INVENTORY OPTIMIZATION WITH LEAN SIX SIGMA – A DMAIC APPROACH

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ABSTRACT

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Effective inventory management is a cornerstone of operational success in manufacturing and supply chain environments. Organizations face ongoing challenges in balancing the need to minimize inventory-related costs with the imperative to maintain high service levels and responsiveness. The increasing complexity and variability of modern supply chains further complicate efforts to optimize inventory, making traditional, intuition-based approaches insufficient.

The aim of this study is to develop and implement a systematic, data-driven approach for optimizing safety stock levels in a manufacturing context. By applying Lean Six Sigma methodologies, the research seeks to identify inefficiencies in current safety stock practices, evaluate alternative calculation methods, and establish robust strategies for sustainable improvement. The study also emphasizes the importance of continuous measurement and adaptation as part of the inventory optimization process.

The results of the study demonstrate that the Lean Six Sigma approach can lead to significant reductions in excess inventory while maintaining targeted service levels. The implementation of a data-driven safety stock calculation method improved working capital efficiency, enhanced process transparency, and supported a culture of continuous improvement. These findings highlight the value of structured, analytical methodologies for inventory optimization and provide practical guidance for organizations seeking to enhance their inventory management practices in dynamic manufacturing environments.

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Tehokas varastonhallinta on operatiivisen menestyksen kulmakivi valmistus- ja toimitusketjuympäristöissä. Yritykset kohtaavat jatkuvasti haasteita pyrkiessään minimoimaan varastointiin liittyviä kustannuksia ja samalla ylläpitämään korkeaa palvelutasoa ja reagointikykyä. Modernien toimitusketjujen kasvava monimutkaisuus ja vaihtelevuus vaikeuttavat entisestään varastojen optimointia, mikä tekee perinteisistä, intuitioon perustuvista lähestymistavoista riittämättömiä.

Tämän tutkimuksen tavoitteena oli kehittää ja ottaa käyttöön systemaattinen, dataan perustuva menetelmä varmuusvarastotasojen optimointiin tuotantoympäristössä. Lean Six Sigma -menetelmän avulla pyrittiin tunnistamaan nykyisen varmuusvarastokäytännön tehottomuudet, arvioimaan vaihtoehtoisia laskentamenetelmiä ja luomaan kestävät parannusstrategiat. Tutkimuksessa korostetaan myös jatkuvan mittaamisen ja sopeutumisen merkitystä varaston optimoinnin osana.

Tutkimuksen tulokset osoittavat, että Lean Six Sigma-lähestymistapa voi johtaa merkittäviin ylimääräisten varastojen vähennyksiin samalla kun tavoitellut palvelutasot säilyvät. Dataan perustuvan varmuusvarastolaskennan käyttöönotto paransi käyttöpääoman tehokkuutta, lisäsi prosessin läpinäkyvyyttä ja tuki jatkuvan parantamisen kulttuuria. Tulokset korostavat rakenteellisten ja analyyttisten menetelmien arvoa varaston optimoinnissa ja tarjoavat käytännön ohjeita organisaatioille, jotka haluavat kehittää varastonhallintaansa dynaamisissa tuotantoympäristöissä.

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Turku, December 8th, 2025

SYMBOLS AND ABBREVIATIONS

Roman characters

SS	Safety stock
K	Service level factor
Z	Service level factor
D	Average demand

Greek characters

σ	Standard deviation of a variable

Abbreviations

CI	Confidence Interval
CTQ	Critical-To-Quality
DPMO	Defects Per Million Opportunities
JIT	Just-In-Time
KPI	Key Performance Indicator
LCL	Lower Control Limit
TPS	Toyota Production System
UCL	Upper Control Limit
VSM	Value Stream Mapping

Table of contents

Abstract

Acknowledgements

Symbols and abbreviations

Declarations

1 Introduction 10
1.1 Objectives and Research Questions 11
1.2 Conceptual Framework 12
1.3 Thesis Structure 12
2 Lean 14
2.1 Lean Principles 14
2.2 Waste 16
2.3 Lean tools 18
2.3.1 Value Stream Mapping 18
2.3.2 JIT 19
2.3.3 Kaizen 19
2.3.4 Kanban 19
2.3.5 Poka-Yoke 20
3 Six Sigma 21
4 Lean Six Sigma 23
4.1 Benefits of combining Lean and Six Sigma 23
4.2 Principles of LSS 24
4.3 Tools of LSS 25
5 DMAIC 27
6 Application of LSS to Inventory 30
6.1 Inventory Management Challenges 30
6.2 Applying DMAIC to Inventory 32
7 Case Study – Optimization of Safety Stock Using Lean Six Sigma 34

7.1 Background 34
7.2 Safety Stock Formulas 35
7.3 Define 37
7.3.1 Problem Statement and Business Case 37
7.3.2 Scope and Boundaries 38
7.3.3 Voice of Customer 39
7.4 Measure 41
7.5 Analyze 42
7.5.1 Lead Time 42
7.5.2 Production Output 46
7.5.3 Scrapping 48
7.5.4 Inventory Differences 51
7.6 Improve 54
7.7 Control 64
8 Discussion 66
8.1 Benefits and limitations 66
8.2 Comparative analysis with prior research 67
8.3 Managerial implications 69
8.4 Answering the research questions 70
8.5 Suggestions for future research 71
9 Conclusions 73
References 75

Figures

Figure 1. DMAIC process
Figure 2. Variables of Safety Stock
Figure 3. Lead Time Variance, Summary Report
Figure 4. Lead Time Variance, I-MR Chart
Figure 5. Production Output, Summary Report
Figure 6. Production Output, I-MR Chart
Figure 7. Scrapping, Summary Report
Figure 8. Scrapping, I-MR Chart
Figure 9. Inventory Differences, Summary Report
Figure 10. Inventory Differences, I-MR Chart

Tables

Table 1. The Five Principles of Lean
Table 2. Types of Waste
Table 3. Lean tools
Table 4. DMAIC objectives and tools
Table 5. Safety Stock Formula Comparison
Table 6. Safety Stock Calculation 1
Table 7. Safety Stock Calculation 2
Table 8. Safety Stock Calculation 3
Table 9. Safety Stock Calculation 4

DECLARATIONS

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The author, Olli Rautiainen, takes full responsibility for the content of this thesis and has reviewed and edited the content generated by the possible use of AI tools.

1 Introduction

In today's highly competitive manufacturing and supply chain environments, effective inventory management has become more critical than ever before. Organizations are under constant pressure to deliver products quickly and reliably, while simultaneously minimizing the costs associated with holding and managing inventory. (Arunadevi, Umamaheswari & Wang, 2025) Achieving this delicate balance is a complex challenge. It requires companies to respond rapidly to fluctuations in demand, supply chain disruptions, and evolving customer expectations, all while maintaining operational efficiency and financial sustainability.

Inventory optimization, therefore, stands at the forefront of strategic priorities for manufacturing firms. The ability to maintain the right amount of inventory, not too much to incur unnecessary costs, and not too little to risk stockouts and lost sales, can have a profound impact on a company's profitability, customer satisfaction, and long-term competitiveness (Transchel, Buisman & Haijema, 2022). However, traditional approaches to inventory management often rely on static rules, historical practices, or intuition, which may not be sufficient in the face of increasing complexity and variability in modern supply chains.

To address these challenges, organizations are increasingly turning to structured methodologies that combine process improvement with data-driven decision-making. Among these, Lean Six Sigma has emerged as a leading framework, integrating the principles of Lean, focused on eliminating waste and enhancing value, with the statistical rigor and quality focus of Six Sigma (Laureani & Antony, 2012). This hybrid approach offers a comprehensive set of tools and techniques for systematically identifying inefficiencies, reducing variability, and driving continuous improvement across all aspects of operations, including inventory management.

Within this context, the optimization of safety stock levels represents a particularly important area of focus. Safety stock acts as a buffer against uncertainties in demand and supply, but setting it at the right level is a nuanced task. Excessive safety stock can tie up valuable working capital and increase storage costs, while insufficient safety stock can lead to production interruptions and diminished service levels (Axsäter, 2015; Demiray Kırmızı,

Ceylan & Bulkan, 2024). As manufacturing environments become more dynamic and data-rich, there is a growing need for methodologies that can leverage empirical evidence and analytical models to inform inventory decisions.

This thesis is situated at the intersection of these developments. It explores how Lean Six Sigma principles and the DMAIC framework can be applied to optimize safety stock in a manufacturing setting. By combining a thorough review of relevant literature with an empirical case study, the research aims to contribute both to academic understanding and to the practical advancement of inventory management practices. The following subchapters outline the specific objectives and research questions, present the conceptual framework guiding the study, and describe the overall structure of the thesis.

1.1 Objectives and Research Questions

The overarching objective of this thesis is to develop and implement a systematic, data-driven approach for optimizing safety stock levels in a manufacturing environment, utilizing the Lean Six Sigma methodology and the DMAIC framework. The research is motivated by the need to move beyond traditional, intuition-based inventory management practices, which often result in either excessive inventory costs or compromised service levels. By applying Lean Six Sigma principles, the thesis aims to identify inefficiencies in current safety stock settings, quantify their impact on operational performance, and establish robust strategies for sustainable improvement.

To guide the research, the following questions are posed:

RQ1: How can Lean Six Sigma, and specifically the DMAIC framework, be applied to optimize safety stock levels in a manufacturing context?

RQ2: What are the comparative advantages and limitations of different safety stock calculation methods when evaluated through empirical data?

RQ3: In what ways does the adoption of a data-driven, Lean Six Sigma-based approach influence inventory costs, service levels, and process transparency compared to traditional methods**?**

1.2 Conceptual Framework

The conceptual framework underpinning this thesis is grounded in the integration of Lean and Six Sigma methodologies, collectively referred to as Lean Six Sigma (LSS). Lean focuses on the elimination of waste and the enhancement of process flow, while Six Sigma emphasizes the reduction of process variation and defects through rigorous, data-driven analysis. The synergy of these two approaches provides a comprehensive toolkit for operational excellence, combining efficiency with quality.

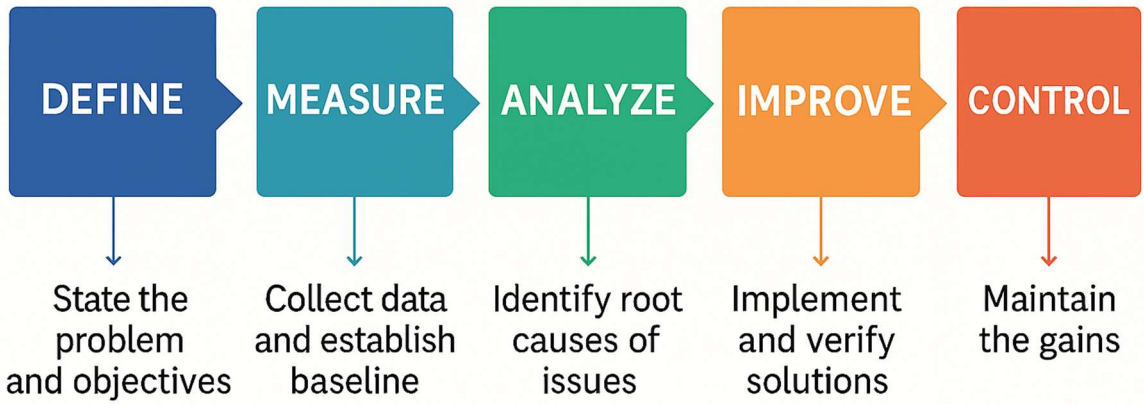

Figure 1. DMAIC process

Central to this framework is the DMAIC cycle (Figure 1), which structures the research into five iterative phases: Define, Measure, Analyze, Improve, and Control. Each phase serves a distinct purpose, from problem identification and data collection to root cause analysis, solution implementation, and the establishment of controls for sustained improvement. The literature review establishes the theoretical foundations of inventory management, safety stock calculation, and Lean Six Sigma principles, while the empirical case study demonstrates the practical application of these concepts in a real-world manufacturing setting.

1.3 Thesis Structure

This thesis is organized to provide a clear and logical progression from theoretical foundations to practical application and critical analysis. The structure is intended to help

the reader understand not only the academic context of inventory optimization but also its real-world implementation through Lean Six Sigma methodologies.

Chapter 1 introduces the research topic, outlines the motivation and objectives, and presents the research questions and conceptual framework that guide the study. Chapter 2 explores the principles and tools of Lean methodology, focusing on its historical development and its relevance to process improvement and inventory management. Chapter 3 examines Six Sigma, emphasizing its data-driven approach to reducing process variation and enhancing quality.

Chapter 4 discusses the integration of Lean and Six Sigma under the Lean Six Sigma framework, highlighting the synergistic benefits of combining Lean's focus on efficiency with Six Sigma's emphasis on rigor and quality. Chapter 5 presents the DMAIC framework, Define, Measure, Analyze, Improve, and Control, illustrating how it serves as a practical roadmap for systematic problem-solving

Chapter 6 turns to the specific challenges of inventory management, examining how Lean Six Sigma principles and the DMAIC methodology can be adapted to address these complexities Chapter 7 presents a detailed case study on the optimization of safety stock using Lean Six Sigma. Chapter 8 offers a critical discussion of the findings, and Chapter 9 concludes the thesis by summarizing the main contributions and implications.

2 Lean

The beginning of Lean production methods started out in Japan in the 1940´s, when Toyota created and adopted what they called the Toyota Production System (TPS). This system, which elsewhere in the world would later be called Lean, aims to eliminate waste in processes, reduce cycle times and inventories and increase customer satisfaction. (Womack et al., 2007; Plenert, 2007) The philosophy is based around finding what value is to the customer, and what parts of the whole process are value-adding (Helmold, 2020). When the value-adding components of a process have been found, the remaining ones can be categorized into those necessary for value-creation and those that are non-value adding and not necessary, and therefore waste. Then the value-adding or value-creating components of a process can be lined up in the best sequence and optimized, leading to a high level of efficiency (Womack & Jones, 2010). These three kinds of operations or activities can be categorized as follows: 1) value adding, 2) non-value adding but necessary and 3) non value-adding. Only category 3 can be considered being fully waste, as certain activities might not bring direct value to the customer but they support the process or the organization in other ways. (Hines & Rich, 1997; Melton, 2005)

2.1 Lean Principles

As per Womack & Jones (2010), Lean is considered to be guided by five key principles: 1) define what value is to the customer, 2) identify value streams and categorize the process steps so that waste can be removed, 3) ensure smooth process flow for materials and information, 4) establish a pull-system, and 5) pursue perfection through continuous improvement (Table 1).

Principle	Definition
Value	Define value from the customer´s perspective
Value Stream	Map all steps in the process to identify waste
Flow	Ensure smooth progression of materials and information
Pull	Produce based on actual demand rather than forecasts
Perfection	Pursue continuous improvement

Table 1. The Five Principles of Lean (adapted from Womack & Jones, 2010)

Value is the foundational principle of Lean and serves as the benchmark for all improvement efforts. It needs to be defined strictly from the perspective of the customer (Womack & Jones, 2010). Determining value requires a deep understanding of customer requirements, which often involves translating broad expectations into measurable critical-to-quality (CTQ) characteristics (Shah & Ward, 2007). Activities that do not contribute to these CTQ´s are classified as non-value-adding and targeted for elimination. By prioritizing customer-defined value, Lean ensures that resources are allocated to processes that enhance quality, reduce lead time and improve responsiveness.

Arguably the most important Lean tool is value stream mapping. It helps in creating an overall understanding of the process, where value is created and where other Lean tools can be implemented for maximum gain. (Bradley, 2015) Mapping the value stream exposes steps that add value and highlights those that do not, enabling organizations to focus improvement efforts where they matter most (Hines & Rich, 1997).

Flow and Pull are essentials principles in Lean. Flow refers to the smooth progression of products and information through the value stream without interruptions, reducing lead times and enhancing responsiveness. Pull is easiest understood when considering a production line. The earlier stations should not produce unless the later ones have indicated a demand. In other words, the system shouldn´t push from the upstream but instead pull from the downstream. Pull systems, such as Kanban, ensure that production is driven by actual customer demand rather than forecasts, minimizing overproduction and inventory waste. (Liker, 2021; Womack & Jones, 2010) Together, Flow and Pull create a flexible and efficient system that responds quickly to changes in demand (Womack & Jones, 2010).

Perfection is an unattainable goal all companies should aim for. Pursuing perfection requires organization-wide efforts, which cannot be achieved without a culture of sustained, continuous improvement culture established within the organization (Bhuyan & Baghel, 2005).

2.2 Waste

As previously stated, one of the key elements of Lean is to identify and eliminate waste. As Womack and Jones (2010) put it, Lean thinking is the "antidote to waste". Waste, or Muda as the Japanese call it, is traditionally categorized into seven types: overproduction, waiting, transportation, overprocessing, inventory, motion and defects. Addressing these wastes systematically enables organizations to achieve shorter lead times, lower costs and improved customer satisfaction. The different types of waste are presented in Table 2.

Type of waste	Description	What can be done
Overproduction	Discourages a smooth flow of goods and leads to excessive lead and storage times and inventories.	Employing the pull or kanban system.
Waiting	Inefficient use of time. Affects both goods and workers, when the process doesn´t flow smoothly.	Ideally waiting time should be eliminated altogether. In case this cannot be done, the time should be used in otherwise productive ways.
Transportation	Movements of goods.	Difficult to remove completely, but double handling and excessive movements should be minimized.
Inappropriate processing	Occurs when complex solutions are found to simple procedures, or when machines are used without sufficient safeguards.	Avoiding over-complexity by finding the simplest solutions capable of producing the required quality.
Unnecessary inventory	Excessive inventory tends to hide problems, increase leadtimes and result in heightened storage costs.	Inventory reduction and optimization.
Unnecessary motion	Involves ergonomics of production where workers have to do unnecessary movements. Tiring for the employees, and leads to poor productivity and possibly quality problems.	Reducing the unnecessary movements and optimizing work station layouts.
Defects	Result in direct costs, and hence are bottom-line waste.	Should be regarded as improvement opportunities. When detected, immediate kaizen activities should commence.

Table 2. Types of Waste. Adapted from Hines & Rich (1997)

Overproduction occurs when products are made earlier or in greater quantities than demand requires. This waste is often driven by forecast-based push scheduling and large batch sizes, leading to excess inventory, higher storage costs and increased risk of obsolescence (Womack & Jones, 2010; Liker, 2021). Lean countermeasures include takt-based scheduling, Kanban systems and demand levelling to align production with actual consumption (Rother & Shook, 1999).

Waiting refers to idle time for people, equipment or materials caused by bottlenecks, unbalanced workloads or poor information flow (Hines & Rich, 1997; Liker, 2021). Waiting lengthens lead times and reduces responsiveness, creating variability across the value stream (Shah & Ward, 2007). Remedies include value stream mapping to identify delays, workload levelling, Single-Minute Exchange of Dies (SMED) for quick changeovers and visual controls to maintain flow (Rother & Shook, 1999).

Transportation waste involves unnecessary movement of materials between processes, adding cost and risk without increasing value (Hines & Rich, 1997; Liker, 2021). This waste consumes time and resources and complicates training. Lean practices such as standardization, quality at the source and design simplification help eliminate unnecessary steps (Shah & Ward, 2007).

Inventory waste, meaning excess raw materials, work-in-progress or finished goods, ties up capital and hides process problems (Womack & Jones, 2010; Shah & Ward, 2007). It increases storage costs and reduces flexibility. To reduce inventory while maintaining service levels, Pull systems, Kanban and SMED are good tools (Rother & Shook, 1999).

Motion waste refers to unnecessary movement by workers due to poor layout or lack of visual management (Hines & Rich, 1997; Liker, 2021). It reduces productivity and increases fatigue. To tackle these issues, solutions like 5S, ergonomic design and visual controls to streamline workstations can be deployed (Womack & Jones, 2010).

Defects generate rework, scrap and customer dissatisfaction, often caused by process variation and inadequate mistake-proofing (Liker, 2021; Hines & Rich, 1997). They disrupt flow and increase costs. To prevent defects at the source, tools such as Jidoka, Poka-Yoke and root cause analysis can be used (Rother & Shook, 1999).

These wastes are interrelated: overproduction inflates inventory and transportation, while defects amplify overprocessing and waiting. Lean combats them through systemic

approaches like value stream mapping, flow creation and pull discipline supported by standard work and visual management (Womack & Jones, 2010; Rother & Shook, 1999).

2.3 Lean tools

In this chapter, Lean tools are explained in more detail. As the amount of Lean tools is vast, only a selected few will be presented. The chosen tools and their objectives can be seen in Table 3.

Lean tool	Objective
Value Stream Mapping (VSM)	Mapping the whole process, identifying VA and NVA activities
Just In Time (JIT)	Right action at the right time. Can be applied to most scenarios, f.ex component arrivals and production planning
Kaizen	Continuously improving processes while eliminating waste
Kanban (Pull)	To supply only when there is demand
Poka-yoke	Error and defect detection at the source

Table 3. Lean tools

2.3.1 Value Stream Mapping

Value Stream Maps (VSM) are extremely flexible and effective tools, which can be used in most processes at any scale. Firstly the current state is mapped, with all the steps in the process written down. These steps can then be categorized into those that create value, and those that do not. Those non-value adding parts of the process that are not required to reach the desired outcome of said process can be considered waste, and should be reduced or eliminated altogether. Then the future state VSM can be mapped, and the performance of the current state and future state can be compared. This then provides factual information on how chosen variables perform currently and how they could perform if the future state is applied. To implement continuous improvement, the future state can then be changed to be the current state, and the process of mapping the value stream and finding inefficiencies can start all over. (Womack & Jones, 2010)

2.3.2 JIT

Womack & Jones (2010) describe Just-in-time (JIT) as a way of achieving single-piece flow by producing and delivering exactly what is needed, when it´s needed and in the correct quantity. It emphasizes streamlined operations, continuous improvement, high-quality standards, and smooth, uninterrupted workflow (Ríos-Mercado & Ríos- Solís, 2012). These different aspects of JIT are not standalone variables, and Holl & Trevor (2019) note as an example that producing or delivering according to JIT is senseless if the quality aspect is not in order. In a production environment, practice-level scheduling (Heijunka) is needed in order for JIT to work as it reduces bottlenecks inside the production system. JIT needs these supportive tools so that continuous flow can be achieved. (Womack & Jones, 2010)

2.3.3 Kaizen

Kaizen is a fundamental part of Lean, and it allows continual organizational learning of how to improve (Coetzee, Van der Merwe & Van Dyk, 2016). It goes beyond individual improvements by establishing a mindset of change in an organization. According to Womack & Jones (2010), Kaizen is essential in creating a culture where the whole organization actively seeks ways to enhance value and eliminate waste. The core idea of Kaizen is not to necessarily do large-scale transformations but to take small and sustained steps that collectively lead to large-scale performance gains. This approach gives the organization a way to continuously identify problems at their source, test solutions and improve processes. Considering the key element of Lean being striving for perfection, Kaizen fosters some of the key elements needed: stability, adaptability and a shared responsibility.

2.3.4 Kanban

Pull is one of the main principles of Lean, and Kanban is one of the tools used to implement a pull-based production approach. A card system is used to imply when the demand-side is in need of refurbishment from the supply-side. (Ríos-Mercado & Ríos- Solís, 2012) This visual system regulates pull by signaling the need for more parts. Aadithya, Asokan & Vinodh (2023) state that Kanban can be an efficient tool with semi-finished products, signals

like light and sound can be used instead of cards and that this approach can help in identifying bottlenecks in the process.

2.3.5 Poka-Yoke

Poka-Yoke refers to a mistake-proofing device or procedure, which is designed to prevent defects at the source. They are applicable in most occasions and in many processes, and can be physical, functional or symbolic. (Womack & Jones, 2010; Saurin et al., 2012) Shingō & Robinson (2017) see that a Poka-Yoke system serves two main purposes: it ensures complete inspection of all items and provides immediate feedback and corrective action whenever an abnormality is detected. The effectiveness of Poka-Yoke in reducing defects varies depending on the type of inspection method it is paired with. These inspection methods include source inspections, self-checks and successive checks.

3 Six Sigma

Six Sigma is a data-driven methodology designed to improve process quality by reducing variability and eliminating defects. Developed by Motorola in the mid-1980s, Six Sigma has become a global benchmark for operational excellence across industries (Montgomery & Woodall, 2008). The term Six Sigma refers to achieving a performance level where defects are limited to 3.4 per million opportunities, representing near-perfect quality (Montgomery & Woodall, 2008; Tjahjono et al., 2010). Its structured approach combines statistical analysis with process management, making it a powerful tool for organizations seeking continuous improvement. It relies on reducing variability in processes through statistical tools (Cudney & Kestle, 2011).

Six Sigma remains a cornerstone of quality management and operational excellence. Its principles, customer focus, data-driven decisions, process orientation, structured methodology and goal alignment, provide a strong foundation for continuous improvement (Linderman et al., 2003). Supported by a comprehensive set of tools, Six Sigma empowers organizations to reduce defects, enhance efficiency, and achieve sustainable competitive advantage (Antony et al., 2019).

The success of Six Sigma depends on adherence to its core principles, which provide the foundation for systematic improvement. These principles ensure that organizations focus on customer needs, make decisions based on data, and maintain a structured approach to problem-solving. They also emphasize the importance of aligning improvement goals with organizational objectives (Linderman et al., 2003).

As with Lean, one of the key principles of Six Sigma is being customer focused. Quality should be defined by customer requirements, and every improvement initiative should begin with understanding what customers value most (Antony, 2006). Also goals for improvements should be established based on customer requirements. These goals should be ambitious, but it´s important they are achievable. When impossible goals are set, performance tends to decrease. (Linderman et al., 2003) At the same time, the customer focus allows organizations to focus their resources on those processes that actually contribute most to the financial results (Adams, Gupta & Wilson, 2003). Another key principle is the focus on data rather than assumptions. With decisions relying on empirical

data and statistical analysis, objectivity and accuracy is ensured (Montgomery & Woodall, 2008). The process orientation of Six Sigma stems from the viewpoint of organizations being a collective of different processes. Reducing variability in processes, hence reducing it organization-wide, leads to predictable and consistent outcomes in the whole organization (Antony & Seow, 2004). Lastly, the structured methodology of Six Sigma is one of its key characteristics. Projects follow a systemic approach, with the DMAIC (Define, Measure, Analyze, Improve, Control) cycle being one of the most common ones (Tjahjono et al., 2010). This approach provides a disciplined framework for problem solving and continuous improvement (de Mast & Lokkerbol, 2012; Quick, 2019). The DMAIC process will be discussed in more detail later in this thesis.

4 Lean Six Sigma

Lean Six Sigma (LSS) represents the integration of two complementary methodologies, Lean and Six Sigma, into a unified approach for operational excellence. Lean focuses on eliminating waste and improving process flow, while Six Sigma emphasizes reducing variation and defects through data-driven analysis (Montgomery & Woodall, 2008; Patel & Patel, 2021). By combining them into LSS, organizations can achieve both speed and quality, addressing the challenges of efficiency and consistency in modern competitive environments (Salah et al., 2010; Laureani & Antony, 2018). De Mast et al (2022) argue that LSS is often understood to mean that companies who deploy it are aiming at the LSS defect rate of 3.4 per million and that this level of quality could be considered optimal across industries, but they dismiss this as nonsense. The true objective of LSS is to strive for operational excellence.

The idea of focusing on improving financial results through increased customer satisfaction, achieved by eliminating defects and waste in processes, is at the core of LSS (Taghizadegan, 2006). Combining the speed provided by Lean with the statistical control techniques and principles of Six Sigma creates value greater than either methodology can achieve alone. Sustainable process improvement enabled by LSS works as a powerful tool for continuous improvement (De Mast et al., 2022). Addressing variation in processes and analyzing its effects is essential to ensure quality, as statistically significant variation leads to unpredictable performance of business activities (Van Aartsengel & Kurtoglu, 2013). Furthermore, understanding where and how value is created for the customer and documenting the value chain forms the basis on which continuous improvement through LSS is built (Mehta, 2024).

4.1 Benefits of combining Lean and Six Sigma

The integration of Lean and Six Sigma offers advantages that surpass the capabilities of each methodology when applied independently. Lean excels at improving speed and reducing waste, but it does not always address process variability. Conversely, Six Sigma reduces defects and ensures consistency but can overlook non-value-added activities that hinder

efficiency. (Salah et al., 2010) By merging these approaches, organizations achieve a balanced improvement strategy that targets both waste and variation simultaneously.

One major benefit is enhanced process efficiency and quality. Lean tools such as VSM and 5S streamline workflows, while Six Sigma techniques like control charts and hypothesis testing ensure stability and predictability (Montgomery & Woodall, 2008; Patel & Patel, 2021). This dual focus enables organizations to deliver faster cycle times without compromising quality standards.

Another advantage is cost reduction and resource optimization. Eliminating waste reduces unnecessary expenses, while defect prevention minimizes rework and warranty costs. Studies have shown that Lean Six Sigma projects often yield substantial financial savings and productivity gains across sectors. (Antony et al., 2019; Timans et al., 2012)

LSS also promotes cultural transformation and employee engagement. The methodology encourages cross-functional collaboration and empowers employees to identify and solve problems, fostering a sense of ownership and accountability (Laureani & Antony, 2019). This cultural shift is critical for sustaining improvements and embedding continuous improvement into organizational practices.

The adoption of LSS strengthens an organizations ability to respond to new challenges and outperform competitors. In an era of rapid technological change and global competition, organizations must adapt quickly while maintaining high quality. LSS provides a structured yet flexible framework that aligns operational improvements with strategic objectives, enabling firms to respond effectively to market dynamics (Albliwi et al., 2014; Timans et al., 2012). Pepper & Spedding (2010) state that the purpose of organizations should not be to just implement these methodologies individually or together in the form of LSS, but preferably they should understand the idea behind the methodologies and implement the parts that fit the goals of the organization.

4.2 Principles of LSS

Lean Six Sigma principles combine Lean's efficiency-driven mindset with Six Sigma's rigorous, data-based approach. At its core, Lean Six Sigma begins with a focus on customer value, ensuring that all improvement initiatives aim to deliver what customers truly need

while eliminating activities that do not add value (Laureani & Antony, 2019). This customer orientation is complemented by a commitment to data-driven decision-making, where empirical evidence and statistical analysis replace assumptions, enabling organizations to identify root causes and validate improvements objectively (Montgomery & Woodall, 2008).

Another fundamental principle is the elimination of waste and optimization of process flow. Lean emphasizes reducing non-value-added steps such as overproduction, waiting, excess inventory, and unnecessary motion, which collectively hinder efficiency and responsiveness (Patel & Patel, 2021). Alongside waste reduction, Lean Six Sigma prioritizes variation reduction, applying Six Sigma tools to minimize inconsistencies and defects in processes. This dual focus ensures that organizations achieve both speed and quality in their operations (Salah et al., 2010).

Structured problem-solving is also central to Lean Six Sigma. The DMAIC cycle (Define, Measure, Analyze, Improve, Control) provides a disciplined framework for identifying problems, implementing solutions, and sustaining improvements over time (Antony et al., 2019). Finally, Lean Six Sigma promotes a culture of employee engagement and continuous improvement, encouraging teams at all levels to participate actively in identifying inefficiencies and driving change. This cultural dimension is critical for sustaining long-term success and embedding operational excellence into organizational DNA (Laureani & Antony, 2019).

4.3 Tools of LSS

The effectiveness of Lean Six Sigma lies in its extensive toolkit, which combines Lean techniques for waste elimination with Six Sigma's statistical methods for quality control. Among the most widely used tools is Value Stream Mapping (VSM), which provides a visual representation of the entire process flow, highlighting bottlenecks and areas of waste. VSM enables teams to map the current state, and design a future state that optimizes flow and reduces cycle time, aligning operations with customer value (Salah et al., 2010).

Workplace organization tools such as the 5S methodology (Sort, Set in order, Shine, Standardize, and Sustain) form the foundation for Lean practices by improving efficiency, safety, and cleanliness (Patel & Patel, 2021). Kaizen events complement these efforts by

facilitating short-term, focused workshops where cross-functional teams collaborate to identify and eliminate waste rapidly, fostering a culture of continuous improvement (Laureani & Antony, 2019).

From the Six Sigma perspective, tools such as SIPOC diagrams help define process boundaries by mapping suppliers, inputs, processes, outputs, and customers, ensuring clarity in project scope (Antony et al., 2019). Failure Mode and Effects Analysis (FMEA) is another critical tool, enabling organizations to assess potential failure points, prioritize risks, and implement preventive measures. Root cause analysis techniques, including fishbone diagrams and Pareto charts, assist in identifying and prioritizing causes of defects or inefficiencies. (Montgomery & Woodall, 2008)

Statistical tools such as control charts, hypothesis testing, and regression analysis are essential for monitoring process stability and validating improvements. These tools ensure that changes are not only effective but also sustainable over time (Salah et al., 2010). Additionally, Lean tools like Kanban systems provide visual scheduling mechanisms that manage workflow and inventory levels, reducing waiting times and improving throughput. The integration of these tools within the DMAIC framework ensures that Lean Six Sigma projects deliver measurable and lasting results (Patel & Patel, 2021).

5 DMAIC

DMAIC is a powerful tool for continuous improvement, and an acronym from its phases Define, Measure, Analyze, Improve and Control. Each phase is an important step in creating a setting where processes can be continuously improved and controlled. (Husby, 2007) According to Quick (2019) the DMAIC process can take four different paths depending on the desired effect: to reduce either variability, the number of failures, waste, or defects. In this chapter we go through the phases individually. The objectives and some of the tools and techniques of each phase are listed in Table 4.

DMAIC operates as a staged problem solving system: each phase poses distinct questions, requires specific evidence, and culminates in a gate decision before moving on. This sequencing prevents premature solutions and ensures that projects remain logically coherent (de Mast & Lokkerbol, 2012). In Lean Six Sigma programs, Lean practices remove non value-adding work while Six Sigma's statistical toolkit reduces variation and defects (Montgomery & Woodall, 2008; Taghizadegan, 2006). Practical handbooks emphasize that DMAIC provides the backbone for modern continuous improvement programs across services and manufacturing, offering phase by phase guidance, case studies, and governance patterns that help maintaining results (de Mast et al., 2022; Pakdil, 2020).

When combined, the phased logic and toolset make DMAIC both disciplined and adaptable. The method's gates ensure improvements are evidence based, while its tools can be tailored to projects targeting variability, failures, waste, or defects. (Quick, 2019) When executed with data quality checks, causal validation, piloting rigor, and robust control, DMAIC consistently produces measurable and sustainable results across operational contexts. (de Mast & Lokkerbol, 2012; Montgomery & Woodall, 2008; Antony et al., 2019)

Phase	Objectives	Tools and techniques
Define	Analyze the process and map the current state	Value Stream Map
	Analyze customer needs and expectations	Flow chart
	Identify stakeholders	SIPOC
	Project prioritization and selection	Voice Of Customer
	Develop project charter	Project charter
	Develop project plan	
Measure	Understand and measure the process	Data collection plan
	Develop data collection plan	Identifying types of variables
	Data collection	Identifying types of sampling methods
	Measurement system analysis	Identifying measurement system components
	Identify sigma level	Measuring limits of the CTQ characteristics
	Measure poor and good cost of quality	Measuring sigma level of the processes and systems
Analyze	Analyze the problem	Descriptive statistics
	Analyze the process and data	Statistical distributions
	Identify the root causes	Inferential statistics
	Prioritize the root causes	Correlation analysis
		Regression analysis
		ANOVA
		Process capability analysis
Improve	Develop alternative solutions to improve sigma level	Design of Experiment
	Select the optimal solution(s)	Simulation
	Map future state	FMEA
	Analyze the potential risks in the new process	
	Pilot test the new process	
Control	Implement the new process	Standardization of the solutions
	Implement ongoing measurements	Control plan
	Standardize the improvement	Control charts
	Project closure	Statistical process control

Table 4. DMAIC objectives and tools (adapted from Pakdil, 2020)

Define is the first phase of DMAIC. The purpose and goal of this phase is to define the problem that needs to be solved, to define the scope and to build the business case. The process is mapped so that, as LSS principles dictate, value and waste can be detected. Optimal tools for this are VSM and SIPOC. While building the business case, the benefits and financial implications are understood. (Pakdil, 2020) VOC is established in this phase, so that the customer requirements can be established. A project charter helps in clarifying the projects goals, boundaries and timelines. (Pande, Neuman & Cavanagh, 2000; George et al., 2005)

When the measurables have been established in the Define phase, it´s time to move on to the Measure phase. In this phase the factual basis for improvement is created. A data collection plan is created, the data-horizon decided and measurement system is assessed to ensure the analyses done later on are trustworthy. (Blackburn, 2022; Pakdil, 2020) Variables which could affect the outcome of the process need to be clarified and mapped, as they are what will be measured. Quick (2019) suggests that the selection of metrics should reflect the

chosen pathway. Variability projects should emphasize dispersion and capability, defect projects look into DPMO (Defects Per Million Opportunities) and defect typologies, failure projects track incident rates and severity while waste projects quantify non-value-added time and inventories. Validity, accuracy and reliability of the data needs to be ensured so that reliable results can be yielded from the dataset (Pakdil, 2020).

Analyze converts evidence into understanding of causes. The data collected in the Measure phase will be analyzed in this phase. Statistical tools are used to understand how much the current state differs from the desired future state (Voehl et al., 2014) Descriptive statistics, also called summary statistics, include measuring the central tendency, variability and type of distribution. Other statistical tools used often in this phase include estimations of confidence intervals, hypotheses testing, correlation analysis, t-tests, ANOVA and process capability analysis. Additionally, regression models can be used to quantify relationships among variables. (Pakdil, 2020)

In this phase, solutions that address verified causes are designed and tested (Blackburn, 2022). After detecting, measuring and analysing the variables which affect the outcome of the process being investigated, in this phase the aim is to identify how to improve the performance of the process (Pakdil, 2020). The Improve phase should conclude only when solution pilots show statistically and practically significant gains consistent with the goals set in the Define phase (Quick, 2019).

The goals of the control phase are to ensure that the improvement solutions found in the Improve phase are implemented and sustained and that the DMAIC project is properly documented. The project as a whole can still fail unless the gains aren´t sustained. Control over continuous monitoring and improvement are essential. (Pakdil, 2020; Blackburn, 2022) Case studies emphasize that defect reductions endure when control plans include defined responses to out-of-control signals and when accountability is explicit (Condé et al., 2023).

6 Application of LSS to Inventory

Inventory plays a crucial role in manufacturing, as it ensures smooth production processes and effective operations management. From a cost perspective, it is vital to have the right components in the right place at the right time. (Makhubele, Mafini & Zvinowanda, 2025) The goal of efficient inventory management is to minimize costs while guaranteeing a steady flow of materials to keep operations running without interruption (Zondo, 2020). In the lubricating oil factory studied by Cabral et al. (2019), inventory processes were found to suffer from overstocking and unnecessary movements, both of which contributed to waste and inefficiency. Traditional inventory practices, frequently based on intuition or static rules, struggled to adapt to fluctuations in demand and supply, highlighting the need for a more systematic and data-driven approach. This chapter looks into common challenges in inventory management, looks into LSS principles adaptable to inventory processes and studies how the DMAIC process can be applied to inventory related challenges.

6.1 Inventory Management Challenges

Robust inventory management is fundamental to achieving operational excellence in manufacturing and supply chain settings. Nevertheless, companies routinely encounter a variety of ongoing and emerging obstacles that can hinder efficiency, drive up costs and limit their ability to respond swiftly to market demands.

Anticipating customer demand with precision is a persistent challenge in inventory management. Variations in order volumes, seasonal trends and changing market conditions can all lead to either an oversupply of inventory or unexpected shortages. When demand forecasts are inaccurate, companies risk accumulating surplus stock that ties up financial resources. On the other hand, running out of components or products and missing sales opportunities can ultimately impact customer satisfaction. (Al Ruqeishi & Ullah, 2024; Wild, 2017) Today´s supply chains frequently involve numerous sites, a variety of products and multiple distribution pathways. Overseeing inventory with these intricate, multi-level networks makes coordination and oversight much more challenging. This demands

advanced methods and tools to maintain appropriate stock levels throughout the entire system. (Axsäter, 2015)

The success of inventory management is closely tied to how precise inventory records are. Errors in entering data, the absence of up to date tracking and mismatches between physical stock and recorded figures can all disrupt operations and create inefficiencies. These kinds of inaccuracies may lead to unnecessary restocking, slowdowns in production or difficulties in fulfilling customer orders. (Al Ruqeishi & Ullah, 2024; Wild, 2017)

Adapting to and integrating new technologies also poses considerable challenges. Although modern inventory management systems can enhance oversight and control, their implementation is often complex. Introducing new technologies typically requires substantial financial investment, changes to organizational processes and comprehensive staff training. Employees may resist these changes, and difficulties in connecting new systems with existing ones can prevent organizations from fully benefiting from technological advancements. (Kumar & Saini, 2021)

Inventory management becomes even more complex when faced with external pressures like supply chain interruptions, delays from suppliers, transportation issues or geopolitical uncertainties. In industries such as automotive manufacturing, these challenges are often magnified by limited resources and a lack of adequate government support. These make it harder for companies to remain resilient and respond swiftly to disruptions. (Makhubele et al., 2025)

Managing costs and ensuring efficient inventory turnover are central concerns in inventory management. Factors such as high minimum order requirements, producing in large batches and storing items that move slowly through the system can all drive up expenses and slow down the rate at which inventory is refreshed. To prevent capital from being unnecessarily tied up in surplus stock while still meeting demand, it is crucial to continually refine and adjust inventory management strategies. (Axsäter, 2015; Wild, 2017)

Inventory management outcomes are also influenced by the organization´s culture, the quality of internal communication and the skill level of employees. When departments operate in isolation, cross-team cooperation is lacking. It might also lead to staff not receiving adequate training. This can hinder the effectiveness of inventory processes and slow the pace of improvements. (Al Ruqeishi & Ullah, 2024; Wild, 2017)

6.2 Applying DMAIC to Inventory

As was studied earlier in this thesis, the DMAIC framework is central to LSS and provides a structured, repeatable approach for tackling various challenges across diverse industries and contexts. Recent studies, such as Cabral et al. (2019) in a lubricating oil factory and Makhubele et al. (2025) in the automotive sector, illustrate how DMAIC can be leveraged to address persistent inventory issues and drive operational improvements.

The first step in DMAIC is to clearly articulate the inventory-related problem, its scope, and the desired objectives. In the lubricating oil factory case (Cabral et al., 2019), the project began by identifying overstocking and receipt lead time related delays as key issues, setting a clear goal to reduce excess inventory and improve responsiveness. Similarly, Makhubele et al. (2025) highlight the importance of defining challenges such as limited resources, supply chain disruptions and inadequate support, which hinder effective inventory management in the automotive sector.

In the Measure phase, accurate and comprehensive data collection is essential for understanding the current state of inventory processes. Cabral et al. (2019) demonstrate this by gathering detailed inventory-level data, demand variability, and receipt lead time components, ensuring subsequent analysis is grounded in reliable evidence. Makhubele et al. (2025) likewise stress the value of qualitative insights from supply-chain professionals to identify gaps in resilience and resource allocation, complementing quantitative measurement with practitioner perspectives.

The Analyze phase involves using statistical and process analysis tools to uncover root causes of inventory inefficiencies. In the lubricating oil factory, this meant identifying sources of waste, process bottlenecks and variability that contributed to overstocking and slow internal receipt cycles. Makhubele et al. (2025) found that challenges such as supply chain disruptions and resource constraints could be traced to systemic issues, including insufficient government support and lack of adaptive practices.

Based on the analysis, targeted solutions are developed and implemented at the Improve phase. Cabral et al. (2019) report that process improvements, revised inventory policies and cross-functional collaboration led to tangible improvements, such as reduced inventory levels, lead time reduction and cost savings. In the automotive sector, Makhubele et al.

(2025) suggest that addressing resource limitations and fostering greater resilience can help organizations respond more effectively to uncertainties and disruptions.

To sustain the gains achieved, the Control phase establishes routines for ongoing monitoring of key performance indicators and regular review of inventory policies. Cabral et al. (2019) advocate for continuous improvement through monitoring performance over time and adaptation of processes as business conditions evolve. Makhubele et al. (2025) reinforce the need for resilience and adaptability, recommending that organizations maintain vigilance and flexibility in their inventory management systems.

Both studies demonstrate that the DMAIC framework is highly effective for inventory optimization, regardless of industry context. By systematically defining problems, measuring and analyzing data, implementing improvements and maintaining control, organizations can overcome persistent inventory challenges, unlock efficiencies and build resilience against future disruptions.

7 Case Study – Optimization of Safety Stock Using Lean Six Sigma

Inventory management plays a critical role in balancing operational efficiency with customer satisfaction. Safety stocks are of one of the key parameters of inventory control, as these buffers serve as protection against unexpected incidents or changes in the environment. This case study looks into the key process drivers which lead to the need for safety stocks, and looks to establish a structured basis for evaluating and refining safety stock calculation methods in alignment with organizational objectives.

7.1 Background

At a company operating in technological manufacturing a need has arisen to optimize the safety stock levels for components. The goal is to reduce inventory-related waste while maintaining or improving service levels and production continuity.

At present, safety stock levels for production components are primarily determined by the planning team based on intuition, past experience, and informal heuristics, rather than through a standardized, data-driven methodology. While this approach has provided a degree of operational continuity, it lacks consistency and transparency and does not adequately account for dynamic factors such as demand variability, supplier lead time fluctuations, or service level targets. This method is reliant on subjective judgement and has led to uneven inventory performance where some components are consistently overstocked while others frequently fall below required levels. The non-data-based method creates risks for production disruptions and makes the methodology very challenging to apply to new projects or changing business conditions.

Hence why a data-based, clearly structured and controllable set of parameters need be to be established. A suitable calculation method needs to be found, as well as a way or controlling the parameters continuously in order to react and prepare for changes which could have an impact on stock performance. By leveraging data-driven analysis and process improvement tools, this study aims to:

- Identify inefficiencies in current safety stock settings.
- Quantify the impact of these inefficiencies on inventory costs and service levels.
- Develop and implement optimized safety stock strategies.
- Establish control mechanisms to sustain improvements over time.

Given the complexity of inventory management and the critical role of component safety stocks in ensuring production continuity, it became clear that a structured and data-driven approach was necessary to address the organization's challenges. After reviewing existing practices and considering the limitations of traditional inventory control methods, the decision was made to adopt the Lean Six Sigma DMAIC methodology for this case study. This approach was selected for its proven effectiveness in process improvement, its emphasis on rigorous measurement and analysis, and its ability to deliver sustainable results through systematic problem-solving. As part of the initial planning, decisions were also made to identify a range of potential safety stock calculation methods, which would then be systematically tested and evaluated during the DMAIC process. By applying this methodology, the project aimed not only to optimize safety stock levels but also to establish a repeatable framework for ongoing inventory management improvements.

7.2 Safety Stock Formulas

As part of the Lean Six Sigma project, a key objective is to transition from intuition-based safety stock settings to a quantitative, data-driven methodology. This will involve identifying and evaluating suitable formulas for calculating safety stock that account for demand variability, lead time uncertainty, and desired service levels. Two different formulas were decided to be used in the study.

The first formula, $SS = K\sqrt{L\sigma_D^2 + \sigma_L^2 D^2})$, is derived from the variance of demand during lead time and explicitly accounts for both demand variability (σD) and lead time variability (σL). Its main strength lies in its comprehensive nature: it provides a more accurate buffer in environments where supplier reliability fluctuates or lead times are uncertain. This makes it highly suitable for volatile supply chains. However, its complexity and data requirements are significant. Accurate estimation of both variability components is essential, and the

assumption of independence between lead time may not always hold. These factors can limit its practical adoption in ERP (Enterprise Resource Planning) systems without advanced analytics capabilities.

The second formula, $SS = Z \times \sigma_D \times \sqrt{AvgLT}$, is simpler and widely used in practice. It requires only demand variability and average lead time, making it easy to implement and explain. This simplicity is advantageous in stable environments where lead times are consistent and demand variability dominates. However, the formula ignores lead time variability, which can lead to underestimation of safety stock in uncertain supply conditions. Consequently, while it is efficient for routine operations, it is less robust when variability in supply performance is significant.

Table 5 summarizes the differences between the two formulas. It highlights that the first formula offers higher accuracy under volatility but demands more data and computational effort, whereas the second formula prioritizes ease of use at the cost of precision. Selection should therefore align with the variability profile of the supply chain and the organization´s data maturity.

Aspect	$K\sqrt{L\sigma_D^2 + \sigma_L^2 D^2}$	$Z \times \sigma_D \times \sqrt{AvgLT}$
Captures lead time variability	Yes	No
Data requirements	High	Low
Ease of Implementation	Moderate	High
Accuracy under volatility	High	Low
Best use case	Unstable supply chains	Stable lead times

Table 5. Safety Stock Formula Comparison

7.3 Define

The Define phase initiates the case study by establishing a clear framework for the inventory optimization project. In this phase, the specific objectives, scope, and boundaries of the case are articulated, and the central problem related to safety stock management is described in detail. The Define phase also involves identifying the key stakeholders, mapping the relevant inventory processes, and outlining the critical factors that influence safety stock requirements within the organization. By setting out these foundational elements, this phase ensures that the subsequent measurement and analysis activities are focused, relevant, and aligned with the operational realities of the case environment.

7.3.1 Problem Statement and Business Case

The central problem addressed in this case study is the suboptimal management of component safety stocks within the organization's inventory system. Excessive safety stock levels can result in unnecessary capital being tied up in inventory, increased storage costs, and reduced operational efficiency. Conversely, insufficient safety stock may lead to stockouts, production interruptions, and compromised service levels. The challenge lies in determining the appropriate safety stock for each component, balancing the need for availability with the imperative to minimize costs.

This issue is particularly relevant given the exclusion of finished goods and other materials from the scope of the project. By focusing on components, the case study targets the segment of inventory that most directly impacts production continuity and working capital utilization. The current approach to safety stock management relies on historical practices and parameter settings that may not accurately reflect present-day variability in production output, lead time, scrapping, and inventory differences.

The business case for addressing this problem is compelling. Optimizing component safety stocks has the potential to unlock significant financial and operational benefits. Reducing excess inventory can free up capital for other strategic initiatives, lower storage and handling costs, and improve overall supply chain responsiveness. At the same time, maintaining adequate safety stock levels ensures that production schedules are not disrupted and customer service targets are consistently met. By applying Lean Six Sigma methodology and

data-driven analysis, the organization aims to establish a more precise, reliable, and sustainable approach to safety stock management, directly supporting its broader goals of operational excellence and cost efficiency.

7.3.2 Scope and Boundaries

This case study is focused on the application of Lean Six Sigma methodology to the optimization of component safety stocks within the organization's inventory management system. The scope of the project is deliberately defined to address only the safety stock levels of individual components used in production processes. Finished goods, raw materials not classified as components, and other inventory categories are explicitly excluded from the analysis.

By narrowing the scope to component safety stocks, the study ensures that the methodology is applied to the area with the greatest potential impact on production continuity and working capital efficiency. This targeted approach allows for a detailed examination of the factors influencing safety stock requirements, such as production output variability, lead time fluctuations, scrapping rates, and inventory differences, while maintaining a manageable and relevant focus for data collection and analysis.

The boundaries of the case study are set to exclude finished goods and other materials for several reasons. First, the demand patterns and replenishment processes for finished goods often differ significantly from those of components, requiring distinct analytical approaches. Second, the reliability and availability of data for components are typically higher, supporting more robust measurement and analysis. Third, the operational objectives of the project are aligned with ensuring uninterrupted production flow, which is most directly affected by component availability.

By clearly defining the scope and boundaries, this chapter establishes the framework for the subsequent phases of the case study. The focus on component safety stocks enables the application of Lean Six Sigma tools and the DMAIC methodology in a way that is both practical and aligned with the organization's strategic priorities.

7.3.3 Voice of Customer

The main customers this process serves and affects were deemed to be internal, and those are the production and the warehouse. For production the continuous availability of components is essential as any stock-outs mean production stops, which create not only costs but also risks the company´s capability of fulfilling customer demand. The costs include:

- Workforce related costs, non-productive time
- Lost output
- Restart costs
- Late delivery penalties
- Lost sales
- Brand reputation

Consequently, as an effect of stock-outs the company might need to keep higher levels of safety stock also for finished goods as a way of preparing for variance in the output from the production lines. This also leads to higher holding costs and the space-requirements for holding the high safety stock leads to further costs further down the line.

In the warehouse, holding high safety stock leads to higher storage costs, tied-up capital, increased risk of damage and potentially an excessive need of workforce to handle the storage. Additionally, the used space is then not available for possibly more productive uses. Also control of stock-accuracy could be affected, as inventory counts become more difficult in a heavily used warehouse.

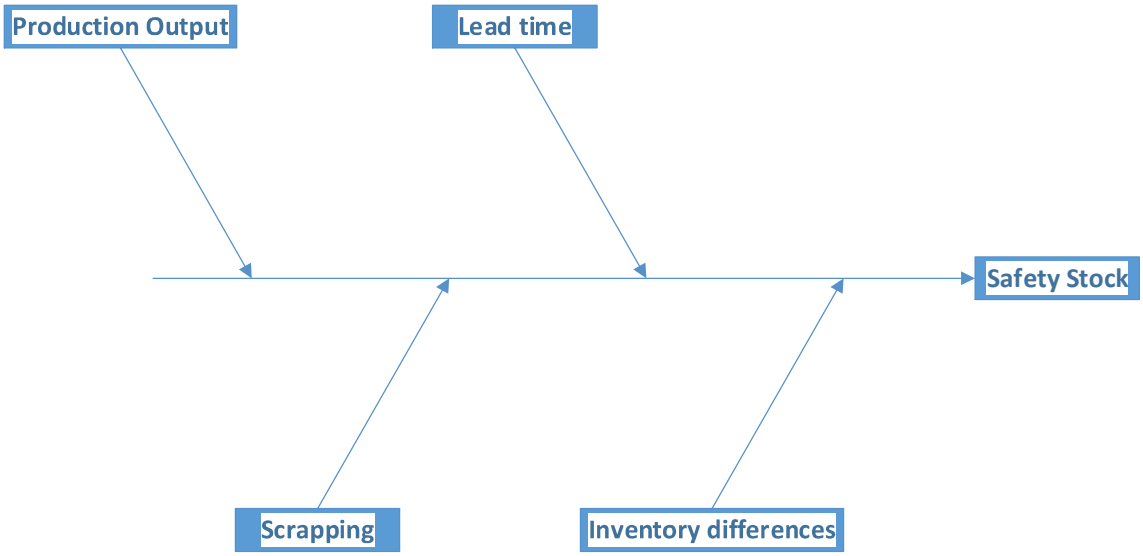

Figure 2. Variables of Safety Stock

The process map presented in Figure 2 illustrates the key factors that contribute to the need for safety stock in an inventory management system. This diagram adopts a cause-and-effect structure, visually mapping the relationship between various sources of variability and the resulting requirement for safety stock. At the center of the process is the recognition that safety stock serves as a buffer to protect against uncertainties in both demand and supply.

The map identifies four principal factors influencing safety stock levels. Production output is a primary driver, as fluctuations in production schedules, batch sizes, or yields can lead to unpredictable material consumption and create variability in demand. Lead time is another critical factor; variability in the time required to replenish inventory, whether due to supplier performance or internal processes, introduces uncertainty that must be compensated for by holding additional stock. Scrapping, which refers to the loss of materials through defects, damage, or obsolescence, reduces the effective inventory available for production and can result in unplanned replenishment needs. Inventory differences, arising from discrepancies between recorded and actual stock levels due to counting errors or process inaccuracies, further contribute to uncertainty and the risk of stockouts.

By mapping these factors, the diagram emphasizes that safety stock requirements are shaped by multiple, interacting sources of variability within the production and supply chain environment. Understanding the influence of each factor enables organizations to target process improvements, enhance data accuracy, and refine safety stock calculations, ultimately supporting more effective and resilient inventory management.

7.4 Measure

The Measure phase of this case study is dedicated to establishing a reliable and comprehensive data foundation for inventory optimization. In this phase, the focus is on collecting and validating quantitative data that reflects the actual performance and variability of the organization's component inventory processes over a twelve-month horizon. The key measurables identified for analysis are lead time, production output, scrapping, and inventory differences, each of which plays a distinct role in shaping safety stock requirements. Special attention is given to data quality, with all collected information systematically filtered to exclude non-process related abnormalities, such as extraordinary events or data entry errors, that could distort the analysis. By ensuring that only relevant and accurate data is used, the Measure phase provides a robust baseline for subsequent analysis and improvement, enabling targeted interventions that are grounded in the operational realities of the case environment.

The data collection horizon is defined as 12 months, due to the production capacity being at a significantly different level previously. This way the dataset is comparable within. The demand is defined to include component consumption directly from production usage, including also scrapping. To have a more complete picture of the inventory performance and the stock levels against which orders have been created, also inventory count results are included in the dataset. In case extreme spikes in the dataset are found, these are to be later removed if they have a business justification and/or a transparent reason. This could include for example quality related production stoppages or unplanned but approved higher production output. These figures will then be compared to the planned demand.

For lead times the same data collection horizon is used, and the performance will be calculated by comparing defined lead times to the actual outcome. After data collection, spikes are to be evaluated case-by-case and for justifiable reasons certain data can be removed. As the planning team has authority to expedite or delay incoming transports, the cases where lead time differs from the defined level due to reasons not related to supplier or transportation company will be excluded. With this method the data is comparable, and the actual performance can be analyzed.

7.5 Analyze

The Analyze phase of this case study focuses on examining the data collected during the Measure phase to identify the underlying sources of variability and their impact on component safety stock requirements. In this phase, the goal is to translate raw data on lead time, production output, scrapping and inventory differences into actionable insights that clarify the drivers of inventory performance. Statistical analysis and process mapping are employed to uncover patterns, quantify the magnitude of variability, and assess how each factor contributes to the overall need for safety stock. By systematically analyzing these relationships, the phase provides a solid foundation for selecting and refining safety stock calculation methods, ensuring that subsequent improvements are targeted and evidence-based.

7.5.1 Lead Time

The lead times for the chosen materials were individually analyzed by comparing the actual results to agreed lead times. Filtering of the data was done to exclude abnormalities not caused by the process. These abnormalities include delays in lead time due company closures at either the supplier or the case company and expedited deliveries due to quality or output related issues. This procedure eliminated spikes in the data, which would have led to higher level of variance.

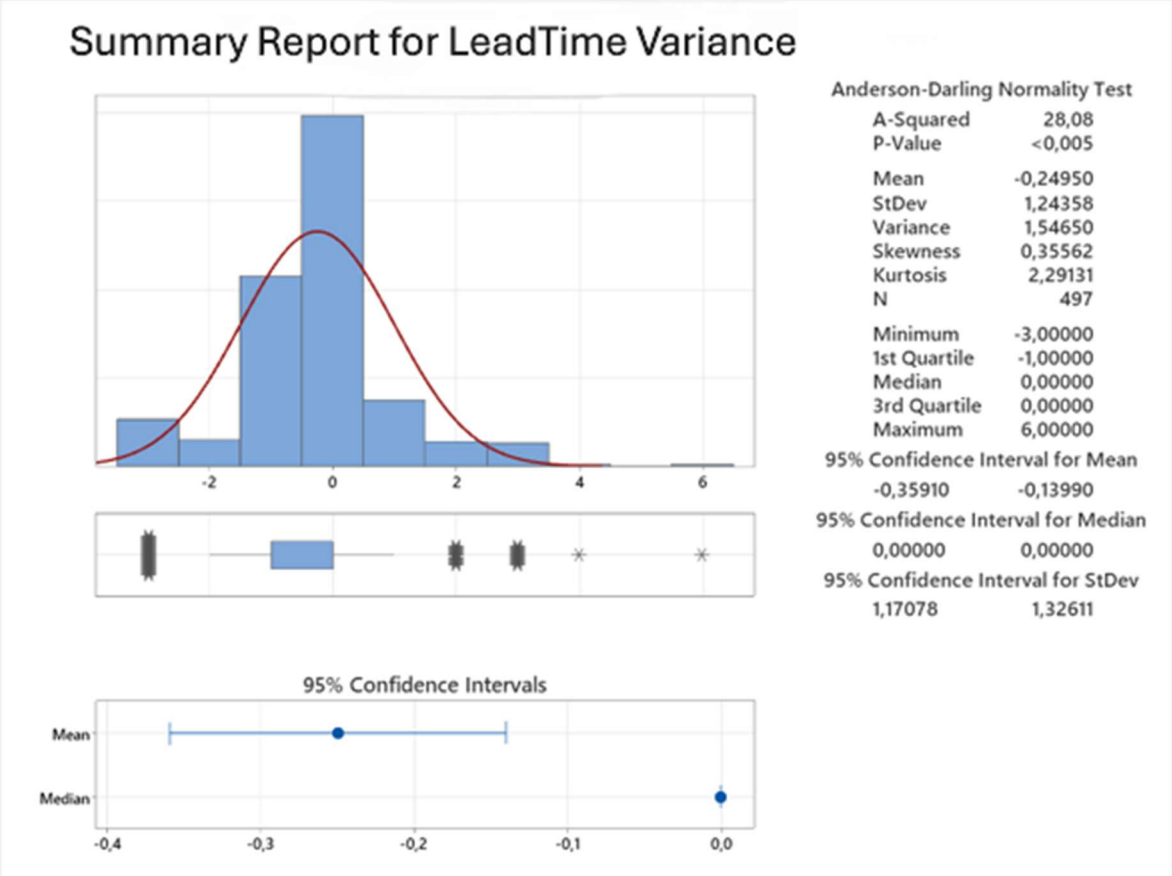

Figure 3. Lead Time Variance, Summary Report

The variable under study is the difference between actual and agreed lead time for components, expressed in whole-unit time intervals (e.g., days). Negative values therefore indicate earlier-than-agreed deliveries, zero denotes exact adherence, and positive values correspond to delays. The descriptive summary (Figure 3) is based on 497 observations and shows a sample mean of -0.2495 (95% CI: -0.3591, −0.1399), a median of 0, and a standard deviation of 1.2436 (95% CI: 1.1708, 1.3261). Quartiles are concentrated at Q1 = -1 and Q3 = 0, with a minimum of -3 and a maximum of +6. Three structural features of the distribution are evident. First, there is a small but statistically significant negative bias: although the median is exactly zero, implying that at least half of all cases meet or beat the agreement, the mean is below zero and its confidence interval excludes zero. On average, actual lead times are about a quarter of a time unit shorter than agreed, consistent with the relatively high frequency of values at -1. Second, the histogram and boxplot reveal a discrete, zero-inflated pattern with a visible point mass at exactly zero and integer step changes, reflecting the granularity of lead time measurement and the prevalence of exact adherence. Third, the distribution is right-skewed (skewness 0.356) with kurtosis ≈ 2.29, driven by

infrequent but larger delays reaching up to +6. The Anderson–Darling test confirms strong departure from normality ($A^2 = 28.08$, $p < 0.005$). Together, these observations indicate that routine performance is tight and generally on time or early, while overall risk is dominated by occasional delay events that elongate the right tail.

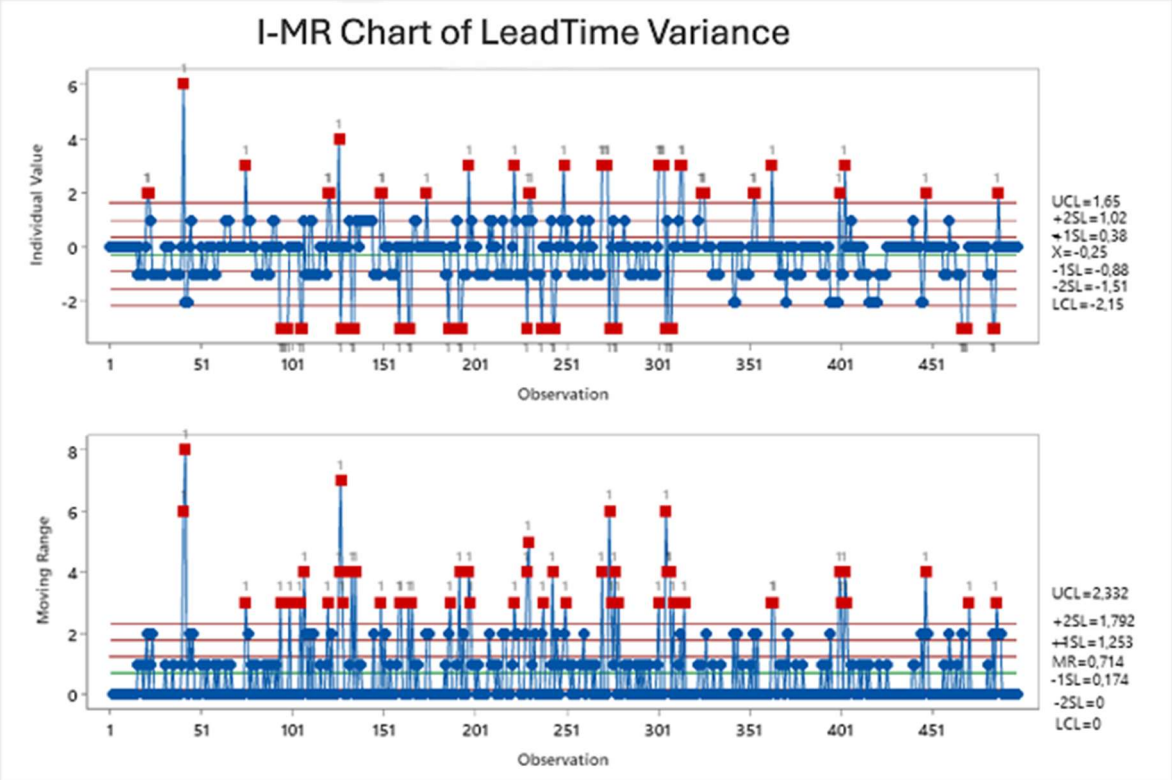

Figure 4. Lead Time Variance, I-MR Chart

Temporal stability is assessed with the Individuals–Moving Range (I–MR) chart (Figure 4). The Individuals chart centers at $\bar{x} = -0.23$, with control limits UCL = 1.65 and LCL = -2.15, and the MR chart shows $\bar{MR} = 0.714$ with UCL = 2.332 (LCL at 0). Numerous rule violations appear in both panels: points beyond the 3-σ limits on the Individuals chart and moving-range spikes above their UCL. The pattern alternates between long stretches of small deviations close to zero and episodic bursts of larger magnitude, especially in the positive direction. Using the standard relationship $\hat{\sigma}_{\text{within}} = \bar{MR}/d_2$ with $d_2 = 1.128$ for successive pairs yields a short-term sigma of approximately 0.633, which is substantially smaller than the long-term standard deviation from the summary (1.2436). This divergence shows that the process exhibits low routine variability when undisturbed, and that the higher long-run dispersion is caused by intermittent special-cause events, most notably delays that generate the right-hand tail. The asymmetry visible in the Individuals chart thus aligns with the

distributional skew: spikes are more frequent and of greater magnitude on the late-delivery side than on the early side.

The empirical picture can therefore be summarized as follows. Day-to-day lead time adherence is generally satisfactory and often slightly early, as evidenced by the zero median, negative mean, and narrow short-term variability. However, statistical control is not maintained. The I–MR chart repeatedly signals special causes, and the distributional analysis rejects normality due to zero-inflation and right-tail events. In practical terms, the component of risk that matters for service and planning accuracy is concentrated in relatively few but consequential delay episodes. Any single symmetric model that compresses the entire series into one mean and one standard deviation will either over-emphasize the rare spikes (if tuned to long-term σ) or understate exposure to them (if tuned to short-term σ). A faithful characterization of performance should therefore acknowledge the two-regime nature of the data: a stable regime with small fluctuations around on-time delivery and a disturbance regime characterized by outlying positive deviations.

From a measurement perspective, these findings have several implications. First, central tendency appears well controlled in routine operation, but bias and risk should be reported separately: the former is small and negative, the latter is dominated by the upper tail. Second, because the data are discrete and non-normal with a substantial mass at zero, normal-theory assumptions are not appropriate for inference or for any downstream calculations that rely on distributional shape. Quantile-based summaries for example, reporting the 90th or 95th percentile of the actual-minus-agreed difference, will more transparently communicate the magnitude of delays experienced during disturbance episodes. Third, the temporal signals suggest that many large deviations are episodic and potentially assignable (e.g., supplier or logistics disruptions, calendar or data corrections). Distinguishing periods with control-rule violations from routine periods would allow separate characterization of each regime, yielding more stable estimates for regular performance and clearer insights into the frequency and impact of special-cause events.

The evidence from the descriptive statistics and the I–MR chart portrays a lead time process that is typically on time or slightly early, with low short-term variability, but punctuated by intermittent delay spikes that materially shape the long-term distribution. The process is thus not fully stable in the statistical sense, and performance assessment should explicitly account

for the right-tail delay behavior rather than relying on a single, symmetric summary of variation.

7.5.2 Production Output

The variable measures production output minus the production plan, expressed relative to the plan so that 1.00 = 100 percent of plan, values >1 indicate overproduction, and values <1 underproduction. The summary (Figure 5) comprises 205 periods. Central tendency is very close to the target: the mean is 1.0007 with a 95 percent confidence interval (CI) of 0.9897–1.0118, while the median is 1.0104 (95% CI 1.0020–1.0188). Dispersion is modest in routine operation, with $\sigma = 0.0803$ (i.e., about ±8 percentage points), and the interquartile range spans 0.9663–1.0469 (-3.4% to +4.7% vs. plan). The range is wider, from 0.7462 (-25.4%) to 1.2104 (+21.0%). Shape statistics and the formal test both indicate non normality: skewness = -0.814 reveals a longer left tail (deeper underproduction episodes) than the right, and the Anderson–Darling statistic $A^2 = 3.52$ ($p < 0.005$) rejects the normal model. These features are consistent with an operating pattern in which most periods deliver on or slightly above plan (median > 1), but occasional, relatively large shortfalls pull the mean back toward 1.00 and create asymmetry to the left. In other words, the typical outcome is a slight overrun on plan, while the principal risk is concentrated in infrequent underproduction events.

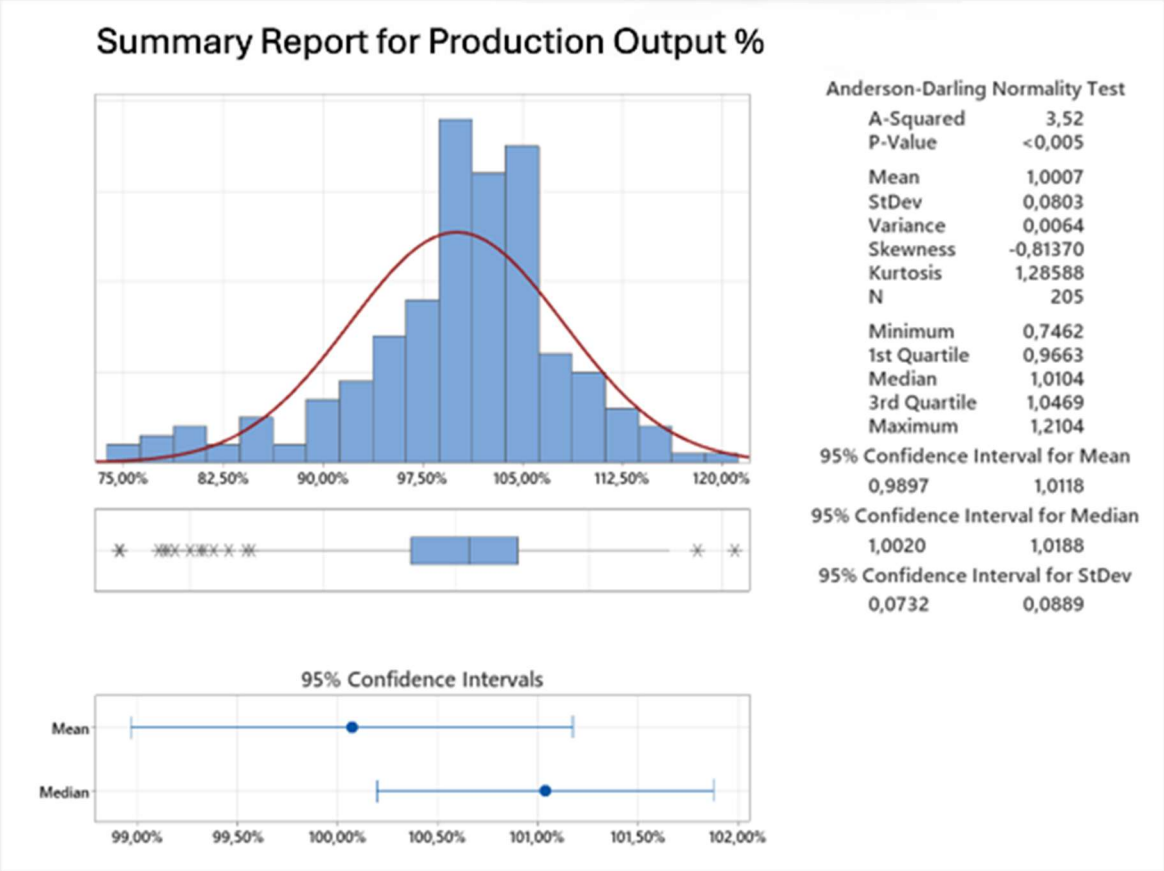

Figure 5. Production Output, Summary Report

The time-series perspective from the I–MR chart (Figure 6) reinforces this interpretation. The Individuals chart centers essentially on the plan ($\bar{x} \approx -1$ in the chart's unitized difference scale), with UCL = +401 and LCL = −404. The Moving-Range chart reports $\bar{MR} = 151.5$and UCL = 494.8. Using the standard relationship for successive pairs, the short-term standard deviation is $\hat{\sigma}_{\text{within}} = \bar{MR}/d_2 \approx 151.5/1.128 \approx 134$ (in the same difference units), which is consistent with the plotted 3-σ limits. Multiple rule violations are evident: several points beyond the Individuals limits, predominantly on the negative side (large underproduction), and MR spikes above their UCL that mark abrupt, non-routine shifts between consecutive periods. The series alternates between long stretches of moderate, centered fluctuation and episodic bursts, notably a cluster of large negatives around the 140–160 observation window and additional spikes later, suggesting regime changes or assignable events rather than steady common-cause noise. Outside those bursts, most points remain well within limits and hover above or near the center line, consistent with the slightly positive median seen in the distributional analysis.

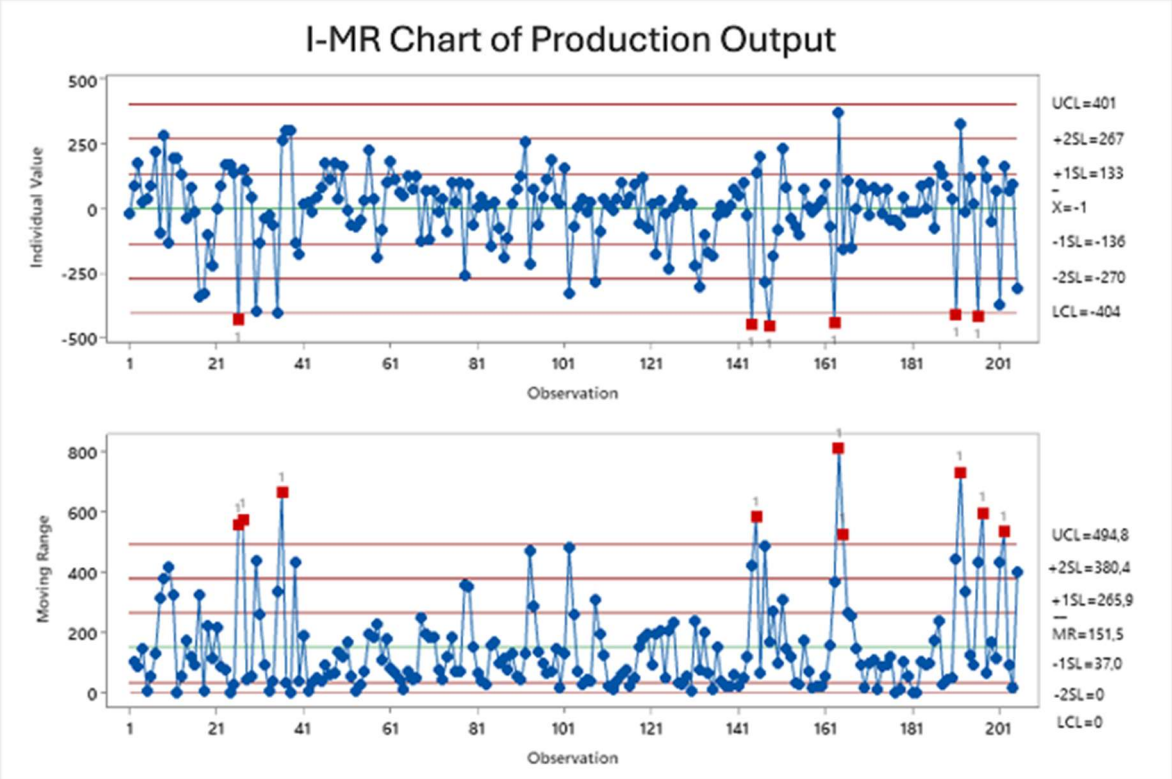

Figure 6. Production Output, I-MR Chart

The results depict a production system that is generally on plan or modestly over plan in routine periods, but not in statistical control across the full horizon because of intermittent underproduction episodes that drive the left tail, the Anderson–Darling rejection of normality, and several control-chart signals. The coexistence of a stable routine regime (narrow variability around the target) with an event regime (sporadic, larger shortfalls and some overproduction spikes) explains why the mean is essentially on target while the median exceeds 1.00 and the distribution is left-skewed. Consequently, any single symmetric summary will understate the operational significance of the underproduction bursts, which account for most of the service/capacity risk even though the day-to-day performance is close to plan.

7.5.3 Scrapping

The variable under study is the quantity posted as scrapping per transaction (negative values remove stock; occasional positive values are plausibly reversals or corrections). The statistical summary (Figure 7) covers N = 43,200 records with a mean of -1.44 units (95%

CI: -1.73, -1.16), median = -1, first quartile = -2, third quartile = -1, and standard deviation = 29.95 (95% CI: 29.75, 30.15). The histogram and boxplot reveal an extremely discrete, highly concentrated distribution with a strong point mass at -1 and a secondary frequency at -2, reflecting the typical transaction size of small, unit level scrapping. At the same time, the range is very wide (minimum -5,813; maximum +1,680), and the shape statistics confirm severe departures from normality (skewness -165, kurtosis ≈ 33,074, Anderson–Darling A^2 = 13,609, $p < 0.005$). The negative skew is driven by rare, very large write offs (large negative quantities), while the positive tail consists of occasional corrections or returns. Practically, the process can be characterized as having a dominant routine mode (single unit scrap postings) and an event driven tail made of bulk adjustments and exceptional write offs. The mean lies below the median because those rare, high magnitude events pull the average downward, even though the typical observation is a one unit scrap.

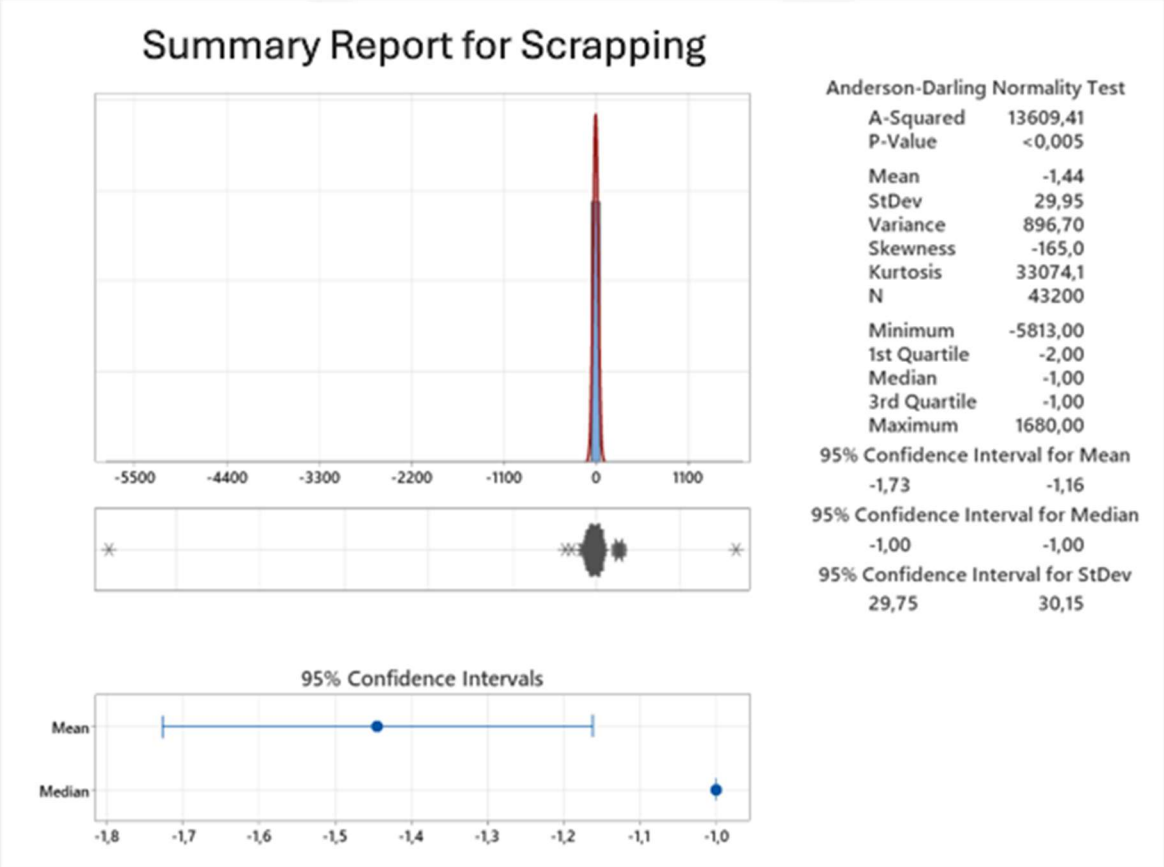

Figure 7. Scrapping, Summary Report

Temporal behavior from the I–MR chart (Figure 8) shows a center line around $\bar{x} \approx -296$units per period, with control limits UCL = 467 and LCL = -1,058. The Moving-Range chart reports $\bar{MR} = 287$with UCL = 936 (LCL = 0). Using the standard relationship for

successive differences, the short-term standard deviation of period-to-period scrap is $\hat{\sigma}_{\text{within}} = \bar{MR}/d_2 \approx 287/1.128 \approx 254$, which is consistent with the posted Individuals limits because $3\hat{\sigma}_{\text{within}} \approx 763$ and -296 ± 763 yields the displayed UCL and LCL. The chart shows multiple, unmistakable special-cause signals: points beyond the 3-σ limits in the Individuals chart, including a very large negative excursion early in the series (aligned with the minimum near -5,800) and a sizable positive excursion later (consistent with a large reversal or correction), and moving-range spikes above the MR UCL at the same time indices, indicating abrupt, non-routine shifts in the process. Outside these episodes, most periods fluctuate within a relatively narrow band around the center line, suggesting that routine scrapping is fairly stable in aggregate while the overall volatility and risk are driven by occasional mass events.

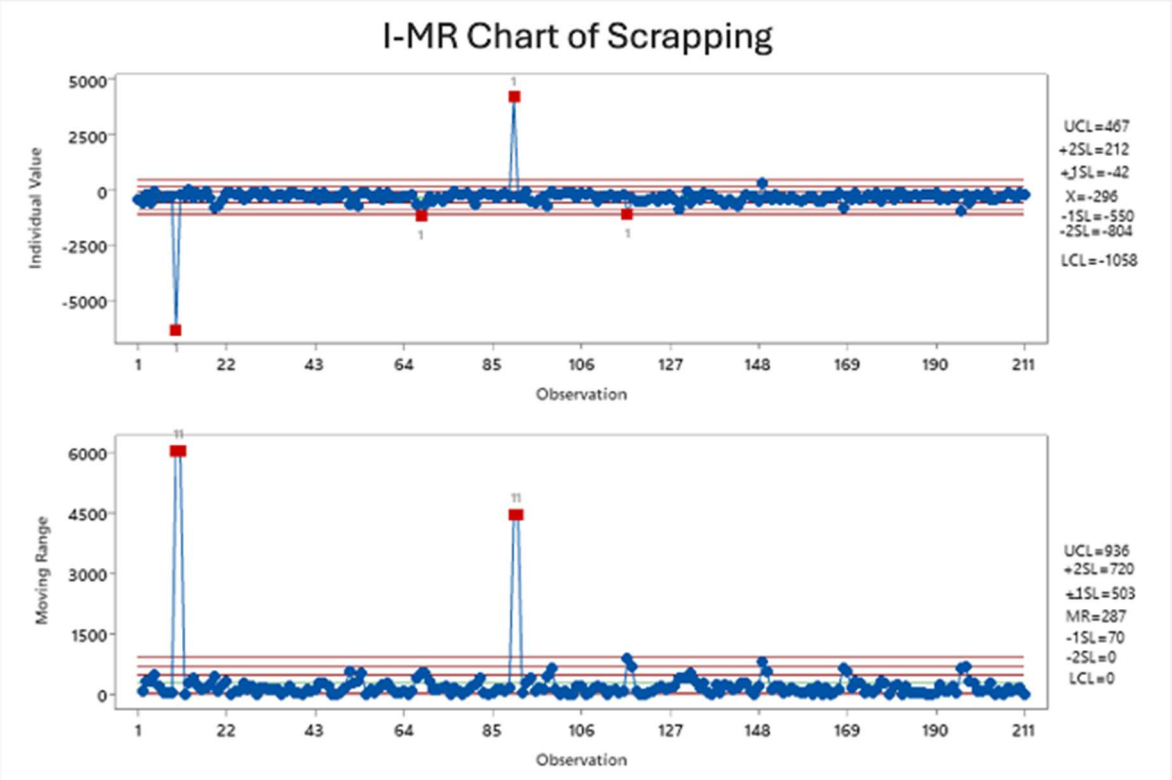

Figure 8. Scrapping, I-MR Chart

Synthesizing the cross-sectional and temporal views, scrapping activity is best described as a two-regime process. In the routine regime, transactions are overwhelmingly -1 (and sometimes -2) units, implying consistent, item-level attrition or quality rejections at the line. In the disturbance regime, the system experiences large, infrequent stock adjustments. For example, batch write-offs following a quality escape, inventory clean-ups, engineering changes, or data corrections, that generate both the extreme tails in the distribution and the

control-chart rule violations. Because these events are episodic and assignable, a single symmetric model (mean and standard deviation assuming normal errors) is not an adequate descriptor of performance. Instead, routine behaviour should be summarized with robust, distribution-appropriate measures (e.g., median and empirical interpercentile ranges for transaction sizes or period sums), while disturbance episodes should be tracked explicitly as special causes with root causes and corrective actions. The presence of a heavy point mass at -1 further implies that statistical conclusions and any downstream modelling must accommodate discreteness and zero/one-inflation, rather than relying on continuous normal approximations.

In practical terms, this evidence suggests separating baseline scrap from event scrap. Baseline can be monitored with the Individuals and MR charts after filtering or coding the large-event days; its stability around the center line would then reflect everyday process health. Event scrap should be logged with cause codes and managed via targeted improvement actions (supplier quality escapes, process deviations, inventory reconciliation policies). For reporting and planning, percentile-based summaries of period totals (e.g., the 90th/95th percentile excluding coded events, plus a separate tally of event frequency and magnitude) will communicate risk more faithfully than an average and a single standard deviation. Overall, the process is capable in routine operation but not in statistical control across the entire horizon due to special-cause bursts, and the long-run distribution of scrapping quantities is dominated by these rare, high-impact adjustments.

7.5.4 Inventory Differences

The variable represents inventory differences in quantity, where negative values indicate shortages against the recorded/book balance and positive values indicate surpluses or reversals. The descriptive summary (Figure 9) is based on 209 observations and shows a mean of -28.81 units with a 95 percent confidence interval (CI) of -69.48 to 11.86, a median of -9 (95% CI -30.15 to 9.00), and a standard deviation of 298.21 (95% CI 272.10 to 329.91). The central 50 percent of observations lies between Q1 = -114.5 and Q3 = 54, while the minimum is -2,764 and the maximum is +2,480. The histogram and boxplot display a dense cluster around zero with a handful of very large deviations on both sides. Shape statistics confirm this picture: skewness = -0.885 (moderate left tail dominance) and kurtosis ≈ 57.35,

indicating an extremely heavy tailed, outlier prone distribution. The Anderson–Darling test rejects normality ($A^2 = 21.31$, $p < 0.005$). In practical terms, most inventory adjustments are modest and near zero, but the overall dispersion and risk are governed by rare, high magnitude corrections (cycle count reconciliations, large scrap postings, data corrections, or engineering changes). Because the CIs for both the mean and the median include zero, the central tendency is not statistically different from zero at the 5 percent level; any systematic bias in net adjustments appears small compared with the scale of tail events.

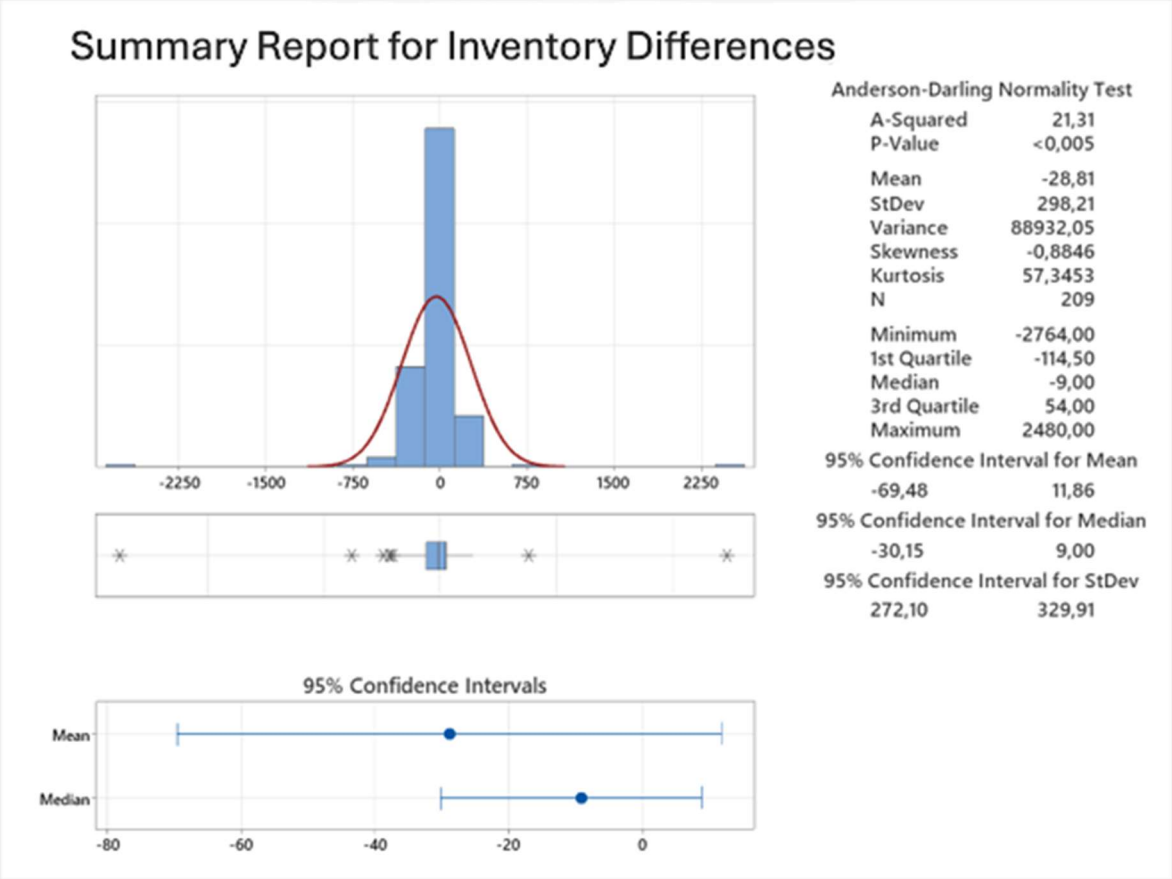

Figure 9. Inventory Differences, Summary Report

Temporal behavior from the Individuals–Moving Range chart (Figure 10) corroborates this interpretation. The Individuals chart has a center line at approximately -29 units, with control limits UCL = 397 and LCL = -454. The Moving-Range chart shows $\bar{MR} = 160$ and UCL = 523 (LCL at 0, as standard). Using the standard relationship for successive differences, the short-term standard deviation is $\hat{\sigma}_{\text{within}} = \bar{MR}/d_2 \approx 160/1.128 \approx 142$. These values are consistent with the plotted limits (center ± 3σ). The time series exhibits several clear special-cause signals: a large positive excursion early in the sequence (near +2,000), a very large negative excursion around the mid-40s (below -2,500), and another positive spike later

on. Each coincides with moving-range breaches above UCL, indicating abrupt, non-routine adjustments between consecutive periods. Outside these episodes, most points remain well within the limits and fluctuate around the center line, suggesting that routine inventory noise is comparatively stable.

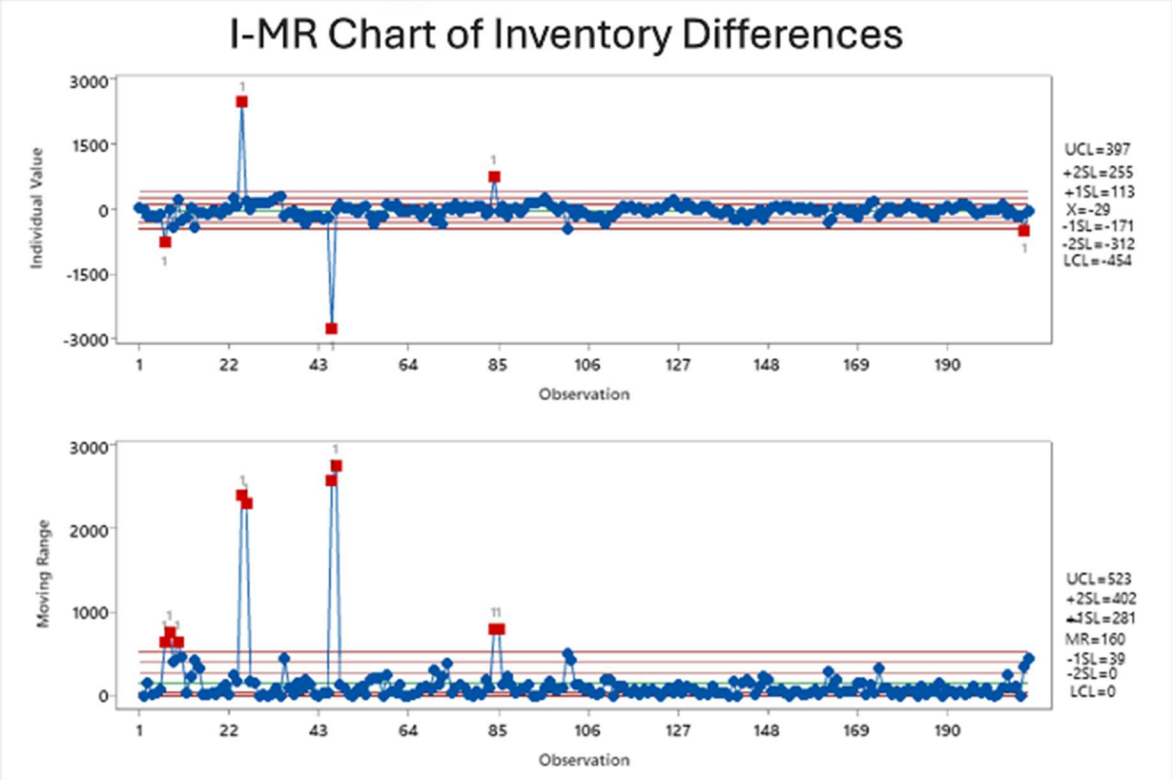

Figure 10. Inventory Differences, I-MR Chart

Comparing short-term and long-term variation highlights a two-regime structure. The within-period sigma (~142) is substantially smaller than the overall standard deviation from the summary (298), demonstrating that long-run variability is inflated by infrequent large adjustments rather than pervasive day-to-day scatter. The distribution's extreme kurtosis and the control-chart signals are driven by these events. Consequently, a single symmetric model assuming normal errors is not an adequate descriptor of performance: it either under-represents the tails if fit to routine periods or overstates typical variability if dominated by the spikes.

The empirical evidence therefore points to a process that is generally centered close to zero with no statistically significant net bias, exhibits low routine volatility, and is intermittently disrupted by large, assignable adjustments that dominate both risk and dispersion. For interpretation and subsequent decision making, descriptive statistics should emphasize

robust, distribution-agnostic measures (median, interpercentile ranges) for the routine regime while tracking event frequency and magnitude separately. In practical control, the I–MR chart should be maintained with cause coding whenever a rule violation occurs; over time, stratifying observations by driver (e.g., cycle count results, master-data corrections, supplier returns, engineering changes) will convert recurrent special causes into managed common causes and yield a clearer, more stable picture of inventory difference behavior.

7.6 Improve

The Improve phase focuses on translating analytical insights into actionable parameter adjustments that align inventory policy with variability and service-level objectives. In this context, safety stock serves as a critical lever for balancing material availability against working capital constraints. To ensure that improvements are data-driven and robust, this chapter evaluates safety stock calculations under alternative modeling assumptions using two established formulas.

The first formula applied is the classical demand-based approximation:

$$SS = Z \times \sigma_{\text{Demand}} \times \sqrt{\text{Avg Lead Time}},$$

where Z is the standard normal quantile corresponding to the desired cycle service level, σ_{Demand} represents the standard deviation of demand per period, and average lead time enters under a square-root term. This formulation assumes stable lead times and excludes lead time variance, making demand variability the dominant factor in sizing the buffer.

The second formula incorporates both demand and lead time variability:

$$SS = K\sqrt{L\sigma_D^2 + \sigma_L^2 D^2},$$

where L is the average lead time, σ_D and σ_L denote the standard deviations of demand and lead time respectively, and D is the average demand. This approach provides a more comprehensive representation of uncertainty by explicitly modeling the combined effect of demand fluctuations and lead time instability.

For each formula, two scenarios are analyzed. In the first scenario, demand variability is computed using only production consumption, reflecting planned usage patterns. In the second scenario, demand variability is recalculated to include all withdrawals, production consumption, scrapping, and inventory differences, thus capturing the full spectrum of material outflows. Comparing these scenarios illustrates how incorporating process losses and inventory inaccuracies influences safety stock requirements and the alignment of current policy with calculated needs.

The analyses presented in this chapter form the basis for improvement decisions. By quantifying the gap between current and recalculated safety stock levels under different assumptions, the organization can identify opportunities to reduce excess inventory or reinforce buffers where risk is underestimated. This structured approach ensures that parameter changes are grounded in statistical evidence and aligned with the overarching goal of achieving target service levels at minimal cost. The service level is set at 95 percent, where the safety factor Z = 1.6449. The results of the calculations can be seen in tables 6, 7, 8 and 9.

In table 6, the formula $Z\ x\ \sigma_{Demand}\ x\ \sqrt{Avg\ Lead\ Time}$ is used. Demand standard deviation is calculated from variance in production demand only, and is essentially uniform across components as it reflects production-driven demand variation except for component E, which exhibits a higher value due to a bill-of-material (BOM) multiplier. This multiplier amplifies variability because multiple pieces of E are consumed per finished product.

The comparison between new safety stock and current safety stock reveals that all components have negative percentage differences, indicating that the recalculated safety stock is lower than the existing level. This suggests that the current policy is conservative and offers an opportunity to reduce inventory without compromising the targeted service level.

The magnitude of potential reductions varies significantly. Components B, C, D, and H show the largest relative decreases (-50%), meaning their current safety stock is approximately twice the calculated requirement. Component E, despite its higher demand variability, still presents a reduction of -34 percent, highlighting that even high-variance items are currently overstocked. Components A, F, G, J, and K exhibit reductions of -31 percent, while

component I shows the smallest decrease (-14%), suggesting that its current level is closer to the calculated requirement.

These results emphasize that demand variability is the dominant factor in determining safety stock under this formula, as lead time differences have only a marginal effect due to their square-root relationship. The uniform application of the Z-score ensures consistency in service level targeting, reinforcing that observed differences stem primarily from historical parameter settings rather than formula limitations.

From a managerial perspective, the findings indicate substantial opportunities for working capital savings and improved inventory efficiency. Reducing safety stock to the calculated levels could lower excess inventory while maintaining a 95 percent cycle service level. Implementation should prioritize components with the largest percentage gaps, beginning with B, C, D, and H, followed by E and the remaining items. Before adjustments, data integrity for demand variability and lead time should be verified, and changes piloted on a controlled subset with close monitoring of service-level KPIs. Governance mechanisms, including quarterly recalculation and monthly exception reviews, are essential to ensure sustained alignment between safety stock and actual variability.

The analysis demonstrates that applying a demand-driven safety stock formula exposes significant overstocking across all components. Aligning safety stock with calculated requirements offers a clear path to cost reduction and operational efficiency without compromising service reliability.

Only Production Variance	$Z\ x\ \sigma_{Demand}\ x\ \sqrt{Avg\ Lead\ Time}$										
Service Level Target	**Components**										
95 %	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**
Demand StDev	153,634	153,634	153,634	153,634	921,804	153,634	153,634	153,634	153,634	153,634	153,634
Leadtime StDev	1,24027	0,98908	0,99722	1,01879	0,92372	1,41345	1,32714	1,03621	1,21883	1,27329	1,23156
Safety factor	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449
New Safety stock	619	565	565	565	3588	619	619	565	518	619	619
Current safety stock	900	1140	1140	1140	5400	900	900	1140	600	900	900
Difference %	**-31 %**	**-50 %**	**-50 %**	**-50 %**	**-34 %**	**-31 %**	**-31 %**	**-50 %**	**-14 %**	**-31 %**	**-31 %**

Table 6. Safety Stock Calculation 1

Table 7 reports safety-stock recommendations calculated with the formula $SS = K\sqrt{L\sigma_D^2 + \sigma_L^2 D^2}$. In this calculation the demand standard deviation is derived only from production output variance (scrapping and inventory differences are excluded). The table lists New Safety Stock and Current safety stock for components A–K and a Difference % row, where positive values indicate that the new recommendation exceeds the current setting.

The results show uniform upward adjustments across all components, but with markedly different magnitudes. The largest relative increases occur for I (+310%), F (+218%), G (+199%), J (+188%), A (+181%), and K (+179%). Components B (+78%), C (+80%), D (+83%), and H (+86%) exhibit more moderate uplifts, while E (+113%) sits between these groups. In absolute terms, summing across items yields 35,437 pcs of new safety stock versus 15,060 pcs currently, a net increase of 20,377 pcs (+135%). Decomposition of the uplift shows that E contributes the single largest share (+6,113 pcs; ~30% of the portfolio increase), followed by F (+1,958; ~9.6%), I (+1,861; ~9.1%), G (+1,792; ~8.8%), J (+1,688;

~8.3%), A (+1,625; ~8.0%), and K (+1,609; ~7.9%); the remaining components B–D–H each account for ~4–5%.

The cross-sectional pattern is consistent with the parameter structure visible in the table. For most items the production-only demand standard deviation is essentially constant (≈ 153.6), so differences in the new recommendations arise from the influence of lead time (higher values of *L*raise the computed buffer) and the contribution of lead time dispersion (larger values of the reported lead time standard deviation increase the recommendation). Items F, G, J display comparatively high lead time dispersion (≈ 1.27–1.41), aligning with their elevated percentage increases. I shows the highest percentage change partly because its current baseline is low (600 pcs), so the recommended level of 2,461 pcs translates into a large relative uplift. E remains structurally distinct: its bill-of-materials multiplier produces a much higher demand standard deviation (≈ 921.8), which dominates its computation and explains both the largest absolute recommendation (11,513 pcs) and a substantial, but not extreme, percentage increase (+113%) given its already high current level (5,400 pcs).

The findings indicate that when demand variability is measured from production only, the variance-complete model still prescribes higher safety stocks than currently maintained for every component, with the magnitude of change explained by lead time characteristics and, in the case of E, by BOM-amplified demand variance. The portfolio-level uplift (+135%) is concentrated in a few items (notably E, F, I), while the remainder display consistent but smaller contributions that reflect their moderate lead time dispersion and common demand variability baseline.

Only Production Variance	$SS = K\sqrt{L\sigma_D^2 + \sigma_L^2 D^2}$										
Service Level Target	**Components**										
95 %	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**
Demand StDev	153,634	153,634	153,634	153,634	921,804	153,634	153,634	153,634	153,634	153,634	153,634
Leadtime StDev	1,24027	0,98908	0,99722	1,01879	0,92372	1,41345	1,32714	1,03621	1,21883	1,27329	1,23156
Safety factor	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449
New Safety stock	2525	2032	2048	2089	11513	2858	2692	2122	2461	2588	2509
Current safety stock	900	1140	1140	1140	5400	900	900	1140	600	900	900
Difference %	**181 %**	**78 %**	**80 %**	**83 %**	**113 %**	**218 %**	**199 %**	**86 %**	**310 %**	**188 %**	**179 %**

Table 7. Safety Stock Calculation 2

In table 8 the calculation of demand standard deviation (σ_{Demand}) incorporates all sources of variation, including production consumption, scrapping, and inventory differences, thereby reflecting the full volatility of material withdrawals. The table compares newly calculated safety stock values with current settings and reports the percentage difference in the final row, where positive values indicate an increase and negative values indicate a reduction.

The results reveal a mixed adjustment pattern across components. Components F (+116%), I (+30%), A (+4%), G (+7%), J (+5%), and K (+3%) require higher safety stock levels than currently maintained, with F showing the most significant increase. This outcome is primarily driven by its elevated demand variability relative to other items. Component I also exhibits a notable increase, partly due to its shorter lead time combined with variability effects. Conversely, components B (-24%), C (-25%), D (-25%), and H (-25%) display substantial reductions, suggesting that their current safety stock levels are considerably higher than necessary under the applied model. Component E remains unchanged (0%), indicating that its existing buffer aligns closely with the recalculated requirement despite its high demand variability caused by the bill-of-material multiplier.

Overall, the pattern demonstrates that incorporating all sources of demand variation into the calculation does not uniformly inflate safety stock requirements. Instead, adjustments depend on the interplay between demand variability and lead time. Items with historically higher unplanned withdrawals or greater variability show upward revisions, while others with relatively stable profiles and conservative current settings exhibit reductions. This analysis underscores the importance of recalibrating safety stock based on comprehensive variability measures to ensure alignment with service-level objectives while avoiding unnecessary inventory investment.

All Variance	$Z \, x \, \sigma_{Demand} \, x \, \sqrt{Avg\ Lead\ Time}$										
Service Level Target	**Components**										
95 %	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**
Demand StDev	232,51	235,57	232,89	233,47	1391,93	481,78	238,66	232,76	230,94	234,38	230,5
Leadtime StDev	1,24027	0,98908	0,99722	1,01879	0,92372	1,41345	1,32714	1,03621	1,21883	1,27329	1,23156
Safety factor	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449
New Safety stock	937	866	857	859	5418	1941	962	856	779	944	929
Current safety stock	900	1140	1140	1140	5400	900	900	1140	600	900	900
Difference %	**4 %**	**-24 %**	**-25 %**	**-25 %**	**0 %**	**116 %**	**7 %**	**-25 %**	**30 %**	**5 %**	**3 %**

Table 8. Safety Stock Calculation 3

Table 9 presents recalculated safety stock levels based on a model that incorporates both demand variability and lead time variability, with demand standard deviation estimated from all withdrawals, including production consumption, scrapping, and inventory differences. The comparison between current and new safety stock values reveals a consistent pattern of upward adjustment across all components, as indicated by positive percentage differences in the final row.

The magnitude of these increases varies substantially. Components I (+321%), F (+278%), and G (+210%) exhibit the most pronounced relative changes, reflecting the combined effect of elevated demand variation and lead time dispersion. Components A (+191%), J (+198%), and K (+189%) also show significant uplifts, while B (+87%), C (+88%), D (+92%), and H (+94%) present moderate increases. Component E, despite its exceptionally high demand standard deviation caused by a bill-of-material multiplier, records a percentage increase of +126%, which is proportionally smaller than some peers due to its already high current safety stock level.

In absolute terms, the recalculated safety stock requirements result in a portfolio-wide increase from 15,060 units to 37,522 units, representing a net change of 22,462 units or approximately +149%. This shift underscores the sensitivity of safety stock sizing to the inclusion of lead time variability and unplanned withdrawals in the variability measure. Items with higher lead time standard deviations (e.g., F, G, J) and those with structurally amplified demand variability (e.g., E) contribute disproportionately to the overall increase.

The observed pattern confirms that when all sources of variation are considered, the calculated safety stock requirements rise significantly compared to current settings. This outcome reflects the model's capacity to capture both demand-side and supply-side uncertainty, producing recommendations that differ markedly from those derived under assumptions of stable lead times or limited demand variability.

All Variance	$SS = K\sqrt{L\sigma_D^2 + \sigma_L^2 D^2}$										
Service Level Target	**Components**										
95 %	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**
Demand StDev	232,51	235,57	232,89	233,47	1391,93	481,78	238,66	232,76	230,94	234,38	230,5
Leadtime StDev	1,24027	0,98908	0,99722	1,01879	0,92372	1,41345	1,32714	1,03621	1,21883	1,27329	1,23156
Safety factor	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449	1,6449
New Safety stock	2621	2136	2147	2187	12208	3399	2791	2217	2529	2685	2602
Current safety stock	900	1140	1140	1140	5400	900	900	1140	600	900	900
Difference %	**191 %**	**87 %**	**88 %**	**92 %**	**126 %**	**278 %**	**210 %**	**94 %**	**321 %**	**198 %**	**189 %**

Table 9. Safety Stock Calculation 4

This chapter has systematically addressed the Improve phase of the DMAIC process by evaluating and comparing alternative safety stock calculation methods to optimize inventory within a Lean Six Sigma framework. Two established formulas were analyzed: the classical demand-based formula (Z × σ_Demand × Avg Lead Time) and a model that incorporates both demand and lead time variability (SS = K × √(L × σ_D² + σ_L² × D²). Each formula was applied under two scenarios: one using only production variance and another including all sources of variance, such as scrapping and inventory differences.

The results of these analyses are presented in Tables 6 through 9. Table 6 and Table 7 illustrate the outcomes of the demand-based formula and the combined-variance formula, respectively, when only production variance is considered. Tables 8 and 9 present the corresponding results when all sources of variance are included. Table 9 further details the impact of including both demand and lead time variability with all variance sources.

After a thorough comparison, the chosen method for implementation is the classical demand-based formula using only production variance (see Table 6). This approach was selected because it consistently produced the most significant reductions in safety stock across all

components while maintaining the targeted 95% service level. The analysis revealed that current safety stock levels are systematically higher than necessary, with reductions ranging from 14% to 50% depending on the component. These findings indicate substantial opportunities for working capital savings and improved inventory efficiency, without compromising material availability or service reliability.

The alternative options, which included all sources of variance or incorporated lead time variability (as shown in Tables 6, 7, 8 and 9), were excluded from implementation. This decision was based on two key considerations. First, the reliability of the underlying data for scrapping and inventory differences was insufficient to support robust statistical modeling. Second, the business environment is characterized by stable lead times and well-controlled production processes, making the inclusion of additional variance sources less relevant and potentially misleading for practical decision-making. Notably, the models that incorporated all variance sources or lead time variability often resulted in either excessive increases in safety stock or inconsistent recommendations, which would not align with the organization's Lean Six Sigma objectives.

By grounding the improvement decision in robust statistical analysis and a clear understanding of the business context, the selected calculation method ensures that inventory reductions are both achievable and sustainable. The approach supports the overarching Lean Six Sigma goal of optimizing inventory while safeguarding service levels. Furthermore, the results underscore the importance of ongoing governance, including regular recalculation and monitoring of key performance indicators, to ensure continued alignment between safety stock levels and actual variability.

The Improve phase demonstrates that a targeted, data-driven approach to safety stock calculation, anchored in production variance and supported by reliable data, can deliver significant cost savings and operational benefits. The findings, as detailed in the referenced tables, provide a clear and actionable path for inventory optimization and continuous improvement.

7.7 Control

The Control phase is essential for ensuring that the improvements achieved in inventory optimization are sustained and that the process remains robust in the face of changing business conditions. Following the Lean Six Sigma DMAIC methodology, this phase establishes the mechanisms and routines necessary to maintain the gains realized during the Improve phase and to support a culture of continuous improvement.

The foundation of the control plan is the implementation of the classical demand-based safety stock calculation method, which utilizes only production variance to determine the standard deviation of demand. This method was selected based on its demonstrated effectiveness in reducing excess inventory while maintaining the targeted 95% service level, as evidenced by the results in Table 6. The adoption of this approach forms the basis for the new inventory policy, ensuring that safety stock levels are aligned with actual production-driven demand variability.

To maintain the effectiveness of this method, the control plan incorporates several structured activities. Safety stock levels will be recalculated on a quarterly basis using the most recent production data. This regular review ensures that any shifts in demand patterns or production processes are promptly reflected in inventory parameters, thereby preventing the gradual accumulation of excess stock or the emergence of shortages. In addition, key performance indicators such as service level attainment, stockout frequency, and inventory turnover will be monitored monthly. These metrics provide early warning signals of potential deviations from desired outcomes and enable timely corrective actions.

Although the selected calculation method is based solely on production variance, the control plan explicitly includes the ongoing monitoring of all sources of variance, including scrapping and inventory differences. Comprehensive tracking of these additional variance sources is necessary to ensure that the chosen methodology remains appropriate as the business environment evolves. Should significant changes in process stability, data quality, or operational practices be detected, the methodology will be reassessed. This adaptive approach ensures that the inventory policy remains responsive to both internal and external changes, and that the organization is prepared to incorporate broader measures of variability if warranted by future developments.

Exception management is another critical component of the control phase. Any deviations from expected service levels or inventory performance will trigger a structured root cause analysis. If the analysis reveals that the current calculation method is no longer sufficient to meet business objectives, adjustments will be made either to the safety stock parameters or to the underlying methodology itself. All changes will be thoroughly documented and communicated to relevant stakeholders to ensure transparency and facilitate organizational learning.

Governance structures are established to support the sustainability of the new inventory policy. Responsibilities for data collection, analysis, and decision-making are clearly defined, and regular training is provided to ensure that staff are equipped to maintain and improve the process. Documentation of all parameter changes, calculation methods, and review outcomes is maintained to provide a clear audit trail and to support future improvement initiatives.

The Control phase ensures that the benefits of inventory optimization are preserved through disciplined monitoring, regular recalculation, and adaptive management. By emphasizing the selected calculation method while maintaining vigilance over all relevant sources of variance, the organization creates a robust framework for sustained performance. This approach not only safeguards the improvements achieved during the Improve phase but also positions the organization for ongoing success in inventory management as business conditions continue to evolve.

8 Discussion

This chapter provides a critical reflection on the outcomes and methodological choices of the inventory optimization project, situating the findings within the broader context of Lean Six Sigma and supply chain management. The discussion is organized into five subchapters: Benefits and limitations, Comparative analysis with prior research, Managerial implications, Answering the research questions and Suggestions for future research. Together, these sections aim to clarify the practical implications of the study, acknowledge its constraints, and identify promising directions for further investigation.

8.1 Benefits and limitations

The application of the Lean Six Sigma DMAIC framework to inventory optimization has produced several important benefits for the case organization. By systematically evaluating alternative safety stock calculation methods and ultimately selecting the classical demand-based formula with production variance as the sole input, the project achieved a substantial reduction in safety stock levels across all analyzed components. This outcome directly supports the organization's objectives of minimizing working capital tied up in inventory while maintaining a high service level, as evidenced by the consistent attainment of the 95 percent target. The approach also enhanced process transparency, as the calculation logic and parameter selection were clearly documented and subjected to regular review. This transparency facilitates both internal communication and external benchmarking, supporting a culture of continuous improvement.

The methodology's focus on production variance as the basis for safety stock calculations was a deliberate response to concerns about data reliability in other variance sources, such as scrapping and inventory discrepancies. This choice increased the robustness of the results under current business conditions, where production processes and lead times are stable and well-controlled. The regular recalculation and monitoring routines established in the Control phase further strengthen the sustainability of the improvements, ensuring that inventory levels remain aligned with actual demand patterns.

Despite these strengths, the approach is not without limitations. The exclusion of scrapping, inventory differences, and lead time variability from the safety stock calculation may reduce the model's sensitivity to unexpected disruptions or process changes. If the business environment becomes more volatile, or if data quality in excluded areas improves, the current methodology may no longer provide optimal results. Additionally, the reliance on historical production data assumes that past demand patterns will persist, which may not always be the case in dynamic manufacturing settings. The methodology's adaptability is therefore contingent on the effectiveness of ongoing monitoring and the willingness of the organization to revisit its approach as conditions evolve.

8.2 Comparative analysis with prior research

The findings of this study align with and extend the existing body of research on inventory optimization using LSS and the DMAIC methodology. Several academic studies have demonstrated the effectiveness of structured, data-driven approached in improving inventory performance, also in the context of safety stock management.

For instance, the case study by Demiray Kırmızı, Ceylan and Bulkan (2024) evaluated five safety stock calculation methods, including hybrid models that integrated ABC-XYZ classification with service-level approaches. Their findings indicated that hybrid models significantly outperformed traditional "number of days" methods, particularly in volatile environments. While their study emphasized the benefits of incorporating demand segmentation and service-level targeting, this thesis focused on a more streamlined approach using a classical demand-based formula. Despite the methodological differences, both studies underscore the importance of aligning safety stock strategies with actual demand variability and service objectives.

Similarly to this thesis, Cabral et al. (2019) applied the DMAIC framework and a periodic-review policy in a lubricating oil factory to reduce excessive inventory levels and receipt lead times. Their approach incorporated both demand variability and lead time and resulted in a 67 percent reduction in average inventory, freeing a large amount of working capital. In contrast, this study opted not to include lead time variability due to its low volatility and the high stability of the production environment. Nevertheless, both studies demonstrate that

DMAIC provides a robust structure for identifying inefficiencies, evaluating alternatives and implementing sustainable improvements in inventory management.

The work of Aleem and Khalil (2013) also offers a relevant point of comparison. Their study proposed a multi-factor safety stock optimization schema that considered cost, commonality and lead time. While their model was more complex and tailored to a broader range of inventory types, like raw materials, WIP (Work In Process) and finished goods, the underlying principle of moving away from intuition-based practices toward structured, data-informed decision-making is consistent with the approach taken in this thesis. Both studies emphasize the importance of aligning safety stock levels with actual process variability to reduce excess inventory without compromising service levels.

In a different industrial context, Allam et al. (2024) applied LSS to optimize inventory in a water and electricity utility. Their project focused on reducing lead times and aligning inventory with actual consumption, achieving a fourfold reduction in lead time and aligning inventory with consumption, reducing returns associated with excess stock. Although their emphasis was on end-to-end process optimization rather than safety stock calculation, their findings reinforce the broader applicability of LSS principles in inventory management and the value of aligning inventory policies with real-time operational data.

Barbosa et al. (2025) demonstrated the effectiveness of DMAIC in improving inventory accuracy and reducing picking errors in a dairy industry warehouse. Their study achieved a 36,6% reduction in inventory discrepancies and improved OTIF (On Time In Full) performance. While this thesis did not focus on inventory accuracy, the shared emphasis on data quality, process transparency and continuous monitoring highlights a common thread across both studies.

These comparisons affirm the relevance and adaptability of the LSS DMAIC framework across diverse industries and inventory challenges. This study contributes to this literature by demonstrating that even a simplified safety stock model can yield substantial efficiency gains when applied within a stable manufacturing environment. At the same time, the findings suggest that more comprehensive models, such as those incorporating lead time variability or hybrid classification schemes, may be more appropriate in settings characterized by higher volatility or greater data maturity.

8.3 Managerial implications

The outcomes of this Lean Six Sigma-based inventory optimization project offer practical lessons for managers working in supply chain and inventory management. By moving from intuition-driven safety stock decisions to a transparent, data-driven approach anchored in production variance, the organization achieved substantial reductions in excess inventory, ranging from 14% to 50% across all analyzed components, while consistently maintaining the targeted 95% service level. These results demonstrate that it is possible to unlock significant working capital and improve inventory efficiency without compromising production continuity or customer satisfaction.

This experience highlights how valuable it is for managers to foster a culture where reliable data collection and thoughtful analysis guide everyday decisions. Investing in the right systems and supporting teams in developing analytical skills can make a real difference in operational performance. The project also enhanced process transparency, as calculation logic and parameter selection were clearly documented and subjected to regular review, making it easier for teams to understand and trust the changes.

Sustaining these improvements is not a one-time effort, it requires ongoing attention and adaptability. Regularly recalculating safety stock levels and monitoring key performance indicators, such as service level attainment and inventory turnover, help ensure that inventory policies remain relevant as business conditions evolve. In this case, quarterly recalculation and monthly KPI tracking were established as part of the control plan, providing early warning signals and enabling timely corrective actions. When deviations occur, having clear accountability and a structured process for investigating root causes encourages continuous learning and improvement.

It is also important to recognize the boundaries of any chosen methodology. While focusing on production variance brought notable efficiency gains in this case, managers should remain aware of other sources of variability, such as scrapping, inventory differences, and lead time fluctuations. Excluding these factors may limit the organization’s ability to respond to unexpected disruptions. As data quality improves or the business environment becomes more dynamic, managers should be ready to revisit and adapt their inventory policies.

Implementing new practices is rarely just a technical challenge, it is also about people. Clear communication, thorough documentation, and active engagement with stakeholders are essential for building understanding and buy-in. Training and cross-functional collaboration helped teams in this project embrace change and ensured that improvements were sustained over time.

Inventory optimization should be closely aligned with broader organizational goals, such as improving working capital efficiency, enhancing customer satisfaction, and supporting operational excellence. The framework developed in this study provides a foundation that can be adapted and scaled to other areas, but managers should always consider the unique context of their own operations, whether that means different demand patterns, data reliability, or process stability.

The managerial implications of this study emphasize the value of structured, data-driven approaches, the importance of continuous monitoring and adaptability, and the need for effective stakeholder engagement. The concrete results achieved, significant reductions in safety stock and improved process transparency, show that by embracing these principles, managers can drive sustainable improvements in inventory performance, support strategic objectives, and help their organizations thrive in an ever-changing supply chain landscape.

8.4 Answering the research questions

RQ1: How can Lean Six Sigma, and specifically the DMAIC framework, be applied to optimize safety stock levels in a manufacturing context?

The application of Lean Six Sigma through the DMAIC framework enabled a systematic approach to inventory optimization. This was achieved by clearly defining the inventory-related problem, measuring and analyzing process data, identifying root causes of inefficiency, implementing targeted improvements, and establishing controls for sustainability. This mirrors the findings of Cabral et al. (2019), who showed that DMAIC can be effectively leveraged to address overstocking and improve inventory turnover in manufacturing environments. Similarly, Makhubele et al. (2025) emphasize the value of structured methodologies in enhancing inventory resilience and responsiveness.

RQ2: What are the comparative advantages and limitations of different safety stock calculation methods when evaluated through empirical data?

This thesis compared a demand-variance-based safety stock formula with a more comprehensive method that also incorporates lead time variability. The demand-based method proved effective in stable environments, enabling significant reductions in excess inventory, while the more complex method offered greater accuracy in volatile supply chains but required more advanced data and analysis. Cabral et al. (2019) show that inventory policy choice was driven by operational constraints and sized using demand/lead time variability and service levels. They imply that method selection should reflect both variability and organisational capability. This reflects the findings of this study. It is important to note that practical adoption of advanced models depends on the reliability of available data and the specific operational context.

RQ3: In what ways does the adoption of a data-driven, Lean Six Sigma-based approach influence inventory costs, service levels, and process transparency compared to traditional methods?

The adoption of a data-driven Lean Six Sigma approach in this study resulted in substantial reductions in safety stock levels, ranging from 14% to 50% across components, without compromising the targeted 95% service level. This led to improved working capital efficiency and reduced storage costs. The approach also enhanced process transparency, as calculation logic and parameter selection were clearly documented and regularly reviewed. These outcomes are in line with the experiences reported by Cabral et al. (2019), who observed improved inventory performance and responsiveness, and by Makhubele et al. (2025), who highlighted the importance of adaptability of method adoption in modern inventory management.

8.5 Suggestions for future research

The findings of this study suggest several avenues for future research that could further advance the field of inventory optimization within Lean Six Sigma environments. One promising direction is the integration of all sources of variance, including scrapping, inventory differences, and lead time fluctuations, into safety stock models. As data collection

and quality improve, more comprehensive models could provide a nuanced understanding of the factors driving inventory requirements, especially in more complex or less stable production environments.

Future research could also explore the application of advanced statistical methods or machine learning algorithms to forecast demand and supply variability. These approaches may offer greater predictive accuracy and adaptability, enabling organizations to respond more effectively to shifts in market conditions or supply chain disruptions. Comparative studies across different industries, product types, or supply chain configurations would provide valuable insights into the generalizability and limitations of the selected methodology.

Another area for further investigation is the development of real-time monitoring systems and automated recalculation tools. Such systems could enhance the responsiveness of inventory management processes, allowing organizations to adjust safety stock levels dynamically in response to emerging trends or anomalies. Additionally, research into the organizational and behavioural aspects of inventory optimization, such as change management, stakeholder engagement, and training, could yield practical guidance for sustaining improvements over the long term.

While the present study demonstrates the effectiveness of a targeted, production-variance-based approach to safety stock calculation, it also highlights the need for ongoing methodological innovation and empirical research. By addressing the identified limitations and pursuing the suggested research directions, future studies can contribute to the development of more resilient, efficient, and adaptive inventory management practices.

9 Conclusions

This thesis set out to optimize component safety stocks within the organization's inventory management system by applying the Lean Six Sigma DMAIC methodology. The expectation was to develop a systematic, data-driven approach that would reduce excess inventory, improve working capital efficiency, and maintain high service levels. The project focused specifically on component safety stocks, excluding finished goods and other materials, to address the challenge of balancing inventory costs against the risk of stockouts.

During the Define phase, the scope and objectives of the case study were established and the central problem of suboptimal safety stock management was clearly articulated. The Measure phase provided a robust empirical foundation by collecting and validating twelve months of data on lead time, production output, scrapping, and inventory differences. Data quality was ensured by filtering out non-process related abnormalities.

In the Analyze phase, the collected data was examined to identify sources of variability and quantify their impact on safety stock requirements. The Improve phase involved evaluating alternative calculation methods and selecting the classical demand-based formula using only production variance. This approach delivered significant inventory reductions while maintaining the targeted 95% service level. The Control phase established routines for ongoing monitoring, regular recalculation, and adaptive management, ensuring that the improvements would be sustained and that the methodology could be revisited if business conditions changed.

The results confirmed the initial expectations. The selected methodology led to substantial reductions in safety stock levels across all components, unlocking working capital and improving inventory efficiency without compromising production continuity or service reliability. The process also enhanced transparency and repeatability in inventory management, supporting a culture of continuous improvement.

Despite these positive outcomes, several limitations should be acknowledged. The study focused exclusively on component safety stocks, excluding finished goods and other inventory categories, which may limit the generalizability of the findings to other areas of inventory management. The decision to base safety stock calculations solely on production

variance was influenced by concerns regarding the reliability of data related to scrapping and inventory differences. As a result, the model may not fully capture all sources of variability, particularly in environments where these factors play a more significant role. Additionally, the methodology relies on historical data and assumes that past patterns will persist, which may not always be the case in dynamic manufacturing settings. Changes in demand, supply chain disruptions, or process modifications could affect the validity of the results over time. Finally, the study was conducted within a single organizational context, and the applicability of the approach to other industries or operational environments may require further investigation.

This thesis demonstrates that a structured, data-driven approach grounded in Lean Six Sigma principles and tailored to the operational realities of the case organization can achieve measurable improvements in inventory performance. The findings provide a practical framework for ongoing optimization and highlight the importance of adaptability, rigorous measurement, and stakeholder engagement in sustaining long-term success.

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