TÜRKİYE CUMHURİYETİ
ADANA ALPARSLAN TÜRKEŞ SCIENCE AND TECHNOLOGY UNIVERSITY

GRADUATE SCHOOL
BUSINESS ADMINISTRATION DEPARTMENT

THE USE OF MULTIVARIATE SPC METHODS IN THE ANALYSIS OF QUALITY CONTROL PROBLEMS: AN APPLICATION IN A TEXTILE COMPANY

MÜLAYİM ÖNGÜN ÜKELGE

Ph.D.

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THESIS ADVISOR
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ADANA, 2024

DECLARATION OF CONFORMITY

In this thesis study, which was prepared following the thesis writing rules of Adana Alparslan Türkeş Science and Technology University Institute of Graduate School, I declare that I provide all the information, documents, evaluations and results in accordance with scientific ethics and moral codes without resorting to any means or assistance that would be contrary to scientific ethics and traditions. I also declare that I refer to all of the articles I used in this study with appropriate references and accept all moral and legal consequences if a situation is found contrary to my statement regarding my work.

08/11/2024

[Signature]

Mülayim Öngün ÜKELGE

ÖZET

KALİTE KONTROL PROBLEMLERİNİN ANALİZİNDE ÇOK DEĞİŞKENLİ SPC YÖNTEMLERİNİN KULLANIMI: BİR TEKSTİL ŞİRKETİNDE UYGULAMA

Mülayim Öngün ÜKELGE
Doktora, İşletme Anabilim Dalı
Danışman: Doç. Dr. Esra KARAKAŞ
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Küreselleşen dünyada kalite, işletmelerin müşteri ihtiyaçlarına cevap vererek yoğun rekabet ortamında ayakta kalmalarına yardımcı olan en önemli faktörlerden biri olarak görülmektedir. Üretim süreçlerinde, ürünlerin kalite değişkenlerinin önceden belirlenmiş standartlardan sapması durumunda, sürece zamanında müdahale edilmesi, olası kayıpların önlenmesi açısından kritik bir öneme sahiptir. Bu tür sapmalar, üretim maliyetlerini artırabilir ve sürecin etkinliğini azaltabilir. Dolayısıyla, üretim süreçlerinin sürekli kontrol altında tutulması ve olası sapmaların hızlı bir şekilde tespit edilerek gerekli düzeltici önlemlerin alınması hem zaman hem de maliyet tasarrufu sağlamak açısından işletmelere önemli avantajlar sunar. Bu çerçevede, İstatistiksel Proses Kontrol (İPK) yöntemlerinin üretim süreçlerine entegrasyonu, prosesin kalitesini ve verimliliğini artırmak için vazgeçilmez bir araç olarak değerlendirilmektedir.

Tekstil sektöründe iplik üretim süreçleri özelinde, Çok Değişkenli İstatistiksel Proses Kontrol (ÇDİPK) yöntemlerinin literatürde yeterince uygulanmadığı ve incelenmediği görülmektedir. Bu çalışmanın amacı, literatürdeki bu boşluğu doldurmak ve iplik üretiminde kalite kontrolü süreçlerinde ÇDİPK yöntemlerinin etkinliğini ortaya koymaktır. Bu amaç doğrultusunda, ÇDİPK yöntemleri incelenmiş ve bu yöntemlerden Hotelling T^2 kontrol grafiği uygulamaları, bir tekstil firmasının iplik üretim tesislerinde gerçekleştirilmiştir.

Uygulama aşamasında, firmanın en çok üretilen ilk üç iplik türüne ait kalite kontrol laboratuvarı verileri kullanılmıştır. Bu veriler, öncelikle tek değişkenli kalite kontrol grafikleri ile analiz edilmiş, ardından kalite değişkenleri gruplandırılarak çok değişkenli istatistiksel proses kontrol yöntemleri ile süreç gözlemlenmiştir. Çalışmanın sonucunda, ÇDİPK

yöntemlerinin, birden fazla kalite değişkenini aynı anda değerlendirerek, bu değişkenler arasındaki ilişkileri dikkate alması sayesinde daha etkin ve kapsamlı bir kontrol sağladığı ortaya konmuştur. Çalışmada; Minitab Statistical Software kullanılarak hesaplamalar yapılmış ve kontrol grafikleri çizilmiştir.

Anahtar Kelimeler: Çok Değişkenli İstatistiksel Proses Kontrol, İplik Üretimi, İstatistiksel Proses Kontrol, Kalite Kontrol, Kontrol Grafikleri.

ABSTRACT

THE USE OF MULTIVARIATE SPC METHODS IN THE ANALYSIS OF QUALITY CONTROL PROBLEMS: AN APPLICATION IN A TEXTILE COMPANY

Mülayim Öngün ÜKELGE

Ph.D., Department of Business Administration

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In today's globalized world, quality is a crucial factor for businesses striving to survive in highly competitive markets and meet customer demands. When product quality deviates from set standards during production, it's essential to intervene promptly to prevent potential losses. Deviations can drive up production costs and reduce process efficiency. Therefore, maintaining constant control over production processes, promptly identifying deviations, and implementing necessary corrective measures can deliver significant time and cost savings for businesses. Considering these factors, integrating statistical process control (SPC) methods into production processes is essential for boosting quality and efficiency.

In the textile industry, it is observed that multivariate statistical process control (MSPC) methods are not sufficiently implemented and studied in the domestic literature, especially in the context of yarn production processes. The aim of this study is to fill this gap in the domestic literature and demonstrate the effectiveness of MSPC methods in quality control processes in yarn production. In line with this aim, multivariate statistical process control methods such as Hotelling's T^2 control chart, the multivariate cumulative sum (MCUSUM) method, and the multivariate exponentially weighted moving average (MEWMA) control chart have been thoroughly examined. The application of Hotelling T^2 method have been implemented in the yarn production facilities of a textile company.

During the application phase, the quality control laboratory data for the top three types of yarn produced by the company were utilized. These data were initially analyzed using single-variable quality control charts, and subsequently, the quality variables were grouped, and the process was observed using advanced multivariate statistical process control methods. The study’s findings revealed that the multivariate statistical process control methods offer a more effective and comprehensive control by considering the interrelationships between multiple quality variables. The calculations and control charts for the study were conducted using the Minitab Statistical Software.

Keywords: Control Charts, Multivariate Statistical Process Control, Quality Control, Statistical Process Control, Yarn Production.

Dedication

This thesis is dedicated to my parents who are my greatest fortune in life.

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First and foremost, I would like to express my deepest appreciation to my advisor Assoc. Prof. Dr. Esra Karakaş, for her invaluable guidance, support, and expertise during the development of this thesis. Her encouragement and insightful feedback have greatly enriched my research, and I am genuinely thankful for her mentorship. I also want to thank Assoc. Prof. Dr. Melik Koyuncu for his contributions and guidance. His constructive feedback and suggestions have significantly enhanced the quality of my work, and I sincerely appreciate his support.

Personally, I am profoundly thankful to my spouse and my son for their unwavering belief in me and their continuous support throughout this journey. Their patience, understanding, and encouragement have been a source of strength, and this thesis would not have been possible without them.

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LIST OF ABBREVIATIONS

QC	: Quality Control
MSPC	: Multivariate Statistical Process Control
SPC	: Statistical Process Control
CL	: Center Line
UCL	: Upper Control Limit
LCL	: Lower Control Limit
RSM	: Response Surface Methodology
DOE	: Design of Experimenrs

LIST OF SYMBOLS

$\boldsymbol{\mu}$	: Mean
$\boldsymbol{\mu}_0$	: Target Mean
$\boldsymbol{\sigma}$	: Standard Deviation
$\bar{\boldsymbol{\sigma}}$	: Standard Deviations' Average
$\mathbf{p_i}$	: Defect Proportion
$\bar{\boldsymbol{c}}$	: Average Number of Defects
$\boldsymbol{u_i}$	: Average Number of Defects Per Unit
$\boldsymbol{x_{max}}$	: Largest values of the observation
$\boldsymbol{x_{min}}$	: Smallest values of the observation
$\bar{\boldsymbol{R}}$	: Average variation range
$\bar{\boldsymbol{x}}$:	Means of each sample
$\bar{\bar{\boldsymbol{x}}}$	: Mean of the means of each sample
n	: Sample size
$\overline{\boldsymbol{MR}}$	: Central Line of MR control chart
i	: Time
$\mathbf{S_i}$	: Cumulative Sum
Z	: EWMA value
Λ	: Weighting factor

1. INTRODUCTION

The most essential aspect of any product can be defined as its quality. Since the early 1900s, there has been a rapid increase in advancements and innovations in the field of Quality Control (QC) due to its importance. This surge can be attributed to the growing awareness among consumers, who have made it evident that meeting their demands is inevitable when it comes to defective products or services. This has heightened competition among companies, compelling manufacturers to produce high-quality products at lower costs.

In today's competitive market, it is clear that the quality of a product significantly affects consumers' purchasing decisions, in addition to the price. Consequently, companies have endeavored to consistently enhance the quality of their products. Their focus is not on the quantity of products manufactured but on the proportion of the produced product that is suitable or functional. Considering consumer expectations and demands, the primary aim of companies should be to offer superior products or services. To achieve this, companies must recognize and address changes in quality and their root causes, thereby enhancing their processes to provide consumers with products of higher quality, greater functionality, and economic feasibility.

In numerous industrial sectors, it has become crucial to take into account multiple quality variables when evaluating product quality. This need has led to research into related methodologies. In processes involving the production of products with multiple quality variables, control is carried out using Multivariate Statistical Process Control (MSPC) methods. These methods entail the application of statistical principles and techniques at all production stages to gather data, analyze it, interpret the results, and propose solutions, with the objective of ensuring that a product is manufactured in the most cost-effective manner while meeting requirements. The goal is to both detect defects within the production process and proactively intervene before defective products are manufactured.

The advancement of inspection activities was driven by the increased need for large-scale production. In response to growing consumer demands, production volumes expanded, leading to the escalating costs of inspection-based control. Consequently, new statistically-based approaches were developed at that time.

Today, the international markets are predominantly influenced by companies that not only produce high-quality products but also ensure prompt delivery to the market while simultaneously improving productivity. In the current competitive landscape, it is evident that product quality plays a substantial role in consumers' purchasing decisions, in addition to price. Therefore, to stay competitive, companies must prioritize the quality of the products or services they offer. The primary goal for firms looking to compete in international markets should be the production of marketable, functional, and reliable products or services.
In many industrial sectors, evaluating product quality now requires the consideration of multiple quality variables. Unfortunately, domestic literature has not adequately addressed the widely used MSPC methods at yarn production , which have been well-documented in foreign literature in recent years. This study explores the process by creating control charts using both univariate and multivariate statistical process control methods.

The study sets up a theoretical framework by conducting an extensive review of academic and popular publications related to multivariate statistical process control methods, both domestically and internationally. Following this, an application of multivariate statistical process control methods is carried out in a yarn production facility of a textile factory using the aforementioned methods.

The study is structured into six chapters. The first chapter covers the concepts of quality, QC, and Statistical Process Control (SPC). After discussing the importance of QC and SPC, the second chapter provides theoretical information and literature review on univariate and MSPC methods and charts. The third chapter presents the application of MSPC methods and control charts in a yarn production facility of a textile factory. The fourth chapter is dedicated to a detailed analysis and discussion of the results of the application. The fifth chapter presents the findings obtained from this study. Finally, the sixth and last chapter offers suggestions for future research.

1.1. Description of Quality

The degree to which a product or service meets customers' requirements and expectations defines quality. This definition is in line with broader academic viewpoints, which emphasize that quality encompasses not just the physical characteristics of a product, such as its design and longevity, but also its performance, reliability, and the value it offers to consumers .

Quality is intricately linked to variability, with the primary goal of QC being to minimize this variability, ensuring consistent adherence to predetermined standards. Montgomery's quality approach underscores the significance of a systematic methodology that integrates statistical tools and techniques to monitor and regulate production processes. By doing so, companies can consistently manufacture goods that meet or surpass customer expectations. Juran’s research views quality as "fitness for use," emphasizing the necessity for products to be free from deficiencies and capable of meeting customer needs (Juran, 1999). Similarly, Deming's quality philosophy stresses the importance of continuous improvement and the reduction of variation as vital elements in achieving high quality (Goetsch & Davis, 2016).

Evans and Lindsay (2010) further elaborates on the concept of quality by identifying various dimensions, including performance, features, reliability, conformance, durability, serviceability, aesthetics, and perceived quality. This multidimensional perspective accentuates the complexity of quality assessment, underscoring the importance of considering different aspects when evaluating the quality of a product or service.

- Performance: The primary operational characteristics of a product or service shall be taken into consideration in this dimension.
- Features: Extra characteristics that enhance the appeal of a product or service.
- Reliability: The likelihood of a product or service to perform consistently over time.
- Conformance: The degree to which a product or service meets established standards and specifications.
- Durability: The lifespan of a product or service under normal usage conditions.
- Serviceability: The ease with which a product can be repaired or maintained.
- Aesthetics: The subjective attributes of a product or service that contribute to its visual appeal.
- Perceived Quality: The customer's subjective assessment of a product or service based on reputation, brand image, or other intangible factors.

This comprehensive definition offers an elaborate framework for understanding quality in diverse contexts. It encompasses both objective criteria, such as measurable standards and specifications, as well as subjective elements, including individual perceptions and preferences.

Furthermore, recent studies in this field have built on Montgomery's foundational principles by examining the impact of advanced statistical methods and Six Sigma practices on improving QC processes. These studies indicate that a strong quality management system, based on statistical analysis, not only enhances product quality but also contributes to operational efficiency and a competitive advantage in the marketplace (Antony, 2006) (Cagnazzo, Taticchi, & Brun, 2010). Therefore, it is essential to incorporate these principles into organizational practices to uphold high quality standards and attain long-term success in today's competitive environment.

Quality is a multifaceted concept that can be approached from distinct perspectives, depending on the context. Whether it pertains to manufacturing, service industries, or broader philosophical discussions, the criteria for determining quality may vary. Each context may consider factors such as precision, accuracy, reliability, customer satisfaction, or adherence to certain principles or standards. Ultimately, quality is a nuanced concept that is shaped by the specific requirements and expectations within each domain.

Manufacturing Quality: Quality in the manufacturing context pertains to the degree to which a product conforms to specified requirements and meets customer expectations. (Antony, Gijo, & Childe, 2012).

Service Quality: In the service industry, ensuring quality goes beyond just physical products. It also encompasses intangible aspects such as reliability, responsiveness, assurance, empathy, and tangible components like physical facilities and equipment (Zeithaml, Bitner, & Gremler, 2018).

Philosophical Perspectives: The concept of quality has been extensively examined by influential figures like Joseph M. Juran and W. Edwards Deming. Juran introduced the "Juran Trilogy," which encompasses quality planning, QC, and quality improvement, offering a holistic approach to quality management (Juran, 1999). Deming's "System of Profound Knowledge" highlights the significance of comprehending variation, psychology, systems thinking, and the theory of knowledge to achieve improvements in quality (Deming, 2018a).

Customer-Oriented Perspectives: Quality is often perceived through the lens of the customer. In this respect, categorizing customer requirements into different groups, ranging from basic expectations to delighters are useful. This can provide guidance to organizations in prioritizing quality enhancements based on customer preferences (Evans & Lindsay, 2010).

These references provide a comprehensive understanding of quality, encompassing theoretical frameworks and practical methodologies for achieving and assessing it in diverse domains.

1.2. Quality Control

Quality control (QC) involves a systematic set of procedures and processes designed to ensure that products or services meet specific standards of quality. It includes monitoring various aspects of production and operations to identify and eliminate defects, ensuring that the final output is consistent with the defined requirements and customer expectations (Montgomery, 2019).

QC focuses on process control and continual improvement, emphasizing management's role in fostering a culture of quality and accountability throughout the organization (Deming, 2018b). The Plan-Do-Check-Act (PDCA) cycle, also known as the Deming Cycle, is a systematic method for continuous quality improvement. The PDCA cycle emphasizes the iterative nature of quality control. It involves planning changes to improve a process, implementing those changes, checking the results, and acting on what has been learned to make further improvements.

QC involves a set of procedures and techniques used to monitor and control processes in order to ensure that products or services meet specific quality standards. The primary goal of QC is to identify and rectify any defects in products or processes before they are delivered to the customer (Goetsch & Davis, 2016). Key components of quality control are as follow:

- Inspection: The process of meticulously examining products or services to ensure they adhere to predetermined standards. This can encompass both manual and automated inspection methods.
- Statistical Process Control (SPC): Involves the use of statistical methods to monitor and manage processes, utilizing techniques such as control charts to monitor process performance variations and identify potential issues.
- Quality Assurance: Activities and procedures designed to ensure that quality standards are consistently met throughout the production process.

QC involves a series of procedures and activities designed to ensure that products or services meet specified quality standards and requirements. The primary objective is to detect and correct defects or variations in products or processes to ensure consistent quality (Mitra, 2016). Key aspects of quality control include the following:

- Definition: QC entails the monitoring and management of processes to ensure that outputs meet specific quality criteria and standards. It aims to identify and rectify defects or variations to uphold consistency and reliability in products and services.
- Tools and Techniques: The approach emphasizes the use of fundamental quality control tools such as control charts, cause-and-effect diagrams, histograms, and Pareto charts. These tools are utilized to analyze process performance, pinpoint root causes of problems, and implement corrective actions.
- Quality Control Process: Mitra (2016) emphasizes that quality control is an ongoing process involving regular inspection, measurement, and analysis to maintain and enhance quality. This method includes setting quality standards, monitoring performance, and taking corrective actions to address any deviations.
- Integration with Quality Management: QC is a key component of a comprehensive quality management system, which engages all levels of an organization in the pursuit of quality improvement and customer satisfaction

The brief description encapsulates an overview of quality control, focusing on its objectives, methods, and its role within a quality management system. In essence, quality control is a crucial aspect of both manufacturing and service provision, utilizing statistical techniques and organizational involvement to ensure that products and services meet established quality standards.

1.2.1. Importance of Quality Control

QC is essential in both manufacturing and service industries for several reasons:
Ensures Product Reliability: Product reliability, which refers to a product's consistent performance over its expected lifespan, is heavily influenced by quality control. Implementing stringent quality control processes enables businesses to identify and eliminate production defects, thereby improving their products' reliability. The effectiveness of quality control systems is closely tied to product reliability. QC techniques are crucial for overseeing

and managing the production process to ensure that the final product meets the necessary reliability standards (Montgomery, 2019). This emphasizes that QC is not only about identifying defects after they occur but also about proactively preventing them through vigilant monitoring and process adjustments.

The importance of reliability cannot be overstated in fields where the failure of a product can have serious repercussions. The robustness of a product and its capacity to function in different circumstances are directly linked to the QC methods employed during its design and production phases. The robustness is accomplished by methodically minimizing variability in the manufacturing process, which is a crucial element of QC (Taguchi, Chowdhury, & Wu, 2004).

Briefly, ensuring product reliability through quality control is crucial, as it helps prevent defects, minimize variability, and strengthen the robustness of products. Comprehensive QC measures not only guarantee that products meet reliability standards but also foster customer trust and improve a company's reputation in the marketplace.

Enhances Customer Satisfaction: Ensuring consistent quality in products and services is crucial for boosting customer satisfaction. Meeting or surpassing customer expectations through quality control practices leads to enhanced customer experiences and the development of loyalty (Evans & Lindsay, 2010). Moreover, maintaining customer satisfaction relies heavily on quality control, as it has a direct impact on the reliability and performance of the product. Consistent quality control processes play a crucial role in building trust with customers and meeting their expectations. Adhering to high QC standards helps in reducing defects and inconsistencies, ultimately leading to fewer returns and complaints(JS Oakland, 2003). In addition, strong QC systems contribute to ongoing improvements in both products and services, thereby enhancing the overall user experience and fostering customer loyalty (Besterfield, 2013). Companies that invest in QC can ensure that their products not only meet but also exceed customer expectations, giving them a competitive edge in the market.

Brand reputation: QC has a significant impact on brand reputation. It's crucial to consistently provide high-quality products and services in order to maintain a positive brand reputation and build trust with customers. Conversely, low quality can cause substantial harm to a company's reputation and lead to a decrease in business. Customer trust and loyalty are established through the consistent delivery of quality, which forms the foundation of a strong brand reputation (Evans & Lindsay, 2010).

Focusing extensively on quality control improves both operational efficiency and brand reputation by maintaining consistent excellence in products or services. Addressing quality issues systematically helps organizations gain trust and loyalty from customers, thereby strengthening their brand's market position and turning intangible reputation into tangible success (Kaplan, 2004).

Reduces Costs: Implementing strong quality control procedures results in the timely identification and rectification of mistakes, ultimately cutting down on expenses related to redoing work, handling returns, and addressing customer complaints. When companies guarantee that their products adhere to high quality benchmarks right from the start, they can reduce their operational expenditures and enhance general productivity, resulting in significant cost reductions and a more efficient manufacturing process (Mitra, 2016). Implementing efficient quality control systems aids in the early detection and resolution of quality issues, resulting in decreased defects and related expenses like rework, scrap, and warranty claims. Organizations can achieve substantial cost savings and improved financial performance by investing in proactive quality control measures (Schiffauerova & Thomson, 2006).

Improves Operational Efficiency: Identifying and resolving process variations and inefficiencies improves operational efficiency and productivity by enhancing quality control. This results in optimized resource utilization, reduced waste, and increased productivity. Quality control plays a crucial role in addressing process variations and inefficiencies, contributing to improved operational efficiency and productivity (Montgomery, 2019).

The impact of internal control mechanisms is underscored by the significance of quality control in boosting operational efficiency. Strong quality control systems are essential for enhancing operational efficiency by upholding strict internal controls, which simplify processes and minimize inefficiencies. Ensuring effective quality control results in standardizing processes and minimizing mistakes, ultimately leading to smoother operations and more efficient use of resources. Integrating quality control into internal controls allows organizations to effectively oversee their operations, minimize wastage, and achieve heightened levels of productivity and efficiency (Q. Cheng, Goh, & Kim, 2018).

Supports Compliance and Standards: Supporting compliance with industry standards and regulatory requirements, QC is essential. Organizations can avoid legal issues, maintain necessary certifications, and secure market access by ensuring adherence to these standards. Through quality control, organizations can ensure adherence to industry standards and avoid legal complications, thus securing market Access (Evans & Lindsay, 2010). Adhering to compliance and risk management is vital for maintaining quality control. Various industries must meet regulated standards and guidelines to ensure compliance with the law and minimize risks linked to product safety, environmental impact, and public health. By implementing quality control measures, organizations can comply with these requirements, thus lowering the likelihood of incurring fines, penalties, and legal responsibilities. Therefore, quality control plays a critical role in meeting regulatory standards and handling risks associated with product safety and environmental impact (Deming, 2018b).

Facilitates Continuous Improvement: Facilitating continuous improvement, quality control provides a structure for ongoing evaluation and improvement of processes and products. The use of basic QC tools underscores the importance of quality control in driving continuous improvement by enabling organizations to systematically identify, analyze, and address process inefficiencies. This proactive quality control approach fosters a culture of continuous improvement by facilitating ongoing refinement and optimization of manufacturing processes. Through consistent application of these quality control tools, companies can achieve incremental improvements in performance, reduce variability, and enhance overall process quality (Magar & Shinde, 2014). The principle of quality control involves continuously improving processes to help organizations adjust to changing conditions and consistently achieve high-quality results in the long run (Deming, 2018b). Quality control relies on continuous improvement, which encompasses not only addressing flaws but also exploring ways to enhance processes and foster innovation. Analyzing quality performance data enables businesses to pinpoint trends, underlying issues, and areas that can be enhanced, ultimately resulting in ongoing improvements and greater competitiveness. Embracing continuous improvement through quality control is essential for staying ahead in the market and adjusting to evolving circumstances (J. S. Oakland, 2014).

Overall, quality control plays a vital role in business operations, playing a significant part in guaranteeing product reliability, customer satisfaction, brand protection, cost reduction, operational efficiency improvement, compliance support, and continuous enhancement facilitation. Through the application of efficient quality management practices, companies can attain operational superiority, maintain competitiveness, and succeed in the current dynamic and demanding business landscape.

1.2.2. Quality Control Tools

Ensuring adherence to high standards and predefined specifications for products and services necessitates the effective use of quality control tools. These tools play a pivotal role in monitoring and regulating processes to guarantee consistency, reliability, and the identification of deviations to prevent defects. Consistency is paramount for upholding customer trust and satisfaction. Additionally, these tools enhance efficiency by identifying and addressing inefficiencies, streamlining processes, reducing waste, and optimizing workflows, ultimately leading to improved operational efficiency and cost savings (Magar & Shinde, 2014).

The main tools for quality control are highlighted as follow:

- **Statistical Process Control (SPC)**

The methodology of Statistical Process Control (SPC) is implemented for the monitoring and controlling of processes using statistical analysis. Control charts are utilized to differentiate between common cause variation, which is inherent to the process, and special cause variation, indicating specific issues that need attention. Montgomery's "Introduction to Statistical Quality Control" book delivers an extensive overview of SPC techniques, encompassing control charts, process capability analysis, and measurement systems analysis. It is essential to employ statistical methods to supervise and regulate processes, thereby guaranteeing consistent product quality through the distinction between common-cause and special-cause variations (Montgomery, 2019).

SPC involves the analysis and response to variation. Effective quality management hinges on understanding variation. SPC differentiates between common cause variation inherent to the process and special cause variation that highlights specific issues requiring attention. By utilizing tools such as control charts, SPC facilitates ongoing monitoring, enabling organizations to uphold process stability, prevent defects, and enhance efficiency. SPC cultivates a deeper comprehension of processes, thereby aiding informed decision-making and continual improvement in quality management (Wheeler, 2000). Detailed information about SPC will be given in section 1.4.

- **Six Sigma**

The Six Sigma methodology is a data-driven approach designed to improve process quality by systematically identifying and eliminating defects, reducing variability. Six Sigma uses the DMAIC framework—Define, Measure, Analyze, Improve, Control—to thoroughly examine and address the root causes of defects, ensuring that improvements are based on empirical data rather than subjective judgments. This systematic approach not only enhances process reliability and consistency but also aligns quality efforts with broader organizational objectives.

Compared to other quality methodologies, Six Sigma stands out due to its focus on achieving measurable financial benefits. Six Sigma emphasizes not only defect reduction but also process improvement and cost-effectiveness, making it particularly beneficial for organizations aiming to enhance both quality and profitability (Pyzdek & Keller, 2014). Additionally, Six Sigma's structured training programs, such as Green Belt and Black Belt certifications, provide practitioners with advanced skills essential for leading and sustaining complex quality improvement projects. Six Sigma's comprehensive approach integrates quality management with strategic business goals, offering a more comprehensive and enduring method for achieving operational excellence (Harry & Schroeder, 2006). Furthermore, Six Sigma distinguishes itself from traditional quality methodologies with its data-driven focus, which may be more limited in scope and less aligned with the organization's strategic objectives. By offering a holistic framework that combines statistical analysis with strategic management, Six Sigma presents a powerful and enduring approach to enhancing both operational and financial performance (Pande, Neuman, & Cavanagh, 2000).

- **Total Quality Management (TQM)**

Total Quality Management (TQM) is an all-encompassing and cohesive method of organizational management that prioritizes ongoing improvement, customer contentment, and the participation of all members of the organization in the quality process. TQM stands out due to its comprehensive nature, as it incorporates various quality tools and methodologies to attain long-term success through satisfying customers. The approach centers on aligning organizational goals with customer requirements and nurturing a culture of continuous enhancement and employee engagement. TQM stresses the significance of leadership dedication, strategic planning, and a customer-centered approach in propelling quality improvement initiatives (J. S. Oakland, 2014).

One of TQM's primary benefits is its capacity to instill a culture of constant improvement throughout all organizational levels. Unlike other quality tools that may concentrate on specific facets of production or service delivery, TQM integrates a broad array of practices, including quality planning, quality control, and quality enhancement, to guarantee that every aspect of the organization contributes to improving quality. TQM's emphasis on managing processes and prioritizing customers leads to heightened levels of customer satisfaction and loyalty, as it ensures consistent fulfillment or surpassing of customer demands (Juran, 1999).

TQM's superiority over other quality tools lies in its extensive scope and strategic direction. While methodologies such as Six Sigma focus on reducing defects and variability, TQM encompasses a broader range of objectives, including enhancing employee involvement, promoting innovation, and improving organizational culture. TQM emphasizes the human factor, such as teamwork and employee empowerment, which sets it apart from more mechanistic approaches to quality management. This focus on people, along with the use of quality tools like Quality Function Deployment (QFD) and Failure Mode and Effects Analysis (FMEA), makes TQM especially effective in creating an environment that supports long-term organizational success (J. S. Oakland, 2014). TQM's seamless integration capability allows for the inclusion of other quality methodologies, such as Statistical Process Control (SPC) and Six Sigma, within its structure. TQM provides a flexible framework adaptable to an organization's specific needs, facilitating the effective integration of diverse quality tools to address complex quality challenges. This adaptability, combined with TQM's focus on leadership and strategic alignment, makes it a versatile and powerful approach to quality management (Deming, 2018b). Furthermore, TQM's comprehensive approach extends beyond internal processes to include supplier and customer relationships. TQM encourages collaboration and partnership with suppliers, ensuring that the entire supply chain aligns with the organization's quality objectives. This emphasis on external relationships enhances the overall quality of the final product or service and contributes to sustained competitive advantage (B. Dale, B. Dehe, & D. Bamford, 2016a).

In summary, TQM offers significant advantages over other quality tools due to its comprehensive, integrative, and strategic approach to quality management. By nurturing a culture of continuous improvement, aligning organizational goals with customer needs, and emphasizing employee involvement, TQM provides a strong framework for achieving long-term organizational success.

- **Quality Management Systems (QMS)**

Quality Management Systems (QMS) encompass formalized systems that document procedures, processes, and responsibilities to attain quality objectives and policies. These systems provide a framework for organizations to consistently deliver products or services that align with both regulatory standards and customer requirements (B. Dale et al., 2016a). A well-implemented QMS integrates various facets of quality management into a cohesive system, thereby aligning organizational processes with the company's strategic goals. This alignment is critical for ensuring consistency, efficiency, and continuous improvement across the organization (B. G. Dale, B. Dehe, & D. Bamford, 2016).

One of the primary advantages of a QMS lies in its structured approach to quality management, as it aids organizations in identification, control, and improvement of processes that affect quality. Adoption of a QMS, such as one compliant with specific standards, ensures that organizations have clear guidelines and best practices for managing quality. Adherence to such standards offers a globally recognized framework that enhances customer satisfaction and operational efficiency by minimizing errors, rework, and waste (Hoyle, 2017).

QMS possesses a significant advantage over other quality tools by offering a comprehensive and standardized approach to quality management that is applicable across various industries and sectors. While tools such as Six Sigma and Statistical Process Control (SPC) focus on specific aspects of quality, QMS encompasses the entire organizational process from product design to customer delivery. Improved coordination and communication across departments, ensures consistent achievement of quality objectives throughout the organization (Beckford, 2016). Furthermore, QMS fosters a culture of continuous improvement through the establishment of mechanisms for regular monitoring, measurement, and review of processes. The continuous feedback loops in QMS enable organizations to identify areas for improvement and promptly implement corrective actions, thereby enhancing overall performance and customer satisfaction. This emphasis on continuous improvement distinguishes QMS from more static quality tools that may lack the same flexibility to adapt to changing market conditions or customer needs (Sroufe & Curkovic, 2008).

An important advantage of Quality Management Systems (QMS) lies in its focus on documentation and standardization, which facilitates compliance with regulatory requirements and supports knowledge retention and transfer within the organization. The documentation requirements of a QMS ensure that processes are clearly defined and consistently followed, thereby reducing the risk of errors and variations. This emphasis on standardization is particularly beneficial in complex or highly regulated industries where adherence to quality standards is of utmost importance (Hoyle, 2017). Additionally, QMS enhances organizational accountability by explicitly defining roles and responsibilities related to quality management. Establishing clear accountability, QMS ensures that all employees understand their role in maintaining and improving quality, contributing to a stronger quality culture within the organization. This explicit attention to human factors associated with quality management sets QMS apart from other quality tools (B. G. Dale et al., 2016).

In conclusion, Quality Management Systems offer substantial advantages over other quality tools by providing a comprehensive, standardized, and adaptable framework for managing quality across all organizational processes. By promoting continuous improvement, ensuring regulatory compliance, and enhancing organizational accountability, QMS plays a critical role in helping organizations achieve and maintain high levels of quality and customer satisfaction.

- **Lean Manufacturing**

The concept of lean manufacturing is centered on the minimization of waste and the maximization of value within production processes, with a strong emphasis on quality control. Originating from the Toyota Production System, lean manufacturing aims to optimize operations by identifying and eliminating activities that do not add value to the final product. Lean principles, such as just-in-time production and continuous flow, enable organizations to achieve heightened efficiency, cost reduction, and improved product quality through streamlined production processes (Womack, Jones, & Roos, 2007).

A prominent advantage of lean manufacturing lies in its focus on waste reduction, leading to significant enhancements in operational efficiency. Waste, within the context of lean principles, encompasses overproduction, waiting, excess inventory, unnecessary motion, and defects. By systematically addressing these forms of waste, organizations can achieve accelerated production times, reduced inventory costs, and heightened product quality. Emphasis on waste reduction not only enhances efficiency but also improves responsiveness to customer demands, as lean processes are designed to be more adaptable and flexible (Liker, 2004).

In contrast to other quality control methodologies, lean manufacturing offers advantages through its holistic approach, integrating various aspects of production, encompassing process design, quality control, and workforce management. Unlike Six Sigma, which primarily focuses on reducing process variation and defects, lean manufacturing addresses the entire value stream to ensure that all activities contribute to the efficient production of high-quality products. The comprehensive nature of lean manufacturing allows for greater improvements in overall system performance compared to more narrowly focused quality methodologies (Shah & Ward, 2003). Lean manufacturing promotes a culture of continuous improvement, referred to as kaizen, encouraging employees at all organizational levels to participate in process enhancement. This focus on employee involvement and empowerment distinguishes it from other quality methodologies, improving operational efficiency, morale, and job satisfaction throughout the workforce. Lean manufacturing, by engaging employees in the continuous improvement process, not only enhances operational efficiency but also bolsters employee morale and job satisfaction (Bhasin & Burcher, 2006).

Additionally, lean manufacturing's ability to diminish lead times and enhance delivery performance is noteworthy. Through the implementation of pull-based systems, such as kanban, lean manufacturing ensures production closely aligns with real customer demand, thus minimizing overproduction and excess inventory risks. Just-in-time production heightens the organization's capability to accurately and promptly meet customer needs, subsequently boosting customer satisfaction and loyalty (Hines, Holweg, & Rich, 2004). Furthermore, lean manufacturing's focus on visual management tools, like value stream mapping and 5S, furnishes a clear and standardized approach for identifying inefficiencies and monitoring performance. Visual management intensifies communication and transparency within the organization, simplifying the identification and resolution of arising issues. Upholding a well-organized and efficient production environment, essential for sustaining the benefits of lean manufacturing over the long term (Dillon, 2019).

In summary, lean manufacturing offers substantial benefits as a quality control methodology through a comprehensive and systematic approach to waste reduction, process enhancement, and continuous improvement. Its emphasis on employee involvement, just-in-time production, and visual management sets it apart from other quality methodologies, rendering it a potent methodology for achieving operational excellence and upholding a competitive edge.

- **Quality Control in Specific Industries**

In different industries, quality control practices are tailored to address specific challenges and meet sector-specific requirements. This ensures that products and services adhere to strict standards of quality, safety, and performance. Implementing industry-specific quality control tools helps organizations comply with regulations, reduce risks, and enhance customer satisfaction (Juran, 1999). Quality management in different industries focuses on various aspects of product quality. The automotive and aerospace industries prioritize performance, reliability, and compliance with safety and durability standards. Meanwhile, the textile industry emphasizes durability, serviceability, and aesthetics to cater to consumer preferences. In healthcare and pharmaceuticals, compliance, reliability, and serviceability are crucial for ensuring safety and regulatory adherence. Each industry customizes its quality management approaches to meet individual operational requirements and customer expectations, ultimately improving competitiveness and operational performance (J. S. Oakland, 2014).

The food and beverage industry relies heavily on customized quality control tools to ensure the safety and consistency of its products. Hazard Analysis and Critical Control Points (HACCP) is a widely used tool in this industry, used to identify, assess, and manage hazards throughout the production process. HACCP's focus on preventing contamination and ensuring product safety is essential in maintaining consumer confidence and complying with food safety regulations. This proactive approach to quality control sets the food industry apart from others, where the focus may be more on post-production testing rather than continuous monitoring (Gowen, O’donnell, Cullen, & Bell, 2008).

In the textile industry, quality control plays a crucial role in maintaining product consistency, ensuring durability, and meeting customer expectations. The industry relies on specific quality control tools such as fabric inspection machines, tensile strength testing, and colorfastness tests to monitor and evaluate the quality of yarns, fabrics, and finished garments. The textile industry faces unique challenges such as variations in raw materials, dyeing processes, and weaving techniques, which necessitate the use of specialized quality control measures. These tools help in detecting defects early in the production process, thereby reducing waste and rework costs (Majumdar, Das, Alagirusamy, & Kothari, 2012).

In conclusion, quality control in specific industries is characterized by the adoption of specialized tools and practices that address the unique challenges and regulatory requirements of each sector. These industry-specific quality control tools offer significant advantages over more generalized tools by providing targeted solutions that ensure compliance, enhance product safety, and improve customer satisfaction. The application of these tools not only helps industries meet their specific quality objectives but also provides a competitive advantage in highly regulated markets.

- **Advanced Quality Control Techniques:**

The implementation of advanced quality control methods, such as multivariate analysis, Design of Experiments (DOE), and Response Surface Methodology (RSM), holds significant promise for enhancing product quality and optimizing processes. These sophisticated techniques facilitate the identification and management of process variables that have an impact on product outcomes. Particularly, multivariate analysis serves as a powerful analytical tool for comprehensively assessing complex data sets with multiple interacting variables, contributing to a deeper understanding of process behaviors and critical quality-affecting factors (Nesselroade & Cattell, 2013).

The DOE methodology enables systematic experimentation to assess the influence of various factors on product quality. DOE facilitates the development of efficient experiments to optimize process settings and determine the optimal conditions for achieving desired quality attributes. This approach offers a structured method for experimentation, minimizing the time and costs associated with trial-and-error methods and ensuring more dependable results (Montgomery, 2019).

RSM augments the capabilities of DOE by modeling and optimizing processes involving multiple variables. RSM facilitates the exploration of interrelationships between variables and their interactions, thereby facilitating the development of predictive models for optimal settings of process parameters. RSM significantly enhances the precision of process fine-tuning and enables the attainment of meticulous control over quality outcomes (Myers, Montgomery, & Anderson-Cook, 2016).

In comparison to traditional quality control tools, these advanced techniques offer superior capabilities for comprehending complex process dynamics and optimizing production processes. They employ a more detailed and data-driven approach to quality management, enabling organizations to achieve higher levels of precision and efficiency. Utilizing these techniques leads to improved decision-making and greater control over process variations, which are crucial for maintaining high-quality standards in competitive industries (Anderson & Whitcomb, 2016).

In conclusion, advanced quality control techniques such as multivariate analysis, DOE, and RSM offer significant advantages by providing a thorough understanding of process variables, optimizing conditions, and enhancing overall quality management. Their implementation enables more precise control, better decision-making, and improved process efficiency compared to traditional quality control methods.

1.3. The Relationship Between Quality Control and Statistics

QC and statistics are closely connected, with statistical methods forming the basis of modern quality management practices. QC encompasses the methodical process of ensuring that products or services meet established standards and specifications, and it heavily relies on data-driven approaches, with statistics providing the necessary tools for data collection, analysis, interpretation, and decision-making. SPC stands out as one of the most important applications of statistics in quality control. SPC utilizes statistical methods to monitor and regulate a process, guaranteeing that it operates at its maximum potential. Through the use of control charts such as the X-bar and R charts, organizations can identify process variations that may indicate underlying problems. These charts aid in distinguishing between common cause variations, which are inherent to the process, and special cause variations, which result from external factors that need attention (Montgomery, 2019). Descriptive statistics are vital in quality control, as they summarize the characteristics of the data gathered during the production process. Measures like the mean, variance, and standard deviation provide insights into the central tendency and variability of the quality characteristics being studied. These descriptive measures are crucial in assessing process capability, which determines whether a process can produce products within specified limits. Understanding the distribution and behavior of data through descriptive statistics enables quality professionals to establish control limits and make informed decisions to maintain the desired level of quality (Srinivasu, Reddy, & Rikkula, 2011).

Inferential statistics expand the use of statistics in quality control by enabling professionals to make inferences and predictions about a population based on a sample. Techniques like hypothesis testing, confidence intervals, and regression analysis are frequently used to evaluate product and process quality and identify factors that may impact quality outcomes. Inferential statistics are particularly valuable in determining whether observed process variations are due to random chance or are statistically significant, thus guiding quality improvement efforts (Ryan, 2011). Briefly, applying statistical methods in quality control is vital for ensuring consistent product quality and process efficiency. Integrating SPC, descriptive statistics, and inferential statistics offers a comprehensive approach to monitoring, controlling, and improving quality, ultimately leading to enhanced customer satisfaction and operational excellence.

1.4. Statistical Quality Control

The aim of utilizing statistical quality control applications is to maintain the intended quality level during the production of products or services through monitoring the entire production process, rather than simply assessing the quality at specific stages of production (Şenol, 2012).

As seen in the figure, the components of statistical quality control consist of the concepts of statistics, quality, and control.

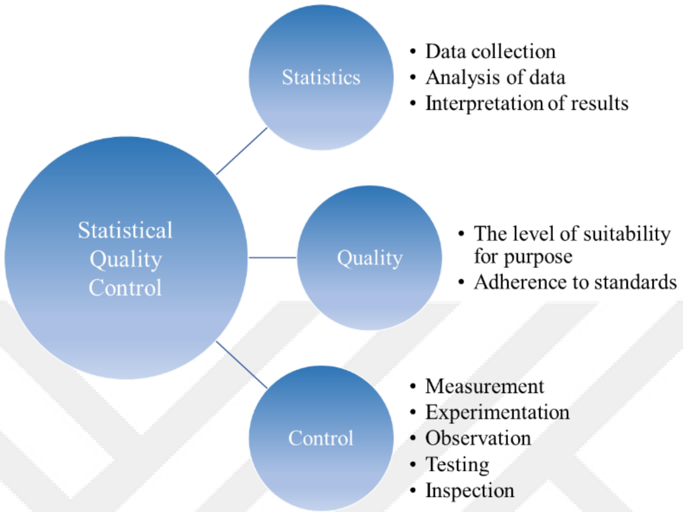


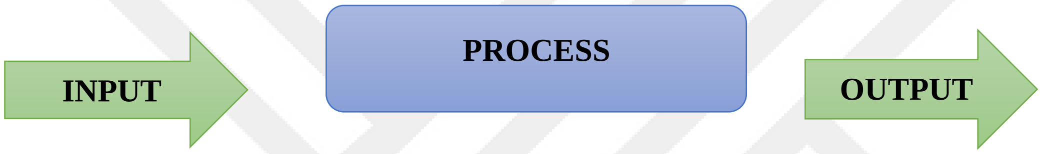
Figure 1.1. Components of Statistical Quality Control

The concepts of statistical quality control include statistics, quality, and control. Data collection is part of statistics, collected through methods like measurement, experimentation, and observation, with subsequent analysis and interpretation. Quality pertains to meeting specifications, satisfying consumer demands, and ensuring compliance with standards and objectives. Control involves planning activities to achieve goals, monitoring these activities, and making necessary adjustments to process inputs when required (Pekmezci, 2005).

2. THEORETICAL FOUNDATIONS AND LITERATURE REVIEW

2.1. Statistical Process Control

Prior to establishing the definition of statistical process control, it is essential to explain the meaning of a process. A process is a sequence of actions carried out to convert different inputs, such as materials, methods, and personnel, into results such as products, services, and information, in a way that enhances value (John Oakland & Oakland, 2007). Figure 2.1 shows the structure of a process schematically.



Management Input Resources

Facilities
Equipment
Staff
Customers
Suppliers
Transport
Materials
Energy
Information

Managing Processes

Process Flow
Work in Progress
Process Design
Planning and Scheduling
Progressing and Control
System Improvement

Managing Outputs

Products and Services
Customer Satisfaction
Profitability
Environmental Impact

Figure 2.1. Typical Structure of a Process

SPC employs statistical methods to monitor and manage processes, aiming for stability and consistency over time within the realm of quality management. It is based on recognizing variations and aims to differentiate between natural process variations and those that require intervention. Organizations utilize SPC to identify early signs of process deviations and uphold desired process performance (Montgomery, 2019).

The concepts of probability and statistical inference form the theoretical basis of SPC. Control limits are established under the assumption of process data following a normal distribution, which enables the use of statistical measures like the mean and standard deviation to define the expected variation range. This probabilistic approach provides a solid foundation for decision-making, allowing practitioners to confidently identify genuine process shifts with quantifiable confidence. However, instances of non-normality, data autocorrelation, and other complexities may necessitate advanced techniques or adjustments in the SPC methodology to ensure accurate monitoring (John Oakland & Oakland, 2007).

The process of SPC is not a one-time event but an ongoing process that necessitates continual gathering, analysis, and interpretation of data. A thorough comprehension of the monitored process, accurate selection and utilization of control charts, and the ability to appropriately address signals of special cause variation are crucial for the successful implementation of SPC (Woodall & Montgomery, 2014). Additionally, SPC forms the basis for subsequent process enhancement initiatives like Six Sigma, which utilize statistical tools for both control and improvement of process capabilities and reduction of variability (Breyfogle III, 2003).

The importance of SPC in quality management is emphasized by its historical development and ongoing evolution. Although Shewhart's fundamental principles remain unchanged, modern SPC practices are constantly evolving to integrate new statistical methods and technologies, improving its effectiveness and applicability across different industries. This continuous evolution highlights the dynamic nature of SPC and its lasting relevance in maintaining process stability and product quality (Woodall & Montgomery, 2014).
An overview of SPC methods involve a range of statistical techniques utilized to monitor and manage processes in order to guarantee consistent quality and productivity. Shewhart control charts, a traditional SPC method, are specifically designed to monitor process performance by graphing data points over time and identifying deviations from expected behavior (Montgomery, 2019). These charts are instrumental in identifying any shifts or trends that might indicate issues with the process. More advanced SPC techniques, such as CUSUM and EWMA charts, aim to overcome the limitations of traditional methods by enhancing sensitivity to minor shifts and trends (John Oakland & Oakland, 2007). Furthermore, Multivariate SPC methods, like Hotelling's T^2 charts, expand on these principles to handle situations where multiple interconnected quality characteristics need to be simultaneously monitored (Jackson, 2005)). The combination of these methods enhances process control and facilitates continuous improvement, thereby ensuring consistent operation within

predetermined parameters and yielding high-quality results. (John Oakland & Oakland, 2007; Woodall & Montgomery, 2014)

2.1.1. Importance of Statistical Process Control

The field of quality management acknowledges Statistical Process Control (SPC) as a crucial methodology, providing a structured approach to monitoring, controlling, and improving production processes. SPC's significance lies in its ability to ensure process stability, decrease variability, and uphold consistent product quality. It is particularly essential in industries that demand high levels of precision and reliability, such as electronics, pharmaceuticals, and automotive manufacturing (John Oakland & Oakland, 2007). Through the implementation of SPC, organizations can systematically identify and address variations within their processes, thereby preventing defects and minimizing the need for expensive rework or scrap.

SPC's main advantage is its ability to minimize process variability, which is crucial for maintaining high-quality standards. Process variability can lead to inconsistencies in product quality, making it difficult for organizations to meet customer specifications and comply with regulatory standards. SPC provides users with the necessary tools to differentiate between common cause variation, inherent to the process, and special cause variation, which indicates external disruptions. By reducing or eliminating special cause variation, SPC enables a more predictable and controlled production environment, ultimately improving overall process performance and product quality (Alt, 2004).

Statistical Process Control (SPC) is crucial for maintaining manufacturing quality by identifying and addressing process deviations promptly. It improves operational efficiency and consistency, leading to higher customer satisfaction and substantial cost reductions. Integrating SPC into the quality management framework ensures ongoing process stability and continuous improvement for a stronger competitive position (John Oakland & Oakland, 2007).

2.1.2. Statistical Process Control Tools

Statistical process control (SPC) is an invaluable tool that enhances process stability and capability by reducing variability. SPC is employed as a methodology to monitor process behavior and to estimate and control product quality during the manufacturing process

(Mizuno, 2020). The seven primary tools of SPC, also known as "the magnificent seven," consists of the Cause-and-Effect Diagram for identifying root causes of quality issues, the Check Sheet for data collection and analysis, the Control Chart for monitoring process stability over time, the Histogram for visualizing data distribution, the Pareto Chart for identifying the most significant factors contributing to quality problems, the Scatter Diagram for examining relationships between variables, and the Flowchart for mapping out process steps to facilitate understanding and analysis. These tools serve as the fundamental pillars of QC practices and empower organizations to systematically maintain and improve their processes.

- **Cause-and-Effect Diagram (Ishikawa or Fishbone Diagram)**

The Ishikawa Diagram, also referred to as the Fishbone or Cause-and-Effect Diagram, stands as an essential tool in quality management. It serves the purpose of systematically identifying the fundamental causes of process-related issues (Mizuno, 2020). Dr. Kaoru Ishikawa introduced this diagram in 1968 as a visual aid aimed at orchestrating potential causes of specific problems, thereby facilitating a structured approach to issue resolution. The diagram derives its name from its fishbone-like configuration, with the problem depicted as the "head," and potential causes branching out like "bones" (Neyestani, 2017). An example of a Cause and Effect Diagram which is drawn on Minitab is demonstrated in figure 2.2 showing downtime reasons in a manifactruing facility.

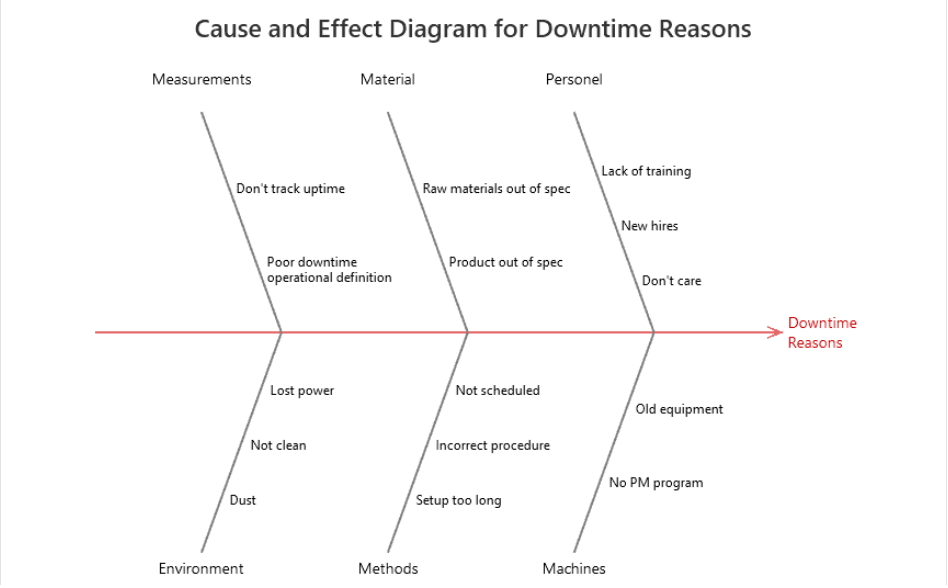


Figure 2.2. Example of a Cause and Effect Diagram

Cause and Effect Diagram categorizes causes into major groups, including People, Methods, Machines, Materials, Measurements, and Environment. These categories represent distinct areas where variations could potentially contribute to the problem at hand. By analyzing these categories, organizations can effectively identify and address the most significant factors influencing quality (B. Dale, B. Dehe, & D. Bamford, 2016b). The Cause-and-Effect Diagram is a crucial tool in Total Quality Management (TQM) and Six Sigma methodologies. It plays a critical role in continuous improvement initiatives by ensuring a comprehensive examination of all potential causes before reaching conclusions. This structured approach, is essential for upholding the high standards required in quality management (Magar & Shinde, 2014). Additionally, the Cause-and-Effect Diagram not only serves as a tool for root cause analysis but also fosters collaboration within teams. By encouraging input from various stakeholders, it helps gather diverse perspectives and expertise, leading to a deeper understanding of the problem (Montgomery, 2019). The effectiveness of this diagram is often enhanced when used alongside other quality tools, such as Pareto analysis, to prioritize significant causes and effectively direct improvement efforts (John Oakland & Oakland, 2007).

- **Check Sheet:**

The check sheet is a vital tool in SPC used to systematically collect, organize, and analyze data. It is a structured form that enables users to record data clearly and in an organized manner, making it easier to identify patterns, trends, and areas of concern. Its simplicity and versatility make it indispensable in quality management, especially for processes that require meticulous data tracking and analysis (B. Dale et al., 2016b). Moreover, offering a structured method for collecting and analyzing data, the check sheet is a powerful and versatile tool in SPC. Its role in real-time data collection, preliminary analysis, and adaptability underscores its importance in quality management. As a foundation for more complex analyses and decision-making processes, the check sheet is essential in achieving continuous improvement and organizational excellence (Magar & Shinde, 2014). One of the primary advantages of utilizing a check sheet is its inherent capability to actively collect real-time data by documenting information at the point of occurrence. This immediacy plays a crucial role in ensuring the accuracy and relevance of the collected data. The real-time aspect of this process enables organizations to expeditiously identify issues and promptly implement corrective actions before they have the opportunity to escalate (Montgomery, 2019). An example of a

Check Sheet is demonstrated in figure 2.3 showing the record of defects on a tank used in an aerospace application (Montgomery, 2019).

CHECK SHEET
DEFECT DATA FOR 2002–2003 YTD

Part No.: TAX-41
Location: Bellevue
Study Date: 6/5/03
Analyst: TCB

	2002												2003					
Defect	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	Total
Parts damaged		1		3	1	2		1		10	3		2	2	7	2		34
Machining problems			3	3				1	8		3		8	3				29
Supplied parts rusted			1	1		2	9											13
Masking insufficient		3	6	4	3	1												17
Misaligned weld	2																	2
Processing out of order	2															2		4
Wrong part issued		1						2										3
Unfinished fairing			3															3
Adhesive failure				1							1		2			1	1	6
Powdery alodine					1													1
Paint out of limits						1								1				2
Paint damaged by etching			1															1
Film on parts						3		1	1									5
Primer cans damaged								1										1
Voids in casting									1	1								2
Delaminated composite										2								2
Incorrect dimensions											13	7	13	1		1	1	36
Improper test procedure										1								1
Salt-spray failure													4			2		4
TOTAL	4	5	14	12	5	9	9	6	10	14	20	7	29	7	7	6	2	166

Figure 2.3. A check sheet to record defects on a tank used in an aerospace application

The design of the check sheet effectively streamlines preliminary data analysis by categorizing information and presenting it in specific formats. This feature enables users to promptly identify recurring issues or trends, providing a foundational analysis that is vital for directing attention to the most significant problems. Subsequently, these issues can be subjected to more comprehensive analysis using other SPC tools (John Oakland & Oakland, 2007). Additionally, the check sheet exhibits high adaptability and can be tailored to suit the specific needs of diverse industries, processes, or products. Its flexibility ensures that the collected data remains relevant and actionable, making it an indispensable tool in quality improvement (Mizuno, 2020).

In the broader framework of Total Quality Management (TQM) and continuous improvement, the check sheet acts as a cornerstone for data-driven decision-making. The data collected through check sheets often forms the basis for more sophisticated statistical analyses, such as control charts or Pareto analysis, making it an essential starting point for any quality improvement initiative (Juran, 1999). Check sheets have practical applications in various business environments, including small and medium-sized enterprises. The chech sheets can effectively improve operational efficiency and effectiveness in business data management, streamlining processes, reducing errors, and enhancing overall business performance (KUSUMAH & GUSFA, 2021).

- **Histogram:**

The histogram serves as a fundamental tool in SPC by providing a visual representation of data distribution, which is imperative for comprehending process variability. Similar to a bar chart, a histogram illustrates the frequency of data points within defined ranges, offering a clear visual summary of data distribution which is important to recognize patterns, identify anomalies, and understand the overall behavior of a process, all of which are paramount in QC (B. Dale et al., 2016b). A primary purpose of a histogram in SPC is to unveil the underlying distribution of process data. Through an analysis of the shape, spread, and central tendency of the histogram, practitioners can ascertain the stability, centrality, and adherence to desired specifications of a process (Magar & Shinde, 2014). Histograms play a crucial role in the identification of deviations from a normal distribution, such as skewness or the presence of outliers. These deviations may signal underlying issues in the process. The immediate visual feedback provided by histograms enables quality managers to take prompt corrective actions to address any issues that arise (Montgomery, 2019). An example of a histogram chart drawn by using minitab is demonstrated in figure 2.4 showing the weight of a patient under dietitian supervision.

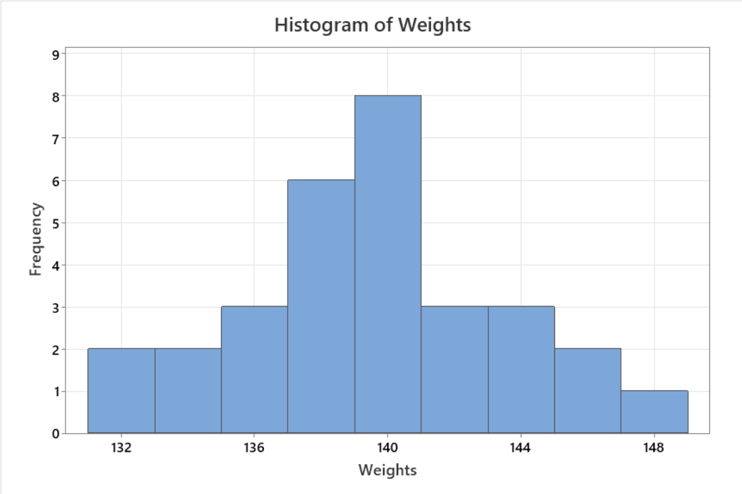


Figure 2.4. Histogram of the Weight of a Patient Under Dietitian Supervision

Histograms are essential in monitoring changes in process performance over time. They support the identification of trends and variations in a process, thus being indispensable for ongoing quality improvement initiatives. By comparing histograms from different time periods, organizations can evaluate the impact of process changes (Soković, Jovanović, Krivokapić, & Vujović, 2009). Furthermore, histograms as a fundamental tool for quality improvement, provides crucial assistance to teams in understanding data distribution and its implications for process control. Thanks to their visual nature, histograms are accessible and easy to interpret, even for individuals without an extensive statistical background. This accessibility is especially important in collaborative environments, where team members from different departments need to collaborate to address quality issues (Mizuno, 2020).

Histograms are useful for pinpointing the sources of variation within a process. By analyzing the data spread in a histogram, practitioners can distinguish between common cause variation, which is inherent to the process, and special cause variation, which requires further investigation and intervention. This differentiation is essential for effective process control and for making well-informed decisions about process improvements (Juran, 1999). In addition to their role in process monitoring and improvement, histograms are often used in conjunction with other SPC tools to provide a comprehensive analysis of process performance. Histograms, control charts, and Pareto analysis can be combined to gain a deeper understanding of process behavior and to prioritize areas for improvement. Integration of tools is essential for achieving the high standards required in quality management (John Oakland & Oakland, 2007).

- **Pareto Chart:**

The Pareto chart is a fundamental tool in Statistical Process Control (SPC) that plays a vital role in identifying and prioritizing significant contributing factors associated with a problem or quality issue (B. Dale et al., 2016b). Renowned for its application of the Pareto Principle, also known as the "80/20 rule," this chart employs bar graphs and a cumulative line graph to visually demonstrate how a small number of causes typically contribute to the majority of issues within a process. The bars within the chart represent individual categories of causes arranged in descending order of their frequency or impact, while the cumulative line illustrates the collective contribution of these causes (Magar & Shinde, 2014). One of the paramount strengths of the Pareto chart in SPC is its ability to direct attention towards the "vital few" causes that exert the greatest impact on quality. This capability allows quality managers to efficiently allocate resources, thereby leading to substantial enhancements in process performance and product quality (Montgomery, 2019). An example of a Pareto Chart is demonstrated in figure 2.5 (Montgomery, 2019).

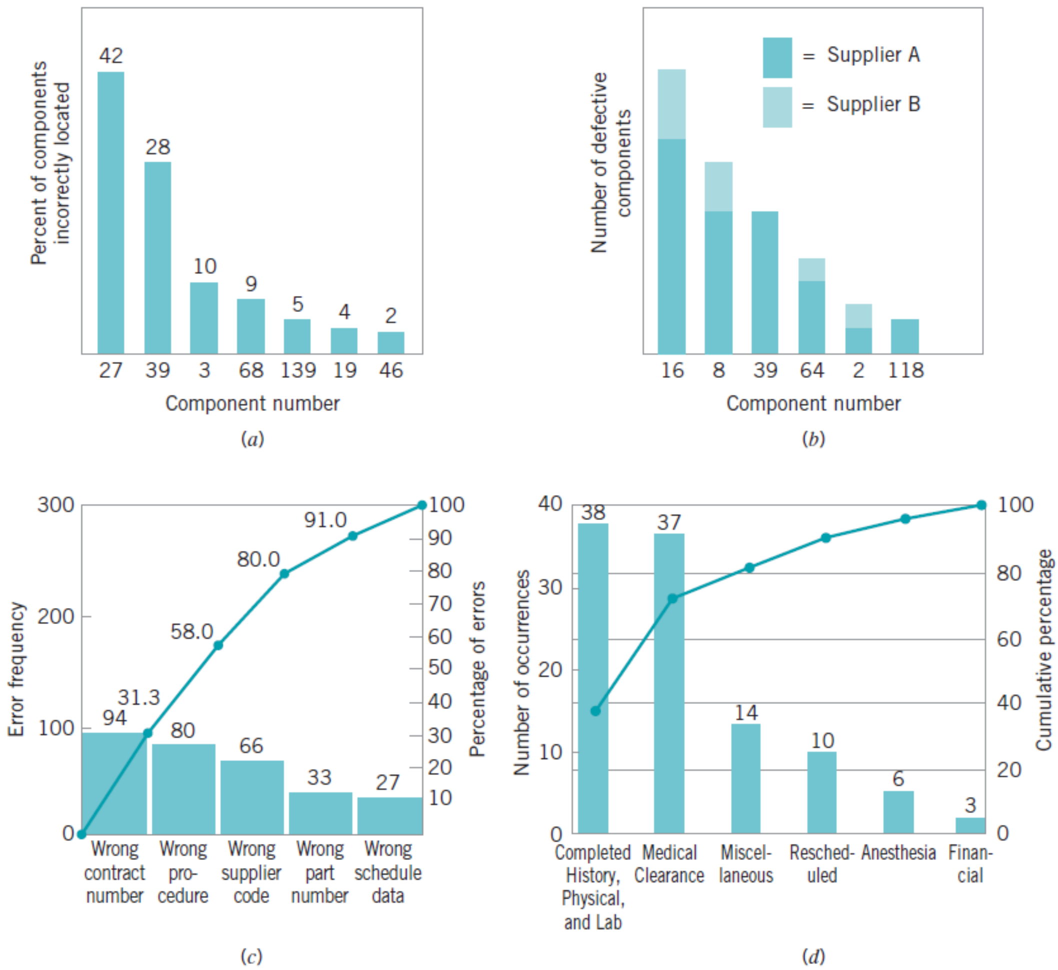


Figure 2.5. Example of a Pareto Chart

The Pareto chart is a tool commonly utilized in practical applications to categorize and quantify problems or defects, followed by the plotting of these categories in descending order on the chart. This allows for a clear visualization of the most critical issues (Alkiayat, 2021). The Pareto chart serves as a vital tool in the continuous improvement process, helping to identify problem areas and prioritize actions based on data-driven insights. Through systematic analysis, organizations can effectively address the root causes of quality issues, leading to sustainable and efficient improvements (Soković et al., 2009). Pareto chart in industrial contexts is used to enhance the quality of products by systematically identifying and reducing the most frequent defects. In QC processes pareto chart can lead to significant improvements in product quality and operational efficiency, validating its utility in both manufacturing and service industries (Nicolae, Nedelcu, & Dumitrascu, 2015). Moreover, within the context of Total Quality Management (TQM), the Pareto chart is a vital tool for driving continuous improvement and operational excellence (Mizuno, 2020). When integrated with other SPC tools such as control charts and cause-and-effect diagrams, organizations can develop a comprehensive approach to identifying, analyzing, and addressing quality issues.

- **Scatter Diagram:**

The scatter diagram is a crucial instrument in Statistical Process Control (SPC) used for examining the connection between two variables and identifying possible correlations influencing process quality. By plotting data on a two-dimensional graph, the scatter plot illustrates how changes in one variable may impact another, aiding in understanding process variability causes (Montgomery, 2019). An example of a Scatter Diagram drawn by using Minitab is demonstrated in figure 2.6 illustrating the relationship between study time and exam score.

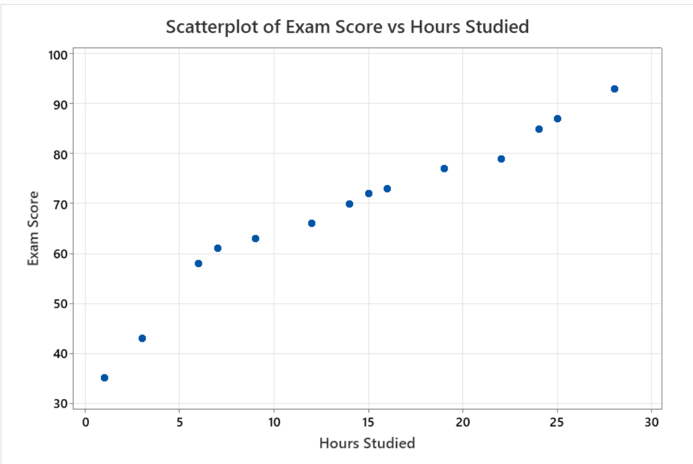


Figure 2.6. Example of a Scatter Diagram

The simplicity and effectiveness of the scatter diagram make it a valuable tool for uncovering patterns or trends not immediately evident through other analytical methods. Determining whether variables are positively correlated, negatively correlated, or not correlated at all empowers decision-making for process quality improvement (Neyestani, 2017). In practical use, the scatter diagram is employed to investigate potential cause-and-effect relationships in a process. For example, a quality engineer might use it to determine if manufacturing process temperature correlates with the number of defects produced (Fouad & Mukattash, 2010). Moreover, the utilization of scatter diagram is fundamental in continuous improvement initiatives, as it facilitates the comprehension of variable relationships, which is critical for optimizing process performance. The visualization of data through scatter plots allows organizations to effectively prioritize efforts on variables that have a substantial impact on quality (Magar & Shinde, 2014).

The scatter plot's versatility and ease of use make it widely applicable across various industries, such as manufacturing, healthcare, and services. Scatter diagrams are commonly utilized to monitor and enhance process quality in everyday situations. Its simplicity fosters collaboration and shared understanding among team members from different functional areas (Bamford & Greatbanks, 2005). Combining scatter plots with control charts or Pareto analysis helps identify not only variable relationships but also their significance in overall process variability. This integrated approach is crucial for effective quality management and continuous improvement (Montgomery, 2019).

- **Flowchart**

The flow chart plays a vital role in SPC as it is extensively utilized to visually display and examine the sequence of steps in a process. By illustrating the flow of activities, decisions, and inputs, a flow chart offers a clear, step-by-step depiction of how a process functions, making it simpler to detect potential bottlenecks, inefficiencies, or areas where quality issues may emerge (B. Dale et al., 2016b). One of the primary benefits of utilizing a flow chart in SPC is its capability to simplify complex processes into easily comprehensible diagrams. This clarity is crucial for both identifying problems and conveying the structure of a process to team members and stakeholders (Magar & Shinde, 2014). Flow charts in QC aid organizations in systematically visualizing processes, which is critical for pinpointing areas of improvement and ensuring that each process step aligns with quality standards (Nadiyah & Dewi, 2022).

Flow charts are especially valuable in the context of Total Quality Management (TQM), where they are employed to guarantee that all process stages contribute to the overall quality objectives. By delineating each process step, flow charts aid in recognizing redundancies, streamlining operations, and diminishing the potential for errors, all of which are essential for maintaining high quality (Almadany, 2024). The application of flow charts extends beyond simple process mapping; they also play a crucial role in identifying critical control points within a process. Visually breaking down a process into its component parts, flow charts assist in pinpointing where controls should be applied to monitor quality and prevent defects. This identification of control points is vital for effective process control and continuous improvement (Montgomery, 2019). An example of a Flow Chart for the process of preparing Form 1040 income tax returns is demonstrated in figure 2.7 (Montgomery, 2019).

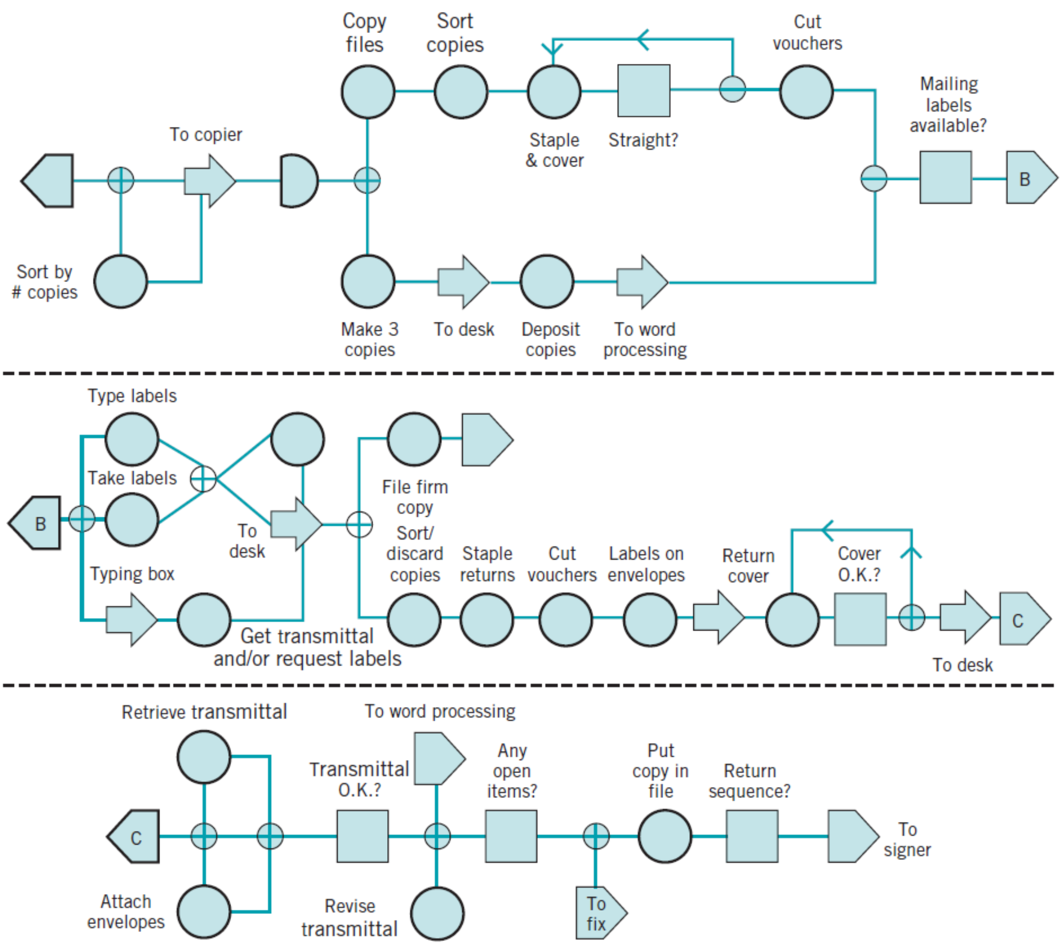


Figure 2.7. Flow chart of the assembly portion of the Form 1040 tax return process

Clearly outlining the sequence of activities and decision points, flow charts enable organizations to systematically analyze each stage of the process, identify inefficiencies, and implement targeted improvements (Soković et al., 2009). In practical applications, flow charts are employed across various industries, from manufacturing to healthcare, to ensure that processes are consistently and efficiently executed. Flow charts facilitate standardization by providing a clear visual reference that can be used to train employees, document procedures, and ensure that quality control measures are consistently applied across different operational contexts (Juran, 1999). Flow charts are commonly utilized alongside other SPC tools to offer a thorough examination of process efficiency. For example, integrating flow diagrams with check sheets or Pareto diagrams enables organizations to not only outline processes but also measure and rank quality concerns within those processes (Magar & Shinde, 2014).

- **Control Chart**

At the heart of SPC is the control chart, an essential tool developed by Walter A. Shewhart in the 1920s. It plots data points over time and utilizes statistically derived control limits to distinguish between expected variation due to common causes and anomalies signaling potential issues (John Oakland & Oakland, 2007). Control charts are crucial for distinguishing between natural variability and anomalies that could impact output quality (Srinivasu et al., 2011). Control charts are utilized to monitor and improve quality by identifying fluctuations in process and product quality characteristics. They provide practitioners with the ability to track quality trends and changes over time, as well as to differentiate between common and special causes of variations. This ability is essential for maintaining quality standards in industrial and manufacturing settings (Woodall, Spitzner, Montgomery, & Gupta, 2004). Control charts adaptability to various contexts, ensures their continued relevance in both industrial and non-industrial applications. By effectively differentiating between common and special causes of variation, control charts help organizations maintain high standards of quality and achieve continuous improvement in their processes (Woodall & Montgomery, 2014).

In a process, sequential samples are used to create control charts. The expectation is that these samples will randomly spread around a mean value with a specific variance. The fundamental principle of all control charts, first introduced by Shewhart, remains unchanged. Each control chart includes a center line (CL), a lower control limit (LCL), and an upper control limit

(UCL). These control limits are determined by the mean and variance. It is anticipated that the samples collected from the process will not surpass these limits unless there are special causes affecting the process. If a sample falls outside the control limits, it indicates that the process is not displaying natural variability and that there are special causes influencing the process (Montgomery, 2019). An example of a typical control chart is demonstrated in figure 2.8 drawn by using Minitab.

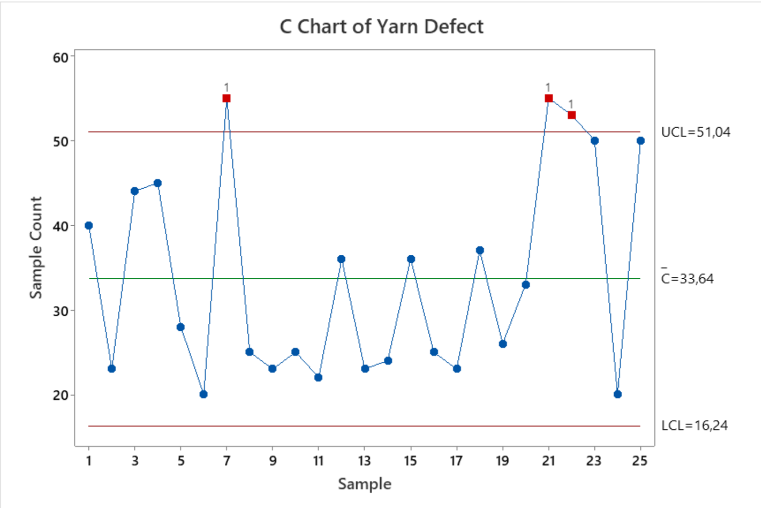


Figure 2.8. C Chart of a Yarn Defect

In order to maintain high-quality processes, specifically designed for industries striving for near-perfect production, control charts are usefull. However, traditional control charts may become less effective, leading to the development of more sophisticated charts capable of detecting subtle shifts in process parameters. Advanced control charts allow for more precise monitoring to consistently meet high standards of quality (Ali, Pievatolo, & Göb, 2016). Various control charts are utilized in SPC to monitor different types of data and processes. Each chart type is tailored to specific data and quality characteristics being monitored, making them versatile in quality control practices (Ryan, 2011).

2.2. Univariate Statistical Process Control Charts

Univariate statistical process control (SPC) constitutes a foundational approach employed to monitor and regulate a singular quality characteristic within a process. This methodology entails the utilization of control charts to trace the variation of a specific variable over time, with the overarching objective of safeguarding process stability and adherence to pre-established limits. Univariate SPC control charts consist of charts like the X-bar chart to monitor the mean and the R chart to track variability. These charts assist in detecting deviations from anticipated performance and offer insights into possible enhancements (Montgomery, 2019). Methods like the X-bar and R charts are useful for monitoring mean changes in processes in real-time when the main focus is on a single variable. Practitioners can use these methods to promptly detect deviations from expected performance in a process, which allows for timely interventions to address any issues (Schat, Tuerlinckx, Smit, De Ketelaere, & Ceulemans, 2021). Single variables control charts showcase their versatility and widespread application in various industries where a single quality characteristic is critical to the process, offering a simple yet effective approach for ongoing process monitoring (S. W. Cheng & Thaga, 2006). In the context of SPC, univariate methods are known for their simplicity and broad applicability. However, these methods may not fully capture the intricate interactions among multiple process variables. As a result, it is recommended to supplement univariate SPC with other statistical methods when addressing complex quality issues (Ali et al., 2016).

Influencing the decision on which type of control chart to use when analyzing a process are factors like subgroup size, sampling frequency, data type, process characteristic, and process limits(John Oakland & Oakland, 2007). There are two types of control charts based on the available data for analysis: Control Charts for Variables and Control Charts for Attributes. Table 2.1 presents a comparison of control charts for variables and control charts for attributes. This table highlights the differences and applications of control charts for variables and attributes, providing a helpful reference for selecting the appropriate chart based on the type of data being analyzed (Montgomery, 2019).

Table 2.1. Comparison of Control Charts for Variables and Attributes

Aspect	Control Charts for Variables	Control Charts for Attributes
Definition	Monitor continuous data that can be measured on a scale, such as weight, length, or temperature.	Monitor discrete data, usually counted as defects or nonconformities.
Data Type	Continuous (e.g., time, temperature, weight)	Discrete (e.g., number of defects, pass/fail)
Typical Charts	X-bar Chart (for the mean of subgroups)	p Chart (for proportion defective)
	R Chart (for range within subgroups)	np Chart (for number defective)
	S Chart (for standard deviation within subgroups)	c Chart (for count of defects per unit)
	I-MR Chart	u Chart (for defects per unit, allowing for varying sample sizes)
Measurement	Measurable quantities (e.g., inches, pounds)	Counts of occurrences (e.g., number of defects, defectives)
Subgroup Size	Small (often 3-5 items)	Large (usually larger than 25)
Application	Used when the quality characteristic is measurable and continuous.	Used when quality characteristic is countable, often in a pass/fail context.
Chart Construction	Based on the mean and variation within subgroups.	Based on the number or proportion of defects or defectives.
Purpose	To detect shifts in the process mean or variability.	To detect changes in the rate of defects or nonconformities.

2.2.1. Control Charts For Variables

Control charts for variables are essential tools in statistical quality control used to monitor and manage processes where quality characteristics are measurable on a continuous scale. These charts help identify variations within a process, which can indicate potential issues or deviations from the desired quality standard. They are useful for distinguishing between common cause variation (inherent to the process) and special cause variation (caused by identifiable and correctable factors). By differentiating between these types of variations, variable control charts help organizations maintain process stability and achieve higher quality levels in production (Montgomery, 2019).

The continuous nature of the data facilitates a more precise examination of process behavior over time, thereby enhancing the detection of trends, shifts, or patterns that may indicate potential quality concerns. Utilization of control charts for variables extends beyond the realm of manufacturing to encompass service industries and healthcare. In these sectors, control charts play a pivotal role in monitoring and improving a diverse range of continuous metrics, including customer wait times, lead times, and the quality of patient care (Woodall & Montgomery, 2014).

- **$\bar{X}$ - R Control Charts**

The Shewhart control chart is a vital component of statistical process control methods, comprising the $\bar{X}$ and R control charts. Calculations of the $\bar{X}$ and R control charts are as follow.

Assuming that a quality characteristic follows a normal distribution with a mean of μ and a standard deviation of σ, and the process parameters (μ and σ) are given, the sample mean for a sample size of n can be expressed as in equation 2.1.

$$\bar{x} = \frac{x_1+x_2+x_3+\cdots+x_n}{n} \tag{2.1}$$

The values μ and σ are typically not known and are instead approximated using samples obtained from the process. If there are m samples, with each sample comprising n observations of the quality characteristic, and $\bar{x}_1$, $\bar{x}_2$, … , $\bar{x}_m$ denote the means of each sample, the mean of the means, serving as the most reliable estimate of the process mean μ, can be computed using Equation 2.2.

$$\bar{\bar{x}} = \frac{\bar{x}_1+\bar{x}_2+\cdots+\bar{x}_m}{m} \tag{2.2}$$

The $\bar{\bar{x}}$ obtained from equation 2.2 is the center line of the $\bar{x}$ chart (Montgomery, 2019).

The difference between the largest and smallest values in a sample of size n, with observations x_1, x_2, x_3, .., x_n, is denoted as R. Equation 2.3 is used to calculate R for each sample.

$$R = x_{max} - x_{min} \tag{2.3}$$

In the equation x_{max} is the largest and x_{min} is the smallest values of the observation in the sample.

While $R_1, R_2, \ldots, R_m$ are the variation range of the m sample, the average variation range is shown in equation 2.4.

$$\bar{R} = \frac{R_1 + R_2 + \cdots + R_m}{m} \tag{2.4}$$

Formulas of center line (CL), upper control limit (UCL) and lower control limit (LCL) of the $\bar{X}$ control charts are given in equations 2.5.

$$UCL = \bar{\bar{x}} + A_2\bar{R} \tag{2.5a}$$

$$CL = \bar{\bar{x}} \tag{2.5b}$$

$$LCL = \bar{\bar{x}} - A_2\bar{R} \tag{2.5c}$$

Variability of the process can be illustrated by displaying the sample range R on a control chart. In equations 2.6, the center line and control limits of the R control chart are shown (Montgomery, 2019).

$$UCL = D_4\bar{R} \tag{2.6a}$$

$$CL = \bar{R} \tag{2.6b}$$

$$LCL = D_3\bar{R} \tag{2.6c}$$

The values of A_2, D_3, D_4 used in the equations for calculating the control limits of the $\bar{x}$ - R chart can be found in the table provided in Appendix A.

The X-bar chart serves the purpose of monitoring the process mean over time, thereby enabling practitioners to identify any shifts in the process average. These shifts may signal underlying issues that could potentially impact overall process performance, underscoring the X-bar chart's significance in detecting deviations from the anticipated central tendency (Montgomery, 2019). Extensive documentation exists on the efficacy of the X-bar chart in detecting these shifts, emphasizing its role in continuous process monitoring and quality improvement (John Oakland & Oakland, 2007).

The R-chart complements the X-bar chart by specifically focusing on the variability or dispersion within subgroups of data. It provides valuable insights into the consistency of process variability by tracking the range of values within each subgroup over time (Montgomery, 2019). This chart is essential for detecting changes in process variability that may not be immediately apparent from the X-bar chart alone. Increased variability can indicate issues such as inconsistent machine performance or changes in raw material quality, which could lead to defects or variations in the final product. Monitoring variability is crucial, as recent studies emphasize the importance of controlling dispersion to maintain product quality (Mitra, 2016).

The X-bar and R-charts are foundational components of SPC, providing a dual perspective on process behavior. The X-bar chart is utilized to monitor the process average, ensuring its adherence to acceptable limits, while the R-chart is utilized to monitor the consistency and control of the variability around this average. This combined approach facilitates effective tracking of process stability and the early identification of potential deviations from expected performance. Integration of these charts into a quality management system enables organizations to uphold stringent control over their processes, identify areas for improvement, and implement corrective actions to prevent defects and ensure high-quality outputs (John Oakland & Oakland, 2007).

- **$\bar{X}$-S Control Charts**

The S chart, also known as the $\bar{X}$ and S chart when used with the $\bar{X}$ chart, is an essential tool in SPC for monitoring process variability. In contrast to the R chart, which is suitable for smaller sample sizes, the S chart is particularly useful when dealing with larger sample sizes (typically $n \geq 10$) because it uses the sample standard deviation to provide a more accurate measure of process dispersion (Montgomery, 2019). The s chart utilizes the standard deviation of each sample to depict process variation instead of using the range. To achieve this, the standard deviation of each sample collected at different time intervals, where i = 1, 2, ..., n, can be computed using the formula provided.

$$S = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}} \tag{2.7}$$

The control limits for the S chart are calculated based on the sample standard deviations' average and specific factors depending on the sample size, ensuring easy identification of any significant changes in process variability (Montgomery, 2019).The following equations can be used to determine the control limits and center line of the s control chart when the process parameters are known (Vardeman & Jobe, 2016).

$$UCL = B_6\bar{\sigma} \tag{2.8a}$$

$$CL = c_4\sigma \tag{2.8b}$$

$$LCL = B_5\sigma \tag{2.8c}$$

σ is determined by analyzing historical data when the parameters are unknown. In this case the center line and control limits for the s chart are as shown in equations 2.9 (Selvamuthu & Das, 2018).

$$UCL = B_4\bar{s} \tag{2.9a}$$

$$CL = \bar{s} \tag{2.9b}$$

$$LCL = B_3\bar{s} \tag{2.9c}$$

Control limits and center line (CL) for the $\bar{x}$ control chart can be calculated using the equations 2.10 (Montgomery, 2019).

$$UCL = \bar{\bar{x}} + A_3\bar{s} \tag{2.10a}$$

$$CL = \bar{\bar{x}} \tag{2.10b}$$

$$LCL = \bar{\bar{x}} - A_3\bar{s} \tag{2.10c}$$

A_3, B_3, B_4, B_5, B_6, and c_4 values in the equations can be found in the table provided in Appendix A.

The S chart is widely applied in manufacturing settings to gain a better understanding of process variability over time and is crucial for maintaining consistent quality. The S control chart monitors the variability within a process by plotting the standard deviation of samples over time. the standard deviation is a more reliable indicator of variability than the range as it uses all data points in a sample, making the S chart more sensitive to changes in data dispersion (John Oakland & Oakland, 2007). The application of the S chart is highly relevant in industries where precision is essential, such as aerospace, pharmaceuticals, and high-precision manufacturing. S chart can quickly identify issues such as tool wear or changes in raw materials, which could affect product quality. By detecting shifts in process variability, organizations can take corrective actions before defects occur, maintaining high standards of quality and reducing costs associated with rework or scrap (Wheeler, 2000).

- **Individuals (I) and Moving Range (MR) Control Charts**

Individuals (I) control charts are commonly used in SPC to monitor processes where data points are collected individually rather than in subgroups, particularly in situations where large sample sizes are impractical or when data cannot be grouped, such as in chemical processing, healthcare, or transactional environments (Montgomery, 2019). The Individuals chart (I chart) tracks individual data points over time to detect changes in the process mean, while the Moving Range (MR) chart plots the range between consecutive data points to monitor variability. In control charts, the absolute difference between two consecutive values is considered. In equation 2.11 absolute difference, which is referred as the moving range, is presented.

$$MR = |X_i - X_{i-1}| \tag{2.11}$$

In a process with k observations, there will be (k-1) MR values; the center line of the MR control chart is the average of these ranges (Doğruel, 2010).

$$CL = \overline{MR} = \frac{\sum MR}{k-1} \tag{2.12}$$

The control limits and center line of the I control chart are given in equations 2.13 (Yılmaz, 2012).

$$UCL = \bar{x} + 3\frac{\overline{MR}}{d_2} \qquad (2.13a)$$

$$CL = \bar{x} \qquad (2.13b)$$

$$LCL = \bar{x} - 3\frac{\overline{MR}}{d_2} \qquad (2.13c)$$

The control limits and center line of the MR control chart are given in equations 2.14 (Yılmaz, 2012).

$$UCL = D_4\overline{MR} \qquad (2.14a)$$

$$\text{CL}=\overline{MR} \qquad (2.14b)$$

$$\text{LCL}=D_3\overline{MR} \qquad (2.14c)$$

I-MR charts are effective tools in situations where subgrouping is not feasible, such as in healthcare, administrative processes, or when every observation is significant, like monitoring blood pressure in a clinical setting or transaction times in banking (Mohammed, Worthington, & Woodall, 2008). Individuals control charts are prized for their simplicity and ease of interpretation. They provide a straightforward approach to identifying out-of-control conditions and trends in processes where data is sparse or cannot be batched into subgroups. However, this simplicity does not compromise their effectiveness (Ryan, 2011). I-MR charts can be highly sensitive to both small and large shifts in process parameters, making them suitable for real-time monitoring and immediate corrective actions (Pyzdek & Keller, 2014). In addition, I-MR charts can handle non-normal data distributions effectively, giving them flexibility for various uses and appropriate for processes with unknown or non-assumed normal data distribution. In settings with diverse quality metrics, like chemical processing, healthcare, and transactional operations, their resilience and flexibility are beneficial. When utilized appropriately, I-MR charts can offer valuable information about both the average and variability of the process, enabling professionals to uphold high quality and efficiency standards (Wheeler, 2000). Through the integration of Individuals and Moving Range charts, companies can obtain a more thorough understanding of their process performance. This dual approach enables them to identify and comprehend shifts in central tendency and variations in process variability, ensuring that both gradual changes and sudden deviations from the process mean are recognized. Ultimately, this leads to enhanced process control and more informed decision-making (Pignatiello Jr & Samuel, 2001).

2.2.2. Control Charts for Attributes

Control charts for attributes are important tools of statistical quality control to monitor processes where data is counted rather than measured on a continuous scale. Distinct from variable control charts, attributes control charts center on the presence or absence of a specific characteristic, such as defects or nonconformities, as opposed to quantifiable measurements like degrees, length, or weight (Montgomery, 2019). The utility of control charts for attributes lies in their simplicity and user-friendliness, particularly in addressing binary or categorical data, such as pass/fail or conforming/nonconforming products. These charts provide a straightforward means of monitoring processes where practical measurements may not be feasible. They empower organizations to uphold quality control by tracking defect proportions or counts. By visually depicting the proportion of defective items or occurrences, these charts are instrumental in identifying production or service process issues such as trends, shifts, or patterns (Ryan, 2011). Control charts for attributes are not only applicable in manufacturing, but also hold considerable importance in service industries, healthcare, and administrative processes. They serve as a crucial metric for monitoring service quality and compliance with standards by tracking the frequency of undesirable events. These charts are instrumental in ensuring consistency in quality and adherence to set standards, enabling practitioners to identify areas requiring improvement and fostering a culture of continuous improvement within organizations (John Oakland & Oakland, 2007).

Furthermore, the resilience and adaptability of control charts for attributes across diverse operational contexts, rendering them an indispensable component of quality management systems. Their capacity to provide real-time feedback on process performance holds particular significance in dynamic environments, where swift corrective measures are essential to prevent the escalation of defects into substantial quality-related challenges. The incorporation of attribute control charts aligns with contemporary quality improvement methodologies such as Six Sigma and Lean, wherein the maintenance of defect levels within acceptable thresholds is fundamental to achieving operational excellence (Woodall, 2000).

When monitoring processes with categorical data based on attributes, different types of control charts, including p charts, np charts, c charts, and u charts, are employed to effectively track quality and stability. Understanding the appropriate type of attribute control chart is crucial for accurately identifying variations and maintaining process control in quality management (Şengöz, 2018) .

- **Fraction Nonconforming (p) Control Chart**

The p chart, also known as the proportion chart, is a crucial tool in SPC for monitoring the proportion of defective items in a process. Unlike control charts for variables that are based on continuous data, p charts are specifically tailored for attribute data, where each item is categorized as conforming or nonconforming. The p chart is most effective when dealing with large sample sizes and focuses on tracking the proportion or percentage of defective units over time (Ali et al., 2016). By plotting the proportion of defective items in each sample against statistically calculated control limits, the p chart helps determine whether the process remains within acceptable control limits or if there is evidence of special cause variation.
To create a p chart, the proportion of defective items is calculated for each sample and plotted over time (Goetsch & Davis, 2016).

Each sample's defect proportion is represented by p_i, with i = 1, 2, …, k denoting the sample number or period, and the sample size being either constant or variable. Equation 2.15 is used to calculate the defect proportion for k samples when the sample size is constant, while equation 2.16 is used when the sample size is variable (Işığıçok, 2012).

$$p_i = \frac{np_i}{n} \quad (2.15)$$

$$p_i = \frac{np_i}{n_i} \quad (2.16)$$

Equation 2.17 can be used to calculate the average defect proportion for constant sample sizes, while equation 2.18 can be used for variable sample sizes (Mitra, 2016).

$$\bar{p} = \frac{\sum_{i=1}^{k} np_i}{nk} = \frac{\sum_{i=1}^{k} p_i}{k} = \frac{p_1+p_2+\cdots+p_k}{k} \qquad (2.17)$$

$$\bar{p} = \frac{\sum_{i=1}^{k} np_i}{\sum_{i=1}^{k} n_i} = \frac{np_1+np_2+\cdots+np_k}{n_1+n_2+\cdots+n_k} \qquad (2.18)$$

The center line of the defect proportion (p) control chart is derived from the calculated values. Therefore, control limits and center line for the p control chart with a constant sample size can be determined using the equations 2.19 (Selvamuthu & Das, 2018).

$$UCL = \bar{p} + 3\left(\sqrt{\frac{\bar{p}(1-\bar{p})}{n}}\right) \qquad (2.19a)$$

$$CL = \bar{p} \qquad (2.19b)$$

$$LCL = \bar{p} - 3\left(\sqrt{\frac{\bar{p}(1-\bar{p})}{n}}\right) \qquad (2.19c)$$

In the case of a variable sample size, the control limits and center line for the p control chart can be determined by using the equations 2.20 (Montgomery, 2019).

$$UCL = \bar{p} + 3\left(\sqrt{\frac{\bar{p}(1-\bar{p})}{n_i}}\right) \qquad (2.20a)$$

$$CL = \bar{p} \qquad (2.20b)$$

$$LCL = \bar{p} - 3\left(\sqrt{\frac{\bar{p}(1-\bar{p})}{n_i}}\right) \qquad (2.20c)$$

These control limits are vital for identifying variations that could indicate a process going out of control. If data points fall outside these limits or display a non-random pattern, it signifies that the process may be influenced by special causes of variation, prompting further investigation and corrective action. One major advantage of p charts is their ability to handle varying sample sizes, making them suitable for processes where the number of inspected units can change frequently (Şengöz, 2018). P charts are extensively utilized in manufacturing settings where quality control aims to minimize the proportion of nonconforming items produced. Effective for monitoring processes that produce attribute data, such as the number of defective units, the frequency of customer complaints, or service errors. These charts offer a simple way to detect shifts in the process, which could result in an increase in defects, enabling timely interventions and adjustments to prevent further quality issues (Woodall et al., 2004). The p chart offers a clear visual representation of process stability, helping organizations maintain consistent quality levels and reduce the risk of nonconformities. The ability to detect increases and decreases in the proportion of defects makes p charts versatile and applicable across various settings where quality assurance is essential (Pyzdek & Keller, 2014).

However, there are limitations to the use of p charts that must be considered. The effectiveness of p charts relies on the assumption that the data follows a binomial distribution and that each observation is independent. When these assumptions are not met, the reliability of the control chart may be compromised. In such cases, other types of control charts for attributes, such as np charts or c charts, may provide more accurate monitoring of the process (Ryan, 2011).

- **Number Nonconforming (np) Control Chart**

The np chart, also known as the number nonconforming chart, is a widely used control chart in SPC for monitoring the quantity of defective or nonconforming items in a consistent sample size. Unlike p charts, which track defect proportions in variable sample sizes, np charts are tailored for situations with fixed sample sizes, enabling a direct count of nonconforming units (Montgomery, 2019). This feature makes np charts particularly valuable in settings like manufacturing or service operations where quality control involves inspecting a specific number of items from each batch or lot, providing a straightforward method for identifying process shifts that may indicate quality issues (John Oakland & Oakland, 2007). Building an np chart involves plotting the nonconforming item count against control limits calculated from the binomial distribution. The average number of defects for the k samples obtained from the process is given in equation 2.21 (Ryan, 2011).

$$n\bar{p} = \frac{\sum_{i=1}^{k} np_i}{k} = \frac{np_1 + np_2 + \cdots + np_k}{k} \tag{2.21}$$

The center line of the np control chart is determined by the average number of defects, which is represented as np (Mitra, 2016). Following 2.22 equations can be used to calculate the control limits and center line for the np control chart (Montgomery, 2019).

$$UCL = n\bar{p} + 3\sqrt{n\bar{p}(1-\bar{p})} \tag{2.22a}$$

$$CL = n\bar{p} \tag{2.22b}$$

$$LCL = n\bar{p} - 3\sqrt{n\bar{p}(1-\bar{p})} \tag{2.22c}$$

Points outside these control limits suggest that the process may be influenced by special cause variations, necessitating further investigation and potential corrective action. The simplicity and ease of interpretation of np charts make them a valuable tool for operators and quality practitioners needing to quickly assess process stability and determine when corrective actions are required (John Oakland & Oakland, 2007).

The control of defect quantities can be effectively achieved using traditional np charts, but recent studies have brought forth several adjustments and improvements to boost their effectiveness. an np chart that involves double inspections, heightens the chart's ability to detect minor process mean shifts. This modification is especially advantageous in high-volume production environments, where early identification of process shifts is essential to avoid large defect quantities (Wu & Wang, 2007). Another innovative approach introduced an np chart for monitoring the mean of a variable based on attribute inspection, combining the advantages of attribute data collection with the need for controlling variable data characteristics. This hybrid method is particularly valuable in cases where exact measurements are challenging or expensive, yet controlling process variables is crucial (Wu, Khoo, Shu, & Jiang, 2009). Economic considerations also significantly impact the design of np charts. The economic design of np charts using fuzzy optimization techniques, emphasizes the need to balance statistical effectiveness with sampling and inspection costs. While the primary purpose of np charts is defect detection, the associated control costs must be optimized to avoid excessive expenses (John Oakland & Oakland, 2007).

The effectiveness of np charts is influenced by specific assumptions, including the independence of observations and a consistent sample size. If these assumptions are violated, the reliability of np charts may be compromised, necessitating adjustments or the consideration of alternative control charts. Nevertheless, np charts continue to be a pivotal tool in the quality management arsenal, particularly in scenarios where a fixed sample size is utilized and defect counts are more feasible than proportions for process monitoring (Ali et al., 2016).

- **Number of Nonconformities (c) Control Chart**

The c chart, also known as the count chart, is a primary control chart for attributes utilized in SPC to monitor the quantity of defects or nonconformities in a fixed area of opportunity, such as a product, unit, or batch. Unlike p and np charts, which monitor the proportion or count of defective items, c charts center on the number of defects per unit when the sample size remains constant, making them especially beneficial when the quality characteristic of interest is the count of defects rather than the proportion of defective items (Evans & Lindsay, 2010). The application of c charts is extensive in settings where each item can have multiple defects, such as in manufacturing processes involving assembly lines, inspection of printed circuit boards, or analysis of defects on textiles or other materials (Chakraborti & Human, 2008) .
The construction of a c chart entails plotting the number of defects observed in each sample or inspection period against control limits, which are calculated based on the Poisson distribution. The center line of the c chart signifies the average number of defects, $\bar{c}$, and it can be calculated as shown in equation 2.23 for k samples, all of which have the same sample size of n, be denoted by c_i (Besterfield, 2013).

$$\bar{c} = \frac{\sum_{i=1}^{k} c_i}{k} = \frac{c_1 + c_2 + \cdots + c_k}{k} \tag{2.23}$$

Following 2.24 equations can be used to calculate the control limits and center line for the c control chart (Montgomery, 2019).

$$UCL = \bar{c} + 3\sqrt{\bar{c}} \tag{2.24a}$$

$$CL = \bar{c} \tag{2.24b}$$

$$LCL = \bar{c} - 3\sqrt{\bar{c}} \tag{2.24c}$$

These control limits play a critical role in distinguishing between common cause variation, which is inherent to the process, and special cause variation, which may indicate an assignable cause that requires further investigation (Juran, 1999). Any points falling outside these limits or displaying non-random patterns indicate a potential shift in the process, suggesting that corrective actions may be necessary to regain control of the process. The c chart is especially valuable in situations where the sample size remains constant and the focus is on monitoring the number of defects per unit of inspection. For instance, in a production process that manufactures automobile components, a c chart might be utilized to monitor the number of surface scratches, dents, or other nonconformities found on each component (Goetsch & Davis, 2016). This method is particularly useful when the cost or effort of inspection does not vary significantly with the number of items inspected, and the primary concern is the overall quality reflected in the number of defects. An advantage of c charts is their simplicity and ease of use, making them suitable for practitioners who need to quickly interpret process stability and detect variations. They are particularly effective when defects occur at a low rate but have significant implications for quality and customer satisfaction (Heizer, Render, & Munson, 2020). Additionally, c charts have been adapted for non-manufacturing contexts, such as monitoring the number of adverse events in healthcare settings or tracking errors in administrative processes, thus broadening their applicability in quality management (Benneyan, 2001).

- **Number of Nonconformities Per Unit (u) Control Chart**

The U-chart, the number of defects per unit chart, is a control chart used SPC to monitor defects or nonconformities per unit when the sample size varies. It is particularly useful in industries where defects are counted across different-sized samples, such as healthcare and textile production (John Oakland & Oakland, 2007).

The construction of a u-chart involves computing the defects per unit for each sample and plotting these values over time against control limits. In equation 2.25, the average number of defects per unit, denoted as u_i, is given by c_i, which represents the number of defects in the i-th sample with n inspection units is shown (Evans & Lindsay, 2010).

$$u_i = \frac{c_i}{n} \tag{2.25}$$

The u control chart developed to monitor the average number of defects per unit, with ui denoting the average number of defects per unit, and m representing the number of samples,equation 2.26 gives the average defect per unit $\bar{u}$.

$$\bar{u} = \frac{\sum_{i=1}^{m} u_i}{m} \tag{2.26}$$

Following 2.27 equations can be used to calculate the control limits and center line for the u control chart (Montgomery, 2019).

$$UCL = \bar{u} + 3\sqrt{\bar{u}/n} \tag{2.27a}$$

$$CL = \bar{u} \tag{2.27b}$$

$$LCL = \bar{u} - 3\sqrt{\bar{u}/n} \tag{2.27c}$$

This formula allows the U-chart to adjust the control limits based on the size of each sample, providing a more accurate representation of process variability. Points falling outside the control limits or showing unusual patterns indicate the potential presence of special cause variation, suggesting a need for further investigation and potential corrective actions (Montgomery, 2019). The use of U-charts is particularly advantageous in scenarios with variability in the inspection area or volume because it normalizes the number of defects to a per-unit basis, enabling more meaningful comparisons across various samples. This adaptability makes U-charts an essential tool for quality control in environments with frequently changing production or inspection conditions. For example, in a hospital setting, a u-chart could monitor the number of patient falls per 1,000 patient days, providing a consistent measure of quality regardless of the daily patient count (Ryan, 2011).

Similarly, in an automotive parts production facility, a U-chart can be utilized to monitor the number of paint defects per square meter of surface area, allowing the quality team to pinpoint and rectify variations affecting the process. Unlike p-charts or np-charts, which monitor fixed sample sizes, U-charts offer flexibility in accommodating fluctuating sample sizes. However, U-charts may exhibit reduced sensitivity in detecting minor process shifts, particularly when the average number of defects is low or when sample sizes vary widely, potentially leading to delays in taking corrective actions (Mitra, 2016).

In addition, u-charts are based on the assumption that defects are infrequent, randomly occurring incidents that adhere to a Poisson distribution. If these assumptions are violated, such as in instances where defects are highly correlated or widely dispersed, the u-chart may not be effective, and alternative methods like CUSUM (Cumulative Sum) charts or EWMA (Exponentially Weighted Moving Average) charts may be more suitable (Kao, 2019). Modifications to the standard u-chart, such as integrating moving averages or adaptive control limits, can also be employed to enhance its efficacy in monitoring processes that do not completely align with these assumptions (Benneyan, 2001).

2.2.3. Cumulative Sum (CUSUM) Control Charts

Cumulative Sum (CUSUM) control charts are essential in SPC as they monitor small shifts in the process mean. Unlike Shewhart control charts, which are designed to detect major shifts, CUSUM charts are highly responsive to gradual changes in process parameters. The chart assesses the cumulative sum of discrepancies from the target value, providing evidence of shifts over time. This accumulation allows CUSUM charts to quickly and effectively identify shifts in the process mean, especially when the shifts are small and occur over a prolonged period, compared to other control charts like the $\bar{X}$ chart (Montgomery, 2019).

The CUSUM control charts function by plotting the cumulative sum of the variances between individual sample values and a specified target or reference value, typically the process mean. CUSUM charts are advantageous due to their capacity to assimilate all preceding data points into the monitoring process, thereby enhancing sensitivity to minor alterations in process conditions (Hawkins & Olwell, 2012). The cumulative sum, denoted as S_i, is computed in equation 2.28 where X represents the observed value at time i_1, and μ_0 signifies the target mean

$$S_i = S_{i-1} + (X_i - \mu_0) \tag{2.28}$$

The equation enables the CUSUM chart to maintain a record of historical data, effectively identifying even slight deviations from the target mean that may remain undetected in other control chart variations. Furthermore, the utilization of one-sided and two-sided CUSUM charts display that the one-sided CUSUM chart is engineered to identify shifts in only one direction (either an increase or a decrease), while the two-sided CUSUM chart monitors shifts in both directions (Lucas & Crosier, 2000). These charts are particularly valuable in industries where maintaining consistent process quality is essential, such as pharmaceuticals, food processing, and chemical manufacturing, where even minor deviations from target parameters can have significant implications (Montgomery, 2019). By setting appropriate decision intervals and head-start values, practitioners can further adjust the CUSUM chart's sensitivity to effectively detect shifts in process parameters. In quality improvement initiatives like Six Sigma and Total Quality Management (TQM), CUSUM control charts are also significantly important. These charts are used in the control phase to monitor process performance and ensure continuous improvements (Riaz, Abbas, & Does, 2011). The cumulative nature of the CUSUM control chart makes it the preferred choice for continuous monitoring, especially in processes that require quick detection and correction of any deviations to maintain high-quality standards. The CUSUM approach is also adaptable and can be used for both normally distributed data and non-normal processes by employing different types of CUSUM charts, such as the V-mask CUSUM or tabular CUSUM (Hawkins & Olwell, 2012).

The effectiveness of CUSUM charts in monitoring small shifts is considerable, but they require more intricate design and interpretation compared to traditional Shewhart charts. This complexity stems from the necessity to establish specific parameters such as reference values, decision intervals, and target shifts. Despite this complexity, the advantages of early shift detection, enabling proactive process interventions, outweigh the challenges. Consequently, CUSUM control charts are often recommended in settings where precision is crucial and process variation costs are significant (Testik, McCullough, & Borrar, 2006).

2.2.4. Exponentially Weighted Moving Average (EWMA) Control Charts

Exponentially Weighted Moving Average (EWMA) control charts are extensively utilized in SPC for monitoring slight shifts in process mean or variability. EWMA charts have an advantage over traditional Shewhart charts as they consider both recent and past observations, giving more emphasis to recent data points. This weighted approach enhances the detection of minor shifts in process parameters, making EWMA charts highly effective in environments where even minor deviations can significantly impact process quality (Montgomery, 2019). Designing EWMA charts involves selecting appropriate control limits to minimize the risk of false alarms while maximizing detection power. The control limits for an EWMA chart are determined based on the process mean and standard deviation, adjusted by a factor dependent on λ and the sample size. This flexibility allows practitioners to tailor EWMA charts to specific process characteristics, enhancing their utility in diverse settings (Chen, Cheng, & Xie, 2001). The EWMA chart is created by calculating the exponentially weighted moving average of the data points. The EWMA statistic at any given time i is computed using equation 2.29 where X_i is the observation at time i, Z_{i-1} is the EWMA value at time i−1, and λ is the weighting factor ranging from 0 to 1.

$$Z_i = \lambda + (1-\lambda)Z_{i-1}X_i \tag{2.29}$$

The choice of λ determines the sensitivity of the chart. Smaller values of λ result in a smoother chart that is more sensitive to small shifts, whereas larger values make the chart more reactive to sudden changes (John Oakland & Oakland, 2007). Typically, λ is set between 0.2 and 0.3 to balance the detection of both small and moderate shifts in the process mean (Montgomery, 2019)

EWMA is a type of weighted average that considers both past and current observations. It is useful in situations where normality is not a critical assumption, and it works well for cases where the subgroup size is one. In such cases, assuming that the x_i observations are independent variables with a variance of σ^2, the variance of $z_i$can be calculated in equation 2.30 (Mason & Young, 2002).

$$\sigma_{Z_i}^2 = \sigma^2\left(\frac{\lambda}{2-\lambda}\right)\left[1-(1-\lambda)^{2i}\right] \tag{2.30}$$

The control limits for the EWMA chart plotted against z_i based on the sample interval or time i can be calculated in equations 2.31(Yeh, Lin, Zhou, & Venkataramani, 2003).

$$UCL = \mu_0 + L\sigma\sqrt{\left(\frac{\lambda}{2-\lambda}\right)\left[1-(1-\lambda)^{2i}\right]} \tag{2.31a}$$

$$CL = \mu_0 \tag{2.31b}$$

$$UCL = \mu_0 - L\sigma\sqrt{\left(\frac{\lambda}{2-\lambda}\right)\left[1-(1-\lambda)^{2i}\right]} \tag{2.31c}$$

As i increases, the term $\left[1-(1-\lambda)^{2i}\right]$ begins to stabilize and in this case control limits can be calculated as in eqautions 2.32.

$$UCL = \mu_0 + L\sigma\sqrt{\left(\frac{\lambda}{2-\lambda}\right)} \tag{2.32a}$$

$$CL = \mu_0 \tag{2.32b}$$

$$UCL = \mu_0 - L\sigma\sqrt{\left(\frac{\lambda}{2-\lambda}\right)} \tag{2.32c}$$

The use of EWMA charts is particularly beneficial in processes where small mean shifts are crucial, such as in chemical processing, semiconductor manufacturing, and other high-precision industries. EWMA charts are more effective than Shewhart charts in detecting small process shifts due to their continuous memory of the process history. Unlike Shewhart charts, which only consider the most recent sample, EWMA charts incorporate all previous data points, improving their ability to detect persistent shifts over time. This makes the EWMA chart the preferred choice for processes requiring close monitoring to ensure high-quality standards and minimize variability (Qiu, 2013). In addition to their sensitivity to slight shifts, EWMA charts can handle non-normal data distributions, making them versatile in various industrial applications. EWMA charts, when used alongside Shewhart charts, create a comprehensive monitoring strategy that addresses both large and small shifts in process performance. This dual approach enables quality practitioners to effectively control both types of variations, ensuring that processes remain in control and capable of producing consistent outputs (Waqas, Xu, ul Amin, & Masengo, 2024). The integration of EWMA charts with other SPC tools is crucial for maintaining robust quality management systems, particularly in industries where the cost of failure is high.

The widespread adoption of EWMA charts in various industries attests to their effectiveness in achieving high levels of process control. Their ability to provide early warnings of small shifts makes them invaluable for continuous quality improvement programs such as Six Sigma and Total Quality Management (TQM), where maintaining tight process control is crucial (Montgomery, 2019). In these frameworks, EWMA charts help ensure that the processes not only remain within specification limits but also continuously improve towards optimal performance.

2.3. Multivariate Statistical Process Control Charts

Multivariate Statistical Process Control Charts (MSPC) charts are an expansion of traditional single-variable control charts used in SPC to monitor and control multiple correlated quality variables simultaneously. In industrial and manufacturing settings, where processes often involve several related quality characteristics, MSPC charts offer a more comprehensive understanding of the process by considering the interrelationships between these variables. This approach is especially valuable in complex processes such as chemical production, semiconductor manufacturing, and automotive assembly, where multiple quality attributes like temperature, pressure, and chemical concentration need to be collectively monitored to ensure overall product quality (Montgomery, 2019).

The use of MSPC charts stems from the limitations of single-variable control charts, which only monitor one quality variable at a time. With correlated quality characteristics, single-variable charts may fail to detect process shifts occurring in the multivariate space. For instance, in a process with two highly correlated quality variables, a change in one variable may be balanced by a change in the other, resulting in no signals on individual single-variable charts, while a multivariate approach could identify such shifts. MSPC charts, such as Hotelling's T^2 chart, take into account the correlation structure among variables, offering more sensitive detection of shifts and changes in the process (Mason & Young, 2002).
While MSPC charts offer advantages over univariate charts, they also have some limitations. One of the main challenges in using MSPC charts is the complexity involved in their implementation. Understanding and interpreting multivariate statistics like Hotelling's T^2

requires a good grasp of multivariate analysis and linear algebra, making it less accessible for practitioners without a strong statistical background (Montgomery, 2019). Additionally, MSPC charts require a sufficient amount of data to accurately estimate the covariance matrix, and the need for large sample sizes can be a drawback in practical applications. When the number of variables is large, the estimation of the covariance matrix becomes less reliable, potentially impacting the performance of the MSPC charts (Bersimis, Psarakis, & Panaretos, 2007).

The benefits of MSPC charts often outweigh their challenges, especially in situations where multiple quality characteristics are interconnected and need simultaneous control. MSPC charts help in minimizing false alarms and missed signals that can occur when relying on multiple univariate charts, thus enhancing the accuracy and reliability of the monitoring system. Moreover, the utilization of MSPC can result in more efficient quality management by enabling the simultaneous monitoring of several variables, reducing the complexity and number of required charts in process control (Jackson, 2005).

Different types of MSPC charts have been developed to address various monitoring needs. The most common is Hotelling T^2 chart, which is used to identify shifts in the mean vector of multivariate processes. For monitoring the covariance structure, the multivariate exponentially weighted moving average (MEWMA) chart and the multivariate cumulative sum (MCUSUM) chart are commonly employed. The MEWMA chart enables the detection of small shifts in the process mean and covariance by assigning more weight to recent observations, whereas the MCUSUM chart accumulates deviations over time, offering a faster response to small shifts in the process (Bersimis et al., 2007). These diverse MSPC charts enhance the adaptability and usefulness of multivariate monitoring, allowing quality practitioners to choose the most suitable chart based on their specific process needs and data characteristics.

2.3.1. Hotelling T^2 Charts

The Hotelling T^2 chart is a commonly used multivariate statistical process control chart for monitoring the mean vector of correlated quality variables in a process. Unlike univariate control charts, which focus on a single quality characteristic, the Hotelling T^2 chart monitors multiple interrelated variables at the same time, providing significant value in industries where several quality attributes need to be controlled together. This chart is frequently used in sectors such as chemical manufacturing, aerospace, semiconductor fabrication, and pharmaceutical production, where processes involve several correlated variables, like temperature, pressure, and concentration, all of which collectively impact product quality (Montgomery, 2019).

Hotelling T^2 serves as a multivariate control statistic that is utilized for identifying changes in the mean vector of correlated variables. It offers a single value that takes into consideration both variances and covariances among the variables. To ensure the validity and accuracy of the results when using Hotelling T^2 charts, several assumptions need to be satisfied, as outlined below (Mason & Young, 2002).

1. Multivariate Normality: The accuracy of the T^2 chart's control limits depends on the data for each variable following a multivariate normal distribution. Failing to meet this assumption may lead to inaccurate control limits.
2. Independence of Observations: Observations should be independent. Correlation between observations can impact the T^2 chart's performance, especially when sampling consecutive data points in a process, necessitating additional steps if autocorrelation exists.
3. Constant Covariance Structure: The covariance matrix of the process should remain constant over time. Any change in the relationships between the monitored variables could lead to incorrect conclusions about the process's control status.
4. Adequate Sample Size: It's important to have a large enough sample size to accurately estimate the mean vector and covariance matrix, and to validate these assumptions before using Hotelling T^2 charts for multivariate quality control to avoid misleading interpretations and inappropriate decisions.

The Hotelling T^2 chart's key benefit is its ability to detect shifts in the multivariate process mean that might be overlooked by individual univariate control charts due to their inability to consider the correlation structure among variables. Considering the joint distribution of variables, the Hotelling T^2 chart offers a more sensitive and accurate method for identifying shifts in the process mean, making it the preferred tool for monitoring interrelated quality characteristics simultaneously in multivariate quality control scenarios (Ryan, 2011).

However, the implementation of Hotelling T^2 charts comes with challenges. One significant drawback is the need for a substantial amount of historical data to precisely estimate the mean vector and the covariance matrix. When the number of observations is not significantly larger than the number of variables, the estimation of the covariance matrix can become unstable, leading to unreliable control limits (Mason & Young, 2002). Additionally, a solid understanding of multivariate statistical methods is required for calculating and interpreting the T^2 statistic, which may not be intuitive for practitioners without advanced statistical training (Ge & Song, 2012). These factors can constrain the practical applicability of Hotelling T^2 charts in some industrial settings, particularly where there are limited resources for extensive data collection and statistical expertise.

Despite these limitations, Hotelling T^2 charts are highly effective for early detection of shifts in multivariate processes, reducing the likelihood of producing nonconforming products or services. They are especially advantageous in industries with high costs associated with defects and where ensuring the simultaneous quality of multiple attributes is critical (Kourti, 2005). Furthermore, Hotelling T^2 charts are flexible and can be adapted to various process monitoring needs, including incorporating time-varying or batch processes, thereby enhancing their usefulness in dynamic production environments (Bersimis et al., 2007).

- **T^2 Control Chart for Subgrouped Data :**

If the means of two quality characteristics x_1 and x_2 are μ_1 and μ_2, and their standard deviations are σ_1 and σ_2 with a covariance of σ_{12}, assuming that these characteristics are normally distributed, then these variables follow a chi-square distribution with 2 degrees of freedom as shown in equation 2.33.

$$X_0^2 = \frac{n}{\sigma_1^2\sigma_2^2 - \sigma_{12}^2}[\sigma_2^2(\bar{x}_1-\mu_1)^2 + \sigma_1^2(\bar{x}_2-\mu_2)^2 - 2\sigma_{12}(\bar{x}_1-\mu_1)(\bar{x}_2-\mu_2)] \qquad (2.33)$$

As long as the process means stay at μ_1 and μ_2, the X_0^2 values must be below the upper control limit (UCL), which equals the α percentile ($X_{\alpha,2}^2$) of the chi-square distribution with 2 degrees of freedom. If at least one value falls outside of the control range, the X_0^2 statistic values surpass the upper control limit (Montgomery, 2019).

A multivariate process can also be represented graphically. When x_1 and x_2 are statistically independent, with a covariance σ_{12} of 0, the equation 2.33 depicts an ellipse with principal axes parallel to the $\bar{x}_1$, $\bar{x}_2$ axes and with its center at μ_1 and μ_2. The X_0^2 values falling inside the ellipse indicate that the process is in control, while any value outside the ellipse suggests that the process is not in control. This ellipse is often called the control ellipse for two independent variables as shown in figure 2.9 (Montgomery, 2019).

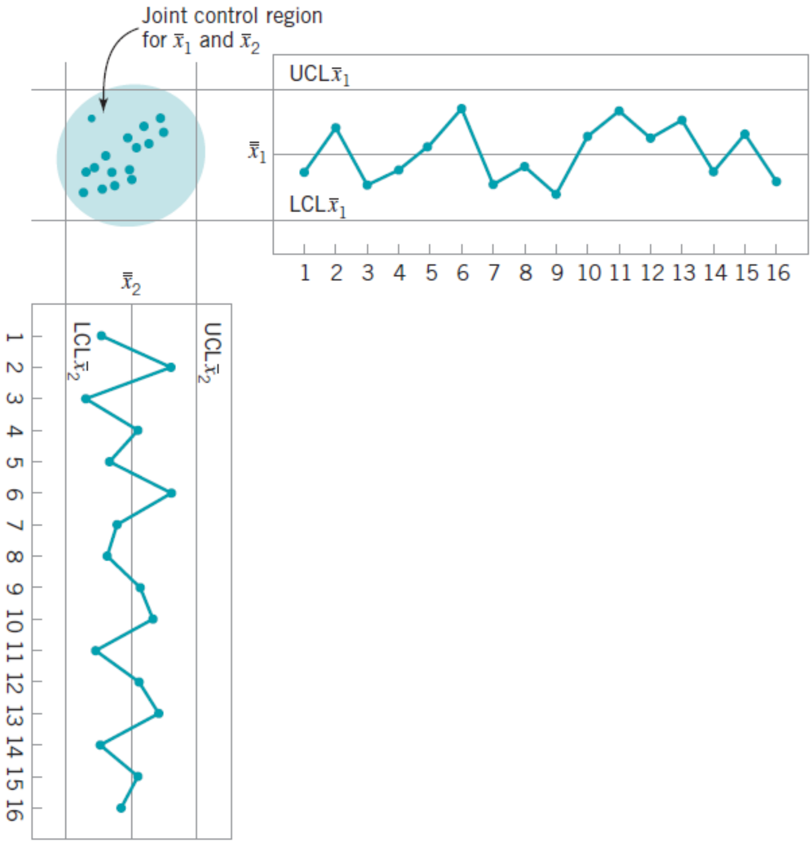


Figure 2.9. A Control Ellipse For Two Independent Variables

When the two variables are dependent, then $\sigma_{12} \neq 0$ and the principal axes of the ellipse are not parallel to the $\bar{x}_1$, $\bar{x}_2$ axes. In this case the control ellipse for two dependent variables will be as shown in figure 2.10 (Montgomery, 2019).

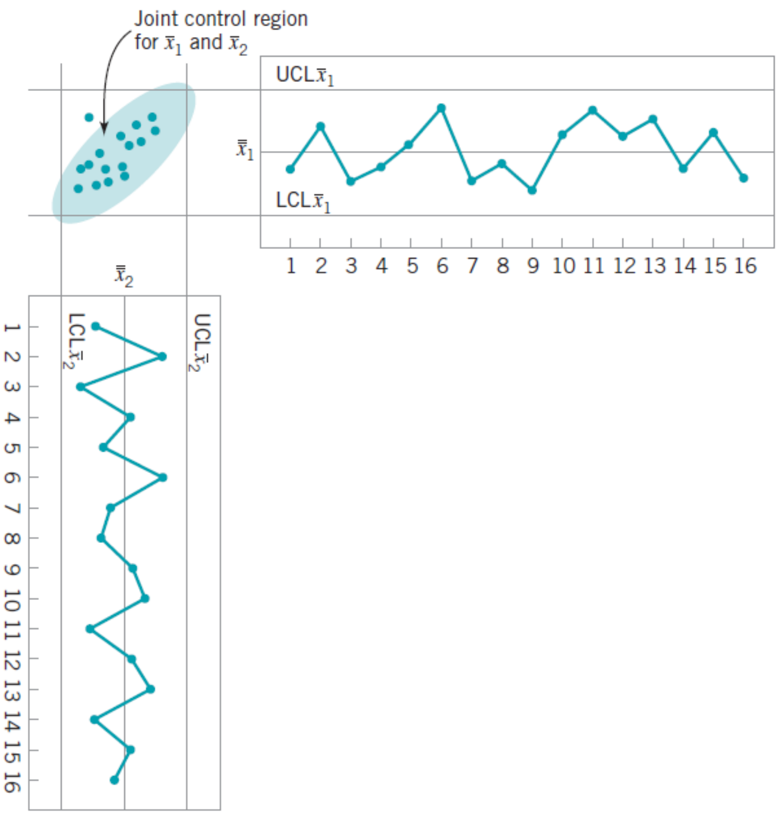


Figure 2.10. A Control Ellipse For Two Dependent Variables

An observation outside the control ellipse indicates a special cause affecting the process, even if there are no out-of-control observations in the individual control charts for $\bar{x}_1$ and $\bar{x}_2$. Therefore, in a situation where two quality variables are dependent, it will be challenging to detect observations falling outside the control ellipse when using univariate control charts. This makes it difficult to identify process variability (Montgomery, 2019).

There are two drawbacks associated with control ellipses. The initial issue is the inability to maintain the time sequence of plotted points on the control ellipse. This concern can be addressed by either numbering the plotted points or employing different graphical symbols. The second, more notable drawback of control ellipses is the challenge of constructing them for more than two quality variables (Mitra, 2016). In order to overcome these challenges, it is customary to graph the computed values for each sample using the equation 2.33 on a control chart that has an UCL only, as depicted in Figure 2.11 (Montgomery, 2019).

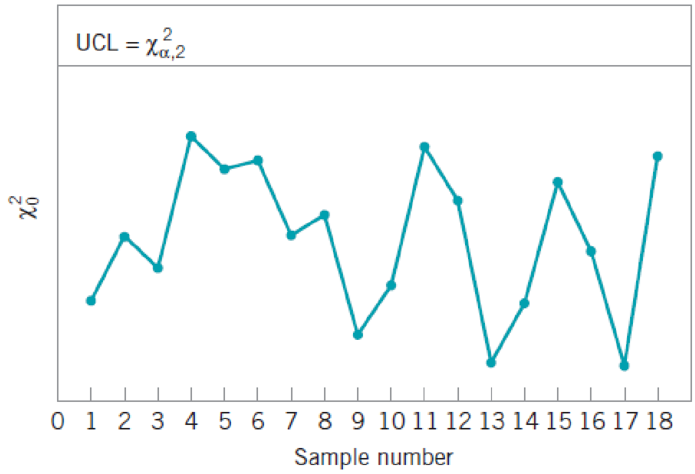


Figure 2.11. A Chi-square Control Chart For p = 2 Quality Characteristics

The test statistic for plotting each sample on the Chi-Square control chart, based on p quality characteristics, where each quality characteristic has a mean vector μ' = [μ1, μ2,… μp] and a covariance matrix ∑, can be found using equation 2.34.

$$X_0^2 = n(x-\mu)'\Sigma^{-1}(x-\mu) \tag{2.34}$$

Chi-Square control chart UCL can be calculated as in equation 2.35.

$$UCL = X_{n,p}^2 \tag{2.35}$$

The mean vector μ and the covariance matrix ∑ are derived from analyzing preliminary samples of size n, which are collected under the assumption that the process is in control. When there are m samples of size n, the mean and variances for each sample can be found using equation 2.36 and 2.37, respectively. x_{ijk}represents the i-th observation of the j-th quality characteristic in the k-th sample.

$$\bar{x}_{jk} = \frac{1}{n}\sum_{i=1}^{n} x_{ijk} \qquad \begin{cases} j = 1,2,\dots,p \\ k = 1,2,\dots,m \end{cases} \tag{2.36}$$

$$S_{jk}^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_{ijk}-\bar{x}_{jk})^2 \qquad \begin{cases} j = 1,2,\dots,p \\ k = 1,2,\dots,m \end{cases} \tag{2.37}$$

Equation 2.38 gives the covariance between the j-th and h-th quality characteristics in the k-th sample.

$$S_{jhk} = \frac{1}{n-1}\sum_{j=1}^{n}(x_{ijk} - \bar{x}_{jk})(x_{ihk} - \bar{x}_{hk}) \quad \begin{cases} k = 1,2,\ldots,p \\ j \neq h \end{cases} \tag{2.38}$$

For m samples, the means of the statistics $\bar{x}_{jk}$, S_{jk}^2 and S_{jhk} are calculated as in equations 2.39.

$$\bar{\bar{x}}_j = \frac{1}{m}\sum_{k=1}^{m}\bar{x}_{jk} \qquad j = 1,2,\ldots,p \tag{2.39a}$$

$$\bar{S}_j^2 = \frac{1}{m}\sum_{k=1}^{m}S_{jk}^2 \qquad j = 1,2,\ldots,p \tag{2.39b}$$

$$\bar{S}_{jh} = \frac{1}{m}\sum_{k=1}^{m}S_{jhk} \qquad j \neq h \tag{2.39c}$$

The set $\{\bar{\bar{x}}_j\}$ is formed by the elements of vector $\bar{x}$, and equation 2.40 provides the mean of the sample covariance matrix S of size p x p.

$$S = \begin{bmatrix} \bar{s}_1^2 & \bar{s}_{12} & \bar{s}_{13} & \cdots & \bar{s}_{1p} \\ & \bar{s}_2^2 & \bar{s}_{23} & \cdots & \bar{s}_{2p} \\ & & \bar{s}_3^2 & & \vdots \\ & & & \ddots & \bar{s}_p^2 \end{bmatrix} \tag{2.40}$$

The sample mean covariance matrix S is an unbiased estimator of $\sum$ when the process is under control. When the values of μ and $\sum$ are not known in the process parameters, and taking into account the aforementioned equations, a new test statistic called Hotelling T^2 is created by replacing μ with $\bar{x}$ and $\sum$ with S. This test statistic is presented in equation 2.41.

$$T^2 = n(\bar{x} - \bar{\bar{x}})'S^{-1}(\bar{x} - \bar{\bar{x}}) \tag{2.41}$$

The Hotelling T^2 control chart is developed through two steps. In phase 1, m preliminary subgroups are formed, and the values of $\bar{\bar{x}}$ and S are computed to verify if the process is under control. The aim of this step is to gather stable observation data required for initiating the phase 2. In phase 2, the upcoming production is monitored. The control limits for phase 1 of the T² control chart are as shown equations 2.42.

$$UCL = \frac{p(m-1)(n-1)}{mn-m-p+1} F_{\propto,p,mn-m-p+1} \tag{2.42a}$$

$$LCL = 0 \tag{2.42b}$$

The phase 2 chart's control limits, which have been set up to monitor future production, can be found in equations 2.43.

$$UCL = \frac{p(m+1)(n-1)}{mn-m-p+1} F_{\propto,p,mn-m-p+1} \tag{2.43a}$$

$$LCL = 0 \tag{2.43b}$$

When the preliminary sample sizes for determining μ and ∑ are extremely large, $X^2_{\alpha,p}$ is equal to the upper control limit in both Phase 1 and Phase 2 (Montgomery, 2019).

- **T² Control Chart for Individual Observations:**

In certain industrial processes, the subgroup size n consistently remains at 1 due to the specific characteristics of the process. This is particularly common in the chemical industry, where despite the continuous monitoring and recording of multivariate data, it represents to a single observation at a particular moment. Therefore, the subgroup size equals 1 (Yang & Trewn, 2004). In a scenario involving m samples of size 1, where each sample exhibits p quality characteristics, the sample mean vector and covariance matrix are represented as $\bar{x}$ and S, respectively. In equation 2.44 the Hotelling T² statistic for this case is provided.

$$T^2 = (x - \bar{x})' S^{-1} (x - \bar{x}) \tag{2.44}$$

Phase I control limits should follow a beta distribution when the sample size is one. Equations 2.45 provides the limits accordingly. During this phase, a T² control chart is constructed using data from a normal process, and any out-of-control observations are eliminated to create a pristine reference sample data set (Mason & Young, 2002).

$$UCL = \frac{(m-1)^2}{m}\beta_{\alpha,p/2,(m-p-1)/2} \tag{2.45a}$$

$$LCL = 0 \tag{2.45b}$$

Phase 2 involves the creation of a new T² control chart utilizing the reference sample data group values, followed by an analysis of the current production. The Phase 2 control limits which are based on an F distribution can be calculated as shonw in equations 2.46.

$$UCL = \frac{p(m+1)(m-1)}{m^2-mp}F_{\alpha,p,m-p} \tag{2.46a}$$

$$LCL = 0 \tag{2.46b}$$

2.3.2. Multivariate Exponentially Weighted Moving Average Charts

The monitoring of process state based on the current sample can be effectively accomplished using multivariate control charts such as Chi-square and T². However, these charts may not be very sensitive to small shifts in the mean vector. To overcome this limitation in univariate cases, Cumulative Sum (CUSUM) and Exponentially Weighted Moving Average (EWMA) control charts were developed. The concept of EWMA was extended to multivariate quality problems with the introduction of the Multivariate EWMA (MEWMA) control chart by (Bersimis et al., 2007).

In the MEWMA control chart, information is accumulated over time by assigning exponentially decreasing weights to past observations, thereby improving the detection of small to moderate shifts in the mean vector of correlated quality characteristics (Yeh et al., 2003). The MEWMA method utilizes the weighted mean of past observations to keep track of the average process mean vector (Bersimis et al., 2007). The MEWMA statistic is computed using a weighting matrix, often represented as λ, which governs the impact of past data on the current chart. The MEWMA statistic is given in equation 2.47 , where $0 < \lambda \leq 1$ and $Z_0 = 0$ (Montgomery, 2019).

$$Z_i = \lambda x_i + (1 - \lambda) Z_{i-1} \; i \geq 1 \tag{2.47}$$

A lower value of λ increases the sensitivity of the MEWMA chart to small shifts, making it a valuable tool for detecting subtle changes in the process. Equation 2.48 provides the T^2 statistic that gives the points on the control chart, while Equation 2.49 gives the covariance matrix (Yeh et al., 2003) .

$$T_i^2 = Z_i' \textstyle\sum_{Z_i}^{-1} Z_i \tag{2.48}$$

$$\textstyle\sum_{Z_i} = \frac{\lambda}{2-\lambda}\left[1 - (1-\lambda)^{2i}\right]\textstyle\sum \tag{2.49}$$

The UCL values of the MEWMA chart were used to derive the corresponding H values, taking into account different lambda and p values. If T^2 surpasses H on the MEWMA chart, it indicates that the process is deemed to be out of control (Khoo, 2004).

2.3.3. Multivariate Cumulative Sum Charts

Univariate CUSUM charts assess individual process variables to detect small shifts. However, in processes involving multiple quality characteristics, considering all variables is essential for making informed judgments about product quality. When measuring product quality using multiple interrelated variables, using univariate CUSUM control charts for detecting small shifts in the process mean is not recommended (Alt, 2004). To address these limitations, the Multivariate CUSUM (MCUSUM) chart, an adaptation of the univariate CUSUM control chart for multivariate scenarios, allows for the detection of small changes in process parameters. This chart accumulates deviations of quality variables from their targets (Bersimis et al., 2007).

The count of subgroups is denoted as n_t; the i-th observed value is represented by X_i; C_t stands for the cumulative sum of multiple variables at the i-th observation time; and μ_0 is the specified mean value in equation (2.50).

$$C_t = \sum_{i=t-n_1+1}^{t}(X_i - \mu_0) \tag{2.50}$$

Equation 2.51 gives the calculation for the distance between the estimated process mean and the target mean μ_0.

$$\|C_t\| = \sqrt{C_t' \, \Sigma^{-1} \, C_t} \tag{2.51}$$

Multivariate CUSUM statistic is calculated as in equation 2.52 (Montgomery, 2019).

$$MC1_t = max\{\|C_t\| - kn_t, 0\} \tag{2.52}$$

2.4. Statistical Process Control in Textile Industry

In the textile and yarn production industry, Multivariate Statistical Process Control (MSPC) is used to simultaneously monitor multiple variables and enhance quality control. MSPC methods such as Principal Component Analysis (PCA), Partial Least Squares (PLS), Hotelling T^2, MEWMA charts are extensively applied in textile and yarn production to monitor and control quality. Combined application of PCA and Bayesian methods enhance to predict yarn strength and improve quality consistency by identifying critical variables such as tensile strength, evenness, and yarn count (Zhang et al., 2021). Similarly, PLS regression is used in yarn production to address multicollinearity issues between variables. Utulization of a hybrid artificial neural network and genetic algorithm model integrated with PLS regression provides prediction on yarn quality, focusing on the most influential factors (Das, Ghosh, Majumdar, & Banerjee, 2013).

Abdulghafour et al. (2021) implemented Hotelling's T^2 control charts to oversee the quality of textile yarns, enabling timely identification and rectification of variations in tensile strength and yarn diameter. This multivariate approach proved effective in detecting process deviations that may have otherwise been overlooked when using univariate control charts (Abdulghafour, Omran, Jafar, Mottar, & Hussein, 2021). Similarly, in their examination of the denim washing process, Ata, Yıldız, and Durak (2020) employed both univariate and multivariate control charts, including the MEWMA chart, to monitor diverse quality factors such as fabric color and weight. The MEWMA chart exhibited heightened sensitivity to subtle shifts in the process mean, thereby enhancing early detection of potential defects in comparison to univariate charts (Ata, Yıldız, & Durak, 2020).

In a comprehensive investigation conducted by Kelly (2014), the relationship between fiber properties and yarn characteristics was explored through the utilization of Multivariate Statistical Process Control (MSPC). The study focused on key attributes such as length and fineness, employing Principal Component Analysis (PCA) in conjunction with multivariate control charts, including Hotelling's T^2, to effectively monitor the uniformity of yarn properties. The findings demonstrated that the implementation of multivariate control charts resulted in more accurate predictions of yarn quality by emphasizing critical variables that significantly influenced the final output (Kelly, 2014). Furthermore, Kula, Tunak, and Linka (2010) applied multivariate control charts, such as the Multivariate Exponentially Weighted Moving Average (MEWMA) and Hotelling's T^2, to enable real-time monitoring of fabric quality. By examining diverse factors such as surface texture and color, the use of these control charts facilitated the prompt detection of deviations in the fabric production process. Their research provided compelling evidence for the effectiveness of real-time MSPC in maintaining consistent fabric quality and reducing defects (Kula, Tunak, & Linka, 2010).

In a comprehensive examination of spinning processes at a textile factory, the study conducted by Gera, Taye, and Bekele (2017) utilized Hotelling's T^2 charts to monitor critical spinning parameters, including yarn twist and evenness. The factory implemented Multivariate Statistical Process Control (MSPC) to establish more stringent control over process variability, resulting in a notable decrease in defects and an overall improvement in product quality. Notably, Hotelling's T^2 method demonstrated exceptional proficiency in detecting minor process variations that may have been overlooked by conventional approaches (Gera, Taye, & Bekele, 2017).

Megahed, Woodall, and Camelio (2011) investigated the utilization of image data combined with control charting methods in diverse industries, including textiles. They highlighted the effectiveness of using image data to monitor fabric characteristics like texture and weave density, enabling the identification of defects that may be overlooked by traditional control charts (Megahed, Woodall, & Camelio, 2011). Building on this concept, Megahed (2012) incorporated point cloud data into Statistical Process Control (SPC), showcasing its relevance in nonwoven fabrics and other textile processes. The integration of image and point cloud data in MSPC enables manufacturers to visually identify deviations in textile production, ultimately enhancing process precision (Megahed, 2012).

Conventional control charts were improved through the application of fuzzy logic, offering particular benefits in textile manufacturing where monitoring yarn count, fabric weight, and other quality characteristics can pose challenges using traditional methods. By combining fuzzy logic with control charts enhance sensitivity in detecting subtle variations, thereby improving overall control of textile production processes (Şengöz, 2018).

Kuo, Huang, and Yang (2021) utilized multivariate control charts and a decision tree classifier to oversee the quality of polypropylene fibers during the melt spinning process. Through the integration of Principal Component Analysis (PCA) and the Taguchi method, their research identified critical processing parameters affecting fiber quality, including factors like fiber uniformity and tensile strength. This amalgamation of multivariate statistical tools and machine learning techniques underscores the advanced methods employed in modern textile manufacturing to optimize product quality (Kuo, Huang, & Yang, 2021). Probability and fuzzy approaches in constructing quality control charts, applying them in a textile company to monitor yarn quality characteristics such as strength and evenness demonstrates the effectiveness of fuzzy theory in managing the uncertainty and imprecision inherent in textile manufacturing, facilitating better control of process variability and improvements in yarn quality (Ertuğrul & Aytaç, 2009). Employing MEWMA control chart to supervise process variability in fabric production displays particular efficacy in detecting minor shifts in critical quality characteristics, such as yarn count and fabric weight, which are crucial for maintaining the desired product quality in textile manufacturing. Through monitoring the covariance structure of these parameters, the MEWMA chart offered a robust method for early detection of quality issues in the production process (Yeh et al., 2003).

Table 2.2. shows the studies using SPC methods in the textile field including quality characteristic and used method.

Table 2.2. Articles focusing on multivariate statistical quality control methods in textile

Article	SPC Method	Quality Characteristic
Yarn engineering using hybrid artificial neural network-genetic algorithm model	Hybrid artificial neural network and genetic algorithm	Yarn strength, evenness, twist
Yarn strength CV prediction using principal component analysis and automatic relevance determination on Bayesian platform	Principal Component Analysis, Bayesian platform	Yarn strength CV
Application of statistical control charts for monitoring the textile yarn quality	Hotelling's T^2 control charts	Tensile strength, yarn diameter
Statistical process control methods for determining defects of denim washing process: a textile case from Turkey	MEWMA (Multivariate Exponentially Weighted Moving Average) charts	Fabric color, weight
Multivariate analysis of fiber properties and their relation to yarn properties	PCA combined with Hotelling's T^2 control charts	Fiber length, fineness, yarn strength
Real-time quality control of fabric based on multivariate control charts	MEWMA and Hotelling's T^2 control charts	Surface texture, color consistency
Implementation of statistical quality control for spinning processes of Dire Dawa Textile Factory	Hotelling's T^2 control charts	Yarn twist, evenness
A review and perspective on control charting with image data	Image data analysis combined with control charts	Image-based quality characteristics
The Use of Image and Point Cloud Data in Statistical Process Control	Image and point cloud data for process control	weaving density of weft yarns
Article	**SPC Method**	**Quality Characteristic**
Control charts to enhance quality	Traditional control charts and case studies	yarn count and fabric weight
Integration of multivariate control charts and decision tree classifier in melt spinning process	Multivariate control charts with decision tree classifier, Taguchi method, and PCA	fiber uniformity, tensile strength, and process consistency
Construction of quality control charts by using probability and fuzzy approaches in a textile company	Probability and fuzzy theory applied to control charts	yarn strength and evenness
A multivariate exponentially weighted moving average control chart for monitoring process variability	Multivariate exponentially weighted moving average (MEWMA) control charts	single-strand break factor and the weight of textile fibers

3. RESEARCH METHODS

3.1. Material

The textile company where the research has been implemented offers a diverse selection of high-quality, creative fabrics, ranging from fiber dyed to piece dyed, textured to digitally printed. Cotton, viscose, polyester, linen, tencel, modal, and wool are among the most popular textile fibers used by the company. Company’s main product range consists of yarn and fabric; most importantly, yarn is the major input for company’s own fabric production. The company operates advanced yarn production facilities that supply high-grade yarns used both in its own fabric production and for external markets. In figure 3.1 part of a Draw Frame machine from the company’s machinery lineup is shown.

Figure 3.1. Part of a Draw Frame Machine

The production of yarn is a crucial step in the textile industry and serves as the basis for a variety of textile products. It involves transforming fibers, whether natural such as cotton, wool, and silk or synthetic like polyester and nylon, into yarn through a series of complex processes. Several methods are used for yarn production, with ring spinning and open-end spinning being the most common, each offering distinct benefits and affecting the final product's quality in different ways (JWW Hearle, 2001) (Lord, 2003). The choice of spinning method is influenced by factors such as the fiber type, desired yarn properties, and end-use applications, making the technological, scientific, and economic aspects of yarn production crucial for maximizing production efficiency and ensuring high-quality results (Lord, 2003). Ring spinning is widely regarded as the most traditional and commonly used method due to its ability to create yarns with exceptional strength, smoothness, and appearance (Lawrence, 2003). This process entails drafting the fibers, twisting them to enhance strength, and then winding the yarn onto bobbins. In contrast, open-end spinning, also known as rotor spinning, has become popular for its high productivity and cost-effectiveness (Oxtoby, 2013). This method eliminates several steps involved in ring spinning, such as roving, which accelerates the production process. Open-end spun yarns are generally bulkier and have a slightly rougher texture, making them suitable for products like denim, towels, and industrial textiles (Lawrence, 2003). The choice between ring spinning and open-end spinning is often determined by the desired properties of the yarn and the end-use application. Fibers coming in bales are transformed into yarn by passing through various stages as seen in Figure 3.2.

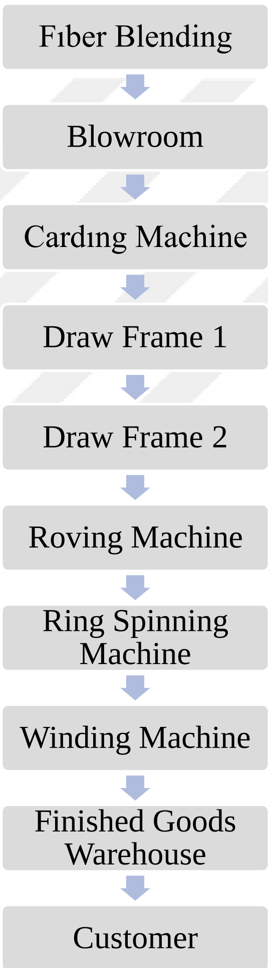


Figure 3.2. Yarn Production Process Flow

3.1.1. Key Quality Characteristics of Yarn

The quality of yarn production depends on various important characteristics that affect the performance, durability, and appearance of the textile product. These characteristics are influenced by the properties of the fibers, the accuracy of the production process, and the control of essential parameters during manufacturing. Yarn strength, evenness, twist, hairiness, and the presence of neps are crucial factors in determining yarn quality (Goswami, Anandjiwala, & Hall, 2004). These characteristics not only impact the physical properties of the yarn but also influence the effectiveness of subsequent processes such as weaving and knitting, as well as the aesthetic and functional qualities of the final fabric (JW Hearle, 2001).

- **Strength**

Strength is a key quality characteristic in yarn production. Yarn strength is typically assessed through tensile tests to gauge its ability to withstand forces during subsequent textile processes such as weaving, knitting, and dyeing (Booth, 1986). High-quality yarns should possess adequate strength to endure these processes without breaking or elongating excessively. The strength of the yarn is mainly influenced by the length and strength of the fibers, the level of twist during spinning, and the uniformity of fiber distribution (Hearle & Morton, 2008).

- **Fineness**

The thickness or linear density of the yarn, usually measured in tex or denier units, is another important characteristic known as fineness. The feel, weight, and texture of the fabric created from the yarn are influenced by fineness. Lighter, softer fabrics are produced by finer yarns, while heavier, more durable textiles are the result of coarser yarns. Fineness also has an impact on fabric drape and comfort, especially in garments designed for close contact with the skin (Saville, 1999).

- **Twist**

The production of yarn is significantly impacted by twist, which influences both the yarn's strength and its appearance. Twist denotes the amount of turns per length of yarn, which serves to bind the fibers together, enhancing their strength and cohesion (Goswami et al., 2004). Nonetheless, an excess of twisting can render the yarn rigid and diminish its softness, whereas insufficient twisting may lead to weak and loosely bound fibers that compromise the fabric's durability.

- **Evenness**

Ensuring the consistent quality of yarn relies on evenness or uniformity, which is essential. Fabric defects such as streaks, uneven dye uptake, and weak spots can result from variations in yarn thickness or mass per unit length, making it important to monitor this key characteristic during production (Saville, 1999). Specialized instruments, such as the Uster Tester, are typically used to measure evenness by detecting variations in yarn thickness and the presence of imperfections.

- **Hairiness**

The presence of fiber ends on the surface of yarn, known as yarn hairiness, can cause complications during textile production, such as entanglement during weaving and knitting, and can also have a negative impact on the appearance and texture of the fabric. Hairiness is significantly influenced by factors such as the type of fiber, spinning technique, and twist level. For instance, ring-spun yarns generally have lower hairiness compared to open-end spun yarns due to the more compact structure of the fibers (Lawrence, 2003). Excessive hairiness can also affect the quality of the final product by causing problems with dyeing and fabric uniformity. Therefore, it is essential to control hairiness in order to maintain yarn quality and ensure optimal performance in subsequent processes (Krupincová & Meloun, 2013).bare

- **Neps**

Neps are small clusters of fibers that are tangled together and can be seen as imperfections in yarn. Their presence can have a negative impact on the quality of the final fabric by causing uneven dyeing and affecting the overall look of the textile. Neps can develop due to various factors, such as the quality of the raw cotton, mechanical pressures during processing, and spinning parameters (van der Sluijs & Hunter, 2016). The properties of the fibers, such as maturity, length, and fineness, play a crucial role in determining the extent of neppiness, and immature or short fibers are significant contributors to the formation of neps (Ozcelik & Kirtay, 2006). Therefore, precise control of both fiber selection and processing conditions is crucial to minimize neps and enhance yarn quality.

3.1.2. Tests Performed at Yarn Quality Control Test Laboratory

The tests conducted in the yarn quality control laboratory of the yarn production facility at the textile factory, where the application of the thesis carried out, are presented in Table 3.1.

Table 3.1. Major quality control checks in the yarn quality control laboratory

JOB	CONTROLLED FEATURES	SAMPLE AMOUNT	PRODUCT CONTROL FREQUENCY	DEVICES USED
Card Strip	Yarn count control	3 yards 3 strip from each card	Once a day and with each new type	spinning wheel - scales
Card Strip	Neps control	From each card 380 inch^2 3 web	Once a day and with each new type	Illuminated neps control device
Card Strip	Irregularity control	25 m/min (t:2,5 min)	Once a day and with each new type (15 card per week)	Uster Tester4
Cer Strip 1. psj	Yarn count control	3 yards from each 3 strips per each cer	Once a day and with each new type	spinning wheel – scales (Uster Auto Sorter 4-Zweigle L232)
Cer Strip 1.psj	Irregularity control	25 m/min (t:2,5 min)	Once a day and with each new type (15 card per week)	Uster Tester4
Cer Strip 2.psj	Yarn count control	1 yard from each 4 strip per each cer	Every two hours and every new type	spinning wheel – scales (Uster Auto Sorter 4-Zweigle L232)
Cer Strip 2.psj	Irregularity control	25 m/min (t:2,5 min)	Once a day and with each new type (Each machine per day)	Uster Tester4
Cord	Yarn count control	10 yards from each 4 cords / 2 samples each	Once a day and with each new type	spinning wheel – scales (Uster Auto Sorter 4-Zweigle L232)
Cord	Irregularity control	50 m/min (t:2,5 min)	Once a day and with each new type (at least two cords of each type per day)	Uster Tester4
Ring	Yarn count control	16 cops at 120 yards from each ring	Once a day and with each new type (Each machine per day)	spinning wheel – scales (Uster Auto Sorter 4-Zweigle L232)
Ring	Yarn twist control	16 cops at 120 yards from each ring	Once a day and with each new type (Each machine per day)	Zweigle D315
Ring	Hairness	16 cops at 120 yards from each ring	Once a day and with each new type (Each machine per day)	Zweigle G567
Ring	Yarn tenacity and elasticity	16 cops at 120 yards from each ring	Once a day and with each new type (Each machine per day)	Uster Tensorapid 3

3.1.3. Devices At Yarn Quality Control Test Laboratory

The yarn quality control laboratory at the textile company uses testing devices to ensure the quality of yarn production. These devices operate according to specific working principles.

- **Uster Tester 4 and Working Principle**

The Zellweger Uster Tester 4 is designed for off-line control and is used to measure yarn unevenness. Off-line testing is essential for maintaining yarn quality, ensuring it meets specific standards, and identifying areas for improvement. The Uster Tester 4 plays a crucial role in facilitating these processes. Unevenness refers to the variation in mass along the material's length. The Uster device operates based on the capacitive method, with the material passing between two plates while being conveyed downwards by output rollers. Mass changes along the length of the plates are detected by the sensor (CS sensor) and transmitted to the capacitor. The capacitor's capacitance changes in response to the mass transmission, and this is then processed by the amplifier to visualize any errors. The error values are separated according to the predefined standards and displayed on the indicator. The spectrograph in the device converts the separated error values into graphics, enabling the detection of periodic errors. In figure 3.3 Uster Terster 4 at the yarn quality control laboratory is shown.

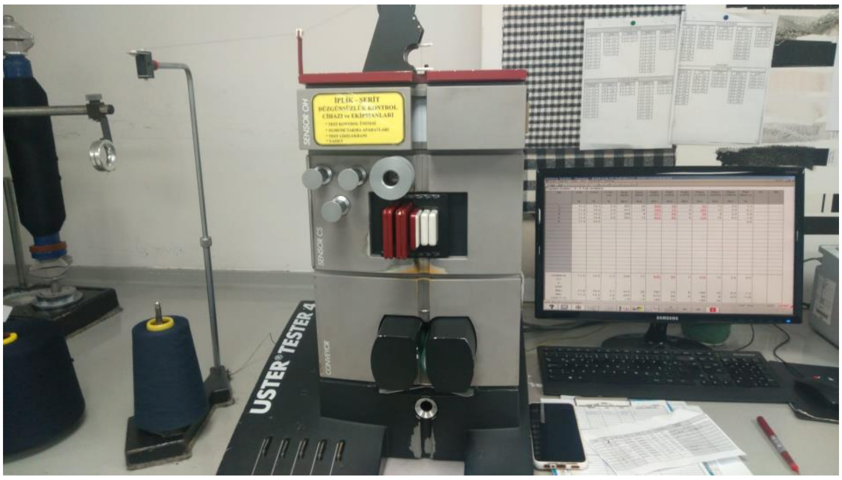


Figure 3.3. Uster Tester 4 at the yarn quality control laboratory

The device detects primary quality values such as % U (Thread evenness), %CVm (Mass variation), Thin and thick threads, Neps status, Hairiness and variation, Index, Relative number, etc. Additionally, it is feasible to replicate the end product using the Uster Tester 4 device.

- **Uster Tensorapid 3 and Working Principle**

The uster tensorapid 3 is utilized for off-line controls during the yarn production process to assess the strength and elasticity of materials. Thread strength, which is the force required to break a thread, depends on factors such as the raw material, yarn number, and twist. This device operates on the principle of an inclined plane and quickly measures at 50 cm long and 5000 mm/min. To conduct the measurement, ten bobbins are taken from each machine and placed in the device's creel. The device's programming includes the yarn number to be tested and provides pre-tension accordingly. This allows the yarn to reach a specific tension value between the jaws before the measurement begins. The results, based on the weight at which the thread broke, are displayed on the screen. The device is capable of determining quality parameters such as breaking force, elongation at break, and strength values in Rkm or CN/tex. Figure 3.4 displays the Uster Tensorapid 3 device at the company's yarn quality control laboratory.

Figure 3.4. Uster Tensorapid 3 at the yarn quality control laboratory

- **Zweigle D315 Twisting Device and Working Principle**

The yarn quality control laboratory of the factory utilizes a twisting device as another tool. Twisting is essential for giving fibers a lasting appearance, ensuring they stay together, and providing strength. The twist measurement helps verify if the spinning machine has applied the desired twist value to the yarn accurately. The measurement principle follows the corrected fiber method. The twisting device consists of two jaws, one of which is movable, while the other is fixed and operates in a circular motion. The yarn is positioned between these two jaws, and the appropriate weight is attached based on the yarn number. Subsequently, the jaw begins circular motion in the opposite direction of the twisting, and a needle is used to check if the twist is fully opened. Once fully opened, the value is read from the device's meter. In Figure 3.5, the Zweigle Twisting Device in the company's yarn quality control laboratory is shown.

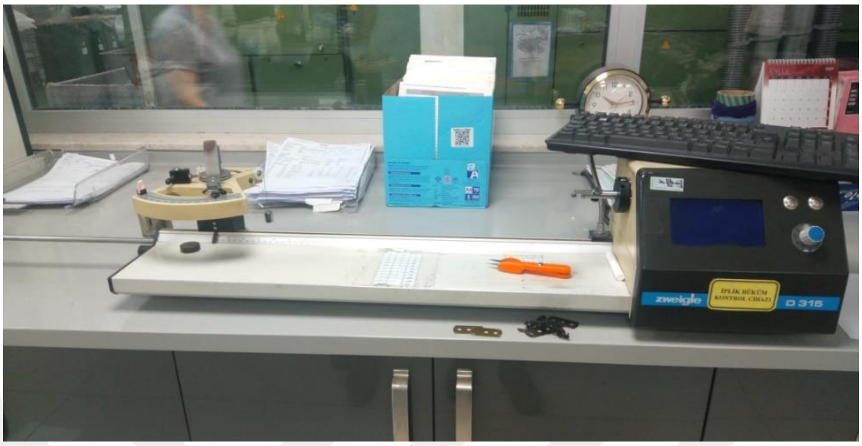


Figure 3.5. Zweigle D315 Twisting Device At The Yarn Quality Control Laboratory

- **Neps Control in Card Web**

Samples are collected from three cards of each type of web. The number of neps on the 380-inch square illuminated table is used to determine if the corresponding web card needs improvement. Quality control laboratory visually inspects bobbin yarns for issues such as abrage (inhomogeneous distorted blended image), foreign thread, cross thread, excessive hairiness, and damaged patterns, among others. Yarns that do not meet the standard are separated and either sent for weaving or to the customer with appropriate quality. The inspection of yarn neps is conducted by utilizing a carding neps control light box, as depicted in Figure 3.6.

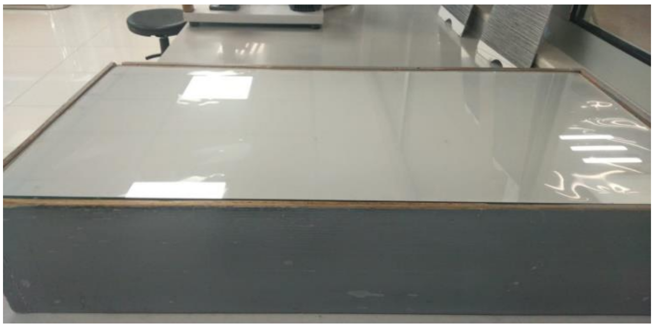


Figure 3.6. Carding Neps Control Light Box

4. ANALYSIS AND DISCUSSION

Yarn quality is significantly impacted by irregularities like thin places, thick places, and neps. It is essential to monitor these imperfections using control charts in the textile industry to ensure quality management. In the textile company's yarn production facility, thin places, thick places, and neps were monitored using control charts based on 500 data points collected in the quality control laboratory for the yarn “28/1 RNG PE/V 67/33 w/o lycra” produced most frequently. These control charts allow the company to effectively oversee and control yarn quality, thus ensuring consistent quality in their production process.

4.1. Univariate Control Charts of Selected Quality Characteristic

Control charts, such as c chart, EWMA, and I-MR charts, offer a visual representation of yarn production variation, allowing for early detection of deviations from desired quality standards. Manufacturers can reduce waste, enhance product consistency, and uphold high yarn quality standards by promptly identifying and addressing these irregularities. Ultimately, the use of control charts improves overall process efficiency and customer satisfaction.

4.1.1. Control Charts for Thin and Thick Place

Following control charts enable the identification of deviations in yarn thickness, pinpointing sections that are either below or above the specified standard. These variations can have a substantial impact on the quality and performance of the end product.

Thin 40% places were monitored using c control charts based on 500 data points as shown in figure 4.1.

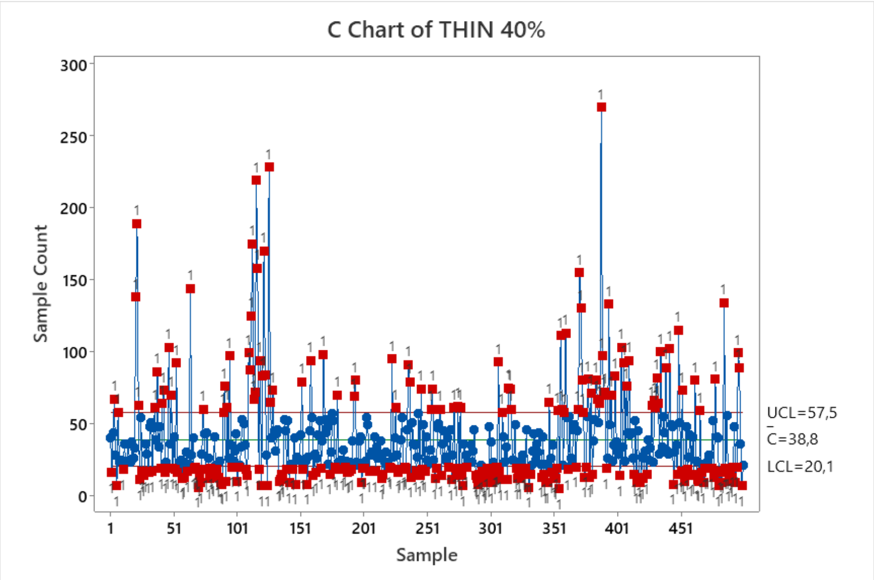


Figure 4.1. C Chart for Thin 40% Places

The "Thin Places (40%) C Chart" illustrates the frequency of defects (referred to as thin places) identified in each yarn sample. This chart features a central line ($\bar{C}$ = 38.8) denoting the average thin places count per sample, an upper control limit (UCL = 57.5), and a lower control limit (LCL = 20.1). Certain points exceed the UCL, and others fall below the LCL, suggesting the presence of both special causes of variation and unusually low defect counts.
Instances where points surpass the UCL or fall below the LCL highlight significant deviations from the average thin places count. This implies potential issues such as machinery malfunctions, raw material defects, or other process disturbances that necessitate thorough investigation. Notably, a few data points register values below LCL = 20.1. While initially suggesting a reduction in defects, this may also indicate a less comprehended shift in the process, such as an undetected adjustment or alteration in measurement practices. Therefore, it is crucial to investigate these points to confirm whether they genuinely represent improvements and not anomalies or errors in data collection. The chart depicts substantial variability in the number of defects, with some data points clustering around the mean and others exhibiting significant deviations beyond the UCL and LCL. This pattern suggests the presence of unstable process conditions leading to periods of unusually high and low defect rates. The existence of data points outside the UCL and LCL underscores the need for a thorough investigation to ensure process stability and consistent quality.

It is strongly recommended to conduct a thorough examination of instances that surpass the upper control limit (UCL) to pinpoint the root cause. Potential areas warranting investigation include machine settings, raw material quality, and operator errors during the specified periods. Although a reduction in defects below the lower control limit (LCL) may be perceived as a positive outcome, it is imperative to validate the authenticity of these occurrences to ensure they genuinely signify process improvements rather than arising from measurement or data recording errors. Following the investigative process, corrective actions based on the findings should be implemented to address the primary factors contributing to high defect counts. Furthermore, it is essential to verify the sustainability of any changes resulting in lower defect counts and ensure accurate documentation for process enhancement purposes.

After initially applying the C chart to monitor thin spots in the yarn production process, it was observed that the process was operating out of control. While the C chart effectively identifies significant shifts in the process by tracking defect counts, it may lack sensitivity in detecting smaller, gradual changes that can impact product quality.

To address this limitation and gain deeper insights into process variations, the Exponentially Weighted Moving Average (EWMA) control chart was introduced. Unlike the C chart, the EWMA chart assigns greater importance to recent observations, enabling a more responsive and sensitive approach to identifying process variations. This attribute proves valuable in detecting subtle, incremental changes that may not be immediately apparent in traditional control charts.

The integration of the EWMA chart alongside the C chart offers a more comprehensive understanding of process behavior. While the C chart effectively highlights significant issues, the EWMA chart is leveraged to further scrutinize the nature and extent of these deviations, ensuring that both major and minor variations are addressed. This dual-chart approach strengthens process control by combining the robust detection capabilities of the C chart with the refined sensitivity of the EWMA chart, leading to a more nuanced assessment of process stability and areas for potential enhancement. EWMA chart for Thin 40% places were monitored based on 500 data points as shown in figure 4.2.

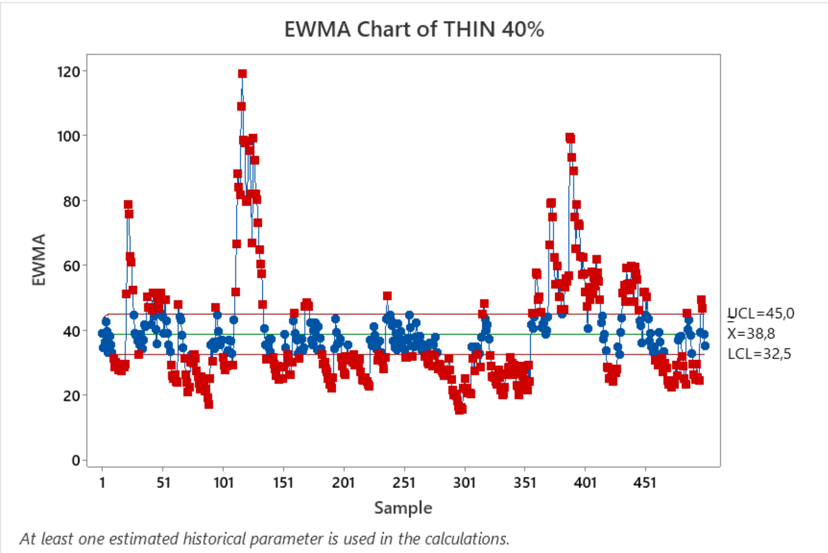


Figure 4.2. EWMA Control Chart for Thin Place

The EWMA chart reveals that the THIN 40% process is unstable due to a significant number of data points falling outside the control limits. The instability is evident from numerous points exceeding both the Upper Control Limit (UCL = 45.0) and the Lower Control Limit (LCL = 32.5), suggesting frequent operation outside the expected range.

The high number of out-of-control points, particularly those surpassing the UCL, signifies substantial variations in the process, likely driven by special causes such as equipment malfunctions, inconsistent raw material quality, or operational errors. The presence of outliers indicates the need for immediate investigation to identify and address the underlying causes of deviations. Additionally, the frequent occurrences of points below the LCL signal periods of unusually low variation, possibly indicating issues such as measurement errors or changes in process conditions that need verification.

To restore process stability, each point outside the control limits should be carefully examined to identify specific causes of variation. This may involve reviewing equipment maintenance records, evaluating raw material quality, and assessing operator performance during affected periods. Corrective actions, such as equipment repairs, process adjustments, or additional operator training, must be implemented once the causes of instability are identified.
Thick 50% places were monitored using c control charts based on 500 data points as shown in figure 4.3.

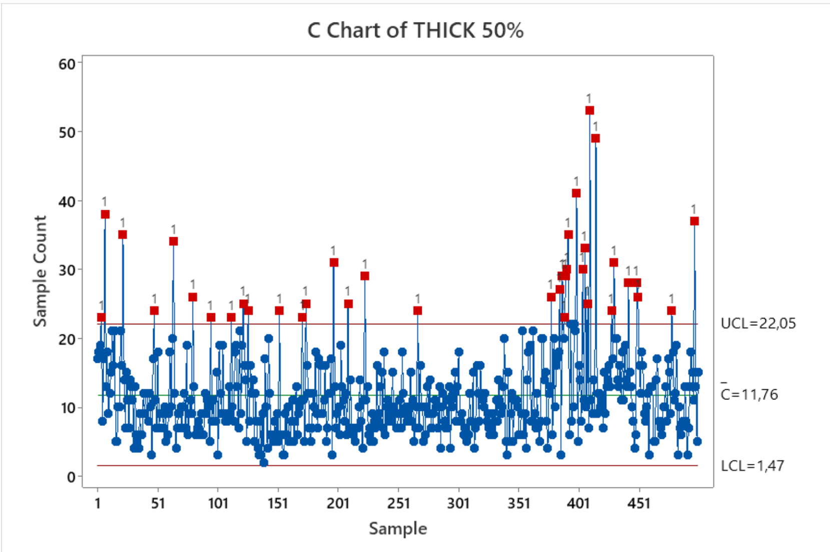


Figure 4.3. C Chart for Thick 50% Places

The C chart relating to thick places (50%) presents the occurrences of defects (thick places) identified in each yarn sample. In this chart, a central line ($\bar{C}$ = 11.76) portrays the average thick place count per sample, along with an upper control limit (UCL = 22.05) and a lower control limit (LCL = 1.47). There are several points surpassing the UCL and some in close proximity to the LCL, suggesting both special causes of variation and periods of low defect rates. The presence of numerous out-of-control points above the UCL indicates significantly higher thick place counts than the average, pointing to potential issues such as equipment malfunction, raw material quality fluctuations, or operational errors warranting investigation. Points near the LCL may signify periods of improved quality or reduced defect rates, but they could also hint at potential process changes or measurement errors, necessitating confirmation of their validity. Furthermore, the chart depicts substantial fluctuation in defect counts, with clusters of points near the average and notable deviations both above the UCL and near the LCL, suggesting an unstable process with both unusually high and low defect rates at different intervals.

It is advised to probe out-of-control points surpassing the UCL to identify their underlying causes, potentially involving reviewing machine maintenance records, examining raw material quality, and assessing operator performance during those periods. Concerning points near the LCL, although defect reduction is generally positive, it is crucial to ascertain whether these points truly indicate process improvements or rather changes in data collection or measurement errors. Following the investigations, corrective actions should be implemented based on the findings to address the root causes of high defect counts, and the sustainability and proper documentation of conditions leading to low defect rates should be verified.

Overall, while the process demonstrates general stability, the presence of points beyond the UCL and near or below the LCL points to variability requiring further investigation to ensure consistent process control and yarn quality.

After initially drawing c chart to monitor thick spots in the yarn production process, EWMA control chart is depicted for more sensitive approach to identifying process variations as shown in figure 4.4.

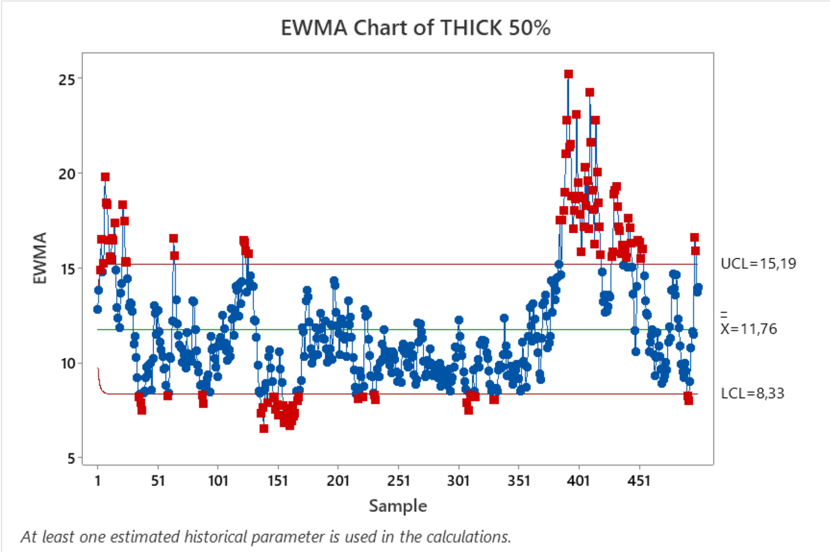


Figure 4.4. EWMA Control Chart for Thick 50% Place

The process control chart for THICK 50% using EWMA indicates significant instability, as evidenced by numerous data points falling outside the control limits. These consist of points exceeding the UCL at 15.19 and points dropping below the LCL at 8.33. The average performance of the process, denoted by the central line X at 11.76, is a key reference point. Notably, there is a critical concern regarding consecutive out-of-control points above the UCL, specifically around the 385th to 450th samples, indicating an extended period of heightened process variation. This sustained deviation suggests a consistent elevation in defects or variability during this timeframe, potentially stemming from equipment malfunction, material inconsistency, or systematic operational errors that require immediate attention. Additionally, there are instances of points falling below the LCL, particularly in the early stages of the chart, indicating significantly lower process variation. The presence of both high and low variation indicates substantial fluctuations, highlighting process instability in both directions. A thorough investigation into the root causes of these instabilities is essential, followed by the implementation of corrective actions to bring stability to the process, which may involve adjusting equipment settings, examining raw materials, retraining operators, or refining the measurement system.

Yarn quality is compromised by variations in yarn thickness, such as thick and thin spots, which also have a negative impact on the final application of the product and subsequent processes. Yarns with a higher frequency of irregularities experience more breakage during spinning and reduced efficiency in winding, warping, and weaving. Furthermore, these inconsistencies can affect the final dyeing process, potentially resulting in fabric that does not achieve the desired appearance (Mwasıagı & Mırembel, 2018). Hence, it is crucial to conduct a comprehensive analysis of occurrences surpassing the UCL to identify the underlying cause. According to Mwasiagı and Mirembe (2018), various factors contribute to a higher frequency of thin and thick areas in yarns, such as inadequate opening and cleaning of the in-feed material, incorrect piecing of yarn breaks during spinning, the inclusion of loose airborne fibers, and malfunctioning machinery operation.

The coefficient of mass variation (CVm%) and imperfections increased with higher rotor speeds, but this trend reversed as the opening roller speed went from 5000 to 7000 rpm. However, beyond this point, thin and thick places started to rise again (Jackowska-Strumiłło, Cyniak, Czekalski, & Jackowski, 2007). Ahmed, Saleemi, Rajput, Shaikh, and Sahito (2014) and Khan, Hossain, and Sarker (2015) have also observed similar findings. Furthermore, yarn count, yarn twist, and the type of rotor used during spinning have all been identified as factors that can increase the occurrence of thin and thick places (Mohamed Taher, Bechir, Mohamed, & Faouzi, 2009).

Minimizing thin and thick spots is important for spinners to produce high-quality yarns, as these spots can result in poor yarn and fabric appearance and reduce yarn strength, leading to more breakages during winding, weaving, and knitting operations.

4.1.2. Control Charts for Neps (%140) and Neps (%200)

The C chart for Neps 140% and Neps 200% displays the occurrences of defects (neps) identified in each yarn sample as shown in figure 4.5.

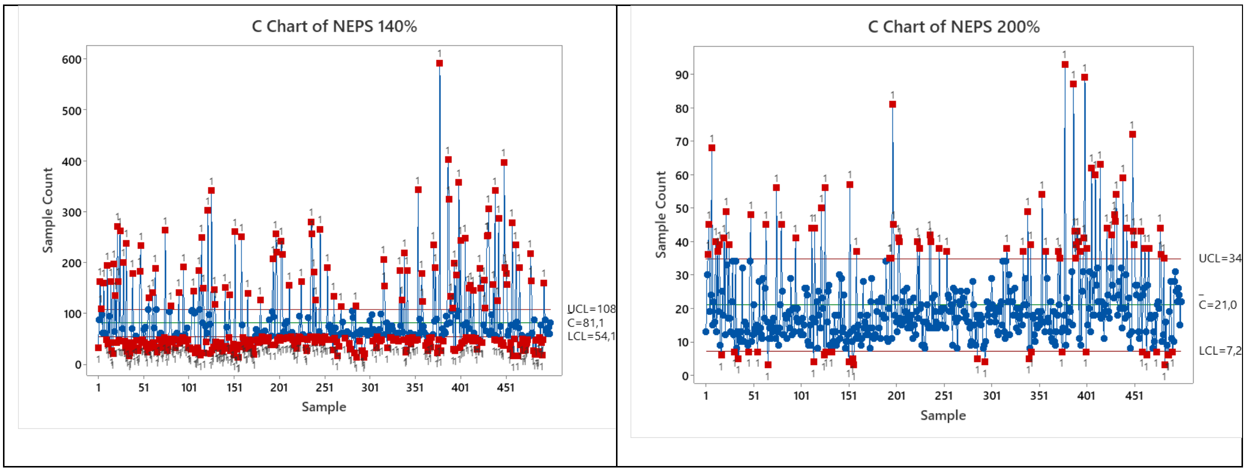


Figure 4.5. C Chart for Neps 140% and Neps 200%

The C chart for Neps 140% comprises a central line ($\bar{C}$ = 81.1) denoting the average neps count per sample, an upper control limit (UCL = 108.1), and a lower control limit (LCL = 54.1). There are multiple points exceeding the UCL and a significant number of points below the LCL, suggesting the presence of special causes of variation. Several data points surpass the UCL, indicating instances of unusually high neps counts

Also, the c chart illustrating Neps 200% displays the frequency of defects (neps) found in each yarn samples. It features a central line ($\bar{C}$ = 21.0) representing the average neps count per sample, an upper control limit (UCL = 34.7), and a lower control limit (LCL = 7.2). There are numerous points above the UCL and a few points below the LCL, suggesting the presence of special causes of variation. Like Neps 140%, multiple data points surpassing the UCL indicate periods where the neps count was significantly higher than the average, signaling potential issues. In comparison to the C chart for Neps 140%, the Neps 200% chart displays fewer points below the LCL, signifying that periods with fewer defects than average are less common compared to the 140% chart. This could imply that the process is slightly more stable at the 200% level, or that occurrences of exceptionally low defect counts are less frequent or better controlled.

Overall, the Neps 200% process appears marginally more stable than the Neps 140% process, with fewer points below the LCL and generally lower defect counts. However, consistent monitoring and investigation of out-of-control points are imperative for upholding quality control.

The EWMA chart presented in figure 4.6 for NEPS 140% and 200% serves as a tool for monitoring neps occurrence in yarn production, with a focus on identifying gradual shifts and trends within the process.

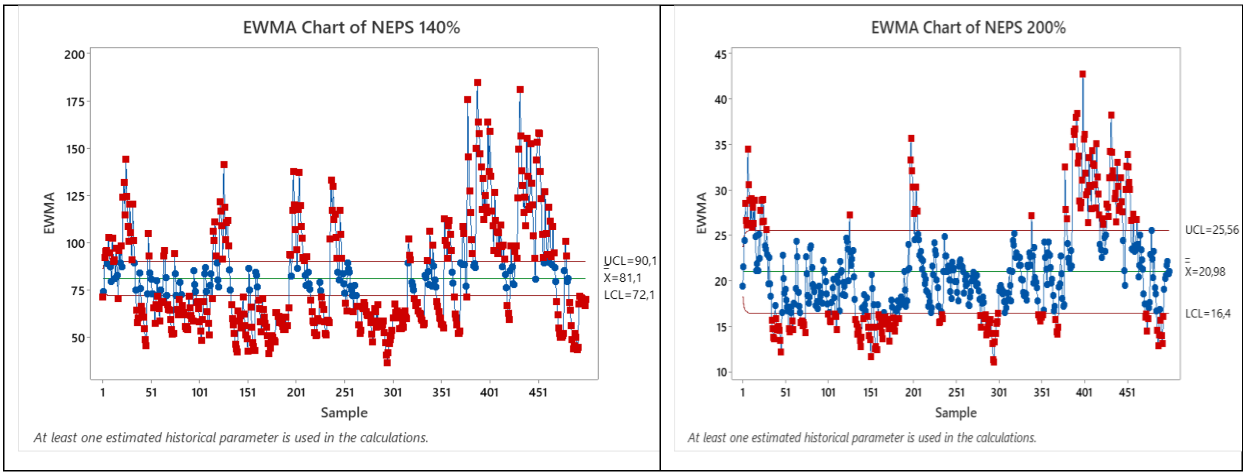


Figure 4.6. EWMA Chart for Neps 140% and Neps 200%

The EWMA charts for Neps 140% and Neps 200% aims to track minor shifts in the process mean concerning yarn quality in terms of neps. There are a considerable number of points exceeding the Upper Control Limit (UCL = 90.1) and falling below the Lower Control Limit (LCL = 72.1) for Neps 140%. The average process value is represented by the center line at 81.1. The numerous out-of-control points above the UCL signify periods with noticeably higher neps levels, indicating an increase in defects. Likewise, points below the LCL indicate periods with unusually low neps levels. The high number of points outside the control limits suggests a highly unstable process with inconsistent operation.

Also, there are a considerable number of points exceeding the Upper Control Limit (UCL = 25.56) and falling below the Lower Control Limit (LCL = 16.4) for Neps 200%. The average process value is represented by the center line at 20.98. Similar to the EWMA chart for NEPS 140%, out of control points indicate periods with a significantly higher number of neps, which may imply potential issues in the production process. Likewise, various points fall below the LCL, indicating periods with a remarkably lower number of neps than anticipated, signaling process instability. The presence of numerous out-of-control points implies substantial variability in the yarn production process for neps 200%.

This variability suggests an unstable process with multiple contributing factors causing these deviations, such as machinery issues, inconsistent raw material quality, variations in operator practices, or environmental conditions like temperature and humidity changes. In the EWMA chart for NEPS 200%, the out-of-control points above the UCL appear to be more concentrated toward the latter half of the samples, while in the 140% chart, the points are more dispersed throughout the entire sampling period.

Overall, to address the instability depicted in the charts, it is essential to investigate the out-of-control points and determine their root causes. The presence of neps reduces the visual appeal of yarn and the resulting fabrics by disrupting surface smoothness and dye uniformity (Frydrych & Matusiak, 2002). It is crucial to identify the primary reasons for a high nep count as these imperfections significantly impact the quality of yarn and fabric. Neps are commonly classified into two main categories: raw/biological neps and processing/mechanical neps. Biological neps are often linked to issues such as abnormal seeds, unfertilized ovules, and dead seeds, while processed cotton fiber (ginned cotton) neps typically contain seed coat fragments (SCF). Mechanical neps mainly consist of fibers and result from the manipulation of fibers during processing. The formation of neps is influenced by the characteristics of cotton lint and the mechanical handling (manipulation) of the fibers from the field to the yarn (van der Sluijs & Hunter, 2016). In light of this information, the company should analyze points that exceed the UCL to identify the causes of increased defect rates. This involves reviewing equipment settings, examining the quality of raw materials, and evaluating operational practices.

As a result, mechanical issues with spinning machinery or incorrect settings could cause frequent changes in yarn quality and neps levels. Also, variations in raw material quality, such as inconsistent fiber properties, might also lead to significant fluctuations. Operator variability, with different practices or non-compliance to standard procedures, could contribute to the observed instability. Environmental factors like temperature or humidity fluctuations could also affect yarn quality, leading to periods of instability. So, the correvtive actions may include;

- Checking and calibrating equipment,
- Reviewing raw material specifications and quality,
- Ensuring consistent operator training and adherence to standard procedures,
- Optimizing process parameters, including machine settings and raw material handling practices.

4.1.3. Control Charts for Coefficient of Variation of Mass Percentage (CVm%)

Another important parameter for assessing the uniformity and quality of yarn is the Coefficient of Variation of Mass Percentage (%CVm). The I-MR chart is used to monitor the %CVm value of each sample yarn as a variable chart for individuals. The chart depicted in figure 4.7 visually illustrates the uniformity of yarn mass by monitoring individual data points and the moving range.

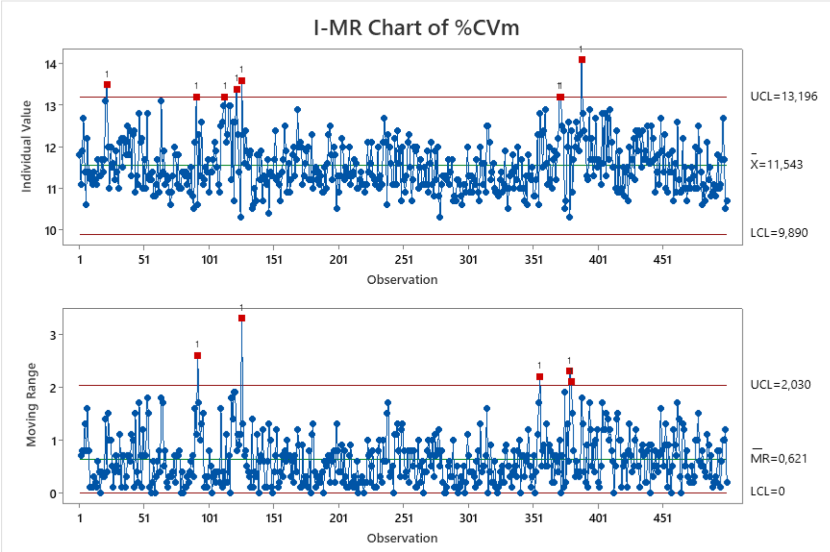


Figure 4.7. I-MR Chart for %CVm

The %CVm I-MR chart illustrates the process variability over time. The Individual Value plot contains a central line (X = 11.543) representing the average %CVm, along with an upper control limit (UCL = 13.196) and a lower control limit (LCL = 9.890). The Moving Range (MR) plot displays the fluctuations between consecutive observations, including an average range (MR = 0.621), an upper control limit (UCL = 2.030), and a lower control limit (LCL = 0).

In the Individual Value Chart, there are some points exceed the UCL, signifying out-of-control conditions. These occurrences suggest that the process has experienced special cause variation, likely due to factors outside normal operating conditions.
Similarly, the Moving Range chart exhibits several points above the UCL, indicating significant variations between consecutive %CVm measurements. These deviations, corresponding to the same observations as those in the Individual Value chart, reinforce the notion of special cause variation affecting the process. The presence of these points suggests abrupt changes in process stability, possibly due to operator errors, sudden shifts in environmental conditions, or inconsistencies in process inputs.

Although the process generally displays stability, the presence of out-of-control points above the UCL in both the Individual Value and Moving Range charts indicates periods of increased variability that deviate from the expected process behavior. It is recommended to investigate these out-of-control points to determine their root causes. This investigation may involve

reviewing equipment maintenance records, analyzing raw material quality, or assessing operator performance during these periods. Addressing these root causes will be crucial in bringing the process back under control and preventing similar issues in the future.
The EWMA chart for %CVm displayed in figure 4.8 presents a comprehensive assessment of process stability over time, bringing attention to gradual changes or patterns in yarn mass consistency.

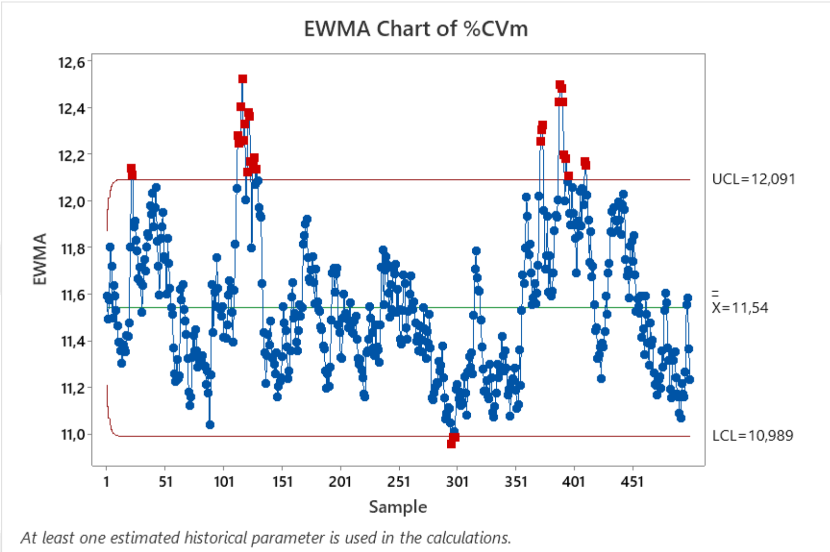


Figure 4.8. EWMA Control Chart for %CVm

In the EWMA chart for %CVm which is designed to detect slight shifts in the process mean related to yarn mass uniformity, there are numerous data points that surpass the Upper Control Limit (UCL = 12.091), and a few points fall below the Lower Control Limit (LCL = 10.989). The center line at 11.54 represents the average process value. Points exceeding the UCL indicate periods when %CVm values were significantly higher, suggesting increased variability in yarn mass. Similarly, points below the LCL indicate periods of unusually low variation. The presence of multiple points outside the control limits indicates an unstable and inconsistent process, signaling the need for further investigation and corrective actions to regain control.

The significance of monitoring mass variation in yarn production is underscored by the analysis of the I-MR and EWMA charts for %CVm, which echoes concerns raised by Carvalho, Pinto, Monteiro, Vasconcelos, and Soares (2004). Both the charts and Carvalho's research highlight the potential for deviations in mass uniformity to result in significant quality issues. The I-MR chart indicates out-of-control points, signifying special cause variation, which Carvalho et al. attributed to factors like raw material inconsistencies and environmental conditions. Carvalho et al. (2004) also emphasized the importance of detecting gradual shifts in yarn mass, which can have a long-term impact on quality. The EWMA chart effectively captures this by monitoring small shifts in the process mean for %CVm. The numerous out-of-control points observed in the EWMA chart align with Carvalho's findings, demonstrating the effectiveness of this method in identifying subtle yet significant variations in yarn mass.

Both studies highlight the need for further investigation into root causes, whether linked to equipment, operator error, or raw material quality. Addressing these variations is essential for restoring process stability and ensuring consistent yarn quality, as supported by both the control charts and Carvalho et al. (2004) conclusions.

4.2. Multivariate Control Charts of Selected Quality Characteristic

Multivariate control charts provide a more comprehensive approach to monitoring yarn quality by considering multiple quality characteristics simultaneously, such as thin places, thick places, and neps. Unlike univariate charts, which assess each quality attribute separately, multivariate control charts take into account the correlations between these variables, offering a more holistic view of the production process. In this study, various multivariate statistical process control techniques, including Hotelling T^2 chart, were utilized to monitor the combined behavior of yarn quality attributes. By analyzing multiple variables, multivariate control charts enable the identification of subtle variations that may not be apparent when examining each attribute individually. This approach improves the understanding of the relationships between defects and facilitates more effective detection of process shifts or deviations, ultimately supporting stronger process control and continuous quality enhancement in yarn production. The multivariate analysis enhances the company’s ability to detect process instability early, thereby reducing the likelihood of producing defective yarn and improving overall quality control performance.

4.2.1. Hotelling T2 Charts of Selected Quality Characteristic

Hotelling T^2 charts are a valuable tool for monitoring the combined variation of multiple correlated quality characteristics in multivariate statistical process control. In yarn production, attributes such as thin places, thick places, neps, %CVm and yarn strength are often interconnected. Hotelling T^2 charts allow for the simultaneous assessment of these variables, leading to a more comprehensive evaluation of the overall process. Unlike univariate control charts, which assess each quality attribute independently, Hotelling T^2 charts take into account the relationships between the attributes. This enables the detection of multivariate outliers or shifts that may indicate potential process disturbances. In this analysis, Hotelling T^2 charts were used to monitor the selected yarn quality characteristics, providing a robust monitoring framework. This approach enables the textile company to gain deeper insights into process stability and identify deviations that could affect yarn quality, ensuring better control and greater product consistency throughout the production process.

- **T^2 Chart for %CVm and Thin Place**

The T^2 chart is utilized to monitor the simultaneous behavior of %CVm and Thin Place, which are crucial quality characteristics in yarn production. Monitoring both attributes through a Hotelling T^2 chart allows for the detection of abnormal variations that may not be obvious when analyzed individually. Figure 4.11 visually represents the overall stability of the production process by considering the correlation between %CVm and Thin Place, ensuring prompt identification of any shifts or deviations from the desired quality standards.

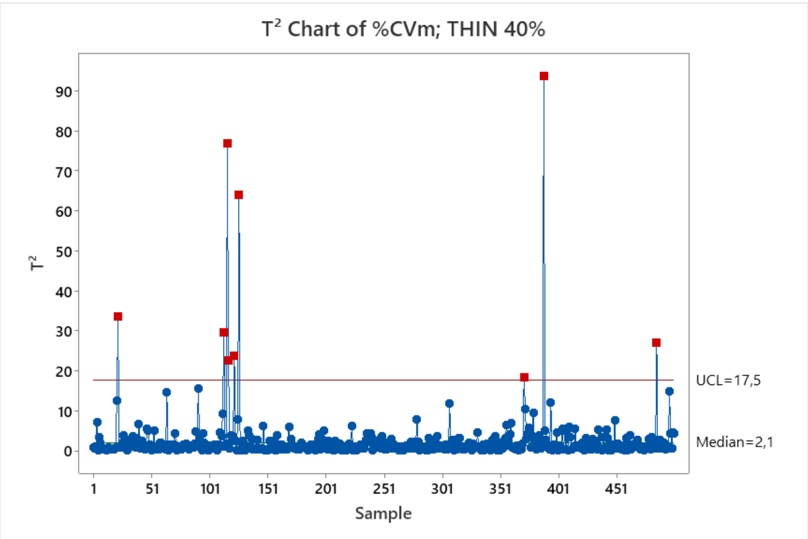


Figure 4.9. T^2 Chart for %CVm and Thin Place

The T^2 chart indicates that both %CVm and Thin 40% have multiple points exceeding the upper control limit (UCL = 17.5), signaling significant process variations that require investigation. These out-of-control points suggest that both %CVm and Thin 40% are experiencing variations beyond the expected process range and high variation in mass uniformity corresponds to increased occurrences of Thin Places. The relationship could be due to factors such as machinery issues, inconsistent raw material quality, or variations in the production process affecting both %CVm and Thin Places at the same time.

It is crucial to promptly investigate these specific points, especially those that significantly exceed the UCL. By addressing the root causes of these variations, the process can be brought back under control to maintain consistent quality in both %CVm and Thin 40%.

- **T^2 Chart for %CVm and Thick Place**

The T^2 chart is an essential tool for monitoring the combined behavior of %CVm (Coefficient of Variation of Mass Percentage) and Thick Place, two critical yarn quality attributes. By assessing both attributes together, the T^2 chart as shown in figure 4.12 provides a more comprehensive view of process stability, detecting shifts or deviations that may not be noticeable when evaluated individually.

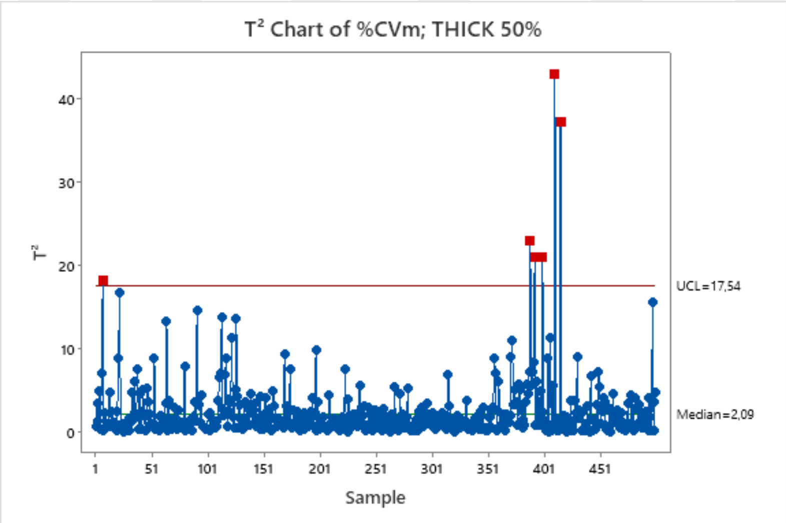


Figure 4.10. T^2 Chart for %CVm and Thick Place

The T^2 chart indicates that both %CVm and Thick 50% have several points exceeding the upper control limit (UCL = 17.54), indicating significant process deviations that require attention. Notably, out-of-control points are identified at samples 7, 388, 392, 399, 410, and 415. Specifically, Thick 50% shows significant deviation for samples 7, 392, 399, 410, and 415, while %CVm exceeds the UCL at samples 388 and 392. This observed pattern suggests a likely connection between higher mass variation (%CVm) and the occurrence of thick places in the yarn, particularly in the later sample periods. The simultaneous exceeding of control limits for both variables around the same time points indicates a potential correlation between fluctuations in yarn mass uniformity and increases in the frequency of thick places. This correlation could be attributed to shared underlying factors such as machinery settings, raw material inconsistencies, or operator errors affecting both the yarn's mass variation and thickness consistency. The presence of red squares above the UCL underscores the importance of further investigation, particularly around samples 388 to 415, where the highest levels of variability and defect occurrence are observed. It is imperative to conduct a root cause analysis to identify issues with the production process, machinery performance, or raw material inputs that may be contributing to these variations. Addressing these deviations will enable the company to work towards stabilizing both %CVm and Thick 50%, ultimately leading to more consistent product quality.

- **T^2 Chart for %CVm and Neps**

The T^2 chart monitors the correlation between yarn mass variation (%CVm) and the occurrence of neps, which are small knots or entanglements in the yarn. By examining these two critical quality characteristics together, the T^2 chart offers a more comprehensive evaluation of process stability. Neps and %CVm are crucial indicators of yarn quality, impacting the consistency and performance of the final textile product. The charts shown in figure 4.13 identifies any departures from the desired process parameters, allowing early detection of shifts or variations that could impact product quality.

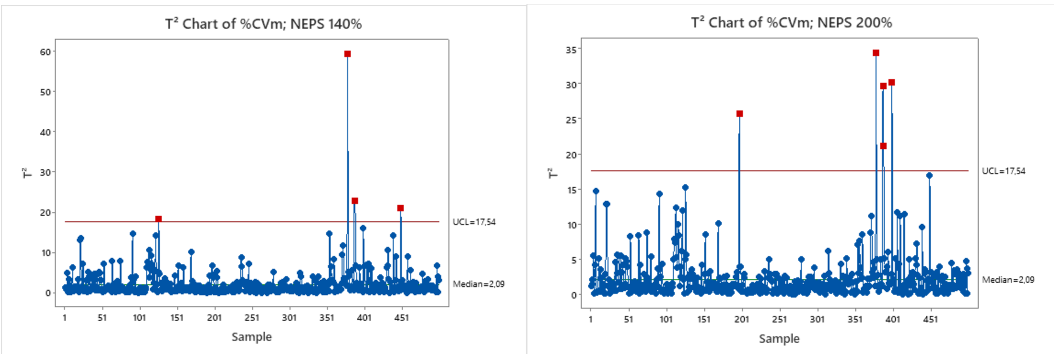


Figure 4.11. T^2 Chart for %CVm and Neps

The T^2 Charts for %Cvm and Neps display the multivariate monitoring of yarn quality, specifically focusing on mass variation (%CVm) and the occurrence of neps. On T^2 Chart for

%CVm and Neps 140% points exceeding the upper control limit (UCL = 17.54) indicate significant deviations from stability in the process. There are extreme outliers with significantly higher T^2 values, suggesting potential special causes of variation.

These points indicate that the process is not entirely stable, where both %CVm and Neps 140% have simultaneously deviated from their expected behavior. Similarly T^2 chart for %CVm and Neps 200% shows multiple points that exceed the upper control limit (UCL = 17.54), indicating significant process deviations. The presence of these out-of-control points indicates the need for corrective actions to bring the process back within control limits, ensuring stable and consistent yarn quality. The extreme points, indicate potential issues such as inconsistencies in raw materials, equipment malfunctions, or process disturbances affecting both the yarn's mass and the occurrence of neps. This suggests that the process during these samples was unstable and requires further investigation to identify and address the root causes of the variation.

- **T^2 Chart for %CVm and RKM**

Both %CVm, indicating the consistency of yarn mass, and RKM, measuring the yarn's tensile strength, are crucial quality indicators. Through the simultaneous evaluation of these two factors, the T^2 chart offers a comprehensive overview of the production process, enabling early identification of deviations or irregularities that may impact the yarn's performance. This multivariate approach ensures the capture of any interconnected variations between yarn mass consistency and strength, facilitating more efficient quality control and process stability.

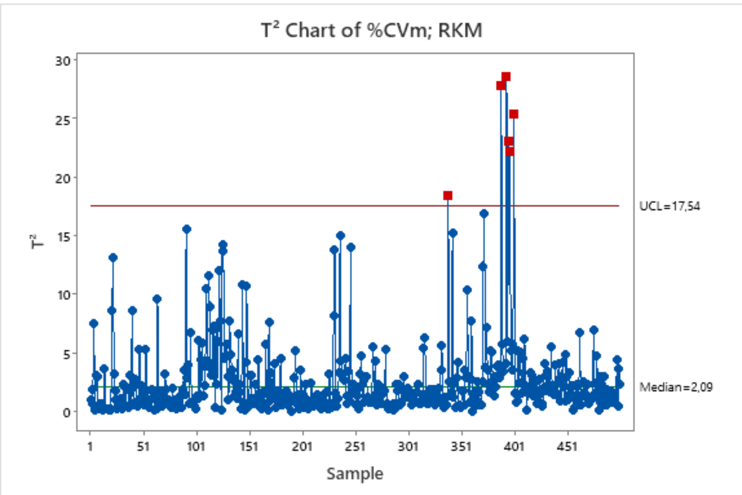


Figure 4.12. T^2 Chart for %CVm and RKM

The T^2 chart for %CVm and RKM demonstrates the correlation between yarn mass variation (%CVm) and its breaking strength (RKM) over time. The chart reveals multiple data points surpassing the upper control limit (UCL = 17.54) and indicates significant process instability during this timeframe. These out-of-control points suggest simultaneous abnormal fluctuations in the yarn's mass variation and breaking strength, potentially stemming from issues such as raw material inconsistencies, machine malfunctions, or environmental conditions affecting both characteristics. The presence of consecutive points exceeding the UCL emphasizes the need for further investigation into the process during this specific period. It is crucial to identify and address the root causes of these variations to restore control to the process. While most of the process seems stable, the period with out-of-control points raises concerns that necessitate corrective actions to ensure consistent yarn quality in terms of both mass uniformity and tensile strength.

- **T^2 Chart for RKM and Thin 40%**

The RKM serves as a crucial measure of the yarn's strength under tension, while Thin 40% is an important indication of unevenness in the yarn. By examining these two factors concurrently, the T^2 chart offers a more comprehensive perspective on the process, aiding in the identification of potential shifts or deviations that could impact both the strength and uniformity of the yarn. The control chart shown in figure 4.14 monitors any connections between weaknesses in strength and an increase in thin areas, allowing for early intervention and ensuring that the yarn adheres to quality standards in terms of both resilience and regularity.

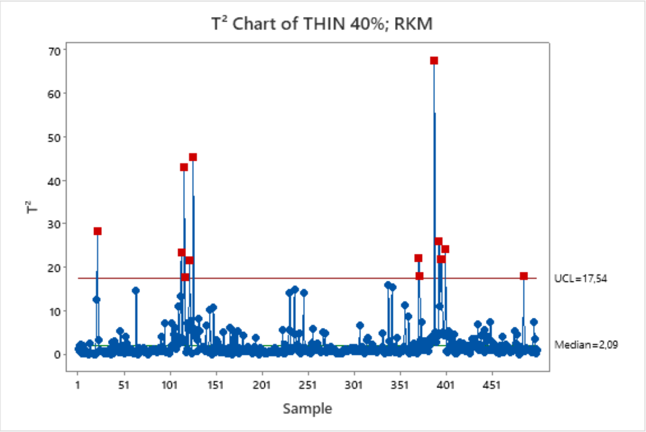


Figure 4.13. T^2 Chart for RKM and Thin 40%

The T^2 chart shows the relationship between the breaking strength of the yarn (RKM) and the presence of thin areas (40% thin places) in the yarn. There are multiple data points that exceed the upper control limit (UCL = 17.54), indicating significant deviations in the production process. These out-of-control points imply that both yarn strength and uniformity were compromised at the same time, highlighting potential issues in the production process. It seems that as the number of thin places increases, the breaking strength of the yarn (RKM) decreases, suggesting that a higher occurrence of thin spots may have a negative impact on yarn strength. This simultaneous deviation in both characteristics suggests a relationship between the two variables, where decreases in yarn strength are connected to an increased presence of thin areas.

In general, the chart indicates that the process is unstable during specific periods, and the potential correlation between RKM and thin places should be further examined. It will be crucial to address the underlying causes of these variations in order to enhance both yarn strength and uniformity, ensuring a consistent production process.

- **T^2 Chart for RKM and Thick 50%**

Just like thin places impact RKM, thick places also have an impact on the strength of the yarn, causing variations in tensile performance. Figure 4.15 demonstrates these interactions, depicting how the combination of these variables aids in identifying process variations that may not be apparent when analyzing each characteristic independently.

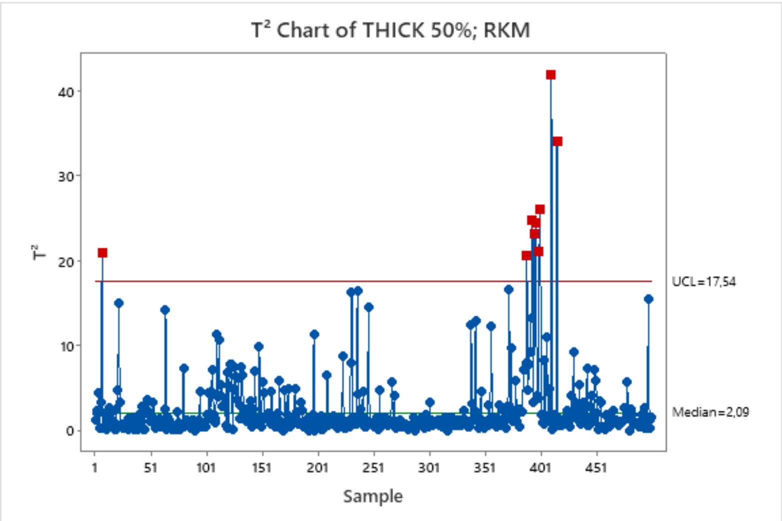


Figure 4.14. T^2 Chart for RKM and Thick 50%

Significant deviations from process stability are indicated by several points exceeding the upper control limit (UCL = 17.54). These out-of-control points suggest a correlation between thick places and RKM, indicating that as the number of thick places increases, the yarn's breaking strength tends to deviate, potentially leading to weaker sections.

The presence of thick places directly influences RKM, as suggested by the spikes in T^2 values, potentially reducing the yarn's tensile strength. Simultaneous deviations in both variables indicate a relationship where increased mass in certain areas of the yarn (thick places) compromises its overall breaking strength. This correlation emphasizes the need for controlling thick places to maintain consistent RKM values and ensure high-quality yarn production.

- **T^2 Chart for RKM and Neps**

The tensile strength of the yarn is influenced by both thin and thick areas, as well as neps, which can weaken the yarn significantly. In Figure 4.16, the interaction between RKM and neps is depicted, and the T^2 charts show the deviations that occur in the presence of neps. This chart offers insight into how neps affect the breaking strength of the yarn, making it possible to identify process variations that may not be readily apparent when analyzed individually.

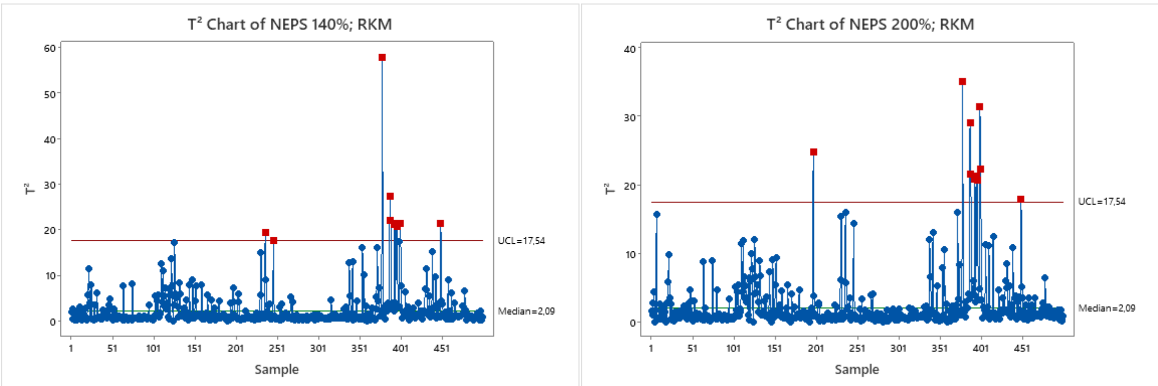


Figure 4.15. T^2 Chart for RKM and Neps

The T^2 charts for Neps 140% and Neps 200% concerning RKM provide valuable insights into the connection between neps and yarn strength. In both charts, there are several points that surpass the upper control limit (UCL = 17.54), indicating process instability. The spikes in T^2 values imply that the presence of neps (both 140% and 200%) is linked to variations in the yarn's breaking strength (RKM), demonstrating that as the number of neps increases, the RKM values tend to deviate, potentially leading to weakened sections in the yarn.

The Neps 140% chart exhibits a more prominent out-of-control point near sample 380, whereas in the Neps 200% chart, the deviations occur more frequently between samples 350 and 450. This indicates that higher levels of neps (both 140% and 200%) directly impact yarn strength, resulting in weak spots that diminish the yarn's tensile strength.

In summary, the correlation between RKM and Neps is evident in both charts, as an increase in neps consistently coincides with deviations in RKM. This underscores the significance of managing neps during the production process to uphold consistent yarn strength and quality.

- **T^2 Chart for %CVm, Thin 40% and RKM**

The T^2 chart for %CVm, Thin 40%, and RKM serves as a multivariate control chart, monitoring three essential quality characteristics concurrently: yarn mass variation (%CVm), the occurrence of thin places (Thin 40%), and yarn breaking strength (RKM). Illustrated in Figure 4.17, the control chart demonstrates how fluctuations in yarn mass and the presence of thin places can impact the yarn's tensile strength, providing valuable insights into ensuring consistent yarn quality and process stability.

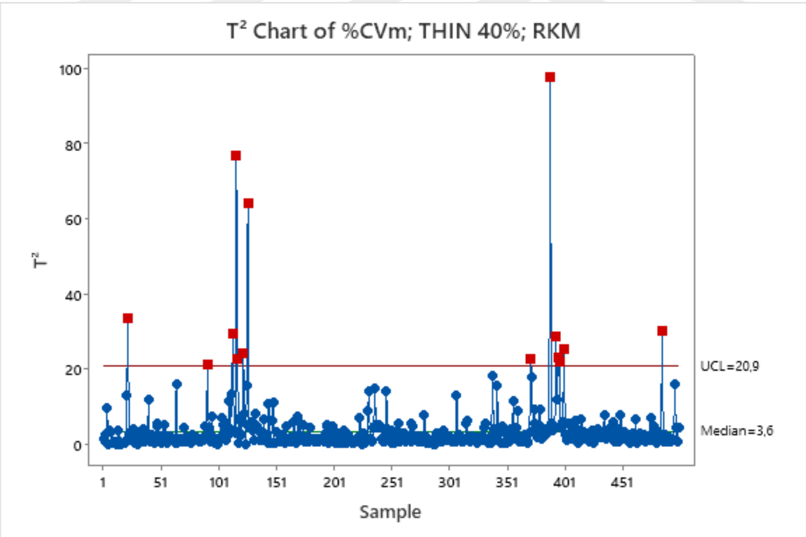


Figure 4.16. T^2 Chart for %CVm, Thin 40% and RKM

The T^2 chart displays the connection between yarn mass variation (%CVm), thin places occurrence (Thin 40%), and yarn breaking strength (RKM). Multiple points exceeding the upper control limit (UCL = 20.9) indicates significant process instability. The presence of out-of-control points for %CVm, Thin 40%, and RKM suggests a correlation between these variables. Specifically, an increase in yarn mass variation and thin places occurrence seems to coincide with deviations in RKM, resulting in reduced breaking strength. This implies that greater mass inconsistency and more frequent thin areas compromise the yarn's tensile strength.

In summary, the chart indicates a clear correlation between %CVm, Thin 40%, and RKM. The variations in these quality characteristics are closely interconnected, with fluctuations in yarn mass and thin places impacting the yarn's overall strength. This underscores the importance of monitoring these characteristics together to ensure yarn stability and quality.

- **T^2 Chart for Thin 40%, Thick 50% and RKM**

The T^2 chart for Thin 40%, Thick 50%, and RKM monitors three important quality characteristics at the same time: thin places (Thin 40%), thick places (Thick 50%), and the breaking strength of the yarn (RKM). By examining these factors together, the chart offers a comprehensive perspective on how yarn defects, like thin and thick places, are related to tensile strength. Illustrated in Figure 4.18, this control chart assists in identifying how variations in yarn consistency impact its overall strength, enabling early detection of process changes that might influence yarn quality.

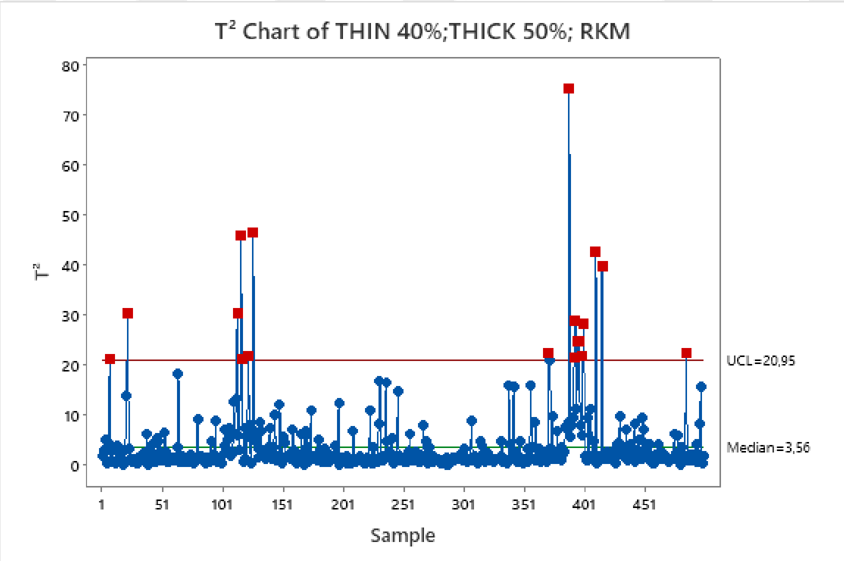


Figure 4.17. T^2 Chart for Thin 40%, Thick 50% and RKM

The T^2 chart delineates the relationship between yarn defects (thin places at 40% and thick places at 50%) and breaking strength (RKM). Multiple data points surpass the upper control limit (UCL = 20.95), signifying substantial process deviations during these periods. The concurrent presence of out-of-control points for these three characteristics implies a potential correlation among them. Specifically, as the number of thin or thick places in the yarn increases, the RKM tends to deviate from anticipated values, indicating a reduction in the yarn's tensile strength. The spikes in T^2 values, signify that both thin and thick places exert a negative impact on the yarn's overall strength. In summary, this chart underscores a correlation between the prevalence of thin and thick places and the yarn's breaking strength (RKM). Heightened yarn irregularities (both thin and thick places) are linked to a reduction in tensile strength, emphasizing the significance of managing these defects to uphold consistent yarn quality.

The T^2 charts' findings for yarn quality characteristics, such as Thin 40%, Thick 50%, %CVm, Neps and RKM, state the correlation between yarn irregularities and breaking strength. These results align with existing academic literature on using multivariate control charts for monitoring yarn quality. Specifically, the out-of-control points on the T^2 charts indicate that increases in thin or thick places coincide with deviations in RKM, suggesting that yarn defects significantly impact tensile strength, a conclusion supported by various studies in the field.

Abdulghafour et al. (2021) state that statistical control charts are effective for identifying deviations in yarn quality and detecting process shifts related to yarn defects such as thin places, thick places, and irregular mass distribution. Their study confirmed that defects in yarn directly influence the overall strength and performance of the final product, aligning with the findings in the T^2 charts analyzed in this study. The appearance of out-of-control points in the charts underscores the need for rigorous monitoring and immediate corrective actions to address variations in mass distribution and defect occurrences, similar to the conclusions drawn by Abdulghafour et al.

Furthermore, the study by Maroš, Vladimír, and Caner (2011) supports the findings in the charts regarding the impact of yarn defects on strength. Their research utilized image processing combined with control charts to monitor yarn defects and showed that irregularities, such as thick and thin places, led to considerable quality issues in the production process. Like the results from the T^2 charts, they observed that defects directly impacted the structural integrity of the yarn, causing fluctuations in tensile strength. This correlation between defect occurrence and quality instability is consistent with the present study's findings, where variations in yarn mass (thin/thick places) negatively affected RKM.

5. CONCLUSSION

The research in this thesis aimed to fill a notable gap in the existing literature by examining the utilization of multivariate statistical process control (MSPC) techniques in quality management, particularly within the yarn production process of the textile industry. The primary objective was to assess whether MSPC methods, such as Hotelling T^2, MCUSUM, and MEWMA charts, could better detect and handle process variations compared to traditional univariate methods. These methods were used to evaluate the quality attributes of yarns, focusing specifically on thin places, thick places, neps, RKM, and %CVm in the "28/1 RNG PE/V 67/33 w/o lycra" yarn type, which was the most frequently produced by the company under study.

The main issue explored in this study was whether traditional univariate statistical process control (USPC) methods, like control charts for individual characteristics, were adequate for identifying quality issues in a complex, multivariate production setting. This concern was addressed by comparing the efficiency and effectiveness of MSPC methods with USPC, specifically in the context of yarn quality control within a textile production facility. The results indicate that MSPC methods provide a more comprehensive insight into the variations in yarn production quality by simultaneously monitoring multiple interconnected quality attributes.

The multivariate control charts showed their capability to uncover relationships between variables like %CVm and defect frequency (e.g., thin places and thick places), which univariate methods couldn't detect. For instance, the Hotelling T^2 charts revealed instances where %CVm and defects deviated simultaneously, indicating a correlation between yarn mass variation and defects, such as thin places. This supports the idea that multivariate control charts offer a more comprehensive view of process variability, aiding in the identification of quality issues' root causes and the implementation of corrective measures.

The techniques utilized in this research, including the analysis of 500 samples and the use of MSPC charts, offered compelling evidence for the benefits of employing multivariate approaches in real-world industrial settings. The experimental findings demonstrated that MSPC techniques could detect process behavior shifts earlier and with higher sensitivity than univariate methods, which frequently missed these shifts in the initial stages. These findings align with previous literature, particularly with studies by Carvalho et al. (2004), who also emphasized the significance of multivariate analysis in intricate production environments. Moreover, this study tackled the practical research inquiry of the most effective way to monitor yarn quality in real-time, offering clear solutions and useful insights for professionals in the industry. By utilizing MSPC methods, not only was the detection of process variability improved, but waste was also reduced, and overall product consistency was enhanced, leading to better quality management practices in the textile sector.

In summary, this research validates the efficiency of MSPC methods in identifying and managing process variability in yarn production. The results align with existing academic research, endorsing the integration of multivariate control charts in the industry to uphold higher quality standards and more streamlined production processes. The successful implementation of these methods showcases their practical value and establishes a groundwork for further exploration in other areas of textile manufacturing. Subsequent studies should focus on investigating how these methods can be employed in various yarn types and production processes to generalize the findings and expand their industrial relevance.

6. RECOMMENDATIONS

The thesis findings suggest several recommendations for future research and advancements in textile specifically in yarn production quality control. These recommendations are based on the results of MSPC methods used in the study and aim to address areas requiring further exploration and refinement. Future research should consider broadening the application of MSPC methods to encompass various yarn types, fiber blends, and production processes to validate their effectiveness across different contexts.

Further research could explore integrating MSPC with real-time data analysis systems, such as Industry 4.0 and smart manufacturing technologies, to enhance real-time quality monitoring and control. In addition to identifying correlations between variables and defects, future research should combine MSPC with root cause analysis techniques to precisely identify factors contributing to process variability.

There is a need to investigate the practical implementation challenges textile companies may encounter when adopting MSPC methods, including assessing the economic and operational feasibility of large-scale adoption in different segments of the textile industry.

Finally, future research should explore how MSPC methods can be adapted and applied in sustainable manufacturing practices to help minimize inefficiencies, reduce waste due to defects, and contribute to more sustainable production processes.

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APPENDIX

Ek A Constants For Univariate Control Charts

Appendix A - Factors for Univariate Control Charts

Observations in Sample, n	Chart for Averages: Factors for Control Limits A	A_2	A_3	Chart for Averages: Factors for Center Line c_4	$1/c_4$	Chart for Standard Deviations: Factors for Control Limits B_3	B_4	B_5	B_6	Chart for Ranges: Factors for Center Line d_2	$1/d_2$	Chart for Ranges: Factors for Control Limits d_3	D_1	D_2	D_3	D_4
2	2.121	1.880	2.659	0.7979	1.2533	0	3.267	0	2.606	1.128	0.8865	0.853	0	3.686	0	3.267
3	1.732	1.023	1.954	0.8862	1.1284	0	2.568	0	2.276	1.693	0.5907	0.888	0	4.358	0	2.574
4	1.500	0.729	1.628	0.9213	1.0854	0	2.266	0	2.088	2.059	0.4857	0.880	0	4.698	0	2.282
5	1.342	0.577	1.427	0.9400	1.0638	0	2.089	0	1.964	2.326	0.4299	0.864	0	4.918	0	2.114
6	1.225	0.483	1.287	0.9515	1.0510	0.030	1.970	0.029	1.874	2.534	0.3946	0.848	0	5.078	0	2.004
7	1.134	0.419	1.182	0.9594	1.0423	0.118	1.882	0.113	1.806	2.704	0.3698	0.833	0.204	5.204	0.076	1.924
8	1.061	0.373	1.099	0.9650	1.0363	0.185	1.815	0.179	1.751	2.847	0.3512	0.820	0.388	5.306	0.136	1.864
9	1.000	0.337	1.032	0.9693	1.0317	0.239	1.761	0.232	1.707	2.970	0.3367	0.808	0.547	5.393	0.184	1.816
10	0.949	0.308	0.975	0.9727	1.0281	0.284	1.716	0.276	1.669	3.078	0.3249	0.797	0.687	5.469	0.223	1.777
11	0.905	0.285	0.927	0.9754	1.0252	0.321	1.679	0.313	1.637	3.173	0.3152	0.787	0.811	5.535	0.256	1.744
12	0.866	0.266	0.886	0.9776	1.0229	0.354	1.646	0.346	1.610	3.258	0.3069	0.778	0.922	5.594	0.283	1.717
13	0.832	0.249	0.850	0.9794	1.0210	0.382	1.618	0.374	1.585	3.336	0.2998	0.770	1.025	5.647	0.307	1.693
14	0.802	0.235	0.817	0.9810	1.0194	0.406	1.594	0.399	1.563	3.407	0.2935	0.763	1.118	5.696	0.328	1.672
15	0.775	0.223	0.789	0.9823	1.0180	0.428	1.572	0.421	1.544	3.472	0.2880	0.756	1.203	5.741	0.347	1.653
16	0.750	0.212	0.763	0.9835	1.0168	0.448	1.552	0.440	1.526	3.532	0.2831	0.750	1.282	5.782	0.363	1.637
17	0.728	0.203	0.739	0.9845	1.0157	0.466	1.534	0.458	1.511	3.588	0.2787	0.744	1.356	5.820	0.378	1.622
18	0.707	0.194	0.718	0.9854	1.0148	0.482	1.518	0.475	1.496	3.640	0.2747	0.739	1.424	5.856	0.391	1.608
19	0.688	0.187	0.698	0.9862	1.0140	0.497	1.503	0.490	1.483	3.689	0.2711	0.734	1.487	5.891	0.403	1.597
20	0.671	0.180	0.680	0.9869	1.0133	0.510	1.490	0.504	1.470	3.735	0.2677	0.729	1.549	5.921	0.415	1.585
21	0.655	0.173	0.663	0.9876	1.0126	0.523	1.477	0.516	1.459	3.778	0.2647	0.724	1.605	5.951	0.425	1.575
22	0.640	0.167	0.647	0.9882	1.0119	0.534	1.466	0.528	1.448	3.819	0.2618	0.720	1.659	5.979	0.434	1.566
23	0.626	0.162	0.633	0.9887	1.0114	0.545	1.455	0.539	1.438	3.858	0.2592	0.716	1.710	6.006	0.443	1.557
24	0.612	0.157	0.619	0.9892	1.0109	0.555	1.445	0.549	1.429	3.895	0.2567	0.712	1.759	6.031	0.451	1.548
25	0.600	0.153	0.606	0.9896	1.0105	0.565	1.435	0.559	1.420	3.931	0.2544	0.708	1.806	6.056	0.459	1.541

For $n > 25$.

$$A = \frac{3}{\sqrt{n}} \qquad A_3 = \frac{3}{c_4\sqrt{n}} \qquad c_4 \cong \frac{4(n-1)}{4n-3}$$

$$B_3 = 1 - \frac{3}{c_4\sqrt{2(n-1)}} \qquad B_4 = 1 + \frac{3}{c_4\sqrt{2(n-1)}}$$

$$B_5 = c_4 - \frac{3}{\sqrt{2(n-1)}} \qquad B_6 = c_4 + \frac{3}{\sqrt{2(n-1)}}$$