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Statistical Methods to Control and Predict Quality Performance of Spare Part Operations

Master's Thesis in the Master's Programme Quality and Operations Management

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ABSTRACT

With the increasing competition in market, automotive companies are constantly seeking opportunities to obtain competitive advantage. Aftermarket services offer big potential to do this. In order to unveil the potential and turn it into customer satisfaction and profits, the companies need to focus on the quality performance of their operations. One of the ways to achieve better quality performance passes through the better use of statistical methods.

At Volvo Group, continuous improvement is a part of the company identity. With the desire of continuous improvement, the purpose of this thesis is set as to explore statistical methods to control and predict spare parts distribution centre operations. By doing so, the delivery fulfilment errors can be hindered to occur before the shipment of the parts and quality performance indicator that measures customer satisfaction can be improved.

With this purpose, a suitable theoretical framework was created and the literature review was conducted to better understand the previous research and applications in this field. Synchronously, the operations in Volvo spare parts distribution centres were investigated through observation and interviews. Moreover, the available historical data was unveiled for using it with statistical methods. The analysis was done by exploring applicable statistical methods by considering two different levels of the organization, global and site.

As conclusion, it is recognized that the available data has high potential for benefiting various statistical methods in order to provide better insights from the operations and show directions to make improved steering decisions based on facts.

Keywords: aftermarket, distribution centre, spare part distribution operations, statistical methods, control charts, predictive modelling, quality performance

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Thanks! Tack! Gracias! Tesekkurler!

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Abbreviations

TQM - Total Quality Management

TPS - Toyota Production System

VPS - Volvo Production System

SML - Service Market Logistics

DC - Distribution centre

CDC - Central distribution centre

RDC - Regional distribution centre

SDC - Support distribution centre

ERP - Enterprise resource planning

KPI - Key performance indicator

SPC - Statistical process control

APSF – Aftermarket Parts Service Failures

APQI - Aftermarket Parts Quality Index

PDC – Parts Distribution Centre

ROC – Receiver operating characteristics

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1 Introduction

In this chapter, first, the background of the company and the thesis is provided. It is followed by the problem definition that leads this thesis to emerge, the purpose of the thesis, research questions that are answered in the following chapters, scope and delimitations of the thesis, and, finally, disposition of this thesis report to help readers to navigate easily.

1.1 Background

Especially in the last two decades, global economy has been revolving towards globalization very rapidly. Automotive industry is one of the main actors in global economy and, along with the other industries, automotive industry, too, has been changing with the trends brought by globalization. With globalization, new players from developing countries have entered in automotive industry (Heneric *et al.*, 2005). Globalization has also made the evolution of the industry faster. The “know-how” has spread faster among companies and the companies have learned from each other. Some examples to this trend are implementation of lean management, Six Sigma, Total Quality Management (TQM) and so on. In many automotive companies, these methods and philosophies are adapted production system by inspiring the success of Toyota Production System (TPS). The main purpose of these systems is setting corporate targets, implementing principles, and working to achieve the targets by practicing the principles (Netland & Sanchez, 2014).

The competition in the industry has never been this intense before; therefore, the stakeholders are continuously seeking for new technologies and methods to take competitive advantage and obtain larger market shares (Christopher, 2005). One of the outcomes of increasing competition in the automotive industry is that the automotive companies have been revolving from product-oriented industry to an industry that provides services along with the products (Nieuwenhuis & Wells, 2015). As Christopher (2005) highlights, this shift is necessary for companies to meet the customer requirements; and therefore, gain competitive advantage by satisfying the customers.

The trend of implementing corporate systems and practicing methodologies help the companies to realize the importance of understanding the customer needs and requirements and working towards satisfying the customer. Volvo Group is not an exception. In accordance with these trends of implementing corporate systems and providing services along with the products, Volvo Group has undergone some corporate changes as well. The company has established a new and structured production system, Volvo Production System (VPS) (Volvo Group, 2010). The group was also launched new mission and strategy in 2016 where customer satisfaction is kept on focus as one of the main aims (Volvo Group, 2018). The main purpose behind the changes from being a product-oriented automotive company to an automotive company that provides products with wide range of service offerings is to increase the customer satisfaction and keep the competitive advantage in the market. Volvo Group calls it “transportation solutions” and the vision of the company is to “be the most desired and successful transport solution provider in the world” (Volvo Group, 2018).

In short, Volvo Group is an automotive company that has the headquarters in Gothenburg, Sweden. The group includes ten business areas where five of them for trucks while the others are Volvo Construction Equipment, Volvo Buses, Volvo Penta, Governmental Sales and Volvo Financial Services (VFS). The truck business is divided into three divisions which are Group Trucks Operations (GTO), Group Trucks Technology (GTT), and Group Trucks Purchasing (GTP). Volvo Parts is a subsidiary organization under GTO where the parts for production and aftermarket are managed (Volvo Group, 2018). This thesis work was done at the aftermarket section of Volvo Parts which has been recently renamed as Service Market Logistics (SML) to highlight the importance of providing services. The slogan of SML is "Proud to Deliver" and the aim of the business here is to keep the uptime of the customer at 100% by providing the right part on the right time. SML operates 47 distribution centres (DC) and administrative offices. While seven of these DCs are central distribution centres (CDC); the rest are either regional or support distribution centres (RDC or SDC) (Volvo Group, 2018).

1.2 Purpose

The purpose of this Master's thesis is to explore statistical methods to control and predict spare parts distribution centre operations to eliminate discrepancies in deliveries for ultimate customer satisfaction.

1.3 Problem Definition

With the new mission and strategy that was launched in 2016, the new vision is set to strive for improved performance in order to increase customer satisfaction (Volvo Group, 2018). The quality performance of SML is directly connected to the customer satisfaction. Every day, vast amount of data is gathered from at DCs all over the world. The data has big potential for controlling and predicting the quality performance with the ultimate goal of performance improvement. The data is mainly used for reporting purposes at the moment. By leveraging this data, the quality performance of SML can be improved; thereby, the customer satisfaction can be increased.

1.4 Research Questions

In the supply chain of aftermarket operations, there is vast amount of data is gathered. Despite the potential it has, this data is not used for improving the customer satisfaction. In order to be able to take effective actions based on the facts, the flow of the operations should be explored and the key parameters that have significant correlation to the quality performance should be identified. Therefore, the following question is asked as the first research question:

RQ1: How can the statistical methods control and predict the quality performance of spare parts operations?

After the statistical methods that can control and predict quality performance metric are explored, an investigation in the organization is required in order to understand the applicability of the statistical methods. The purpose is to explore the ways to leverage "raw data" by applying statistical methods that make sense for everyone in the organization, both global and site perspectives. This leads to the second research question:

RQ2: How can the results be used to support the operations at global and site levels of the organization?

1.5 Scope and Delimitations

Volvo Group is a big organization with over 100,000 employees. It has facilities in 18 countries and operations in 116 countries (Volvo, 2018). Considering the time and financial limits, this thesis work has several delimitations. First, the main source of data is obtained only from one DC which is the one in Gent in Belgium. At the beginning, the databases and cooperation levels of some large DCs (Byhalia CDC, Curitiba CDC, Eskilstuna SDC, Gent CDC) were analysed. It was concluded that the most suitable one is Gent CDC which is the largest in terms of order lines and operational capacity. Secondly, Gent CDC generates tens of thousands of parts every day and these parts belong to different brands of Volvo Group. According to our experience, it is common that there are different data system and operations in the same DCs for different Volvo Group brands. It was the same at Gent CDC. In this thesis, there is only one database is used and it includes only the operations of Volvo Trucks and Volvo Buses which consist of 95% of the all operations. Last limitation was about a field visit. Eskilstuna SDC was visited to map the process and understand the operations better where the size of the operations is relatively small compared to some DCs such as Gent CDC and Lyon CDC.

Due to confidentiality terms, the sensitive figures in this thesis are changed.

1.6 Disposition of the Thesis Report

This report has seven main chapters and the disposition of this report is explained along with the summary of the chapters below.

The first chapter is Introduction and in this chapter, first, the background of the company and the thesis is provided. It is followed by the problem definition that leads this thesis to emerge, the purpose of the thesis, research questions that are answered in the following chapters, scope and delimitations of the thesis, and, finally, disposition of this thesis report to help readers to navigate easily.

The second chapter is Research Methodology where the methodology that is followed throughout the research is explained. The chapter starts with the definition of the research strategy and design. Then, the methods of data collection are explained. It is followed by the proposed framework for this thesis work. Finally, the trustworthiness and ethical considerations are mentioned.

The third chapter is Literature & Theory. In this chapter, the literature review and scientific research fields are explained. First, the aftermarket context in general and in automotive industry is investigated. It is followed by warehouse operations and its management. Then, the investigation of suitable statistical models for the purpose of the thesis is presented. The chapter is finalized with the conclusion on theoretical framework for the thesis.

The fourth chapter provides empirical findings that are found through the course of this thesis work. Firstly, Volvo Group is analyzed in depth from the different perspectives and the aftermarket organization is investigated. Then, the processes and operations in aftermarket logistics are explained. Lastly, findings from data collection are given.

The fifth chapter is dedicated for the analysis of this thesis work. First, the process of data analysis with collected data is explained. Then, several statistical methods are explored with the data. At the end, the perception of the global and site level isprovided to understand the usefulness of this analysis.

The sixth chapter covers the discussion conducted by thesis students on this thesis work.

The last chapter is the conclusion chapter where the research questions are answered briefly and some limitations encountered over the thesis work is shared along with suggestions.

The report is finalized with appendices and reference list.

2 Research Methodology

In this chapter, the methodology that is followed throughout the research is explained. First, the research strategy and design is defined. Then, the methods of data collection are explained. Moreover, a conceptual framework is proposed. Finally, the trustworthiness and ethical considerations is discussed.

2.1 Research Strategy and Design

There are different strategies and designs to consider while conducting a business research. They are decided according to the characteristics and the purpose of the research. Defining the appropriate strategy and design is very important as they take on the role to provide directions to the researchers through the research (Blessing & Chakrabarti, 2009).

There are two main strategies in research strategy. These are qualitative research strategy and quantitative research strategy. Qualitative research strategy has an inductive approach for the relationship between theory and research; therefore, there is tendency to create new theory out of empirical findings. Data collection methods are usually unstructured or semi-structured. Some common data collection methods are interviews, observations, and focus groups. On contrary, quantitative research strategy has a deductive approach for the relationship between theory and research; therefore, there is tendency to test existing hypotheses and theories. Data collection methods are usually much more structured compared to qualitative methods and there is emphasis on the quantification of the data. Some common data collection methods are surveys, polls, and interviews (Bryman & Bell, 2015).

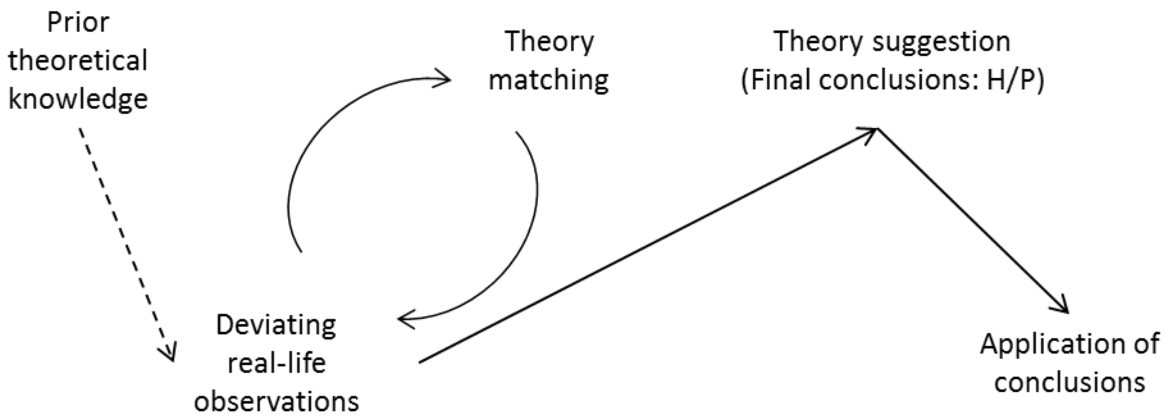


Figure 2.1 Abductive Approach (Kovács and Spens, 2005)

Beside these two main research strategies, there is an alternative strategy that is called mixed methods strategy. This strategy covers features of both qualitative and quantitative research strategies (Bryman & Bell, 2015). It has abductive approach which gives flexibility to the researchers to follow a inconsequential research by moving between theory and empirical data (Kovács and Spens, 2005). Abductive approach provides continuous cycles of learning and being surprised by the data. It is especially suitable for exploratory qualitative researches to unveil potentials for further quantitative research (Gummesson, 2000). Considering the immaturity of the research field and the exploratory purpose of the thesis, the research methodology for this thesis is chosen as mixed methods strategy with abductive approach. The process for abductive approach can be seen in Figure 2.1.

Case study as research design is good way to conduct an exploratory investigation in depth to understand the context, identify the potentials, and develop concepts (Bryman and Bell, 2015). This thesis is designed to be a case study which will serve as a preliminary research for building the basis for a wide-scale implementation of statistical methods to control and predict performance in Volvo Group.

2.2 Data Collection

The data collection for this Master's thesis included several sources and methods.

2.2.1 Literature Study

Due to the abductive nature of this study, the literature was continuously consulted; the main sources were Chalmers' online library and Google Scholar. The researchers were intended to find available information by searching individual or combination of words such as: aftermarket, quality performance, distribution centres, warehouse, operations, service, predictive analytics, (enterprise resource planning) ERP systems, big data, change management, statistical analysis. Due to the specificity of the research field, namely, automotive aftermarket quality performance, most of the sources lied in the spectrum journals and articles of logistics and services operations management. For 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 APA referencing style and are ordered alphabetically in the reference list.

2.2.2 Interviews

Bryman & Bell (2015) describe unstructured interviews as unguided conversations. They are important specially to clarify observations and questions that emerge during the course of the research. On the other hand, semi-structured interviews are the sole information source for qualitative research projects in some cases. They are scheduled and are guided by predetermined, open-ended questions. For this research, both structured and unstructured interviews were carried out. They took place in continuous basis according to how the access to new sources of information was granted. Each interview provided valuable inputs and opened new doors for more sources of information. Bryman and Bell (2015) describe this phenomenon as the "snowball effect", when the interviewees contribute the researchers to build larger professional networks in the organization to get new contacts for potential interviewees. The unstructured interviews had exploratory purposes to understand the usage of databases and some details of the key performance indicator (KPI) calculations and target settings. On the other hand, the semi-structured interviews were intended to collect information about the quality management system and how statistical methods would fit within the existing structure while contributing to steer the process. There were always two interviewers to assure reliability.

On the beginning of the project a set of semi-structured interviews were set in order to understand and define the scope of the project. Afterwards, when the project scope was framed and the DCs to focus were defined, an “unofficial” project team was created in order to guide and clarify findings in the data collection and analysis. This team was composed of 3 quality engineers located in CDC Gent. A weekly forum was set in order to bring up points of discussion and variables to investigate. These forums were lead as unstructured and semi-structured interviews with specific topics and questions that were prepared one week in advance. As complement to the forum, interviews with managers from global perspective were scheduled with the intention of findings patterns and inputs from experience within the Volvo network that might be useful for the project.

2.2.3 Observations

One of the main activities of the project was process mapping in order to understand the nature of the information and material flow within SML DCs. To fulfil this purpose, a visit to the SDC Eskilstuna was scheduled. The agenda included tracing of a product life cycle within the warehouse which covered the inbound and outbound activities. Furthermore, a review of the dashboard and information, stand-up meetings and how issue resolutions are handled within the DC were conducted. The observations were done in an overt way, taking into consideration that people may change their behaviour while they are being observed (Bryman and Bell, 2015). To tackle this issue, the observations were focused on processes, places and technology instead of focusing on particular persons or teams.

2.3 Data Analysis

In this research, numbers would not mean anything without a context. In order to test the suitability of statistical methods in SML, it was necessary to collect qualitative and quantitative data from different corporate sources.

2.3.1 Qualitative Data

Information about operations and processes were retrieved from the corporate data sources. This information was used to trace the sources of quantitative data which may feed the statistical models and methods. For processes, the source was Volvo Group Management System (VGMS), the database consulted to generate understanding of the inbound and outbound transaction. Furthermore, the level of alignment with Volvo’s manufacturing vision was observed by retrieving information from VPS. These documents provide relevant information on how problem solving and data visualization can be handled from the shop-floor to the management level. For details on KPI’s calculations, internal documents (e.g. manuals, instructions, procedures) were consulted. Finally, details on issue resolution a root cause analysis were found in ARGUS which is the global tool to collect intercompany and dealer complaints.

2.3.2 Quantitative Data

As a part of finding the suitability of statistical methods to be applied at SML, sample data was retrieved by means of queries from warehouses’ ERP systems and the global dashboard. First data of interest was the reporting and monitoring data for quality performance KPI that is used at corporate office. Second data of interest was the detailed historical data that includes warehouse movements of CDC Gent. For this data, special request for access was asked and granted. For this data, several verification cycles were carried out jointly with the quality representatives of DCs with the purpose of selecting the most relevant parameters for analysis. The last data of interest was the data of "discrepancies" which encompasses the customer complaints for delivery fulfilment errors. It is important to highlight here is that all the statistical method analyses are done with Chalmers licensed statistical analysis software, JMP v. 13.0.0.

2.4 Proposed Framework

The research strategy for this Master's thesis is based on the literature review. Statistical Quality Control (SQC) is the most wide-spread practice among services and manufacturing when it comes to the applications of statistics for controlling and predicting. The underlying thinking of it is to eliminate special causes of variation in order to make the process predictable. In this context, predictability is understood as the certainty that a metric or measurement will vary in between two control limits. A second premise for SQC is to exercise control on process "inputs" instead of the "output" (Wood; 1994); therefore, it is important to understand the relationship between them. At this point analytical techniques are needed in order to fill the gap in between them. Several authors (Ning et al. 2009; Shang et al. 2013; Steiner & MacKay, 2004) have shown example of this in manufacturing contexts. Furthermore; recently, the arisement of ERP (Enterprise Resource Systems) and informatics have facilitated the storage of huge amounts of information. This information may be "inputs" and "outputs" of manufacturing and services processes. This information represents an important opportunity of exploitation. This has given room to the emergence of analytical tools to find these correlations and, further, build predictive models which complements the concept of predictability from a different angle in comparison to SQC. In addition, this abundance of information leads to large, unstructured and complex problems where solutions might not be documented in textbooks or scientific research Hoerl & Snee, 2017). This situation bring the need to give a kind of structure to such problems by approaches such as statistical engineering which may guide the utilization of statistical techniques for quality performance in business contexts (Britz et. al 1997; Hoerl & Snee, 2017).

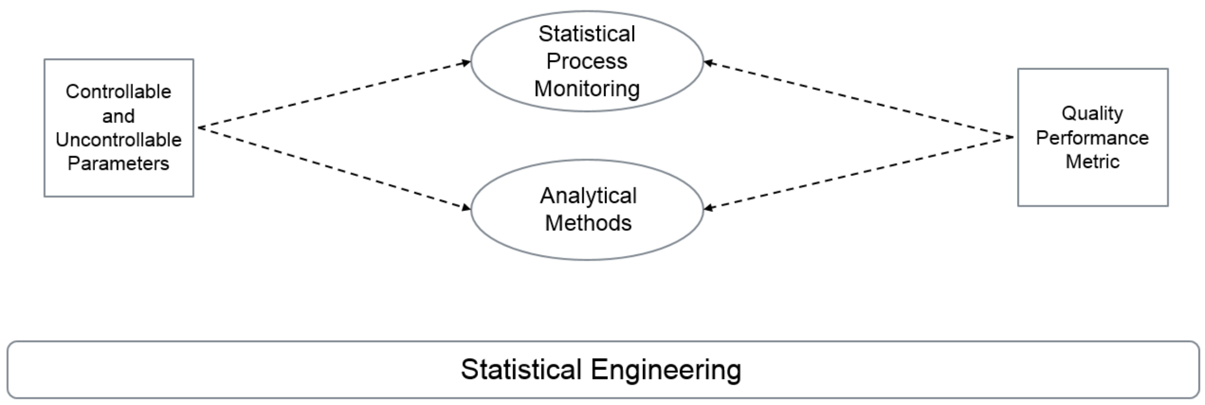


Figure 2.2 The proposed framework

With this in mind, Figure 2.2 depicts the proposed framework which guided this research. The main idea was to monitor the output (APSF) of the studied process and strive to identify controllable and uncontrollable parameters ("inputs") in order to find their correlation and pose control strategies in order to tackle the effects of variation in the process. Since, in practice, business problems are large, unstructured and complex (Hoerl & Snee, 2017), statistical engineering guided the utilization of statistical methods for quality performance management with business acumen.

2.5 Trustworthiness

Trustworthiness of a research depends on four criteria, namely, conformability, credibility, dependability, and transferability (Bryman & Bell, 2015). These criteria are explained below.

2.5.1 Conformability

Conformability is about the influence of subjective ideas on the conclusion of the research. The importance of objectivity is kept as a priority during the research. For quantitative part, the decisions are taken based on facts rather than personal interests and opinions. For qualitative part, the decisions are taken based on the qualitative findings of data collection. By nature, the unstructured and semi-structured interviews are open to subjective opinions and personal tendencies. In order to increase the objectivity, the findings are checked and their objectivity is validated by multiple people in the organization. Therefore, common views are assumed as objective (Bryman & Bell, 2015).

2.5.2 Credibility

In this research, both primary and secondary data is used. Primary data refers to the data gathered for this research and secondary data refers to the data that was already available (Hox & Boeije, 2005). The triangulation is done by supporting the secondary data with literature review; whilst, increasing the credibility by gathering new data from different sources as primary data (Bryman & Bell, 2015). For the primary data, interviews, collaborative weekly meetings with key informants, and observations are done. In order to correctly conduct triangulation, an attention is paid carefully to ensure credibility by observing different people in different settings for gathering the data from as much different perspective as possible. It is also important to mention that while different data gathering methods are used, the aim has always remained the same.

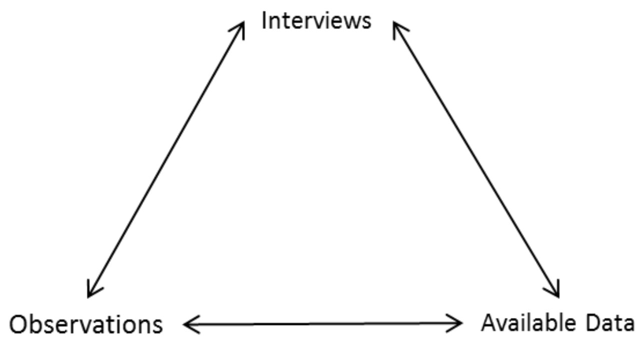


Figure 2.3 Triangulation that was conducted for this research

2.5.3 Dependability

For the dependability of this research, the thesis students take auditor roles to be sure that the records of data collection are done properly from problem framing until the end. It includes the activities such as transcription of interviews, note taking during observations, and analysing the data (Bryman & Bell, 2015).

2.5.4 Transferability

According to Bryman and Bell (2015) transferability in case studies corresponds to the possibility of applying the findings of the research to other contexts. This Master’s thesis was took place under the context of the aftermarket operations at Volvo Group. The company has strong customer-centered approach which is reflected in its motto “Proud to Deliver”. This is a trend in line with concepts such a servitization where companies provide much more than a physical product. In this case, Volvo strives to be an ally of its customers by keeping the highest uptime for the trucks, buses and heavy equipment of their customers. Therefore, there is no room for failures in the deliveries of spare parts; since, they can cause disturbance in customer´s operations. Nonetheless, the approach developed on this document can be transferred to other contexts. Within the automotive industry, the metric on focus, APSF, has been standardized and there exist companies that share information about this indicator (eg. Carlisle Benchmarking Focus Days). These philosophies are also applicable in other manufacturing companies which are into this servitization approach. Several examples of this in railway, informatics and aerospace industries are well-known (Baines & Lightfoot, 2013). Furthermore, the utilization of ERP (Enterprise Resource Planning) and WMS (Warehouse Management System) are wide-spread practice in distribution centre operations; therefore, the approach of this Master’s thesis can be even transferred to any context which involves distribution centre operations. There is an immense possibility to use the information generated in the operations and find correlations with analytical tools in order to find the relationship between independents variables (inputs) and a quality performance indicator (output) in order to design strategies for tackling variation.

2.6 Ethical Considerations

Bryman & Bell (2015) present four ethical principles that should guide business research namely, harm to participants, lack of informed consent, invasion of privacy, and deception. In this research project the most sensitive aspect was dealing with quality performance in a process whose is mostly driven by people. A part of the project involved to break down the parameters to the operator level in order to observe individual contribution and patterns on overall performance. Therefore, to prevent harm to participants and lack of informed consent, operator names were omitted in the analysis and they are replaced with numerical codes.

3 Literature & Theory

In this chapter, the literature review and scientific research fields are explained in depth. First, the aftermarket context in general and in automotive industry is investigated. It is followed by distribution centre operations and its management. Then, the investigation of suitable statistical models for the purpose of the thesis is presented.

3.1 Aftermarket

In this section, there are two sub-sections on aftermarket. In the first one, a literature review on aftermarket concept in general and importance of servitization is conducted. In the second sub-section, the literature review covers aftermarket in automotive industry in depth.

3.1.1 Aftermarket Concept and Servitization

In today's world, even in the highly product-oriented industries, relying only on one-time product selling is not enough anymore. Because of the ever-increasing competition in the industries due to globalization, demand has lowered, profits margins have decreased, and loyalty to the brands has faded away (Bundschuh & Dezvane, 2003). Attracting customers with product features is not enough anymore. They are seeking for service offerings that come with the products (Herbig & Palumbo, 1993). These changes and trends have leaded the companies in the manufacturing industries to establish aftermarket services. As a result, the companies have shifted their missions from "pushing" sole products to offering "solutions", products and services together, with a distinct focus on customer satisfaction (Heneric *et al.*, 2005).

Aftermarket consists of various service activities, e.g., spare parts, reparation, maintenance, equipment upgrades, customer support & service, training, inspections. Compared to the manufacturing of the actual products with highly standardized processes & operations, these aftermarket services are less systematic; therefore, difficult to standardize. There is a mistake that many previously sole product-oriented companies tend to do which is not distinguishing aftermarket operations than manufacturing operations. These two operations have similar features, e.g. material flow, information flow, operations, but what is underestimated is that while manufacturing requires deterministic approach; aftermarket requires stochastic approach (Cohen *et al.*, 2006). Table 3.1 distinguishes clearly the differences between manufacturing and aftermarket services with several parameters.

Despite the facts that aftermarket business is crucial for companies to attract customers and make profitable sales out of it, it is not so easy to succeed. The aftermarket business itself is a peculiar one and, as it is an emerging business area, it is risky due to lack of best practices. Only the companies that can spare enough amount of resource to implement an efficient aftermarket supply chain can leverage the benefits of the business (Cohen *et al., 2006)*. In recent years, the companies have started to realize the importance and benefits of efficiently organized aftermarket supply chain. Therefore, there are now some examples in the industries where companies take aftermarket business into serious consideration (Herbig & Palumbo, 1993). These companies make decisions for their aftermarket business based on facts and include it into their strategic missions by senior management. The activities of aftermarket services are segmented according to the customer needs (Bundschuh & Dezvane, 2003).

Table 3.1 Manufacturing vs. Aftermarket Services (Cohen *et al.*, 2006)

Parameter	Manufacturing	Aftermarket Services
Nature of demand	Predictable, can be forecast	Always unpredictable, sporadic
Required response	Standard, can be scheduled	ASAP (same day or next day)
Number of SKUs	Limited	15 to 20 times more
Product portfolio	Largely homogeneous	Always heterogeneous
Delivery network	Depends on nature of product, multiple networks necessary	Single network, capable of delivering different service products
Inventory management aim	Maximize velocity of resources	Pre-position resources
Reverse logistics	Doesn't handle	Handles return, repair, and disposal of failed components
Performance metric	Fill rate	Product availability (uptime)

Suomala *et al.* (2002) briefly claims that spare parts sales is 'the most profitable' business of a company. The companies that have successful aftermarket business increase customer satisfaction. This success increases their profit margins as well (Bundschuh & Dezvane, 2003). Aftermarket business consists only 24% of their revenues but this 24% brings 45% of the gross profit. According to a research, there is positive correlation between customer loyalty and the ratings of aftermarket services. Loyal and satisfied customers mean continuous sales, either a new end-product or aftermarket sales. In fact, according to a research firm, Aberdeen Group, people in the United States spent over $1 trillion for the services of the products they already had which corresponds to 8% of the annual gross domestic product (GDP) of the United States of America (USA) (Cohen *et al.*, 2006).

3.1.2 Aftermarket in Automotive Industry

Automotive industry is considered one of the biggest industries in term of revenue. It includes wide and complex network of supply chains from raw material extraction to end-product and aftermarket services. Considering financial size of the industry and profitability of aftermarket business in general, automotive companies can leverage the benefits of aftermarket services greatly. Cohen *et al.* (2006) claim that some industries, including automotive industry, companies make so much money that the size of the aftermarket operations can get up to five times larger than car making. It is not just the size of the business but the profitability of the business for the companies in automotive industry is very high. For example, in 2001, General Motors (GM) made more profit with $9 billion aftermarket revenue than $150 billion vehicle sales. Moreover, there are several proven examples in the industry that some brands' excellent aftermarket services succeed to keep the customers happy; therefore, the customers chose the same brands while purchasing a new car (Cohen *et al,* 2006). This shows that successful aftermarket does not only provide continuous profit from one end product but cause to start a new cycle of profit with a newly sold product. Unlike the selling of new car, successful aftermarket business can affect the revenue and profit of both aftermarket and new car selling. It is particularly important factor considering the fact that attracting a new customer may cost to companies five to twenty-five times more, depending on the industry and source, than keeping the current customer (Gallo, A., 2014).

It is getting more and more difficult to satisfy customers due to the constant increase in their demands. Moreover, new technologies and liberalized markets bring new actors in the industry and increasing the competition (Herbig & Palumbo, 1993). Under these circumstances, the importance of the quality of aftermarket operations is increasing as well.

3.1.3 Aftermarket Performance Measurement

The supply chain performance indicators can be categorized as follows (Murray, 2016):

1. Cost
2. Time
3. Quality

According to Gaiardelli *et al.* (2007), most of the performance measurement research focuses on internal company performance metrics. There is a lack of focus on quality performance of the services and metrics to evaluate customer satisfaction (Gaiardelli *et al.*, 2007). Patton & Bleuel (2000) conducted one of the few researches on this matter by proposing some service features and performance metrics for performance measurement. They also mentioned service quality and its effects on customer satisfaction. Their focused only on operational level and the part on customer satisfaction was not comprehensive. Gaiardelli *et al.* (2007) claim that performance measurement should include both financial and non-financial indicators, consider short- and long-term perspectives, and cover different levels of an organization. They proposed “The After-Sales performance measurement framework”. The framework contributes to increase communication of performance parameters and metrics among different stakeholders. This would help organizations to speak the “same language” and have the same purposes for strategic goals.

In the next section, a big part of aftermarket business, DCs will be focused with the explanation of their management, operations, and quality & performance improvement in relevant operations.

3.2 Distribution Centres

A distribution centre (DC) is where specific kinds of products are accepted from external suppliers, stocked until they are ordered from customers, and shipped to the customers according to the order. The customer can be dealers, retailers, wholesalers, or individual end customers (Holste, 2009). DCs are much more than a warehouse and play a key role in supply chain for customer satisfaction. In this thesis, the operations of Volvo aftermarket DCs and their quality performance regarding order fulfilment is on focus. Therefore, these features were one of the main elements of the literature review.

3.2.1 Operations in DCs

The main purpose of DC operations is to gather products from multiple sources in one place and distribute these products to multiple locations in the region that the DC is located. DCs are important part of any supply chain network. According to Holste (2009), DC operations are very customer-oriented and fast-moving rather than static storage facilities. A DC has an intermediary role between the suppliers and the customers. They can provide value-added services and contribute customer satisfaction. It is a challenging task and DC operations should focus on customer satisfaction but also have good performance, both financially and non-financially (Holste, 2009).

The operations in a DC consist of some main activities that generally all the DC have in common. These can be divided into two categories as inbound and outbound activities (Gu *et al*., 2007). Inbound activities usually consist of receiving and storing. Outbound activities usually consist of picking, packing, and shipping (van den Berg and Zijm, 1999).

Figure 3.1 The flow of operations at a DC (van den Berg and Zijm 1999)

- Receiving: the activity that is performed to receive goods from external sources (e.g., suppliers and manufacturing plants).
- Storing: the activity that includes the received goods to be included in the inventory and to be placed on the right locations.
- Picking: the activity that initiates the order preparation after the order is received. An operator goes to the location of the ordered items and picks the right items in the right amounts. It is considered the most critical and most labour-intensive activity.
- Packing: the activity that the items are packed properly to be shipped to the customer.
- Shipping: the activity that finalize the process in DC by loading the packed orders into the right vehicles to be sent to the customers (Staudt *et al.*, 2015).

Even though, these activities are generally common in any DC context; the complexity of in-house operations can vary from one DC to another. There are three main aspects that define the complexity level of a DC. (1) The number of different products handled, (2) the number of orders handled, and (3) the number of different activities that from inbound to outbound (De Koster and Warffemius, 2005).

The higher the time that an item is handled by a person; the higher the variation increases (Battini *et al*., 2015). Picking activity is one of the most crucial and time-consuming activities in DC operations. There is intensive human involvement in the activity (Battini *et al*., 2015). A wrongly picked product can cause direct and indirect costs to the company. Therefore, one of the managerial priorities of DCs is to improve the performance of picking activity to prevent errors (Grosse & Glock, 2013). It requires implementation of new technologies, e.g., paperless picking systems, and it means investment. There are several researches (Bergerbower and Ludwig, 2007; Reif et al., 2010; Yeow and Goomas, 2012) prove that such technologies decrease the probability of errors. For example, an automated system with light sensors can decrease human factor; therefore, the probability of errors.

The general aim of any DC operations is to supply the demands of the customers efficiently and correctly. To do so, there are many indicators that are used by the companies. In the next sub-section, performance indicators for quality are investigated.

3.2.2 Quality Performance in DCs

Logistics activities in general have revolved drastically in the 20th century and in today's business circumstances, these activities seen as great opportunity to get the competitive edge (Bowersox *et al*., 2002; Kent and Flint, 1997). Despite the fact that logistics has strategic influence on companies' success, the quality performance of these activities had not been in the agenda of the organizations until recent years (Voss *et al.*, 2005).

In order to improve quality performance indicators that are related to the customer, organizations should first focus on improving their internal quality performance (Lings, 1999). Conduit and Mavondo (2001) claim that the highest quality can only be possible if the internal quality is kept as the priority. Two examples for internal quality performance in DC context could be the departments that exchange goods during the process and the tools used for communication (Voss *et al.*, 2005). Finn *et al.* (1996) include this assumption with TQM and highlight the importance of internal quality.

The performance of the employees at a DC is highly and directly related to the quality that perceived by the customer (Mentzer *et al.*, 2001). Especially the operators on the floor who handle the goods and information during operational activities (e.g., picking and packing) have important role to the quality of the service provided by the organization. The quality performance of the DC operators affects the right goods to be delivered to the right customer at the right time; therefore, their quality performance influences the efficiency and quality performance of the operations and the value chain as a whole (Voss *et al*., 2005). Moreover, the operational quality performance can influence the financial performance of the company. Considering the influence of customer satisfaction on loyalty and the cost of gaining a new customer is much higher than serving to current customers, the efficiency and quality of the in-house DC operations contribute or damage the financial figures of the aftermarket business of the companies (Heskett *et al.*, 1994).

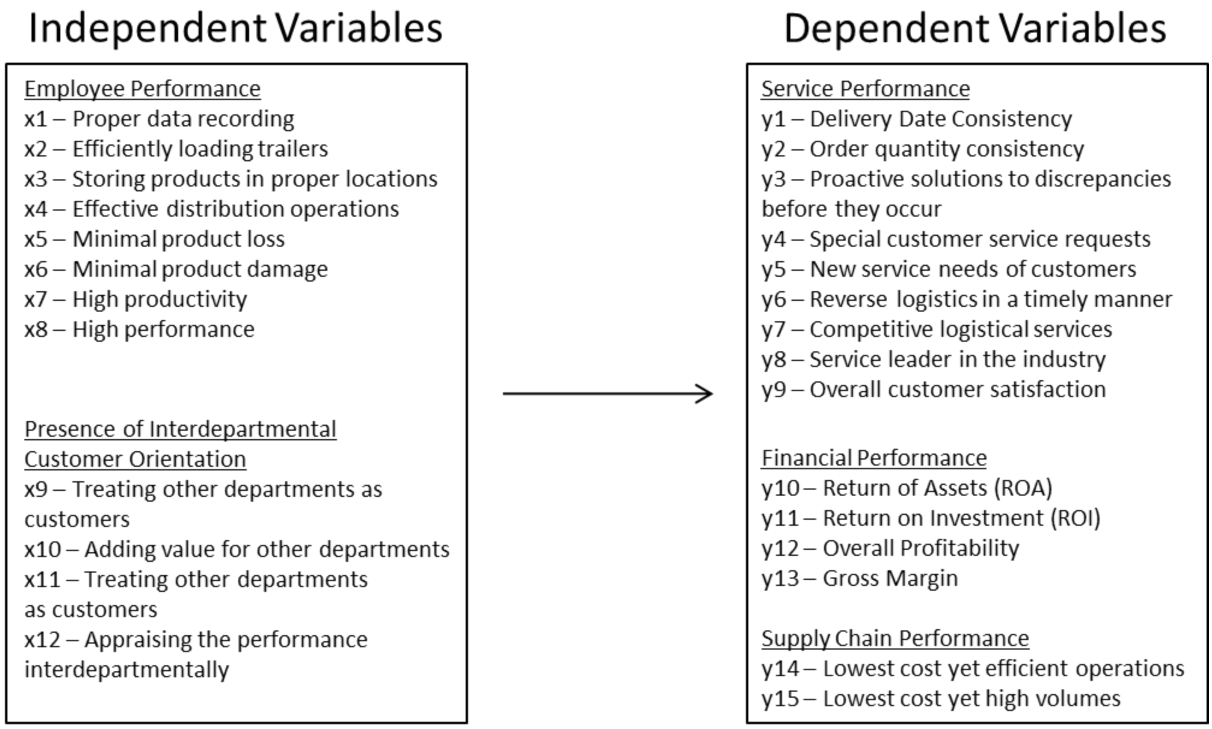


Figure 3.2 Independent Variables that Affect Dependent Performance Variables (Voss *et al*., 2005)

The quality of the delivery depends of several factors (Hollnagel, 1997). These factors can be divided into two as human-related and machine-related. For example, human-related can be the skills of the picker and machine-related can be the information that is delivered through in-house IT systems (Hollnagel, 1997). Information delivery is critical in quality of the deliveries and they can be improved by lean tools and experience.

Figure 3.2 shows the x variables (independent variable) that affect the y variables (dependent variables) in DC context (Voss *et al*., 2005). It shows that employee performance has significant effect on service performance.

Within warehouse application, there is two commonly used measurements and by Park (2012) described as most important. These are order lead time and delivery accuracy. Order lead time is defined as the time interval from request release to floor until request completion. Because this measurement is directly affected by how fast order lines can be handled, it is closely related to productivity. Delivery accuracy is defined as the percentage of error-free deliveries (de Koster and Warffemius, 2005). What defines an error-free delivery here could be explained as the delivery of right item in the right quantity (Battini et al., 2015). The right item is interpreted as the by customer ordered item in an acceptable condition. Worth noting is that Bartholdi and Hackman (2016) state that it is typically advantageous to do quality checks in the packing process, as it is typically the last process where each item is handled separately.

3.3 Statistical Methods

This literature review for statistical methods is intended to present the available statistical methods used in both manufacturing and service contexts by explaining their applications, rationales, limitations, and strengths.

On one hand, the well-known statistical methods used by quality professionals are explained. These methods are gathered under the first part of this section as statistical quality control. On the other hand, an immature statistical analysis field, predictive analytics is explained. Companies have generated more and more data from their operations due to the developments in computer sciences and information technologies. These developments lead companies to explore more complex ways of analysing their data which contribute predictive analytics to gain popularity to leverage their data for improvements.

3.3.1 Statistical Process Control

Statistical quality control encompasses set of tools classified in three categories (Reid & Sanders, 2015):

- Descriptive Statistics: These are used to describe what the data shows. It is a set of simple summaries and graphs which provide information about the characteristics and relationships of a sample from a population.

- Acceptance Sampling: This is a set of sampling methods in order to determine the acceptance of rejection of a batch of products.

- Statistical Process Control (SPC): SPC is a set of graphical and statistical tools which aims to provide information about the stability of a process through collecting random samples of a process output. It checks if the samples fall within a determined range of control limits. It determines if the process is “in control” or “out of control”.

In this research, SPC is kept as the major control approach.

SPC is a set of tools in order to evaluate and improve a process (Keller, 2011). It was created by Walter Shewhart (1891 – 1967) and popularized by Edwards Deming (1900 – 1993). The purpose of SPC tools is to monitor the variable of interest and steer the process in order to take it towards a state of statistical control. Statistical control means that the measured characteristics behave under a stable distribution which, in most of the cases, is the normal distribution (Keller, 2011).

Shewhart (1931) defined statistical control as follows: " A phenomenon will be said to be controlled when, using past experience, we can predict, at least within limits, how the phenomenon may be expected to vary in the future. Here it is understood that prediction within limits means that we can state, at least approximately, the probability that the observed phenomenon will fall within the given limits."

SPC is based on plotting information that is collected from the process. The information is a set of individual observations that are taken in certain interval of time. This set is called subgroup. Each subgroup tells information about the process location and variation. Once several subgroups are collected and analysed, it is possible to use this data to predict the process location and the expected variation (Keller, 2011).

The underlying rationale behind setting control limits in a chart is to separate causes of variation in two categories: natural variation and special causes. The results are then used to improve the quality by eliminating special causes of variation to lead the process to a state of "in control" which implies that only natural causes of variation govern the process. If a process reaches this level, it is possible to use the control limits to predict the future performance of the process or make decisions based on facts. For example, the control limits of delivery time in aftermarket services might be applied to set the level of the service to the customers (Ryan, 2000).

According to Keller (2011), there are several types of SPC. The appropriate one is chosen by observing if the data is continuous or attribute and the type of the sample.

P-chart

P-chart is the technique used to represent attribute data which is measured in proportions. $\bar{\rho}$ is the centre line of the proportion of the attribute to control and it is calculated by means of the equation 3.1 where $\hat{P}_i$ is the proportion of defective of one observation, D_i is the defects observed, and corresponds to the number of units evaluated. Therefore the $\bar{\rho}$ (centre line) corresponds to average of the $\hat{P}_i$ in a group of samples m. The control limits for upper and lower control limits are calculated by the equations 3.2 and 3.3, assuming the observed events have binomial distribution. When the sample sizes n is not constant, the control limits of this control chart are calculated for each observation. A sample chart that is built with JMP can be seen in Figure 3.3.

$$\hat{P} = \frac{D_i}{n} \qquad i = 1, 2, 3, \dots, m \qquad \bar{\rho} = \frac{\sum_{i=1}^{m} \hat{p}_i}{m} \tag{3.1}$$

$$\text{UCL} = \bar{\rho} + 3\sqrt{\frac{\bar{\rho}(1-\bar{\rho})}{n}} \tag{3.2}$$

$$\text{LCL} = \bar{\rho} - 3\sqrt{\frac{\bar{\rho}(1-\bar{\rho})}{n}} \tag{3.3}$$

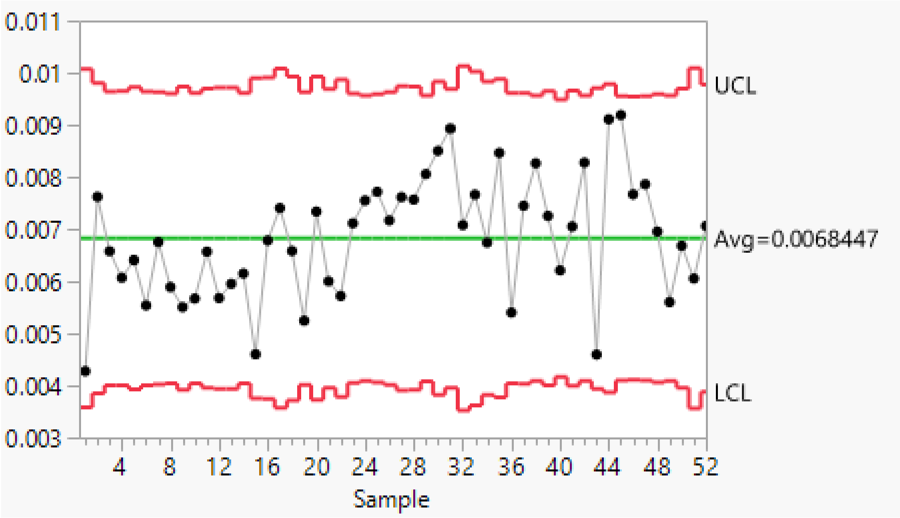


Figure 3.3 A sample control chart where n is not constant.

SPC for High Performance Operations

Montgomery (2009) recommends sub-group sizes to be large enough to detect one defect with a probability of at least 95%. In this case, the author recommends using the formula 3/*p* where *p* is the probability to detect a failure. For example, the values of 400 ppm and 1800 ppm correspond to the proportions of 0.0004 and 0.0018; therefore, the recommended sub-group sizes are 7500 and 1700 respectively. Other authors like Morris & Riddle (2008) are even stricter and they suggest sample sizes even larger to detect improvement or shifts in p-charts. The Table 3.2 shows some low proportions with suggested sample sizes. The authors recommend the rule of thumb for sample size calculation which is 6.6/*p*. Therefore, in the aforementioned example, the sub-group sizes are 16500 and 3700, respectively.

Table 3.2 Samples Sizes Determined by Four Different Methods

	p					
	0.1	0.05	0.02	0.01	0.005	0.001
Standard method	81	171	441	891	1791	8991
Modified method	58	119	300	602	1206	6037
Exact method	63	129	328	658	1319	6605
Rule-of-thumb	66	132	330	660	1320	6600

T-chart

Montgomery (2009) poses the problem of high performance operations, namely the ones which are measured by per million. For this purpose, the author proposes the implementation of time in between events charts. However, this control charts have a very skewed distribution (Nelson, 1994). Therefore some transformations, at least, in the context of manufacturing are needed in order to make this control charts more understandable for operative personnel. Similar approaches are presented by Wu et al. (2014) where several transformations are needed for taking to the normal distribution these time of control charts in manufacturing contexts. The equation 3.4 shows the transformation suggested for Montgomery (2009) for this type of control charts.

$$x = y^{1/3.6} = y^{0.2777} \tag{3.4}$$

However, for simplicity, the control charts will be posed in this Master's thesis as a mean to establish shifts in the delivery process and as an alternative for operator performance measurement. Therefore, no transformations would performed and the control limits are suggested to be calculated according to business needs.

Utilization of SPC

The upper control limit (UCL) and lower control limit (LCL) are set at +/- standard deviations of the mean. Therefore, the dot should fall above UCL or below LCL to be considered as an alarm signal. The probability of delivering a false alarm is "0.027" or 1 out of 370, which is considered insignificant, since changes in reality occur more often than that. Consequently, a shift either in the variation of the process or location may be detected by means of the control chart (Keller, 2011).

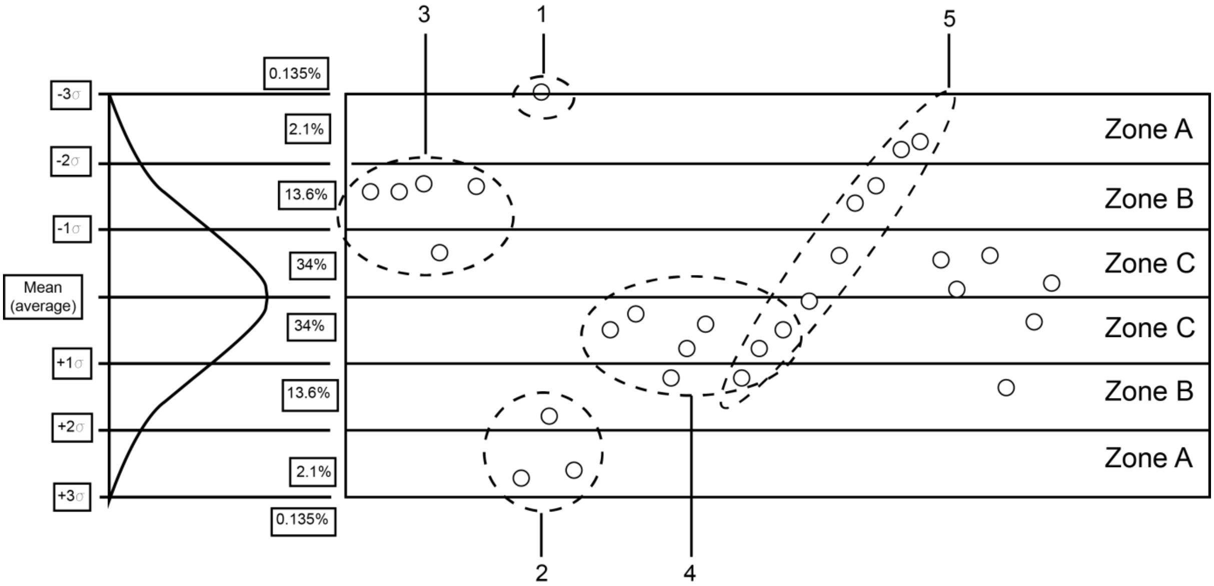


Figure 3.4 Normal distribution, control charts, sensitivity levels (Western Electric Rules) (Keller, 2011)

However, the sensitivity of the control charts can be increased by the application of certain rules, commonly known as the Western Electric Rules (Keller, 2011). With this purpose, Figure 3.4 shows the division of 6 sections which correspond to zones delimited from 1 to 3 standard deviation of the process.

Table 3.3 explains the Western Electric Rules by referring Figure 3.4 above.

Table 3.3 Western Electric Rules

Rule	Description
Rule 1	Point beyond the control limit
Rule 2	2 out of 3 in Zone A or beyond
Rule 3	4 out of 5 Zone B or beyond
Rule 4	Eight or more on one side of centreline without crossing
Rule 5	Six or more in a row increasing or decreasing

Even though, a process might be in "in-control" state, it does not necessarily mean that it meets the customer expectations (Wood, 1994). Therefore, the need of a measure to compare the process output with the voice of the customer (VOC) is required. For this purpose, the capability analysis is used.

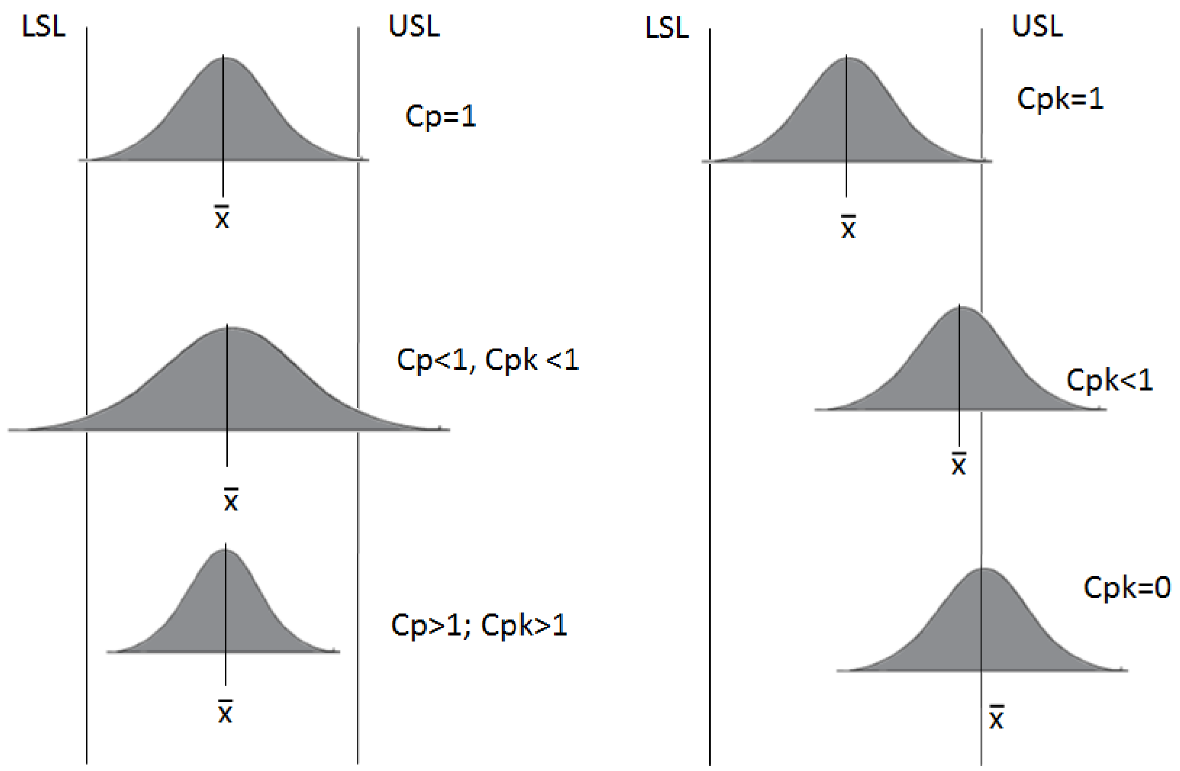


Figure 3.5 Cp and Cpk, explained

The capability analysis consists in determining if the process is capable of fulfilling upper and lower specification limits (USL and LSL). These limits define the limits to satisfy customer requirements. “Cp” is a measure to assess the capability of the process according to the specification limits; “Cpk” measures the capability of the process according to “the target”. Therefore, a high ratio Cp/Cpk is desirable in order to reach a stable and capable process. Figure 3.5 explains Cp and Cpk with their equations (Montgomery, 2009).

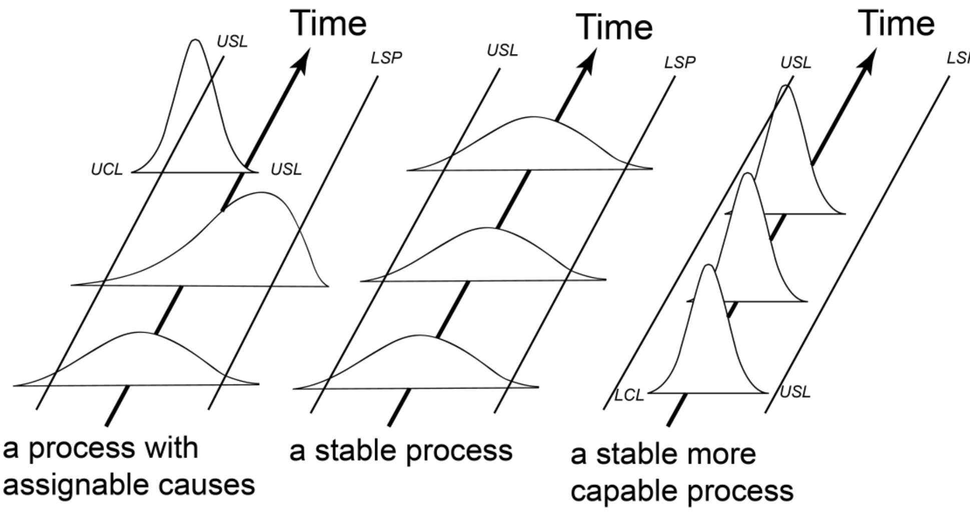


Figure 3.6 First stable; then capable (Bergman & Klefsjö, 2010)

The Figure 3.6 depicts the rationale behind the SPC methodology. At the beginning, a process may be “out of control”; so, the first step is to take it towards a state of stability. Once the process is stable, the goal is to reduce the variation; therefore, to make the process capable against the specification limits.

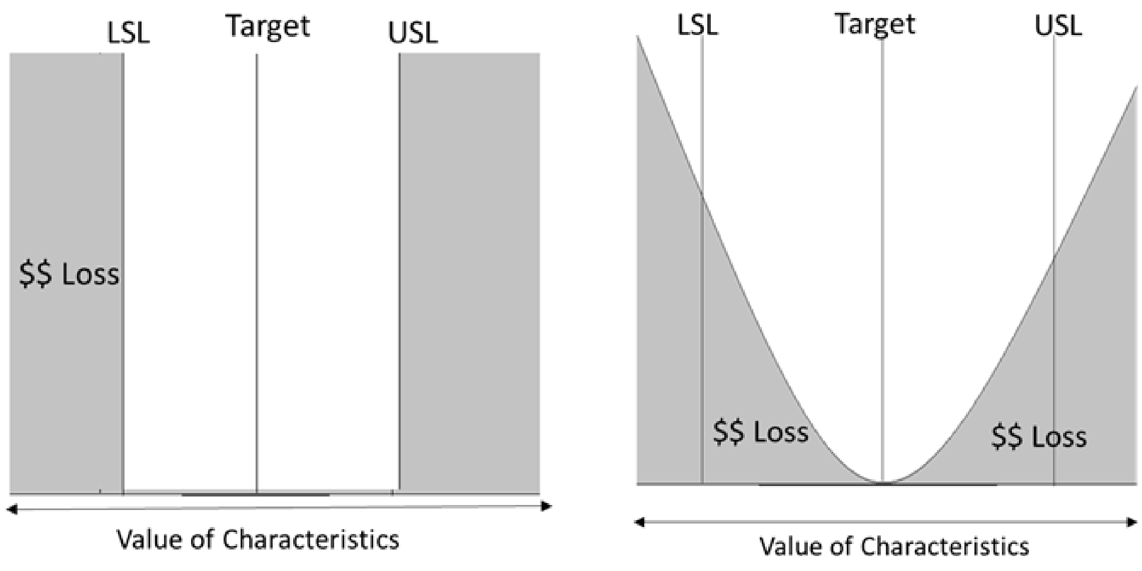


Figure 3.7 Taguchi’s loss function

Taguchi's Loss Function

As exposed above, the process capability strives to keep the process within the specification limits, USL, LSL. However, Taguchi (1924 – 2012), proposed that, in certain cases, the target is the exact value that meets the customer requirements and moving away from this exact value will cause monetary loss (Boyles, 1991). This function brings out the concept of Cpm, Cpkm, in order to complement the aforementioned capability index (Montgomery, 2007). The functions and visualization can be seen in Figure 3.7.

3.3.2 Statistical Methods in Services Industry

Several authors (Woodall & Montgomery, 1993; MacCarthy & Thananya, 2002) point out the need to conduct more research on SPC in non-manufacturing applications.

According to Wood (1994), there have been discussions on which tools to include under the umbrella of SPC. However, the most common ones are Shewhart control charts, process capabilities studies, and Pareto analysis. Moreover, he summarizes the main assumptions of SPC and its alignment with the quality management philosophy as follows (Wood, 1994):

- The critical quality characteristics should be measured.
- Preventing problems with proactive mindset rather than "fire-fighting" with them.
- The priority of analysis should be the process rather than the output.
- Inspections should be eliminated.

Wood (1994) explains some examples of statistical methods in services context. For example, invoicing errors and number of rings before a phone call is answered. An example of such control charts can be seen in Figure 3.8.

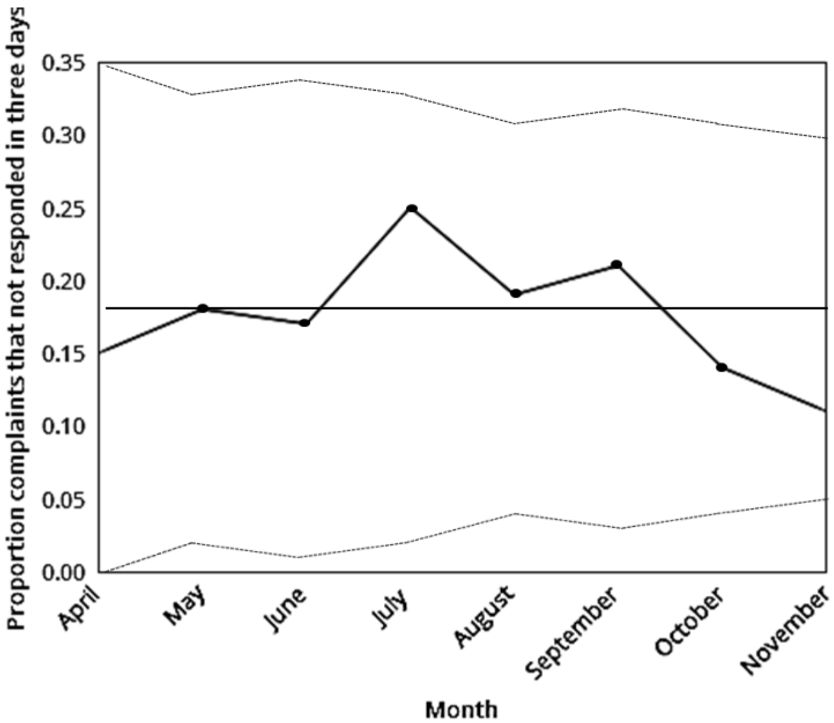


Figure 3.8 Control Chart Example for Services Industry (Wood, 1994)

Wood (1994) tackles the differences between the customer satisfaction in services and in manufacturing contexts. In the Figure 3.9, the Taguchi's loss function is expressed for both services and manufacturing processes. In the left one, which is for manufacturing, the aim is the "middle point" and getting away from this point causes customer dissatisfaction. However, the one at the right, which is for services, the loss function is one sided; therefore, the aim is to reach the "highest point" or "lowest point" (Wood, 1994). This case for services entitles the concepts of "variation" and "control" to weaken their meaning of their application in services context.

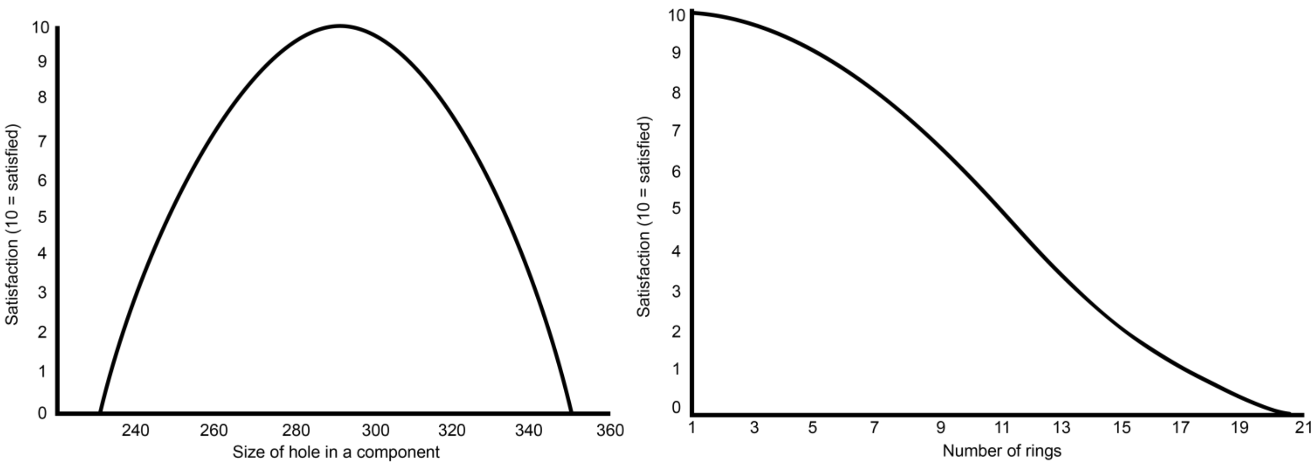


Figure 3.9 Taguchi's loss fuction (manufacturing vs. services) (Wood, 1994)

For the graph for services industry, the author highlights that once the mean reaches the end of the curve, there is no more room for improvement. Therefore, there are several arguments for changing the interpretation of the control charts in services applications. For instance, instead of utilizing phrases such as "control charts" or "control limits", it is suggested that the names as "quality level charts" and "evidence of change lines" would be more suitable (Wood, 1994). Moreover, phrases such as "in control" might be improper from the SPC perspective. The reason is that the graph might show that the entire sample is "in control" but the process' itself might still not meet the customer requirements (Wood, 1994).

Sulek (2004) adds to the discussion, the prevalence of counting and proportion data lead to reliance on attribute control charts. However, they may fail to generate alarms on unusual variation if the measurements do not reflect the process flow; therefore, the author emphasizes on the importance of flow and step mapping in services and having a systems perspective.

MacCharthy & Thananyara (2002) classify non-conventional applications of SPC in the following fields: (1) engineering, industrial and environmental applications, (2) health care applications, (3) general service application, and (4) statistical applications. The authors remark how health care applications are gaining momentum. They highlight the suitability of advanced techniques such as CUSUM, ARIMA, and residuals analysis. Moreover, Scordaki & Psarakis (2005) identify four different objectives for applications of SPC in non-manufacturing applications: (1) process monitoring, (2) planning, (3) evaluate customer satisfaction, (4) forecasting.

Furthermore, the authors present a guideline for setting up a control charting initiative. It constitutes five main steps. Figure 3.10 shows the steps.

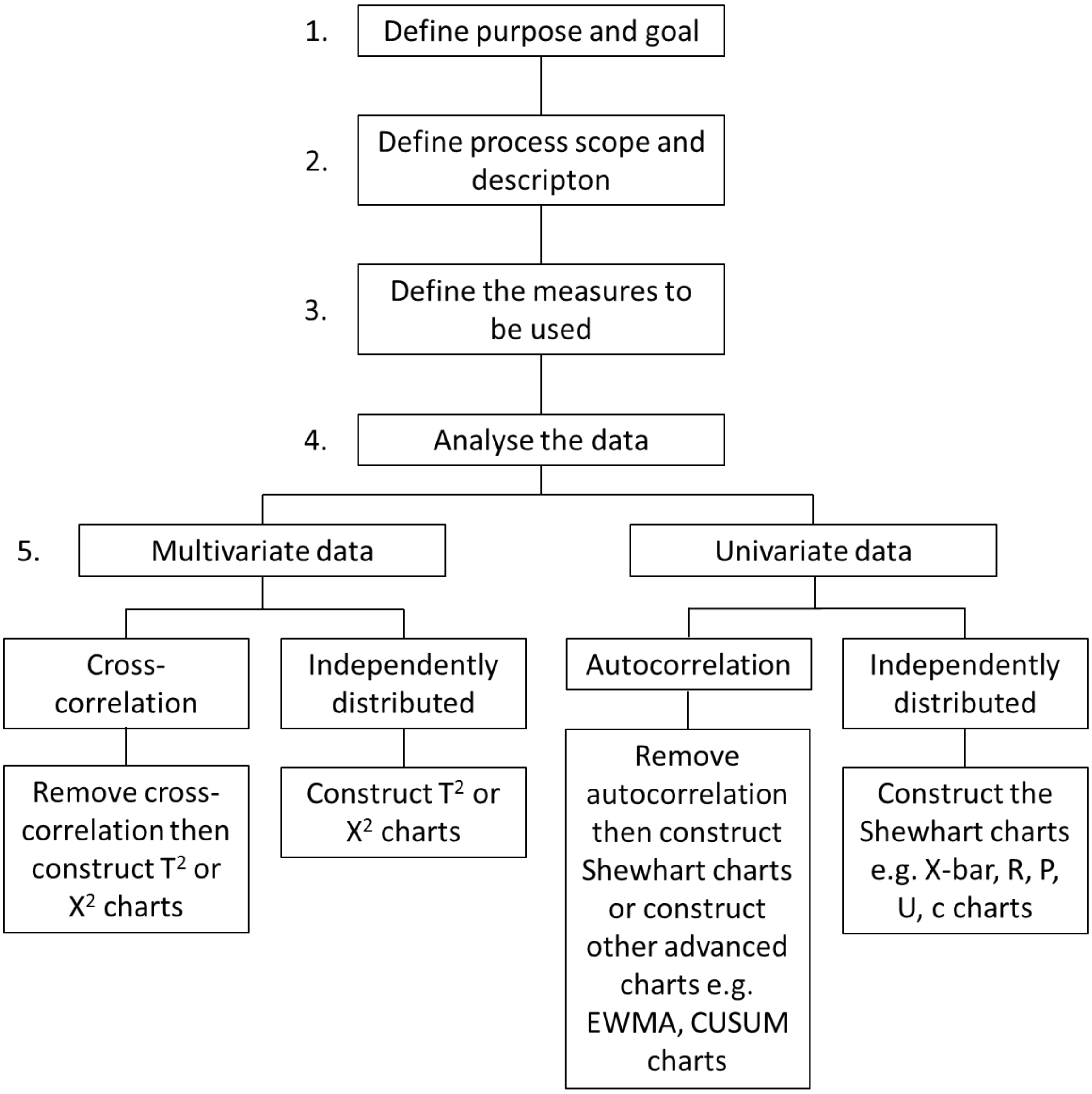


Figure 3.10 Control Charting Initiative (Scordaki and Psarakis, 2005)

3.3.3 Statistical Methods in Warehouse Operations

The literature lacks specific examples on how statistical methods can control and predict quality performance of warehouse operations. One of the researches on this subject is that Lightfoot & Kauffman (2003) present a proposal on how to use control charts to control warehouse quality performance. The authors propose to use x-bar and R chart. They provide examples of applications in several KPI´s such as service deliveries performance (the ratio of the number of order lines issued to the number of order lines requested). They argue the suitability of control charts in situations where the capability of the process is centred on a target and tend to be normally distributed.

Despite the fact that there is scarcity of research in literature when it comes to applications of SPC in warehouse operations, there are several consulting firms which provide advices on using SPC for monitoring different performance indicators in warehouses. For example, McNeese (2007) proposes an application of a p-control chart for operator performance (the ratio of the number of picking errors to the number of picking and total number of pickings per day per operator). Moreover, it is suggested that Pareto diagrams would be useful to trace the main special causes for picking errors. Finally, Montgomery (2007) shows an example of c-chart for an inbound process in a warehouse that checks the discrepancies between quantities and documentation.

3.3.4 Analytic Techniques

The developments in computer sciences and information technology lead companies to be able to collect and store larger amounts of data than ever. Some of the most accepted systems are called ERP systems which let companies to collect information from different departments under the same database. ERP systems provide increased communication infrastructure and allow the data to be utilized interdepartmentally. Due to the very large amounts of data collected and stored, the companies struggle with managing their data. These kinds of challenges cause the emergent of new trends such as big data and data warehousing (Slack and Lewis, 2015).

Utilization of Big Data

Klimberg and McCullough (2013) highlight the importance of the appropriate utilization of “big” data requires significant investments to be transacted to IT (Information Technologies) departments and of how business intelligence (BI) can enhance better return of these IT investments (ROI). The authors discuss a framework that consists of the relationships and interactions of 3 BI disciplines, namely, IT, statistics, and modelling. They propose the usage of the terms of data mining and predictive modelling for the process of analysing extensive business data. They clarify that these terms are a part of predictive analytics and should be used to find correlations, explanatory variables, and build models.

Bivariate Method

Hosmer and Lemeshow (2005s) claim that the most accepted method in predictive analytics is bivariate method where many independent variables with expected predictive value for dependent variable are put in individual logistic regression and the ones with obvious relationship are taken to the next step for multivariate regression (Klimberg and McCullough, 2013).

Multivariate Logistic Regression

Klimberg and McCullough (2013), present another framework for predictive analytics for multivariable data. They categorize the techniques as discovery and interdependence for unsupervised techniques and dependence for supervised techniques. The unsupervised ones have no target or y variable (dependent variable). These techniques analyze the relationship between the variables without considering causality. The goal is to find affinities or, in other words, “what goes together”. The beers and diapers relationship in retail business would be a good example to understand these techniques. The supervised techniques seek for explanatory x variables (independent variables) that cause variations in y variables (dependent variables) and are used to find a model that describe the correlation between these two different kinds of variables (Klimberg and McCullough, 2013).

Data Mining

Berry and Linoff (2004) state that a predictive analytics project shows can follow the phases of a data mining process. They define data mining as "a business process for exploring a large amount of data to discover meaningful patterns and rules". Klimberg and McCullough (2013) explain the data mining process with approximate time frame to spend for each of the phases. They highlight the fact that the amount of time shared for data preparation is the largest; since, the data might come from different data sources which require long time in depuration and matching. Table 3.4 shows the phases and the time frame.

Table 3.4 Data Mining Process (Klimberg and McCullough (2013)

Data Mining Process	
Phases	Time Spent
Project definition	5%
Data collection	20%
Data preparation	30%
Data understanding	20%
Model development and evaluation	20%
Implementation	5%

Attention on Analytics Frameworks

The awareness of these new trends in analytics techniques has increased very recently. This awareness has contributed to refresh old techniques such as SPC. Now, it is possible to come across with the names of these trends in international quality environments. For example, The Malcolm Baldrige National Quality Award, one of the most prestigious awards in the quality fields, mentions the term “big data”, “data analytics”, and the new opportunities that they open to transform data into knowledge (Evans, 2015). Likewise, in Japan, the Deming Prize has one of its six categories called “collection and analysis of quality information and utilization of IT” (Liedtke, 2014).

3.3.5 Assessment of Analytics Techniques

Predictive analysis is assessed with the application of confusion matrix with the available data (Fawcett, 2006). The confusion matrix is a classifier which distinguishes the predicted condition and real condition. The model indicates how accurate a prediction depending on the classification is. If the objective is to predict “A”, then a true positive (TP) corresponds to the number of matches between the number of “A” predicted and the ones that “A” in reality. The same occurs with “B” condition, a true negative (TN) corresponds to the number of matches between the number of “B” predicted and the ones that “B” in reality. On the other hand, there is also classification of unsuccessful predictions in two classes. First one is the false positive(FP) or Type-I error which corresponds to the number of predicted “B” but is not “B” in reality. The other one is the false negative (FN) or Type-II error which corresponds to the number of predicted “A” but is not “A” in reality.

From the confusion matrix it is possible to calculate sensibility and specificity of the results (Fawcett, 2006). Figure 3.11 shows the confusion matrix and the formulation of sensitivity and specificity. Sensitivity measures the fraction of positives that are correctly identified and specificity measures the fraction of negatives that are correctly classified.

		Actual Value	
		Positives	Negatives
Predicted Value	Positives	True Positive (TP)	False Positive (FP)
	Negatives	False Negative (FN)	True Negative (TN)

Figure 3.11 Confusion Matrix (Fawcett, 2006)

$$\text{Sensibility: } \frac{\mathrm{TP}}{\mathrm{FP+TN}} \tag{3.5}$$

$$\text{Specificity: } \frac{\mathrm{TP}}{\mathrm{FP+TN}} \tag{3.6}$$

In reality, the perfect results are seldom achieved and the level of sensitivity and specificity can vary among different threshold or cut-off point for the classification of the matrix. To do so, there is a tool called Receiver Operating Characteristics (ROC) to optimize the sensitivity and specificity of a model (Fawcett, 2006). The tool is shown in Figure 3.19. With this tool, the power of prediction is calculated by the area under curve (AUC). Swets (1988) explains that if AUC is in the range of 0.5-0.7, it represents no to low discriminatory power; 0.7-0.9 represents moderate discriminatory power; and >0.9 represents high discriminatory power. The author also notes that, however, the assessment of one model may depend the skewness of the ROC curve and economic considerations.

Figure 3.12 is interpreted as the sensitivity would be “1” and the specificy would be “0” in the best-case scenario and, both, the sensitivity and the specificy would be “0.5” in the worst-case scenario. This means that the model has a random performance. In other words, a *“random classifier will produce a ROC point that ‘‘slides’’ back and forth on the diagonal based on the frequency with which it guesses the positive class”* (Fawcett, 2006).

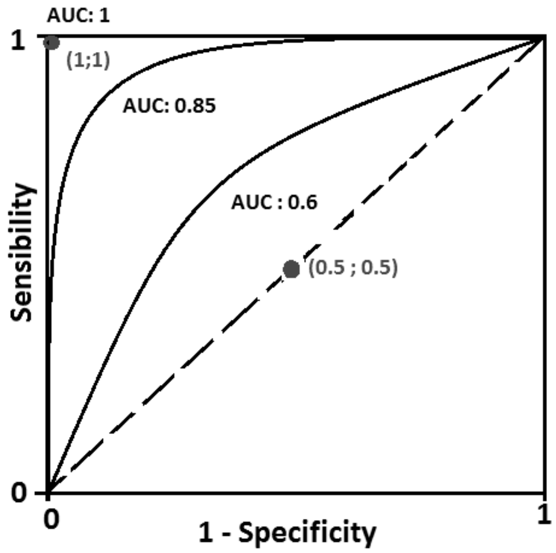


Figure 3.12 ROC and AUC (Fawcett, 2006)

3.3.6 Analytics Techniques Applications

Several authors have explored the usage of analytical techniques in the field of quality, especially for the identification of relationships, impacting factors, and explanatory variables (Ning *et al*. 2009; Shang *et al.* 2013). One approach is the usage of logistic regression for controlling quality in processes which are measured in "parts per million", the rationale behind that is that sample sizes to find errors tend to get higher when deliver high performances and the time in between failures becomes higher (Steiner & MacKay, 2004). Therefore, instead of measuring the output, the author suggests identifying continuous explanatory parameters which may affect the process (Jin R., 2007). Shang *et al.* (2013) describes the usage of the model for multi stage processes and Samohyl (2013) uses this to propose control charting in a transactional process.

The logistic or logit regression in the context of quality control may be used in order to compare the characteristics for the "failures" and "no-failures" (Steiner& MacKay, 2004). The equation 3.7 represents how the proportion of defectives (p) can be estimated through the characteristics, x_1, x_2, x_3, …, x_k, which may be continuous or categorical variables. The expression p/(1-p) is called odds which, in other words, is the number of times success occur compared to the number of times a failure occurs. βs are the regression coefficients and are commonly calculated with the maximum likelihood method (ML) which is designed to maximize the probability of reproducing the data given the parameters estimate (Peng 2002).

$$\log\left(\frac{\rho}{1-\rho}\right) = g(x) = \beta_0 + \beta_1 x_1 + \cdots \beta_k x_k \qquad (3.7)$$

The model is also widely spread in healthcare sciences (Fawcett, 2006). It is utilized for prognosis and diagnosis for binary outcomes. Models based on this approach provide the ability to distinguish patients who will have or not have an event of interest. In the context of prognosis, the interpretation of its outcome is to identify risk factors associated with the probability to get a disease Royston, P., & Altman (2010). For assessing the ability of a model to discriminate who will or not have a condition, Receiver Operation Characteristic (ROC) is a wide spread method. This approach has been extended beyond the medicine practice (Fawcett, 2006) and has been popularized for assessing classification models in other contexts. The basics of this method are presented in the previous section.

3.4 Statistical Engineering

In literature, statistics are related with mathematics and there is gap between theoretical statistics and applied statistics. The gap occurs because in theoretical statistics are usually based on straightforward problems with pre-defined parameters. In reality, the problems are not defined and the objectives are not clear (Hoerl and Snee, 2017). Hoerl and Snee (2017) discuss a new perspective with a framework which documents theory and practice together in literature. This approach would give the engineers a roadmap regardless the uniqueness of the projects and room to develop the framework by researchers in academia. They define some dimensions as common in the contexts that their approach is designed for:

1. Large
2. Complex
3. Unstructured
4. Data Challenges
5. Lack of a “correct” solution
6. The need for strategy

The aim of statistical engineering is “to achieve enhanced results” by utilizing statistical methods in contexts that includes these dimensions in their characteristics.

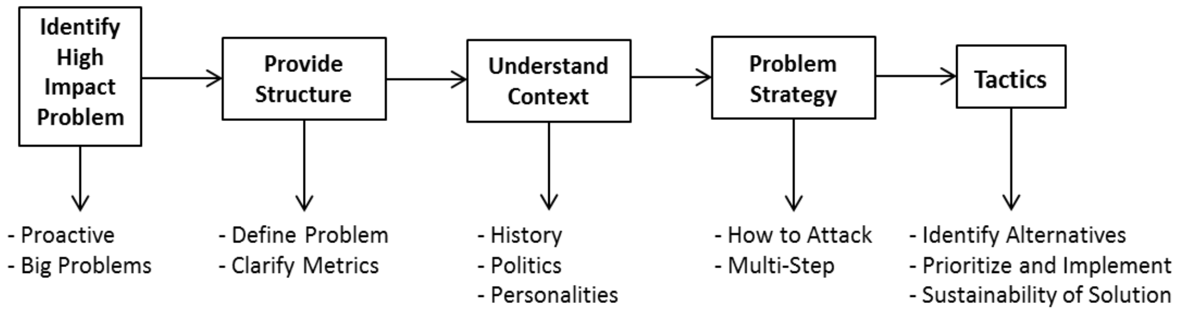


Figure 3.13 Statistical Engineering Framework (Hoerl and Snee, 2017)

The framework they propose has five main steps that would guide engineers through the statistical engineering projects. The authors clearly indicate that there is no intention providing s fixed structure to follow; instead, they encourage engineers to tailor the framework according to their projects (Hoerl & Snee, 2017). The framework can be seen in Figure 3.13.

4 Empirical Findings

In this chapter, the data gathered in different means are explained. First, an overview to the company is from organizational, structural, and operational perspectives. Secondly, how a Volvo DC works is explained by using the observations and interviews conducted at CDC Gent and SDC Eskilstuna. Thirdly, the investigation on what kinds of data is gathered for what and information flow in the organization is provided. The chapter ends with a short conclusion.

4.1 Volvo Group Overview

4.1.1 Volvo Group

Volvo Group is a world-leading manufacturer of trucks, buses, construction equipment, and marine and industrial engines. Along with manufacturing, the group also provides financial services. The group is headquartered in Gothenburg, Sweden and employs about 100,000 people. The global footprint spreads widely with facilities in 18 countries and products in almost 200 markets. The group defines its areas of activity according to the forms of operations of the vehicle types that they manufacture (i.e., on the road with trucks, at the site with construction equipment, in the city with buses, and at sea with marine engines (Volvo Group, 2018).

In 2016, the group adapted new vision and mission along with five core values. The main reason to these updates is the recent trend in the automotive industry which is providing services along with the products for satisfying the customer and obtaining better market shares. The mission runs “Driving prosperity through transport solutions” (Volvo Group, 2018). The group takes customer focus to the next level by considering all the economic and social dimensions of value mission is that the group considers that it provides solutions by combining products with services in a harmonized way in accordance with the mission, the vision is to “be the most desired and successful transport solution provider in the world" (Volvo, 2018). To achieve this, the company adapts five values which are (1) customer success, (2) trust, (3) passion, (4) change, (5) performance. The group’s increasing interest in seeking sustainable ways to conduct business also needs to be mentioned. The annual reports of the group have been called “Annual and Sustainability Report” since 2015.

The organization structure of the group involves ten business areas, five of them are truck business (Renault Trucks, Mack Trucks, UD Trucks, Volvo Trucks, and Group Trucks Asia & JVs) and the rest is Volvo Construction Equipment, Volvo Buses, Volvo Penta, Governmental Sales, and Volvo Financial Services (VFS). Due to the relatively larger size of the truck business to the rest, it divides into three further divisions, Group Trucks Technology (GTT), Group Trucks Operations (GTO) and Group Trucks Purchasing (GTP) (Volvo Group, 2018).

As a part of GTO, there is an organization that is called Volvo Parts. Volvo Parts is a sub-division that belongs to GTO. Volvo Parts’ main activity involves managing supply chain of parts for production and aftermarket. This research takes place in Volvo Parts aftermarket department (SML) (Volvo Group, 2018).

4.1.2 Volvo Production System (VPS)

Volvo Production System (VPS) is the production system that is designed and adapted by Volvo Group. As many other examples in the industry, it has some similarities to the production system that is considered the origins of all, Toyota Production System. VPS covers the aspects of way of working, standards, ethics, and organizational elements.

The system is designed as a dynamic system that key elements steer the organization with the aim of continuous improvement.

The key elements consist of:

1) Performance management
2) People development
3) Improvement structure
4) Lean practices
5) End to end alignment
6) Management commitment

Figure 4.1 Volvo Production System (VPS) (Volvo Group, 2018)

Performance management emphasizes on the importance of data & facts management to measure and improve performance. It covers visual management as well in order to deliver information among stakeholders. This element includes a tool kit for problem-solving. Depending on the complexity of the problem, different approaches are undertaken. There are statistical and non-statistical tools. Figure 4.2 show the suggested methods depending on the complexity of the problem. In other words, "a proper medicine for each sickness".

People development covers the subject of knowledge management for learning and spreading the best practices among the organization. It also emphasizes on teamwork and competence development.

Improvement structure is inspired by PDCA. It includes the activities for improvement methods, problem solving, and standardization.

Lean practices element pursues to implement built-in quality and just-in-time mentalities into the organization.

End to end alignment focuses on the importance of integration and alignment of different stakeholders under the same values for common targets.

Management commitment creates the base of VPS. The system says that all the other elements should be steered by committed leaders to improve culture for continuous improvement. It mainly emphasizes on the importance of leadership in the organization.

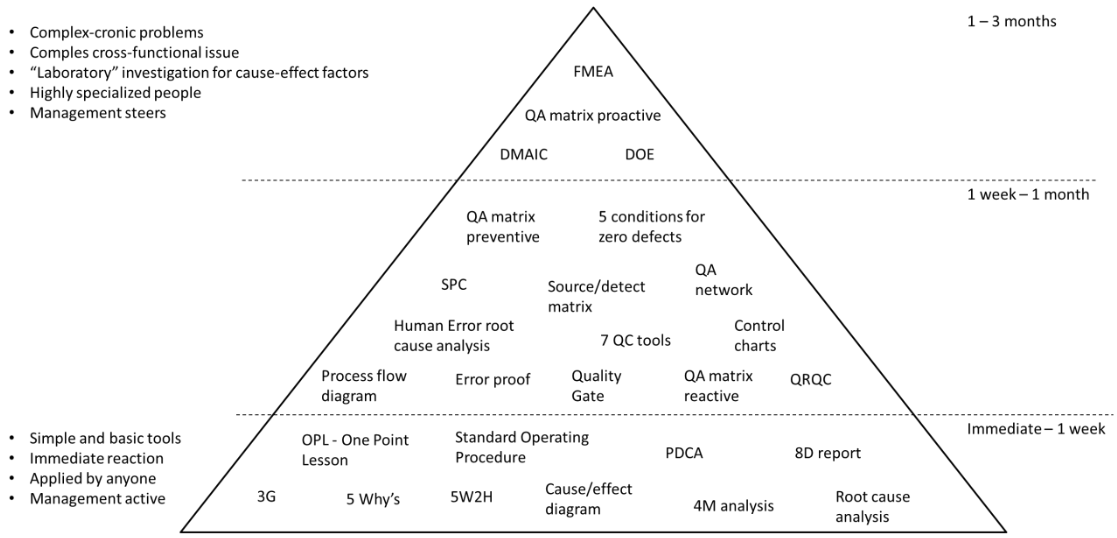


Figure 4.2 Methods hierarchy in VPS

VPS is applicable to every single function of Volvo Group. Its main purpose is to reach ultimate customer satisfaction. The key elements provide directions and standards how to succeed. VPS is the core of any activities at Volvo Group and there are experts in the organization that check the maturity level of the functions to see how well they meet the VPS requirements.

4.2 Volvo Parts Aftermarket

For aftermarket operations, Volvo Parts is responsible of managing and operating the operations in more than 40 locations over the world. The regions are divided into six as APAC, Gent & EU, Japan, Lyon & RMEA, North America, and South America. The structure and responsibilities of DC's are categorized according to the functional categories of the DC. Currently, there are three main categorizes which are central DC (CDC), regional DC (RDC) and support DC (SDC). Despite the fact that they have similar processes in-house, there also some functional differences. The main difference is that while support DC's ship only for external customers; CDC's serve not only for external customers but also for internal customers, which are the RDC or SDC's. Depends on the location of the customers, CDC can ship items directly to the external customers but their main responsibility is to refill the SDC's and RDC's.

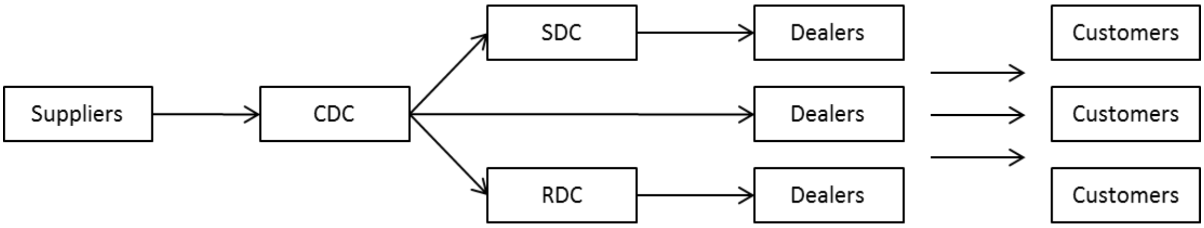


Figure 4.3 Volvo aftermarket supply chain

This subsection is divided into two as global and site levels. Global level stands for the administrative headquarter for the aftermarket operations of Volvo Parts. Site level stands for the local perspective of an individual DC where the warehouse operations are operated by the site. Figure 4.3 demonstrates the supply chain of aftermarket operations at Volvo Parts.

4.2.1 Global Level

Global level stands for the headquarters where the researchers work at. This level consists of managers that work with various aspects quality (e.g. customer satisfaction, KPI, quality improvement projects). This level's responsibility is to manage the DCs, take actions to improve their quality performance, set targets, and make strategic decisions. There are many improvement projects managed concurrently. The importance of statistical methods to control and predict quality performance metric has been added on the agenda recently. This research is an initiative of these kinds of projects. The results of the research are expected to provide global level solid insights of their site operations, a bridging model to improve the communication between global level and site level, and, eventually, to make decisions based on the facts to improve overall quality performance.

Aftermarket Quality Performance Indicator & KPI Setting

The quality performance indicator for aftermarket business, APSF, is a target that set quarterly. While the target is set, a mix of two dimensions is used, mathematical and non-mathematical. Volvo management is aware that not all the DC has the same complexity and maturity level. Besides, there is cultural aspect that has to be observed. This cultural aspect covers the culture of the countries where the sites are located. It might involve both the attitude of the operators towards quality improvement and the site management for setting the difficulty of the targets.

Global level gives DCs liberty to set their targets at a certain level, although it should be approved by global level for approval.

The DCs all around the world report the weekly results of the indicator in a global data visualization and business intelligence platform, QlikView. The platform provides different options of visualization and stratification of the data. The data can be clustered regionally or individually. A sample of how a performance indicator is visualized on QlikView can be seen in Figure 4.4. This sample is actually the APQI monitoring of Gent CDC which is used in Global Level control chart exploration. There is same kind of data comes from all the sites. Sites convert their operational data into a standardized format for global level. The charts are used at global level for monitoring purposes and make strategic decisions according to the visuals.

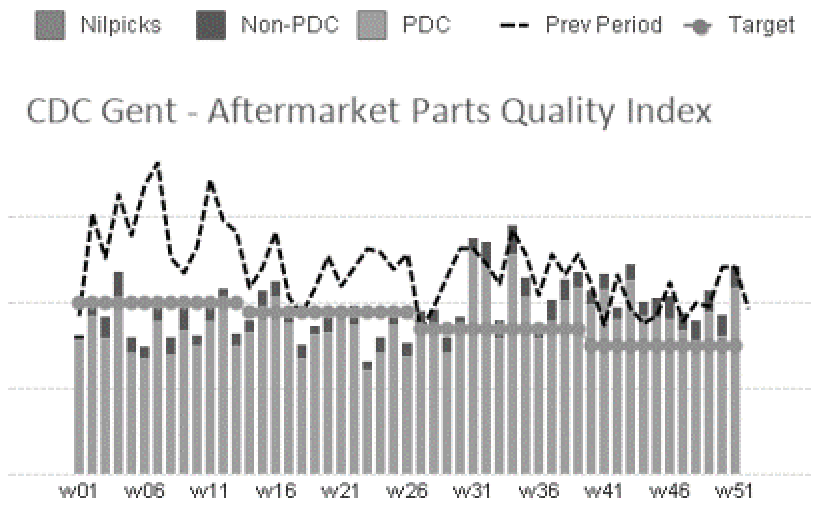


Figure 4.4 Current dashboard for reporting APQO in Gent in 2017

Discrepancy Records and Argus

Considering the variation and human factor, discrepancies are inevitable, at least in today's circumstances. The ideal situation is zero discrepancy but when it happens, it is still crucial to provide a good service to the customer to ease the process of resolution and gain the satisfaction. After a discrepancy happens, there is intranet software called Argus where access is granted by Volvo Group to the customers. The software is used to report discrepancies and to follow the process for resolution. The software is still in development process. It provides a common platform for stakeholders and increases the efficiency of resolution process.

The interface allows customers to enter a written description of the discrepancy and attach a photo if desired. As mentioned above, there are several reason codes to identify the type of discrepancy occurred. The interface also has a section to choose the reason code for the discrepancy to keep track for internal quality. The track of updates is kept as logs and can be seen by the stakeholders.

Having a universal customer complaint platform as Argus is important for two main reasons. First, provides a standardized way of efficiently handling complaints as soon as possible. Secondly, it allows the global complaint data to be stored in one database which could be beneficial for further comparison, regression, and root-cause analysis.

4.2.2 Site Level

The research mainly focuses on two sites, CDC Gent and SDC Eskilstuna. There are other sites that were contacted during the research for interviews to understand general perceptions of operations and data management as well. All the quantitative data is gathered from CDC Gent. The site visit for observations is done at SDC Eskilstuna. The main connection between these two sites is that they belong to the same region and SDC Eskilstuna inventory is fed by CDC Gent. The process flow of a DC at Volvo SML is provided in Figure 4.5.

Site level investigation is a crucial part of this research as it is the source of most of the data collected. Between the headquarters and sites, there is a balance of freedom which might sometimes cause decentralization of some sites. In this research, the data gathered from site level is analysed and give insights to global level to make decisions on facts to improve the quality performance of sites individually for overall improvement.

As mentioned under VPS that there are experts that measure the maturity level of the functions. Sites are not an exception. An interview with an expert and the documents of recent measurements show several measures that prove the data collected with interviews and observation. Briefly, the usage of visual quality tools and statistical analysis is limited and there is opportunity for further developments to improve quality performance.

CDC Gent

The CDC Gent in Belgium is the largest DC of Volvo Group in terms of the number of items, the variety of items, the number of order lines, and so on. The findings of De Koster & Warffemius (2005) that discussed in literature review apply for CDC Gent as well. The facts that CDC Gent has the highest number of items, the largest product portfolio, and the busiest DC, make this DC the most complex one among all the other Volvo Group DCs. CDC Gent's biggest customers are the internal customers which are the other DCs around the world. The brands that CDC Gent has in its inventory are Volvo Trucks, Renault Trucks, Volvo Penta, and Volvo Construction Equipment.

SDC Eskilstuna

The SDC Eskilstuna in Sweden is responsible of the distribution of aftermarket parts in Scandinavia part of Gent & EU region. The DC was used to be CDC but, due to the operational requirements, the functionality of the DC is changed to SDC level.

For mapping the process and making observation at site level, this DC was visited by the researchers. During the visit the process flow is observed. Interviews with quality coordinators were done on operational data gathering, quality performance, and audits. Interviews with site coordinators were done on material handling and activities that create variation during the process. The activities that might increase the variations and cause delivery errors are observed in order to consider for the analysis of this research.

Process Flow in DCs

The process flow in DCs are specified and standardized with Volvo Production System (VPS). Even though, all DC's share some operational similarities, there are some major differences as well in terms of the maturity level, functional importance, and workload. In this research study, one central DC, Gent, and one support DC, Eskilstuna, are investigated in depth along with the general evaluation of some other DCs.

The operational process flow can be categorized into two as inbound and outbound. Inbound has three major activities which are (1) receiving, (2) sorting, and (3) putting away. Outbound has four major activities which are (1) order from customer, (2) picking, (3) packing, and (4) shipping.

- Receiving: The first step is receiving the items from external sources. It can be a supplier or a CDC. The items are brought by trucks. When the items are received first, they are stored in big wooden pallets.
- Sorting: After the wooden pallets are received, the items are taken out of the pallets. Operators check if the items are sent correctly. The check is done by matching the unique order numbers. If they are correct, the operators create a unique inventory number and set location for the items. There are several open pallets in sorting area that are dedicated to certain locations in the DC. Operators place the items into the right wooden pallets; so, the pallets can be taken to the locations and the items inside can be put away to their locations to store.
- Putting Away: The open pallets with sorted items inside are taken for putting away. Operators place the items onto the specific locations one by one.
- Order Receiving: This is the activity that initiates outbound process. One order from one customer can have one or many order lines. According to the locations of the items ordered and the shipping time (RFS), work lists are created and the lists are sent for picking.
- Picking: This is considered the most crucial part of the process that has influence on the quality of the delivery sent. Operators go to the locations that are defined by the work lists. They pick the items in the list and place them into their open boxes to be sent for packing.
- Packing: Depends on the size of the items and the order lines in one order, several items can be packed together they belong to the same order. There is no systematic decision mechanism into this phase. It is up to the operator who packs the items. The items should also be packed well with proper protection and placement into the cardboard boxes. A wrongly placed item can get damaged during the delivery. Then the operator prints a shipping barcode and put the box into the designated area for the same delivery location along with the other boxes that are packed to be sent in the same truck.
- Shipping: This is the end of outbound operations in the DC. The previously packed items are taken from their designated areas to be placed into the trucks to be shipped. Volvo uses external delivery providers for shipping.

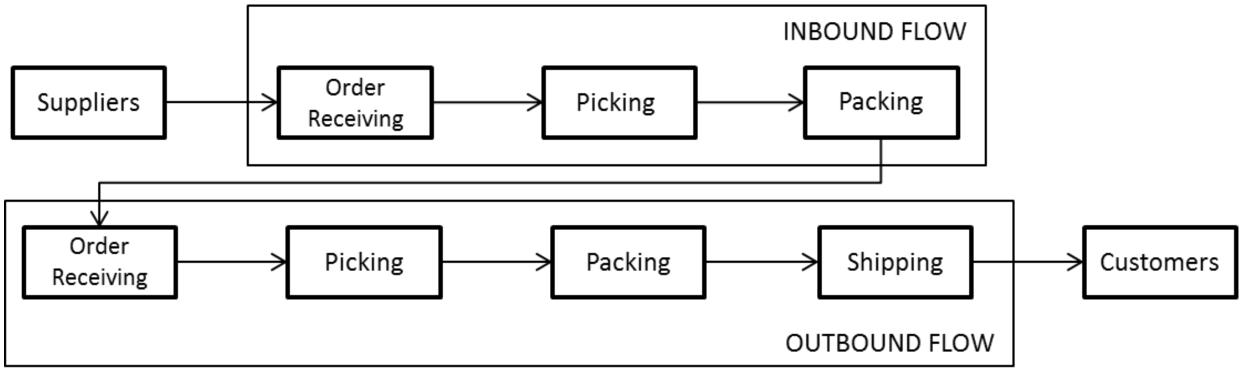


Figure 4.5 Distribution Centre Operations Flow

4.3 Aftermarket Parts Service Failures

Volvo Group's main performance indicator of quality in aftermarket operations is called Aftermarket Parts Service Failures Index (APSF). This indicator is divided into two categories, Aftermarket Parts Quality Index (APQI) and nilpicks. APQI covers all the order fulfilment failures and nilpicks cover inventory accuracy failures. The dimension of these metrics is expressed in parts per million (ppm). The calculations of APSF, APQI and nilpicks are as follows:

APQI = (No. of wrong delivery + No. of under delivery + No. of over delivery + No. of damaged parts + No. of faulty kits + No. quality issues)/Shipped order lines in the period

Nilpicks = (No. of complete line + No of partial line)/Shipped order lines in the period

APSF = APQI + Nilpicks

The major order fulfilment failure metric, APQI, divides into two main categories in itself as Parts Distribution Centre (PDC) claims and Non-Parts Distribution Centre (Non PDC) claims. APQI measures the quality of the deliveries in terms of (1) wrong parts delivery, (2) under delivery, (3) over delivery, (4) damaged parts delivery, (5) delivery of faulty kits (if the ordered items are kit), and (6) general quality issues. Both PDC and Non PDC claims cover these six types of failure. PDC and Non PDC show if the failures are occurred internally or externally. For example, if there is a supplier involvement in wrong delivery, it is non PDC; if the product is damaged during packing at the DC, it is PDC.

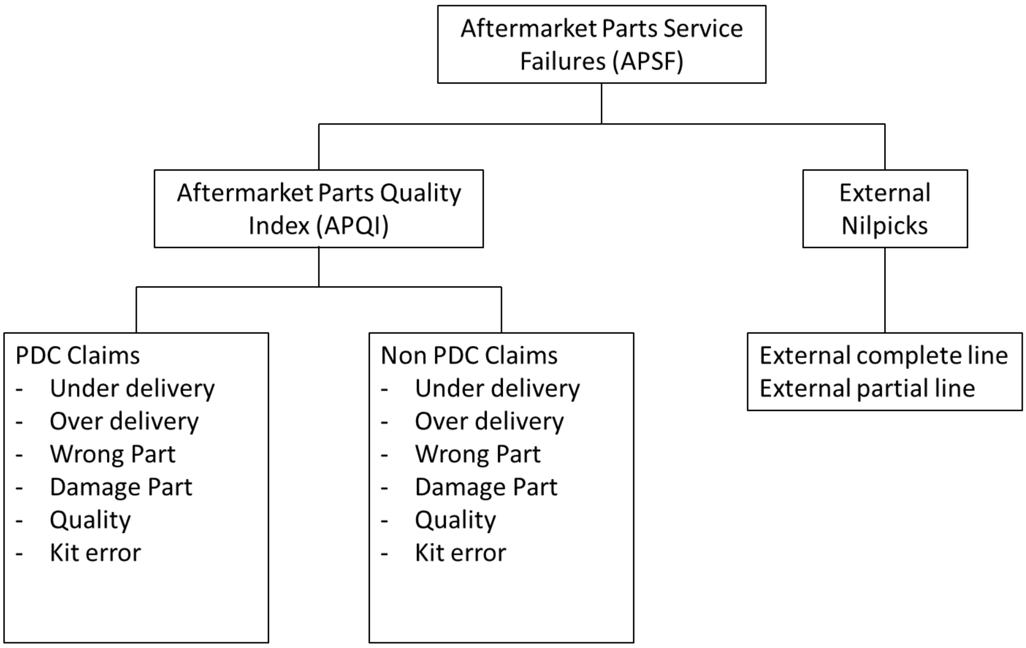


Figure 4.6 APSF Breakdown

Nilpicks are the inventory accuracy failures that occur if there is mismatch between the number of an item in the system and in reality. For example, the items might be counted wrong while putting away or picking. Nilpicks might occur internally or externally, as it is for APQI.

4.4 Data Management

The starting point of this research is the vast amount of data gathered in the organization. Even though the potential of the data is known for a while, there has not been enough time or sources to investigate the data at a large extent, due to several organizational reasons. One of the reasons is that the time spent on reactive actions is too much that the organization cannot create enough time to focus on proactive actions. Moreover, statistical methods can get very confused by the people who are not familiar with them. The results of a statistical analysis should be delivered among different functions and levels. Therefore, even though the results would be very interesting, there would still be communication issue to deliver the results among the different functions and levels. Another reason is that there are functional differences between global and site level and one of the most important examples to this is that there are many different databases are used for different purposes. Even at the same site, there might be several databases which make the data to be gathered and analysed very challenging. Below, the structure of databases and the data types that are used in this research is explained.

4.4.1 Database

The data and operational inputs that are to be used in the analysis of this research are stored in databases. As mentioned above, the development process is on to implement Argus software globally for handling the customer complaints more efficiently. The importance of efficiency of customer complaint handling is obvious and directly affects the customer satisfaction. This is a reactive quality approach. This thesis scope is to approach quality performance proactively and prevent the complaints to happen. As discussed in literature review, the operational DC activities' effect on quality performance and customer satisfaction is still very immature. Therefore, there has not been done any comprehensive and big-scoped project at Volvo regarding this proactive approach.

The size of the databases is determined by the number of parts stored in the DC and the amount of order lines handled in a determined period of time. The number of part at Gent CDC is approximately 200,000. In addition, the DC manages around 600,000 order lines per month. For this reason, quality engineers of Gent CDC experience difficulties to handle such a large amount of information with common software such as Microsoft Excel which limits the data which can be retrieved to 1,048,576 rows which disencourage the utilization of statistical tools; since, managing the data is time consuming (Microsoft, 2018).

4.4.2 Operational Data

The global aftermarket operations have not been yet implemented a universal database to store and monitor operational data. The DCs are decentralized in this sense and they use local databases for their own operations. At some large CDC's they even have different databases for different brands such as different data management for Renault Trucks aftermarket operations and Volvo Trucks aftermarket operations.

Table 4.1 Operational Data

Time	Invoice Date	Shows the date that the order invoice is approved.
	Packing Time	The time that the parcel is packed.
	RFS	The time that the shipping vehicle leaves the DC.
Order Specific	Customer No	Code dedicated to a customer.
	Colli No	Code dedicated to the package to ship.
	Order No	Code dedicated to the order.
	Invoiced Quantity	Number of items ordered.
	Order lines	Number of orderlines in an order.
Product Specific	Price	Price of single item.
	Brand	The brand that item belongs to.
	Part No	Unique code dedicated to an item.
	Name	Name of the item.
	Volume	Volume of the item in centimetre squares.
	Weight	Weight of the item in grams.
	Origin of Country	The country that the item is made in or that the supplier is sent the item.
Geographical	Area	Area code in the warehouse.
	Row	Row number in the area.
	Level	Level number of a shelf.

4.4.3 Discrepancy Data

The data that includes discrepancy is the key aspect of this research. In an ideal world, the company would not have such data as the desired aim is to reach zero APQI. In this research, this data is used to match with the operational data to see which order lines are reported as discrepancy. Therefore, further analysis to see correlations between operational data and discrepancy data would be possible.

This data is currently stored at site level. Quality engineers at the sites use this data with simple charts to visualize the data and see commonalities and trends. Some of the examples how this data is used are histogram charts to visualize the number of discrepancies are done per operator team and Pareto charts to visualize the customers with highest discrepancy reporting. These tools do not help to understand any root cause to take proactive approach at the moment.

Table 4.2 Discrepancy Data

Time	Invoice Date	Shows the date that the order invoice is approved.
	Date occurred	Date that the item is picked.
	Credit Date	Shows the date that discrepancy is reported.
Order Specific	Customer No	Code dedicated to a customer.
	Colli No	Code dedicated to the package to ship.
	Order No	Code dedicated to the order.
	Invoiced Quantity	Number of items ordered.
	Class	Code to classify the type of delivery.
	Order lines	Number of orderlines in an order.
Product Specific	Price	Price of single item.
	Brand	The brand that item belongs to.
	Part No	Unique code dedicated to an item.
	Name	Name of the item.
Geographical	Area	Area code in the warehouse.
	Row	Row number in the area.
	Level	Level number of a shelf.
Discrepancy Specific	Reason Code	The codes that define the discrepancy type and the action taken.
	APQI	Show if the discrepancy is APQI or not.
	Discrepancy Quantity	Number of items reported as discrepancy.
	Report No	Code given to the discrepancy report. It is unique to the month but it could be repeated in another month.
Picker Specific	Picker Name	Name of the picker who picked the reported item.
	Picker Team	Team of the picker who picked the reported item.
	Picker No	Unique code dedicated to a picker.

4.4.4 Audit Data

Audits are being an important part of the DC operations. Every site has its own procedure for auditing. For the analysis, audit data is used to monitor the performance of audit data. According to the interviews, CDC Gent conduct audits to approximately 7% which is the orders they ship. This corresponds to around 1200 audits per day. Figure 4.7 show the flow of audits in 2018. The samples are selected randomly and there is no systematic approach to steer this effort at the moment. The attitude is “everything is suitable to be audited”. However, there is a focus on floating or temporary personnel; the purpose is to design strategies to reinforce training and feedback for the labour force.

The desire of steering their audit is very high as it takes so much time and effort. With the selection of right parameters to conduct further regression analysis to identify orders that are more likely to fail would give steering directions for audit operations.

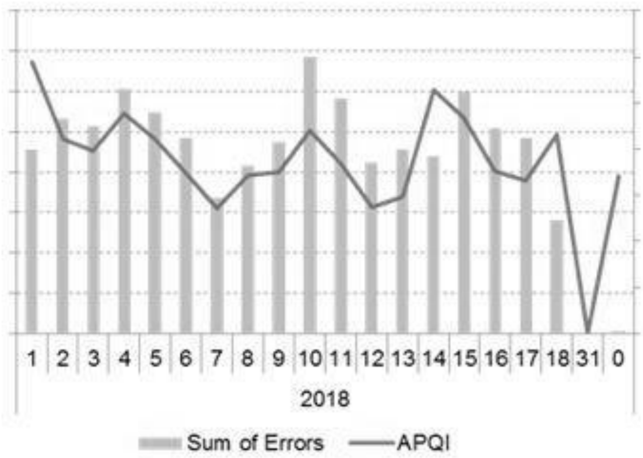


Figure 4.7 Histogram of audit and APQI flow in 2018

4.4.5 Making Decision Based on Gut Feeling or Facts?

The main part of this thesis covers statistical methods. Due to the nature of statistical methods, the decisions are desired to be made on facts. It is an essential factor of quality improvement activities. It is also observed and learned over the research that the “gut feeling” based on feelings are of high importance as well and could be effective starting point to make decisions on facts. Therefore, even though the decisions are still made on facts, the process of reaching these facts started with “gut feeling” of experienced engineers who have comprehensive knowledge and sensing abilities to show directions for fact-based decisions.

In the interviews that are conducted with quality engineers at sites and manager at the headquarters, there are some “gut feeling” information is collected. In order to increase validity of the answers, they are confirmed with other interviews to double check that there is consensus among the employees towards “gut feeling”.

The biggest consensus is towards “summer effect”. It means that there is a trend in APQI data and it increases. This falls in quarter three which corresponds to summer period. This occurs due to two reasons. One of them is that, at sites, the experienced operators go on vacation and their positions are filled with inexperienced summer workers, mostly students. The other reason is that the number of orders decrease during the summer; therefore, discrepancy data that is calculated per million becomes more sensitive to changes.

Table 4.3 Factors that influence discrepancies

Parts Factors	Small parts	Likelyhood of discrepancy with parts with smaller volumes is higher as they can get lost.
	Small and many pieces	There are mistakes happen due to miscount of parts with many and small pieces (i.e. bag of nuts).
	Bulky items	Some items are packed in multiple numbers (i.e. six pack of filters). There are counting mistakes as operators confuse if the order is number of filters or packs.
Order Factors	Large orders	Some orders have so many order lines; therefore, likelyhood of discrepancy is high.
	Backlog	Backlog (falling behind of schedule) creates pressure which might trigger discrepancies.
External Factors	Suppliers	There are quality differences among suppliers.
	Customers	Some customers report more discrepancies than others.
Operational Factors	Performance vs. Quality	The balance between time performance and quality performance at site operations.
	Different team leaders	Some team leaders have better leadership skills which reflects to the performance of teams.

The other factors that can affect APQI are provided in Table 4.3. The difference of these factors than summer effect is that they can affect APQI any time regardless it is summer or not. These factors are provided during interviews with site engineers.

There reason of why these factors are gathered as data is that to understand the process better. Moreover, it is desired that these factors can give directions to the researchers to frame the parameter choices and statistical analysis with these parameters.

5 Analysis

In this chapter, the research questions are answered in order. First, the analysis for key parameters is explained. Then, the appropriate statistical methods are analysed. Finally, the whole statistical model is provided.

5.1 Potential of Investigated Data

There is vast amount of data gathered through the supply chain of aftermarket at Volvo. It has great potential for opportunities in term of statistical analysis. There are over 20 parameters gathered but only a few of them are used with some simple visualization tools for data visualization and monitoring day-to-day operations. But there has not been much exploration done to understand the opportunities of the data to control and predict the quality performance.

As literature review points out, customer satisfaction is of high important in aftermarket. This reality leads the company to take actions to improve the customer satisfaction. Literature and interviews in the company validate that there is direct correlation between operational data and customer satisfaction in distribution context.

According to literature, the quality of the process directly related to the perceived quality. It is important to understand the process well to take the required actions. As spare parts business has enormous potential on financials, it requires focus (Suomala *et al.* 2002). But it also needs to be efficient to make the most out of it. To do so, statistical methods to use with process data have very useful to improve the efficiency and increase the customer satisfaction and leverage financial benefits eventually.

One of the challenges at Volvo SML is that the data stored in different databases and access needs to be granted for each by responsible managers. Our interviews show that extensive statistical methods to apply with just large amount of data are time consuming to take proactive actions. Moreover, it is difficult to deliver findings to different layers due to the size of the organization. It was told by several interviewees from global and local perspectives that they don’t have the source to understand, investigate, apply, and use the statistical methods. In order to solve it, a collaboration between global and local perspective, cross-functionality, concurrent engineering, and communication are needed.

The results of this research contributed us to explore the potential usage of statistical methods that are suitable to service context, DC operations, and Volvo policies. To do so, the organization is investigated, the operations are understood with observations and interviews, the deep dive is conducted to database systems after they are learned and understood how to use. As our secondary data, historical data is analysed and understood to see what is possible to achieve by leveraging this data. Moreover, how this data is used at the moment for what purposes with what tools is also observed. Optimization of data categorization is done to simplify its handling for further application. The statistical methods that are suitable are applied as test. They are, then, discussed for possible applications to control and predict with the purpose of continuous improvement.

5.2 Exploring the Application of Statistical Process Monitoring

5.2.1 Understand the Purpose and Expected Outcome

As commented in the literature review, service quality performance indicators are characterized by metrics and the goal is to minimize these numbers. Furthermore; our observations and interviews support that the culture of zero defect at Volvo Parts is the ultimate goal of all the levels in the organization. In this research, APSF is not an exception and the goal is to minimize the failures to maximize customer satisfaction. APSF and its categories are explained under Empirical Findings section but, for convenience, a brief explanation here would be useful. APSF stands for Aftermarket Parts Service Failures. It has two main categories which are APQI, Aftermarket Parts Quality Index, and nilpicks. As it can be seen in the Figure 5.1, a considerably big portion of APSF occurs due to the failures that categorized as APQI. Moreover, the nilpicks directly related to inventory management and it was defined at the beginning of the research that inventory management is not the consideration of the research.

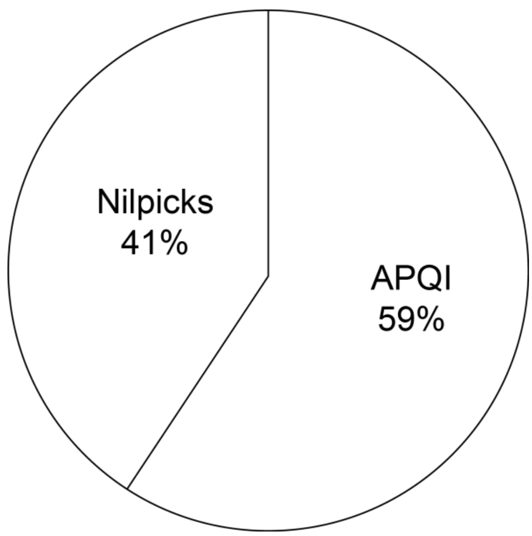


Figure 5.1 Pie Chart for APSF Breakdown

A delivery fulfilment failure in Volvo SML operations may impact the most important performance indicator which is uptime of the customers. The corporate aim is to keep the uptime at 100% and keep their trucks, buses and heavy equipment running all the time for prosperity.

The usage of control charts has a different connotation in this research compared to many of its applications where the aim is to reduce variation and strive for hitting a determined target. In this context, they are used to monitor the process, detect process mean (average) shifts, and identify special causes of variation. If there is a subgroup that is outside the UCL, it would create awareness to take action plans in order to reduce the high defects. On the other hand, if there is a subgroup that is outside the LSL, it can be used to identify what has been done better to get closer to zero which is the ultimate goal of the process.

5.2.2 Definition of Scope and Measurements to Be Used

For this exploratory analysis, only one but big portion of the failures was analysed. These failures are the ones that occurred due to the errors in warehouse operations. It is categorized as APQI-PDC and as, all the categories explained in Empirical Findings, it stands for Aftermarket Parts Quality Index Parts Distribution Centre. Figure 5.2 shows the proportion of APQI-PDC with the other metrics. The reason to choose only APQI-PDC is due to the availability of operational data which can be used to identify potential control parameters with analytical tools. This is explained in depth in the following sections.

There are two scopes of APQI-PDC used in the analysis. One of them is the customer complaints data that is gathered weekly for KPI and monitoring. The other one is outbound audit data which reflects the fulfilment errors that are found prior the items to be shipped to the customer.

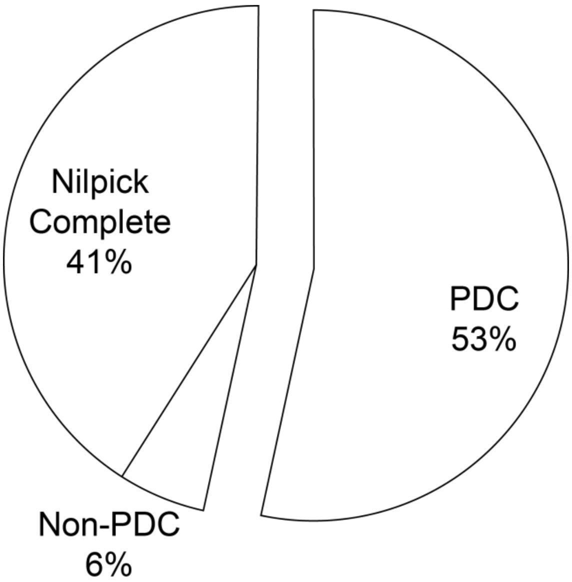


Figure 5.2 Pie Chart for APQI Breakdown

Unlike mass production and manufacturing processes, each delivery and order line is an independent event. Therefore, independence of the measurements is assumed. The metric corresponds to a proportion and not the exact number of failures. The proportion is taken as parts per million (ppm). If it was the exact number of failures, the most suitable control chart would be the p-chart. However, as it will be discussed later, given the statistically high performance of the process (Montgomery, 2009), other control charts such as p-chart, cumulative count of conforming (CCC) or monitoring time in between failures should be considered at the site level.

Both at global or local level, there is a consensus within the organization that using proportion as “ppm” distort the utilization of control charts. Moreover, there is another consensus within the organization that there is a well-known “summer effect” which mentioned in Empirical Findings. This “summer effect” means that the data is auto correlated and more advanced charting techniques are required to smooth this effect. Embracing the point of view that this effect is an inherent part the process and the type of variation due to this effect cannot be eliminated, the control charts for site level is explored with p-charts.

5.2.3 Assessing the Measurement System

As presented in the Empirical Findings, APQI is defined by a guideline which is applied in all the Volvo's network. Besides, how to classify whether a complaint is caused by PDC or non PDC is well defined. However, there are factors that may affect the ability of this metric to effectively reflect shifts in the process average. For instance, the fact that there exists a lead time between the day a failure occurs in the operations and when the customer reports a discrepancy. Furthermore; handling the complaint adds time in classification activities and root cause analysis. Due to these reasons, a discrepancy is reported some time ahead of the time that occurred in the warehouse. This lead time may vary depending on the capacity of the complaint handlers which may be influenced by vacation time, amount, and complexity of the complaints. This situation can be interpreted as all the weekly measurements have the same disruption and showing the results must be interpreted considering the performance of past performance.

5.2.4 Exploring the Control Charts for Global Level

As mentioned in the Empirical Findings, APQI is measured in a weekly basis and corresponds to the relationship between the totality of the order lines handled during the week and the complaints settled during that period. Therefore, the historical reports of the APQI were collected and visualized with control charts as an alternative of the current dashboards. The p-charts were built by setting the total number of order lines as sample size. Moreover, for business reasons, the results are track on a quarterly basis to make the charts comparable with the current visualization tools. Furthermore, the different settings were tried in order to accentuate changes. For example, it creates awareness of variation and shifts in the process. The results are shown in the Figure 5.3. The control charts fulfil its purpose of visualizing shifts in the process mean, variation, and control. For example, the Figure 5.3 shows how the KPI changes its mean when the data is grouped on a quarterly basis. The Figure 5.4 utilizes the same data set but it is a control chart with control limits calculated according to the performance of the first semester of the year. This would help to evidentiate a change in the average and control the state of the indicator.

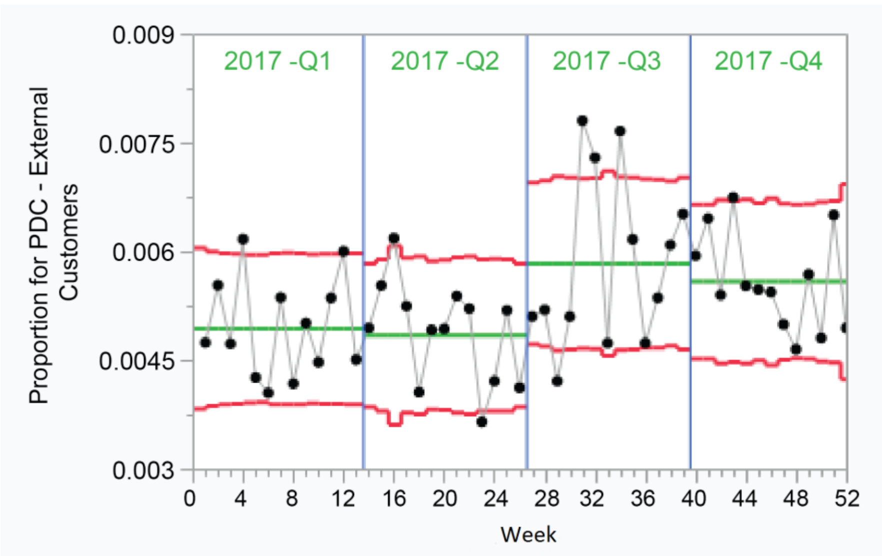


Figure 5.3 Control Chart 1 for Global Level

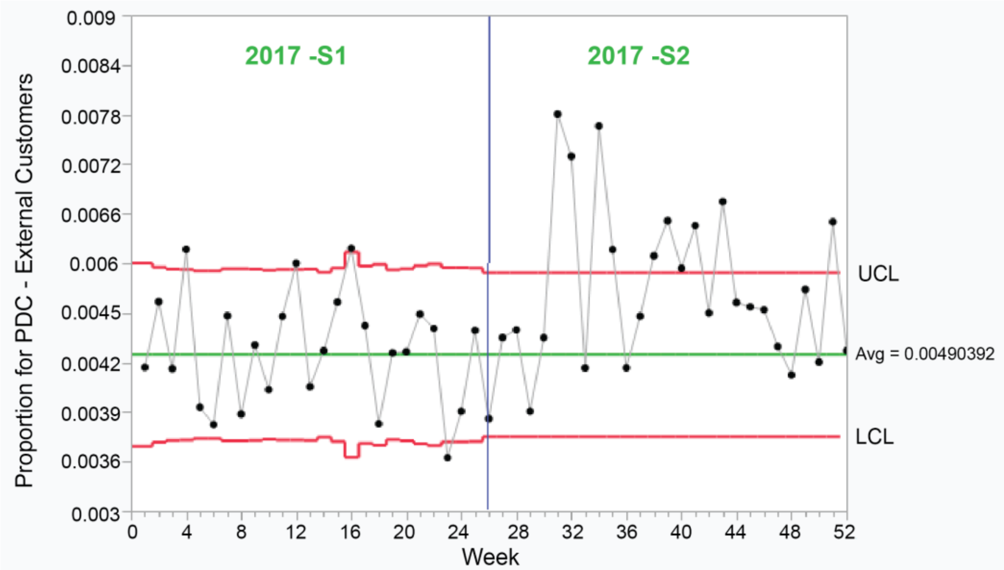


Figure 5.4 Control Chart 2 for Global Level

5.2.5 Exploring Control Charts for Site Level

The secondary data of this research is gathered from the weekly report and databases of Gent CDC and the purpose is to decrease the metric by taking actions on the operations that are handled at site level. Therefore, control charts are desired to be explored at site level as well in order to find applicable usage of them.

Since the site, Gent CDC, where this case study takes place is the largest in the Volvo SML, there is a significant amount of data was found in order to build trial of control charts. The available data, operational requirements, and interviews direct the researchers to focus on two main data, audit and operator. The reason why audit data is chosen is that auditing is done almost randomly or based on simple usage of historical data. Auditing is a critical step in the process and consumes vast amount of time and resources. The potential is discovered as very high. Moreover, there is available data that is gathered from audit activities but it is not used for any further analysis to steer the audit operations based on facts.

As it is possible to observe in the Figure 5.5, the average proportion of defectives found during the audits at Ghent is 0.00878. According to Morris & Riddle (2008) approach, it implies the need to gather a subgroup of at least of 750 observations. For Gent, which is the largest DC at Volvo SML, may be viable to monitor quality performance through control chart, since the numbers of audits surpass the recommended sub-group size but it is not the same for the sites with lower proportions of defectives and smaller operations. For example, at some RDC and SDC, charting technique may not be suitable because it would imply a large investment in resources for inspections (*Morris & Riddle, 2008)*. This contradicts one of the fundamentals of SPC which is "The resources devoted to testing, monitoring and inspection should be as few as possible" (Wood, 1994). Therefore, for such cases, alternative control charting techniques for high performance warehouses can be considered. For instance, time in between complaints as showed in the "*Control Charts with Operator Data"*.

Control Charts with Audit Data

The data can be stratified in different ways: team, operator, brands and so on. Figure 5.5 depicts the behaviour of the overall audits results of week 1 to week 18 for 2018 (year-to-date). As it can be seen in Figure 5.5, the process is stable and "in control"; since, many of the points are under the control limits. Moreover, the proportion of failures is stable. The control limits vary from week to week; since, the number of audited order lines is not constant.

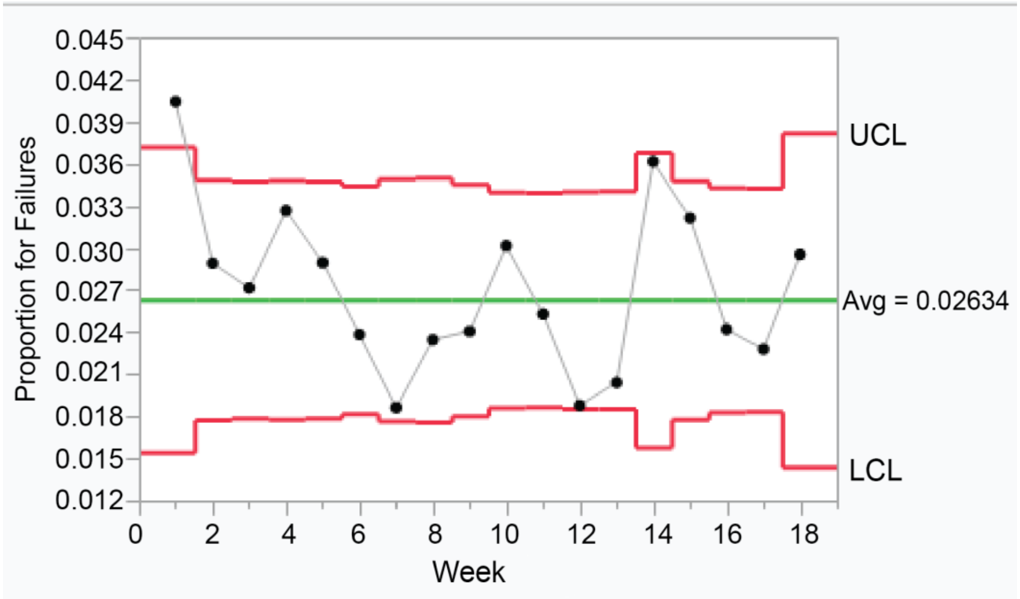


Figure 5.5 Control chart with audit data

Please note that, these operations are considered as "high performance" due to the number of defects detected is very low compared to the sample size. Therefore, instead of taking the exact number of failures, the proportions of the failures to the total amount is calculated and used in the charts (Montgomery, 2009; Morris & Riddle, 2008).

Control Chart with Operator Data

At the moment, it is possible to extract information on operator performance at Gent CDC. One of the directions for what to audit is given according to histogram charts of operator teams. Since, auditing operator by operator is a resource consuming activity; it is impractical to audit the outbound or picking activities every day for each operator. For example, there may be a long period of time when a high performing operator makes a mistake. For this scenario, Montgomery (2009) recommends the proposal to set-up a control chart for the time in between events, which in this case would correspond to the time interval in days an APQI failure assigned to an operator. The control charts in Figure 5.6 and Figure 5.7 depict the control of this type of data for two types of operator, high and medium performance. This means that operator represented in Figure 5.6 makes mistakes more often than the operator represented in Figure 5.7. The LCL for these charts was set manually.

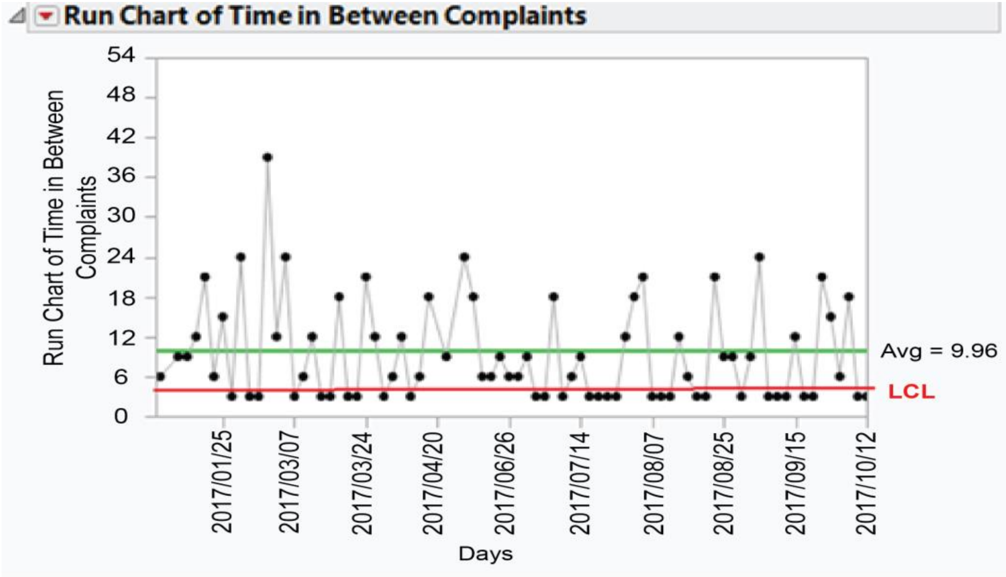


Figure 5.6 Control chart with operator data 1

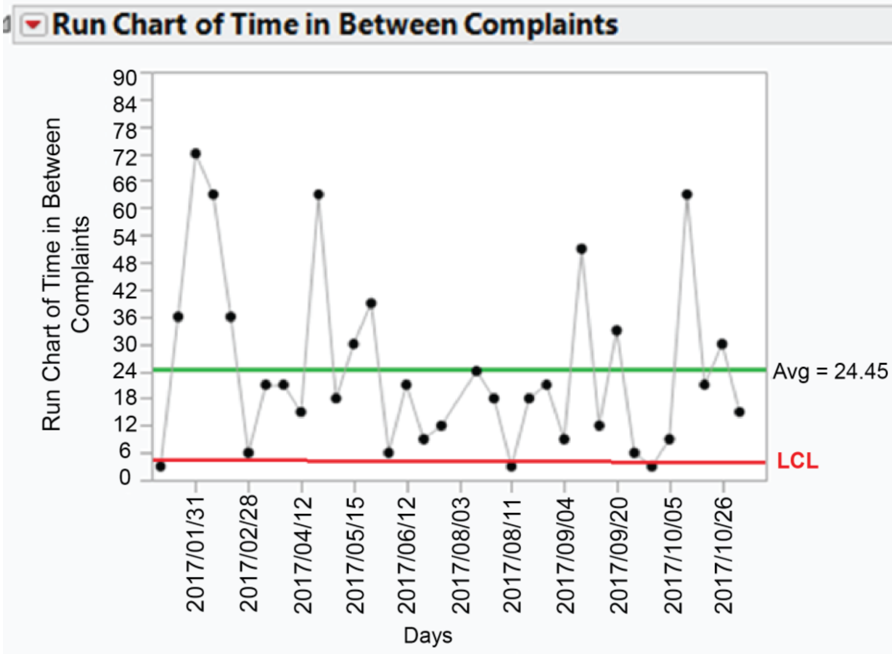


Figure 5.7 Control chart with operator data 2

5.2.6 Predictability from Statistical Process Monitoring Perspective: Differentiating Common and Special causes

As mentioned in the literature review, SPC tackles the question of predictability from an action perspective. In other words, the users are the ones who make the process predictable by eliminating special causes of variation and making the process vary within two control limits. Besides setting up the charting technique for the process, it is necessary to identify systematic sources of variation. The classification of the failures can be complemented by registering special causes. For example, counting errors may be a common cause of variation since there is an inherent human factor involved. However, internal or supplier labelling errors may be classified as a special cause. By observing such differences, the results can be visualized in simple charts such a Pareto in order to create action plans and complement root cause analysis with the rest of 7 quality tools which are covered in the VPS.

5.3 Exploring Analytical Methods

From the literature review, several approaches coincide in the fact of looking which explanatory variables (inputs) are correlated with quality performance (outputs). This way of thinking is supported by the TQM mind-set where the aim is to take preventive and proactive approaches in the process (Bergman & Klefsjö, 2010) and the rationale of Statistical Process Monitoring of analysing the process instead of the output (Wood, 1994; Montgomery, 2009).

The purpose of this analytical part of this research is to build knowledge on how the identified controllable and uncontrollable inputs (parameters) affect the output (APQI-PDC). To do so, regression analysis is conducted. Furthermore, the findings can be used to subsequently set up a prediction model. The model, then contribute to enhance the creation road map to "cease dependence on inspection to achieve quality (Deming 1900 – 1993)" (Stotz, 2015; Bergman & Klefsjö, 2010). The results of a prediction model can be used in analogy to the healthcare sciences where it is widely used. Its usage is explained in Theoretical Framework. In this research, "population" corresponds to the order lines with high risk of getting the "illness" which is the order fulfilment failure (APQI-PDC). The actions taken to tackle the identified "risk factors" are "controllable and uncontrollable inputs". In this way, a preventive, and proactive, approach is accepted instead of a reactive approach.

5.3.1 Building a Prediction Model

Data Organization

The parameters to use in predictive model are chosen based on both the "gut feelings" gathered with interviews with the subject matter experts and the assessment of the available data in the databases.

Table 5.1 Focus Parameters with their effect.

Types of Causes	Rationale	Data to Consider	Units of Measure	Expected Relationship to APQI-PDC
Counting Errors	Order lines with more than one piece lead to more errors.	Quantity of the order lines	Units	Positive
Parts Dimensions	Smaller parts are more difficult to count; therefore, they are prone to get lost within the DC during in-house transportation.	Weight	kg	Negative
		Volume	cm3	Negative
Stress	When the cut-off time (RFS) is approaching, people feel stressed and make more mistakes. (Measured as the time difference between packing and shipping)	RFS (YYYY.MM.DD, hh:mm) Packing time (YYYY.MM.DD, hh:mm)	Hours	Negative
Complexity	Production orders with large number of order lines may pass through several hands which leads to a higher complexity for handling them.	Number of order lines	Units	Positive
Sequence	Used as a classifier for production sequence in the DC. (1- day orders; 3- stock orders; 4-stock orders in containers)	Order class	Category (1; 3; 4)	Neutral

The focus points and insights come from interviews can be seen in Table 5.1.

Please note that for expected relationship, “Positive” means the higher the value of the explanatory parameter the higher the expected value of the APQI and “Negative” means the lower the value of the explanatory parameter the higher the expected value APQI.

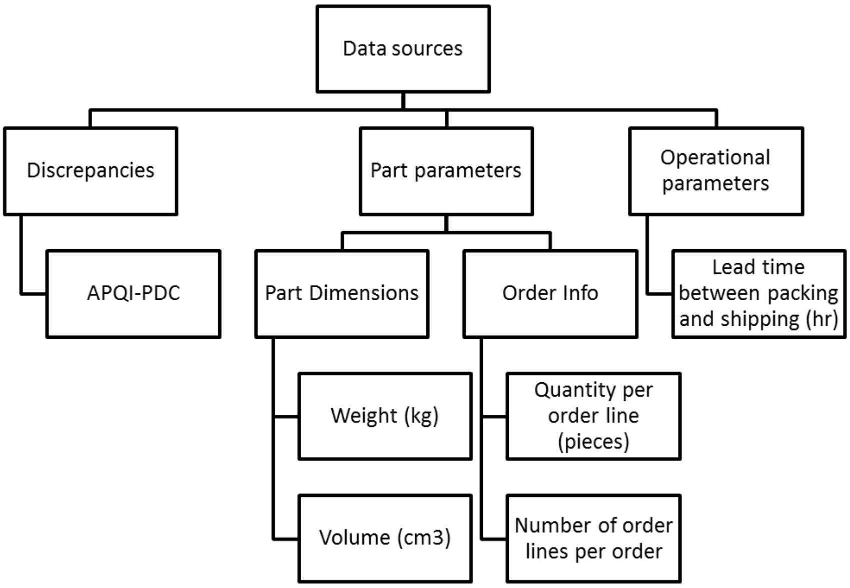


Figure 5.8 Data tree for regression analysis

Moreover, the available data in databases are classified in three main clusters for research purpose. The classification of the data with the data that is available in the databases and selected for the analysis is depicted in the Figure 5.8.

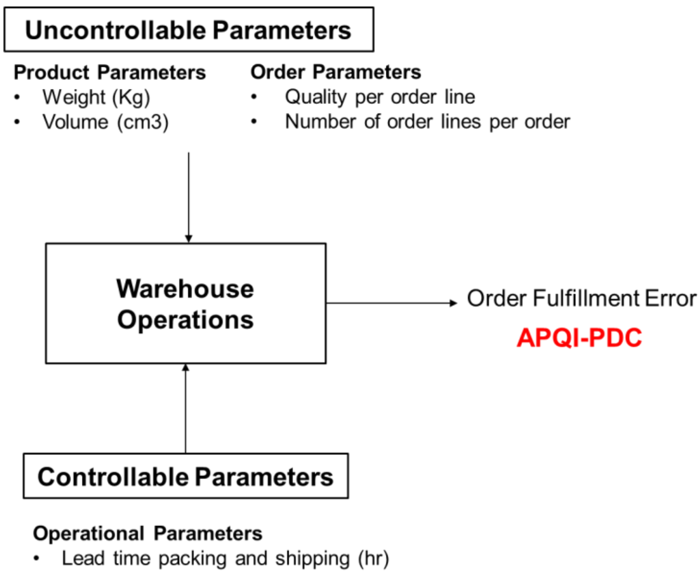


Figure 5.9 Controllable and Uncontrollable Parameters

The parameters are identified as controllable and uncontrollable parameters that are affecting the APQI-PDC. The identification is done with the subject matter experts and managers in order to point out the steering points in the process. The chart in Figure 5.9 shows the identified controllable and uncontrollable parameters.

Information to build a logistic regression model, the available data is arranged in order to characterize an order line and differentiate the defective and successful ones (Steiner, S. H. & MacKay, R. J., 2004). In Table 5.2, there is a small portion of the complete data shown for illustration.

Table 5.2 Sample from data that shows if an order line is failed or not.

Order Identification			APQI	Order Data		Part Data		Operational		Prediction (Thereshold >.0020)			
Invoice Date	Part Number	Production Number	FAILURE (ACTUAL)	Quantity per Order Line	Number of Order Line per Order	Volume (cm3)	Weght (Kg)	Order Class	Lead Time (Packing-Shipping)	PROB (PDC)	PROB (NO-PDC)	FAILURE (PREDICTED)	Validation Column
20170108	102726	908507	NO-FAILURE	225	259	11,5	0,027	4	7	0,0005	0,9995	NO-FAILURE	Validation
20170108	10506	917793	FAILURE-PDC	17	29	17,8	0,058	3	16	0,0025	0,9975	FAILURE-PDC	Training
20170108	10506	918225	NO-FAILURE	11	31	17,8	0,058	3	2	0,0009	0,9991	NO-FAILURE	Training
20170108	10507	917745	NO-FAILURE	12	34	18,8	0,087	3	18	0,0005	0,9995	NO-FAILURE	Validation
20170108	10507	917852	NO-FAILURE	10	79	18,8	0,087	3	9	0,0022	0,9978	FAILURE-PDC	Training
20170108	10507	920243	NO-FAILURE	5	18	18,8	0,087	3	1	0,0004	0,9996	NO-FAILURE	Validation

The total sample size that is used in the analysis is the total of order lines for January, February and March 2017 which corresponds to the first quarter on calendar. The main reason why this time interval is taken as sample is that, as it can also be seen in Figure 5.3, the process is stable. Furthermore, as mentioned in Empirical Findings, information from the brands is stored in different data sources; therefore, to simplify the calculations, only data for Volvo Trucks and Penta which corresponds to 85% of the total order lines. Each order line is sorted out randomly as training and validation to corroborate if the explanatory parameters present the same behaviour with different subsamples of the sample data. The models are built with the intention to reflect one-day operations; therefore, order lines which are packed for one or more days are not included in the data. After matching the data and sorting out incoherent values by consulting the subject matter experts at Gent CDC, the sample size was reduced to approximately 800,000. The order lines were classified randomly between training and validation data and the classification was done 50%/50%.

Bivariate Method

Following the proposal of Steiner & MacKay (2004), bivariate method is followed with the exploratory parameters by using them in single logistic regression. The findings of the regression analyses are, later, used to build a multiple logistic regression model with the explanatory parameters that have "significant relationship" with APQI-PDC.

The variables to correlate are a binary output (PDC; NO-PDC) correlated with continuous predictor or independent variable. PDC corresponds to the failures caused by the DC operations and NO-PDC are observations with no failures. The function that was used was logistic regression.

The mathematical formula for single logistic regression is the same as equation 3.7 but with only one parameter.

$$\log\left(\frac{\rho}{1-\rho}\right) = g(x) = \beta_0 + \beta_1 x_1 + \cdots \beta_k x_k \qquad (3.7)$$

The graphs of single logistic regression analyses can be seen in Appendix A.

To assess the results, it is important to understand the reports generated by the software. For example, it is observed in the unit odds ratios report of “Lead Time” parameter is that, the ratios are lower than one (0.8983). This means that the odds ratio gets lowers per each unit change in the regressor. Or precisely, per each hour an order is packed prior the the shipping time the odds diminishes by a factor of 0.8983. In practical terms, it means that it is less probable to fail when the products are packed more in advance to the shipping time. This assessment and interpretation can be done for the other parameters as well.

In the same example of “Lead Time” parameter, the range odds ratio is 0.2 which means that the odds decreases in a factor of 0.2 alongside the whole range of this variable which varies from 0 to 16 hours. Maybe a better way to observe this variation is to take the reciprocal value which means that the odds are 5 times lower in the range of 0 to 16 hours. As it is stated in the previous paragraph, this assessment and interpretation can be done for other parameters as well.

The logistic regression equation 3.7 corresponds to a linear model. Therefore, the test checks the null hypothesis that the slope for the parameter is equal to zero. If Prob>ChiSq is lower than 0.05, the null hypothesis is rejected, indicating that the slope is different than zero. There are three parameters that meet this rule which are ““Quantity per Order Line”, “Lead Time”, and “Number of Order Lines”.

After the results are assessed according to these rules, three out of five parameters that have significant relationship with APQI-PDC are selected:

- Quantity per Order Line
- Lead Time
- Number of Order Lines

The graphs of these selected parameters are shared with the subject matter experts and assessed with them. It is stated that while, “Quantity per Order Line” and “Lead Time” gives expected trends; the “Number of Order Lines” graph shows a surprising trend. “Number of Order Lines” parameter was expected that if the number of order lines increases, the likelihood of failure would also increase. The result shows the relation is opposite. The reason for this unexpected trend is explained by two subject matter experts that the orders with larger number of order lines are packed more than one day in advance to shipping time but in this case, as mentioned above, only the orders that packed and shipped in the same day are considered.

Multiple regression

After the single logistic regression analyses are completed, the parameters with significant relationship to APQI-PDC are used to run multiple logistic regression (Steiner & MacKay, 2004). Appendix B has the results of the profiler.

When multiple regression is applied with JMP, the software provides an effect summary. It is measured by using the LogWorth or False Discovery Rate (FDR). LogWorth's equivalent to 2 corresponds p-values lower than 0.01 which is the value that indicates a significant level.

There, the p-values are lower that 0.01 which means that the effect of the chosen parameters are significant on PDC. Moreover, the whole model test shows that Prob>ChiSq is < 0.001. Therefore, the slope of the regression is different than zero which means that there is a correlation between the parameters. Lastly, JMP generates a saturated model which is built with as many parameters as observations. This analysis can be seen under "Lack of Fit" section of the results in Appendix B. In this case, JMP evaluates the null hypothesis that there are not differences between the saturated model and the estimated model. Prob>ChiSq is greater than 0.05 means that the null hypothesis is rejected and there is no need for more parameter.

The multiple logistic regression profiler is assessed for further analysis in order to predict the failures to occur. In this sense, the results are shared with the subject matter experts along with the purpose of the analysis. It is pointed out that; even though, it provides useful insights for the process, there is the reality of not being able to control some parameters. It is discussed that two of the parameters, "Quantity of Order Lines" and "Number of Order Lines", are not always uncontrollable, depending on if the order is internal or external. In other words, "Quantity of Order Lines" and "Number of Order Lines" can be controlled at a certain extent within business rules where the delivery is done from one DC to another. If the delivery is to a customer, it is not possible to control the parameters as it is not feasible to restrain customer orders. It is confirmed that "Lead Time" is very valuable parameter that can be controllable for all the orders.

The effect summary of the multiple regression analysis in Appendix B shows, "Lead Time" has the LogWorth value of 27.49, which can be interpreted as the only completely controllable parameter has the highest affect in the profiler which increase widens the opportunities to benefit from the profiler. The second strongest parameter is "Quantity of Order Lines" with the LogWorth value of 25.51 and the last one is "Number of Order Lines" with the LogWorth value of 18.13.

Assessing the analytical methods for predicting

For the assessment, the confusion matrix is used. The detailed explanation can be found in Literature & Theory section.

In the context of this research, if the objective is to predict "APQI-PDC", then a true positive (TP) corresponds to the number of matches between the number of "APQI-PDC" predicted and the ones that "APQI-PDC" in reality. The same occurs with "NO-FAIL" condition, a true negative (TN) corresponds to the number of matches between the number of "NO-FAIL" predicted and the ones that "NO-FAIL" in reality. On the other hand, there is also classification of unsuccessful predictions in two classes. First one is the false positive (FP) or Type-I error which corresponds to the number of predicted "NO-FAIL" but is not "NO-FAIL" in reality. The other one is the false negative (FN) or Type-II error which corresponds to the number of predicted "APQI-PDC" but is not "APQI-PDC" in reality.

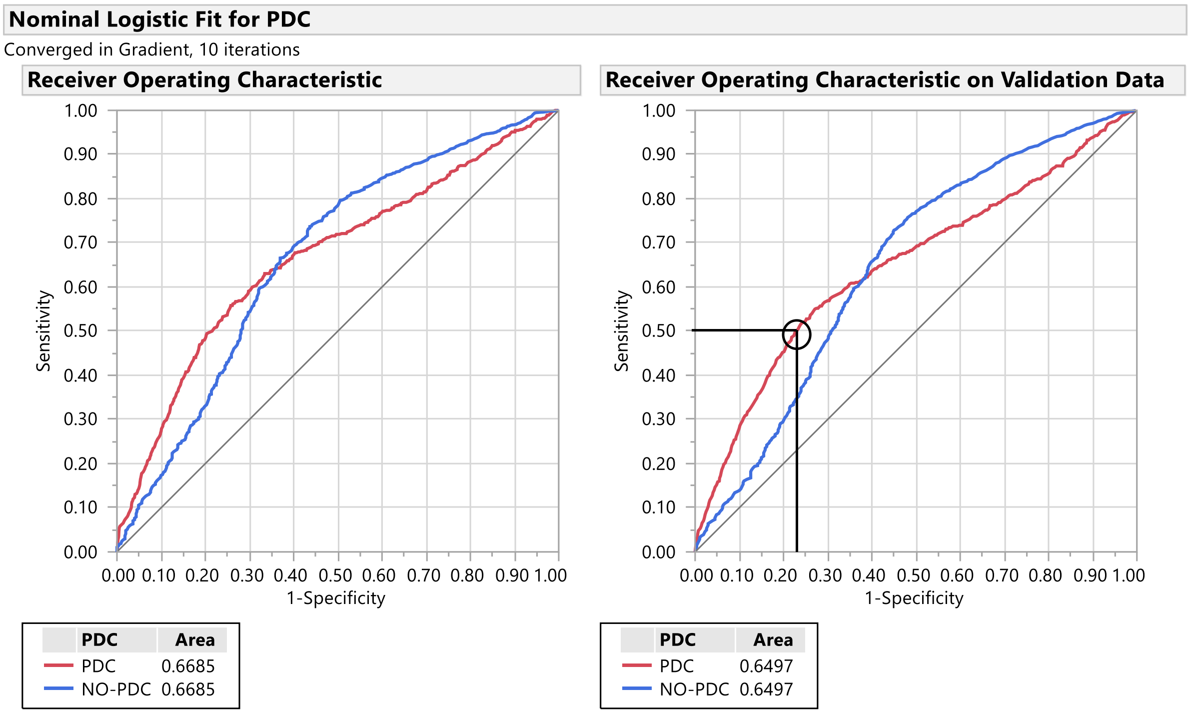


Figure 5.10 ROC for training and validation data

In an ideal situation, with the available data for this research, a model with high sensitivity would predict high number of “FAIL” and with high specificity would predict high number of “NO-FAIL”. However, in practice, it is very seldom to get a model with 100% sensibility and 100% specificity (Fawcett, 2006).

In order to optimize the model, several threshold values were assessed for a reasonable cut off. Since, the aim is to provide a tool to optimize the audit process; a high sensitivity test is needed. In other words, it is required to maximize the chances to detect a failure in the sample. The results of tested cut off points and ROC analysis are can be seen in Appendix C and Figure 5.10, respectively.

According to the general agreement for ROC values, the model is unable to predict with a high degree of sensitivity and specificity whether an order line is going to be successful or not. However, in order to interpret the analysis correctly, an analogy from the health sciences would be useful. For example, the prediction model is not capable of accurately tell which specific people (order lines) with certain characteristics (parameters) have the “illness” (PDC failure) but it is helpful to identify a subgroup of the population which is prone to have the “illness” (PDC failure) given certain risk factors. As the analogy explains better, this is relevant for steering outbound audits. Instead of conducting audits randomly, they may be focused on certain group of order lines that has higher likelihood to fail according to the profiler. Furthermore, the results from the predictive modelling can complement the information from basic data visualization strategies such as the histograms.

With the new threshold, the confusion matrices give higher chances to find a failure compared with a random procedure. The estimated gain with the tested historical data contributes finding 50% of the failures by taking out only 20% of the total population (predictive condition positive).

5.4 Perception of the Analyses in the Organization

The statistical analyses explained above are tested with employees at different levels to measure their perceptions and gather opinions based on the methods' effectiveness and user-friendliness.

Global Level

The consensus among the managers at global level is towards the need of such tools to be used. One of the quality managers quoted as "*Histograms and Pareto charts are, apparently, not enough to control and predict the processes at the desired level. We need more application tools with our data to improve the processes*". On the one hand, it was recorded by the same quality manager that "*We have to use simple tools as they are easy to use, manage, and understood by many people*". On the other hand, the desire for more advanced tools is expressed as *"We need to use more complex methods for deeper understanding and proactive approach".*

The findings of the exploration of statistical analyses are found very valuable. A manager pointed out *"These significant parameters can be used to conduct FMEA to increase the robustness against variation".* When the current dashboard and control chart results with the same data are shared and explained, another quality manager that has no previous experience with statistical quality charts stated "*The dashboard now seems too simple to rely on for effective decision making*. *Statistical method gives better insights from our processes in order to make decisions based on facts and steer the processes better. With this chart, we would avoid taking unnecessary actions*". This statement points out that the charts bring the awareness of variation and understanding of special causes. The general perception is that they are not familiar with such terms; therefore, it is important to note that the interpretation of the charts with such terms is also explained while sharing the results.

It is noted that analytical methods are very useful for deep understanding and taking proactive approach for quality improvement but they are very time consuming and confusing. A quality manager stated that "*We don't have time to explore such methods".* The same manager also quoted "*You should know exactly where to click on the software*". This can be interpreted as it might be relatively easy for someone how to use the software but, at global level, it is something that they are not competent.

Site Level

At site level, the current quality activities are mostly reactive. It is quoted by a quality engineer at Gent CC as *"We are extremely busy and we definitely don't have the time to applying such statistical methods to take proactive approach for controlling and predicting our process".*

While the methods are explained and the results were shared, it was observed that the quality engineers at sites can understand the usage of the statistical analysis software, statistical methods, and interpretation of the findings of this research. They have the skill and experience with such statistical applications.

The results of control charts that are explored for site level are perceived as useful and better way of usage than how they are used now. As stated in Section 5.2.5, the performance of operators is monitored at a certain extent but the way that control charts are utilized with operator data has never applied before. A quality engineer at Gent CDC stated, "*It provides solid understanding of operator performance for steering audits and making other operational decisions more effectively".*

The main challenge that is observed is that the organization is undergoing fundamental organizational changes that bring more focus on performance improvement. On the one hand, global level request better performance from sites constantly and the analysis in this thesis provides global level some directions how to steer the process at site levels with better understanding. The managers are aware why such statistical methods, which are explored in this thesis, are needed and can contribute to control and predict the processes. On the other hand, the site has the same awareness but they also know that they need more time and source for such applications.

6 Discussion

Global Level

As mentioned earlier, control charts are originally developed and used in manufacturing processes (Wood, 1994). Even though, they cannot be used in services context with the same way and purpose as they are in manufacturing, they can still be beneficial to create awareness of variation of the processes.

The APSF metric is being monitored on regular basis in global quality management meetings and the fluctuations that occur week by week give false alarms to the management. They are interpreted as causes to take actions which are very frustrating and source consuming. The global quality management team requires a tool which can help them to identify when a site requires intervention and avoid triggering the increase of the variation even more due to “tampering”.

For this purpose, using a periodic p-chart with the same data would be useful to observe shifts in the process that cannot be perceived with the current tools.

The application of statistical methods to control and predict to quality performance can complement the current visualization strategy of the global quality management by providing the managers elements for understanding the process at sites, taking actions based on facts, steering directions for efficiency, and promoting proactive approach at global level.

Site Level

As Wood (1994) proposes, actions to reduce variation in the process may be taken for tactical reasons. For example, understanding variation caused by a group of workers or customers. Reducing variation may lead to a more consistent process than reducing the efforts in complaint handling. Moreover, customers value consistency that the correct spare part with the requested amount will arrive.

Audits should not be taken a measure to prevent defects to reach the customer but as a measurement of process performance. The discipline that brings the application of them with the complementary tool kit of control charting like 7 quality tools would help to create awareness of special causes and provide visibility to the main causes of variation. The current outbound audits may be a starting point to build the charting scheme; nevertheless, it is necessary to create a standard sampling procedure in order to reflect the real quality performance. The results of an analytic modelling may be the starting point for steering the sampling process and overcome the sample size restriction for establishing this practice.

Predictive modelling responds to the aim of the TQM philosophy of focusing on the process rather than the output. This trial for finding a controllable variable and to predict failures should not be considered “the model” but “a model”. There are immense possibilities to find more parameters which may help to create a more accurate prediction. The time scope of the project did not allow adding one or more variables from the databases such as operator performance, warehouse sub/location, product family, or enriching the information with findings from outbound audits. However, the main point with predictive modelling is that its ability to build knowledge about the process and understand how variation from controllable and uncontrollable parameters affects the output variable (APQI-PDC) and APSF in overall. Nonetheless, in the practice of warehousing and aftermarket, it is very difficult to steer the parameters which in theory are controllable. Therefore, embracing other concepts (e.g. robust design, Design for Six Sigma) to make the process insensitive to variation would another direction to benefit from such statistical methods.

Ryan (2000), states that medicine is analogous with statistics in the sense that quality "illnesses" can be cure with "astucius" combination of statistical methods. Deep knowledge of the process can be built by analytical tools such predictive models presented in this work. Therefore, the continuous improvement can be leveraged by statistical thinking (Britz et. al 1997) and similar approaches such as Statistical Engineering (Hoerl & Snee, 2017). Spare part operations present a wide range of large, complex and unstructured problems where there is not any "strictly correct" solution. A combination of business acumen, qualitative research and statistics are needed to solve these kinds of challenges. The application of them would exploit the abundance of data which lies in the databases and is complementary to the current tool kit which lies in the VPS framework.

Future Development

This research had exploratory purposes in a field that has not been focused much before in practice. Yet, according to the literature and the organization, the potential of using the data to control and predict is very high. This research unveils some statistical methods how to control and predict the quality performance in services context but the work explained here is neither the only methods to do it; nor is a framework to control and predict. There are still many opportunities to be explored and developed with the same purpose.

One of the ways to further develop the work done in this research is that the explored statistical methods can be practiced with other parameters. A company with similar context might have some parameters that are not collected in the spare part distribution operations at Volvo. These parameters can be tested with the statistical methods explored in this thesis for applicability and used if applicable. Using other parameters in the same context might require different types of controlling or prediction methods depending on the type of the data. Therefore, there is also room for exploration of other types of methods for controlling and predicting in services context.

Another development field could be an investigation to close the gap between control and prediction methods. Developing a model to gather these two approaches can provide more comprehensive structure and better increased collaboration between global and site levels.

Last but not least, the findings that are acquired with the methods that are explored in this research can be input for further applications. For example, the significant parameters that are identified with predictive methods can be, then, investigated with DfSS approach and methods as FMEA or design for experiments.

7 Conclusion

In this chapter, the research questions are answered with the findings of the research and some limitations and suggestions are shared.

The purpose of this Master's thesis was to explore statistical methods to control and predict spare parts operations to eliminate discrepancies in deliveries for ultimate customer satisfaction. As shared in early chapters, there has not been much research on the applications of statistical methods in distribution centre context. Yet, Suomala *et al.* (2002) mention how efficient aftermarket can leverage the drastically increase of profits of the company and Voss *et al.* (2005) propose parameters to increase the quality performance for efficient operations. Below, it is explained how the research questions are answered over the thesis.

RQ1: How can the statistical methods control and predict the quality performance of spare parts operations?

As the question is very comprehensive, the researchers started by understanding the organization and supply chain. It is followed by deep diving into the DC operations and processes. At the same time, the databases are investigated to check eligibility of the data. After the processes and available data are acknowledged, the statistical methods to control and predict are explored to improve the quality performance of the spare part operations.

RQ2: How can the results be used to support the operations at global and site levels of the organization?

Over the course of the thesis work, the employees from both global and site level are interviews constantly to understand their perceptions on the user-friendliness and effectuality of the statistical methods. As discussed in Analysis and Discussion sections, there is gap between global and site level regarding the perception of the statistical methods. Moreover, these two levels have different motives and capabilities for using the statistical methods which explained in Analysis section. However, both levels have the desire to lower the APQI-PDC and increase quality performance. Both levels are aware that there is need of further applications to have proactive approach, make decisions based on facts, and steering the processes better.

As mentioned in the Discussion chapter, the results from the multiple regression models have potential for improvement by adding one or more parameters that may strengthen the predictive power. However, due to limitations of time and learning curve, they could not be included in this project. Furthermore, the size of the information stored in the databases is too large to be handled by common software such as Microsoft Excel which was used to match the information from the different sources in this thesis work. The data limit for this software is 1,048,576 which strongly restrict number of months which can be fully analyzed as Gent CDC has more than 600,000 shipments per month. This limitation may have two ways to be overcome. On the one hand, the databases can be sampled. On the other hand, analytics software to deal with big data might be helpful.

This Master's thesis took place in the city of Gothenburg where the headquarters of Volvo SML are located. Since there is not any spare parts DC in the city, one of the main limitations of this research was the impossibility to do field work in order to put ideas into practice and test which would complement the data used for statistical analyses. For example, one of the main motivations for building the prediction model was to provide a tool to steer the current audit practices which is already established in Gent CDC. One interesting exercise would be to compare the results of the current audit strategy and an audit guided by the level of risk provided by the prediction model. In addition, having the chance of obtaining first-hand information may lead us to provide recommendations on how to tackle variation of the controllable and uncontrollable parameters.

During the course of this research, it was evident that the level of difficulty to explain statistical models and the meaning of control charts to employees with different backgrounds. The main work was performed in collaboration with quality professionals of Gent CDC. Nonetheless, due to the distance, it was impossible to interview or get feedback from actual operators and pickers about t-chart (time in between complaints) and the p-chart suggested for visualizing information for outbound audits. Furthermore, the possibility of experiencing the process and complaint handling in the day-to-day operations would give the researchers insights of possible special causes of variation. This would lead to identify opportunities of their standardization and aid the construction a Pareto charts which is a complementary tool for control charts.

As future work, the researchers suggest to set up this project at a site level in order to exploit all the information from the databases and "gut feelings" better. Moreover, the closeness with the subject matter experts at site would provide faster and constant feedbacks, alignment with local initiatives, and opening new ways or approaches. Last but not least, it is important to consider how to deliver the findings of statistical analyses to the different audiences, how to leverage the statistical thinking, and how to create awareness of variation as a first step to apply such statistical methods in the organization.

Appendix A

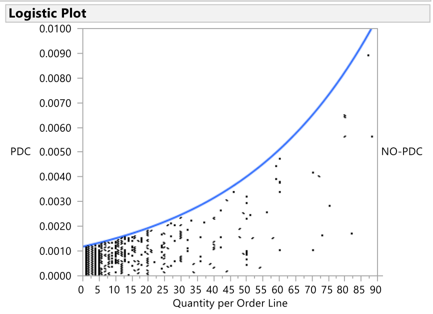
Below, the results of single logistic regression analyses are provided with its interpretation. The software used for all the analyses in this thesis research was JMP 13.0.0. The interpretations are based on the examples and explanations given by Klimberg & McCullough (2013).

Unit odds ratios: This measure refers to the change of the odds ratios per unit of the predictor or independent parameter. The values depends on the direction of the relationship.

Range odds ratios: It indicates the change of the odds alongside the entire range of the predictor or independent parameter.

Nominal Logistic Fit for PDC

Logistic Plot



Converged in Gradient, 9 iterations

Whole Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	34.0343	1	68.06859	<.0001 *
Full	8659.5412			
Reduced	8693.5755			

RSquare (U)	0.0039
AICc	17323.1
BIC	17346.3
Observations (or Sum Wgts)	817136

Lack Of Fit

Source	DF	-LogLikelihood	ChiSquare
Lack Of Fit	87	72.0096	144.0192
Saturated	88	8587.5316	**Prob>ChiSq**
Fitted	1	8659.5412	0.0001 *

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-6.703611	0.0344705	37820	<.0001 *
Quantity per Order Line	0.02401432	0.0025494	88.73	<.0001 *

For log odds of PDC/NO-PDC

Effect Likelihood Ratio Tests

Source	Nparm	DF	L-R ChiSquare	Prob>ChiSq
Quantity per Order Line	1	1	68.0685946	<.0001 *

Odds Ratios

For PDC odds of PDC versus NO-PDC

Unit Odds Ratios

Per unit change in regressor

Term	Odds Ratio	Lower 95%	Upper 95%	Reciprocal
Quantity per Order Line	1.024305	1.0192	1.029436	0.9762717

Range Odds Ratios

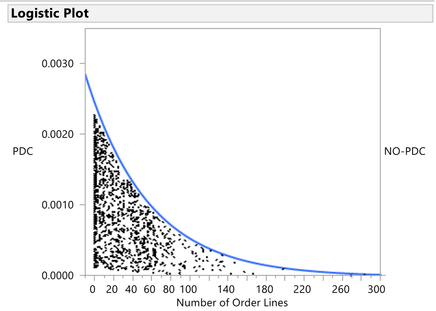
Per change in regressor over entire range

Term	Odds Ratio	Lower 95%	Upper 95%	Reciprocal
Quantity per Order Line	8.275178	5.331015	12.84531	0.1208433

Tests and confidence intervals on odds ratios are Wald based.

Nominal Logistic Fit for PDC

Logistic Plot



Converged in Gradient, 10 iterations

Whole Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	86.0311	1	172.0623	<.0001 *
Full	8437.3906			
Reduced	8523.4217			

RSquare (U)	0.0101
AICc	16878.8
BIC	16901.9
Observations (or Sum Wgts)	776068

Lack Of Fit

Source	DF	-LogLikelihood	ChiSquare
Lack Of Fit	207	297.2477	594.4953
Saturated	208	8140.1429	**Prob>ChiSq**
Fitted	1	8437.3906	<.0001 *

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-6.0057215	0.0489263	15068	<.0001 *
Number of Order Lines	-0.0152738	0.0013269	132.50	<.0001 *

For log odds of PDC/NO-PDC

Effect Likelihood Ratio Tests

Source	Nparm	DF	L-R ChiSquare	Prob>ChiSq
Number of Order Lines	1	1	172.062252	<.0001 *

Odds Ratios

For PDC odds of PDC versus NO-PDC

Unit Odds Ratios

Per unit change in regressor

Term	Odds Ratio	Lower 95%	Upper 95%	Reciprocal
Number of Order Lines	0.984842	0.982284	0.987407	1.0153911

Range Odds Ratios

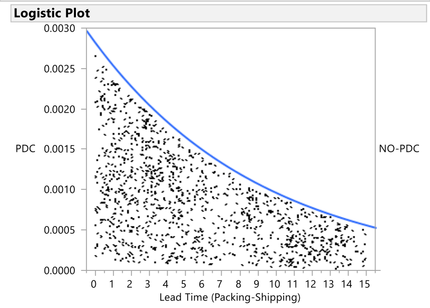
Per change in regressor over entire range

Term	Odds Ratio	Lower 95%	Upper 95%	Reciprocal
Number of Order Lines	0.012105	0.005709	0.025668	82.61019

Tests and confidence intervals on odds ratios are Wald based.

Nominal Logistic Fit for PDC

Logistic Plot



Converged in Gradient, 9 iterations

Whole Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	104.4014	1	208.8028	<.0001 *
Full	8589.1740			
Reduced	8693.5755			

RSquare (U)	0.0120
AICc	17182.3
BIC	17205.6
Observations (or Sum Wgts)	817136

Lack Of Fit

Source	DF	-LogLikelihood	ChiSquare
Lack Of Fit	898	579.0269	1158.054
Saturated	899	8010.1472	**Prob>ChiSq**
Fitted	1	8589.1740	<.0001 *

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-5.8692859	0.0519965	12742	<.0001 *
Lead Time (Packing-Shipping)	-0.1071629	0.0075751	200.13	<.0001 *

For log odds of PDC/NO-PDC

Effect Likelihood Ratio Tests

Source	Nparm	DF	L-R ChiSquare	Prob>ChiSq
Lead Time (Packing-Shipping)	1	1	208.802838	<.0001 *

Odds Ratios

For PDC odds of PDC versus NO-PDC

Unit Odds Ratios

Per unit change in regressor

Term	Odds Ratio	Lower 95%	Upper 95%	Reciprocal
Lead Time (Packing-Shipping)	0.898379	0.88514	0.911817	1.1131155

Range Odds Ratios

Per change in regressor over entire range

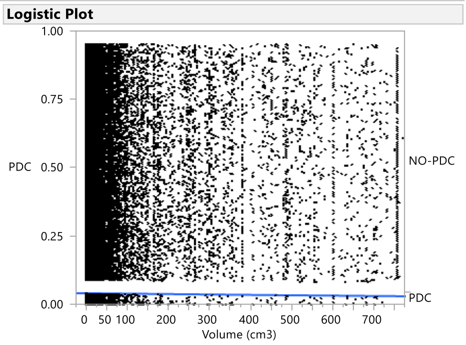
Term	Odds Ratio	Lower 95%	Upper 95%	Reciprocal
Lead Time (Packing-Shipping)	0.200758	0.160717	0.250775	4.98113

Tests and confidence intervals on odds ratios are Wald based.

Parameters with significant relationship with APQI-PDC

Nominal Logistic Fit for PDC

Logistic Plot



Converged in Gradient, 6 iterations

Whole Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	1.592	1	3.184645	0.0743
Full	21880.340			
Reduced	21881.932			

RSquare (U)	0.0001
AICc	43764.7
BIC	43784.1
Observations (or Sum Wgts)	119335

Lack Of Fit

Source	DF	-LogLikelihood	ChiSquare
Lack Of Fit	22672	6848.577	13697.15
Saturated	22673	15031.763	**Prob>ChiSq**
Fitted	1	21880.340	1.0000

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-3.0500349	0.0143817	44977	<.0001*
Volume (cm3)	-0.0003764	0.0002171	3.01	0.0829

For log odds of PDC/NO-PDC

Effect Likelihood Ratio Tests

Source	Nparm	DF	L-R ChiSquare	Prob>ChiSq
Volume (cm3)	1	1	3.184645	0.0743

Odds Ratios

For PDC odds of PDC versus NO-PDC

Unit Odds Ratios

Per unit change in regressor

Term	Odds Ratio	Lower 95%	Upper 95%	Reciprocal
Volume (cm3)	0.999624	0.999198	1.000049	1.0003765

Range Odds Ratios

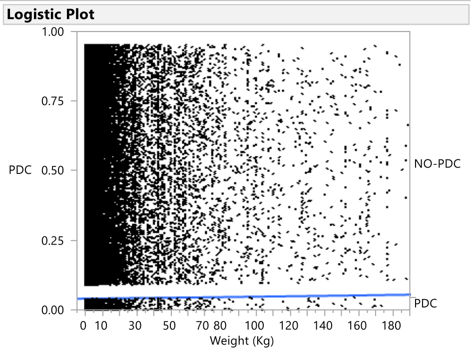
Per change in regressor over entire range

Term	Odds Ratio	Lower 95%	Upper 95%	Reciprocal
Volume (cm3)	0.749314	0.540768	1.038286	1.3345532

Tests and confidence intervals on odds ratios are Wald based.

Nominal Logistic Fit for PDC

Logistic Plot



Converged in Gradient, 6 iterations

Whole Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	1.124	1	2.247768	0.1338
Full	21796.822			
Reduced	21797.946			

RSquare (U)	0.0001
AICc	43597.6
BIC	43617
Observations (or Sum Wgts)	118639

Lack Of Fit

Source	DF	-LogLikelihood	ChiSquare
Lack Of Fit	4903	1938.628	3877.255
Saturated	4904	19858.195	**Prob>ChiSq**
Fitted	1	21796.822	1.0000

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-3.0594162	0.0145653	44120	<.0001*
Weight (Kg)	0.00152118	0.0009934	2.34	0.1257

For log odds of PDC/NO-PDC

Effect Likelihood Ratio Tests

Source	Nparm	DF	L-R ChiSquare	Prob>ChiSq
Weight (Kg)	1	1	2.24776813	0.1338

Odds Ratios

For PDC odds of PDC versus NO-PDC

Unit Odds Ratios

Per unit change in regressor

Term	Odds Ratio	Lower 95%	Upper 95%	Reciprocal
Weight (Kg)	1.001522	0.999574	1.003474	0.99848

Range Odds Ratios

Per change in regressor over entire range

Term	Odds Ratio	Lower 95%	Upper 95%	Reciprocal
Weight (Kg)	1.331067	0.923069	1.919401	0.7512769

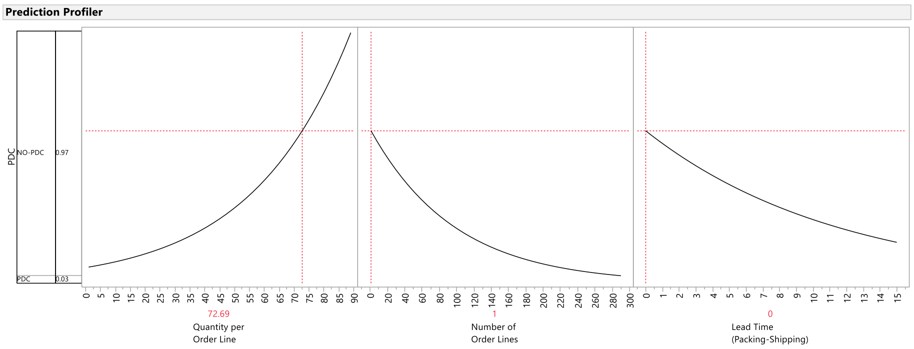
Tests and confidence intervals on odds ratios are Wald based.

Parameters with no significant relationship with APQI-PDC

Appendix B

Below, visualization of the profiler, effect summary, and odds ratios are provided.

The interpretation given to a single logistic regression may be guide for a multiple logistic regression as well.



Prediction profiler

Nominal Logistic Fit for PDC

Effect Summary

Source	LogWorth	PValue
Lead Time (Packing-Shipping)	27.490	0.00000
Quantity per Order Line	25.516	0.00000
Number of Order Lines	18.136	0.00000

Converged in Gradient, 10 iterations

Whole Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	195.4767	3	390.9533	<.0001 *
Full	8327.9451			
Reduced	8523.4217			

RSquare (U)	0.0229
AICc	16663.9
BIC	16710.1
Observations (or Sum Wgts)	776068

Lack Of Fit

Source	DF	-LogLikelihood	ChiSquare
Lack Of Fit	200421	5464.8265	10929.65
Saturated	200424	2863.1185	Prob>ChiSq
Fitted	3	8327.9451	1.0000

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-5.7635825	0.05674	10318	<.0001 *
Quantity per Order Line	0.03171833	0.0025071	160.05	<.0001 *
Number of Order Lines	-0.0105263	0.0013284	62.79	<.0001 *
Lead Time (Packing-Shipping)	-0.0892601	0.0082544	116.93	<.0001 *

For log odds of PDC/NO-PDC

Effect Likelihood Ratio Tests

Source	Nparm	DF	L-R ChiSquare	Prob>ChiSq
Quantity per Order Line	1	1	112.313701	<.0001 *
Number of Order Lines	1	1	78.6760462	<.0001 *
Lead Time (Packing-Shipping)	1	1	121.331967	<.0001 *

Odds Ratios

For PDC odds of PDC versus NO-PDC

Unit Odds Ratios

Per unit change in regressor

Term	Odds Ratio	Lower 95%	Upper 95%	Reciprocal
Quantity per Order Line	1.032227	1.027167	1.037311	0.9687794
Number of Order Lines	0.989529	0.986956	0.992109	1.0105819
Lead Time (Packing-Shipping)	0.914608	0.89993	0.929525	1.093365

Range Odds Ratios

Per change in regressor over entire range

Term	Odds Ratio	Lower 95%	Upper 95%	Reciprocal
Quantity per Order Line	16.30078	10.57813	25.11932	0.0613468
Number of Order Lines	0.047734	0.022493	0.101301	20.949459
Lead Time (Packing-Shipping)	0.262524	0.206012	0.334537	3.8091809

Tests and confidence intervals on odds ratios are Wald based.

The results of multiple regression analysis

Appendix C

Below, a screen shot of ROC Table is presented to show the optimal cut off point. For the optimized result, a point where TP and FN are as close as possible to each other can be taken.

Nominal Logistic Fit for PDC Validation=Validation

Receiver Operating Characteristic

ROC Table

Prob	1-Specificity	Sensitivity	Sens-(1-Spec)	True Pos	True Neg	False Pos	False Neg
0.0020	0.2380	0.5017	0.2637	291	295230	92208	289
0.0020	0.2381	0.5017	0.2637	291	295208	92230	289
0.0020	0.2381	0.5017	0.2636	291	295191	92247	289
0.0020	0.2382	0.5017	0.2635	291	295154	92284	289
0.0020	0.2382	0.5017	0.2635	291	295144	92294	289
0.0020	0.2383	0.5017	0.2634	291	295120	92318	289
0.0020	0.2383	0.5017	0.2634	291	295100	92338	289
0.0020	0.2384	0.5017	0.2633	291	295068	92370	289
0.0020	0.2384	0.5034	0.2650	292	295060	92378	288
0.0020	0.2385	0.5034	0.2650	292	295038	92400	288
0.0020	0.2385	0.5034	0.2649	292	295027	92411	288
0.0020	0.2386	0.5034	0.2649	292	295009	92429	288
0.0020	0.2386	0.5034	0.2649	292	295003	92435	288
0.0020	0.2386	0.5034	0.2648	292	294992	92446	288
0.0020	0.2386	0.5034	0.2648	292	294983	92455	288
0.0020	0.2386	0.5034	0.2648	292	294980	92458	288
0.0020	0.2387	0.5034	0.2648	292	294974	92464	288
0.0020	0.2387	0.5034	0.2648	292	294968	92470	288

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