Prioritization of the product characteristics for implementation of process control in powertrain production.

Master's Thesis in the master's Program

Product Development

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CHALMERS UNIVERSITY OF TECHNOLOGY

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MASTER'S THESIS 2019

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Abstract

The purpose of this research is to explore the method used by Volvo Group trucks operations to prioritize the product characteristics for implementing Statistical process control (SPC) and identify its limitations and to propose a new method that can overcome its limitations. This thesis focusses on Statistical process control (SPC) in the gear machining processes of Volvo powertrain manufacturing center at Köping. The company has a need for developing a better model for prioritizing product characteristics for implementing SPC and in order to be prepared for SPC in the new manufacturing realm of industry 4.0. The company is looking to understand the future form of SPC like the advantages and differences in methodologies. This thesis project was conducted by Harikrishna Balakrishna Kurup. The method used at Volvo powertrain manufacturing center at Köping for prioritizing product characteristics for implementation of SPC was analyzed and was compared against the best method used in the industry for the same purpose and a new method is proposed in this thesis which can be used in the context of Köping factory environment making the best use of available data at Köping factory. A theoretical study about changes that new technological improvements have made on statistical process control was conducted and It was tried to understand future SPC process and how it will be like and what are the additional benefits of the new form of SPC were evaluated. a comparison of new and old forms of statistical process control was made.

Keywords: SPC, Product characteristics, Industry 4.0, IoT, MPC, PPC.

ABBREVIATIONS

AI Artificial intelligence

AIAG Automotive industry action group

ANN Artificial neural network

AR Augmented reality

CIM computer integrated manufacturing

CPS Cyber-physical systems

DOE Design of Experiments

FMEA Failure mode effect analysis

GTO Group trucks operations

HR Human Resources

IIOT Industrial internet of things

IoT Internet of things

ISO International organization for standardization

KQC Key Quality characteristics

MPC Model predictive control

PPC predictive process control

R&D Research and Development

SPC   Statistical Process Control

TQM Total quality management.

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Thesis Disposition

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- The first chapter gives an introduction to this thesis, Research case is described here, Aim, purpose of the thesis, research questions, the thesis scope and limitations are also presented here.

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- In this chapter, the chosen research strategy and design, data collection, and analysis, are presented and explained how it has been implemented in the study.

Chapter3 Theory

- This chapter presents relevant theories related to process control and TQM.

Chapter 4 Results

- this chapter presents the results from the analytical study regarding the current method used at Volvo powertrain regarding prioritizing product characteristics for the implementation of process control.

Chapter5 Conclusion

- This chapter presents the conclusion of the comparison of current method used by Volvo against theoretical method and best practice in the industry.

Chapter6 Reccomendations

- This chapter presents the new recommended model for prioritizing the product characteristics for the implementation of process control.

1. Introduction

1.1. Background

A process in the manufacturing industry can be kept under control by monitoring the process with statistical means and making the right steering actions to bring back the process under control by identifying and fixing the anomalies (D. C. Montgomery, 2009). Statistical process control (SPC) is a method used to easily collect and analyze the data which enables monitoring of the process and achieving sustainable and effective improvements in quality, as a result improving the profitability and financial performance of an organization along with customer satisfaction. SPC makes it happen by monitoring the process and identifying special causes of variation thus making it possible to take corrective and preventive actions to eliminate sources of variation so that characteristics of interest will always remain within the predefined boundaries (Lisha Ma, 2016). Automotive supply chain manual TS 16949 defines product characteristics as features of a product, part, an installation, or an assembly, or detail of a part with dimension and having representation in engineering drawing. variation in a product characteristic can have an impact on the form, fit, performance, or service life of a product. In today's competitive market, when consumers are more demanding than ever, while they demand highest level of safety they are also concerned about cost and energy efficiency and environmental impact of the vehicles.

If customers delight is what an organization striving to achieve. It is critical not only to meet but also to exceed customer expectations. Products rolling out of the production lines should comply with the highest quality standards (Bauer, C. & Wee, 2015). It has been proved that statistical process control is an effective method with the help of which products with the highest level of quality can be delivered to the customer (Bo Bergman, 2010).

In contemporary organizations, technological development and innovation play an important role. The fourth industrial revolution (Industry 4.0) has already started and reshapes the future by radically changing the entire manufacturing processes and the way how manufacturing was thought about in a conventional way, by integrating a large number of new and recently developed technologies into the existing manufacturing processes.

Also, Industry 4.0 will influence the entire value chain and offer many new opportunities for innovative business models, improved production technology, creation of new jobs and better work organization.

Liu and Zhou (2015) defined Industry 4.0 as the integration of information and communications technologies with industrial technology. According to Pereira and Romero (2017). Industry 4.0 will lead to potential deep changes in several domains that go beyond the industrial sector. Industry 4.0 includes many fast-changing and disruptive factors, such as digital manufacturing, network communication, computer, and automation technologies. Moreover, many companies are adopting a set of new technologies such as Cyber-Physical System (CPS), Internet of Things(IoT), Robotics, Big Data (BD), Cloud Manufacturing (CM) and Augmented Reality (AR) to improve their products and processes and increase the efficiency and productivity of their production (Schmidt, et al., 2015).

1.2. Case Description

Volvo Group is a global truck manufacturer with headquarters in Gothenburg Sweden under the ownership of AB Volvo. It is the second-largest manufacturer of heavy-duty trucks by sales. Customer satisfaction has always been a priority and always will be a priority for the Volvo group and it has been at the forefront of adopting new methods and technologies not only in the products but also in the process as well as management.

Volvo Group's global trucks operation organization encompasses all production of the Group's engines and transmissions as well as all production of Volvo, Renault, Mack, and UD trucks. (Volvo Group, u.d.)

The organization also includes spare parts supplies to the Group's customers as well as logistics. This thesis is based on an industrial project at the Köping factory of Volvo powertrain production under Volvo group trucks operations. And the scope of the thesis focuses on the gear machining area of Köping manufacturing factory.

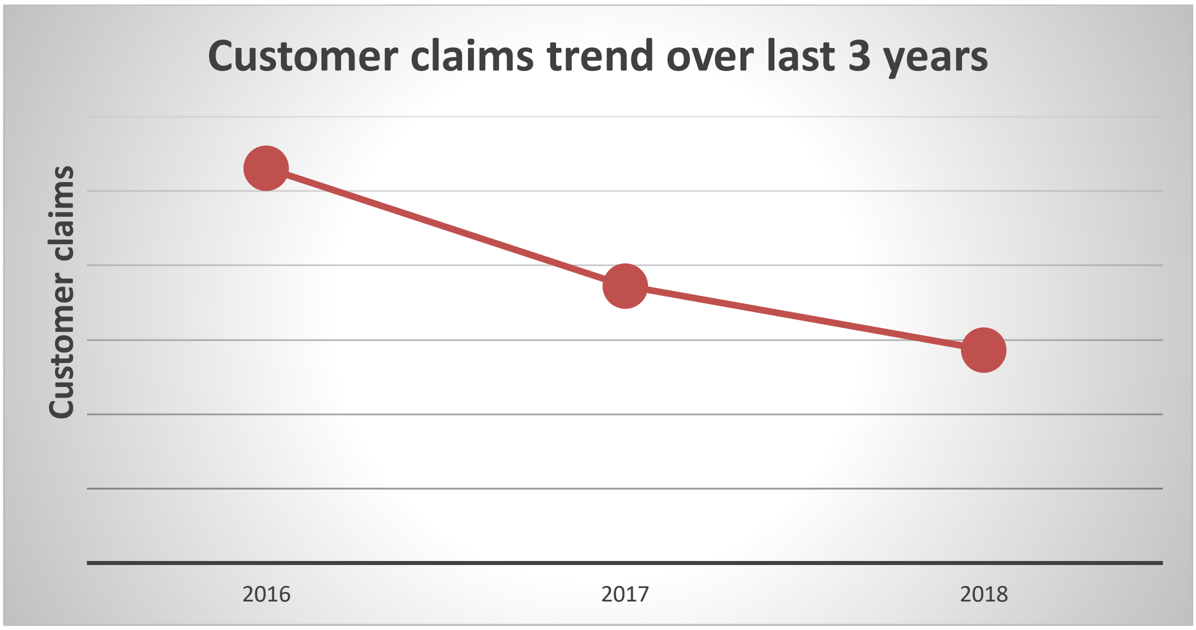


Figure 1 Trend of customer claims

This graph shows the trend of customer claims in Köping over the last three years. Although as a result of various quality improvement initiatives number of customers claims is continuously decreasing. Statistical process control was identified as a solution for attaining further reduction of defects and to achieve the goal of zero defects.

This thesis is a part of a big industrial project aimed towards quality improvement and reduction of customer claims at Volvo powertrains, A pilot area in the gear machining was identified and SPC monitoring is being implemented in the pilot area, over the course of time more areas will be brought under Statistical process control. In order to be prepared for SPC in the new manufacturing realm of industry 4.0, The company was in a need to understand the future form of SPC like the methodology, the advantages, and differences with respect to current form of SPC.

1.3. Scope and Limitations

The scope of this thesis focusses on Statistical process control (SPC) in the gear machining processes of Volvo powertrain manufacturing center at Köping. This thesis focusses only on machining operations and other manufacturing operations do not come under its scope. information regarding current practices are gathered mainly by interviews and retrieving the data from various sources within Volvo Group such as reports and databases

Although recommendations and suggestions have been given at the recommendations part of this report, the implementation of the same does not come under the scope of this project. Other implementation aspects apart from prioritizing the product characteristics for implementing Statistical process control do not come under the scope of this thesis.

The recommended method may or may not be possible to implement in other factories of Volvo Group's trucks operations depending on the availability of data used in the recommended model.

1.4. Acknowledgments

First and foremost, I would like to thank everyone who made excellent contributions to this research by participating in this research for providing valuable information and insights. I would especially like to thank every member of Quality in the powertrain production team at Volvo Group truck operations Lundby for their valuable insights and patience to answer my questions in detail even when they were very busy. I honor their valuable time and dedication to my research project.

A particular thanks to Malin Bagge Lindroth, who was the industrial supervisor for this thesis and contributed with valuable insights on the topic out of her experience and knowledge and also made it possible for me to get in contact with Key people who could contribute to this study at different parts of the organization.

In addition, I would also like to thank Tommislav Acimovic and other managers and Technicians at Volvo group trucks operations for helping me with their expertise, experience, and dedication. I would like to mention my special thanks to my supervisor Dag HenrikBergsjö who has provided me with valuable advice and input. Your feedback and support have helped me throughout the process of conducting this thesis.

Last but not least I also would like to thank my friends and family members for providing meaning and support to my life outside studies.

Harikrishna Balakrishna Kurup

1.5. Research Questions

The research questions to which the researcher was seeking an answer is presented here.

- *How can product characte*ristics *be prioritized for implementing SPC in the gear machining area of the Volvo GTO Köping factory?*
- *What are the major differences between today's SPC and SPC in the manufacturing paradigm of Industry 4.0*

2. Methodology

This thesis mainly focusses on the robustness of the model for prioritizing the product characteristics for implementing Statistical process control in manufacturing factory of a leading automobile manufacturing company and this section presents the methodology used for developing a new model that can overcome the limitations of the existing model which was used by the company. The new model which was developed in this thesis was discussed and presented to experts in the organization and they are convinced about the advantages of this model and they are of the opinion research findings in this thesis would be considered for implementation in the factory replacing the existing model.

2.1. Research Approach

This thesis has conducted an analytical study on the current methodology that is being used in Volvo Group trucks operations powertrain production for prioritizing the product characteristics for implementing Statistical process control and compared against literature to identify gaps where Volvo Group trucks operations could possibly fill. Deductive conclusions were made to propose a new model for prioritizing product characteristics. and literature review on the following areas such as statistical process control, Industry 4.0, identifying the key product characteristics, challenges of industry 4.0, adoption of Industry 4.0, Multivariate SPC and Model predictive control (MPC) was conducted to arrive at an understanding of the future SPC's.

This research with a focus on Statistical process control was designed and conducted as per the methodology of systematic combining see Figure 2. Systematic combining is a research method in which an empirical method and a case analysis evolve together, it can be very useful for the development of new methods and theories (Dubois, 2002).

Based on deductive logic. two processes are conducted simultaneously, initially matching theory and reality, then taking the framework as direction, with insights from the case study to arrive at conclusions. In this research deductive logic was used mainly to reduce apprehensions about conclusions.

It was decided that this research work will start with a theoretical study 0n SPC after attaining sufficient theoretical knowledge on SPC focus will be given to practical aspects of SPC like how to prioritize product characteristics for implementation of SPC was explored and current method followed at Volvo Köping factory for prioritization of product characteristics for implementation of SPC was compared against the theoretical methods and best practices in the industry . The intention here was to identify gaps that Volvo could possibly fill to make the current SPC implementation a robust one. The next phase of the research was about future SPC's, various factors were explored about the future of SPC's such as what are the advantages of future SPC. How does the future SPC look like? what are the skills required for operators to work on future SPC?

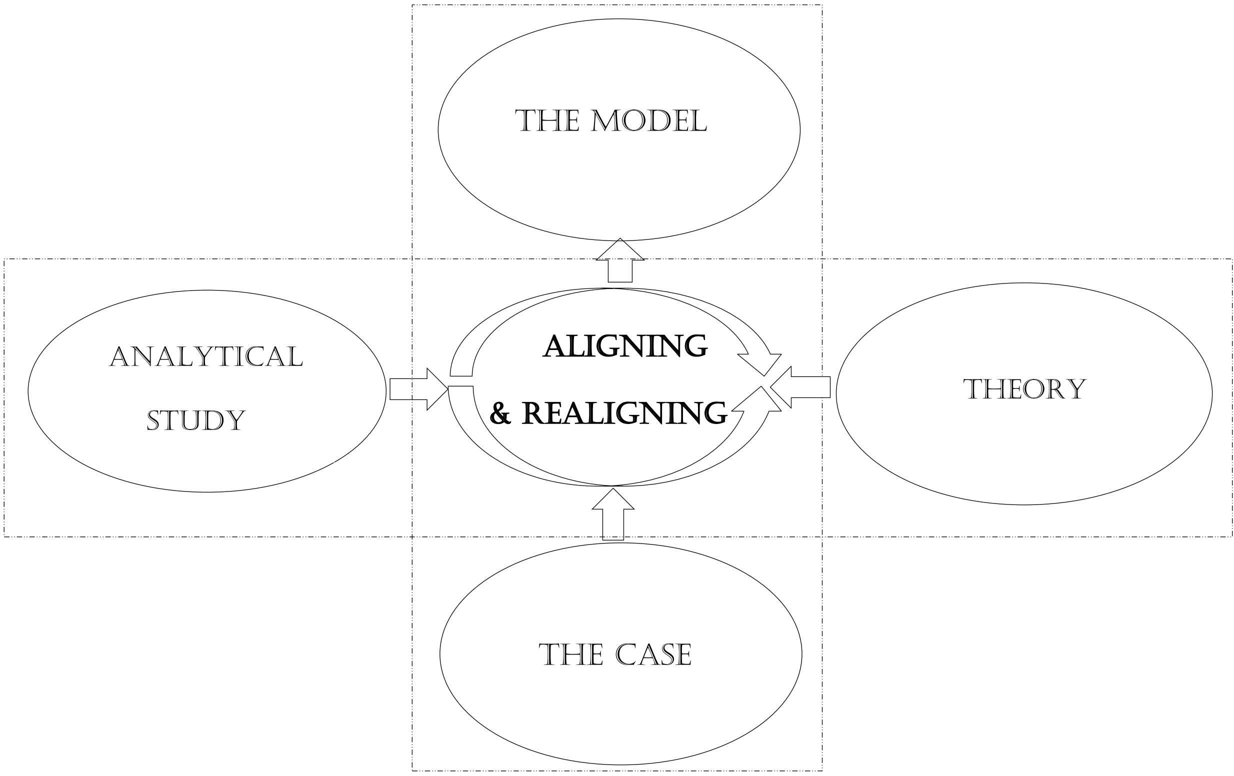


Figure 2 Systematic combining

2.1.1. Data Collection

The data was collected for this master's thesis from several sources and using methods such as literature study, interviews, observations and retrieving the data from various sources within Volvo Group such as reports and databases and VGMS was extensively used.

2.1.1.1. Literature Study

During this study various literature was continuously referred, the main sources were Chalmers' online library and Google Scholar and peer-reviewed publications. The researcher intended to find available information by searching individual or combination of words such as: statistical process control, quality engineering, Industry 4.0, IIOT, IOT, Big data analytics, ,multivariate process control, perspective process control, artificial neural network, predictive process control, SPC 4.0 predictive analytics, statistical analysis,. Due to this specific research area, most of the sources were available in the quality and manufacturing journals and articles of manufacturing and services and moreover this is an area where a lot of research is happening at this point and time. For a more general theoretical framework for the subjects as statistical methods and quality performance, mostly, books and previous lecture notes were used. All the sources in this report are denoted with the proper APA referencing style.

2.1.1.2. Interviews

Bryman & Bell (2015) describe unstructured interviews as unguided conversations. In this research unstructured interviews were used especially to clarify observations and questions that emerged during the course of the research. On the other hand, semi-structured interviews were the sole source of information for qualitative research questions in some cases. They were scheduled and were guided by predetermined, open-ended questions. During this research, both structured and unstructured interviews were carried out depending on the type of question for which the answers were sought for, they were conducted on a continuous basis according to how the access to new sources of information and interviews was granted. Each interview provided very valuable inputs and opened the new doors for more sources of information.

During many interviews, the interviewees contributed to the researcher to build larger professional networks in the organization and to get new contacts for potential interviewees. Which in turn resulted in to be able to reach more sources of information within the organization thus resulted in getting larger access to information from the organization.

The unstructured interviews had exploratory purposes and it was mainly intended to understand the present method used to prioritize various product characteristics for implementations of SPC. and to know how these identified important product characteristics are focused on during manufacturing processes. On the other hand, the semi-structured interviews were intended to collect information about the quality management systems and how new statistical methods would fit within the existing structure and how it can be implemented.

At the beginning of the project, a set of semi-structured interviews was set in order to understand and define the scope of the project. Afterward, when the project scope became clear and was accurately defined. Relevant changes were made to interview questions in order to be able to get the maximum amount of information within the focus area. Information's collected from the initial interviews helped the researcher to prepare interview questions for the later semi-structured interviews with specific topics and questions were prepared in advance in order to be more methodological and structured for collecting information.

Interviewees were requested to describe until the contextual depth and were requested to explain some practical examples in some cases. The interview guidelines had 15-20 questions most of the interviews lasted for about 60 to 120 minutes and were held individually either at interviewees office or on Skype if it was unable to have a face to face interview With an intention to obtain unbiased answerers the interview guideline was designed to influence interviewees as little as by the preconception special consideration were always given about this aspect . Interviews were analyzed mostly on the very next day. During cases of follow up questions or clarifications, interviewees were contacted through Email and in some cases follow up interview was also scheduled.

2.1.1.3. Observations

One of the main initial activities of the project was to understand the existing implementation of SPC at Köping factory, like what are the various software that is being used at the factory now. how are various processes monitored, computational infrastructure, level of implementation of SPC at Köping factory? Measurement systems and procedure that is being used at the factory during the regular production. and to understand the level of rework and rejection rate at the factory. To fulfill this purpose, a visit to the powertrain manufacturing Centre at Köping was conducted. The agenda included understanding the initial implementation of SPC at Köping. The observations were made on how various SPC stations are working now in an unconcealed way, taking into consideration that people may change their behavior while they are being observed (Bryman and Bell, 2015).

2.1.1.4. Data Analysis

In order to ascertain the suitability of statistical methods in Köping factory, it was necessary to collect qualitative and quantitative data from different corporate sources.

2.1.1.5. Qualitative Data

Information about operations and processes was obtained from the corporate data sources and interviews. This information was used to trace the sources of quantitative data. For processes, the source was the Volvo Group Management System (VGMS) was used. Documents such as. manuals, instructions, procedures which provide relevant information on the method of problem-solving and data which would help to develop a structured approach for root cause analysis and for the standard operating procedure, when the process goes out of control and for making the preventive and corrective action was collected and analyzed,

2.3.2 Quantitative Data

Quantitative data were collected from the database of manufacturing factory and were used for understanding the current methodology used for prioritizing the product characteristics for implementing SPC and comparing the methodology followed with best practices in the industry thus making it possible to develop a new method which encompasses all the best practices in the industry for prioritizing the product characteristics for implementing SPC.

3. Theoretical framework

3.1. Theory

This section gives the reader an overview of the theory of SPC and it is based on literature studies of earlier researches has conducted on the topic of SPC and the conclusion is based upon this theory.

3.1.1. Introduction to SPC

To continuously make products with high quality which can exceed customer expectations. Products should be manufactured with processes that are stable and repeatable (D. C. Montgomery, 2009). which means processes should be able to be operating with the least possible amount of variability from the target specification of quality characteristics of the products. Statistical process control (SPC) is a collection of problem-solving tools that can be effectively used for achieving the process stability and maximizing the capability through reduction of variability (D. C. Montgomery, 2009). There are seven major tools of SPC: Histogram, Check Sheet, Pareto Chart, Cause-and-Effect Diagram, Defect Concentration Diagram, Scatter Diagram and Control Chart (Bo Bergman, 2010).

Statistical process control (SPC) is an approach to process control that is being widely used in several industrial or non-industrial fields.SPC is based on the so-called Shewhart's conception of the process variability and process control.

SPC distinguishes variability caused by obviously affected common causes from variability caused by abnormal assignable causes (the process is considered not to be statistically stable). (Darja Noskievičová, 2013)

The main goals of SPC is an identification of abnormal variability caused by assignable
causes with the aim to

1. make the process stable,
2. minimize the process variability,
3. improve the process performance

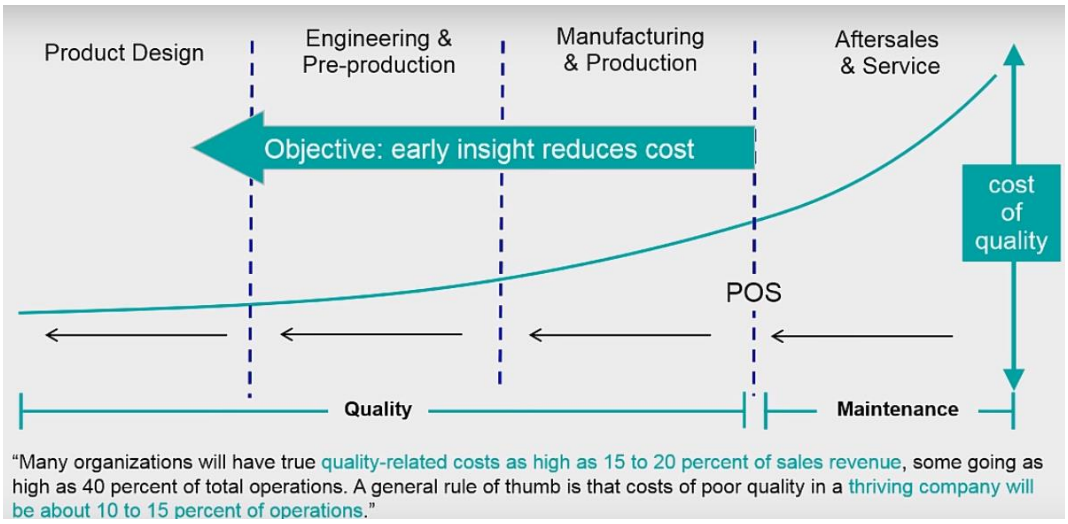


Figure 3 Cost of Quality vs time

Grace L.Duffy *(2013.) [Image] The ASQ Quality improvement pocket guide: Tools and relationships*

Origin of SPC

In 1924, Walter A. Shewhart of the Bell Telephone Laboratories developed the statistical control chart concept, which is being often considered as the beginning of statistical quality control. Towards the end of the 1920s, Harold F. Dodge and Harry G. Roming, both of Bell Telephone Laboratories, developed statistically based acceptance sampling as an alternative to 100% inspection which was the usual practice at that time. By the middle of the 1930s, statistical quality-control methods were widely used at Western Electric, which is the manufacturing arm of the Bell System. Greatly influenced by Walter’s conception of process variability
A. Shewhart, Williams E. Deming developed Deming's 14 points and seven deadly diseases of management, which is an important framework for implementing quality and productivity improvement (D. C. Montgomery, 2009)

3.2.SPC

Statistical process control (SPC) is generally regarded as a set of tools that are meant to increase the quality of a process by reducing variability in the process, thus making each individual product produced conform to a certain same set of standards. There are both technical and philosophical aspects of SPC (Bo Bergman, 2010). The philosophical aspect consists of a consistent will and motivation in the organizations continuously to improve the process, as well as management strategies to achieve continuous improvement, while the technical aspect is a set of statistical methods which in various ways can monitor and observe the variability and alert the possibility of a defect in process (Bo Bergman, 2010),.This thesis focusses on the technical aspect of SPC, and in particular tool of control charts.

3.3.SPC an integral part of TQM Total Quality management

Total Quality Management is a management approach that originated in the 1950s and has steadily become very popular and received quick acceptance. Total Quality management is a philosophy which describes the culture, attitude, and organization of a company that works towards to provide customers with products and services that exceed customer expectation and needs. The approach requires quality in all aspects of the company's operations, with processes being done right the very first time and defects and waste being completely eradicated from operations (Erdem Gerard Tetteh, 2014).

Total Quality Management, TQM, is a method by which management and employees can become involved in the continuous improvement of the production of goods and services. It is a combination of several quality and management tools aimed at increasing business and reducing losses due to wasteful practices. (Hashmi, 2019) (I Six sigma, n.d.)

Some of the companies who have implemented TQM include Ford Motor Company, Phillips Semiconductor, SGL Carbon, Motorola and Toyota Motor Company (Hashmi, 2019). The essential components of TQM are listed here and are as follows.

- Commitment by senior management and all employees
- Meeting customer requirements
- Reducing development cycle times
- Just in time/demand flow manufacturing
- Improvement teams
- Reducing product and service costs
- Systems to facilitate improvement
- Line management ownership
- Employee involvement and empowerment
- Recognition and celebration
- Challenging quantified goals and benchmarking
- Focus on processes/improvement plans
- Specific incorporation in strategic planning

this shows that TQM must be practiced in all activities, by all personnel, in manufacturing, marketing, engineering, R&D, sales, purchasing, HR, etc (I Six sigma, n.d.)

3.3.1. Principles of TQM

Management Commitment

- Plan (drive, direct)
- Do (deploy, support, participate)
- Check (review)
- Act (recognize, communicate, revise)

Employee Empowerment

- Training
- Suggestion scheme
- Measurement and recognition
- Excellence teams

Fact-Based Decision Making

- SPC (statistical process control)
- DOE, FMEA
- The 7 statistical tools
- TOPS (Ford 8D – Team-Oriented Problem Solving)
- Continuous Improvement
- Systematic measurement and focus on customers
- Excellence teams
- Cross-functional process management
- Attain, maintain, improve standards

Customer Focus

- Supplier partnership
- Service relationship with internal customers
- Never compromise quality
- Customer-driven standards

Thus, it can be understood that SPC is a tool used for the Fact-based decision process which is a key pillar of TQM philosophy.

SPC methods can provide better insights from the operations and show directions to make the right decisions not only for the steering action of the process but also for taking management decisions. (Hashmi, 2019).

3.4. The relation between Spc and sustainability

"Lean is green" is anymore not a new phrase. Process improvements that start with quality management can reduce waste, as a result, reduce adverse environmental effects while yielding other operational advantages also (Napier, 2015). Porter and van der Linde (1995) have observed that viewing pollution as resource inefficiency can be traced back to the quality revolution which happened in the 1980s. In agreement with that observation, Mannion (1996) and Pojasek (2002) also have conclusively defined the logical relationship between environmental management and quality management (Napier, 2015). Many Other researchers have also identified a trend towards convergence of quality management and environmental management. Quality management initiatives that can be viewed as evidence of quality innovation include TQM implementation and adoption of the Six Sigma methodology for reducing defects and process variability. In agreement with these researchers, it can be concluded that SPC implementation can help an organization to reduce rejection and wastage and thereby can help to make operations to go sustainable.

3.5. An overview of control charts

No serially produced products are ever exactly identical to each other in all respects. Regardless of industry, there always exists some degree of variation between products. However, with SPC, causes of variation can be identified and classified as chance Cause variation and assignable cause variations (Bo Bergman, 2010). Chance causes are deviations from the nominal value that are always present, and natural for the process to have. Assignable causes, on the other hand, are variations caused by some error in the process, which usually can be a representation of either improperly adjusted machines, operator errors or defective raw materials or due to countless reasons (D. C. Montgomery, 2009). Regardless of the source, assignable causes tend to significantly change the variation pattern that chance causes create. Whenever a process has assignable causes present, it is said to be out of control, and when only chance causes variation is present, the process is said to be in control. The purpose of the control chart is to identify the presence of assignable cause variations, i.e. to determine when the process is out of control. If the assignable causes are detected early, and corrective action is taken proactively, products will have fewer defects and quality deviations can be avoided. This is the advantage of using control charts. The way control charts generally achieve this is by plotting sample measurements (e.g. a sample mean or variance) of the monitored quality characteristic, as a time series along with one or two tolerance limits representing the limit for chance cause variation. (D. C. Montgomery, 2009) For example, see Figure 5

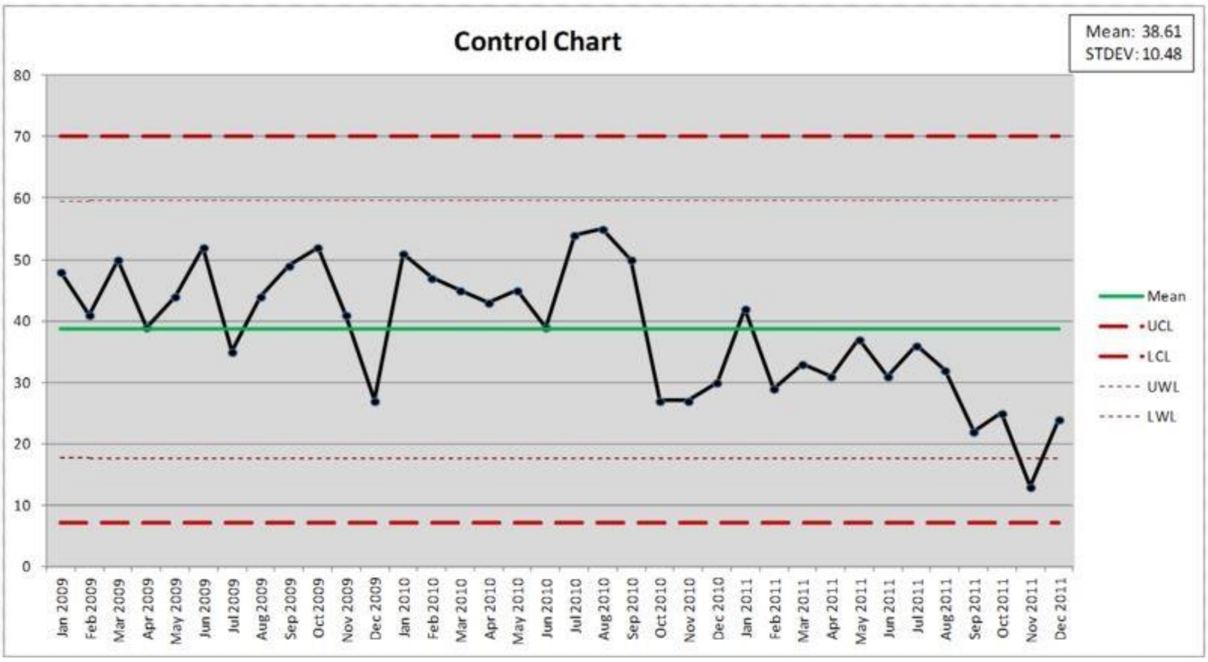


Figure 4 Control chart

Grondemar. *(2012.) [Control chart], Retrieved from*
https://commons.wikimedia.org/wiki/File:En.wp_Featured_Article_Candidates_FAs_promoted_control_chart.png

3.5.1. Different types of control charts

Broadly data can be classified into two types Quantitative data and qualitative data. (Hashmi, 2019)

Quantitative data deals with numbers and things that can be measured objectively e.g. dimensions such as height, width, and length. Temperature and humidity. Prices. Area and volume.

Qualitative data deals with characteristics and descriptors that can't be easily measured, but can be observed subjectively—such as smells, tastes, textures, attractiveness, and color

Quantitative data, which is also referred to as numeric data can still be classified as two more categories **continuous and discrete**. As a general rule, counts are discrete and measurements are continuous. (Minitab, Inc, u.d.)

Continuous data can be measured on a continuum or scale. Continuous data can have almost any numeric value and can be meaningfully subdivided into finer and finer increments, depending upon the precision of the measurement system. (Minitab, Inc, n.d.)

Compared to discrete data like good or bad, off or on, etc., continuous data can be recorded at many different points (length, size, width, time, temperature, cost, etc.).So depending on the type of data plotted Control charts broadly fall into two categories: Variable and Attribute (Minitab, Inc, n.d.)

3.5.2. Selecting a control chart

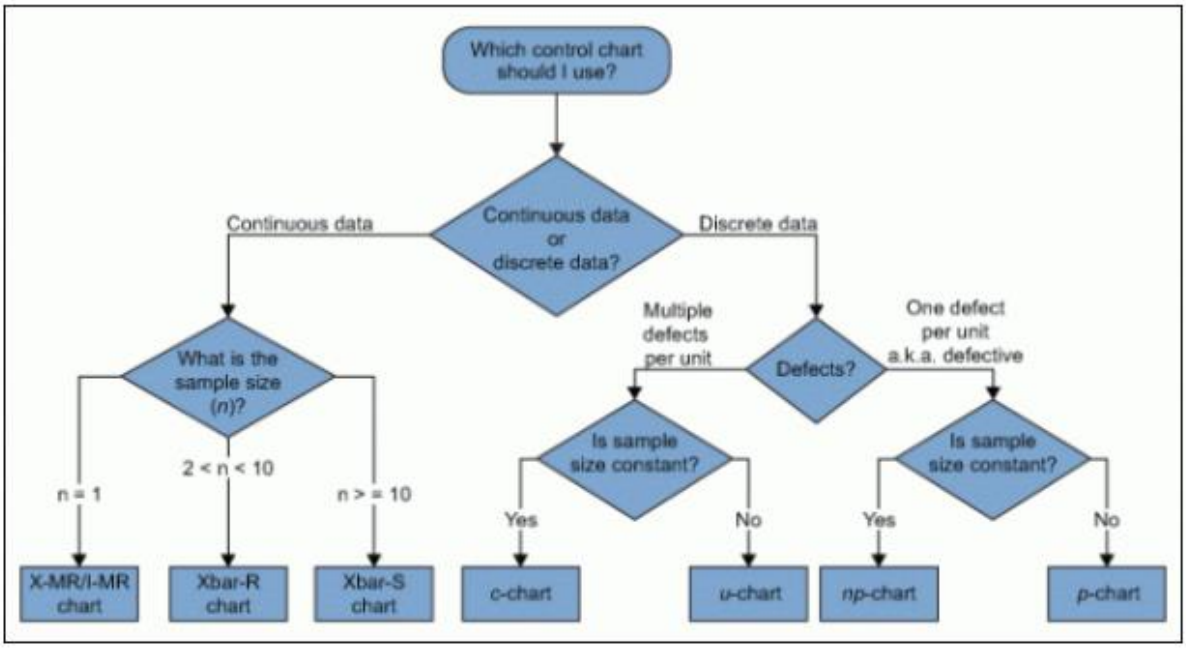


Figure 5 Selection of control chart

Carl Berardinelli. *(2017.) [Image], Retrieved from* ***https://www.isixsigma.com/tools-templates/control-charts/a-guide-to-control-charts/***

The first step in choosing an appropriate control chart is to determine the type of data as continuous or attribute data.

Continuous data usually involve measurements and often include fractions or decimals. Weight, height, width, time, and similar measurements are all continuous data. If the control chart for individual measurements is to be plotted an I-MR control chart should be used. If data are being collected in subgroups, the Xbar-R control chart must be used if the subgroups have a size of 8 or less, or an Xbar-S chart has to be used if the subgroup size is larger than 8. (Minitab, Inc, n.d.)

3.5.2.1. Control Charts for Continuous Data

3.5.2.1.1. Individuals and Moving Range Chart

The individuals and moving range (I-MR) chart are one of the most commonly used control charts for continuous data. I-MR chart must be used when one data point is collected at each point in time. The I-MR control chart has two charts used and should be read simultaneously.
Together they monitor the process average as well as process variation. With the x-axis that is time-based, the chart shows a history of the process please refer to Figure 7 which shows an I-MR chart used in an assembly unit.

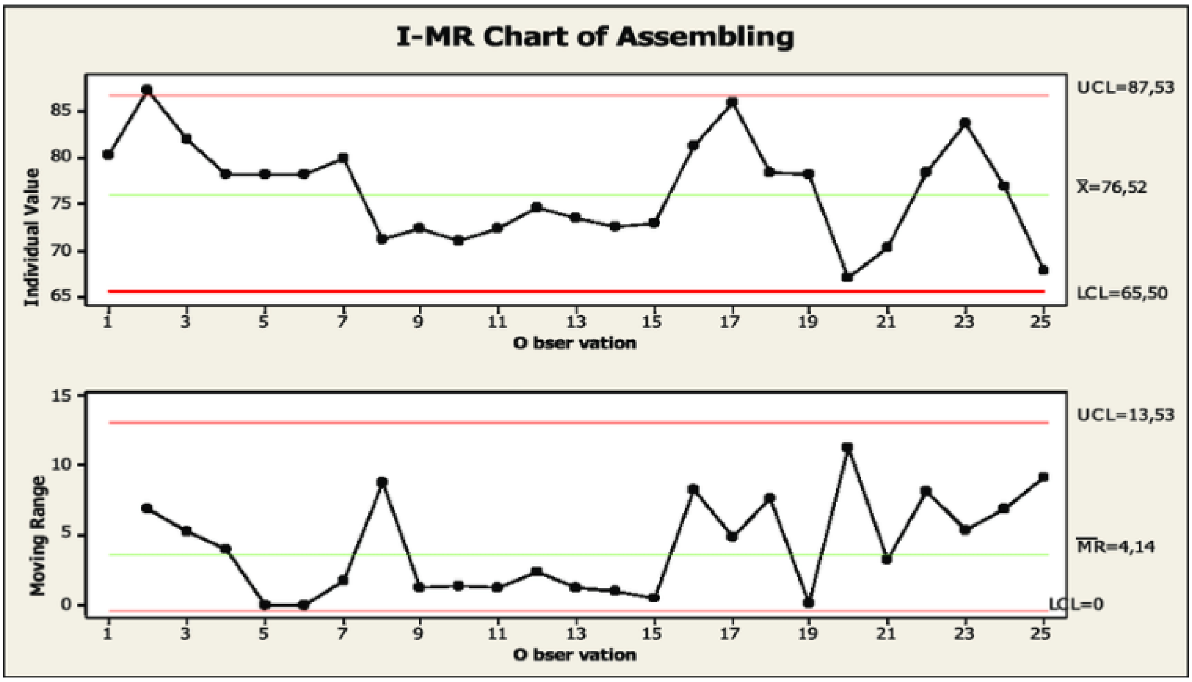


Figure 6 I-MR control chart

Hanantya Dino Rimantho.*(2017.) [Image], Retrieved from Article.* ***Enhancing the management of the noise level using six sigma method: a case study on the machining industry***

3.5.2.1.2. Xbar-Range Charts

Another commonly used control chart for continuous data is the Xbar and range (Xbar-R chart. is Similar to the I-MR chart previously discussed; it also comprises of two charts to be read simultaneously. The Xbar-R chart is used when measurements can be logically collected in subgroups of between two and 10 observations. Each subgroup can be considered as a representation of the process at a given point and time. The chart's x-axis is time-based so that the chart shows a history of the process. For this reason, it is important that the data should be in time-order. (I Six sigma, u.d.) See figure 8 which shows an Xbar- Range chart.

The Xbar chart is used to evaluate the consistency of process averages by plotting the average of each subgroup. It is very efficient at detecting relatively large shifts (typically plus or minus 1.5 σ or larger) in the process average (D. C. Montgomery, 2009).

The R chart, on the other hand, plots the ranges of each subgroup. The R chart is used to evaluate the consistency of process variation. For understanding Xbar-R chart One should Look at the R chart first; if the R chart is out of control, then the control limits on the Xbar chart are meaningless, hence should not be considered (I Six sigma, u.d.)

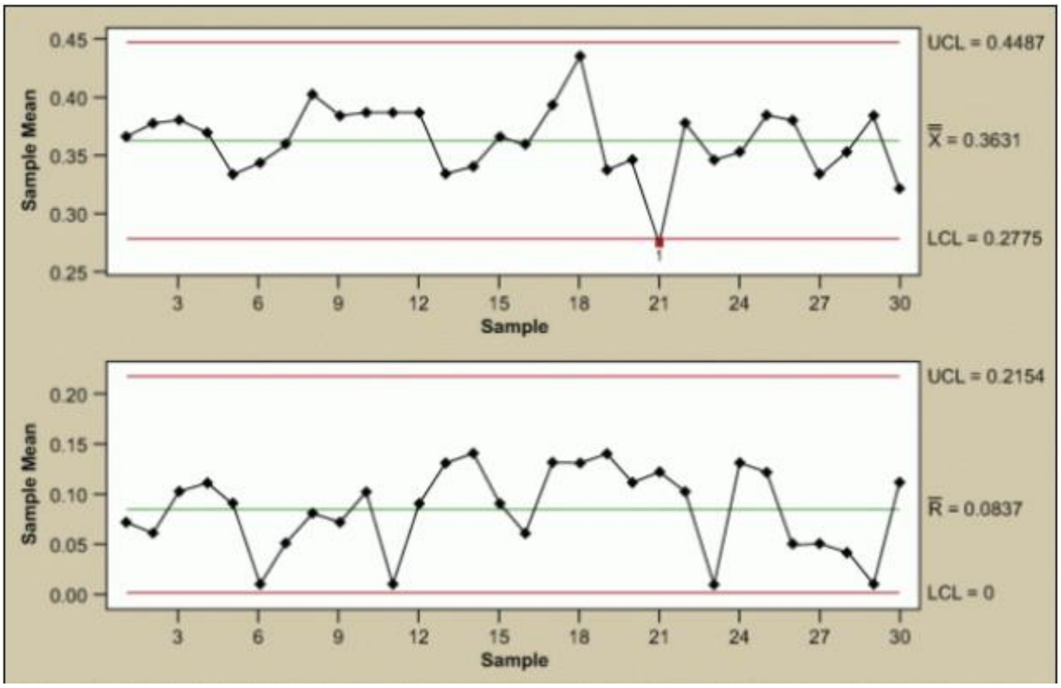


Figure 7 Xbar-R control chart

Carl Berardinelli. *(2017.) [Image], Retrieved from* ***https://www.isixsigma.com/tools-templates/control-charts/a-guide-to-control-charts/***

Fig3. Xbar-R control chart

3.5.2.2. Control Charts for Discrete Data

3.5.2.2.1. C-Chart

This type of chart is used when identifying the total count of defects per unit (*c*) which occurred during the sampling period, the *c*-chart makes it possible for the user to assign each sample more than one defect. C- chart is applicable when the number of samples of each sampling period is essentially the same (I Six sigma, n.d.). Refer to figure 9 which shows a C chart used to capture the defect in the manufacturing industry to observe the number of defects as a variable.

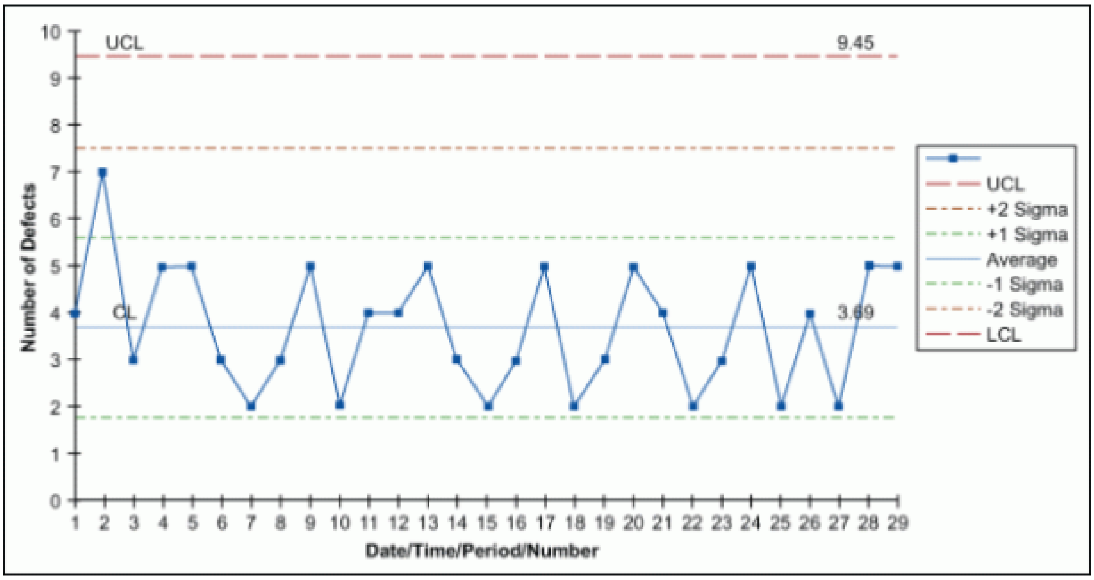


Figure 8 c-chart

Carl Berardinelli. *(2017.) [Image], Retrieved from* **https://www.isixsigma.com/tools-templates/control-charts/a-guide-to-control-charts/**

3.5.2.2.2. U-Chart

Likewise, *c*-chart, the *u*-chart is also used to track the total count of defects per unit (*u*) that occur during the sampling period and can track a sample having more than one defect. However, unlike a *c*-chart, a *u*-chart is used when the number of samples of each sampling period might vary significantly (D. C. Montgomery, 2009).

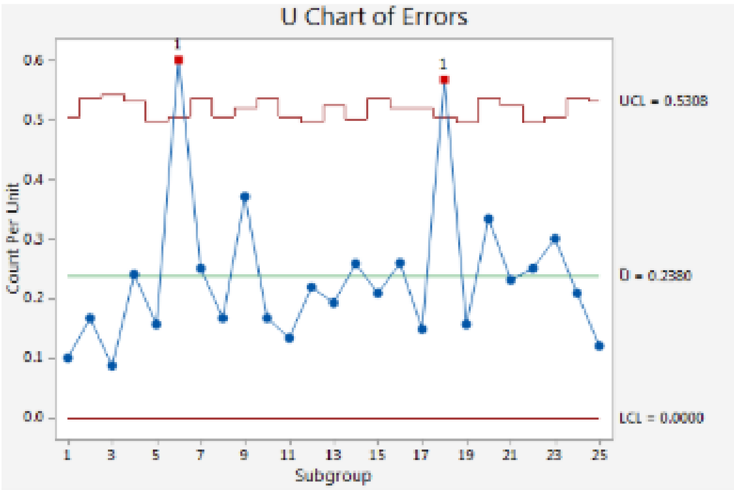


Figure 9 U-Chart used for monitoring of errors in production

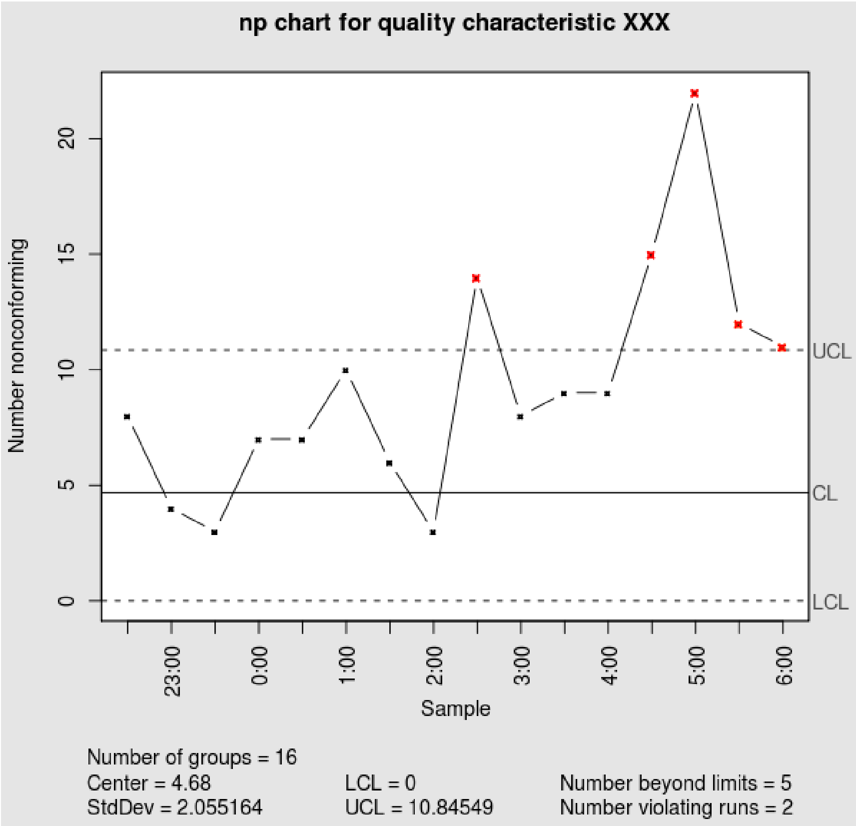
Minitab.*(2018.) [Image], Retrieved from https: https://support.minitab.com/en-us/minitab-express/1/help-and-how-to/control-charts/how-to/attribute-control-charts/u-chart/before-you-start/example/*

3.5.2.2.3. np-Chart

an *np*-chart is used when identifying the total count of defective units (the unit may have one or more defects) with a constant sampling size. (I Six sigma, u.d.)

The vertical axis of an np- the chart will show the number of defectives/nonconformities instances in every subgroup and the horizontal axis shows the sample size.

A subgroup is mostly a time sequence (for example daily production in a factory). Subgroup sizes should always be carefully selected in order to ensure that they are large enough for statistical calculations but still contain a few defective items.



Stephanie. ***(2018.) [Image], Retrieved from*** *https://www.statisticshowto.datasciencecentral.com/np-chart/*

Figure 10 shows a sample Np-chart being used for nonconformities to quality specifications in the manufacturing industry.

3.5.2.2.4. P-Chart

P-chart is used when each unit can be considered as either pass or fail category – no matter the number of defects – a p-chart shows the number of tracked failures (np) divided by the number of total units (n) (I Six sigma, n.d.). The P-chart is based on the binomial distribution hence each item on the chart has only two values that is either: pass or fail. An "item" can be any variable which we are interested in charting,

Groups of different sizes can be charted together. Proportions make more logical sense than individual counts for some applications, which would give too much weight to larger samples. The proportions are shown on the y-axis. The x-axis shows the size of the sample, which is usually around 20-40 groups. Fewer than 20 groups will not show an accurate picture of the process and hence not considered as statistically credible. P-charts are not very useful for tracking trends over time, or small shifts in the process. (D. C. Montgomery, 2009)

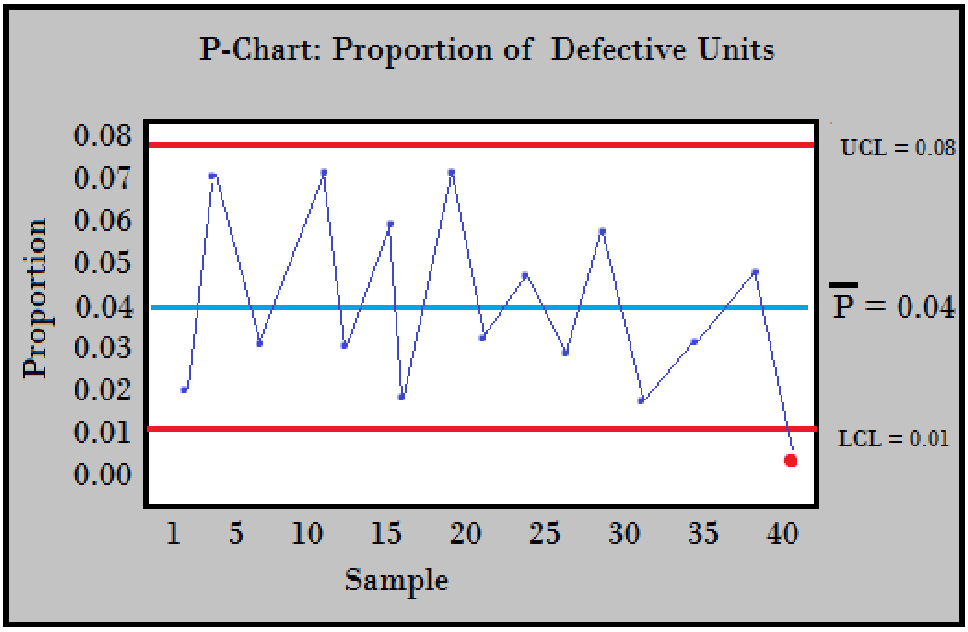


Figure 11 p-chart

Stephanie*(2016.) [Image], Retrieved from, **https://www.statisticshowto.datasciencecentral.com/p-chart/***

3.5.2.2.5. Xbar-s Charts

When the sample size is more than 10, the range of the subgroup is inappropriate to estimate the variation within the group and hence standard deviation is used for estimating the variation. This type of control chart is used with variables data - data that is taken along as a continuum such as Time, density, weight, and length are examples of variables data. Like most other variables control charts, it is actually two charts used together. One chart is for the subgroup averages (X). The other chart is for the subgroup standard deviations (s) (I Six sigma, n.d.) (D. C. Montgomery, 2009)

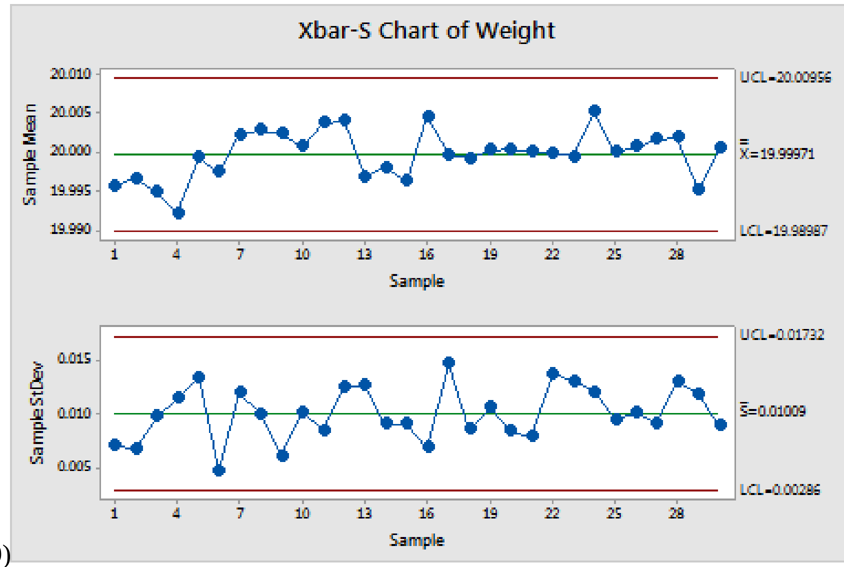


Figure 12Xbar-s chart

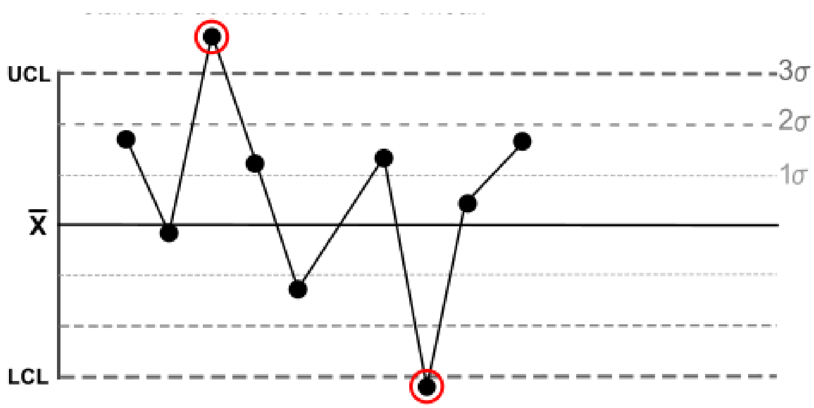
Andrew Milivojevich *(2016.) [Image], Retrieved from https://andrewmilivojevich.com/xbar-r-chart-versus-xbar-s-chart/*

the Xbar-S chart is very similar to the X-R chart. The major difference is that the subgroup standard deviation is plotted when using the X-S chart, while the subgroup range is plotted when using the X-R chart. One advantage of using the standard deviation instead of the range is that the standard deviation takes into account all the data, not just the maximum and the minimum. The constants used to calculate the control limits and to estimate the process standard deviation are different for the X-s chart than for the X-R chart. As for the X-R chart, frequent data and a method of rationally subgrouping the data are required to use the Xbar-S chart. (I Six sigma, n.d.)

3.5.3. Interpreting the control chart

Stewart's rules were postulated by Walter A Shewhart in the 1920s for deciding if a process is in control or not by monitoring a control chart. If the process is influenced by some random conditions on the control chart the process is said to be unstable and not in control. Later in 1956 Western electric company published a handbook that proposed some more rules for identifying the stability of a process from a control chart similar to Shewart's rules All these proposed rules by the Western electric company were based on Statistical mean and standard deviation of the measured samples in SPC process. The Western electric handbook became a standard text of the field and was widely adopted.

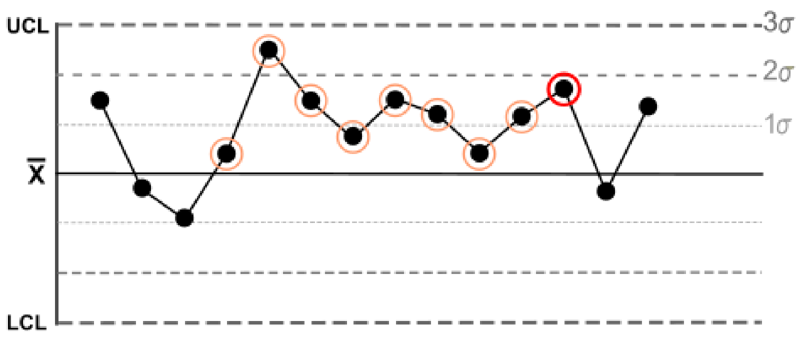
Later Nelson rules were proposed by Lloyd S Nelson in 1984. Nelson proposed 8 rules for determining the stability of a process. These 8 rules are widely accepted and followed by different SPC manuals across the industries and across the world. Different SPC manuals follow a different set of rules. Some SPC manuals follow all eight rules proposed by Nelson while some other manuals follow only a few of the eight rules. A summary of a set of different rules followed by different SPC manuals was prepared and is presented later in this report. As per Nelson rules Whenever a similar situation as in the following figures occurs during the process. The process is deemed unstable.



Lloyd. S.Nelson *(1984.) [Image], Retrieved from* ***http://leansixsigmadefinition.com/glossary/nelson-rules/***

Figure 13 Rule1.

According to this rule, a process is considered as out of control whenever a point on control chart crosses beyond three standard deviations from the mean



Lloyd. S.Nelson *(1984.) [Image], Retrieved from http://leansixsigmadefinition.com/glossary/nelson-rules/*

Figure 14 Rule2

According to this rule, a process is considered as out of control whenever nine or more continuous points are on the same side of the mean

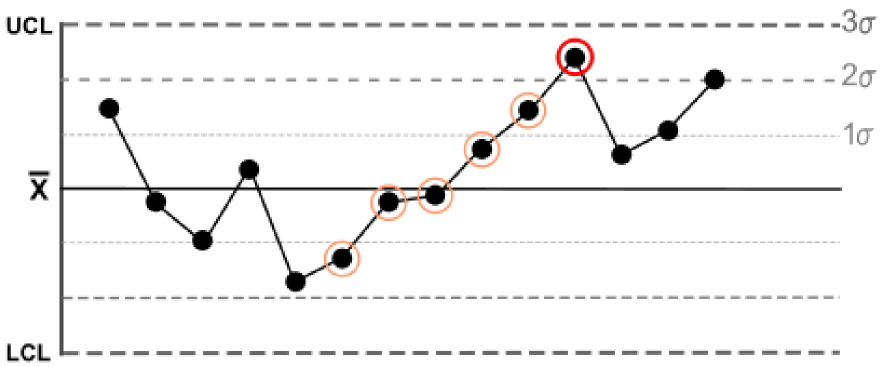


Figure 15 Rule3

Lloyd. S.Nelson *(1984.) [Image], Retrieved from http://leansixsigmadefinition.com/glossary/nelson-rules/*

According to this rule, a process is considered as out of control whenever six or more points in a row continuously increasing or decreasing trend.

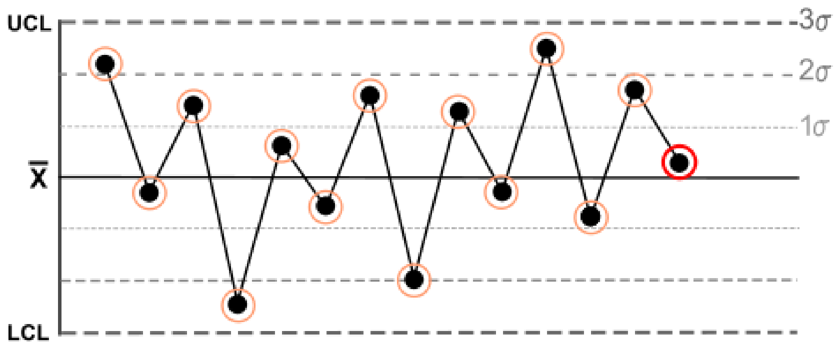


Figure 16 Rule 4

Lloyd.S.Nelson *(1984.) [Image], Retrieved from http://leansixsigmadefinition.com/glossary/nelson-rules/*

According to this rule, a process is considered as out of control if fourteen or more points fall in alternate directions increasing then decreasing

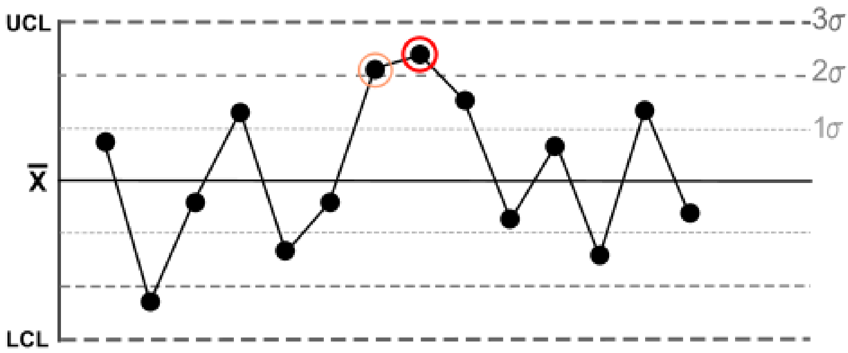


Figure 17 Rule5

Lloyd.S.Nelson *(1984.) [Image], Retrieved from http://leansixsigmadefinition.com/glossary/nelson-rules/*

According to this rule, a process is considered as out of control if two (or three) out of three points in a row are more than 2 standard deviations from the mean in the same direction.

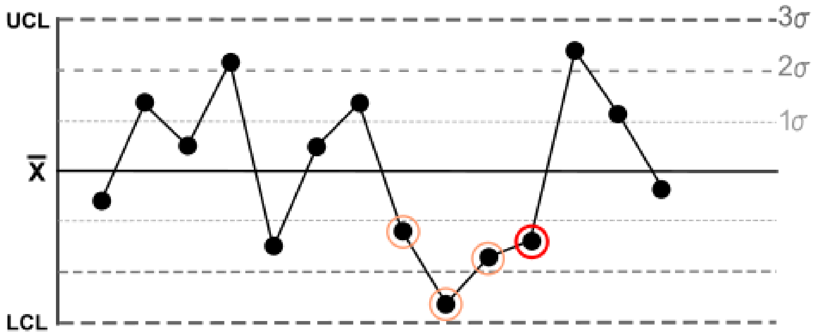


Figure 18 Rule 6

Lloyd.S.Nelson *(1984.) [Image], Retrieved from http://leansixsigmadefinition.com/glossary/nelson-rules/*

According to this rule, a process is considered as out of control if four (or five) points in a row are more than 1 standard deviation from the mean in the same direction.

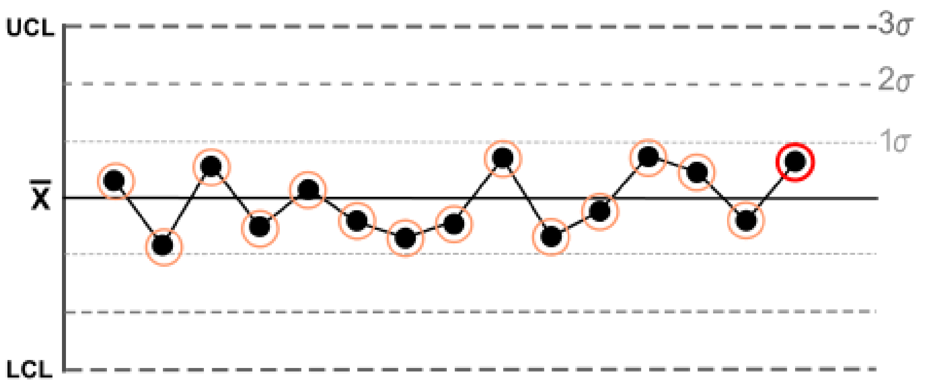


Figure 19 Rule 7

Lloyd.S.Nelson *(1984.) [Image], Retrieved from http://leansixsigmadefinition.com/glossary/nelson-rules/*

According to this rule, a process is considered as out of control if fifteen points in a row are all within 1 standard deviation of the mean on either side of the mean.

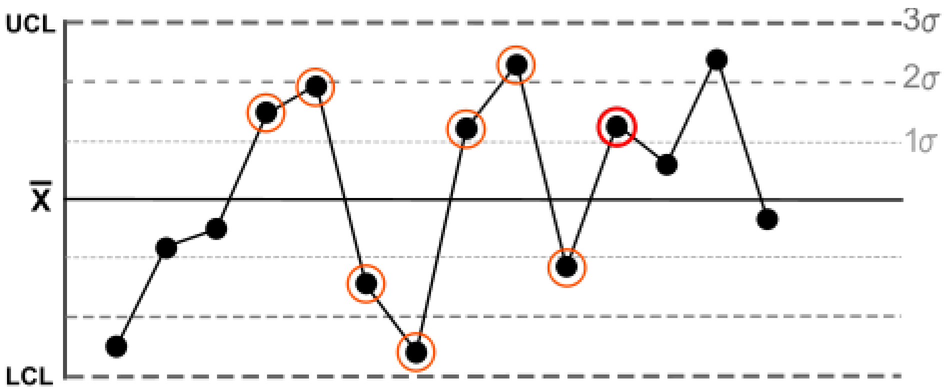


Figure 20 rule 8

Lloyd.S.Nelson *(1984.) [Image], Retrieved from http://leansixsigmadefinition.com/glossary/nelson-rules/*

According to this rule, a process is considered as out of control if eight pints in a row exist with none within 1standard deviation of the mean and the points are in both directions from the mean.

3.5.4. Widely followed SPC Standards

AIAG SPC Manual

Automotive Industry Action Group (AIAG) is a not-for-profit association founded in 1982 and is headquartered in Michigan. It was formed to develop recommendations and a standard framework for the improvement of quality in the North American automotive industry.

AIAG's Quality initiatives span along a wide spectrum of product development such as manufacturing, service, and customer experience improvement activities to support the manufacturing technology and product innovation methodologies that are required from successful and growing suppliers and OEM's. While grounded in the quality. Standards and core tools are the foundation of automotive quality excellence, the current AIAG quality initiatives are exploring new issues, providing insights, and the latest tools and methodologies to support the manufacturing technology and product innovation advancements that are required from successful and growing suppliers and OEM's. (AIAG, 2019)

The AIAG publishes automotive industry standards and offers educational conferences and training to its members, including the advanced product quality planning (APQP) and production part approval process (PPAP) quality standards. These documents have become the most preferred quality standard in the automotive industry (AIAG, 2019) similar to these publications AIAG has published a standard that solely focusses on SPC that particular standard is called AIAG SPC Manual and is one of a commonly used SPC standard in the automotive industry.

Boeing AQS manual

AQS is a continuous improvement system used by Boeing to achieve measurable improvement in cost, cycle time, quality, waste reduction customer satisfaction and profitability. Boeing insists all of its suppliers to use the same to achieve economic and quality benefits.

Custodian of this document is Boeing Commercial airplane Group. The purpose of the Boeing AQS manual is to provide a description of the Boeing quality management system to its suppliers

This manual presents a systematic approach to process and product improvement that can be used in areas like production, design, testing, and inspection as well as in business processes and research. The approach emphasizes decision-based on facts, data, and statistics.

In new product development, AQS improves quality and decrease long-term cost by encouraging quality built into the product during the early design and engineering phases

In production, AQS improves quality by systematically improving the production system by managing and reducing variation through process understanding and process control (Boeing, 2019).

Boeing AQS manual specifies clear specifications about the implementation and operation of Statistical process control and is Considered as an industry benchmark.

ISO 7870

This standard Establishes a guide to the use and understanding of the control chart approach to the methods for statistical control of a process. (ISO2019). Many manufacturing organizations and industry follow ISO 7870 and is considered as a credible document with a comprehensive and systematic approach towards interpreting control chart.

	AIAG Manual	Boeing AQS Manual	ISO 7870 Standard	Nelson rules	Shewart rules	Western Electric rules
Rule1	Yes	Yes	Yes	Yes	Yes	Yes
Rule2		Yes	Yes	Yes		Yes
Rule3		Yes	Yes	Yes		Yes
Rule4	Yes	Yes	Yes	Yes		Yes
Rule5	Yes		Yes	Yes		
Rule6			Yes	Yes	Yes	Yes
Rule7			Yes	Yes		
Rule8			Yes	Yes		Yes

Table 1. Summary of rules followed in different SPC standards

3.6. Why product characteristics need to be prioritized for implementing SPC

Most of the products are produced through a series of processes in mass production, where each product's characteristics are the result of one or more processes hence each process may influence the quality of the final product. It would be an ideal kind of scenario if an SPC system could be set up on each process to ensure each process are always in control but in practice this could be impossible since there can be huge number of processes may be hundreds or even thousands of processes to monitor and resource required to monitor such huge number of processes in terms of manpower and money can be very high (Dahai Liu, 2005) making it impossible to cover all the processes.

In order to overcome this situation product characteristics that are critical to quality should be identified and SPC should be implemented to monitor those product characteristics which contribute to the quality of the product most. Since the prioritization procedure usually involves hundreds of processes and conflicting decision-making attributes, mathematical models can be applied as a framework for prioritizing the product characteristics. (T. N. Goh, Prioritizing Processes in Initial implementation of SPC, 1998).

4. Results

In order to identify various factors that can be used for prioritization of product characteristics, an analytic study was conducted with interviews and literature studies. Interviews were mainly targeted to understand current methodology that is being used by Volvo GTO for prioritization of product characteristics and literature study was conducted to identify various factors which can be used for prioritization of product characteristics and to understand the importance of those factors, it was also attempted to study best practices in the industry for prioritization of product characteristics by referring to standards and manuals like AIAG SPC manual, ISO TS 16949 and DFMEA5th Edition Handbook.

4.1. Analytical study results

From literature study, it was identified that best practice in the industry is to use the following factors for prioritizing product characteristics

a) Risks identified in DFMEA
b) Risks identified in PFMEA
c) Process capability decided during the design phase
d) Process capability achieved in the process
e) Cost of reaction plan for containing the defect in the subsequent process
f) probability of detection of defect
g) Critical product characteristics
h) Implemented process controls

4.2. The current method used at Volvo GTO for prioritization of product characteristics.

Product characteristics are prioritized into four categories AA, A, B, C in the decreasing order of importance based on a priority number. Most important product characteristics are categorized into the Group AA and the least important ones to Group C.

1	AA
2	A
3	B
4	C

Table1. Product characteristics groups used at Volvo GTO most important to least important.

Priority number(PN)

Priority number Determines the significance of product characteristics. Characteristics which score the highest priority number are considered as the most important. It is calculated by multiplying various factors from analytic tools like DFMEA and PFMEA, Criticality rating, etc.

Derived at various product development and process development stages.

Presently Priority number is calculated by the following formula.

PN=Criticality score*Detectabiltiy Grade *Cost grading

Criticality Score

Criticality Score is Derived based on special characteristics.

Special characteristics are product characteristics or manufacturing process parameters that can affect safety or compliance with regulations, function, performance, requirements, or subsequent processing of a product.

A special Characteristic can be any feature such as dimension, tolerance, finish, material or assembly, manufacturing or inspection process, that if nonconforming, missing or degraded may cause the failure or malfunction of the product. (Lisha Ma, 2016). In Volvo GTO Special characteristics are identified during the design phase of a product and it is based on Risk priority number RPN derived in the DFMEA.

Volvo now uses two symbols for special characteristics [CC] and [SC]. where [CC] represents very critical and [SC] represents critical ones.

Special characteristics	Criticality score
[CC]	7
[SC]	5
No Criticality	1

Table 2. Criticality score.

Detectability

Detectability assesses the probability of detecting the defect during the process or in subsequent processes and a grading scale is prepared based on the level of difficulty to detect.

Product characteristics	Detectability Grade
If impossible to detect in subsequent processes	7
If a defect can be detected in subsequent processes	5
If easy to detect defect during processes due to multiple times of measurements during processes	1

Table 3.Detectability grading

Cost grading

Cost Grading is obtained based on the assessed cost risk for the customer and the cost of correcting the defect during the process.

The risk for costs and disturbance at customer	**Cost Grade**
The fault will affect critical characteristics. or will cause safety or ergonomic problem for the Assembly worker	**7**
Production line stopped more than > 30 min	**5**
Corrective action in the magnitude of 2 to 20man hours	**3**
The defect is minor but should be treated and solved	**1**

Table 4. Cost grading

4.2.1. Limitations of the current method

Since the current prioritization methodology is based on a priority number it is not always easy to determine exactly which product characteristics should be grouped into each of the four categories AA, A, B, C. even though it is decided that Group AA shall be considered for implementation of SPC but often times there is an ambiguity that, product characteristics with what value of priority number shall be filled in Group AA and other subsequent categories. Resulting in several product characteristics being categorized in the group AA.

4.2.2. Comparison of the current method against theoretical methods and best practices in the industry

While implementing SPC always give priority for the processes which are not in control statistically (Carnell, 2019). which implies that cpk should also be considered as a factor for prioritizing process and this factor is not being considered in the prioritization methodology followed at Volvo GTO. It is always important to consider the risks identified in Process FMEA while implementing process controls for processes (Andrzej Ordys, 2007). In the manufacturing process, Risks can arise due to the nature of the materials in use, the equipment, the people, etc. Depending on the individual perspective the focus of a risk management program. Process FMEA can show us the unreliable processes and risk-mitigating actions must be taken against unreliable processes (Schippers, 1997). Statistical Process Control (SPC) methods can be used to combat risks where the impact of risk lies mainly on Quality or on the cost of quality which has long term effects such as damage in reputation and trust of the customer. Therefore, the process risks which could impact on the customer experience, and thereby reputation of the organization can be identified using PFMEA and controls like SPC should be implemented based on risk identified in PFMEA to minimize the potential of such risks by allowing to monitor processes and ensure that processes are operating at full potential while minimizing waste and rework SPC has been recognized for its risk aversion capabilities. (Maxted, 2016). It can be concluded that inputs from process FMEA should also be considered for identifying unreliable processes. Whenever Failure Modes have Severity ratings of 9 or 10, process (and/or design) actions must be considered to reduce the criticality (Severity and/or Occurrence ratings). (Ford Motor Company, 2011) Emphasis must, however, be placed on preventing defects (i.e., reducing the Occurrence) rather than detecting them. It is highly recommended to use tools like Statistical Process Control and process improvement rather than random quality checks or associated inspection. (Ford Motor Company, 2011). Risk priority number RPN identified in Design FMEA can also be an important factor to be considered for implementing the process controls. In the current methodology followed at Volvo GTO. Risks identified in PFMEA is not being considered for prioritization now. But from the theory, it can be understood that processes with high risk in PFMEA should be considered for implementing SPC. Processes with high risk can be recognized by using RPN from PFMEA as a factor for the prioritizing process.

It is also a good practice not to implement too many process controls on the same process. While considering a process for implementing SPC it is important to see that if any other process controls or Poka-yoke are already implemented on the process (Schippers, 1997)

Summary of comparison

Factors to be used as per theoretical Method	**Factors used in Volvo Method**	**Remark**
Risks identified in DFMEA	Special characteristics	Special characteristics are deduced based on RPN from DFMEA
Risks identified in PFMEA		This factor is not used in Volvo methodology
Process capability requirements defined during the design phase	Special characteristics	Special characteristics specify the process capability required in the process
Actual Process capability obtained in the process		This factor is not used in Volvo GTO methodology
Cost of a reaction plan	Cost of a reaction plan	This factor is used in Volvo GTO methodology
Detectability of defect	Detectability of defect	This factor is used in Volvo methodology
Poka-yoke implemented		This factor is not used in Volvo GTO methodology

Table 5. **Summary of comparison of theoretical method and Volvo method**

From the comparison of theoretical study and methodology followed at Volvo GTO, it can be concluded that the current methodology followed at Volvo GTO for prioritizing the product characteristics is a good one and it is developed thoughtfully but some factors which also could have been used for the purpose is not being considered. If those missing factors also can be considered in the methodology for prioritizing the product characteristics. It will be a much better method that encompasses all of the theoretical factors for prioritizing the process and will make the prioritization methodology a robust one.

4.2.3. Risk caused by missing factors

a. PFMEA helps to establish the impact of the failure and identify and prioritize the action items with the goal of alleviating risk. It is a living document that should be initiated prior to the process of production and maintained throughout the lifecycle of the product (Tsinopoulos, 2005). The risk identification capability of PFMEA is well established. By not considering input from PFMEA for prioritizing the processes for implementation of SPC there is a high probability that some high-risk processes which are already identified by PFMEA go unnoticed during the prioritization of processes resulting in those high-risk processes not being considered for implementation of process control.
b. To develop meaningful methods for prioritizing processes, reflecting both the statistical and technical factors, both statistical and technical factors should be considered in the build-up of SPC systems (T. N. Goh, Prioritizing Processes in Initial, 1998). By not considering statistical parameters like cpk attained in the process, the statistical aspect is being ignored which in turn can affect the ability to pick processes that are not in statistical control for implementation of SPC process. One of the key criteria for picking processes for implementation of SPC should be if the process is in statistical control or not. By implementing SPC processes which are not in statistical control can be brought into control (D. C. Montgomery, 2009).
c. It is also a good practice not to implement too many process controls on the same process. While considering a process for implementing SPC it is important to see that if any other process controls or Poka-yoke are already implemented on the process (Schippers, 1997). By not considering already implemented process control or Poka-yoke can result in too many process controls being implemented on the same process which is not a best practice.

Research Question 2

The following sections of the report address Research Question2

Roadmap of Statistical process control

Results of literature study about the future version of statistical process control are presented from here in this report

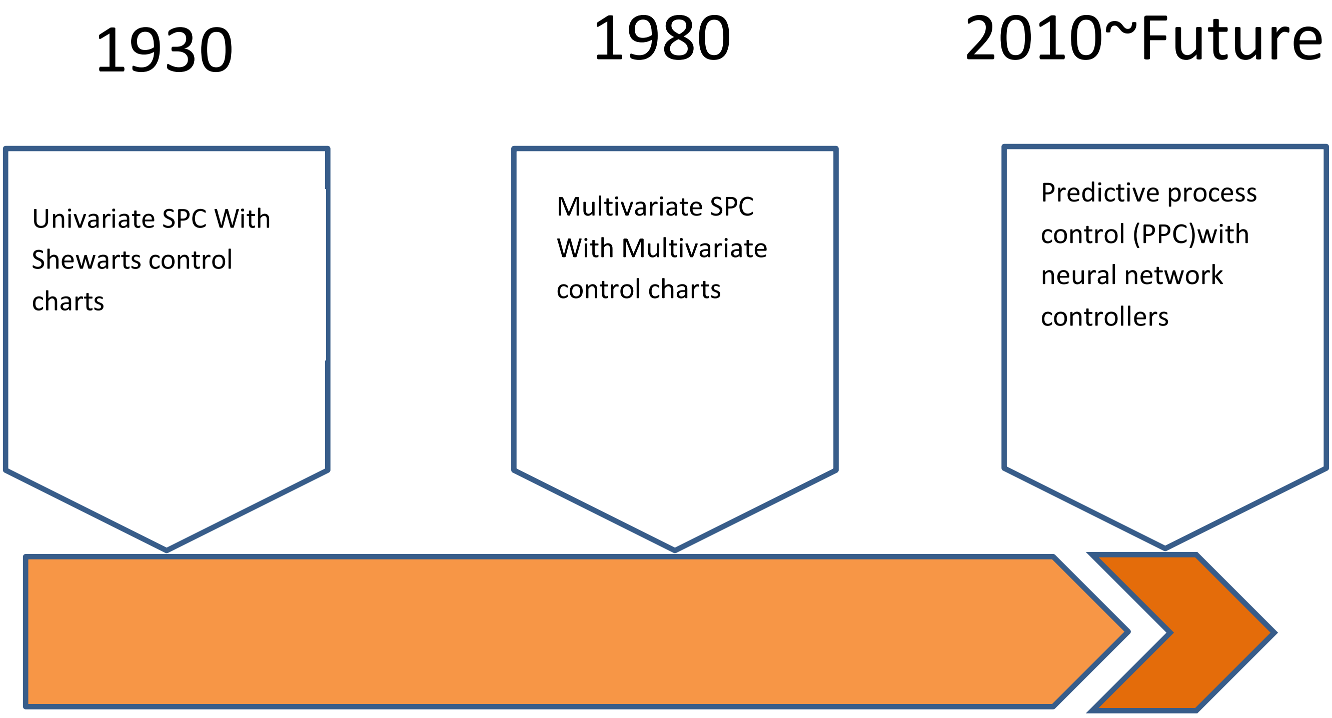


Figure 25. A roadmap of Statistical process monitoring

a roadmap of statistical process monitoring (SPM) is shown in Fig.25, which divides the development of SPM into three generations: 1st generation: statistical process control (SPC); 2ndgeneration: multivariate statistical process monitoring (MSPM);and 3rd generation: yet to be properly defined and named Predictive process control (PPC) (Q. Peter He, 2017).

A statistical process control broadly comprises of 5 components which are listed below.

a) Measurement of variables
b) Standard operating procedure.

c) Calculations
d) Steering the process
e) Control chart

Radical changes have come into all these five components of SPC methodology from the time Walter shewart conceptualized SPC in the 1930s (Bauer, C. & Wee, 2015).

.

4.3. Measurement of variables

The major change in the method of measurement of variables is that in 1930s univariate SPC methodology was followed which evolved into multivariate SPC's by the 1980s. The key difference between both methodologies is in the number of variables being monitored for assessing the process and deciding upon the steering actions.

4.3.1. Univariate SPC with Shewarts control charts

Statistical Process Control (SPC) or Univariate SPC's are based upon the idea of plotting a control chart based on a single variable, usually a product characteristic outcome after manufacturing operation, and examining as a single variable at a time. This can be inappropriate in cases of several industrial applications where several variables are to be monitored simultaneously typical such kind of applications exist in complex manufacturing processes where multiple of factors can interact with each other ,this limitations can be overcome by multivariate SPC because, univariate method completely ignores the information collected on the other process variables – possibly hundreds which can be utilized for understanding the process variation (Petros Maravelakis, 2002). The operator cannot really study more than two or three univariates control charts to maintain a process or product quality. The advantage with multivariate control charts is that several variables can be monitored on a single control chart hence for monitoring three different variables operator need not refer three different control chart but instead referring to a single control chart is enough (Ferrer, 2014).

The basic fundamentals of statistical process control (SPC) proposed by Walter Shewhart were suitable for the production environments typical in the 1920s and 1930s. when data was not that abundant, but today's production environment has completely changed and it has turned to be a data-rich environment with highly automated and computerized modern processes. These data often exhibit high correlation, rank deficiency, low signal-to-noise ratio, multistage and multiday structures, all these aspects make it possible to conduct multivariate calculations. Conventional univariate techniques are not suitable in these environments. (Ferrer, 2014). Univariate Statistical process control is based on the making control chart based on a few variables usually a dimension or a product characteristic and examining them at a time.
Multiple other factors which might influence on process are ignored, Interaction of factors which might lead to process deviations is also ignored.

The use of univariate control charts gives the first evidence for which the variables are responsible for an out-of-control signal. However, there are some problems in using a univariate control chart. These problems are that the overall probability of the mean plotting outside the control limits is high even if the process is in control and the problem of ignoring the correlations among the variables cannot be solved. (Filliben, 2018)
and the correlations among the variables are ignored. In several cases, correlation due to interacting factors affects the process rather than individual factors multivariate SPC can detect and trends of interaction between contributing factors. Which makes it a proactive form of SPC than univariate SPC. (Petros Maravelakis, 2002)

4.3.2. Multivariate SPC with multivariate control charts

Current sensor technology (ranging from simple flow meters to process analyzers to near infra-red spectrometers to digital cameras) makes process measurements available at a much faster rate and a much lower cost than just a few years ago (IBM Analytics, 2019). Consequently, massive amounts of data (“**Big data** “) coming from manufacturing processes are now routinely available in real-time to the process engineers (Ferrer, 2014). This has led to a widespread diffusion of the use of data-driven models. Among these, models based on multivariate statistical techniques have demonstrated their great potential to exploit data (whether real-time or historical) in order to provide information about the process behavior and the product quality (Data analytics and process digitalization, 2019).

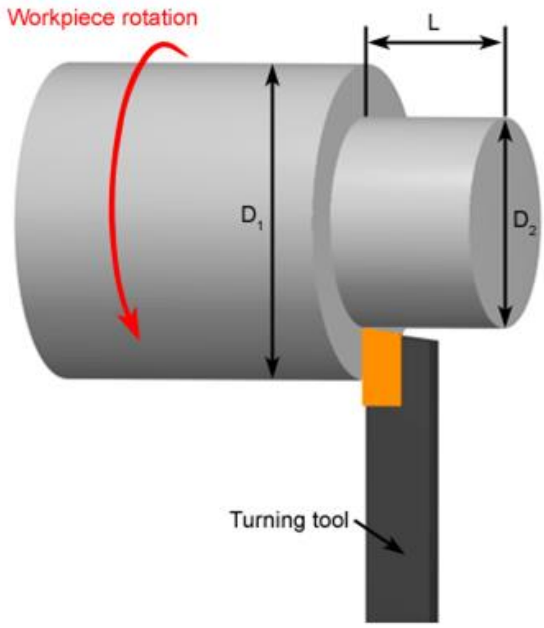
Multivariate SPC is a method with a set of advanced techniques for the monitoring and control of the operating performance of batch and continuous processes. More specifically, multivariate SPC techniques reduce the bulk of the information contained within all of the process variables down to two or three composite metrics through the application of multivariate data analysis

Hence Multivariate data analysis can be considered as an advanced statistical methodology that identifies all of the critical variables and underlying patterns in a data set using mathematical tools like correlation and regression. Importantly, it also shows the relationships between variables and how they interact with each other and this is highly important when trying to understand complex process behavior.

Multivariate Statistical Process Control (MSPC) applies all these powerful multivariate statistical methods to process and manufacturing data, giving a better understanding and insight which leads to better control over processes.

Multivariate SPC monitors process variables, including relationships that cannot be detected with multivariate statistics, on just one or two control charts. This removes the need for control charts for every individual variable and hence reduce the number of control charts to be used in the manufacturing process.

The multivariate analysis could easily recognize the parameters interacting with each other and finally leading to process variation and quality deviation. Making it possible to precisely identify where the faults are happening so that faults can be resolved easily and precisely minimizing the cost of quality in the lowest reaction time without affecting the cycle time of the process.



CustomPartNet. (2019) [Image], Retrieved from *https://www.custompartnet.com/wu/turning*

Figure26. SPC Schematic diagram of turning operation

Consider a turning operation as shown in figure 26 above. In the case of univariate SPC, if D_2 was the controlled variable all steering actions would have been based on measurements and deviations of dimension D_2. In the case of multivariate SPC, the steering would not be based solely on one variable D_2. But instead, a number of variables which can affect the quality of the machining operation. Several factors that can affect the quality of the machining process will be monitored and analyzed using big data analytics and IoT Sensors.

For the purpose of understanding a few variables are being listed here, time completed after tool change, coolant temperature, Machine bed vibration, Humidity, Voltage fluctuations, number of workpieces completed, etc. this list is not inclusive of all factors which can be considered for monitoring in multivariate SPC's and the advantage is that each installation of SPC station can be unique by deciding on which factors to monitor in other words the factors which each SPC station monitors is typically specific to operation that is happening at the SPC station. The number of factors that can be monitored is limited only computing power computer systems with high computing power would make it possible for us to monitor a large number of variables maybe even hundreds of variables at a time.

4.3.3. Multivariate SPC control charts types

- The contour plot and λ^2control chart
- Hotelling T^2 control chart
- Multivariate exponentially weighted moving average control chart(EWMA)
- Multivariate cumulative sum control chart (CUSUM)
- Principal component analysis control charts

These are the various types of multivariate control charts but Cumulative sum (CUSUM) and exponentially weighted moving average (EWMA) control charts are the most frequently used multivariate control chart for industrial applications

4.3.4. Limitations for using multivariate control charts

- The underlying assumption made for the multivariate methods is that the data are independent and identically distributed., which implies that the process data with the following characteristics would violate this assumption such as multimodal distribution; dynamic; non-Gaussian time-varying characteristics; other characteristics such as outliers, gross errors and or failed sensors. For these cases, the traditional methods can still be applied and sometimes they may perform well depending on how well the normal process operation data can be approximated (Q. Peter He, 2017) .

- A problem with utilizing traditional multivariate charts like CUSUM and EWMA or other similar control chart schemes is that it might be too difficult and impractical for high-dimensional systems with collinearities.
- When a univariate control chart gives an out-of-control signal, the practitioner may easily conclude what the problem is and arrive at a solution since a univariate chart is related to a single variable. In a multivariate control chart, the solution to this specific problem is not straightforward since any chart is related to a number, of variables and also correlations exist among them making it difficult for operators to work with it and resolve the issue but this limitation can be overcome by giving extensive training to operators.

Working on multivariate SPC requires the knowledge of multivariate statistics and computer systems used for multivariate statistically calculations can be very costly because it necessitates the use of high-end computer systems for complex multivariate calculations. (Muluneh, 2014)

4.3.5. Statistical process control with artificial neural networks

As a solution for the limitation of using multivariate control chart widely in the production process
Recently achieved ability to interface process control with computer integrated manufacturing techniques (CIM) and rapid emergence of Artificial neural networks has resulted in the application of artificial neural networks (ANN) for the use of control chart pattern recognition (Muluneh, 2014).

4.3.6. Artificial neural networks (ANN)

Artificial neural networks are a recently evolved technique from the use of mathematical formulations to model biological nervous system operations. ANN comprises of highly parallel computing systems comprising of interconnected artificial neurons or processing units. Neural networks use logical parallelism combined with serial operations as information in one layer is transferred to neurons in another layer. (Pignatiello, 2015)

Most important characteristics of the ANNs are:

the self-adaptive behavior that allows adapting the forecast to changing of the environment, in this way improve the networks' ability to learn and to predict;

the parallel computing architecture, that has a great application in multiple disciplines and, from speech and natural language processing, to image processing or problems in bioinformatics and biomedical engineering.

Therefore, they could be of great help for today's computer integrated manufacturing and in smart factories, according to Industry 4.0 paradigm were IOT sensors produce data in abundance.

It has been scientifically proved that ANN can be modeled to solve complex statistical prediction and pattern recognition from datasets (Muluneh, 2014). This has led to the adoption of ANN for interpreting the data and control charts.

4.3.7. Advantages of SPC with ANN

- The neural network approach for detecting patterns offers the advantage that knowledge of statistics is not required for the operator in order to understand if the process is in control or not.
- Neural network models are also effective in solving the problem of multiple distributions within a process.
- Statistical anomalies can be ignored to reduce false alarm rates with ANN's. A false alarm is a wrong indication from the SPC system that the process is not in control while the process is still in control.

- Timely detection of unacceptable process behavior while maintaining a low false alarm rate.
- An early indication of process deviations compared to normal SPC systems
- Ignores harmless changes only alert on trends that could create a real problem. (Ramdani, 2017)

4.4. Standard operating procedure

This section describes the significant changes in the second component of the SPC process that is the standard operating procedure

During an SPC steering process, all those activities done by an operator for steering a process is called standard operating procedure. changes that have come into standard operating procedure due to changes in technology is being discussed in this section.

4.4.1. Augmented reality in SPC standard operating procedure

Augmented reality has a great impact on the standard operating procedure of SPC due to following reasons

- Guided workflow instructions
- Continuous access to data or information
- Keeps the operator informed about process variables always

How an operator works on statistical process control has become more structured and framework oriented with the use of augmented reality smart glasses. Augmented Reality complements the real world by superposing virtual objects in the user's visual environment, Allowing a complete interaction with them in real-time. Several process details will be shown at the operator's sight keeping both of the operator's hands-free for working on SPC standard operating procedure. Which keeps the operator informed how the process is progressing along with the deviations in the process while he is wearing Augmented reality smart glass. for instance, control chart and other process parameters. See Figure 27**.**

Guided workflow instructions regarding Standard operating procedure for steering the processes will be displayed on augmented reality enabled smart glass at the eyesight of the operator sees Figure 28. The operator has to just follow the instructions being displayed on the glass eliminating a huge percentage of human error by the operator and gives comfort to the operator because. he /she does not need to memorize a large number of working instructions. Traditional tasks performed with heavy reliance on instruction manual can be quickly completed with accuracy and precision with the help of augmented reality glasses a device worn like a traditional pair of glasses project step by step set of instructions for the task and steering processes in SPC in his field of view of the operator. without interrupting the operator's work. Operators can interact with smart AR glasses through voice commands, swiping and tapping at the side of the glass.

Continuous access to information right at the fingertip of operators For accessing information operator need not go back and forth between nearest computer screen and machining station, Continuous access to information at fingertips and assistance on the go will make a radical difference in speed, efficiency, and accuracy on how standard operating procedures are executed by the operator for SPC See Figure 30..

Figure 27. Field of view of an operator through augmented reality glasses.

Daniel Segovia Et Al *(2015.) [Image] source article, Augmented Reality as a Tool for Production and Quality Monitoring*

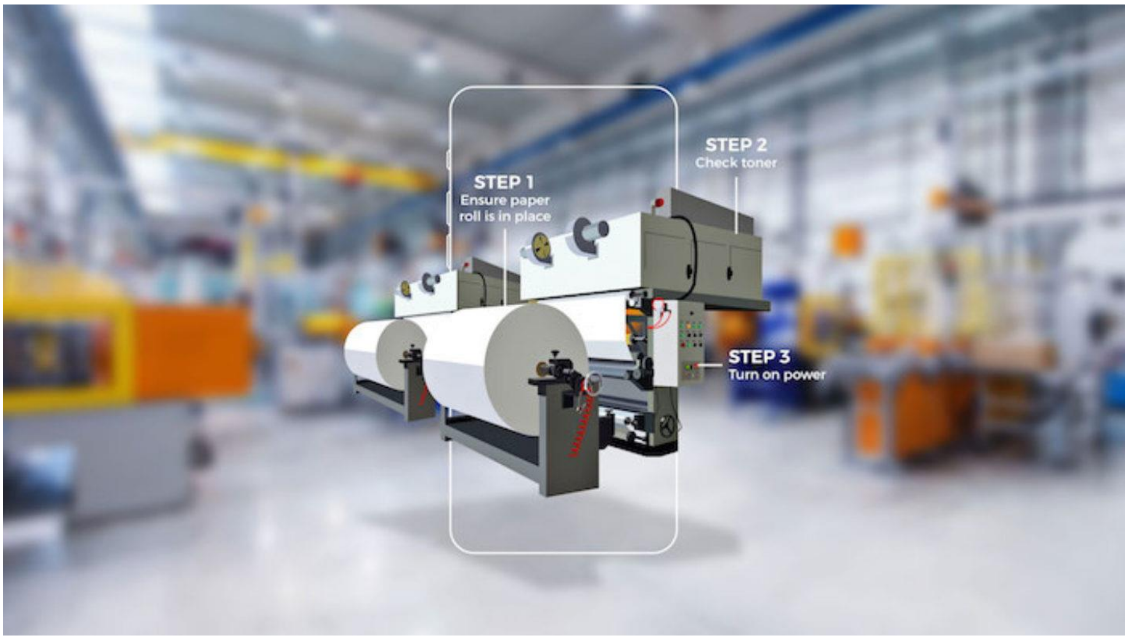


Figure 28. SPC standard operating procedure as guided workflow instructions in Augmented reality smart glass

Ian Wright *(2017.) [Image] Retrieved from, https://www.engineering.com/AdvancedManufacturing/ArticleID/14904/What-Can-Augmented-Reality-Do-for-Manufacturing.aspx*

Figure 29, Guided workflow instructions using virtual reality at Volvo cars.

Ian Wright *(2017.) [Image] Retrieved from,* ***https://www.engineering.com/AdvancedManufacturing/ArticleID/14904/What-Can-Augmented-Reality-Do-for-Manufacturing.asp***

Figure 30. easy access to information for the operator

Rainer Claassen *(2018.) [Image] Retrieved fro**m**, https://www.smart-industry.net/ar-and-vr-in-manufacturing-being-there/*

4.5. Multivariate SPC calculations

This section presents how the third component of the SPC process that is calculations are conducted in the new form of SPC

The goal of SPC data analysis is to extract information from raw data with the highest accuracy level of estimation. One of the most important and common questions concerning is that if there is a statistical relationship between a variable (Y) and explanatory variables (Xi). The method to answer this question is to conduct regression analysis in order to model the type of relationship. There are various types of regression analysis. The type of the regression model which should be used depends on the type of the distribution of Y; if it is continuous and approximately normal computational systems use linear regression model; if it is dichotomous logistic regression will be used; if Poisson or multinomial log-linear analysis will be used. (Alexopoulos, 2010)

By modeling the correlation, the system predicts the outcome (Y) based on the values of a set of predictor variables (Xi). These methods allow the system to assess the impact of multiple variables (covariates and factors) in the same model. (Alexopoulos, 2010)

For multivariate SPC calculations, a linear regression model is generally used. Linear regression is the procedure that estimates the coefficients of the linear equation, involving one or more independent variables that best predict the value of the dependent variable which should be quantitative. Logistic regression is similar to linear regression but is suited to models where the dependent variable is dichotomous. Logistic regression coefficients are used by the computational system to estimate odd and ratios for each of the independent variables in the model. While determining correlations between different variables that are being monitored. (Alexopoulos, 2010). The computer system is intelligent enough and decides on which type of regression it should use depending on the type of data.

Hence, It can be said that multivariate statistical calculations are complex and computationally expensive and require much better computational infrastructure than univariate SPC calculations but produce many results that have several dimensions.

4.6. Steering action

This section presents the changes in the fourth component of the SPC process that is steering action., feedback loop strategies for steering action in automatic SPC machines are mainly discussed here.

The vast majority of process control loops(~90%)) still depend upon various forms of the omnipresent PID controller consequently it can be said that substantial capabilities of modern computer control systems are greatly underutilized (Seborg, 1994). PID controllers and other linear controller structures are no longer good enough for controlling complex nonlinear multivariate systems. By using standard classical structures such as proportional-integral (PI) control., the set of control gains required for desired system performance at different operating conditions, however, might be different. The use of constant-gain controllers is not desirable in many circumstances because many process parameters change throughout the system lifetime as a result of wear-and-tear. Such behavior necessitates the need for on-line adaptation, or self-tuning, of controller parameters to achieve the level of desired process response., several methods have been developed for self-tuning of controller parameters, and currently many control vendors offer such solutions. Model predictive control (MPC) refers to the direct use of an explicit and separately identifiable model for controlling a process (Alexander G. Parlos, 2001). The crux of all MPC algorithms is the moving horizon approach, also known as the open-loop optimal feedback approach. MPC models can predict the changes in the dependent variables of the modeled system that can be caused due to changes in the variables. For example, In a chemical reaction process, independent variables that can be adjusted by the controller are often either the setpoints of regulatory PID controllers or the final control element. Independent variables that cannot be adjusted by the controller are used as disturbances. Dependent variables in these processes are other measurements that represent either control objectives or process constraints (Seborg, 1994). The MPC designs yield control systems capable of operating without expert intervention or minimum intervention for extended periods of time (Alexander G. Parlos, 2001). An identified process model predicts the future response and then, the control action is determined so as to obtain the desired performance over a finite time horizon. The control problem that must be solved is an on-line optimization of the manipulated variables to satisfy multiple, changing performance criteria in the face of changing process characteristics, including constraints. For resolving this problem MPC (Model predictive control) technique is being used The MPC technique is a dynamic optimization approach to control problems. The flexible constraint-handling capabilities of MPC make it most suitable for process control problems. Neural networks can be used to determine controller parameters, because of their well-known ability to solve complex problems by learning relationships directly from data. In this decade, certain neural networks have generated a lot of interest for use in nonlinear system identification and control. It can be concluded that future SPC machines with model predictive control with neural networks controllers will be much more precise in steering the process and require pretty much less human attention and intervention than the present-day machines and can be rightly said as the control strategy for future machines for compensating and steering action to bring back the process in control.

4.7. Predictive process control (PPC)

PPC is still an evolving form of SPC but it is considered to be the future form of SPC. PPC which will become matured enough for industrial application in the next few years to come. Due to the emergence of the Industrial Internet of Things (IoT)and ever-advancing computing power and new radical improvements of wire-less networking technologies, a new generation of networked, information-based technologies, data analytics, and predictive modeling are providing previously unimaginable embedded computing capabilities as well as access to previously unknown potential uses of data and information. These capabilities provide possibilities for new, radically better ways of doing manufacturing. the essence of these is the application of increasingly powerful and low-cost computation and networked information-based technologies in manufacturing enterprises. There is a general consensus that factories and plants connected to the Internet are more efficient, productive and smarter than their non-connected counterparts (Q. Peter He, 2017).

Similar to traditional SPC Prescriptive Process Control (PPC) uses reference data to learn. This reference data can be of multiple times of magnitude compared to the conventional form of SPC. It makes use of more data than the SPC and is capable to use Big Data sources like high-frequency sensors. This data is used to create a machine learning model; Depending on the use case these might be traditional or it can be a deep learning model as well. These models are (often) assumption-free, multi-variate and optimized for best performance. The fundamental principle behind PPC is a multivariable control strategy called Model predictive control (MPC).

The derived model is capable to predict the quality of the product for given conditions of, environmental, sensor and process parameters. Taking this model, a process engineer can simulate changes in the process parameters before implementing them. This includes most prominently different combinations as input.

prescriptive techniques can be used to automate the processes. In prescriptive analytics, a model is used to advise on the best action that can be taken by the operator to solve a process deviation. In normal SPC process operator change input process parameters to get the very best quality possible. In the case of predictive process control the system can advise the operator on which parameters to set to which value. The predictive model is now used in a prescriptive way.

The idea is that by analyzing data statistics can show what is inside the data (quality deviations). By combining statistics and artificial intelligence it can not only show what is inside the data but can identify the patterns in the data and can predict the future recognizing trends in data. Which is very helpful to identify the quality problems even before it happens.

Predictive maintenance

Another important application area in predictive process control is predictive maintenance or just in time maintenance instead of scheduled maintenance or preventive maintenance planned at fixed intervals where the equipment is taken off the line and performing the maintenance activities even though machines are working absolutely fine. With smart manufacturing and predictive process control where machines are communicating with each other, the process monitoring algorithm will be able to predict when the equipment needs maintenance. Hence maintenance needs to done only when its needed which could be earlier or later than the scheduled maintenance event, as a result, predictive maintenance not only reduces the process downtime and eliminate unnecessary maintenance but also improve process profitability by avoiding catastrophic events by foreseeing the potential problems by analyzing the trends in the datasets captured and addressing them at quite an early state. In order to be able to achieve predictive maintenance information sharing between different pieces of equipment, tracking of health and self-adaptive modeling would likely have to come together to be able to achieve an optimal decision in real times (Q. Peter He, 2017)

4.7.1. Challenges of PPC

From the data science point of view, PPC is a new hybrid methodology in analytics. Which combines sophisticated modeling techniques with optimization, now being developed for PPC. The optimization as the core of being prescriptive is a non-linear, derivative-free, constrained minimization. This leads to challenging problems for complex constraints. If there is not only one quality parameter but many, it ends up in a multi-objective optimization problem. Research is still going on in this area and it is still evolving so it might become few more years to get enough matured enough to be able to get adapted for industrial application, (Schmitz, u.d.)

4.7.2. Challenges in using VR/AR for manufacturing

It is beyond doubt that VR/AR in manufacturing is something that is very useful and will be here for a long time. This section discusses some of the challenges that some of the early adopters of this technology are facing. Field of view (FOV) is one of the biggest constraints that today's VR headsets need to overcome.

The field of view represents the area in which virtual objects can be projected in front of the user. The field of view is a very crucial aspect because it directly affects how much information can be displayed to the user. (Anna Syberfeldt, 2017)

Today's VR headsets have a FOV of a maximum of up to 90 degrees vertical and 160 horizontal fields of view when compared with 120 degrees vertical and 190-degree horizontal field of view of normal human vision. As a result, AR/VR devices have to project images in a large FOV in front of the human eye to make a complete immersive effect because of which all available VR headsets in today's market are bulky and heavy. The average weight of different VR headsets available in the market today is very much higher than120 grams (Anna Syberfeldt, 2017). 120 grams is considered as the optimum weight for such sort of a wearable device which is to be used for long hours. As a result, prolonged usage of today's VR headsets can be uncomfortable for the operators in several ways. Continuously wearing a VR headset for long hours of working can cause ergonomic and physical discomfort (Sattler, 2017).

Another important limitation is that while a person wears a VR headset, he is partially blind because the VR headset can create a blind spot. So, safety is a factor that draws importance in this kind of scenario. As a result, training has to be given to operators to ensure that blindness caused due to wearing a VR does not affect the safety of the person and he can still remain safe within a manufacturing environment with automated machines, robots, trucks, chemicals, etc., and it is critical that the operator's sight should not be negatively affected, so that he/she can be constantly aware of what is happening in the surrounding environment this turned out to be a critical factor which manufacturers have to consider while companies adopt VR based methodologies in production (Sattler, 2017).

Since AR/VR is still an emerging technology processing power required to generate a complete immersive effect is not yet achieved on today's VR headsets. As a result today's VR headsets need to be tethered to a computer or a console which limits the movement of the user, to ensure that wireless connection is not interrupted the operator can move only in a limited area and this limitation is expected to be overcome with the launch of 5G in next few years since 5G enables high bandwidth communications with connected devices.

The battery life of VR headsets, for usage in industrial shop floor VR headsets, has to be powered by a battery that can sufficiently power the VR headset for at least nine hours many of the VR headsets available in the market today fail on this criterion. New and more powerful batteries have to emerge it will of course happen but it will take a couple of years more.

New partnerships for making VR applications, of course making VR applications is not a core competency of manufacturing companies which makes them bound to depend on somebody else, or to forge a new partnership for developing VR applications this also makes adoption of VR in manufacturing more resource-intensive apart from the cost of VR headsets and other infrastructural aspects (Sattler, 2017).

Because of the low maturity of VR technologies in manufacturing at this point. It is a bit difficult to analyze the return on investment for this technology as a result top management remains skeptical about the investment and abstains from investing in VR in manufacturing.

Operators who are already wearing glasses Won't be able to work with current VR headsets this is another setback for adopting VR headsets in regular production.

A low level of digitalization or digital infrastructure is also turning out to be a crucial factor that is becoming a roadblock for the implementation of VR in manufacturing. Some of the machines used in manufacturing are very old because of which collecting data for the preparation and maintenance of VR techniques can be a bit cumbersome. In such cases, complete overhauling and reinstallation of machines may be necessary. Making VR still more costly for management to adopt and implement.

The last category of limiting factors is linked to the employees themselves. Resistance to change or some do not see value in this new technology or are fearful of embracing new technologies and due to conservative thinking because of which operators do not like new gadgets and resists to wear AR glasses for example.

Widespread adoption of VR smart glasses to the full potential in the manufacturing industry shall happen when the VR smart glass technology further evolves and the weight of smart glasses further reduces, Battery life further increases. And when VR headsets can also be used by people with visual defects (Anna Syberfeldt, 2017).

5. Conclusions

This chapter of the report presents the conclusions made by the researcher with regard to both the research questions.

Research Question 1

- *How product characteri*stics *can be prioritized for implementing SPC in the gear machining area of the Volvo GTO Köping factory?*

  From the comparison of theoretical study and methodology followed at Volvo GTO, it could be concluded that the current methodology followed at Volvo GTO for prioritizing the product characteristics is a good one and it is developed thoughtfully but some factors which also could have been used for the purpose is not being considered. If those missing factors also can be considered in the methodology for prioritizing the product characteristics. It will be a much better method that encompasses all of the theoretical factors for prioritizing the process and will make the prioritization methodology a robust one. By conducting the literature and theoretical study it was concluded that the following factors should be used for prioritizing a process.
- process Risks identified in DFMEA
- Risks identified in PFMEA
- Process capability decided during the design phase
- Process capability achieved in the process
- Cost of reaction plan for containing the defect in the subsequent process
- probability of detection of defect
- Critical product characteristics
- Implemented process controls.

From the analytical study of the current methodology used by Volvo, it was identified that Volvo does not use factors such as risks identified in PFMEA, Actual process capability attained in the process and implemented process control. whereas other factors are considered in Vovos's methodology In order to overcome this limitation, A new method that Volvo could potentially use is recommended in the recommendations.

Research Question 2

- *What are the major differences between today's SPC and SPC in the manufacturing paradigm of Industry 4.0?*

From the research, it was identified that future SPC processes will be much more proactive than today's univariate SPC. Since a large number of variables are monitored simultaneously for steering the controlled variable.

With the help of multivariate statistical calculations such as multivariate regression, correlation between different variables can be identified and the system can exactly instruct the operator because of which variable, process is going out of control as a result operator can take necessary actions to fix the particular variable hence the process can be steered back into control with much more accuracy and proactively in the future SPCs .In addition to that With the help augmented reality enabled smart glasses the system can instruct the operator with workflow instructions. When those workflow instructions are followed process will be back in control. with the help of a predictive process control system that can predict quality deviations based on the trend analysis of historical data using big data analysis, this makes future SPC capable to predict the process deviations even before it happens and makes it very proactive compared to the existing form of SPC.

The system can also ensure the operator is exactly following the work instructions given by the systems with the help of a light guide system. If the operator does the instructions right. The light guide system will address it with an indication and if the operator doesn't follow the instructions exactly light guide system will address it with indication error for procedure and caution the operator that he is doing something wrong. So the future SPC process can be said as an error-proof process. Even though VR/AR in manufacturing is still not a matured technology there are a lot of challenges Discussed in Section 4.7.2 which still needs to be ironed out. But in the next few years, because of active research in the area, all those limitations will be sorted out and will become a matured technology for industrial adoption.

6. Recommendations

In order to overcome the limitation of not considering all relevant factors for prioritizing product characteristics, A new model is being proposed.

In this model, processes are classified into four groups based on two types of grading numbers.

1. Statistical criticality.
2. Functional importance.

In this graphical method statistical criticality grade is plotted on the horizontal axis and functional importance grade is plotted on the vertical axis. A process is said to be statistically critical when the estimate of its capability index is low or when the process is found to be unstable. A process is said to be functionally important, if failures of that processes to meet specifications can directly or indirectly produce defective end products (T. N. Goh, Prioritizing Processes in Initial, 1998).
Processes can be categorized into four groups based on statistical significance and functional importance.

a) Group1(AA)
b) Group2(A)
c) Group3(B)
d) Group4(C)

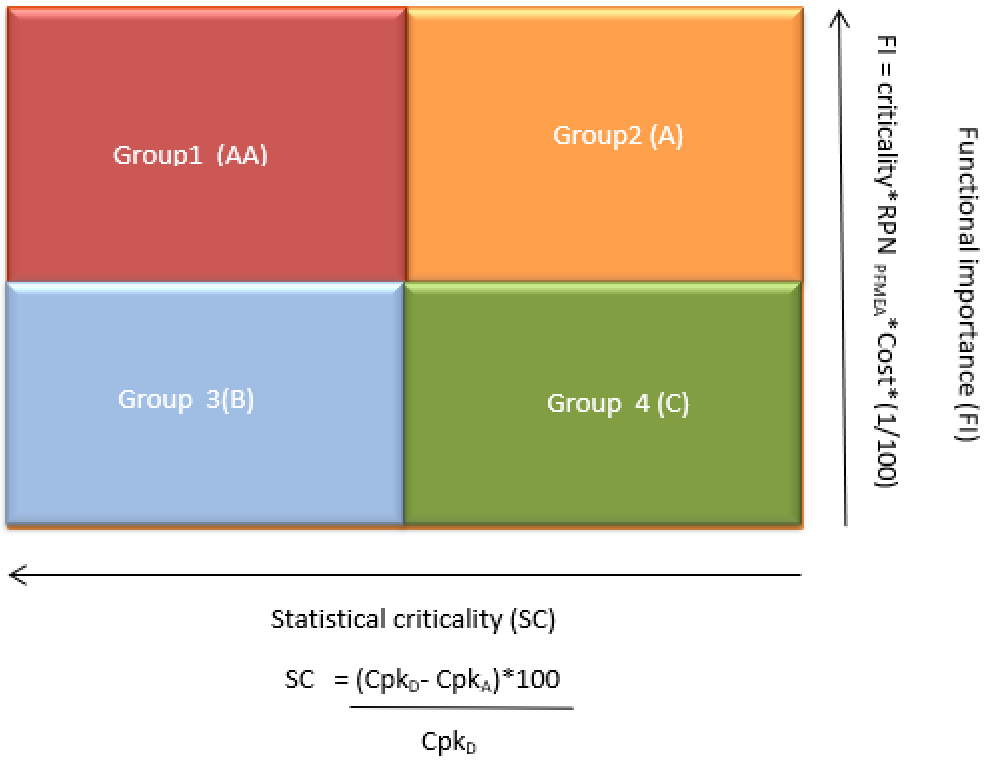


Figure 23. Recommended model for prioritization of process.

Statistical criticality (SC)

Statistical criticality is a grading number calculated using the Process capability index (Cpk) decided during the design phase and actual process capability attained during the manufacturing process. Statistical criticality is a representation of how far the process is in control. Statistical criticality can be calculated by the following formula

$$SC = \frac{(Cpk_D - Cpk_A)*100}{Cpk_D}$$

CPK_D : Process capability decided by the designer

CPK_A : Process capability attained in the process

Functional importance (FI)

Functional importance is a grading number obtained using parameters from different analytical tools like DFMEA, PFMEA prepared during different phases of product and process development and it represents how far is the particular process important towards making undefective end products which adhere to functional and performance requirements as well regulatory compliance.

Functional importance grade is calculated by the following formula.

FI= Criticalityscore*RPN $_{PFMEA}$*Cost Grading*Detectability

RPN $_{PFMEA}$: Risk priority number obtained in Process FMEA.

The criticality score and cost Grading from VPS followed in the Volvo methodology for prioritization can be used in this formula as well.
Volvo now uses two symbols for critical characteristics [CC] and [SC]. where [CC] represents very critically and [SC] represents critical ones.

Critical characteristics	Criticality score
[CC]	7
[SC]	5
no criticality	1

Table6. Criticality grading

Detectability

Detectability assesses the detectability level of the product characteristics.

Product characteristics	Detectability Grade
If difficult to detect in subsequent processes	7
If a defect can be detected in subsequent processes	5
If easy to detect defect during processes due to multiple times of measurements during processes	1

Table 7. Detectability grading1

Cost grading

Grading is obtained based on the assessed cost risk for the customer and the cost of correcting the defect during the process.

The risk for costs and disturbance at customer	Cost score
The fault will affect critical characteristics. or will cause safety or ergonomic discomfort for the operator.	**7**
Production line stopped more than > 30 min	**5**
Corrective action in the magnitude of 2 to 20-man hours	**3**
The defect is minor but should be treated and solved	**1**

Table 8. Cost Grading

Group1(AA)

Processes in group1 (AA) are both statistically critical as well functionally important hence all those processes in this group should be given high consideration and should be considered for implementing SPC immediately.

Group2 (A)

Processes in group2 (A) are functionally important but not statistically hence these processes only need to be given a second priority for implementation of Statistical process control. Processes in this group need to be considered for implementation of SPC only after implementing SPC for all processes in Group1(AA).

Group3 (B)

Processes in group3 (B) are statistically critical but not functionally important. hence, they only need to be given a lower priority for implementation of Statistical process control. Processes in this group need to be considered for implementation of SPC only after considering implementing SPC for all processes in Group1(AA) and Group 2(A).

Group4 (C)

Processes that belong to group4 (C) are neither functionally important nor statistically critical hence they can be eliminated without considering for implementation of SPC.

Remark

- Always more importance should be given to functional importance than statistical criticality.

In other words, if two processes score exactly the same on statistical criticality then the priority should be given to the process which has a higher functional importance score.

- If statistical criticality grade is obtained as zero. Then prioritization shall be solely based on functional importance score.

6.1.1. How does the proposed prioritization model include all important factors

This section explains how all those important factors which are to be considered while prioritizing a process for implementation of statistical process control as identified in the analytic study is being considered in the new recommended method for prioritizing the process.

FI= Criticalityscore*RPN $_{PFMEA}$*Cost Grading*Detectability

RPN $_{PFMEA}$: Risk priority number obtained in Process FMEA.

$$SC = \frac{(Cpk_D - Cpk_A)*100}{Cpk_D}$$

CPK_D : Process capability decided by the designer

CPK_A : Process capability attained in the process

a) Risks identified in DFMEA

For calculating Functional importance Grade (FI) criticality score is being used as a parameter, the criticality score is derived based on critical characteristics determined during the design phase of the product. Risk priority number RPN obtained in DFMEA is the key criterion for determining critical characteristics during the design phase of a product. Thus, by considering the criticality score for functional importance grade, Risks identified in DFMEA is being considered in the newly proposed method of prioritization.

b) Risks identified in PFMEA

For calculating Functional importance Grade (FI) Risk priority number (RPN) determined in Process FMEA developed during the process development phase is being considered as a factor. Thus, by considering RPN from PFMEA inputs from PFMEA is. being considered for prioritization of product characteristics.

c) Process capability decided during the design phase

For calculating Statistical criticality grade Cpk_d is used as a factor Cpk_d can have two values either 1.667 or 1.33 depending on which special characteristics marking does that particular product characteristic have [CC] or [SC].

d) Process capability attained in the process

For calculating Statistical criticality grade, Cpk_A is used as a factor Cpk_A represents actual process capability attained in the process.

e) Cost of reaction plan for containing the defect

For calculating Statistical criticality, the grading scale regarding the cost of the reaction plan for containing the defect is being used as a factor.

f) Probability of detecting the defect in subsequent processes

For calculating functional importance grade, grading scale regarding the detectability of finding the defects at later processes are being used as a factor, as a thereby, this factor is being considered in the recommended model.

6.1.2. Demonstration of the recommended model

This section presents a demonstration of the recommended model using an example for the purpose of a better understanding of the model.

Sl No	Characteristics	Criticality	Cost	Criticality score	Detactability	Cpk_D	Cpk_A	RPN PFMEA	Functional importance index	Statistical criticality index
1	Diameter 100mm	1	7	3	7	1.66	1.11	80	11760	33.13253012
2	Torque 15NM	4	3	5	5	1.33	0.87	180	54000	34.58646617
3	length 45m	3	5	7	3	1.33	0.75	166	52290	43.60902256
4	Radius 10mm	2	3	5	3	1.66	1.56	278	25020	6.024096386

Table 9. Example for a demonstration

The data shown are not from the production line, it's for the purpose of demonstration of the recommended model.

The functional importance index and statistical criticality index are calculated using respective formulas and plotted in vertical and horizontal axis respectively.

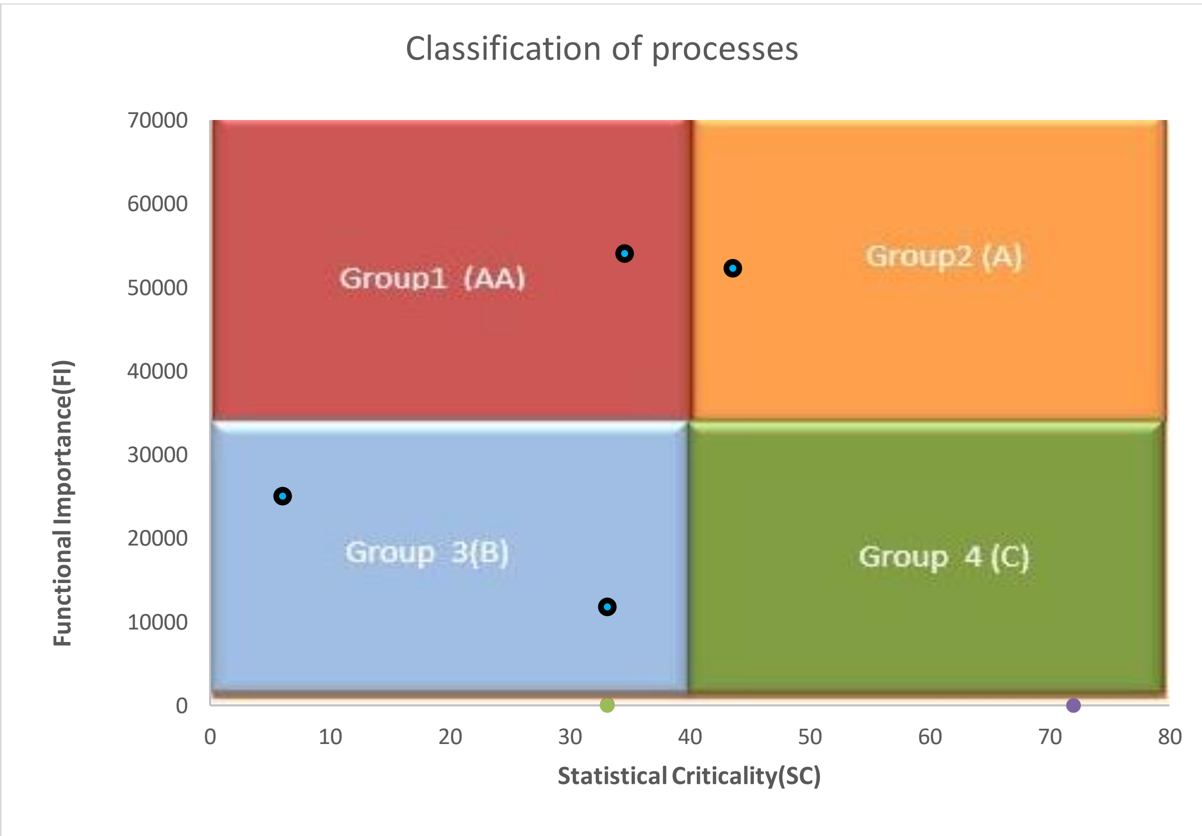


Figure 24, process classified into different categories

The process which fell in Group1(AA) should be considered for implementing SPC. Thereby this model shows that process no 2 in table 9. Shall be considered for implementation of SPC process

Note: Always functional importance has to be given importance than statistical criticality which means when two processes score equal values on statistical criticality more priority should be given to process which has higher functional importance index.

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Appendix

Interview Questions

current prioritizations methodology followed

- Could you please explain the current methodology followed for prioritizing the product characteristics for implementing SPC?
- Do you think the current method followed has any limitations? if so could you please elaborate on it?
- How long the current methodology for prioritizing the product characteristics have been following?
- How was the existing method for prioritizing the product characteristics developed?
- Could you please explain how is priority number for prioritizing the product characteristics calculated?
- How were various parameters for calculating the priority number decided?

- What is the importance of these factors currently being used for prioritizing the process for implementing SPC?
- How many SPC stations are planned to be implemented in the pilot area?
- How are special characteristics determined?
- How is it ensured that customer requirements are adequately focused while selecting a process for implementing SPC?
- How Is the process capability decided during the design phase considered while implementing an SPC station?
- How is the process capability attained in the process considered while implementing SPC stations?

- Could you please explain how is MSA conducted?
- Which SPC manual is being followed today?

- How are process risks determined?
- How are process risks considered while implementing an SPC station?
- How is the history of repeating quality problems considered while implementing an SPC station?
- How is the cost of rework considered while implementing an SPC station?
- How are SPC calculations done at this point in time?
- What are the various types of control charts used in routine production?
- At what stage of process implementation, details regarding SPC stations are decided.
- How is it being planned to adopt SPC in industry 4.0 manufacturing paradigm.?
- How is it planned to incorporate AI and Big data analytics into routine production?
- Next how many years, is being envisioned to incorporate industry 4.0 methods in regular production.
- What are the current quality improvement initiatives being undertaken in the organization now?
- What are the various AIAG core tools used in manufacturing?
- What is the various training given to operators with regard to SPC?
- What are the various analytical tools used during product development stages and process development stages?

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