at the measurement station would facilitate the research of the visual inspection station, no further analyze were performed at that step.

Based on this, the research question was reformulated to shift focus on the measurement procedure and more specific the bypass station, an important step to follow the purpose of the project and to not run into sub-optimizations. The new research questions was formulated as:

- Does all rollers need to be measured between the turning and honing operation?

4.7 Effective scoping 2

As the project went back to the define phase and with a new research question formulated, a new effective scoping was performed. This scoping showed that there are few measures, small (y) that supplies the measurement station, which affect how much that should be measured when it comes to machined rollers from the turning operation. The inputs that supplies the measurement station were defined to be; Machined rollers from the turning machine, temperature of the detail (roller), ambient temperature, roller dimension (diameter and length), gripping tools, pneumatic systems, and hydraulic systems. Based on the scoping, focus shifted to what comes out from the turning machine as it was defined to be the only controllable and the most important (y) to determine how much that should be measured. Therefore, as a result of this, a second new research question were added to specify the first new one, and defined as:

- How robust is the outcome of the turning process to variation?

5
Analysis

The following chapter constitutes the empiric and analytical core of the study, and includes the *Measure*, *Analyze*, and *Improvement* phases of the DMAIC framework. After the project's extent and definition had been defined in the previous chapter, this chapter shifts focus towards quantifying the current production flow and identifying causes to process variation.

5.1 Measurement System Analysis

As a first step according to the Measure phase, a Measurement System Analysis (MSA) was performed to analyze the possibility to actual detect and measure the variation that occur in the turning process.

5.1.1 Summary Statistics and EMP Classification

The initial phase of the MSA aims to quantify the overall precision and reliability of the measurement equipment by dividing the observed variation into measurement error and actual part-to-part variation [37]. The measurement error is primarily evaluated through Gauge Repeatability and Reproducibility (Gauge R&R). Repeatability represents the inherent consistency of the equipment, and reproducibility represents the variation introduced by the system itself when handling the different parts. The results from the Gauge R&R Study is presented in 5.1.

Gauge R&R

Measurement Source		Variation (6*StdDev)		which is 6*sqrt of
Repeatability	(EV)	6,453144	Equipment Variation	V(Within)
Reproducibility	(AV)	5,565609	Appraiser Variation	V(Rulldiameter) + V(Rulldiameter*Gruppering)
Rulldiameter		5,116878		V(Rulldiameter)
Rulldiameter*Gruppering		2,189421		V(Rulldiameter*Gruppering)
Gauge R&R	(RR)	8,521682	Measurement Variation	V(Within) + V(Rulldiameter) + V(Rulldiameter*Gruppering)
Part Variation	(PV)	14,368741	Part Variation	V(Gruppering)
Total Variation	(TV)	16,705681	Total Variation	V(Within) + V(Rulldiameter) + V(Rulldiameter*Gruppering) + V(Gruppering)

Summary and Gauge R&R Statistics

6	k
51,0107	% Gauge R&R = 100*(RR/TV)
0,59307	Precision to Part Variation = RR/PV
2	Number of Distinct Categories = Floor(sqrt(2)*(PV/RR))

Using last column 'Gruppering' for Part.

Variance Components for Gauge R&R

Component	Var Component	% of Total
Gauge R&R	2,0171963	26,02
Repeatability	1,1567517	14,92
Reproducibility	0,8604446	11,10
Part-to-Part	5,7350196	73,98

Figure 5.1: Gauge R&R Study

In addition to the Gauge R&R study, the system is also evaluated through the Evaluating the Measurement Process (EMP) methodology [38]. It provides an alternative and complementary perspective on the actual performance. While a standard Gauge R&R study primarily focuses on measurement error percentages, the EMP approach assesses the relative utility of the measurement system by calculating the Intraclass Correlation (ICC) [38]. ICC represents the specific proportion of total variance that is due to the product itself, rather than the measurement process.

EMP Results

EMP Test	Results	Description
Test-Retest Error	0,7614	Within Error
Degrees of Freedom	33,098	Amount of information used to estimate within error
Probable Error	0,5135	Median error for a single measurement
Intraclass Correlation (no bias)	0,9562	Proportion of variation attributed to part variation without including bias factors
Intraclass Correlation (with bias)	0,8621	Proportion of variation attributed to part variation with bias factors
Bias Impact	0,0941	Amount by which the bias factors reduce the intraclass correlation

System	Classification
Current (with bias)	First Class
Potential (no bias)	First Class

Monitor Classification Legend

Classification	Intraclass Correlation	Attenuation of Process Signal	Probability of Warning, Test 1 Only*	Probability of Warning, Tests 1-4*
First Class	0,80 - 1,00	Less than 11%	0,99 - 1,00	1,00
Second Class	0,50 - 0,80	11% - 29%	0,88 - 0,99	1,00
Third Class	0,20 - 0,50	29% - 55%	0,40 - 0,88	0,92 - 1,00
Fourth Class	0,00 - 0,20	More than 55%	0,03 - 0,40	0,08 - 0,92

*** Probability of warning for a 3 standard error shift within 10 subgroups using Wheeler's tests, which correspond to Nelson's tests 1, 2, 5, and 6.**

Figure 5.2: EMP Results

Figure 5.2 presents that the EMP analysis yields an ICC of 0.8621 (with bias) and 0.9562 (without bias), which mean that the system is being classified as a "First Class" monitor [38]. This specific classification suggests that despite any high numerical errors identified via Gauge R&R, the measurement process still maintains a strong capability to detect actual product variation.

5.1.2 Part-to-Part Variation (EMP X-bar Analysis)

The measurement system analysis performed partially resulted in an X bar chart from the EMP analysis. In this scenario, the chart is aimed to evaluate if the system can detect differences between different details [38]. In the presented chart in figure 5.3, control limits (UCL and LCL) represent that part of variation which can only be attributed to the measurement error. The plotted points created by the band swept out by the running record, represents the variation between the measured details. In this case, the details are grouped by four different diameter sizes, with three different groupings within each, "-5", "N", and "+5".

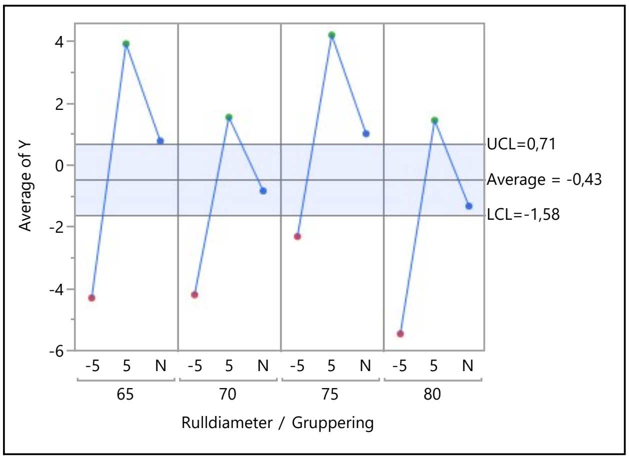


Figure 5.3: X bar chart Part variation

Apart from standard process control, the target of an EMP study is to identify the points that occur outside of the control limits [38]. In the presented chart, the mean values for -5 and +5 groupings are located outside of the limits. This indicates that the measurement system has no problem in handling and detecting the variation between small and large parts.

The blue area within the control limits represent the measurement error of the system, it is calculated based on the repeatability. The area within these limits is the blind spot of the measurement machine.

5.1.3 Analysis of Means: System Accuracy

As a part of the MSA, a variance analysis (ANOVA) has been performed, with the purpose to identify and evaluate the measurement error. The result of this study is presented by main effect and interaction plots, divided in how the system register mean values, respective standard deviation.

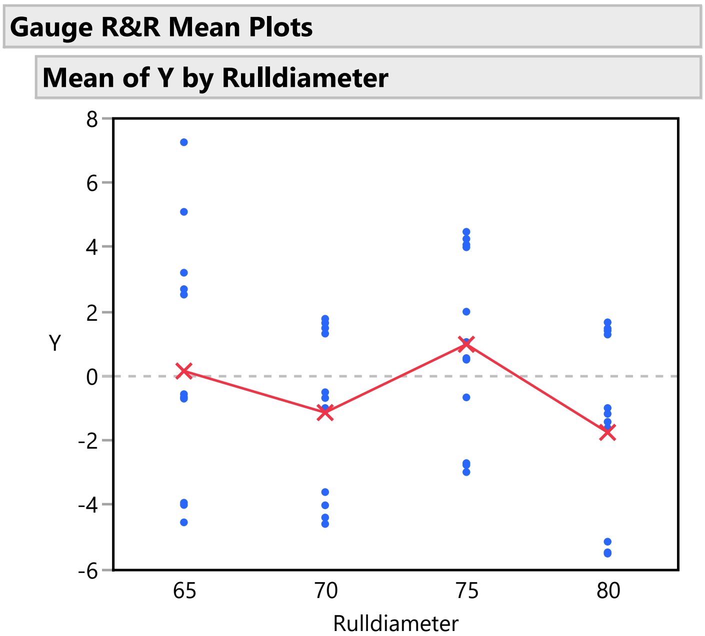


Figure 5.4: Mean Plot by Roller diameter

Figure 5.4 shows that the spreading between measuring points is larger for grouping size 65 and 75, compared to size 70 and 80. It indicates that the actual size of the roller does not effect the repeatability, the system is capable of detect the difference between smaller and bigger parts.

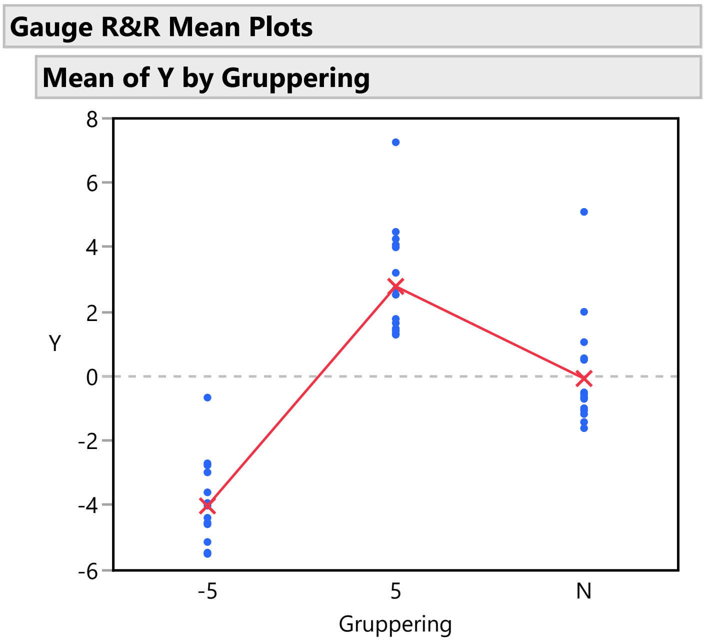


Figure 5.5: Mean Plot by Grouping

Figure 5.5 confirms that the system understands what is being measured, as the smallest group "-5" is placed at the bottom and the largest, "5" is located in the top space. If one factor is changed and the mean value also is changed, it indicates that the system can register the actual variation. As the angle of the graph is changed rapidly when the grouping factor is changed, it means that the system can handle the actual variation between the different groupings [39] [38]. However, there are some alarming points as some measurement points exceeds the other groupings.

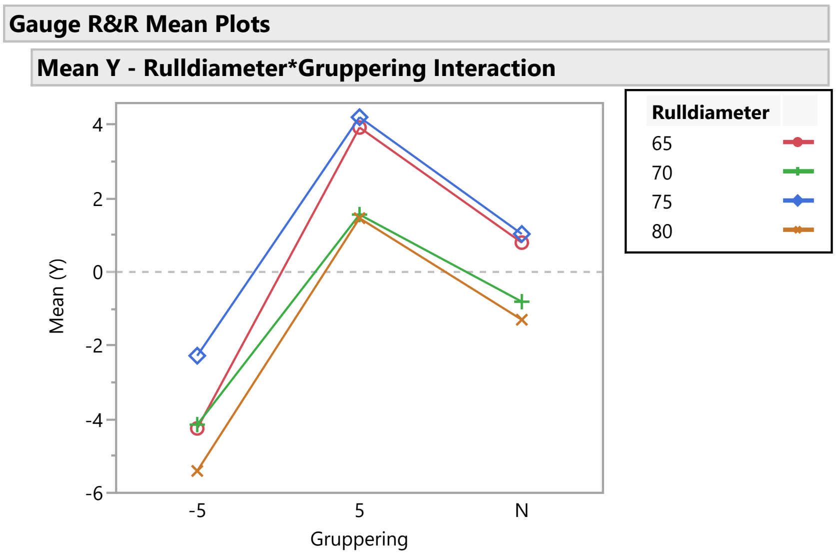


Figure 5.6: Mean Plot by Interaction

Figure 5.6 presents that an interactions effect occur, as the response between the grouping levels are not constant over the diameter levels [39]. In an ANOVA- model, which is the fundament of these graphs, the interaction term represents the variation which cannot be explained by the main factors alone.

Interaction effects and the lack of parallelism in a diagram is mathematically the same thing [38]. If the Measurement system would have been completely robust, all lines in Figure 5.6 would have been parallel. The fact that the lines for roll diameters 65 (red) and 75 (blue) have a steeper slope is direct evidence that the machine's sensitivity changes depending on the physical size it measures.

This behavior indicates that the measuring system has an "amplified" response at certain diameters [39]. The machine exaggerates the actual differences between the groupings for roller 65 and 75 compared to 70 and 80. This means that mathematically, the measurement error is not random noise, as it systematically linked to specific combinations of details. When a certain interaction occurs, it is important to not only evaluate the mathematical effect [38], as the actual reason for the interaction often is physical.

While the previous figures presented and analyzed the system's ability to measure the correct average value, the following graphs evaluate the standard deviation, which represents the measurement noise or repeatability [38]. A capable measurement system should exhibit a low and consistent standard deviation across all measured parts.

5.1.4 Analysis of Variance: System Repeatability

Figure 5.7 reveals a significant deviation from this ideal state. There is a massive spike in measurement variation specifically for roller diameter 65, while the noise levels for diameters 70, 75, and 80 remain relatively low and stable.

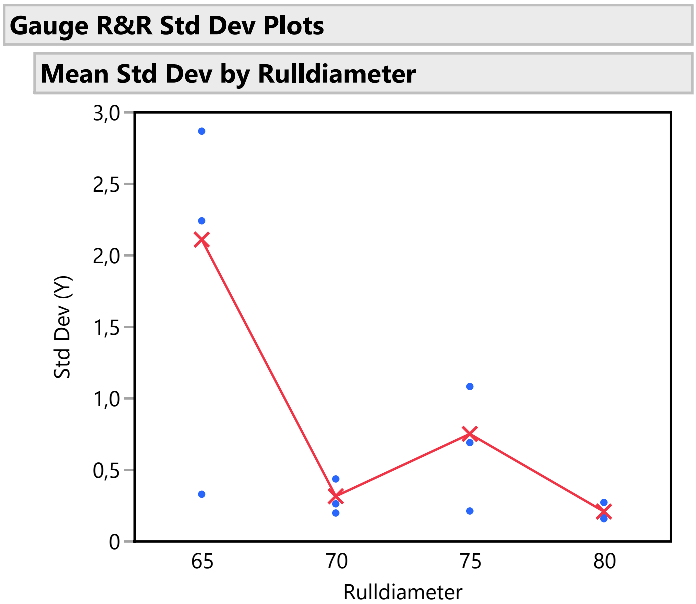


Figure 5.7: Standard Deviation by Diameter

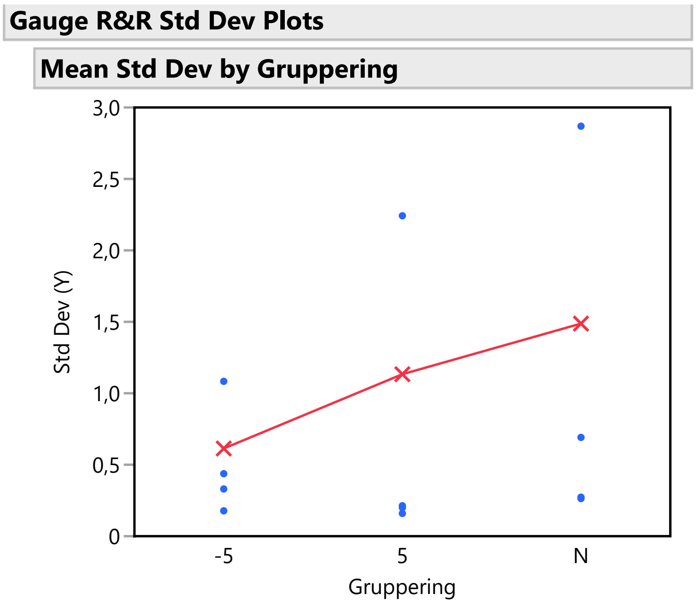


Figure 5.8: Standard Deviation by Grouping

Figure 5.8 illustrates the main effect of the grouping factor on the standard deviation [39]. A slight upward trend is visible, suggesting that the measurement noise increases marginally as the grouping size goes from "-5" to "5".

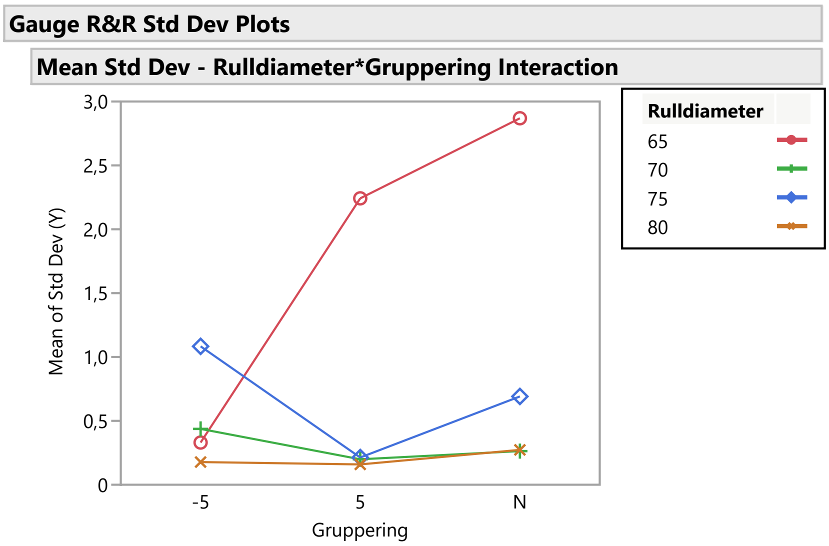


Figure 5.9: Standard Deviation by Interaction

The main cause of measurement error is pinpointed in Figure 5.9. Similar to the analysis of means, non-parallel lines in a variability plot signify a critical interaction effect [39]. The spike in the red line at diameter 65, grouping "5" and "N" demonstrates that the loss of repeatability is not a general system failure, but is highly isolated to these specific combinations. In an ANOVA-based measurement system analysis, identifying such extreme localized variance is crucial, as it is this specific interaction that inflates the total Gauge R&R percentage [39]. As a result of this, the lack of reliability in the measurement system is driven by how the machine physically handles diameter 65 at size "N" and "5", narrowing down the scope for physical troubleshooting [38].

5.1.5 Physical troubleshooting

Given the results from the performed MSA, a presentation was made internal within SKF, where experts within MSA participated. During the presentation, the reproducibility was discussed to be a bit misleading as the same machine measures the part several times, and no operator affects the outcome. The high level of repeatability was not as worrying as the theory define it, and no radical conclusions were drawn based on that. By that the focus shifted from the actual numbers to the graphs. From a SKF perspective, the graphs over the mean and standard deviation was perceived as positive and the alarming points for diameter 65 at size "N" and "5" was not worrying. Instead of condemning the actual measurement system equipment for the alarming points, it was concluded to have a high capability and fully acceptable.

The reason for the deviations and the high Gauge R&R numbers were instead discussed to be an outcome of dirt and dust on the rollers, that affects the measurement results in the equipment. This was defined to be noise factors that were hard to detect and control. Therefore, a decision was made together with the company to not further investigate that variation, and instead continue to the analyze phase om the project.

5.2 Clarification of Y and x

The first step heading into the analyze phase was to identify and clarify the different (x) that possibly could had a impact on the (Y). Based on the new formulated research question, the new (Y) was defined to be the outcome of the turning machine. The outcome from the turning machine is measured in two way, diameter (Dw), and roundness (vDw). However, the measurement step between the turning and honing operation was identified to only control the diameter while the roundness was more interesting after the honing operation. That was an outcome of the built in compensation function that can adjust the diameter in turning machine, controlled by the measured value and the offset value set by operators. Based on that, focus was shifted towards the diameter and the (Y) was defined as the diameter outcome of the turning operation.

5.2.1 Fishbone Diagram

To identify all possible (x) that could had an impact on the diameter outcome, a fishbone diagram were performed together with operators from the production flow. The diagram is presented in Figure 5.10.

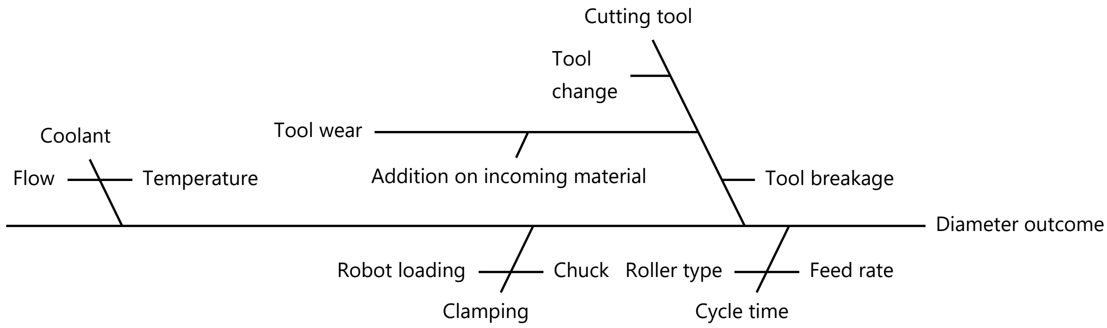


Figure 5.10: Fishbone Diagram

With the help of the fishbone diagram, four different main causes with existing sub-causes were identified and these were; Cycle time, Cutting tool, Clamping, and Coolant. The coolant is supplied from another department connected to the turning machines. There are sensors in the turning machine that control both sub-causes, temperature and the flow. When some of them deviates, the machine stops and alarms the operator. This shows a good robustness to variation as the machine only operates when the two parameters are correct and that there is a system to detect and indicate when it deviates. As a result of this, it was decided not to involve the coolant when evaluating how the variation affects the diameter outcome of the turning machine.

Clamping involves how the roller is clamped in the turning machine. The roller is loaded by the robot and then clamped by the chuck in the turning machine. The chuck needs the correct signal before the robot can open the grippers and unload the roller. That signal is only achieved if the roller is clamped correct and if it is not, the process stops and operator is alarmed. It means that the process can not run if the clamping is not performed correct and it indicates that the clamping is robust and were therefore not further evaluated in relation to the diameter outcome.

The cutting tool has a calculated useful life of 7 km before it is changed. It means that the tool is changed after different amount och processed rollers depending on the dimension. The actual tool change is performed with a standardized tool that has set newton meter value that can not be changed. If a tool breakage occur, there is no function in the turning machine that can detect it, it is first detected when the roller is measured. There were no information or knowledge regarding how the tool wear can affect the diameter outcome, and no study hade been performed on it before. Therefore it was to decided to further investigate and involve it in the further analysis. It was also decided to do some samples and measure variation of the addition on incoming material.

The addition on incoming rollers were evaluated by performing sample measurements on five different roller types. The result from the sample indicated an acceptable robustness to variation, as the average for the different types were similar, with an acceptable variation. The result form the sample is presented in Figure 5.11, and it was decided to not involve this factor in the final design.

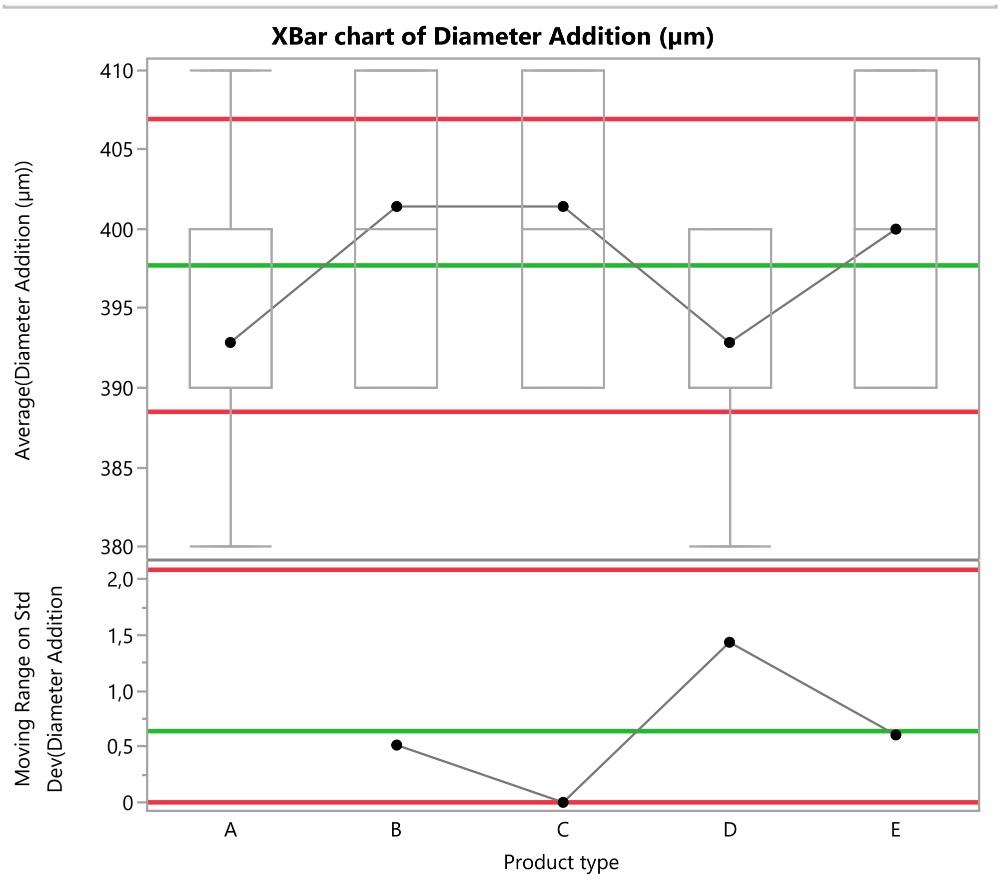


Figure 5.11: X-Bar, Moving Range, and Box Plot for addition on rollers

Regardless roller type, the turning process is controlled by the same parametric numerical control programming with the same feed rate. It means that the only thing that is changed over the different types is the coordinates telling where the cut should be performed, resulting in a varying cycle time for the different types. No study had been performed and no function in the process flow were aware, on how the diameter outcome is affected by different roller types and their varying dimensions. As the dimension can vary in both length, diameter, and radius, focus was shifted to cycle time. The cycle time of different rollers were therefore decided to further analyze.

5.3 Design of Experiments

5.3.1 Design evaluation

For the Design of Experiments (DOE), diameter variation was defined as the response. It was chosen to present how much the diameter is changed after each processed roller in the turning machine, depending on different factors. The response is measured and presented in micrometer [μm].

Tool wear was determined to be one of the three factors and it was defined as Continuous with a value between 0 and 7 based on the standardized useful life of 7 kilometers. As the machine measured tool wear in amount of parts being machined, a formula was used to convert kilometers to amount of parts depending on the type being produced. The tool wear is presented in kilometers [km] in the DOE report.

The cycle time was the second of three factors and also defined as continuous with a value between 0 and 180 seconds, based on the span of cycle time for the different product variants produced in the production flow. As there are two turning machine, they both were defined as the third factor, as a categorical role with value 1 and 2. All factors and their effect between each other are presented in Figure 5.12.

Evaluate Design

Factors

Name	Role	Values	Units
skärslitage	Continuous	0 7	km
Cykeltid	Continuous	100 180	s
Svarv	Categorical	1 2	

Model

Intercept
skärslitage
Cykeltid
Svarv
skärslitage*Cykeltid
skärslitage*Svarv
Cykeltid*Svarv
skärslitage*Cykeltid*Svarv
skärslitage*skärslitage
Cykeltid*Cykeltid

Figure 5.12: Design evaluation

When the design was created in JMP, the software generated the data table for the different settings and runs. The diameter variation were then measured in reality with the different settings. For each setting, six rollers were measured and then the difference between each measurement were summed and divided by 6 to get a mean value of the variation for each setting. The function that compensates the diameter setting in the turning machine depending on the value that is gathered form the measurement station, were turned off during the experiment. The generated data table is presented in Table 5.1

5.3.2 Prediction profiler

The first run of the model after measuring the desired samples indicated a good stability in the turning machine. Figure 5.13 displays some graphs over the predicted

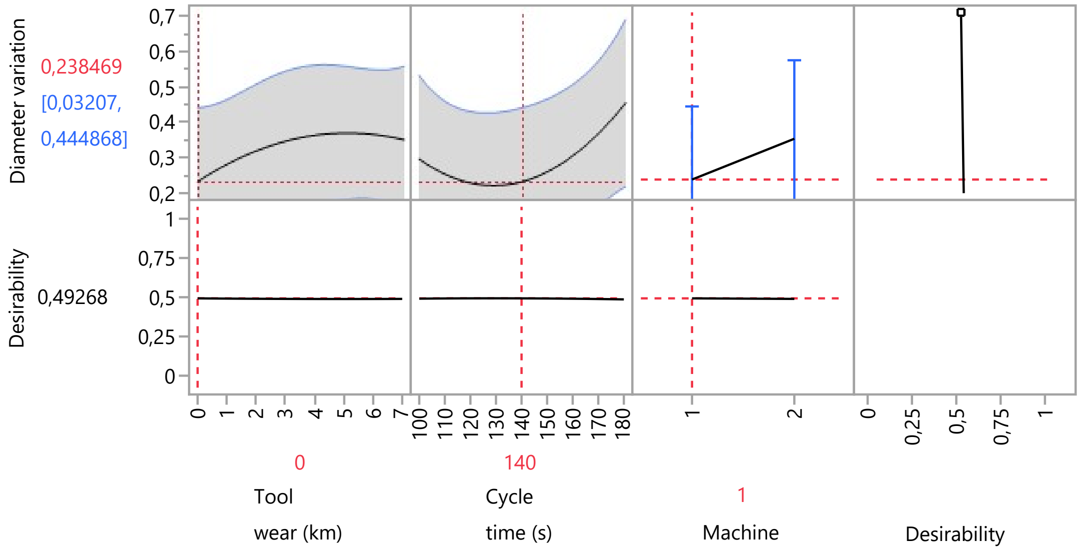
	Tool wear (km)	**Cycle time (s)**	**Machine**	**Diameter variation**
1	7	140	1	
2	0	180	1	
3	7	100	1	
4	7	180	1	
5	7	100	2	
6	3,5	100	1	
7	0	140	1	
8	0	100	1	
9	0	180	2	
10	7	180	2	
11	3,5	180	1	
12	0	100	2	
13	3,5	140,8	2	
14	7	180	2	
15	0	100	2	
16	7	100	2	

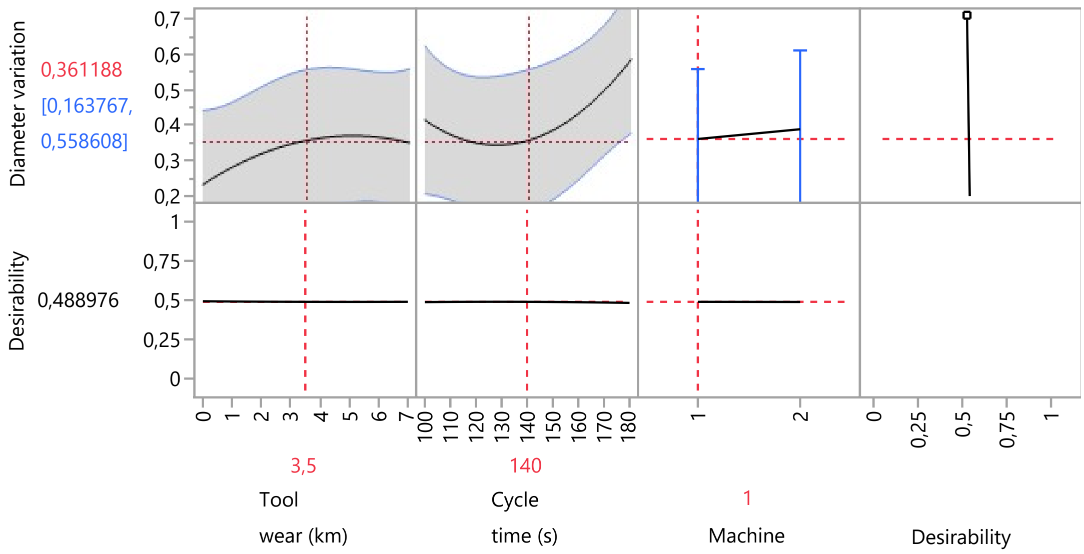
Table 5.1: Data table for DOE design

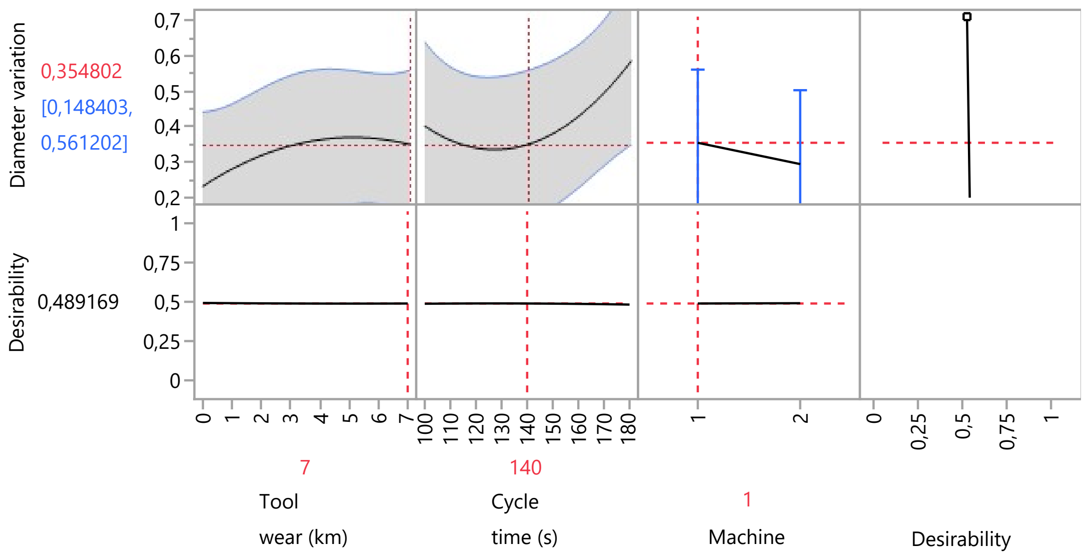
diameter variation on the y axis in red numbers, depending on the different settings on the x axis.

Response Diameter variation

Prediction Profiler







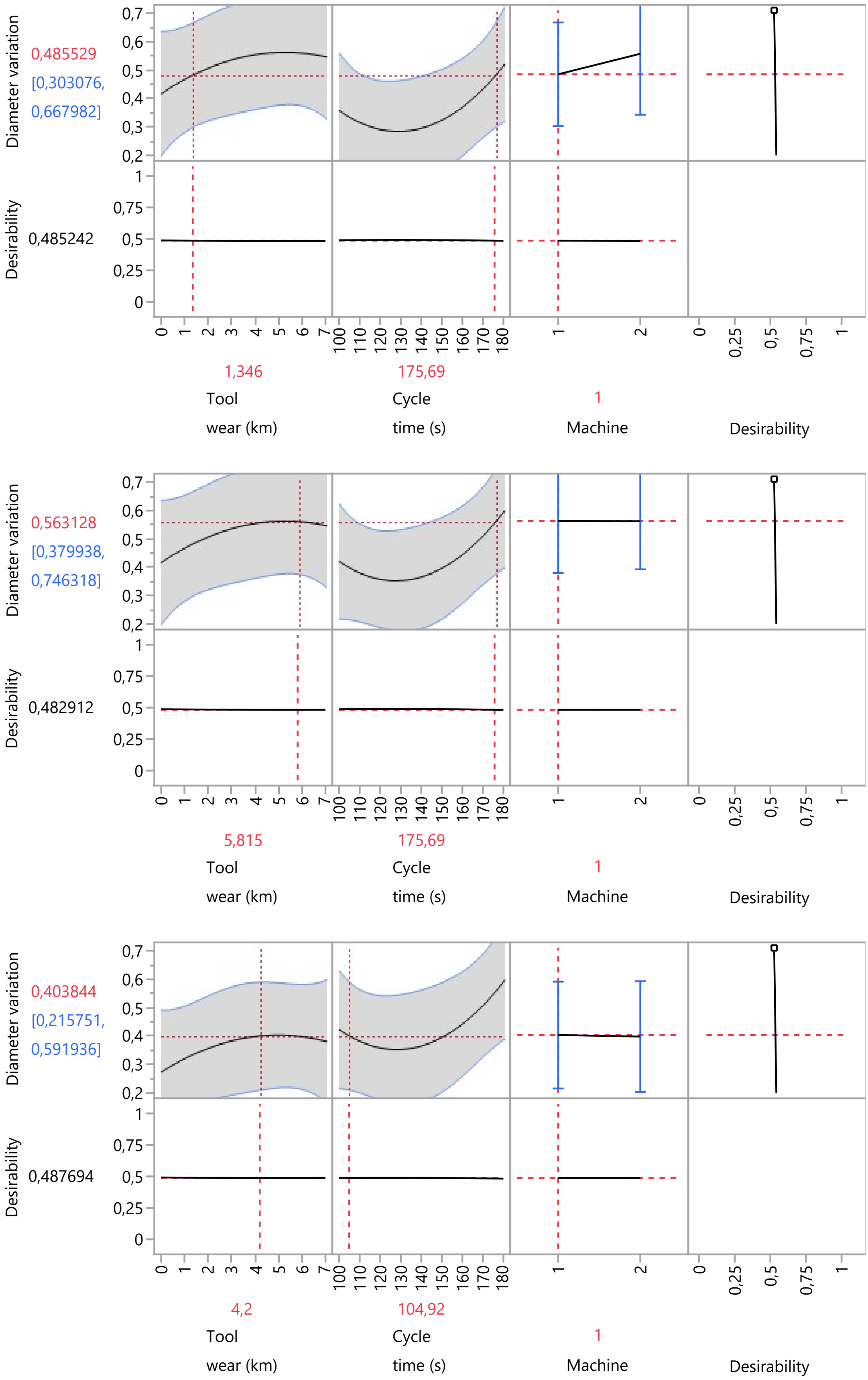


Figure 5.13: Prediction profiler 1

The graphs presents that the diameter variation after each processed unit is quite small, regardless setting on the factors. However, the first analysis shows that the variation is larger when the tool wear has reached half its useful life, and that rollers with longer cycle time tends to have a slight larger variation. Regarding the different turning machines, number one is seen to have smaller variation than 2 in the beginning of the tool life, and then in the end of the tool life it is the opposite. To generate an even more accurate model, it was decided to improve by adding some real replicates and use Bayseian optimization.

5.3.3 Improvement of the model

To be able to see a better significance between the factors, and to increase the amount of degrees of freedom (DOF), some "real replicates" were added to the data table. It means that four random settings were observed and measured from the process, and then added to the experimental plan. The added replicates that were added are displayed in Table 5.2

	Tool wear (km)	**Cycle time (s)**	**Machine**	**Diameter variation**
1	2	130	1	.
2	5	130	2	.
3	6	165	1	.
4	1	165	2	.

Table 5.2: Replicates added

5.3.3.1 Bayesian Optimization

To address the initial uncertainty in the DOE- model, Bayesian optimization (BO) was used to augment the experiment design. It was applied to avoid resource demanding replicates or experiment on new settings based on random samples and decisions. Instead, BO provided a data driven method with an algorithm balancing efficient exploitation and exploration.

Through this algorithm, three additional runs were generated in the data table . One of these consisted of a true replicate of the most stable run observed thus far, providing a direct and reliable measure of the process's measurement noise. The remaining two measurement points were directed toward areas with the highest probability of optimal dimensional stability, exploiting the model to identify the "sweet spot". Through this targeted augmentation, the model was provided with the missing degrees of freedom required to ensure statistical significance, while the machine's optimal cutting parameters could be analyzed with minimal material and time consumption. The runs that were added are presented in Table 5.3

	Tool wear (km)	Cycle time (s)	Machine	Diameter variation	Iteration	Reason added
1	6,686375075	131,3537...	2	.	1	Max Desirability
2	7	140	1	.	2	Replicate Best Training Run
3	4,64286480...	129,6580...	2	.	3	Max Desirability

Table 5.3: Bayesian points added

5.3.4 Final design

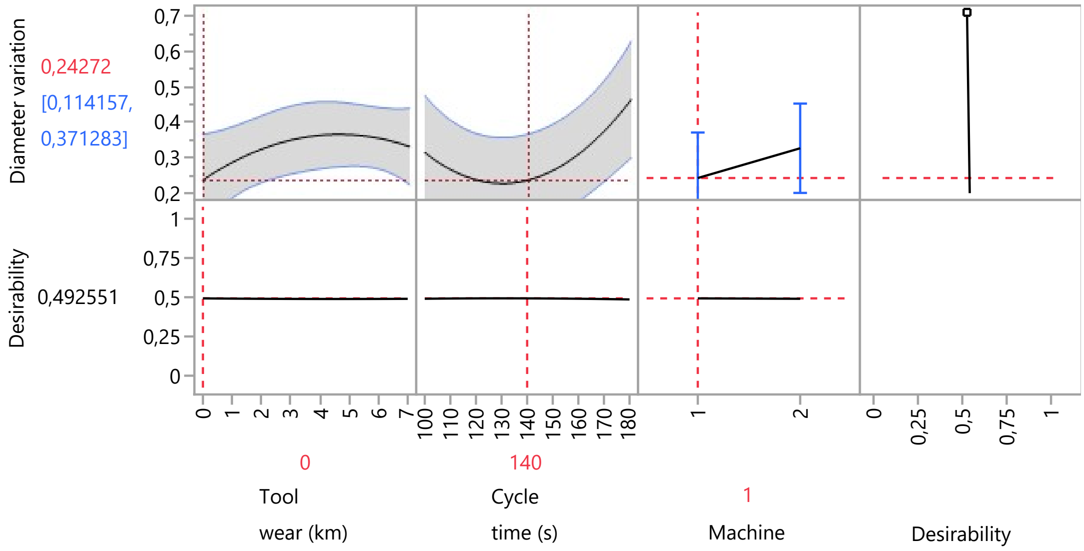
	Tool wear (km)	Cycle time (s)	Machine	Diameter variation	Iteration	Reason Added
1	7	140	1	0,226	0	
2	0	180	1	0,485	0	
3	7	100	1	0,48	0	
4	7	180	1	0,692	0	
5	7	100	2	0,276	0	
6	3,5	100	1	0,398	0	
7	0	140	1	0,266	0	
8	0	100	1	0,298	0	
9	0	180	2	0,524	0	
10	7	180	2	0,528	0	
11	3,5	180	1	0,506	0	
12	0	100	2	0,336	0	
13	3,5	140,8	2	0,492	0	
14	7	180	2	0,59	0	
15	0	100	2	0,52	0	
16	7	100	2	0,3	0	
17	2	130	1	0,384	0	
18	5	130	2	0,236	0	
19	6	165	1	0,44	0	
20	1	165	2	0,396	0	
21	6,686375075	131,3537...	2	0,267	1	Max Desirability
22	7	140	1	0,316	2	Replicate Best Training Run
23	4,64286480...	129,6580...	2	0,434	3	Max Desirability

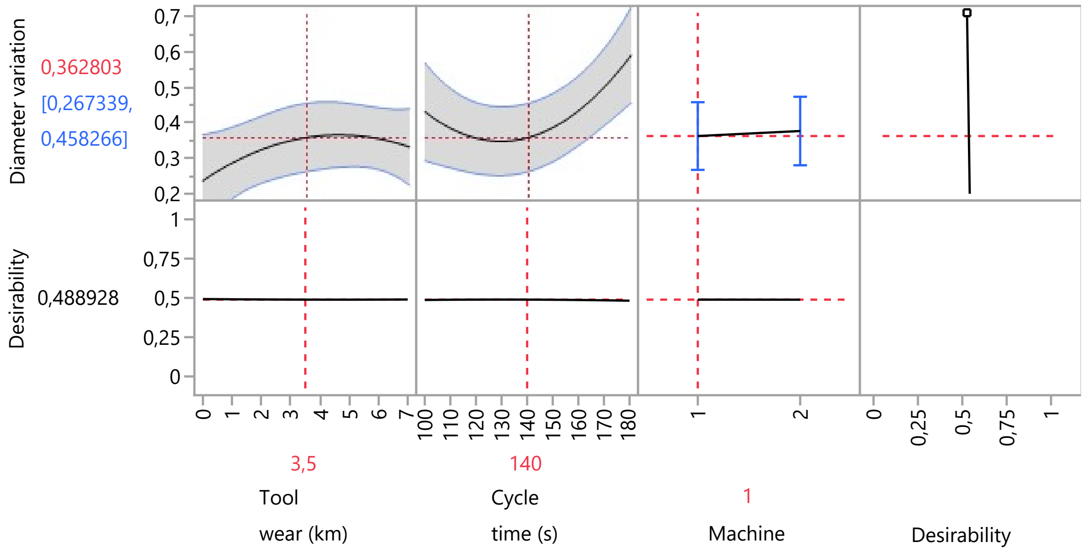
Table 5.4: Final data table for DOE design

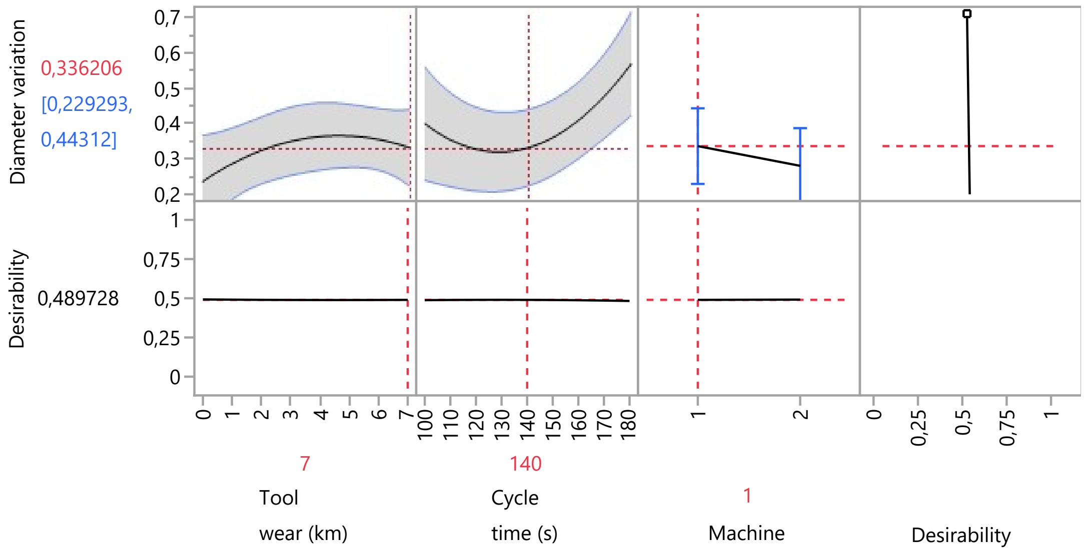
The final data table with the measured mean value for the different settings is presented in Table 5.4 the same model and effect between the different factors were still the same as in Figure 5.12, and the results from the prediction profile is displayed in Figure 5.14

Response Diameter variation

Prediction Profiler







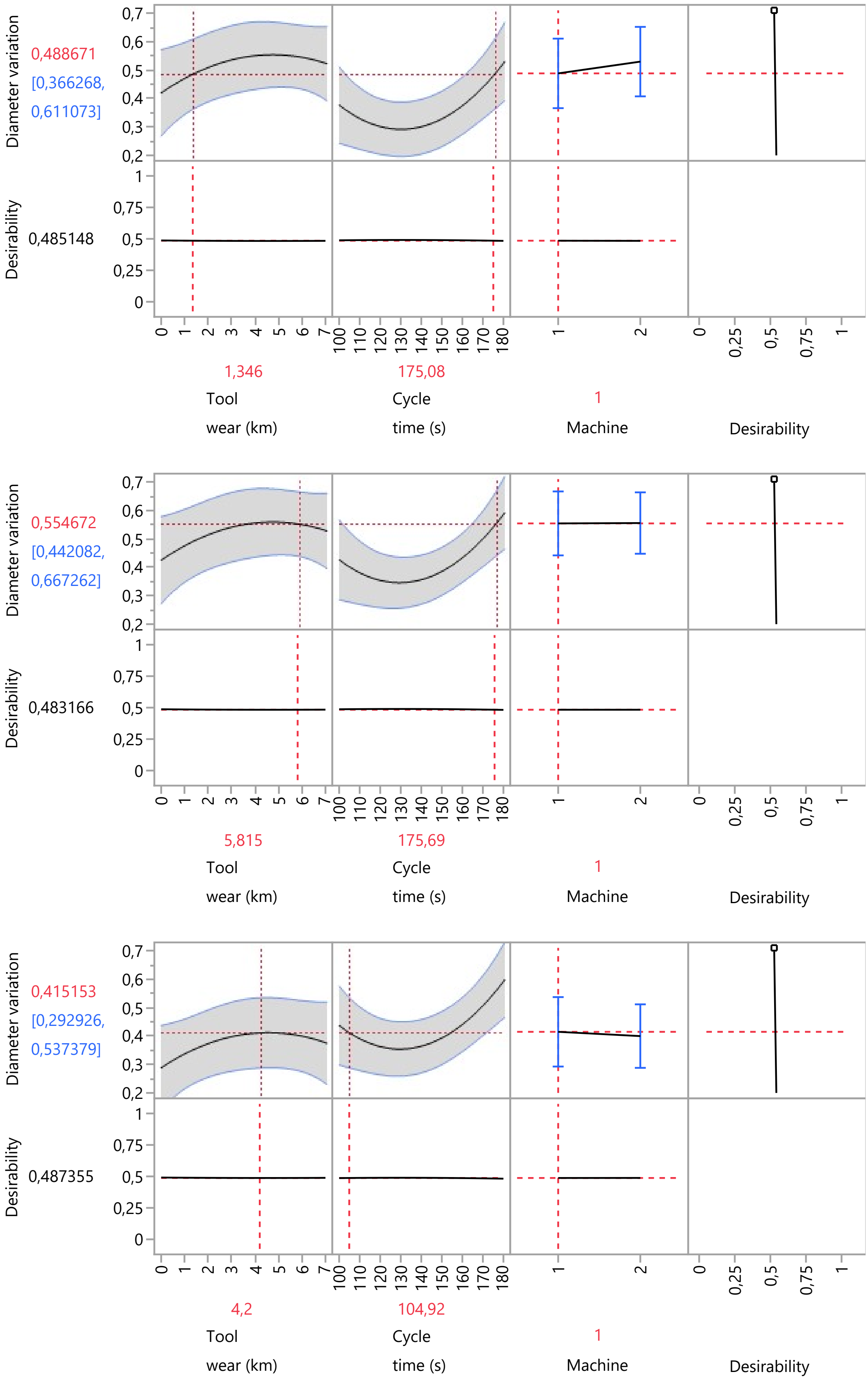


Figure 5.14: Prediction profiler 2

A visual comparison between the prediction plots before and after the Bayesian augmentation and the real replicates, indicates a significant improvement in the precision of the model. Despite that the predicted diameter variation for the different settings is more or less unchanged, the 95% confidence interval were almost halved. This is visualized by the gray shadowed area that surrounds the prediction line. It verifies that the addition in degrees of freedom, in particular the measurement of the process's pure noise by real replicates, successfully reduced the models uncertainty and resulted in a significantly more robust prediction model.

In Figure 5.15 the model is compared before and after the new points were added. Before the update, the model had a R-square value of 73%, but the the P-value were far to large with a value of 0.2376. It means that the model were not statistic significant, and there was a high chance that it just showed random noise.

When the new points were added, the reliability of the model was heavily improved. The P-value decreased to 0.02200, which indicated that the model was statistic significant. A decreased to R-square value to 70% is fully acceptable and normal when natural variation is added by a real replicate. Overall, the narrower red area in the new graph shows that the uncertainty has been reduced and that the model is now much more confident in its predictions."

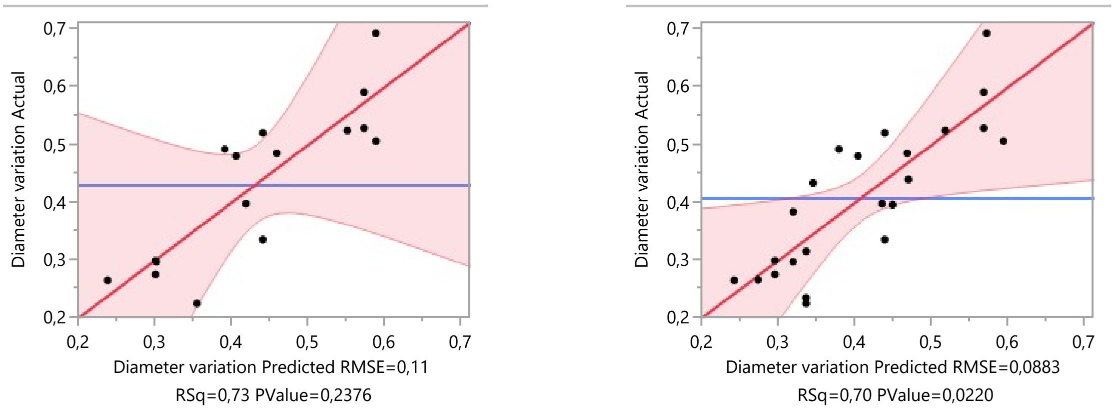


Figure 5.15: Predicted plot before and after

5.3.4.1 Improvement of final design

To further improve the final design, the AICc value of the model was observed in relation to the effect summary. Looking at Figure 5.16 all effects have a "LogWorth" value, which is JMP's recalculated P-value by the formula;

$$\text{LogWorth} = -\log_{10}(p\text{-value}) \tag{5.1}$$

The blue line is drawn at LogWorth = 2, which corresponds to a P-value of 0.01. Effects that do not cross the blue line are generally considered nonsignificant and are candidates for removal when reducing a model.

Source	Logworth	PValue
Cycle time(100,180)	2,390	0,00407
Cycle time*Cycle time	2,343	0,00453
Tool wear*Machine	0,847	0,14217
Tool wear*Tool wear	0,785	0,16397
Tool wear*Cycle time	0,455	0,35101
Tool wear*Cycle time*Machine	0,353	0,44379
Tool wear(0,7)	0,214	0,61110 ^
Machine	0,147	0,71279 ^
Cycle time*Machine	0,066	0,85843 ^

Figure 5.16: Effect summary of the model

Figure 5.17 shows the AICc value with all effects kept, after that each effect that did not cross the blue line were removed one by one. After each removal, the AICc kept decrease, indicating that the effects were not necessary for the model. By that, all effect on the left side of the blue line were removed and it resulted with an AICc value of -39, presented in Figure 5.18

Source	Logworth	PValue
Cycle time(100,180)	2,390	0,00407
Cycle time*Cycle time	2,343	0,00453
Tool wear*Machine	0,847	0,14217
Tool wear*Tool wear	0,785	0,16397
Tool wear*Cycle time	0,455	0,35101
Tool wear*Cycle time*Machine	0,353	0,44379
Tool wear(0,7)	0,214	0,61110 ^
Machine	0,147	0,71279 ^
Cycle time*Machine	0,066	0,85843 ^

Summary of Fit

RSquare	0,703466	AICc	-13,4775
RSquare Adj	0,498174	BIC	-24,9871
Root Mean Square Error	0,088332		
Mean of Response	0,408261		
Observations (or Sum Wgts)	23		

Figure 5.17: AICc value with all effects

Source	Logworth	PValue
Cycle time(100,180)	2,892	0,00128
Cycle time*Cycle time	2,420	0,00380

Summary of Fit

RSquare	0,548666	AICc	-39,5942
RSquare Adj	0,503532	BIC	-37,2744
Root Mean Square Error	0,087859		
Mean of Response	0,408261		

Figure 5.18: AICc value with removed effects

As a result of this, the cycle time setting was shown to be the only factor with statistically significant. The other factors are therefore, statistically, only noise that does not impact the stability of the diameter measure. The final prediction profile which is presented in Figure 5.19, 5.20, 5.21, indicates that the optimal cycle time for the smallest diameter variation is around 130 seconds. However, it shows that all roller types, regardless cycle time have a good stability as the highest variation only exceeds up to 0,55 μm, found at the longest cycle time at 180 seconds.

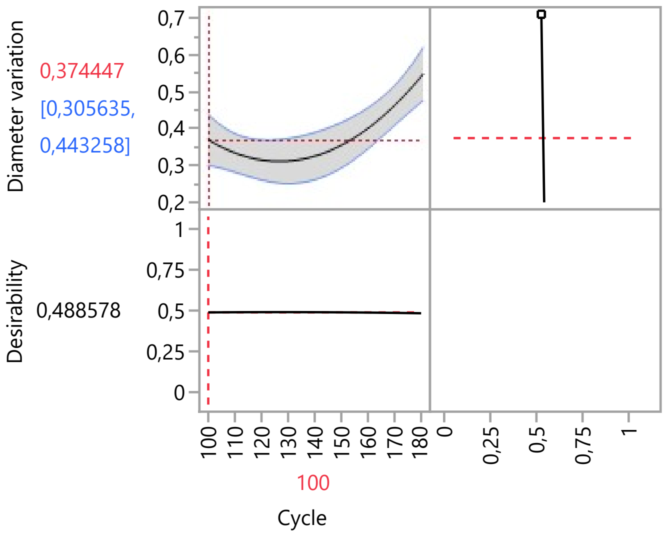


Figure 5.19: Prediction of cycle time 100 s

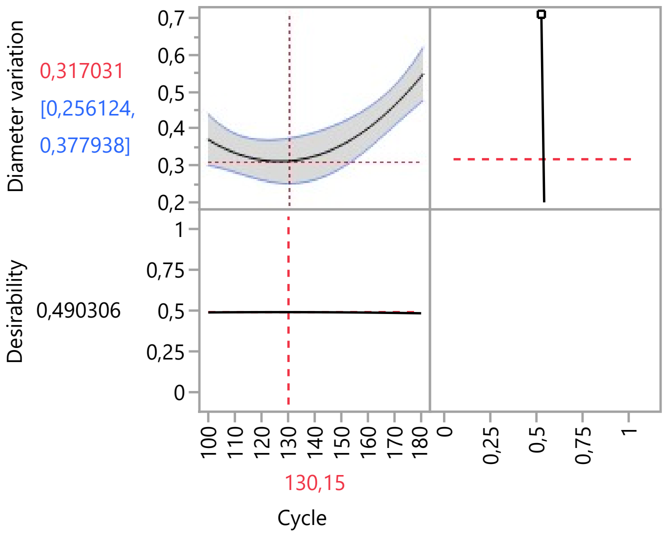


Figure 5.20: Prediction of cycle time 130 s

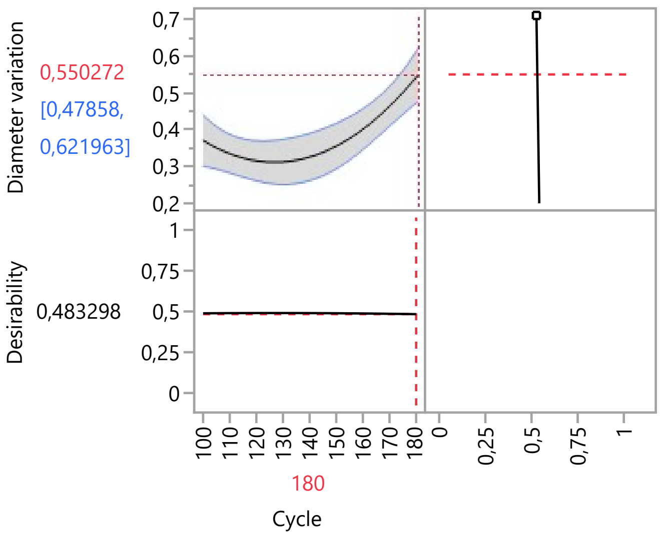


Figure 5.21: Prediction of cycle time 180 s

5.4 Analyze of final model & answer to research question

The last step of the analysis is to reach back to the new formulated research questions, which were defined as:

- Does all rollers need to be measured between the turning and honing operation?

- How robust is the outcome of the turning process to variation?

The performed analysis answers that the diameter outcome from the turning machine indicates a good robustness to variation. There is a variation depending on the cycle time, but looking at the diameter variation and comparing it to the actual diameter measure of the rollers, the occurring variation is fully acceptable. The rollers produced are between 50 to 100 mm in diameter, with groupings between -10 to +10 μm, meaning that a variation between 0,30 to 0,55 is defined as fully acceptable.

Based on the final improved design, the tool wear did not affect the diameter outcome. Therefore, the findings from the first analysis about a greater variation when tool has reached half of its useful life, can be defined as noise and that the diameter outcome has a good robustness to variation caused by the cutting tool.

The final model of the analysis brought the project into the improve (I) phase of the DMAIC framework, it answers what can be improved and also what should not be changed. As the cycle time is a standard operating procedure (S) that can not be changed, the study was used to determine the first reformulated research question. Which covers the frustration and confusion that existed about how much that should be measured between the turning and honing operation.

Looking at the first reformulated question about how many rollers that need to be measured, the findings from the final model can be evaluated together with the measurement system analysis (MSA). The variation measured from the turning machine and that is predicted in the DOE includes both positive and negative variation, meaning that one roller can increase 0,35 after one cycle, while it can decrease 0,35 after the next. As a result of this, it was decided to accept a maximum variation of 2 μm before a measurement should be performed again. Meaning that all roller types with a cycle time of maximum 160 seconds needs to be measured every fifth cycle, and types with a cycle time between 161 and 180 seconds every third cycle, based on the prediction profile presented in Figure

6

Discussion & Conclusion

This chapter evaluates the empiric results that have been obtained from the DMAIC framework and discuss its meaning, both from a methodological and an operational perspective, supported by established theories within statistical process control.

6.1 Discussion of the results

The main purpose with this project was to analyze and identify which factors that affects the production flow's robustness, to push the frontier of knowledge forward, to be able to solve the problem with long cycle times at the given production flow. By applying the DMAIC framework, the main causes of the problem have been identified, and improvements have been developed.

6.1.1 System design and robustness

In the early phases of the project, the AIM and the effective scoping succsesfully isolated the material handling and the measurement logic as primary problem areas, rather then adressing a problem directly connected to a mechanical problem in a machine. This initial delimitation was validated by the Cause and Effect- Matrix, which highlighted that roller dimensions, cycle times, measurement frequencies, and buffer levels was the critical parameters that affected the whole production flow.

When a system is evaluated in a macro perspective, Balestracci arguments for that each system is perfectly design to achieve, exactly the result it gives [10]. The historical cycle time losses that defined that main problem given by the company was not a result of a human error, or a specific problem related to a certain machine. Instead, it was consequence of a system design that forced a 100 % measurement frequency, that actually was not required.

The performed Design of Experiments (DOE), supported by Bayesian Optimization, proved that the turning process is extremely robust. Factors as tool wear, and the different turning machines (1 and 2) were proven to only be background noise. The resulted diameter variation of 0,3-0,55 μm was remarkably small and well within the technical tolerance limits. Given by the theory for statistical process control, these results indicates that the turning machine is driven by common cause variation [10]. The small variations in diameter represents the *"the voice of the process"* [12], meaning that the machine is robust, predictable, and have high capability .

6.1.2 MSA- the fear of "Tampering"

While the turning machine itself proved to be stable, the Measurement System Analysis (MSA), revealed an important finding, the upcoming of measurement noise and a blind spot probably caused by environmental factors, such as dirt and dust. This finding is critical when new operational guidelines should be designed.

If the production flow continues with applying a 100 % measurement frequency where each roller is measured, both operators and automated control system risks to react on data that is affected by surrounding noise, rather than actual processing errors. To go in and adjust a fundamentally stable process, based on noisy measurements, is a school book example of tampering [10]. Instead of improving the quality, tampering introduces an artificial special cause variation, to an already stable system, which in the end increases the total process variation, and decreases the product quality.

6.1.3 Optimization Vs. Mass Inspection

The core of this project is located in the identification of factors affecting the diameter outcome. It shows that every movement by the robots when they are moving back and forth to the measurement station with a turned roller, creates a structural bottleneck. The suggested improvement, to use the bypass function in a structured controlled way, solves this reduction of the flow.

From a theoretical point of view, this shift from 100 % inspection to a more dynamic sampling, aligns perfect with Demings third point, which advocates that the dependence on mass inspection should be eliminated [11]. Gitlow empathizes on that mass inspection does not add any quality to a product, it only detects defects afterwards, at the same time as it adds unnecessary time and cost to the process.

As the DoE- analysis verifies that the turning process performs under statistical control and possess a high capability, the measurement of each roller does not add any value for the company. It only entails an alarming cycle time loss. By implementing the framework for the bypass function, the company can eliminate unnecessary mass inspection and optimize the production flow, without risk the product quality.

6.2 Discussion of the Method

The procedure of research the robustness of variation, and adopt Six Sigma's DMAIC methodology resulted in a rigorous and data driven structure that avoided rushed conclusions. Instead of guessing which parameters that needed to be studied, the method and the framework ensured that the project moved logically from defining the problem, to controlling the new condition. Indicating the power of Six sigma, and the importance of variation.

One common pitfall within industrial production economy is to base capacity- and flow models on statistical average values. A traditional analysis would have looked at the average cycle time of turning machine, comparing it with the average cycle time of the robot, drawing the conclusions that the system is in balance. As Savage points out, decisions based on average value is historically wrong, the so called phenomenon *"The Flaw of Averages* [13].

6.2.1 Delimitation of the method

Even though the combination of DoE and Bayesian Optimization was very efficient, some delimitations need to be mentioned. The experiments was performed under a limited time frame, leading to that some long term variation can have been missed out. Tool wear developed over a longer time frame could not be investigated. The ambient temperature were consistent over the whole experiments, due to a forgiven temperature outside the factory. However, the experiment could not cover how an increased ambient temperature, which often is the case during summer, would have affect the results.

The addition on incoming raw material was measured by random samples, and indicated a good robustness. However, it would be even more reliable to add it as a covariance factor in the experimental. The reason for not doing this was partly the result of the good robustness, but also that the process did not support any function to both measure a specific incoming Rq roller, and then follow its path into the turning machine.

6.3 Control-phase & Long term implementation

To ensure that the achieved result is maintained over time, is the core of the DMAIC-frameworks last step, the Control phase. Within Six Sigma, one of the biggest threat to successfully improvement projects, is that the process slowly returns to it origin, inefficient state when the project is finished. To avoid this at the production flow, the new measurement logic need to be built in, rather than trust human routines.

6.3.1 Automation & Poka-Yoke

To build in the improvement in the flow, the most critical action in the control phase is to integrate the bypass function as an automatic function in the PLC-system. By letting the robot automatically activate the bypass function depending on the cycle time in the turning machine, it would be a solution with *"Poka-Yoke"* characterization.

If the choice to activate bypass depending on cycle time had been handed over to the operators, for them to control manually by the monitor, the process would been vulnerable to cognitive loading, shift handovers, and varying experience levels. By programming the logic into the PLC-system, the improvement becomes a permanent design of the system design. This eliminates the human factor and ensures that mass inspection is not reintroduced due to old behaviors.

6.3.2 Standardization and monitoring via control charts

To operate the control phase, a robust and standardized monitoring system can be implemented. A system that ensures that the turning process maintain its optimal performance over time and does deviates from is nominal performance.

Traditional Shewhart charts, such as XmR is efficient for identifying sudden and large machine errors. As the low variance from the turning machine requires special demands on statistic sensitivity, and that the long term special cause variation is expected to be gradient and continuous, a standard control chart tends to react to late as it only evaluates the latest measurement value isolated [14].

A solution for this would be the use of Exponentially Weighted Moving Average (EWMA)- chart. By applying an EWMA model to the reduced data flow, the system can exploit historical measurement data where older points is given a exponential decreasing weight. As the literature mention, a small value of λ makes the chart extremely sensitive to slow and smaller changes of the process average.

This would mean that the control system predictive can alarm for incipient deviations long before the measurement of the rollers risks to reach the actual technical tolerance limits. Despite not being needed today, as there is room for measuring every fifth or third roller, this can be beneficial if another turning machine is brought in. Combining this study with an implementation of EWMA could have resulted that you more or less can eliminate all measuring between the turning and honing operation.

6.3.3 Standardizing the movement of the robot

The previous uncertainty about the measurement frequency has not only affected the throughput at the measurement station. It has also introduced a secondary variation in robot 1:2's material handling cycle. As the robot was forced to work in a flexible, reactive flow, where movement constantly shifted depending on which sub process that happened to be finished first, it created a built in variance to the robots own cycle times.

If the underlying variation in a system is not well known and in statistical control, there is a big risk that the whole system is built in a way, that forces is to compensate for that noise. [9] Therefore, the movement of the robot can be defined as emergency solution to handle a non stable measurement procedure.

Thanks to this study, the measurement station can now be built away, and as a result of that, a radical reprogramming of the robots control logic can be made. Instead of a reactive pattern, the robot can now be programmed in a sequential, "straight" flow. It means that the robot can perform all of its task in a standardized order, cycle after cycle.

In a Six Sigma perspective and its control phase, this possible standardization is an ultimate prove of a successful process improvement. By reducing the variation in the measurement station, the next mechanical link can be standardized. This creates a repetitive and robust production flow that is run close to its full potential.

6.4 Conclusion

This research project have been embossed by a dynamic and systematic research process. The project was initiated with a broad an open mandate, to research the overall production flow and its robustness to variation. During the project's run, in time with the use of the introducing scoping tools, the project took an early turn. It went clear that the robustness of the flow was heavily affected by the measurement station, and the bottleneck was strongly connected to it.

This insight lead to a more narrowed down perspective, with the focus on correlation between the turning process and measurement station. This resulted in that the two first formulated research question more facilitated as "Investigate question", as they set the direction for the formulation of the two new final research questions. By summarizing the project's conclusions based on these questions, the study is brought to a close, from the initial mapping of the process, to data driven recommendations for the company.

6.4.1 Answer to Research questions

- How robust is the outcome of the turning process to variation??

The turning process exhibits a very high degree of robustness and capability under current production conditions. Short term tool wear was identified as random noise in the process, without affecting out coming quality. Cycle time was defined as the only statistic significant factor, with the help of DOE and Bayesian Optimization. The resulted variation was well within the acceptable tolerance limits, making the turning operation well predictable in the total flow.

- Does all rollers need to be measured between the turning and honing operation?

No, a 100 % mass inspection is either academically or industrial motivated. As the process is fundamentally robust and that the measurement equipment shows a "blind spot", which prevent it from detecting sudden changes, a continuous measuring does not add any value to the flow. On the contrary, mass inspection instead constitutes to unjustified "Tampering". The recommendation is to only measure every third or fifth cycle depending on the cycle time.

As a result of the study, the already reformulated research question can be defined as investigation questions, as they facilitated the whole study and set the direction after the scoping and Define phase. However, in the end, the final research question is formulated as:

- Can mass inspection be eliminated in order to optimize the material handling between machines, to increase the resource efficiency in bottleneck machine?

As the previous answer displays, a 100% mass inspection within the process is not necessary, and by that it can be eliminated to increase the resource efficiency in the bottleneck machine.

6.4.2 Industrial and academic contributions

For SKF, the result of this study brings a concrete solution to a critical bottleneck in the production flow. By eliminating the mass inspection and replace it with a more strategic interval, the flow's robustness is heavily improved and facilitates improvement of robot 1:2, which will help the company to solve the incipient problem with long cycle times and low resource efficiency in the bottleneck machine. The research will also support future improvement work, as a big variation source will be gone forever, and enhance the avoidance of sub-optimizations in the future.

Academically, the research contributes with a concrete example about how Six Sigma's DMAIC can be used to analyze a whole production flow and successfully combine it with statistical tools as Design of Experiments and Bayesian Optimization. It also shows the power of performing a research of robustness to variation and to adopt a flexible, agile research design were the problem definition is allowed to grow and develop simultaneously as empiric data is gathered.

6.4.3 Future work

To build on this study and to ensure long term implementation in SKF, there are some recommendations. The findings from this study is planned to form the basis of reprogramming in the upcoming weeks after the project. This reprogramming will consist of an implementation in the PLC program, where the measurement interval is going to be built in to the system, and the robot's movement after the measurement station will be changed to a straight flow.

Besides that, the recommendation is to analyze the possibility to implement an EWMA chart, linked to the turning machine. This could both eliminate even more measuring, but also facilitate an even more adaptive tool change interval. Instead of always changing after 7 km, the machine could detect itself when its time for change. As a result of this, a third turning machine could have been brought in, to reduce the cycle times even more.

From a bigger point of view within SKF, this study could serve as foundation for the use of certain statistical tools in other departments. As the common culture about the tools that has been used in this research is somewhat reluctant, this proves the opposite. Measurement System Analysis is discussed as something to hard to understand, from an mathematically perspective, and also very time consuming. Design of Experiments is directly connected to factorial design, which is also discussed as too much mathematics. Bayesian optimization is not that familiar for people within the company. However, this study shows the power of the tools, but also how a software like JMP can enhance the usage, by doing the mathematical calculation itself.

In the end, this project emphasizes that the ability to understand and handle variation in a process is crucial to solve complex problems within industrial production flows. By systematically research the upcoming causes to variation, SKF could build in a robustness to their production flow, which in the end can be the key to success.

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A

Appendix

A.1 Effective Scoping 1

Process owner (org): SKF Sverige AB | Project sponsor: Damir Todorovac | Six Sigma trainee: Hugo Ringeby

Effective Scoping of continuous improvement projects

The __sequence in itself__, of questions Q1-Q4, Q5-Q7 and Q8-Q9 below, is key to facilitate consensus in the shift of an organisation's mindsets from push to pull, in accordance with the principles of Lean Six Sigma

Supplier	Input		Process	Output		Customer
8b. Who supplies the inputs?	Q8a. What are the inputs to the system?	Q9. What does the system require of the inputs?	Q7a. Team/project jurisdiction of changes	Q1. What comes out (of the physical flow) - OUTPUT?	Q3. What is required of the output from this particular user (List of big Y's and improvement proposals)	Q2. Who uses the output?
External suppliers for raw material. Pallets and plastic dividers are resued within SKF. Other emballage is provided by external suppliers. Cutting tools is provided by external suppliers and changed by operators Machine tools and systems are responsible by internal technicans and maintenance workers. Manpower is supplied by production manager. Quality standards supplies the inspection settings. Machine settings and programming are developed by Process development department, and then supported by operators.	Raw material, soft machined heat treated rollers, wood pallet, plastic divider, rust protection, foam. Cuttting tools, honing stones, honing tape. Grippping tools, suction cups, pneumatic systems, hydraulic systems. Operators, adjustable buffer levels, manual visual inspection, manual control of rollers. Machine settings, NC programming.	Incoming raw material needs to meet requirments regarding dimension, hardness, and visual apperance on parts that is not processed in this process. Machine and robot tools needs to meet specific standards, regarding quality and dimensions depending on what type is being produced. Correct process data choosed by operator.	Material handling in production, Machine settings, PLC programming, Robot programming, Work methods, Maintenance standrads.	Finished rollers that meet all quality requirements, which are assembled into complete roller bearings.	**Product according to specification, Quality assurance,**	There are two users of the output. The first one is the person that assembles the finsihed bearing in the final application. The second user is the end customer
			Q7b. What competences are needed in the team (WHO)?		**Q4. __What ONE MEASURE (y)__ should be understood and improved? The y that scope the project and drive further exploration. Each small y has its own underlying system of influencing parameters, sometime overlapping. Use one template per y to reduce complexity Scope on y (not x - upstream) and don't proceed until Q1-Q4 is thoroughly understood!**	
			Operators, Production manager, Reliability engineer (Industrial, Maintenance, and Quality), supply chain, and Processs development		**Reduce cycle time for one produced unit**	
			Name of the flow to be improved:		Q5. What is the baseline of the y and can that precis y be measured today (and can old data be trusted)? In other words: What is the **facts** behind the problem that form the base for our improvement promise? Show the data/proof of a problem!	
			RR05		Low efficiency of bottleneck machine is the fact behind the problem. No prevoius reserach in variation has been performed but historical data, gathered from different puproses is available and can to some extend be used for analyzing the variation.	
			From where is the physical output shipped?		Q6. What other Y can not be lost in the process (constraints)?	
			Roller bearing assembly departments, both internal and external within SKF.		Quality standards, union related questions, work enviroment, physical impact on operators.	

A.2 Effective Scoping 2

Process owner (org):	SKF Sverige AB	Project sponsor:	Damir Todorovac	Six Sigma trainee:	Hugo Ringeby

Effective Scoping of continuous improvement projects

The __sequence in itself__, of questions Q1-Q4, Q5-Q7 and Q8-Q9 below, is key to facilitate consensus in the shift of an organisation's mindsets from push to pull, in accordance with the principles of Lean Six Sigma

Supplier	Input		Process	Output		Customer
8b. Who supplies the inputs?	Q8a. What are the inputs to the system?	Q9. What does the system require of the inputs?	Q7a. Team/project jurisdiction of changes	Q1. What comes out (of the physical flow) - OUTPUT?	Q3. What is required of the output from this particular user (List of big Y's and improvement proposals)	Q2. Who uses the output?
The turning machine supplies with machined rollers. Turning machine together with enviorment supplies the temperature of the detail. Enviroment supplies the ambient temperature. Industrial robot supplies the Gripping tools, pneumatic systems, hydraulic systems.	Machined rollers from the turning machine. Temperature of the detail (roller), and ambient temperature. Roller dimension (Diameter and length) Gripping tools, pneumatic systems, hydraulic systems.	The correct product type. A machined roller form the truning machine. Correct delivery from the industrial robot.	Turning opperation, measurement opperation, PLC programming. Q7b. What competences are needed in the team (WHO)? Operators, Production manager, Reliability engineer (Industrial and Quality), and Processs development. *Name of the flow to be improved:* *Marposs machine* From where is the physical output shipped? To the honing station.	Measured rollers, in both diameter and roundness.	**Correct measurment results, correct signal for robot to pick and place.** **Q4. __What ONE MEASURE (y)__ should be understood and improved? The y that scope the project and drive further exploration.** **Each small y has its own underlying system of influencing parameters, sometime overlapping. Use one template per y to reduce complexity** **Scope on y (not x - upstream) and don't proceed until Q1-Q4 is thoroughly understood!** **Does all roller need to be measured after the turning operation? How many unit can be processed in turning machine before they need to be measured? Does the measurment machine need to compensate for every roller?** Q5. What is the baseline of the y and can that precis y be measured today (and can old data be trusted)? In other words: What is the **facts** behind the problem that form the base for our improvement promise? Show the data/proof of a problem! No historical data to determine the baseline, measurment can be done directly to see how the turning machines behave if the measurments are reduced. Q6. What other Y can not be lost in the process (constraints)? After honing process, all rollers need to be measured to meet quality standards. No improvement work can be done there.	Operators, turning and honing machine.

A.3 Cause & Effect Matrix

Six Sigma Cause & Effect Matrix

SKF Six Sigma

			1	2	3	4	5	
		Rating of Importance to Customer	10					
		Key Process Outputs	Cycle time for one produced unit					
	Process Step	**Process Input**						**Total**
1	Infeed	Roller dimension (S)	9					**90**
2	Infeed	Preventive Maintenance (S)	1					**10**
3	Infeed	Pallet height (C)	1					**10**
4	Infeed	Suction cup (C)	1					**10**
5	Buffer	Buffer level (C)	3					**30**
6	Buffer	Pick and place positions (C)	3					**30**
7	Buffer	Robot gripper (C)	1					**10**
8	Turning	Tool change (S!)	3					**30**
9	Turning	Preventive Maintenance (S)	1					**10**
10	Turning	Cycle time (S!)	9					**90**
11	Turning	Loading time (S)	3					**30**
12	Turning	High speed feed (C)	3					**30**
13	Turning	Tool wear compensation (C)	3					**30**
14	Bypass station	Roller dimension (S)	9					**90**
15	Measurement	Loading time (S)	1					**10**
16	Measurement	Roller dimension (S)	3					**30**
17	Measurement	Roller temperature (N)	0					**0**
18	Measurement	Ambient temperature (N)	0					**0**
19	Honing	Cycle time (S!)	3					**30**
20	Honing	Tool change (S!)	1					**10**
21	Honing	Preventive Maintenance (S)	1					**10**
22	Honing	Loading time (S)	1					**10**
23	Honing	Tool dimension (C)	1					**10**
24	NDT	Roller dimension (S)	3					**30**
25	NDT	Cycle time (S!)	3					**30**
26	NDT	Preventive Maintenance (S)	1					**10**
27	Measurement	Loading time (S)	1					**10**
28	Measurement	Roller dimension (S)	3					**30**
29	Measurement	Roller temperature (N)	0					**0**
30	Measurement	Ambient temperature (N)	0					**0**
31	Manual inspection 1/2	Buffer level (C)	9					**90**
32	Manual inspection 1/2	Operator experience (N)	3					**30**
33	Manual inspection 2/2	Buffer level (C)	3					**30**
34	Manual inspection 2/3	Operator experience (N)	3					**30**
35	Final Pallet	Pick and place positions (C)	3					**30**
36	Final Pallet	Robot gripper (C)	1					**10**
		Total	**940**	**0**	**0**	**0**	**0**	

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