Complementing traditional forecasting for the service market through telematics

A case Study at Volvo Group

Master's Thesis in the Master's Programme
Supply Chain management

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CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2017
Report No. E 2017:033

MASTER’S THESIS E 2017:033

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Chalmers Reproservice
Gothenburg, Sweden 2017

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Abstract

Purpose - The purpose of this master thesis is to understand the current service market supply chain of the studied company as well as to investigate which connected vehicle data is suitable for complementing the current forecasting approach. Furthermore, how can the suitable data set be used to perform a more accurate forecast. Through an investigation of a company case the research describes various existing connected vehicle parameters and explains how they could affect the forecast. Additionally, this thesis investigates if the selected data set leads to a higher forecasting quality regarding demand out of the central distribution center.

Methodology - This study combines quantitative and qualitative methodologies. Therein, the qualitative evaluation is supporting the quantitative findings from the connected vehicle data, in order to fulfill the purpose. The empirical data were collected and analyzed from semi-structured interviews with employees, in order to understand the current process. Historical data collection from the company's database was analyzed to identify potential of the data. Due to the enormous amount of data from different sources a data management tool was needed to be developed to understand how the data is related. The company can afterwards continue with the tool in their daily work. The main limitations of the study are the limited amount of seven service parts as well as the focus on the European market.

Findings - The findings of the analysis are presented parameter by parameter and give a clear description on how connected vehicle data influence the current forecast approach. Using the mileage and the age of trucks as a leading indicator when forecasting service parts, has the potential to contribute to higher forecast quality and therefore, reduction of inventory levels, total inventory costs as well as higher up-time and lead to a higher customer satisfaction.

Contributions - This thesis contributes by investigating a framework for the complementation of traditional forecasting with the use of connected vehicle data. The created forecasting framework supports the decision making process for spare parts in the service market and include not only the company, but also the dealers. Furthermore, new insights are given how to handle the data within the different company units.

Keywords - Service market, Forecasting, Telematics data, Maintenance, Mileage, Spare part, Availability, Down time

Acknowledgement

First and foremost we would like to thank our supervisors; Marcus Bohman and Joakim Andersson for their supporting guidance and helpful advice throughout the entire research process. Without their contribution and engagement this master thesis would not have been possible. Additionally, we would like to thank Volvo Group Material Management and their employees for taking the time to participate in this research. Without their contribution and engagement this thesis would not have been possible.

Furthermore, we like to express our appreciation to our families and friends for their understanding and help. All of which has lead us to this master thesis and thus it is dedicated to you all. Martin would like to particular thanks his boyfriend Simone Creci. He gave him the necessary support from home. At the same time, he had also counterbalanced the stress during researching and facilitated room for new perspectives for the master thesis possible.

Gothenburg, 2017

Martin Granić Arnold Merkwart

Table of contents

List of figures

List of tables

List of equations

List of definitions

Subject	**Definition**
Bullwhip effect	A phenomenon in distribution channel, meaning an increasing swing in inventory upwards the supply chain due to shift in customer demand.
Corrective maintenance	Action to identify and isolate a fault in a truck or machine and finally correcting it.
DIM	Dealer inventory management.
DIP	Demand and inventory planning.
Down time	Time interval while a truck or machine unavailable for use.
Lead time	The time interval between the initiation and completion of an action.
Mileage	Total driven distance in kilometer.
OEM	Original equipment manufacturer.
Predictive maintenance	Determining the condition of a machine or truck in order to predict then should the maintenance be performed.
Refill	The action of restocking regional and support distribution centers.
Service market	Spare parts, accessories and components market for trucks or machines.
Service part	Replacement of a failed part that is kept in inventory.
Supply chain management	The flow management of goods and services from the point of origin to the point of consumption.
Telematics	Transmission of information over long distances in real time.
Vehicle introduction	The week/period a truck was sold.

1. Introduction

The first chapter of the thesis introduces the general background of the problem and narrows the topic. The following purpose formulation and research questions concretize the aim of the thesis. The introduction chapter will conclude with the delimitations of this thesis.

1.1 Background

The service market became an important domain for manufacturing companies as it brings advantages in profitability, customer loyalty and therefore, endorsing the revenue. Furthermore, it has been shown that the revenue is much larger than for the new product market. The revenue stream of the new market for a 13 year old vehicle lifecycle time in Western Europe is 37%, whereas the revenue stream for the service market is 63% (Gebauer, Tennstedt, Elsässer, & Betke, 2010). The advances in technology enable new opportunities and new solutions for concepts. Further, the dimension of the service market and the ambition to gain market share are enablers why innovative value adding services, such as connected vehicle, have been developed over the last years. Other reasons are traffic safety, traffic information in general or the usage in material planning. Connected vehicles and their telematics data can enable companies to manage fleets in real-time, gather data about the mechanical state of trucks and decision making based on these data. Telematics technology enables vehicles to interact with their environment, by connecting to the internet and continuously sending and receiving data, such as mileage and temperature, in real-time (Mikulski, 2012). Those value adding services allow the firms to create long-term relationships with their customers along the whole product lifecycle. Therefore, the companies have to secure high availability of spare parts at different locations around the world be able to achieve competitive advantage, to differentiate from competitors and to increase the customer's satisfaction (Dombrowski & Engel, 2013; Gebauer et al., 2010).

Tests, measures and part replacements are the basis of preventive maintenance and are done in order to prevent failure and to keep operating time as high as possible. Forecasting the supposed failure or replacement of a service part would lead to the abovementioned benefits. Further, given the characteristics of the service market supply chain, shortening the total lead time would also lead to great advantages. Both predictive maintenance and total time shortening could be possibly reached by accurately forecasting spare parts demand.

1.2 Problem discussion and research gap

A fundamental aspect in achieving this service market revenue is accurate forecasting, which would lead to higher availability, reduced down time and lower inventory cost. Companies are faced with different challenges, like the high breakdown uncertainties in this area, which brings uncertainty in demand of spare parts and therefore pressure on balancing the quantity of stock levels. Another challenge is the wide range of different spare parts, to meet customers' needs. It becomes very important to minimize the costs related to the huge number of stock keeping units, hence synchronizing supply with demand and increasing the uptime of the products

(Gebauer et al., 2010). Further, failing to satisfy customer needs can lead to reduction in loyalty of these customers that eventually leads to losing market share.

Predictive maintenance is one way to tackle the above mentioned challenges, by using sensor data to complement the currently used forecasting process and prevent unexpected equipment failure. Those sensor data techniques being continuously improved over the last years and are able to provide the forecasting process with useful alerts to only maintain spare parts when there is need for (Kobbacy & Murthy, 2008; Mikulski, 2012).

Generally, there is research in the area of forecasting maintenance models available. However, currently is no framework existing that shows how to use telematics data in the forecasting process of service parts and does not consider the aspects of the service market supply chain. Therefore, this new telematics technology and the ability to complement the forecast have to be investigated in order to be successful. Accordingly, it is important to identify and map the available data within this area in order to determine the various steps that involve the actual demand. The stage that incorporates the telematics data and creates complementation is further crucial in order to create a new framework for this forecasting approach.

1.3 Purpose

The purpose of this thesis is to investigate how telematics data from trucks can influence or complement the current forecasting method used at Volvo Group. Due to lack of historical data in the first three introduction years of service parts, the forecasting cannot be based on history. The motivation behind this approach is that it will allow accomplishing a more accurate forecasting based on complementary up-to-date data.

1.4 Research questions

Through the study, a correlation between the above mentioned areas, location of sales and demanded parts, type of trucks and other relevant data has been investigated. The main aim of the thesis work is to investigate how complementary data can influence or potentially improve the currently used forecasting process. The aforementioned purpose leads in particular to the following research questions:

1. How is the current forecasting process defined?
   Motivation: To understand the usual way of working in order to detect the area for improvements.

2. Which telematics data is available on a continuous basis and which data is suitable for complementing the current forecasting approach?
   Motivation: The connected vehicle might not save the information accurately; hence the data is not always available in full range. It can happen that the mileage reporting dropout and will not be saved. Thus, it has to be investigated which data is available on a fluently basis.

3. How can the suitable telematics data be used to perform a more accurate forecast, which leads to higher forecasting quality regarding demand out of the central distribution center?

Motivation: The answer of this question will lead to a forecasting framework that allows to not only reacting to breakdowns, rather preventing and controlling the maintenance process. Additionally, an investigation will be done to create a data management tool for the company, so that the improvement can take place directly.

1.5 Delimitations

The scope of this thesis focuses on the service market for Volvo Group to cover the range of trucks that are using the telematics technology, also including all models and types. Therefore, this study does not consider vehicles that are not using the telematics technology. Furthermore, the vehicles are divided by their service arrangements. Currently Volvo is offering three different service contracts to their customers: gold, silver and blue, hence different data sets are provided. Considering the spare parts supply chain, the scope of this case study will be the central distribution center in Gent and sales on the European market. The reason is to simplify the inbound and outbound flow of parts. The scope of this thesis is not to study different forecasting methods, but to complement the currently used one. Methods will shortly be described with the aim to better understand the current process.

The life cycle of trucks can be divided in phases, which will be discussed in later chapters. This study focuses on the initial phase, which covers the first three years from introduction of a new product. One reason for this is that the telematics data will be more reliable within the first phase of a part, as well as the difficulty in following up the truck when it has been sold several times after specific life-cycle time and it is not guaranteed that the new owner is buying the spare parts from authorized Volvo dealers. On the other hand, this delimitation is due to restricted research time and the proposal from Volvo, since in the initial phase is no historical data available that could be used. Only a limited number of service parts and data sets will be investigated, since frequent spare parts are less difficult to forecast and also due to time limitations to accomplish the thesis. Those selected parts and data will be presented in the empirical data chapter.

2. Theoretical framework

The second chapter is structured around the maintenance process of service parts and discusses the service market supply chain, maintenance, telematics technology and forecasting of service parts. The chapter provides an overview of existing literature to increase the understanding of the topic and its contribution in the field of research to reader.

2.1 Service market supply chain

The service market can be divided into automotive services, spare parts and the maintenance business (Book et al., 2012). Furthermore, the service market constitutes of four levels: the parts manufacturer level, the distribution level, the workshop level and the customer level. Several stakeholders within each level are having different interests, which are presented in the upcoming section (Dombrowski & Engel, 2013).

The stakeholders in the first level are on one hand, the original equipment manufacturers (OEM) as well as the original equipment suppliers (OES), who provides the customers with relatively expensive original equipment spare parts. On the other hand, there are the grey market manufacturers, which usually supply the more generic parts with high sales volumes as a copy for a lower price. Within the second level original equipment spare parts are sold through OEM distribution channels, whereas generic spare parts are sold through the independent part distribution channel. The authorized service market is one option for a workshop, where the OEMs' vehicle dealerships are settled as well as repair shops with a contractual commitment to the OEM. That results into single-brand workshops and multi-brand workshops. The other option is the independent service market, with its large workshop chains and small independent repair shops. The scope of those workshops differs widely as well as for various automotive brands, which allows the individual shop to be specialized within a service area. Workshop chains as well as small repair shops offer typically a full range of services, whereas the former are a part of a dealer network while the latter are a completely independent unit. There are automotive centers with standardized and usually limited service range. In general enables a workshop direct contact to the customer and the opportunity to detect the needs of the customers to sell additional services. The Customer level is the last and the most important level in the service market chain, which is divided in private and business customers (Dombrowski & Engel, 2013).

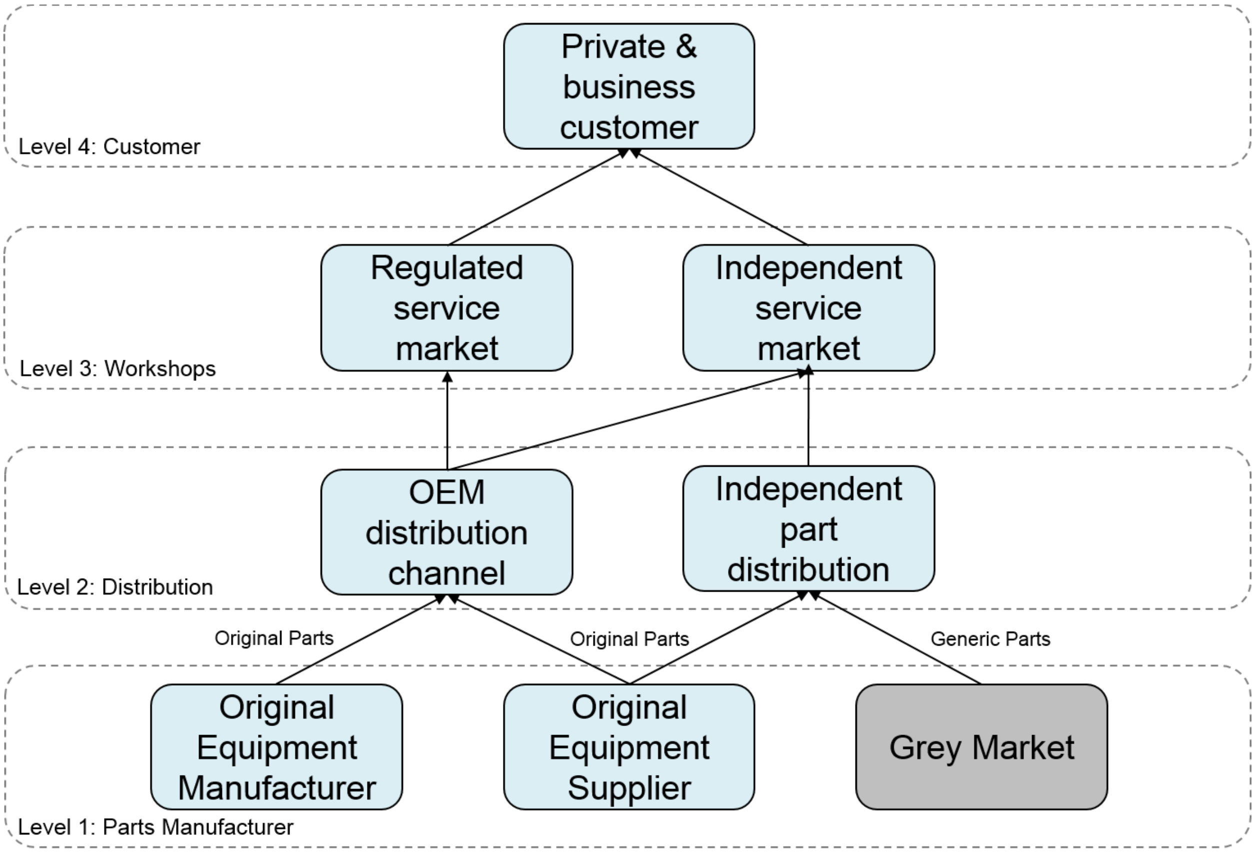

Figure 1: Service market supply chain (based on Dombrowski & Engel, 2013).

The automotive spare parts market's value is based on the retail selling price. The spare parts are divided according to MarketLine (2012) in wear & tear, service and mechanical parts. Wear and tear are batteries, emission systems, brake pads and ride control. Service parts can be filters, wiper blades, plugs and engine oil components. Mechanical or breakdown parts are those that are not changed during service and can be transmission and powertrain parts. Other parts that do not fit into these categories can be considered as consumables and accessories. When considering the spare parts market value, the labor cost and dealer revenues are not included.

	Manufacturing supply chain	Service market supply chain
Nature of Demand	Predictable, can be forecasted	Unpredictable, Sporadic
Number of parts	Limited	15 to 20 times more
Product Portfolio	Largely Homogenous	Always Heterogeneous
Delivery Network	Multiple Networks	Single network different services
Inventory Management	Max velocity	Pre-position
Reverse Logistics	Non existing	Return, scrap, buyback, core
Performance metric	Fill rate	Product availability (uptime)
Inventory Turn	6 to 50 a year	1 to 4 a year

Figure 2: Supply chain differences (based on Cohen, Agrawal & Agrawal, 2006).

As a matter of principle Cohen et al. (2006) differentiate the manufacturing supply chain and the spare parts supply chain in several parameters, which are presented in Figure 2. According to those characteristics, the spare parts supply chain is more unpredictable and sporadic in comparison with a manufacturing supply chain, as well as the higher amount of part numbers and the lower turnover rate. Both supply chains have to forecast their product demand and this is based on the above mentioned different circumstances (Cohen et al., 2006).

2.2 Maintenance

The aim of maintenance is the process of keeping the vehicles in functioning conditions. Hence, the maintenance is highly relevant in the service market, since it is connected to the availability of the needed spare parts. Moreover, breakdowns are the main cause for lowering the uptime of vehicle utilization. Standard EN 13306 classifies maintenance in corrective maintenance and preventive maintenance, which is shown in Figure 3. The main difference being that the former is performed after detecting a fault and the latter is performed before detected a fault. Over time the maintenance techniques have shifted from corrective to preventive and continuously improving (Kontrec, Milovanović, Panić, & Milošević, 2015). Furthermore, the preventive maintenance is divided into predetermined-, condition based- and predictive maintenance (Schmidt & Wang, 2016). In order to reach the augmentation in the forecasting process, to achieve predictive maintenance is desired.

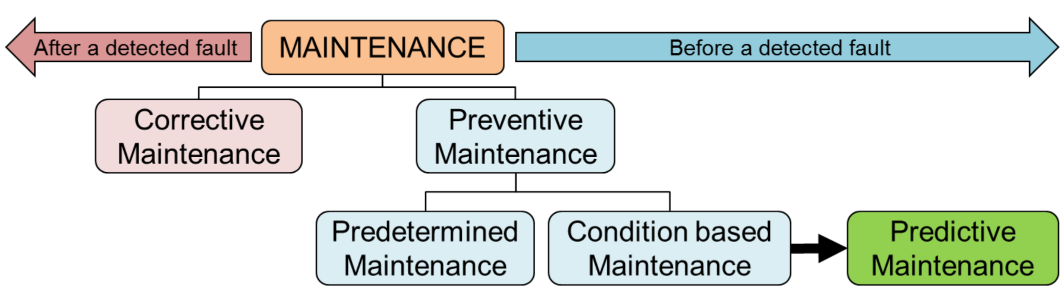

Figure 3: Maintenance classification based on EN 13306 (based on Schmidt & Wang, 2016).

Levitt & Knovel (2011) describe corrective maintenance as a process that returns the product back into working conditions. Due to the fact that corrective maintenance is happening after the breakdown, is affecting the down time the most, see Figure 4. Simultaneously, this will affect the maintenance cost, since a company needs to find, deliver and replace the required item as fast as possible. This leads to corrective maintenance being more costly than preventive maintenance, since the later can be planned and therefore the executed time and the spare parts delivery is better adjusted (Schmidt & Wang, 2016). Therefore, corrective maintenance is regarded as waste; while preventive maintenance can be seen as value adding (Cavalieri, Garetti, Macchi, & Pinto, 2008).

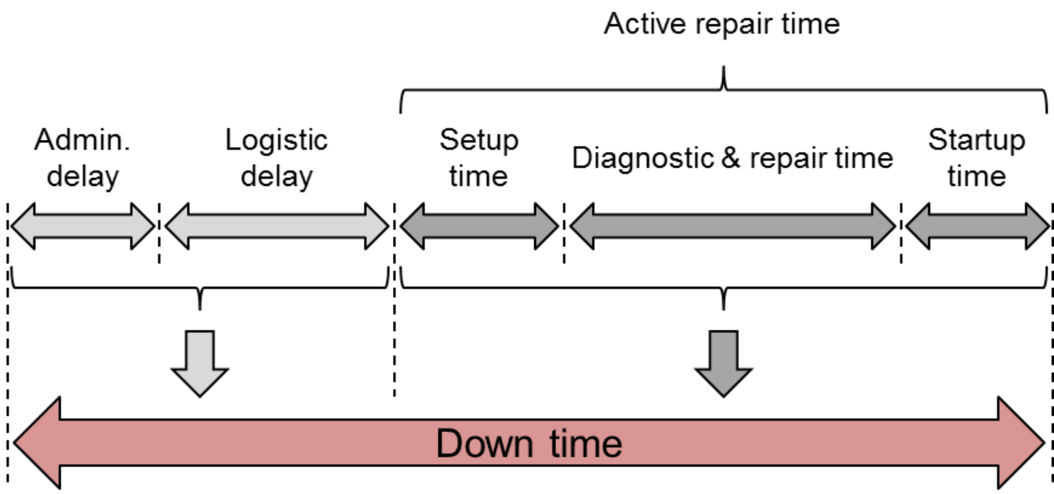

Figure 4: Typical repair after the occurrence of a failure (based on Cavalieri et al., 2008).

Down time consists of administrative time, logistic time and active repair time. Across the whole down time is a product not operational, while the aim is to keep the time period as short as possible. Before the active repair time starts it might occur first an *administrative delay*, when the spare part is not available at the workshop and the supplier has to be contacted first. A second delay could be due to procurement or replacement from a distribution center to the workshop, which can amount to several weeks for specific parts and is called *logistics delay*. The *active repair time* starts with the *setup time*, which includes the preparation of the workshop and the needed equipment. Followed by the *diagnostically delay* for locating and repairing the occurred fault. The active repair time ends with the final check of the functionality and is called *startup time* (Cavalieri et al., 2008).

Preventive maintenance is, according to Cavalieri et al. (2008), time based and consists of routine maintenance schedules based on vehicle mileage or elapsed time, without considering the current state of health of a part. In a preventive process will information only be reported when it is above a predefined limit. It reduces the risk of unexpected breakdown and can lead to replacements of spare parts ahead of time. Levitt & Knovel (2011) state that there is one difference between predictive maintenance and preventive maintenance; which is time. Predictive maintenance compares a measured value to some determined technical measured values. This can be explained with a simple example, that a state should be always reported when it is 10 degrees C above at the defined location. In that way, predictive maintenance helps to create a trend and not just provide status information.

Reliability is the probability that a system performs specific tasks over a given time period (Kontrec et al., 2015). Whereas the reliability in predictive maintenance is based on how to use the data and will be increased by detecting failures earlier than it would be possible to detect manually. Detecting in an earlier stage allows the company to perform a more accurate forecasting, make optimized spare parts ordering and maintenance scheduling as well as reducing the downtime to a minimum (Levitt and Knovel, 2011). In order to reach this performance level it requires a holistic view over the physical products. Schmidt & Wang (2016) mention this requirement of real-time data exchange as one of the problems in the current maintenance process, since the data might be gathered by different units and with different information technologies.

2.3 Telematics technology

Bounds in information technology such as storage, telecommunication capabilities and network give companies access to a large variety of data in real-time which leads to view information as a strategic asset. The advances in these fields impacts whole supply chains. Since the linear view of a supply chain is no longer typical and the network view is more accurate, information sharing in real-time leads to innovative technologies and applications (Kache & Seuring, 2015). One such application is the use of telematics.

Customers' unique service requirements are one driver in the service market, hence it is necessary to use real-time data within the whole supply chain network (Dombrowski & Engel, 2013). This is supported by Gebauer et al. (2010) who state that companies need to optimize their information and communication technology, such as connected vehicles via telematics, in order to perform a higher service level. This is connected to the previously mentioned maintenance processes, for which reason the reduction of information lead time from customer to supplier is urgent to be more responsive to the demand.

Mikulski (2012) describes telematics technology as a process that combines information technology, telecommunication, vehicular technology and electrical engineering in order to send and receive computer based data over long distances. According to Mikulski (2012) telematics give connected vehicles the opportunity of monitoring road, weather and traffic conditions in order to increase the efficiency and effectiveness of the transportation system. Frowein, Lang, Schmieg, & Sticher (2014) are further discussing this and state that telematics enables interactive scheduling of maintenance operations and identification of malfunctions in real-time. This goes in hand with Pellitta (2015) and the detection of failure trends in vehicles of the same model, which allows preventive maintenance. Vehicles are able to send information such as engine functions like battery voltage, coolant temperature and powertrain malfunctions. Due to this remote diagnostic data, it is possible to detect fault and send alerts in case of unexpected maintenance (Cassias & Kun, 2007). This will lead to an optimized service process, where the telematics technology schedule a maintenance appointment for the vehicle owner and the maintenance provider, including parts ordering, which increase uptime and simultaneously reduce maintenance costs (Cassias & Kun, 2007; Frowein et al., 2014). Nevertheless, Fletcher (2016) mentions challenges within the use of telematics when monitoring multiple vehicle classes. The transmitted data differs from the vehicle types, creates an overload of unnecessary data and makes it difficult to capture data that is relevant for each unique vehicle. Furthermore the installations process and the inclusion of all members in the chain can function as a barrier, since their technology has to interact in the best way with the vehicle technology. The reliability of the data is a topic that companies have to face. It is not guaranteed that the received data is complete and correct; this uncertainty in data quality can lead to incorrect data evaluation and decision making (Fletcher, 2016).

2.4 Forecasting of service parts

Many uncertainties in the service market have significant impact on the forecasting and inventory management, where poor customer service level and obsolescence parts can be a consequence of precipitant stocking decisions. Therefore is it urgent to have an effective forecasting system, as well as order and inventory controlling in order to perform a satisfying maintenance service to customers and to reduce costs (Kobbacy & Murthy, 2008). The aim is to keep the stock of spare parts at minimum and simultaneously ensuring a high level of availability of spare parts to be cost efficient. Kontrec et al. (2015) state that due to the uncertainty of part failures is the traditional way of forecasting, such with exponential smoothing and the use of only historical data is no longer accurate enough. Exponential smoothing is a weighted averaging method, where each new forecast is based on the previous forecast plus a percentage of the difference between that forecast and the actual value of the series at that point. Hellingrath & Cordes (2014) empathize with the previously mentioned article, that demand forecasting approaches cannot estimate the demand of the next forecasting periods accurately. Since they are based on time series and are using historical demand, such as trend or seasonality. Kontrec et al. (2015) argues as well that traditional forecasting methods are not suitable for the service part context for slow moving parts, due to their extreme variance in demand quantity in general.

To predict the demand for service parts, the forecast can be complemented with external data like mileage, parts life, seasonal period length and type of maintenance process. Forecast can be complemented only in a case when various data sets are available (Boylan & Syntetos, 2008).

Forecasting for service parts need to include advanced demand data, whereby premature information from vehicles are collected and evaluated to adjust the forecast manually (Hellingrath & Cordes, 2014). Advanced demand data and external conditions, such as vibration, pressure, oil analysis, and temperature or environment data and support the measurement of the condition of a technical system. Such condition monitoring is a part of condition-based maintenance and allows making predictions about the reliability of a service part, its conditions of use, when the part is going to fail in the future and the required service performance. However Kennedy, Patterson, & Fredendall (2002) state that those reliability information are not always available at the quality needed for the prediction of failure times, as not all equipment have the needed technology installed.

Reliability based forecasting according to Cavalieri et al. (2008) is to estimate the number of parts needed in the future based on cumulative operating time, that is run time or mileage. The estimation can be done with historical data or information from databases. Service intervals, part condition, calculated failure rate, working cycle or required performance can be investigated. The article suggests making a life data analysis that requires the history of failures.

2.5 Mean absolute percentage error and correlation formula

Mape

The forecast accuracy is an important factor when deciding among different forecasting approaches (Goodwin & Lawton, 1999). Another use is to track the error performance over time to decide if action is needed. The mean absolute percentage error is a measure used to determine prediction accuracy of a forecasting method in percentages with the weights according to relative error. The formula for this is the following Equation 1:

$$Mape = \frac{100}{n} \sum_{t=1}^{n} \frac{\left|Y_t - \widehat{Y_t}\right|}{|Y_t|}$$

Equation 1: Mape (based on Goodwin & Lawton, 1999).

Where n is the number of points analyzed, Y_t is the actual value and $\widehat{Y_t}$ is the forecasted one (Goodwin & Lawton, 1999). The presented formula has been selected and used, due to the simplicity and the suitability in the context.

Correlation formula

The correlation formula in statistics measures the strength between two variables. The strength of these two variables is between the values -1.00 and 1.00 (Benesty, Chen, Huang, & Cohen, 2009).

The formula to calculate correlation is the following, where x and y are the two variables:

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}$$

Equation 2: Correlation (based on Benesty et al., 2009)

2.6 Conceptual framework

The theory presented in this chapter has its use in different research questions and is presented in the next Figure 5. In order to understand the current way of forecasting at the studied company, the theory section *service market supply chain* and *forecasting of service parts* will give insights on how the service market generally looks like, its specific characteristics as well as areas for improvement.

The theory about *telematics technology* will help to find available data that is useful and continuously available at the studied company. Simultaneously, the obtained knowledge about the *forecasting* will support the previously mentioned data investigation from research question 2.

In order to answer research question 3 the theory about *predictive maintenance, down time* and *availability* will be used and build on the findings from research question 1 and 2. The last part of the thesis will create a framework on how to use the telematics technology in the future for the forecasting process.

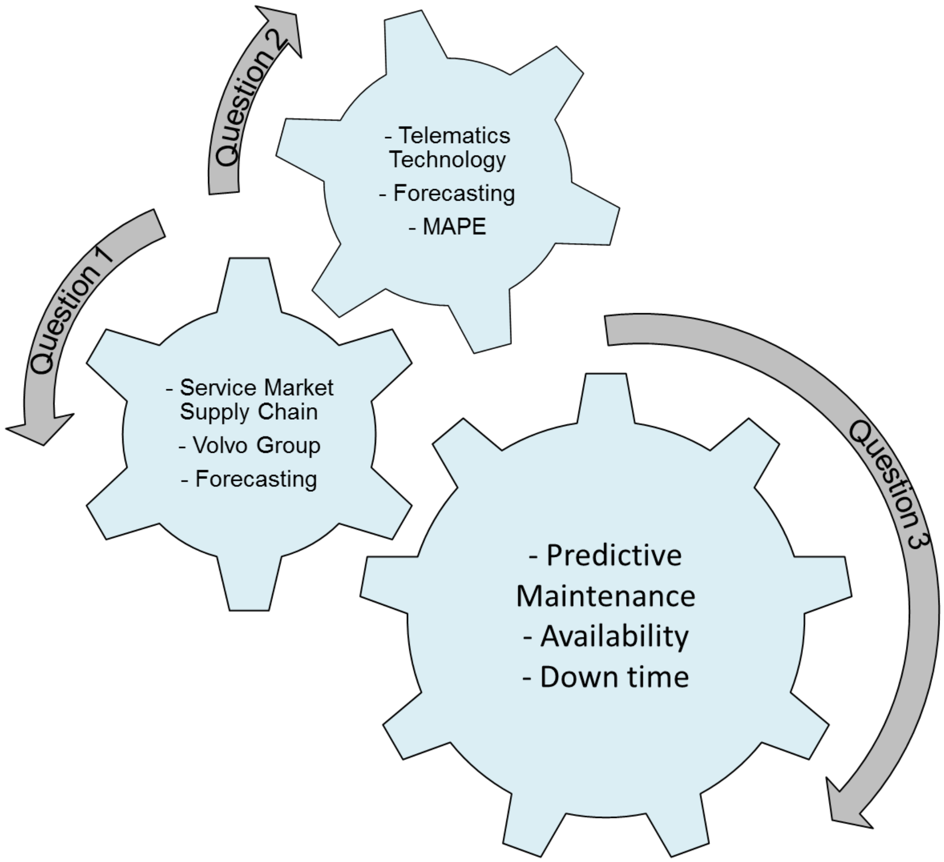

Figure 5: The presented theory and its use to answer the research questions.

3. Method

This chapter will describe the methodology used to conduct this thesis and is divided into four subchapters. Those present the research strategy and the design of the study, how the data will be collected and analyzed. Data collection and needs are described and lastly the research questions, reliability and validity of the study are discussed.

3.1 General research strategy

Research can be carried out by two main strategies, either conducting a qualitative research or a quantitative research (Bryman & Bell, 2015). Deciding which strategy is most suitable for a specific project depends on what data the research needs. Bryman & Bell (2015) are describing that qualitative strategy focuses on subjective analysis with non-quantifiable measurements to help understanding beliefs, incentives and motives. Whereas quantitative strategy focuses on collecting and measuring data in a statistical analysis. Another difference between the two strategies is based on the relationship between theory and research. The relationship can either be deductive; which is used for quantitative research or inductive; which is more common for qualitative research. In the former; theory is tested by using numbers and facts and in the latter; theory is generated (Bryman & Bell, 2015). A deductive approach goes from the general to the particular, by looking at related theory, creates hypotheses based on that and then continues to test that theory. On the other hand, induction begins by looking at the focus of the research, which can be a business problem, and then with the aid of selected research methods it pursues to generate theory from the research (Greener, 2008).

Yin (2013) is describing abduction as a third method. An abductive approach is mostly used where the nature of the research objective is given and can change the theory before, during or after the research process, which not goes in line with the other two above mentions methods. The main drawback is that the conclusion formulated with an abductive approach is quite uncertain, it can be coincidently true and there is no guarantee for the correctness of the case. Hence, the conclusion of the abductive method is rather a hypothesis, which establishes a connection between the evidences. By expressing in it an assumption, which would leads to the second premise (Yin, 2013).

Nevertheless, there exists an abductive research approach, where qualitative and quantitative research is done for one study. The use of mixed methods differs and can include being complementary for the other method, to initiate a new perspective of a research or to broaden a research by using different methods for different purposes (Bryman & Bell, 2015). One reason for using a mixed approach in this study is triangulation, which means to use different methods for collecting and analyzing data of the same topic. The purpose of this is not necessarily to cross-checking data from at least two sources, but rather to capture different dimensions of the same phenomenon. Furthermore, it will help to enrich and confirm the investigated research from various perspectives, by increasing the level of understanding about the phenomenon (Greener, 2008). That is similar with the possibility in the abductive approach to change the theory within the research process. Furthermore, this constantly going back and forth process overcomes the weakness in a research of “describing everything, and as a result describe nothing” (Weick, 1979, p. 38), where the researcher is challenged with selectivity. Additionally, systematic combining is based on a longer time frame than the usual abductive approach, since studied theory can change over the elaboration process and requires flexibility. Dubois & Gadde (2002)see similarities between systematic combining an abductive approach and describe it as an iterative process between a theoretical framework, empirical fieldwork and case analysis, which is presented in Figure 6.

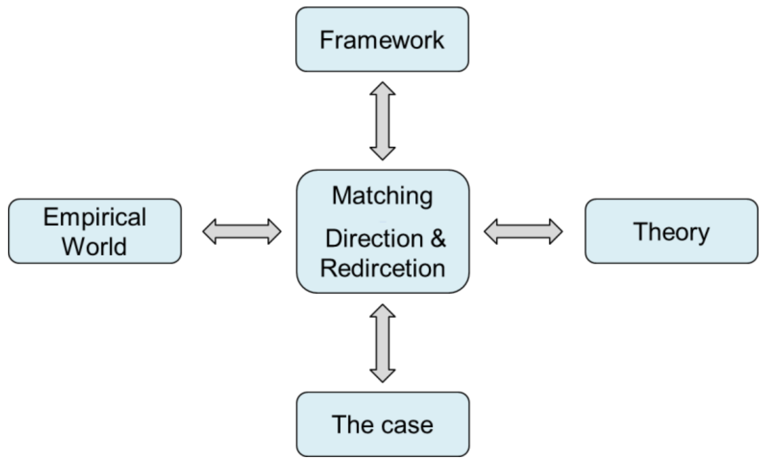

Figure 6: Principles in systematic combining (based on Dubois & Gadde, 2002).

This master thesis is following the systematic combining approach and is using a qualitative evaluation to support quantitative findings from telematics data, in order to provide a more comprehensive analysis, to triangulate the qualitative findings and complementing the current forecasting approach at the studied company. Within this method is a continuous movement between theory and practice taking place to successfully reorient the research cause and the analytical framework. Dubois & Gadde (2002) define this as the matching process and it also reflects the part of inductive reasoning, since it is difficult to select in advance which theory will be most useful in interpreting the investigated phenomena. A framework needs to be developed on a continuously base and findings in the empirical data are expanding the literature study. This goes in line with qualitative aspect when the researcher is uncertain about the most important variables that have to be evaluated. This step corresponds to fulfillment of research question one for gather information of the current process at the studied company, afterwards the data needs to be analyzed to create themes and categories. The deductive and quantitative part starts with testing relationships between the selected theories from the literature and the findings from the data collection. This step would equal the identification process of discrepancies between the theoretical framework and the current process at the company, as well as corresponding with the conclusive recommendations of the master thesis, hence comprising research question three.

Furthermore, for this master thesis a case study, researching a contemporary phenomenon is appropriate as the case study will be on a specific situation within a process at a company, which is aligned with the theory presented by Yin (2013). For the thesis have several part numbers been given and based on that the telematics data collection, selection as well as data analysis have been experienced, in order to use the finding for all part numbers. The research method contains multiple sources of evidence that will be used; including a literature review of relevant theory and empirical data gathered from relevant sources.

3.2 Data collection

Yin (2013) discusses the reliability and chain of evidence and how important these two principles are for the data collection when conducting a study. Using multiple sources for data collection allows the researcher to achieve a broader perspective, a more convincing and accurate conclusion (Yin, 2013). The usage of internet and information gathered there should be collected carefully and critically analyzed to minimize the potential of having false data, or data without credibility. For this case study, two main data collection methods have been used: Interviews and desk research. Several different persons have been interviewed to further diminish the potential of misleading data. The following Table 1 is presenting the data that is needed for this master thesis and also describe how the data is collected. Afterwards, the needed data is more precisely explained.

Table 1: Data gathering.

Data need	Data collection
Theoretical framework	Literature study
Company description	Interviews and internal documents
Forecasting processes	Interviews
Demand, sale, forecast, mileage	Internal documents
Parts, products and descriptions	Internal documents

3.2.1 Primary data

Primary data is gathered specially for the subject of study and collected directly from first-hand experience. Interviews have been conducted with employees in order to collect primary data, analyze the current forecasting process for the service market and understand its needs and challenges.

Interviews

Using interviews is a very important way of gathering information (Yin, 2013). This approach helps researchers gain access to data that cannot be measured using numbers, and to get a holistic picture of the studied problem (Bryman & Bell, 2015) Carrying out interviews can be done through different techniques, such as structured, semi-structured and unstructured interviews (Bryman & Bell, 2015). Unstructured interviews can be compared with having a discussion without an agenda to carry out the interview (Bryman & Bell, 2015). The opposite are structured interviews, which are carried out following a strict agenda with questions. Usually this technique is used when having a quantitative approach and a lot of data shall be gathered without having asked the questions in different ways. This often requires that the questions asked should be of a yes and no character with the potential of an easier data handling (Bryman & Bell, 2015). The middle way, using a semi-structured interview, means that the interview is carried out with a questionnaire but remaining open for discussion and the potential of following up questions to a response.

In order to answer research question 1, interviews with employees from the studied company have been carried out and the results are presented in chapter 4. Nine different interviewees have been selected according to their working area to get an overview about the connection to the studied process and to understand on what level the teams are collaborating and where a need for more is. The interviews with persons from the different team, which are connected to the studied area, have been carried out by using semi-structured interviews and were in the form of personal meetings planned to take about one hour. Interview questions were prepared beforehand, but there was room for follow-up questions and discussion outside of the prepared questions. This helps the researchers to gain access to data that cannot be measured, and to get a holistic picture of the studied problem (Bryman & Bell, 2015). The interview guide that was used can be found in Appendix I. Using semi-structured interviews in this case have increased the potential of gathering all the information which could be necessary for the study. Furthermore, the interviews have been also carried out on a qualitative level in order understand the potential need for telematics data in each team and their options regarding the value. As a starting point, interviews with each person from the studied team was carried out, to understand the current way of forecasting and the possible ideas for improvements with the help of telematics data. Furthermore, people from other relevant teams have been interviewed to understand their correlations to the function of the studied team as well as their possible need for telematics data. A performance manager was interviewed, in order to understand the current use of telematics data for similar areas. Finally, an interview with a business analyst was carried out to gain knowledge about the scope of service agreements. A summary of the interviewees can be found in Appendix II.

3.2.2 Secondary data

Secondary information, briefly explained, means that the researchers did not participate when the data was collected, hence the data is collected by someone else (Bryman & Bell, 2015). Secondary data has also been collected in the past and is not specific for the research study. Information used in this master thesis were deducted from literature study as well as from documents published on the internal company network. The data was used to get background information about each business areas as well as to get a broader understanding of the collaboration among the teams within Materials Management. Lastly, telematics data has been used and analyzed to understand their potential for the forecasting process. It is important to be aware of the origin of data and databases might be incomplete.

Literature study

Complementary data about existing methods were mainly carried out with so called desk research. This literature study was performed using a combination of theories gathered from course literature, books and articles within the selected area. A combination of literature from different authors has been used to get a broader background and to find different views on certain topics. The used literatures are published papers and since they have passed through specific evaluation before being released, they are considered trustworthy. Within the used research method of systematic combining is a continuous movement between theory and practice taking place to successfully reorient the research cause and the analytical framework. The desk research was conducted to gain information about the service market characteristics and the difference to a manufacturing supply chain. Furthermore, telematics technology as well as maintenance principles have been analyzed to gather more knowledge for possible improvements. Moreover, selected telematics data have been explored to analyze its use and support in the forecasting process. For this purpose were different programs and data-sets needed, which have been first explored and incorporated, in order to understand how the systems are working, which data is available and how to use in the later analysis.

Internal documents

Internal documents from the company's internal database were used to gain a better understanding of the company structure and to support assertions stated in the conducted interviews. The documents were in the form of presentations and word documents as well as informative data on the database. The main information used from those sources was company presentations, process descriptions and annual reports.

Historical data

Quantity data from the studied company and their connected trucks have been used to identify the potential of the data. The data includes historical demand, chassis number, assembly date, mileage of trucks, country of operation, dealer location, forecasts and dealer sales. The data was extracted from different systems at the studied company. This thesis investigated seven service parts from the initial phase, because those parts do not follow regular sales patterns in the initial phase. Furthermore, those parts are breakdown parts and without replacing a defected part the truck is not able to continue driving. Another reason is that the first trucks within the scope are currently reaching their first service interval of three years and will start to increase. This will lead to a change in demand, where the traditional forecasting process is not suitable. Due to the large amount of data from different sources, systems and programs as well as in different formats, there was a need to create a tool in the program from the studied company called Qlikview. A lot of effort was needed to create the base for that data management tool, in order to unify the data sources for a complete view of information and with the aim that the company can use it in their business work after this study has been finished. The tool was used to take a deeper look and understand how the data is related, to find hidden value, hence to turn data into insights across all aspects of the scope. Additionally, it was able to create visualizations that made it easier to analyze the data find the correlation within them. Nevertheless, it has to be considered that the quantity telematics data from the studied company might not be complete.

3.3 Model of analysis

Analyzing the gathered data has followed the principles of grounded theory, where data is analyzed along the way (Dubois & Gadde, 2002). Analyzing data continuously ensures that data remains updated when processing it which is eliminating the potential of losing data to oblivion. The aim of the master thesis was fulfilled by answering the research questions stated in chapter 1. A model of analysis is presented in the following Figure 7 and describes the methods used for answering each research question.

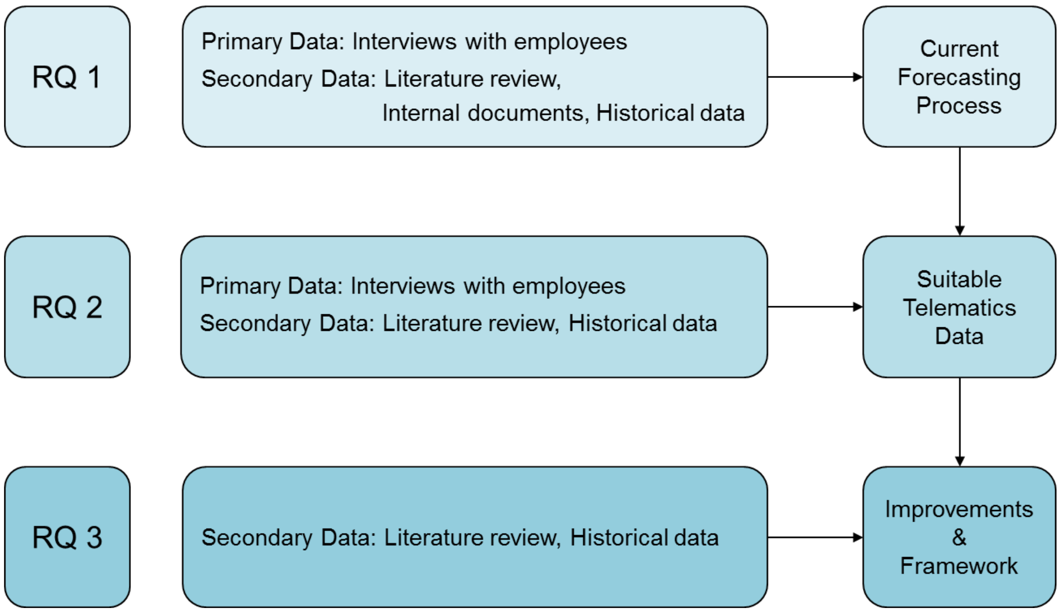

Figure 7: Model of the methodology process.

3.3.1 Research question 1

How is the current forecasting process defined?

The first research question about the current forecasting process is answered in chapter 4 and gives an understanding and description of the company's current service market supply chain. In order to answer the first research question both primary information from semi-structured interviews as well as secondary information from literature study and internal documents have been used. When starting the research, theory regarding service markets and its maintenance models were gathered and processed, along with a light study of potential technologies. Nevertheless, with the use of systematic combining the desk research has never stopped throughout the study. The interviews have given insights on what historical data might be useful for the four main roles of the company's service market supply chain. Hence, the found telematics data is presented to verify the findings in detail.

3.3.2 Research question 2

What telematics data is available on a continuous basis and which data is suitable for complementing the current forecasting approach?

The second question is based on analyzing the data and the findings from research question 1 and is presented in chapter 5. A literature study was conducted in order to get more insights from theory about telematics technology and different forecasting approaches. Next, selecting the relevant data sets and simultaneously creating the data management tool to extract the enormous amount of secondary data. Semi-structured interviews were conducted to understand the extracted secondary information. The quantitative data provided information about the spare parts and the connected vehicles: Part number, Chassis ID, Assembly date, Mileage, Country of operation, Dealer city, Forecast, Demand and Dealer sales. Through the help of the data management tool it was possible to analyze the telematics data, to understand their correlations with each other and to see which data is suitable for a forecasting method. The combination of part number and Chassis ID gives all the trucks within the scope of the master thesis. Assembly date and Country of operation present the day when the truck was finished and in which country it was sold. The mileage shows the driven mileage per week. The Dealer city gives the location of the dealer. The forecast and the demand are stored per period, whereas Dealer sales are stored per month.

3.3.3 Research question 3

How can the suitable telematics data be used to perform more accurate forecasting, which leads to higher forecasting quality regarding demand out of the central distribution center?

The third research question was stated in order to use the findings and create a framework that leads to improvements of the current forecasting process. The final step of this master thesis is presented in chapter 6. To discover possible improvements that can be overcome with the findings, literature review about maintenance and availability was done. That goes in line with the approach of systematic combining, where new literature research can be done in order to get new insights from various perspectives. This way the level of understanding about the phenomenon was increased. The results from qualitative evaluation are supporting the quantitative findings from the telematics data and are summarized in a framework of the new forecasting approach.

3.4 Discussion about reliability and validity

Reliability means that the data can be easily imitated. Validity is more detailed and covers aspects such as if the data fits the objectivity being studied and if the conclusions that are being drawn are accurate. For this research, employees will be interviewed so that the report does not become too reliant upon a single person’s opinion, making the qualitative data more reliant. The results provided from the interviews will be compared to scientific studies performed within the similar field to verify the information. In case the quantitative data collected is provided by national/regional databases, it is considered high quality and reliable. If the data is provided internally, additional data may be needed to verify the reliability (Bryman & Bell, 2015).

4. Case description

This chapter presents the studied company, their organization structure and the selected business area in order to answer research question 1. Furthermore, this chapter summarizes the results and findings of the interviews as well as from the telematics data collection. Firstly, an overview of Volvo's supply chain and the four main roles of the company within their service market are presented, in order to understand the connections and correlation between them. Additionally the telematics data is presented to verify the findings in detail. Further, a part of the second research question is described in this chapter, about what data is available that can supplement the forecasting process.

4.1 Introduction to the Volvo Group

The Volvo Group [Volvo] is a multinational publicly held manufacturing company headquartered in Gothenburg, Sweden. The core activities are production, sales and distribution of trucks, buses, construction equipment and also supplies marine and industrial drive systems. Further, Volvo also provides its customers with financial solutions and services. The company's production facilities are located worldwide in 18 different countries and around 100 000 people are employed to reach the market in more than 190 countries.

Volvo was established in 1915 as a subsidiary of SKF, a Swedish bearing manufacturer. However, the official foundation was in 1927 with their first car, the Volvo ÖV4. Originally a car manufacturer but over the years the business areas expanded. In 1999 Volvo Cars was sold to Ford Motor Company and the current business areas gathered more focus. Currently Volvo provides different products and brands to the customers. This was possible through joint ventures, mergers and acquisitions.

In 2016, the company went through organizational changes, meaning that each brand is responsible for their own sales and services. The decentralization is presented in Figure 8. Within the business areas are all brands and products from Volvo included, as well as the financial services and governmental sales.

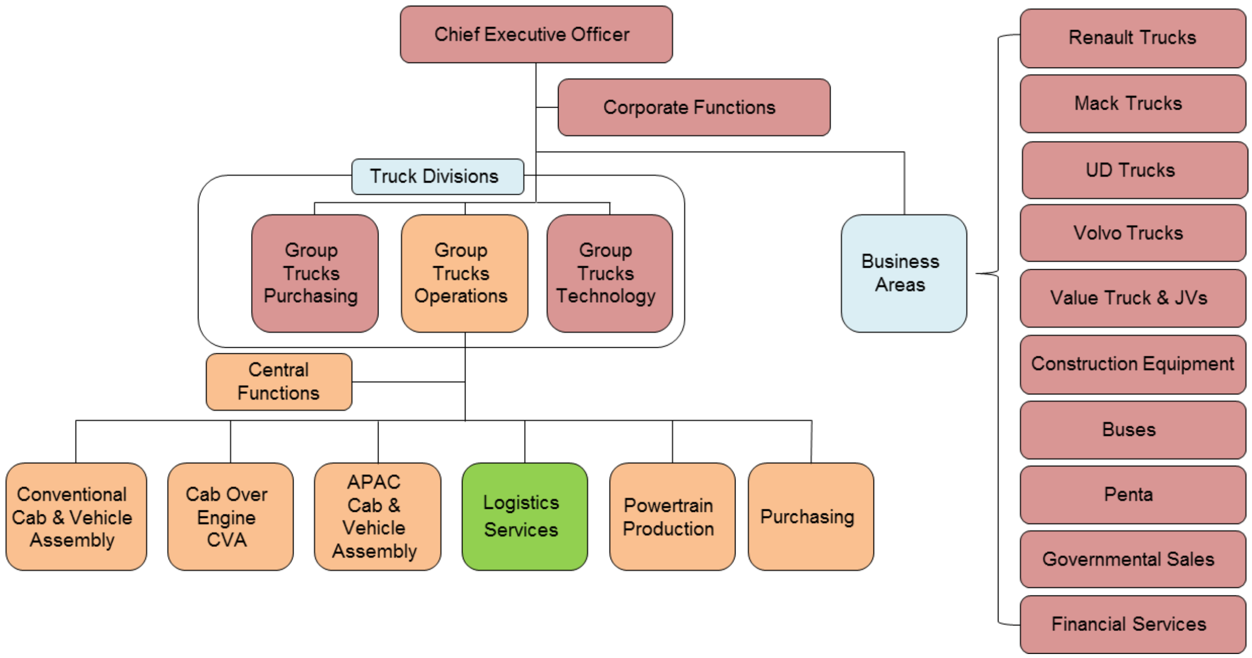

Figure 8: Organization structure (based on Volvo AB, 2016).

Truck divisions are constituted by three divisions: Group truck technology (GTT), Group truck purchasing (GTP) and Group truck operations (GTO). GTT has its main focus on research and product development of the vehicles and related components and services. GTP covers the procurement of parts, products and services for all brands. GTO are responsible for the production of the trucks for Volvo, Renault, Mack and UD trucks. Further, this includes the manufacturing of engines, transmissions for these brands as well as spare part supply to the customers and logistics services. Due to the scope of this thesis only the studied business areas will be presented. Hence, GTO and its bottom department of logistics services are having the main focus.

Logistics services, presented in Figure 9, are responsible for global availability and distribution of the service market. Designing, managing and developing the supply chain are also their responsibility. This includes the operation and management of distribution centers for the service market. Right time, right place and right cost are the driving forces for this department. On a more operational level this department determines the stock and service levels, forecasts and optimizes the inventories throughout the supply chain. Materials Management division is within the Logistics services department and their main responsibility is the material flow in the service market supply chain, from the suppliers through the warehouses structure to final customers. The aim is to ensure the right customer service balanced with inventory and cost levels (Volvo Group Trucks Operation, 2017).

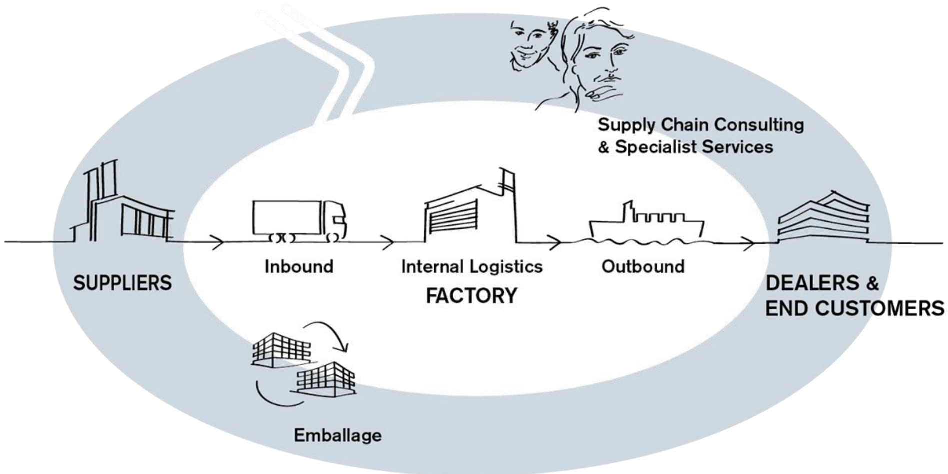

Figure 9: Volvo logistics services (Volvo Group Trucks Operation, 2017).

Trucks, buses, construction equipment and marine engines are the Volvo brands today. These brands are individual business areas and each of them offers sales and service market parts.

Figure 10: Volvo group brands (Volvogroup.com, 2017).

The different types of Volvo trucks have a wide range of use, such as construction, distribution, petrochemical, car transportation, narrow track as well as fire services sectors. In general can the trucks divided in the following four segments, which are within the scope of this thesis.

- Construction trucks; heavy loads, harsh environment, and very high uptime
- Heavy long haul trucks; timber industry, heavily loaded, long distances, and lower working hours in comparison to construction
- Light long haul trucks; loads can vary, long distances, and general use
- Distribution trucks; light loads, short distances, and mostly urban distribution

4.2 Volvo's supply chain

Volvo's service market supply chain is a complex network from the suppliers to the final customers and is presented in Figure 11. The network consists of central-, support- and regional distribution centers as well as the dealers and its customers. The task is to reduce the information lead time for the customer to the supplier, as well as reducing the lead times and simultaneously increasing the stability within the physical flow. Around 5 000 suppliers are shipping parts to 6 central distribution centers (CDC). These centers are located around the world and are supplying further 10 support distribution centers and 80 regional distribution centers. In total 10 500 pickup points are available worldwide. The regional centers are supplying the parts to the dealers, that are around 3 000 individual one, both owned and independent. The distribution of parts is started from the central distribution centers and can supply all types of distribution centers and dealers as well. The dealers are the final link to the customers, whereby a return flow also exists to all distribution centers.

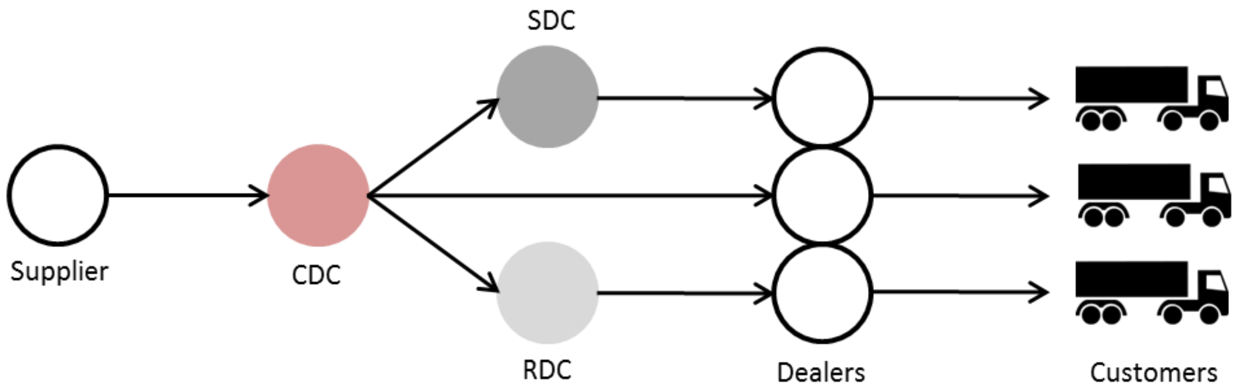

Figure 11: Distribution network.

The six CDCs are located on three continents, namely Europe, America and Asia. The main and largest one is located in Gent (Belgium), contains around 200 000 stock keeping units and handles around 7 million order lines in a year. For comparison are all order lines combined at Volvo around 26 million.

The role of the support distribution center (SDC) is to reduce transport costs, to connect the central distribution center to the dealers in Europe as well as to avoid expensive express deliveries from CDC since day-orders from a SDC can be ensured. The regional distribution centers (RDC) are further supplying the dealers and their main focus is to maintain availability in a specific region. The reason for this distribution network is that due to the long geographic distances the lead time would be unwantedly high. With the current network design lead time to dealers is reduced to less than two days.

RDCs are only outside Europe since the central distribution center in Gent has the possibilities to supply all support distribution centers in Europe. These centers are mainly focusing on parts with high demand frequency and criticality. This way the availability at each point of the network is satisfied.

In order to have the right stock levels at the right time at each node of the supply chain, accurate forecasts and continuous development of the planning process is necessary. Within Logistics Services, Materials Management division is responsible for these tasks. Further, in order to monitor their work and reach better performances, certain key performance indicators

(KPI) are used. Those can be categorized in quality, environment, delivery, cost & capital. Within Materials Management, each team has different performance indicators. Further, these indicators are divided for Materials Management as a whole and the demand and inventory planning team separately. Descriptions of these KPIs are presented on Table 2.

Table 2: KPI for Materials Management.

Category	KPI
Delivery	Availability
Environment	CO2 Emission from Transports
Delivery	Service market parts Backorder recovery
Delivery	Dealer service index
Cost & Capital	Service market productivity gross
Cost & Capital	Transport Products Inventory Days
Cost & Capital	Service market Inventory Days

4.3 Service market planning process

The following four main roles are present within the Materials Management division:

1) Continental material planning: management of part replenishment to the central distribution center.
2) Demand and inventory planning: material flow management from the central distribution center and forecast generation.
3) Refill material management: material flow from and to central, regional and supporting distribution centers.
4) Dealer inventory management: manages dealer’s inventory of spare parts for both owned and independent dealers.

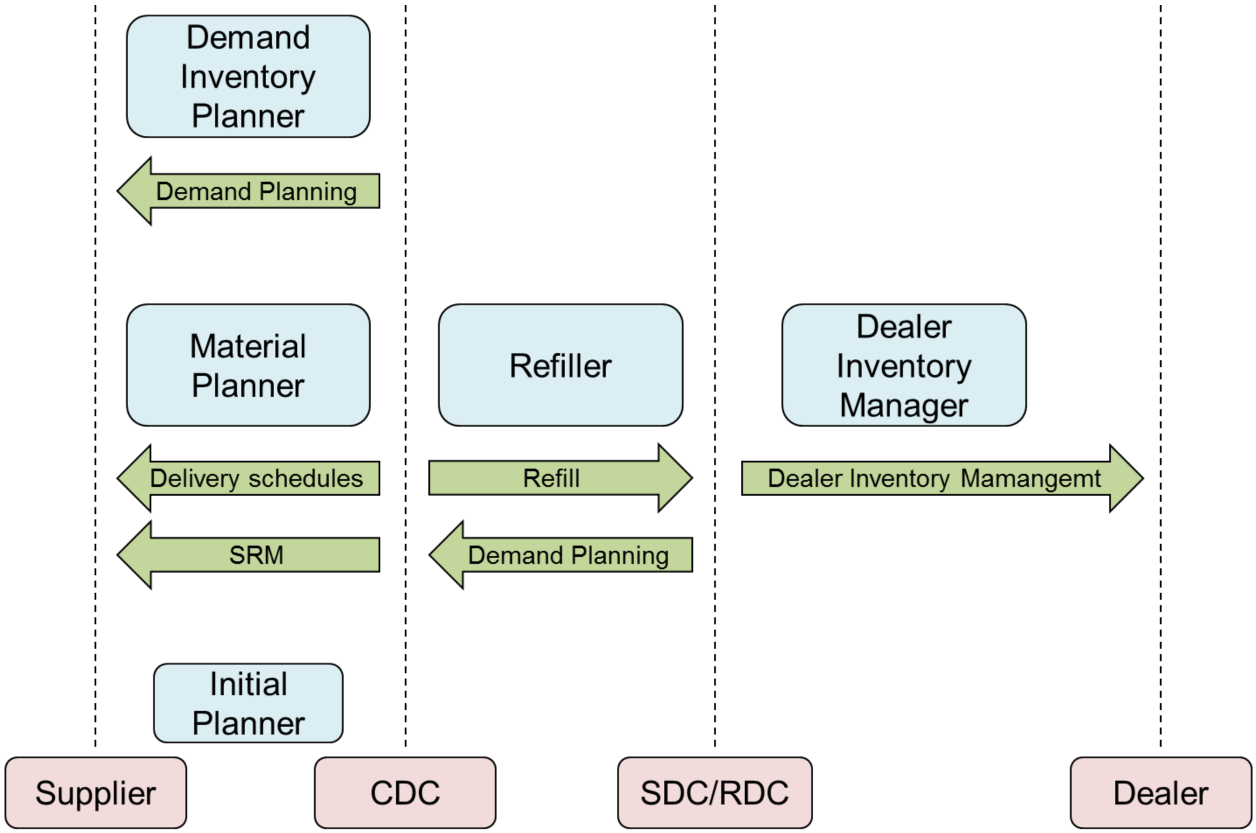

Figure 12: Demand flow of Materials management and the roles within.

4.3.1 Dealer inventory management

Availability of parts at dealer level is the main responsibility of this function. This way the uptime of the trucks can be lengthened and customer satisfaction increased. Furthermore, cost efficiency and high service level are also of importance. Due to the availability of point of sales data, this function can follow actual customer demand.

Volvo has a contract with each dealer in the distribution system, a so called Logistics Partnership Agreement and it means that it sets each member's responsibility. This can range from being an exclusively transactional up to Volvo having full control over the dealer's inventory. Generally, Volvo has a vendor managed inventory contract with their dealers. Buybacks of obsolete parts or stocks are also regularly conducted by Volvo. This includes securing the performance of dealers by optimizing their inventory, calculating safety stocks, economic order quantity and reorder points. In some cases also to coach the dealers in how they manage their parts of the network.

In order to keep the above mentioned variables in optimal limits, the dealer inventory management team has key performance indicators to work towards. Turnover rate and dealer service index are their main ones.

Currently traditional forecasting and historic sales data from dealers are used by the dealer inventory management team in order to plan the processes. With monthly intervals, new forecast are made on a part number level, which means new safety stocks, order quantities and reorder points. The replenishment at the dealers can be done by either the dealers placing manual orders for Volvo or automatic order via the vendor managed inventory system mentioned above. In the case when the dealer places the order, the replenishment lead time usually takes one day. On the other hand, when managed by Volvo, it is an automated process based on the previously mentioned reorder point. The parts flow to dealers can be either directly from the central distribution center or through the support or regional ones.

A software system is used in order to communicate, manage and coordinate the inventory at dealers and also to capture sales data, order picks and inventory levels both on part number and aggregated level. This information flows daily from dealers to Volvo.

4.3.2 Refill material management

The material flow between central, regional and support distribution centers are the responsibility of the refill team. They are working in accordance to three different policies. These are the stock holding, refill and return policy. By working with these policies, the team's main focus is on keeping availability at each node, keep tied up capital low and reduce supply chain costs. Another important part of the work it their close collaboration with the local markets in preparing sales campaigns, service campaigns, seasonal demand as well as initial stocking new vehicles. This proactive demand planning through collaboration with local logistics functions and sales organizations is necessary, since the system calculated forecast is not able to react on those demand changes. It might be possible to handle this automatically in the future through vehicle connectivity as well as a fully aligned supply and demand chain system.

The first policy is the stock holding, meaning the part range selection and the decision to keep these on stock or not. This is conducted by analyzing historical demand and economic incentive. Further, based on a personalized matrix, the refill team can decide whether to use economic order quantity or not.

The refill policy means the time and quantity variables when it comes to ordering parts. Firstly, the safety stock levels are determined after which the reorder point and the economic order quantity taking in consideration the demand during lead time. These two variables are the bases for the refill processes and decide the stock levels.

The return or scrap policy consists of deciding when to return or scrap the parts and also managing the return logistics. Each distribution center has its own policy but the refill team manages the return flow between regional and support distribution centers. Keeping the lead time at each node in the system is also done by the refill team, and this task consists of monitoring the deviations, managing corrective actions when needed.

The above mentioned variables are significant for the whole logistics services department since this can negatively impact the availability, inventory cost and also express of air freight transports.

4.3.3 Demand and inventory planning

Managing the processes of demand and inventory planning for the central distribution center is performed by this department. Volvo trucks, buses and Penta segments are the scope of the team. Since the scope of this thesis work is the demand and inventory planning team, a more detailed presentation will be made in this section. Generating forecasts, determining the inventory and safety stock levels for each part and deciding when to scrap is also the responsibility of the team. The roles within the team are in relation to different service market parts and life cycle. Due to the scope of this thesis work to complement the forecasting process, the current process will be investigated and described in detail.

A year is divided into 13 periods of 4 weeks which represents the forecasting periods. Forecasting, scheduling and inventory levels are determined automatically by software. The software also has a notifying function which means that manual intervention is required. This would happen in a case when changes in forecast over a short period of time are significant. These deviations are investigated by the demand and inventory planning team and manual changes made in order to meet the demand. Changes in call-offs are not the scope of this team. The forecasting method used for new parts and parts that have intermittent demand is single exponential smoothing with trend consideration and it is entirely based on historical demand.

The processes for managing demand and to forecast are grouped both in terms of flow and function. To make the description within scope, only relevant processes will be discussed. Hierarchically the processes are as the following: Group trucks processes, Produce and distribute products, Plan and schedule parts aftermarket, manage demand and capture demand. The last two are the processes that relate to forecasting and demand capturing. Managing demand has the main purpose to make sure appropriate actions are taken when planning for future inventory and demand.

Capturing and aligning demand history, forecasting, inventory planning, order quantity calculations, safety stocks, obsolescence and supersessions are the main tasks within this process. To reduce the dependence on chance and to become more scientific, the need for accurate forecasting increases. Safety stock and order quantity calculations are the focus of inventory planning. The objective for demand management is to ensure high level of customer service while keeping ordering and stock holding cost at lowest possible level. Removing inventory levels from the service market network that exceeds the forecasted future demand is the surplus and obsolescence aim. Supersessions are made so gradual transition from old parts to new without changing the supply chain process. Within demand management, capturing demand has the final goal to calculate gross demand. Gross demand means the total demand in a time period while net demand takes in consideration current inventory levels as well. The team has the same KPIs as mentioned in the previous chapter, with the addition of forecast quality.

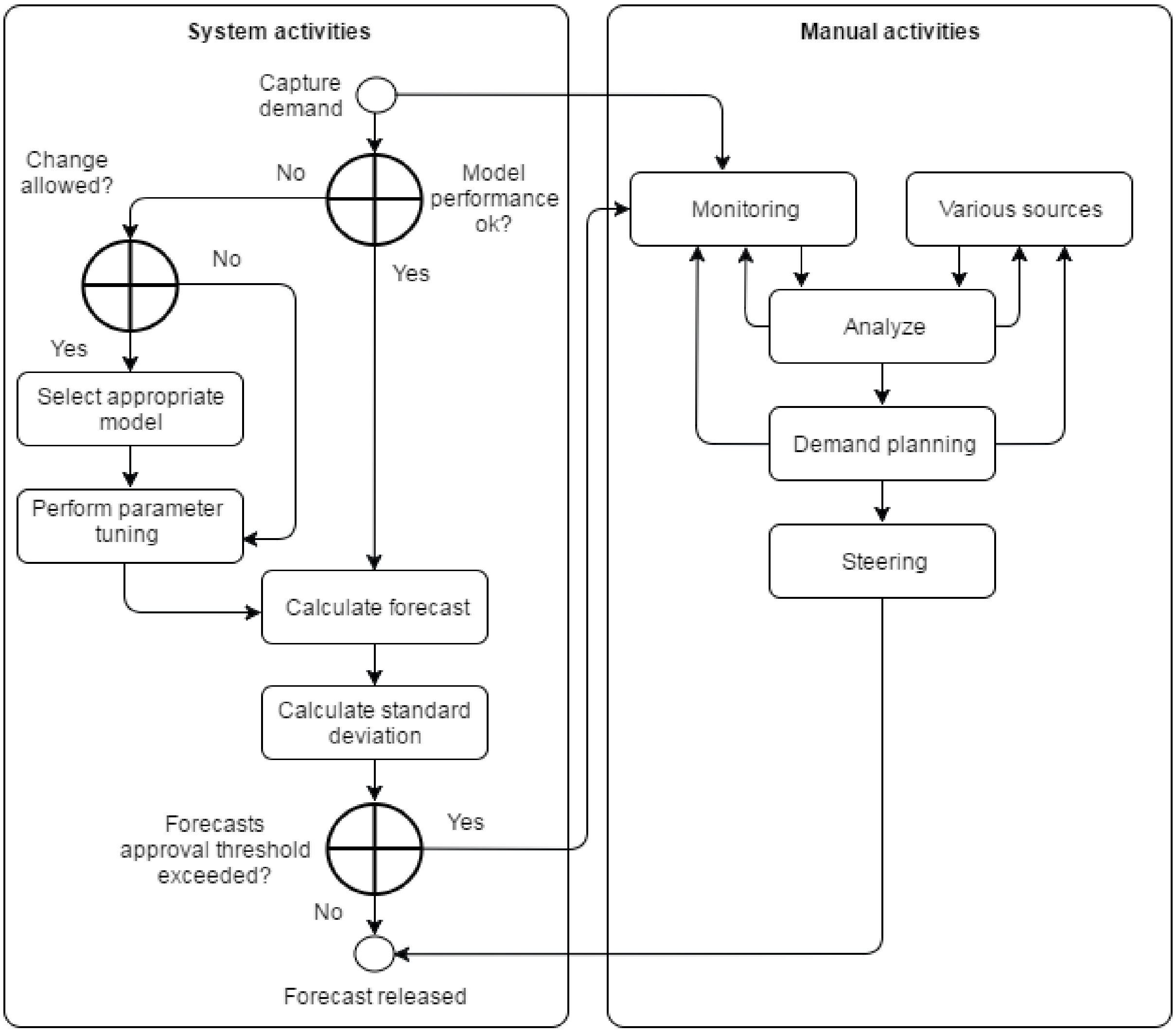

Figure 13: The current forecasting process for DIP.

In Figure 13, the process flow for capturing demand is visualized. The current forecasting model's performance is investigated in the first step. In a case that the model is not appropriate for the forecast, it is changed and parameters are tuned. Next, the forecast is calculated together with the standard deviation. At this point if everything is in order from the system's perspective, the forecast is released. These parts of the process are system activities and are done automatically. Single exponential smoothing forecasting method is used by the system. The process has a manual part where activities are done in a case when the system observes deviations for a number of consecutive periods. The manual assessment can be done on both part number and segment levels. In the first place are the factors and circumstances monitored, which could affect the forecast as well as reviewing various information and leading indicators to determine the root cause. Next, these data are analyzed and the cause for deviations is evaluated to understand the reason for that occurrence. Replanning based on demand is done next and finally the changed factors and the forecast is updated in the system. Due to the characteristics of the service market, forecasts can be frequently inaccurate which leads to many manual interventions to the process.

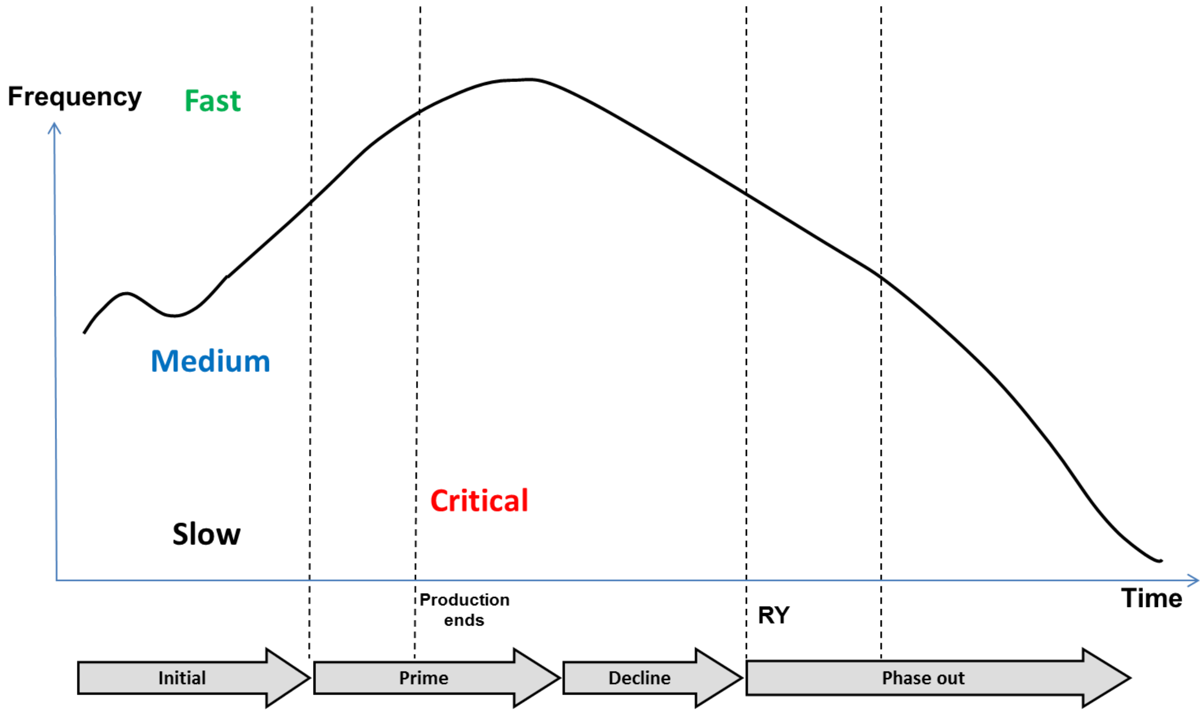

Figure 14: Product life cycle.

In Figure 14, the life cycle and segmentation of service parts are presented. Some dimensions are simplified in order to have a better overview. Segmentation is based on four dimensions, lifecycle, frequency, criticality and price. In total 90 different segments are created. In this case frequency means order lines per period and one order line can contain any quantity of spare parts. The length of each phase is variable for each part. Generally the responsibility year (RY) is at 15 years from the end of production. The responsibility year means that all service parts have to be available for this period. Based on frequency, the parts are segmented into fast, medium and slow throughout the life cycle. Four different lifecycle phases are created based on the time horizon in relation to the responsibility year. Initial, prime, decline and phase out, starting at the end of production of the truck.

Within the first *initial phase* a spare part is introduced into the service market, where the initial stock levels are decided. No historical demand data is available at this point. The next phase is called *prime phase* and represents the time where the spare part has a steady demand, the market matures. In this time it is important to ensure high availability downstream the supply chain. Usually the end of the vehicle production is in this period and is followed by the *decline phase*, where the demand is decreasing and the inventory will be reduced. The consequence is to reduce the inventory levels and minimize the purchase batches in order to lower the risk for obsolescence of parts. At the same time service level should be kept high to avoid lost sales. The responsibility year initiates the last phase. In the last *phase out* period the responsibility year is exceeded, where inventory and availability are reduced. In a case that keeping parts on inventory is not profitable, these parts will be made unavailable. The number of order hits per period determines if a part is slow, medium or fast. Critical parts are another segment and it is determined by function groups decided by the company, such as a small electronic component that is important for the truck to operate.

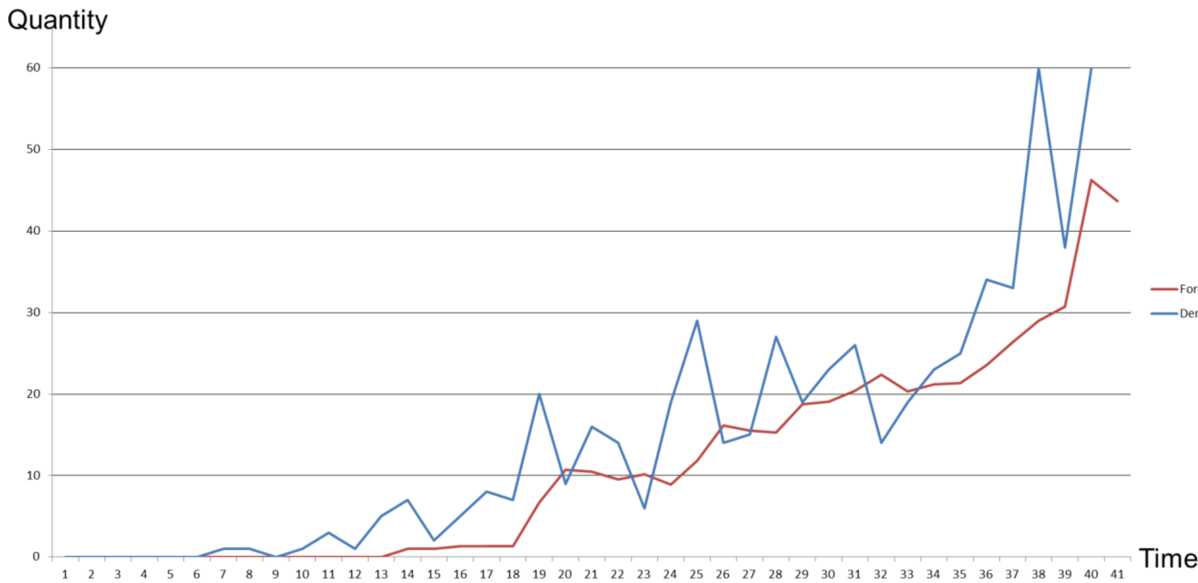

Figure 15: Example of a demand curve and its forecast.

One example of the real demand and forecast is presented in Figure 15. The part forecasted is a belt at the beginning of its life cycle in the fast moving category. Due to the lack of historical data, accurate forecast is difficult to make and frequent manual override is required. On aggregated level matches the forecast the demand but more prevention is required in the initial phase of the life cycle.

4.4 The use of telematics and the selected parts

Currently Volvo has around 700 000 connected vehicles and a positive trend of 15 000 vehicles per month. The final goal is to have a fleet completely connected. Telematics data is available due to the around 70 sensors in each vehicle that send various information on a daily base. The purpose of connected fleet is to utilize the gathered information in a way that vehicle uptime and customers satisfaction are increased. The use of telematics data and technology are present at Volvo in decentralized activities with pockets of excellence. Not sharing and using the data on a centrally governed level leads to loss of valuable opportunities to develop.

Available data is not stored currently on a common platform, which is making it difficult to access different departments. In order to have high quality data, manual intervention is required, since not every stored data is reliable. Volvo currently is in initial phase to fully benefit from real-time telematics data provided by the connected fleet to improve their spare parts planning process. This would potentially give the opportunity to both internal and external supply chain improvements. Various data is captured through telematics technology and stored in databases. The most important ones are the mileage, driving hours, sale location and chassis number. Furthermore, population, part numbers, point of sales, assembly date, country of operation are also in the database. The studied parts are fitted in new trucks that were introduced in 2013 and after. Due to their age, being in the introduction phase, these parts are is the scope of this thesis.

Figure 16: V-ribbed belt and belt tensioner.

4.5 Collection of empirical data

The observation and analysis, done in the next chapter, include the forecast and demand for each part number in relation to mileage and other telematics data, such as country of operation, dealer sales and dealer location. The use of specialized software will help to elaborate and visualize the founded data. This will also support to reduce the amount of data by creating population, with the opportunity to create a setup, from the data of the studied part numbers, for a bigger group of part numbers within the initial phase. The expected output will be to investigate how this data can be used to increase the forecast quality for the studied spare parts.

The number of trucks that use one or more of these parts are 137 783, were introduced worldwide from 2013 and onwards. Since the scope is within Europe, only the 129 990 trucks will be taken into consideration, which was selected by *Country of Operation.* Unless otherwise stated the numbers are always based on the scope of Europe. This number will be investigated when referred to population. The total number of spare parts in the population in Europe is 375 454. Broken down on a single truck level does that mean 2.88 service parts per truck. The forecasting at the studied company is performed on part number level and using aggregated calculations would lead to unrealistic forecast. However, aggregated calculations in this master thesis were investigated in order to understand the correlation between demand and mileage as well as to cross-check the calculations on part number level. The country split as well as the dealer split within the scope of Europe is presented in the next Figures 17. The numbers show how much trucks have been sold in each country as well as the dealer city in Figure 18 and support to obtain the overall spread of trucks in Europe. By using the created tool, the population can be displayed on country level, with the result that the demand on country level can be predicted on general level.

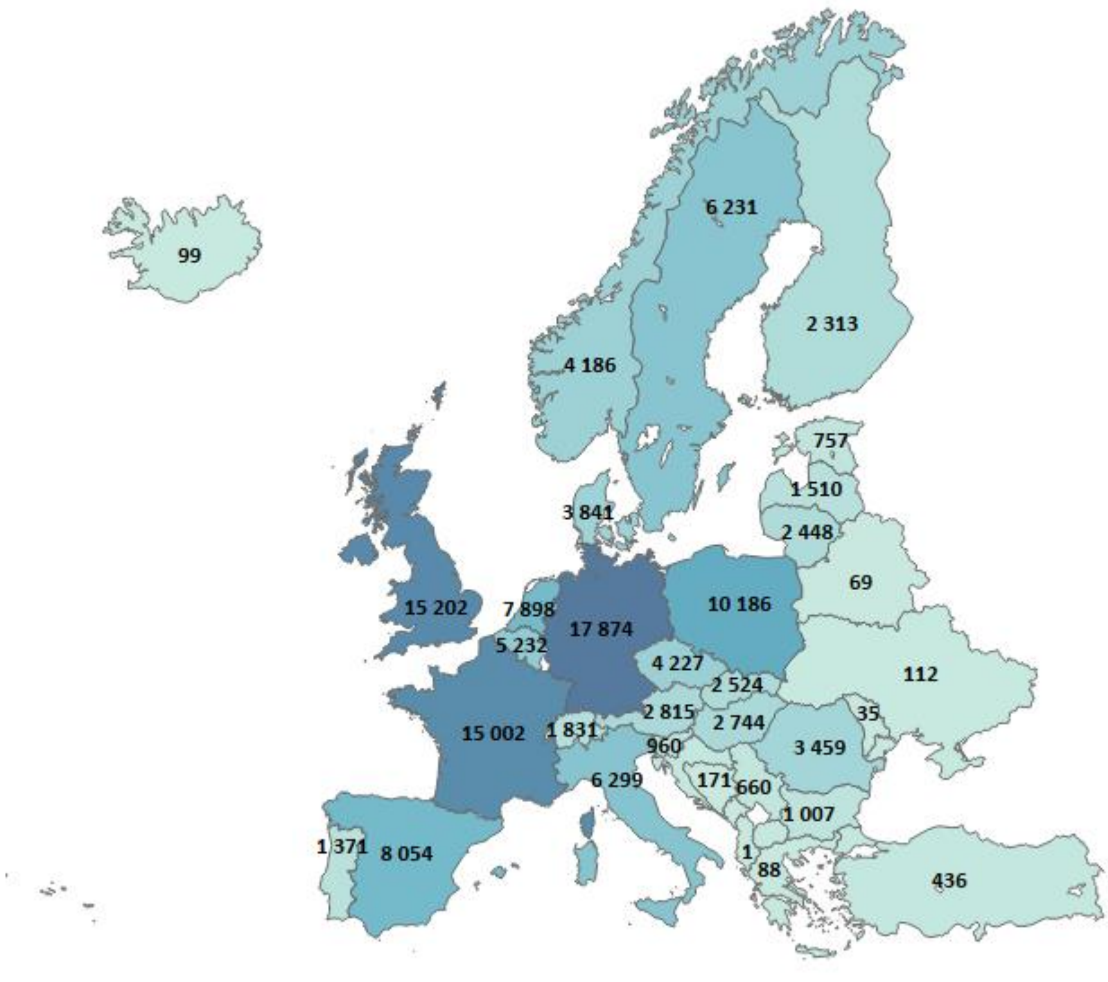

Figure 17: Country split of the connected trucks.

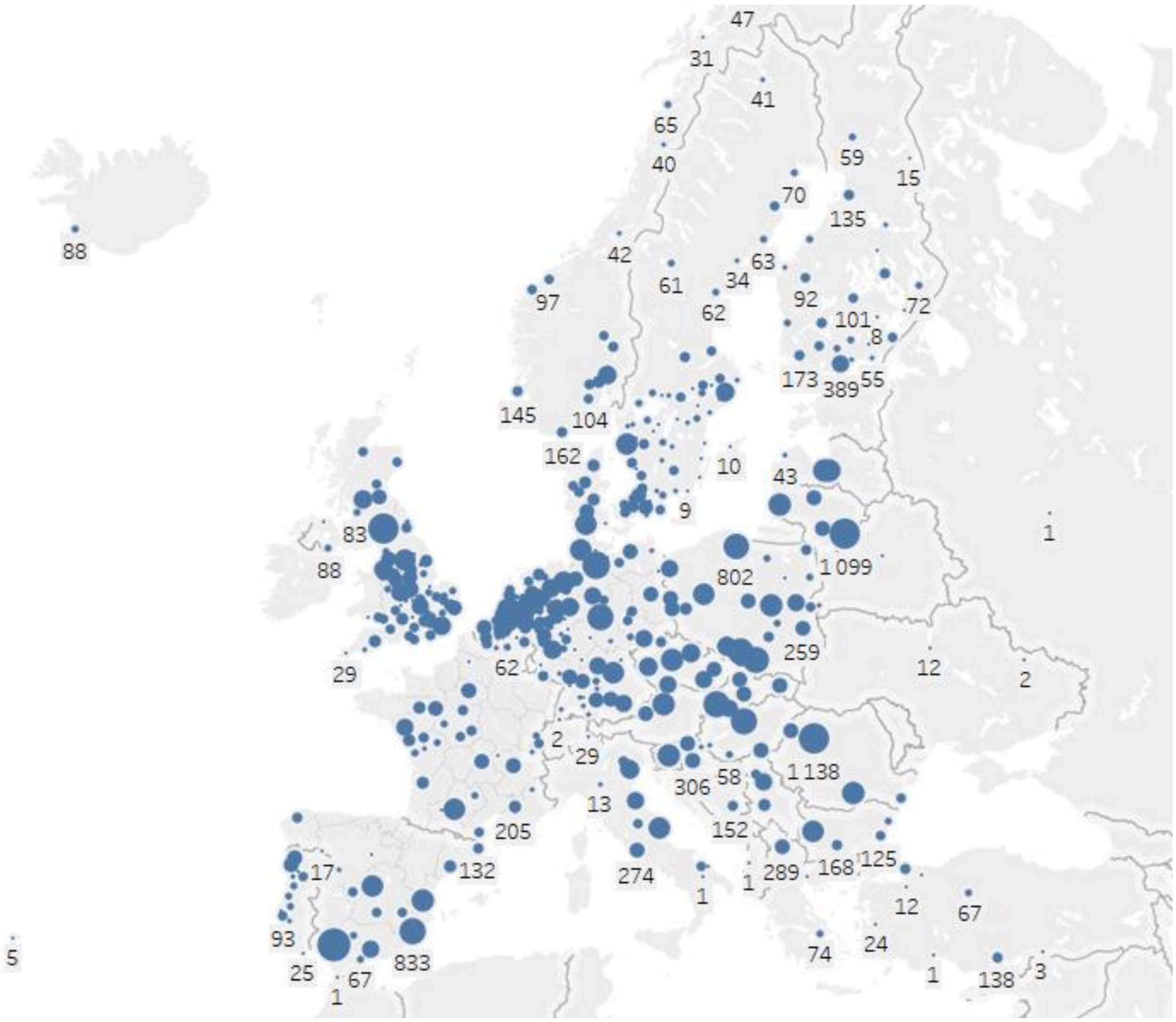

Figure 18: Dealer split of the connected trucks.

Dealer sales and orders towards the central distribution center in Gent are two different types of demand at different locations in the supply chain. The scope of this study focuses on demand centrally in the distribution center. In relevant sections for comparison purposes the dealer sales will be presented as well. Volvo's internal database and software will be used to connect data sets and extract only relevant data for this study including the mileage, demand and forecast. Due to syntax or reading errors by external software, data has to be cleaned in order to be usable.

The service interval of these trucks in general is every 3 years or 500 000 km driven. Hence, a first investigation was to obtain the driven mileage from a single truck. It has shown that a total amount of 178 877 trucks have sent mileage data throughout their entire life cycle, since the telematics has been introduced in 2012. Out of this total amount, 41 094 trucks are not having one or more of the seven selected parts built-in, which leads to the previous mentioned numbers of 137 783 on a global level and 129 990 for the Europe scope. Table 3 below illustratively depicts on the one hand, the spread of the seven selected service parts in column

Population. On the other hand, it shows the average driven mileage per week on a part level. The last column is representing the total demand for each service part.

Table 3: Average driven mileage and demand for the scope of Europe.

Part Number	Abbreviation	Population	Ø Mileage per week	Demand
21983651	A	129 956	2 018 km	7 611
21983655	B	117 001	2 089 km	6 992
21915556	C	87 830	2 243 km	5 691
21983653	D	12 954	1 326 km	654
22070525	E	12 950	1 326 km	752
21742017	F	10 962	1 125 km	638
22315025	G	3 801	1 488 km	635
Total	**-**	**129 990**	**2 018 km**	**22 883**

In order to enable an easy flow of reading the individual part numbers have been given letters, starting with A for the highest populated part and ending with G for the service part with the lowest amount of connected trucks and are visible in the Figure 19.

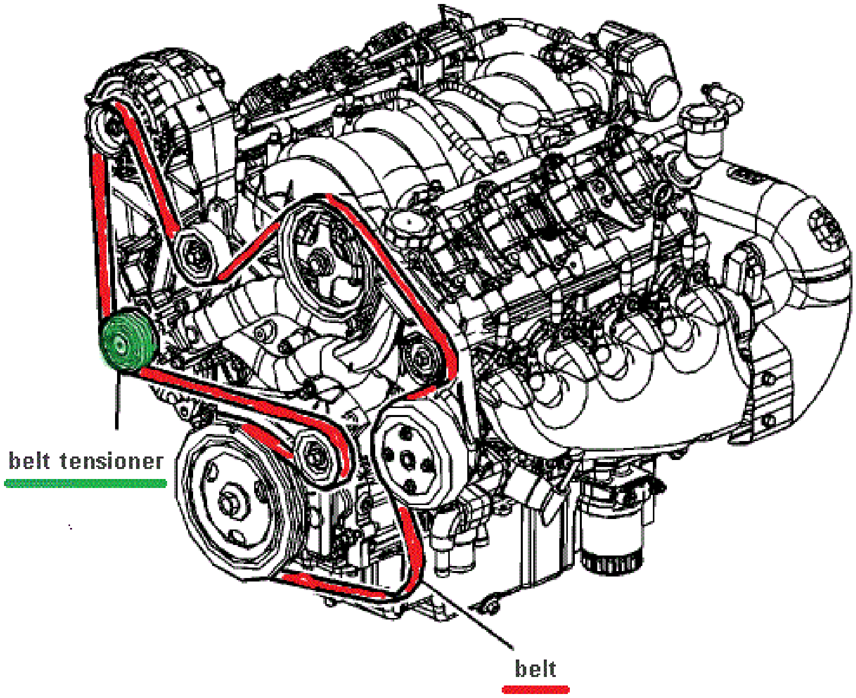

Figure 19: Breakdown service part (Source Fastfieros, 2004).

Belt tensioner	21983651	= A
Belt tensioner	21983655	= B
V-ribbed belt	21915556	= C
Belt tensioner	21983653	= D
V-ribbed belt	22070525	= E
V-ribbed belt	21742017	= F
Belt tensioner	22315025	= G

5. Analysis

The theoretical framework is used to make an analysis of Volvo service market’s current forecasting process and to answer the third research question. In order to see the possibilities on which data is suitable as a leading indicator for the current forecasting approach, historical data sets provided by telematics data as well as demand and sales data are analyzed.

5.1 Mileage analysis on a service part number level

The analysis chapter focuses on the central distribution center and when demand or sales are mentioned it means everything that distributed out of this center unless mentioned otherwise. Lead time is the time difference between the ordering of spare parts and these parts being available in the distribution center. By forecasting on a central level, availability on lower levels on the supply chain can also be impacted. Due to the time limitations and scope of this study, the impact on regional or dealer levels will not be investigated in detail.

The received data parameter *mileage* was used to calculate the growth in mileage for the next periods as well as to calculate the average mileage in total and on part number level. The data can be seen as not 100% complete, since trucks have not frequently sent their driven mileage or sometimes not the right value. Additionally, a number of trucks in the population are not connected and have not sent any telematics data. Nevertheless, the huge amount of trucks will compensate the data issues and provide a reliable mileage quality. In this section the average mileage on part number level is analyzed as well as compared with each other, in order to understand the coherences and the observed difference in their average mileage. Appendix III presents a more detailed evaluation of the average mileage. The next Table 4 gives the spread of the parts and the detected difference of the average mileage per part number.

Table 4: Average driven mileage on a part level.

Part number	Population	Ø Mileage per week
A	129 956	2 018 km
B	117 001	2 089 km
C	87 830	2 243 km
D	12 954	1 326 km
E	12 950	1 326 km
F	10 962	1 125 km
G	3 801	1 488 km

Each part number has been selected individually, for the purpose of detecting how many trucks are connected to each part. It has been observed that the part numbers are having a defined connection with each other and is based on the type of truck, which they are built-in. On average level, there are three service parts built-in one trucks, while part A and B are built-in 99% and 90% of the 129 990 trucks. Hence, the other parts C, F and G are having a defined combination with those two parts. Part D and E are different; they are built together and are having the connection only existing with part A. Since part A is having a connection to each of the other parts, its average driven mileage depends on the combination. For example, part A has a total average 2 018 km per week, but in combination with the 3 801 trucks of the lowest populated part G the average mileage per week is only 1 488 km. The average mileage with the combination to part C is 2 243 km per week and is almost double as with part G, hence this counterbalances the previous mentioned lower average. Those results represent the dependency of the mileage to the usage of the truck type and not to the single part number. This leads to the assumption that the truck type for each part combination is different and can be useful when breaking down the analysis of the forecast even more detailed on a truck type level. The above executed analysis has been done for each service part number and is shown in the Appendix IV.

The following Table 5 represents the combinations that have been found and analyzed for the average mileage.

Table 5: Combinations of part numbers within the population.

	A	B	C	D	E	F	G
A	**129 956**	116 967	87 830	12 954	12 950	10 962	3 769
B	116 967	**117 001**	87 830	-	-	10 930	3 081
C	87 830	87 830	**87 830**	-	-	-	-
D	12 954	-	-	**12 954**	12 950	-	-
E	12 950	-	-	12 950	**12 950**	-	-
F	10 962	10 930	-	-	-	**10 962**	-
G	3 769	3 081	-	-	-	-	**3 801**

The next section represent the share of combinations based on the total population of 129 990 trucks and is divided by the amount of parts within one combination.

Combinations with 3 part numbers:
ABC = 87 830
ADE = 12 950
ABF = 10 930
ABG = 3 769

Combination with 2 part numbers:
AB = 14 438
AD = 4
AF = 32
BG = 32

Built-in with none other part number:
A = 3
B = 2

After finding out, a truck type is connected to the driven average mileage; another comparison is needed to be analyzed. Table 6 shows the spread of service part for each truck range and underlines the statement that the average mileage is connected to the type of truck and not directly to the service part. The Volvo FM is having its application in the *Regional distribution, Distribution, Construction and Auto transport*. The Volvo FH Part is having its application in the *Long-haul, Regional distribution and Construction.* The two most populated parts are built-in each truck type, part C & G are only built-in FH types, whereas the other ones are only built-in FM. The long-haul truck type FH 42 T and its combination is making 54.5% of the total spread of service parts. That can be one reason why the average driven mileage per week for part A and its combination is 2 243 km and simultaneously higher than the total average from 2 018 km. It also supports the statements that those 54.5% raise the total average by counterbalancing the low average mileage trucks. On the other hand, the average mileage for FM is below the total average and shows that this range is more used for regional distribution. The analysis of this empirical data shows that the correlation between part number, truck type and average mileage is something that can be used to predict real demand in order to achieve predictive maintenance rather than corrective maintenance and ultimately to secure uptime.

Table 6: Spread of the service parts on a truck type level.

Product Type	A	B	C	D	E	F	G	Grand Total
FH 42 R	915	915	799				8	2637
FH 42 T	70868	70872	62273				461	204474
FH 62 PT	9984	9984	9511				159	29638
FH 62 TR	10600	10604	8745				383	30332
FH 62 TT	3982	3983	2670				245	10880
FH 64 R	2298	2312	887				763	6260
FH 64 T	1948	1951	661				744	5304
FH 82F R	317	317	255				21	910
FH 82PTR	436	436	387				20	1279
FH 84 PR	162	163	66				93	484
FH 84 PT	286	286	19				199	790
FH 84 TR	1842	1848	1159				523	5372
FH 84F R	645	646	304				142	1737
FH104FTR	82	82	41				34	239
FM 42 R	2984	1040		1943	1943	934		8844
FM 42 T	5240	1616		3618	3618	1354		15446
FM 44 R	126	38		88	88	29		369
FM 44 T	57	35		20	20	36		168
FM 62 PR	224	109		115	115	98		661
FM 62 PT	1148	434		710	710	431		3433
FM 62 TR	5460	1999		3457	3457	1706		16079
FM 62 TT	138	118		20	20	102		398
FM 64 R	1575	1109		465	465	918		4532
FM 64 T	227	185		41	41	127		621
FM 66 R	251	212		37	37	203		740
FM 66 T	6	6				5		17
FM 82F R	495	378		117	117	330		1437
FM 82PTR	390	378		11	11	358		1148
FM 84 PR	98	91		7	7	85		288
FM 84 PT	1	1				1		3
FM 84 TR	1765	1235		524	524	1091		5139
FM 84F R	5124	3355		1764	1764	2912		14919
FM 86F R	202	198		2	2	178		582
FM104FTR	98	98				91		287
FM106FTR	2	2				2		6
Grand Total	129976	117036	87777	12939	12939	10991	3795	375453

5.2 Analysis of the population, demand and dealers sales

Population and demand data is coming directly from Volvo's internal documents. Another data parameter that has been used was dealer sales, which are sales data directly from the dealers and therefore considered as correct. According to the findings, the percentage of the distribution of parts in the population is closely related to the percentage of the demand for these parts to the total demand. The visual presentation can be seen in the next Figure 20 as well as in Table 7. In other words, the parts used in the trucks are proportionately demanded on both dealer and central level without really large deviations.

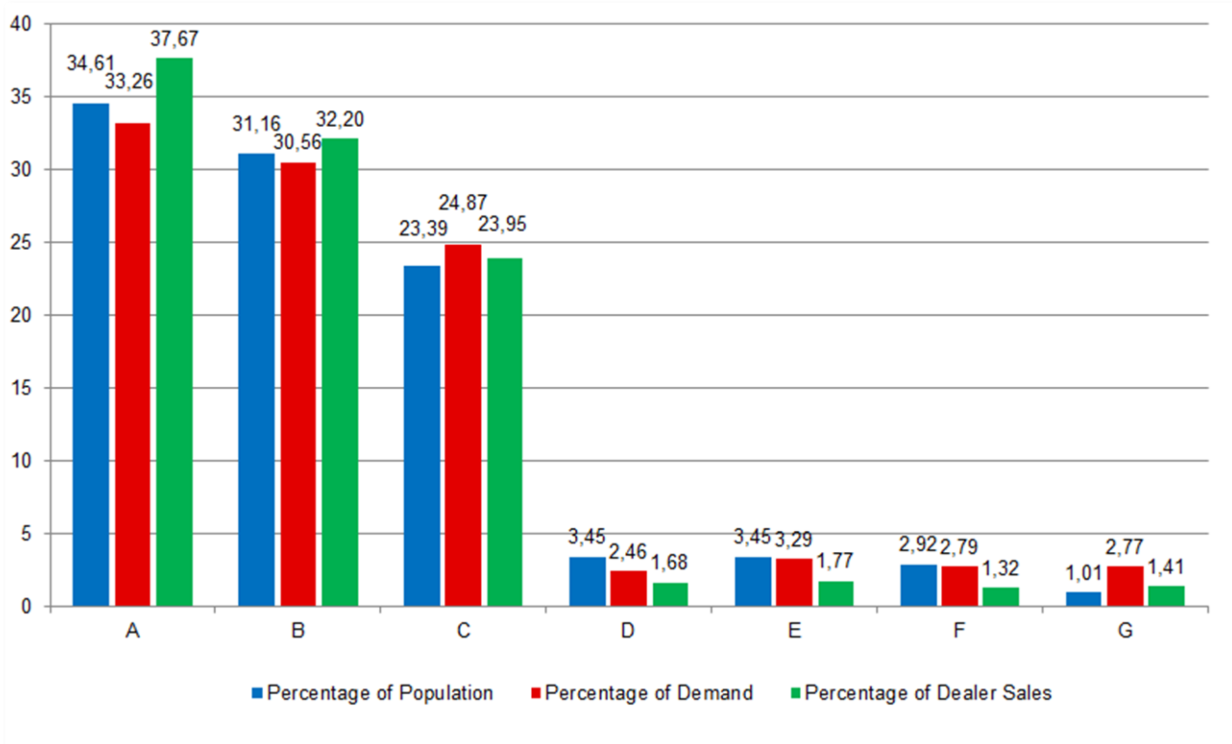

Figure 20: Number of parts, demand and dealer sales in percentage.

As mentioned in the previous chapter, 129 990 trucks are using the selected spare parts. The percentages of trucks involved with the seven parts are distributed in the following increasing order: 2.9%, 8.4%, 10.0%, 10.0%, 67.6%, 90.0% and 99.9%.

Looking from another perspective by comparing the dealers' sales to the actual share in population, Table 7 shows that percentage on a part number level. That means that the total dealer sales for part G are 4.21%, in the last year on the total population. This is the highest share, although the number of sold parts is not the highest compared with the whole population. However, dealer sales are given in a monthly rhythm whereas mileage, demand and forecast is given either in weeks or periods, which makes a deeper comparison of those numbers on a specific time interval difficult.

Table 7: Comparison of number of parts, demand and dealer sales.

Service Part	Number of parts	Demand	Demand / Number of parts	Dealer Sales	Dealer Sales / Number of parts
A	129 956	7 611	5,58 %	4 268	3,28 %
B	117 001	6 992	5,97 %	3 648	3,12 %
C	87 830	5 691	6,48 %	2 714	3,09 %
D	12 954	564	4,35 %	190	1,47 %
E	12 950	752	5,80 %	200	1,54 %
F	10 962	638	5,82 %	150	1,37 %
G	3 801	635	16,71 %	160	4,21 %
Total	375 454	22 883	6,04 %	11 330	3,01 %

After the demand was compared with the population it needs to be compared with the focus on its periods. This has given a broader perspective of the correlations between the different parameters. Figures 21 and 22 are showing the growth of the demand of the service parts. The former, represent the three service parts with the highest populations, while the latter represents the four other service parts. The trend curves within each figure are similar in their increase. On the one hand, the former once are having an exponential increase and reaching a demand of more than 1000 parts per period. On the other hand, the trend curves from the latter one are having a smaller increase as well as a more fluctuate demand curve over the whole time line. A reason for this can be that there is no historical demand data from those service parts, that could help in the forecasting process, as well as that they are not fast moving service parts. Further, they are lower in the total population and in the number of the demand. It has to be taken in consideration that the recording of the demand has started in the middle of year 2014, with 13 periods per year. Whereas the data from the dealer sales are saved on a monthly level, which makes a direct comparison difficult and are presented in Appendix V.

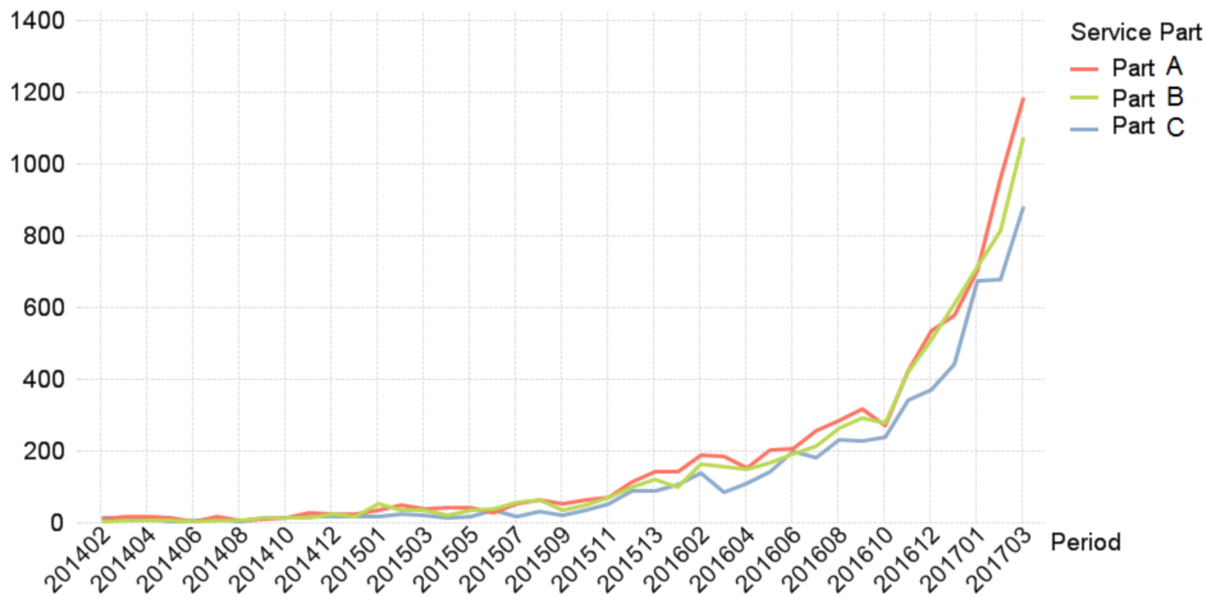

Figure 21: Demand from the three most populated service parts - A, B & C.

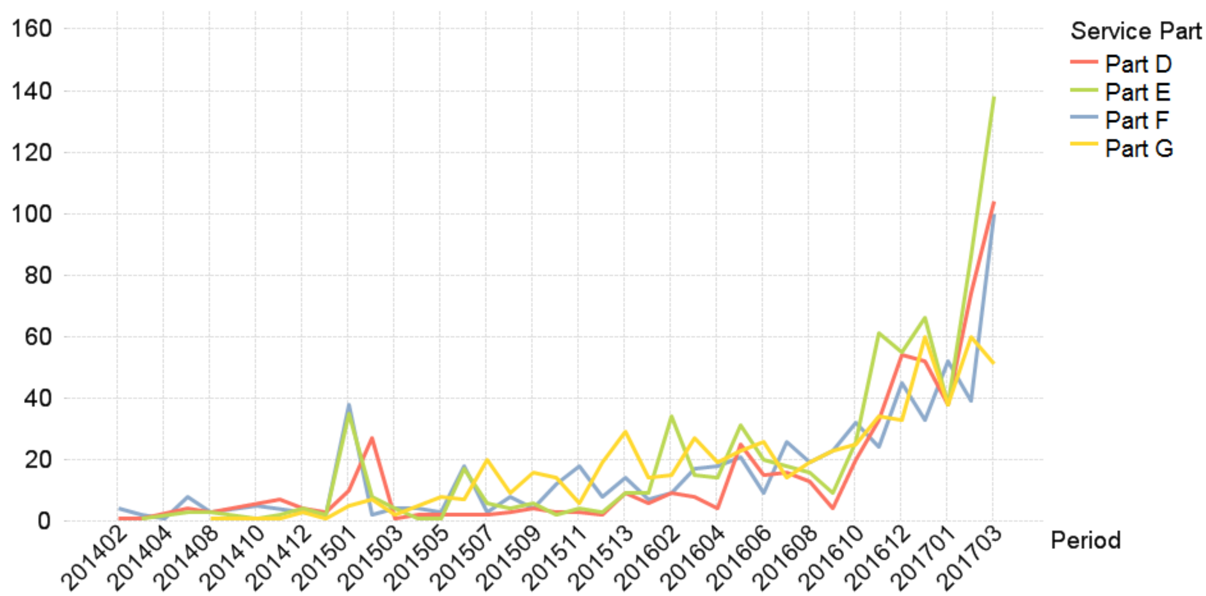

Figure 22: Demand from the other four service parts - D, E, F & G.

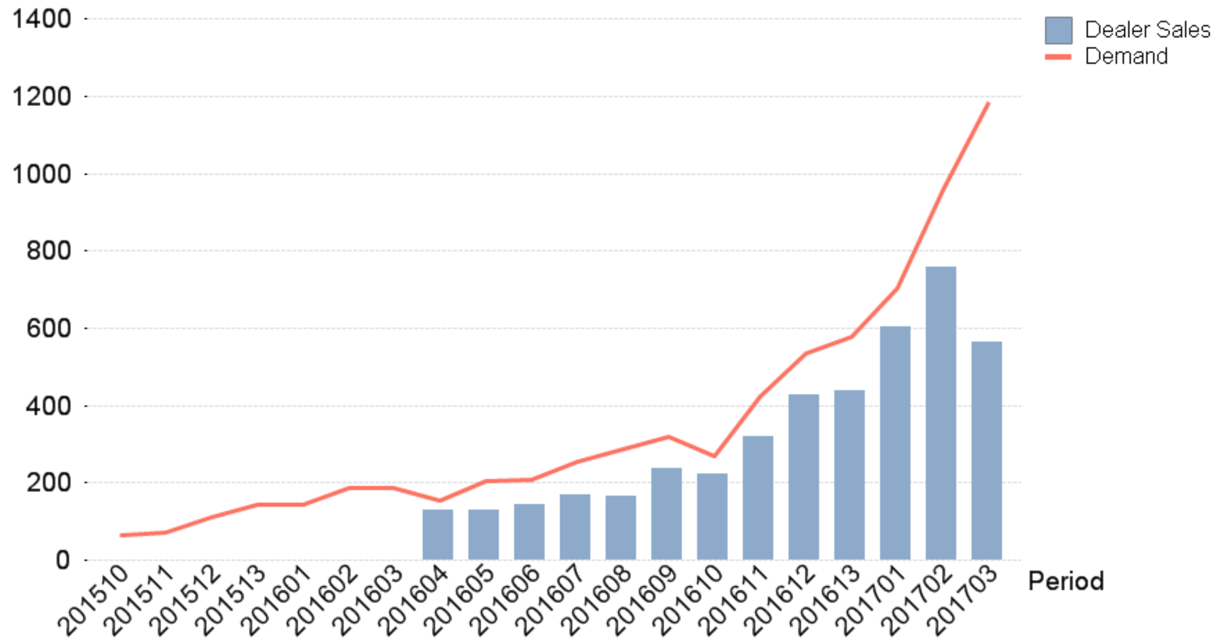

Figure 23: Comparison of demand and dealer sales from service parts A.

On the graph above, the comparison between demand out from Gent and dealer sales are presented for service part A. This investigation was performed in order to cross-check the validity of the data used as demand as well as to see the similar trend of the two curves in each graph. In Appendix V are the comparisons for the other service parts presented.

In order to forecast demand with telematics data, the mileage has to be related to demand. The studied parts are suggested to be changed when the truck reaches 500 000 km or the time interval of three years. Thus, the investigated mileage interval and planned service date is based on this statement. Figure 24 presents the number of trucks that have reached the 500 000 km service interval and gives the number of parts that need to be replaced. In order to calculate the number of truck that will reach that mileage interval in the future periods the average driven mileage can be used and allows foreseeing the number of parts.

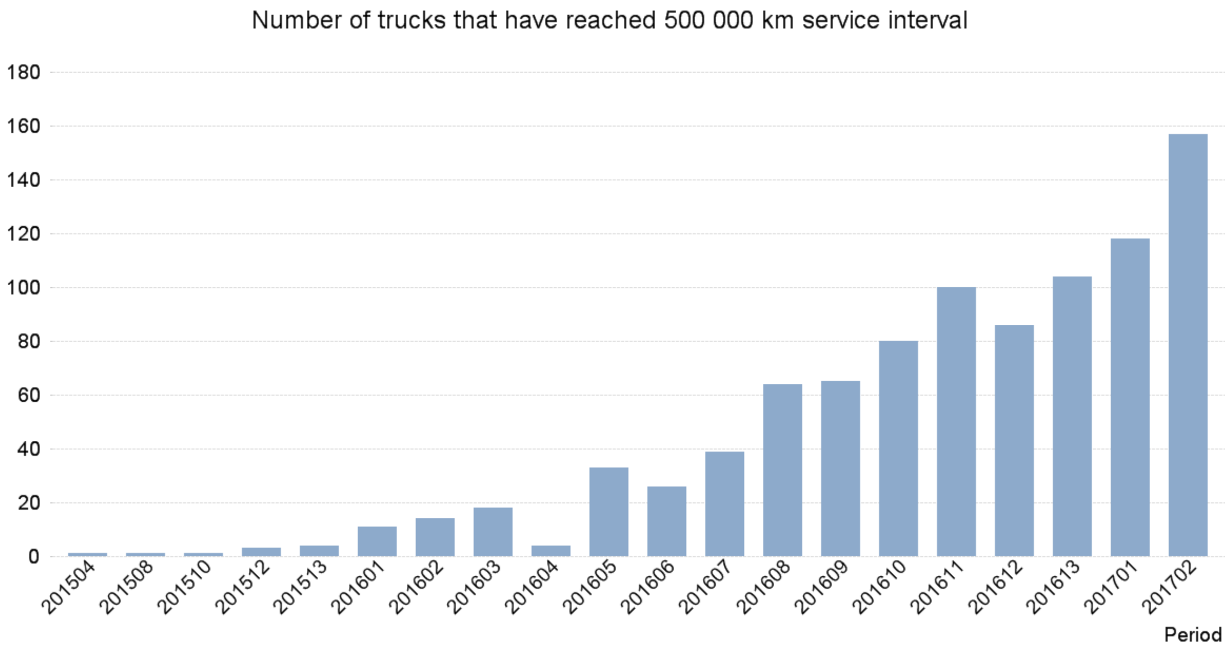

Figure 24: Number of trucks per period that reach 500 000 kms

The connection between only the mileage and demand on period is presented in the Figure 25 below.

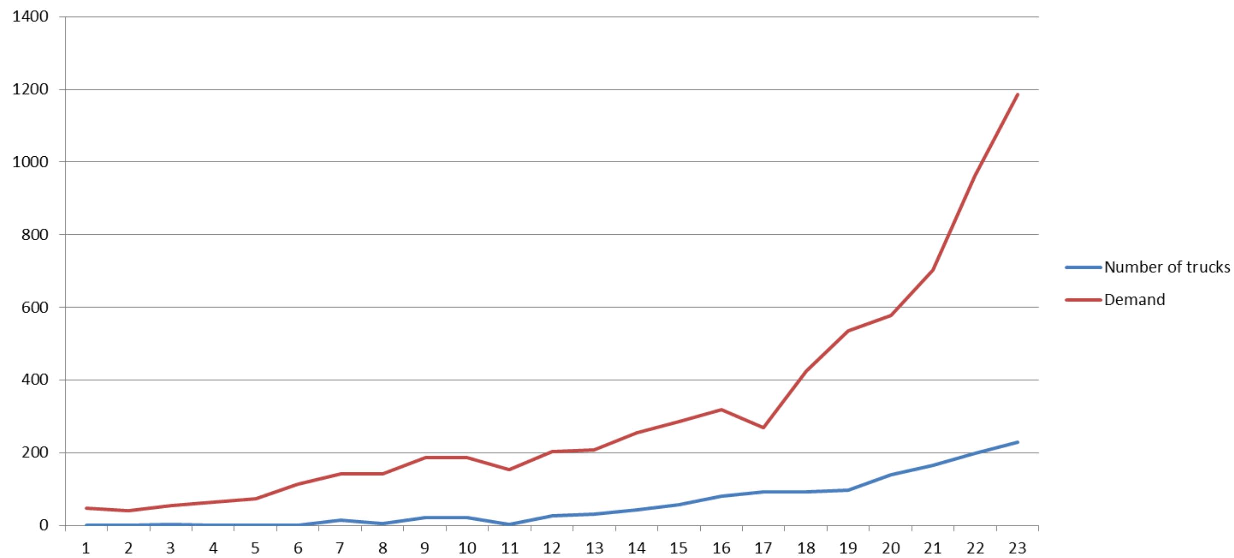

Figure 25: Demand and mileage in relation for part A per week.

The calculated correlation (using the equation 2) between these two variables is 0.97. Given the sets of data for both demand and number of trucks that reach 500 000 kilometers and demand for part A for the given periods, the correlation was calculated with a formula in Excel. This number can be considered significantly high to follow the same trend and be used as highly correlated.

As presented in Figure 25 above, the demand for this part grows exponentially. Using the population of trucks that use these parts, the maximum or ideal demand number of sales can be estimated. The real population and the number of trucks that send telematics data is not the same. In order to get a more accurate prediction of demand a coefficient has to be calculated. This is a simple percentage of trucks that send data out of the known population. In this case this will be 83% or a coefficient of 1.21. Accumulating the number of trucks that reach the service interval and multiplying with a coefficient calculated above, would give an estimate about when the increase in demand will flatten out. In this case the percentage of trucks that reached the service interval is 2.39% (or 1.97 if using the adjusted population) out of all the trucks that use the studied part numbers.

Figure 26 represents the first truck introduced with part A in 2013 week 35 as well as the starting phase of vehicle introduction until the beginning of year 2014. Following this, a big increase of numbers of vehicle introduced per week can be seen. Due to the maintenance regulation of three years, the parts needed to be changed by that time. That leads to the assumption that the first trucks introduced 2013 should already have been to the workshops. Based on that, the period of the number of trucks introduced was shifted to three years later. 201401 became 201701. Having the number of trucks that reach either service intervals, the total number of parts can be calculated.

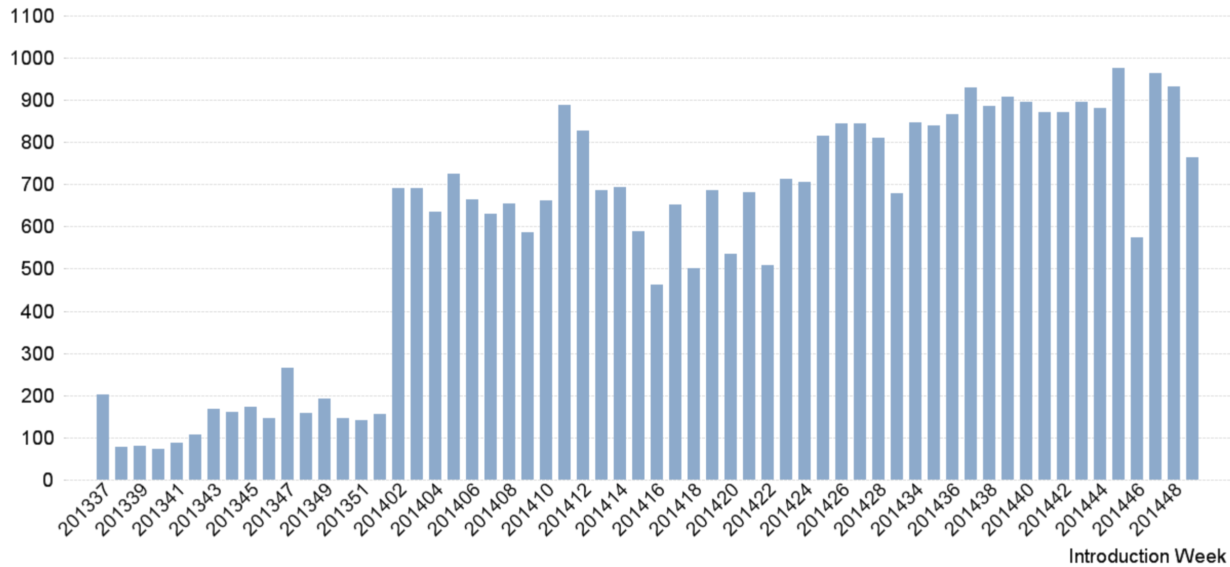

Figure 26: Number of trucks that have been introduced with the selected spare parts.

5.3 Testing the method

Boylan & Syntetos (2008) have stated that external data, such as driven mileage can be used to predict the demand for service parts, but can be complemented only in a case when different types of data are available, in this case mileage and age of trucks. The multiple data sets from the studied company and the different data files are fulfilling this requirement and are done in the next section.

By using the average driven mileage per truck allows to predict the mileage for the coming periods therefore, the number of trucks that will reach the 500 000 km service interval can be forecasted. A couple of periods from 2016 were selected to test the forecasting accuracy. In the first step the absolute difference between real and forecasted mileage was calculated. Next, the percentage of this difference in relation to real mileage was determined. On average this resulted in 13%. In other words this means 87% accuracy of the forecasted mileage based on the average per truck. Comparison between the forecasted and real mileage can be seen in Appendix VII.

Previous analysis has shown that for three part numbers, such as part A, the demand and forecast have had an exponential growth, whereas the other four parts had a more fluctuated curve. Part A is built-in 99% of the trucks, for this reason and its exponential growth of the demand was this part chosen for testing the forecast based on telematics data. In that way the forecast can be done on part level. However, all the seven selected parts are in the introduction phase, where the demand is exponential and difficult to forecast. Testing periods were chosen when the data is accurate and in quantities that can be generalized. Within the first 13 periods, there was no forecast done by the Demand and Inventory planner at Volvo.
Furthermore, the calculated numbers of trucks reaching the specific mileage interval of 500 000

km and for this reason need a visit at the workshop were added to the other number of trucks. As analyzed, 5.2% of the trucks have not sent any mileage data, for that reason are those added to the number of trucks that have driven the specific mileage interval. This leads to the result of the total number of trucks that need a part replaced and is seen in Figure 27, which shows only the need for service part A. The first truck who reached a mileage interval was in 201601, which is the reason why the X-axis of this figure has this period as a starting point.

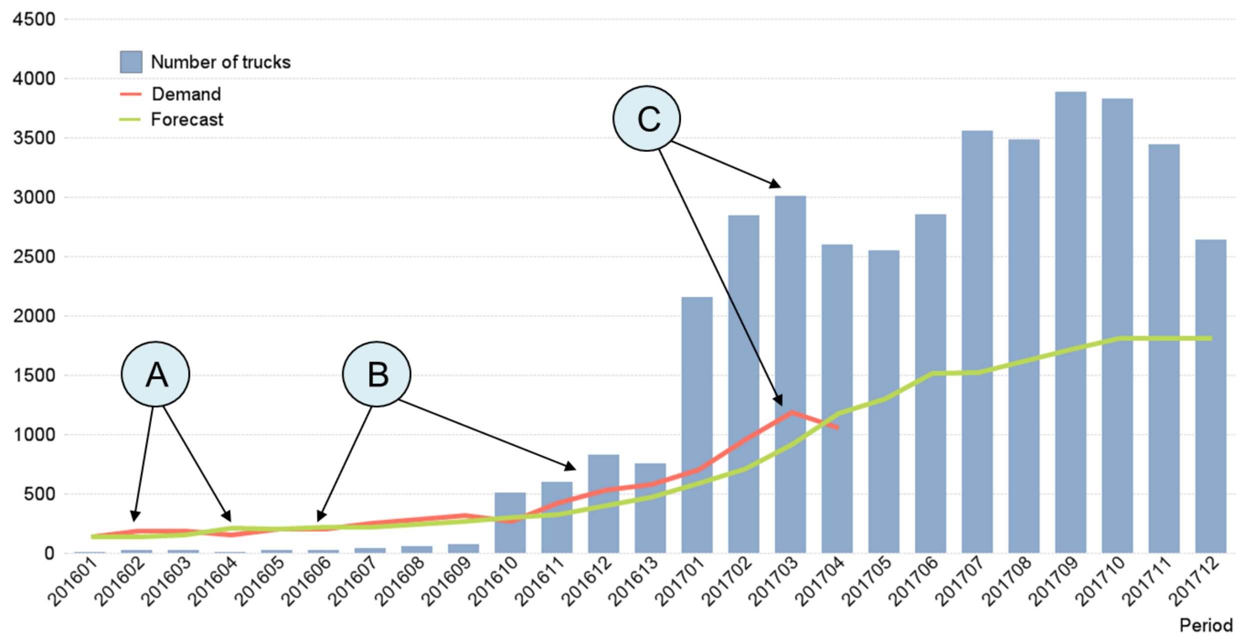

Figure 27: Trucks that reached the service interval per period for service part A.

Until the end of year 2016, the demand was higher than the number of trucks that might need a spare part replacement. A reason can be that the dealers were stocking up their inventory, which can be seen in the comparison of dealer sales and the central demand out of Gent in Appendix V. A first reason for higher number of trucks from that moment on can be that the trucks have not gone to the scheduled service check. Another possibility is that the dealers have bought their spare parts from the grey market, since the availability from the studied company was at this point too low. The tag A is showing the peak in the demand with a decline afterwards in period 201604 and the same trend can be seen for the trucks that have reached the service interval. Within the period of tag B the demand curve as well as the number of trucks showing a similar trend, both end up with a peak in period 201703 as well as followed by a decrease. It can be noticed that the forecast is a more steadily increasing curve and is not showing the same highs and lows. Nevertheless, Figure 27 is helping to get a better understanding of the subsequent progression of the demand. A drop in the periods from 201704 to 201708 can be seen, this is due to the fact of missing mileage reading as well as that in the periods three years ago, especially in period 201408, less trucks were introduced. This goes in line with the other years 2015 and 2016, were also less trucks have been introduced over the summer periods. Since the manufacturing facility is closed in August. Furthermore, it can be considered that within the periods before 201610 the demand was so high due to the fact that the dealers were stacking their inventory for the upcoming demand. The comparison for the other six service parts can be found in Appendix VIII.

Using the regression method to forecast the number of parts A demanded in the coming periods, the result is shown on Figure 28. The reason to use regression is that the gap between actual parts that need replacement and the demand for these parts is very big.

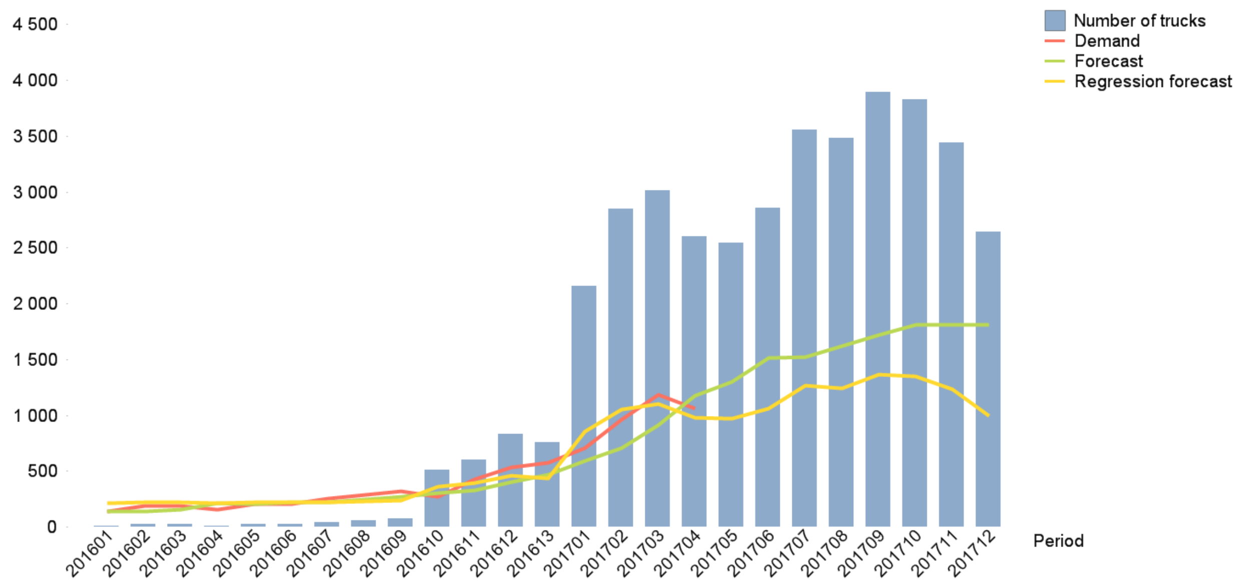

Figure 28: Forecasting based on regression and telematics data.

As presented in Figure 27, the number of truck reaching 500 000 km or 3 years leads the demand for the service parts. Using the MAPE method to analyze the accuracy of this method gives the following results: For the total number of 23 periods the mean absolute percentage error for the forecast is 16% while using the regression method as forecast is 18.24%.

By taking into consideration only the periods where the trucks started to reach their service intervals, 201611 and onwards, the MAPE changed. The system forecast had an error of 19.1% while the regression based forecast an error of 15.8%.

As expected from the Figure 25 the demand as well as the prediction based on mileage and age should be more correlated in the coming periods. The significant difference between the demand and the mileage as well as age of trucks in the beginning can be due to various reasons as dealers stacking up, bullwhip effect, lead time. In Appendix IX, the same analysis is presented on part number level.

Based on the above mentioned findings, the forecast based on leading indicators give a more accurate forecast in a case when the demand starts to increase (onwards from period 201611) based on statistical method. After the first demand for these parts, system forecast was lacking in the first 13 periods. Mileage and age of trucks can be used as a leading indicator not only for forecasting but also to predict when the demand will start to increase.

Currently due to the lack of necessary historical data for these parts, a conclusion cannot be made whether the regression forecasting is better or not as the system forecast. A follow up is needed to investigate the results in 2-3 months period.

6. Discussion

The investigation of predicting the growth of mileage data from the analysis chapter is supporting the third research question, which lead to a higher forecasting quality regarding demand from central distribution center. Furthermore, the findings lead to a framework that is expressing the optimal flows on how to handle telematics data for the forecasting process.

6.1 Maintenance

The analysis has shown the unsteady demand in the initial phase of a spare part as well as that the telematics data is able to expose the upcoming number of trucks that reach a service interval and this can be used to emend the forecast. This result can resolve in a slight way the statement of (Cohen et al., 2006), that a spare parts supply chain is more unpredictable and sporadic, especially in the phase-in section. Due to the fact that a more accurate forecast could be done, the spare parts are available in time at the dealer's point and lead to a lower down time of the truck. As stated in the theory section is the maintenance of the future a feature based monitoring to ensure real-time diagnosis for advanced prognostics. Vehicles are already equipped with sophisticated sensors, connected with each other and are able to deliver status data. However, it needs to be considered that the data is available but there are still issues in data saving, storing and reading.

Levitt & Knovel (2011) mention that corrective maintenance occurs after a breakdown, which is why it affects the down time the most. The emerged telematics indicators could have a positive impact to the forecast process and would lead to higher availability. Furthermore, the current maintenance cost could be reduced, since a company delivers and replaces the required item faster or before it needs to be replaced. Cavalieri et al. (2008) characterize the down time with administrative time, logistic time and active repair time. Due to the addition in the forecasting methodology is it possible to lower the down time over the whole time slot. Firstly, the *administration delay* will be lower since the spare part is in best case already available at the workshop. Secondly, the available spare part does not need to be first transported to the workshop, which cuts the *logistic delay*. At the end, the *diagnostic delay* might be lower, due to the fact that there will be no delay done by locating and repairing the fault, since the spare part will be replaced before it actually breaks or needed to be replacement. The summary of the reduction in the down time is presented in the following Figure 29. Levitt & Knovel (2011) support the previous statement, that predictive maintenance does not only optimize the spare parts ordering and maintenance scheduling, but also reduce the downtime to a minimum.

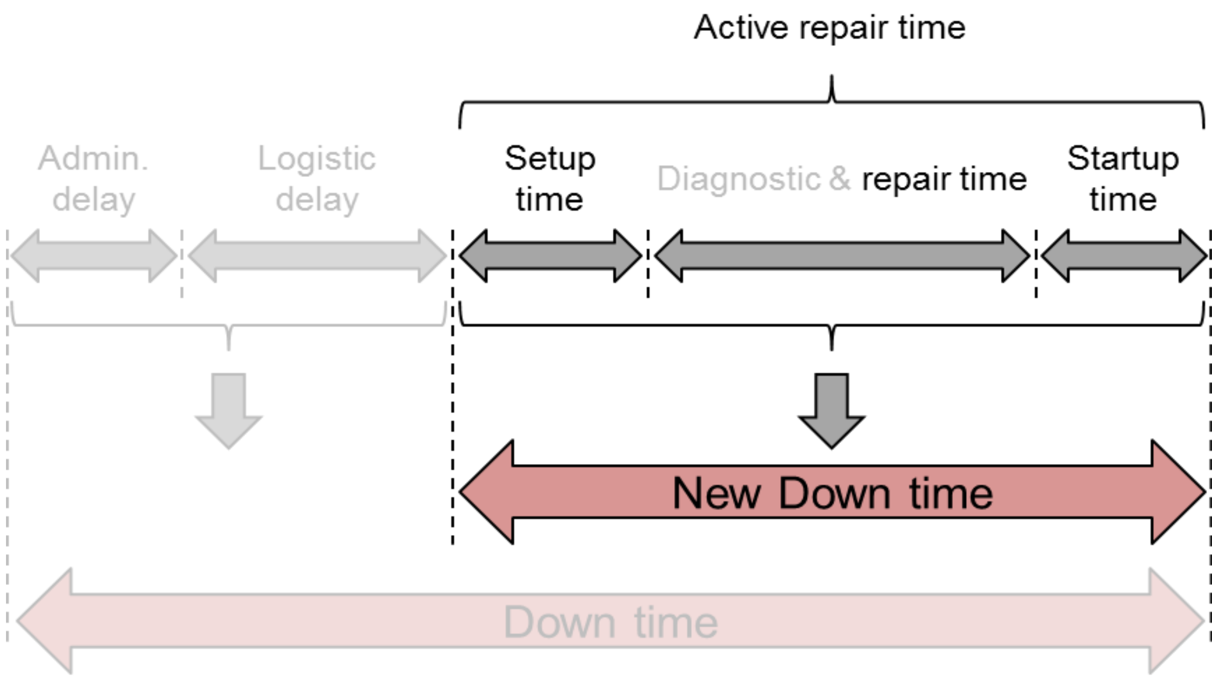

Figure 29: The new and reduced down time.

According to Cavalieri et al. (2008) preventive maintenance is time based and consists of routine maintenance schedules based on vehicle mileage or elapsed time, without considering the current state of health of a part. During the process of the empirical data collection, it was not possible to get useful information about the maintenance schedules, which is why no analysis is done, related to this topic. However, in a preventive process will information only be reported when it is above a predefined limit. This is covered by the analysis of the average mileage and is even on a higher level since it is forecasted, when the truck is reaching a predefined interval. In this master thesis it has been observed that the mileage interval is 500 000 km and the time interval is three years, with the result that both parameters are suitable for a leading forecast indicator. This reduces the risk of unexpected breakdown and can lead to replacements of spare parts ahead of time. The previous mentioned benefit connects the statement of Levitt & Knovel (2011) that there is one difference between predictive maintenance and preventive maintenance; which is time. Predictive maintenance compares a measured value to some determined technical measured values. In this research analysis the telematics data can be considered as the technical values that help the predictive maintenance to create a trend and not just provide status information. The analysis and the result of the possible detection in an early stage fulfill the definition of Kontrec et al. (2015) that the reliability in predictive maintenance is based on how to use the data and will be increased by detecting failures earlier than it would be possible to detect it by manual means. Nevertheless, it needs to be considered as Schmidt & Wang (2016) mentioned, that this need of real-time data exchange are one problem in the process, since the data might be gathered by different units and with different information technologies. Fletcher (2016) supports this by mentioning the challenge when monitoring telematics data where an overload of unnecessary data occurs and that makes it difficult to capture the relevant data.

6.2 Telematics technology

Within this study a data management tool was created to overcome this problem and allowed to use and connect the data in the most reliable way. According to Kache & Seuring (2015) the use of real-time telematics data within the supply chain network leads to higher accuracy in the information sharing. In the studied case real-time das was saved on a daily base. However, the forecast process presented above is done per period and would not need the data on a daily level, so that the time span for storing the data can be weekly or monthly. At the same time, it is not guaranteed that the received data is complete and correct. Fletcher (2016) states uncertainty in data quality can lead to incorrect data evaluation and decision making. That has been observed during the analysis in chapter 5 that is why parameters, such as country of operation, needs to be evaluated carefully. This specific parameter is giving the country in which the truck was sold, but it is not ensured, that the truck is only operating in this country. Furthermore, the analysis has shown some missing mileage data in the beginning of year 2017, due to problems within the system in which the telematics data is stored. This can lead to misinterpretation of data, so that the number of trucks introduced is lower than the actual case and the future demand is affected by this. Another challenge that occurred during the analysis was that the time intervals for some parameters were not the same and made a comparison of their values difficult. Demand and forecast were captured in 13 periods per year, whereas the dealer sales are captured on a monthly base. It might be possible to translate dealers sales into periods, but those calculated values are only roughly and should not be used for the forecasting approach.

6.3 Forecasting of service parts

The current forecast at the studied company is based on a single exponential smoothing approach. However, exponential smoothing should start several periods back to allow forecasts to adjust to the given data, instead of beginning one period back. This approach might be not the most suitable for the scope of this master thesis with the spare parts of the initial phase, since in the first periods there is no historical data from previous forecasts. The analysis has shown that the method used in this master thesis is not giving directly a forecast for the observed spare parts. Nevertheless, the analysis shows the future trend line of the trucks that need to have the parts replaced. Since the maintenance time interval of three years has just passed for the first trucks, it might be a few months too early in order to use the mileage data and introduction day in the most effective way. The results have shown that the average driven mileage lead to the number of trucks that have reached the 500 000 km service interval. However, the amount of those trucks is currently not high enough to use them clearly for the forecast. This leads to the conclusion that the method might lose its supportive characteristic for the forecasting process for low demand service parts from the phase-in area. For service parts, such as A, B and C this method is showing his potential, since those parts are built-in almost every truck and therefore, a huge amount of telematics data could be used. Due to the fact that this method is calculating the number of trucks reached the 500 000 km service interval separately from the number of trucks that reached the three year service interval, it is possible that some trucks are counted double and has to be considered.

Dombrowski & Engel (2013) mention that original equipment spare parts are sold through OEM distribution channels, whereas the cheaper replicas of a spare part are sold through the independent part distribution channel. Since availability is an important indicator for the service market, the dealers might not always consider only buying the spare parts from the OEM. In the case a spare part is unavailable the dealer will simply buy it from another supplier. This goes in line with the findings during of analyzing the number of trucks that reached the service interval. The curves in Figure 27 have shown that from year 2017 the demand will be lower than the number of trucks. Thus, one reason for this can be the above mentioned availability and that the dealers are able to receive their spare parts from the grey market. Furthermore, the replacement of a service part itself is another challenge for the automotive company. According to Dombrowski & Engel (2013) there are two different types of workshops: regulated service market and independent service market. Trucks with a golden service contract are having scheduled maintenance services at the regulated workshops. Almost every truck from the studied company is having a golden contract with a regulated workshop. That is why the gap between demand and number of trucks that reached the service interval is not comprehensible. It could be connected to the above mentioned result, that the dealers are buying the service parts from another supplier, in case the spare part is not available. Nevertheless, it could not be clearly detected that the truck driver sticks to those service intervals and is not choosing another workshop as well as that the workshop might not replace the spare part.

Beside this above mentioned concerns about telematics, the used methodology in the analysis has proven the use of telematics in the forecasting process. Not as expected at the beginning of the study, where the result of the telematics data would directly show the required demand. In fact, the telematics data enables to look forwards with the number of trucks that reached the service interval, instead of just looking into the past. The DIP team at the studied company will test the developed approach by adjusting their current forecast with the analyzed data in this study. However, for the moment it might be too early to face about a higher forecasting quality, since there is no demand for the future time interval to compare. The comparison can be done in five months. The studied company is considering the use of telematics data as beneficial and stated that they want to use methodology for other parts and launch another pilot.

6.4 The service market forecasting framework

Kobbacy & Murthy (2008) state it is urgent to have an effective forecasting system, in order to perform a satisfying maintenance service to customers. By the help of the findings in the empirical data collection and the analysis a framework, which focuses on the key elements of a forecasting process, has been developed. This is trying to overcome many uncertainties in the service market, since they have significant impact on the forecasting and inventory management, where poor customer service level and obsolescence parts can be a consequence of precipitant stocking decisions.

During the interviews it has been observed that it can be beneficial when the dealers are included into the telematics data flow. As a consequence, the dealers can manually generate their demand on a more reliable base and send this to the central distribution center. In a long term perspective, this would allow to make a forecast on dealer level and to increase the availability. Due to the reason that it could be forecasted which truck needs to have a service part replaced and where the closest dealer might be located. According to Fletcher (2016) might this be a problem for dealers to be able to translate and to understand the telematics data. The installations process and the inclusion of all members in the chain might be a barrier, since their technology has to interact in the best way with the vehicle technology. In that way, an automotive company such as Volvo needs to pre-translate the telematics data in a step between. Hellingrath & Cordes (2014) mentioned that advanced demand data can support the forecast of service parts by manual adjustments of those. This can be seen as a short term improvement, whereas, the long term solution should be automatically adjust the forecast. In that way, the information from vehicles generates a better forecast without manual activities, which make the process even faster. In that way all service parts could be covered.

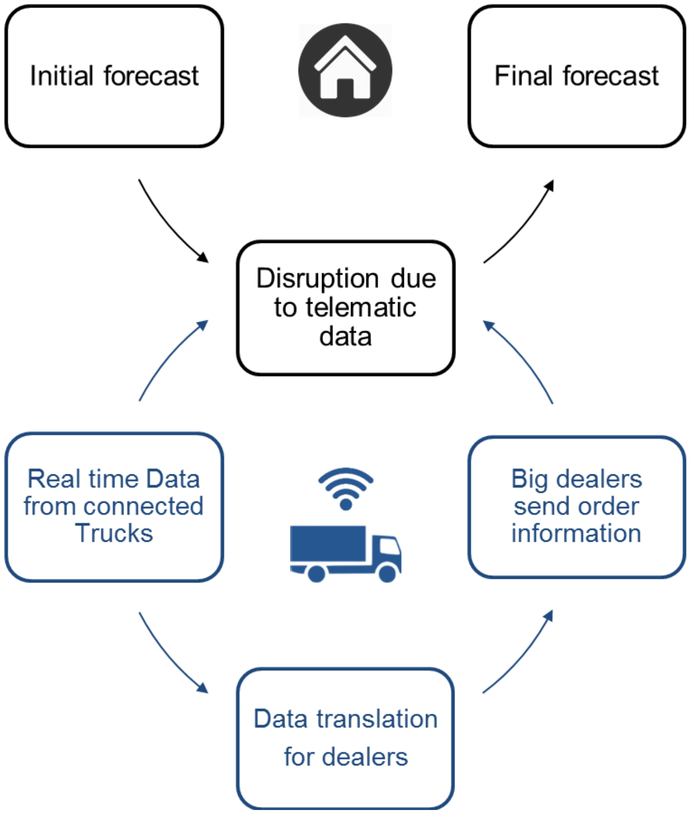

Figure 30: Framework for supporting the traditional forecasting through telematics.

The upper flow is representing the office unit, which is creating the forecast for spare parts on a central level. All starts with an automatically initial forecast. Simultaneously, the bottom telematics flow starts and sends the collected data from the vehicles on the road. In this case are telematics data the external input in the forecasting process. Mileage, service parts, dealer location, population, country of operation and other relevant data will be used. The next two steps can be done manually in a short term perspective, whereas, the long term solution should be automatically adjust the forecast by the help of the developed data management tool. Therefore, the information from vehicles generates a better forecast without manual activities, which make the process even faster. In that way all service parts can be covered. In the telematics flow, the data will be also in a long term automatically translated for the dealers, so that they can use the data in the best way. In the beginning, only the bigger dealers might be involved, since the smaller dealers might not have the technical support. However, in the longer perspective, each dealer should be involved in the bottom telematics flow, in order to ensure a complete flow. All the previously mentioned steps are connected when the data is sent to the office unit of the company and where the two flows are being connected. The complementation is done as tested in the analysis chapter and will lead to the final forecasting.

The analysis of the number of trucks that have been introduced and the driven mileage from telematics has led to the number of trucks that have reached either the 3 year or the 500 000 km service interval. In which the former two variables represent the ***Vehicle consumption***, whereas the latter two variables represent the ***Part consumption*** connected to the maintenance frequency. This is summarized in chapter 5 in Figure 28 for service part A. The huge gap between the demand and the number of trucks that have reached the service interval is starting in period 201701 and can be translated as a high market share. In other words, the ***Truck demand*** and the actual ***Dealer demand*** are not the same. On the one hand, the **Dealer behavior** can affect the market when they consume the service parts from the grey market. On the other hand, the ***Customer loyalty*** might have an impact on the actual demand, when the scheduled service interval was not complied. The relations between the different variables are presented in the equations below.

$$\boldsymbol{Truck\ demand} = Vehicle\ comsumption \times Part\ consumption$$

$$\boldsymbol{Truck\ demand} \neq \boldsymbol{Dealer\ demand}\ =\ Dealer\ behavior \times Customer\ loyalty$$

Equation 3: Discrepancies of truck demand and dealer demand.

The above presented framework in Figure 30 is trying to reduce the gap between the truck demand and the dealer demand, by ensuring higher availability for the service parts with the help of reaching the status of predictive maintenance as well as reducing the down time of a truck. Companies with a high availability on their spare parts have a competitive advantage over companies that offer lower availability. In case the needed spare part is not available at the workshop, the responsible dealer would buy it from another supplier or even on the grey market. This will lead to a more sustainable service market supply chain and a reduction in the CO2 emissions.

7. Conclusion

This chapter reveals the overall conclusions of the research. In addition it discusses the practical as well as scholarly contributions and gives recommendations for future studies in regards to this topic.

7.1 Summary

The purpose of this study was to explore the telematics data and how they affect or complement the traditional forecasting process of service parts. This case study gave insights into different parameters within the telematics technology in the automobile industry. Additionally, a data management tool was created to understand and to use the given data as well as to see the correlation between historical service parts sales data and telematics mileage data.

Studying the current processes and ways of working at the company answered the first research question, that was to understand the bases of forecasting processes and it is described in chapter 4. Further, the second research question, to have an understanding about available data was answered through chapter 5. The last or third research question, how can the found data be used in the forecasting process is presented in chapter 6.

The results show that mileage and the age of trucks can be used as a leading indicator for a regression based forecasting approach and potentially lead to higher forecast quality. Hence, continuing by using only historical demand data in the initial phase of the service parts does not coincide with the actual demand. The root cause for this discrepancy can be due to various reasons as lead time or bullwhip effect.

7.2 Contribution

Existing literature focuses on store telematics data in a system, often limited due to gaps in readings as well as incorrect savings. This research however revealed that there is an opportunity for telematics data in the forecasting process. This study puts the identified indicators into a practical context and gives insights into the execution of the possibilities. Additionally this master thesis gives insights in how telematics data affects maintenance work, as well as forecasting approach and by that a new framework was developed, which translate the findings into real business use.

Telematics data as well as data programs studied are two rather new phenomena for the company, but will be of increasing importance in the future. Therefore this research shed light on the data usage opportunities that can have influence in the forecasting process. The investigated areas include driven mileage as well as demand and can be a role model for the future way of forecasting. Furthermore, this study revealed a data management tools for the company, in order to have a smooth transition when starting the new forecasting approach.

Finally, the developed framework provides a new connection for the different actors in the data telematics flow, which is helping to implement the new approach.

7.3 Recommendations

Looking at the current forecasting process with the use of the single exponential smoothing method at the studied company is not suitable any longer for each service part as well as for each phase in the life cycle. The use of only historical demand and previously calculated forecasting is especially in the initial phase not accurate enough. Here, the telematics data can create value both by using the implemented technology as well as looking into the future number of trucks that will reach the service interval. Due to the fact that the 3 year service interval just have taken place and the first trucks have reached the 500 000 km mileage service interval, the company needs to continue with analyzing the service parts in scope.

Figure 31 is showing the next steps that are recommenced when continuing the new forecasting approach. It is possible for the company to gain more insights from the analyzed data and to understand their full potential. Therefore, the gap between truck demand and dealer demand needs to be first understood. By learning to understand how to evaluate and use the telematics data for the upcoming forecasting, it is achievable to complement the already made forecast for the next periods. Nevertheless, a direct evaluation of the amended forecast and its forecast quality cannot be done. A comparison can be done in the upcoming months, after the actual demand has communicated. The result of the forecast quality allows the company to make more detailed analysis of the new forecasting method, which can be used for future investigations to extend this master thesis, regarding which service parts, in which life cycle phase or for which market area.

This master thesis has shown that there are benefits in the telematics data for the forecasting process, by using a regression based forecast. Therefore, it is suggested that the company to continue the data analysis in order to increase the knowledge of the benefits in the short term. The comparison of the amended forecast and the already calculated forecast makes it possible for the company to further develop the new regression method and start with future targets. In the long term the company should change the current forecasting method into the regression based approach as well as include the dealers in their forecasting process and supply them with already translated telematics data, in order to optimize the use of the data and to get the most desirable outcome. This will also fulfill the investigation of dealer behavior and customer loyalty from equation 2. Additionally, it can be beneficial to elaborate the location of the truck on a daily level, in order to foresee where the truck would be when reaching the service interval. This leads to an ultimate availability, where the spare part was delivered to the exact dealer workshop, before the truck has arrived and is the last step of the recommendation flow plan.

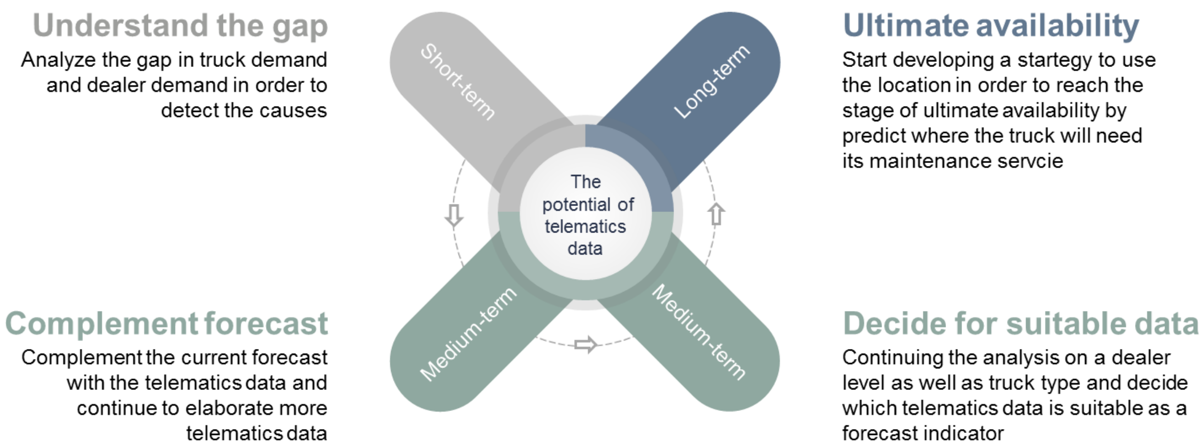

Figure 31: Recommendation flow plan for Volvo.

7.4 Future research

Limited by the scope of this study only a certain number of parts were investigated. A further discussion would be to analyze other parts as well. The seven part numbers used in trucks in Europe gives an initial idea about how mileage and age of trucks could be used as a leading indicator for forecasting. The population investigated is only a fraction of all Volvo trucks. Investigating other parts would give a more detailed understanding of the behavior of the population and the effects of mileage on the demand.

Using the method found in this thesis work benefits forecasting but needs manual assessment. By making mileage and the age of trucks as leading indicators in the forecasting system would mean skipping the manual intervention. Further, by making part of the system, the data would benefit more departments and the information would be spread.

Another benefit from further investigation would be to understand the type of trucks involved in the study. How different types behave, as long haul, city distribution or construction. An initial supposition would be that different types of trucks have different demand patterns for parts. A further discussion could be based on this investigation.

In order to make the information through the supply chain as transparent as possible, sharing the forecast of parts with dealers would be beneficial for each party. One supposed effect would be the reduced bullwhip effect due to dealer's knowledge about the customer real demand. A further study would be needed to investigate the effects of forecast sharing.

In the supposed forecasting method, mileage and age of trucks are used. Lifetime, reliability of parts, loyalty of truck owners could be further factors to take into consideration in the future. This way a more detailed analysis could be made and possibly higher forecast quality.

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Appendix I. Interview questions

This Appendix is presenting the questions from the interviews with the employees of the studied company.

Introduction:

- Description of the thesis topic and its purpose.
- Purpose of the interview.

General question:

- What department are you working in?
- What is your role in that department?
- How do you think it is working?
- Where in the aftermarket supply chain does your department control the material flow?
- What are your operational tasks (daily/weekly/monthly)?
- What are your long term strategic “tasks”?

Forecasting process: (Please describe your process)

- What improvements within forecasting are you working towards?
- What other things would you like to improve?
- What KPIs do you have and how are these measured?
- What are the main challenges within the process?
- What have you changed within the process over the last year?
- And Why?

Current data:

- What data is generated in your department?
- What data is sent out from your department?
- Are there any other parallel information flows meetings that are included into the decision process?
- What data is used as basis for your forecasts – both qualitative and quantitative?
- What data is used to initiate replenishment?
- What data initiates your demand?
- Who is your customer?
- What is your average lead time to customers?
- What is the total value of your tied up capital, on average?
- Which spare parts are difficult to forecast and why?
- Do you segment the parts?
- What characterizes spare parts that reduce your overall forecast quality the most?
- Better information from dealers?
- Dealers use the same system?

Questions about telematics:

- What do you know about telematics?
- Are you using today any data directly from the customers?
- What telematics data would be useful for your forecasting process?
- What data from other teams in your division or outside the organization could improve your forecast accuracy?
- Which products have the greatest potential to improve your overall forecast accuracy?

Further questions:

- Is there anything else you would like to add that has not been discussed?
- May you be contacted again if additional information will be needed?

Appendix II. Interview partners

This next Table A is presenting the employees of the studied company, which have been selected for the interviews.

Table A: Interview Partner.

Date	Employee	Topic
2017-01-04	Marcus Bohman	Basic understanding
2017-02-10	Matthieu Laurent	DIP general
2017-02-15	Marcus Bohman	Forecasting
2017-02-15	Anders Monden	DIP general
2017-02-22	Anders Nordstörm	Refill
2017-02-22	Tomas Göransson	Forecasting process
2017-02-24	Jan-Åke Åsman	DIM
2017-02-27	Lina Liljenberg	DIM
2017-03-02	Yohan Bramas	First hit, Population
2017-03-24	Max Joelson	Contracts

Appendix III. Average driven mileage

This Appendix is showing more detailed data evaluation from the average mileage and the split on a part number level.

Due to problems in the system and missing mileage reading are there several trucks which have so far none or only one mileage reading throughout their entire life cycle. That leads to an average of 0.00 in the system. Table B1 shows those 2 397 trucks within Europe which have only sent once a mileage read, but that cannot be used for an average. Nevertheless, Table B2 is given the average mileage including the zero average.

Excluding them from the selection leads to the real average mileage for the European share, which is represented in Table B3. Simultaneously shows that within the scope of Europe only 123 223 chassis numbers have sent mileage data and 6 767 trucks have not sent any data. But the most interesting result is that the average mileage without the zero values is only 50 km per week higher than having those values included. That leads to the assumption that there is no need for adjustments.

Table B1: Trucks that have not sent mileage data.

Part Number	Population	Ø Mileage per week	Ø Mileage per day
A	2 397	0 km	0 km
B	2 128	0 km	0 km
C	1 481	0 km	0 km
D	267	0 km	0 km
E	267	0 km	0 km
F	251	0 km	0 km
G	70	0 km	0 km
Total	**2 397**	**0 km**	**0 km**

Table B2: Average mileage including 0 km.

Part Number	Population	Ø Mileage per week	Ø Mileage per day
A	123 191	2 018 km	403 km
B	111 794	2 089 km	417 km
C	85 735	2 243 km	448 km
D	11 410	1 326 km	265 km
E	11 406	1 326 km	265 km
F	8 767	1 125 km	225 km
G	3 667	1 488 km	297 km
Total	**123 223**	**2 018 km**	**403 km**

Table B3: Average mileage in Europe.

Part Number	Population	Ø Mileage per week	Ø Mileage per day
A	120 794	2 058 km	411 km
B	109 666	2 130 km	426 km
C	84 254	2 283 km	456 km
D	11 143	1 357 km	271 km
E	11 139	1 357 km	271 km
F	8 516	1 158 km	231 km
G	3 597	1 517 km	303 km
Total	**120 826**	**2 058 km**	**411km**

The next two Tables are representing the average mileage in total, hence, not only within the scope of Europe but on a global level. Additionally, 41 094 trucks are included which have not built-in any of the seven selected part numbers.

Table C1: Average mileage in total.

Part Number	Population	Ø Mileage per week	Ø Mileage per day
A	137 647	2 004 km	401 km
B	123 388	2 075 km	415 km
C	91 138	2 228 km	445 km
D	14 360	1 310 km	262 km
E	14 356	1 310 km	262 km
F	13 248	1 129 km	226 km
G	3 964	1 483 km	296 km
-	41 094	1 999 km	400 km
Total	**178 877**	**2 003 km**	**400 km**

Table C2: Average mileage excluded 0 km mileage reading.

Part Number	Population	Ø Mileage per week	Ø Mileage per day
A	123 642	2 045 km	409 km
B	112 275	2 117 km	423 km
C	86 121	2 269 km	454 km
D	11 382	1 342 km	268 km
E	11 378	1 342 km	268 km
F	8 706	1 162 km	232 km
G	3 623	1 512 km	302 km
-	38 996	2 106 km	421 km
Total	**162 670**	**2 060 km**	**412 km**

Appendix IV. Combination of spare parts

Within this Appendix is showing the different combinations of spare parts and how the average mileage is changing.

Each part number has been selected individually, for the purpose of detecting how many chassis are connected to each part within the scope of Europe. The first part number is G, which has with 3 801 the lowest population of connected chassis.

Table D1: Part number G in the population.

Part Number	Population	Ø Mileage per week	Ø Mileage per day	Demand
G	3 801	1 488 km	297 km	635
Total	**3 801**	**1 488 km**	**297 km**	**635**

The next investigation is showing the previous selected part number, as well as the connection to those part numbers, which are built-in the same chassis. It has been observed that this part number is only having a combination with two other part numbers, and those are the two parts with the highest population. Service part A is only built-in with the other two parts in 3 769 cassis, whereas part B is built-in with each of the 3 801 part and makes it a fix combination made out of those two part numbers. So that is basically saying that the part number G is only having a combination with those two part numbers.

Table D2: Part number G and its combinations.

Part Number	Population	Ø Mileage per week	Ø Mileage per day	Demand
G	3 801	1 488 km	297 km	635
B	3 801	1 488 km	297 km	6 992
A	3 769	1 488 km	297 km	7 611
Total	**3 801**	**1 488 km**	**297 km**	**15 238**

The next picture is given the normal spread of the parts and its mileage and it is detected that the average mileage per part number is different with each combination. For example has the previous mentioned part number B as a total average 2 089 km per week, but in combination with the part number G it is only 1 488 km per week. This represents the dependency of the mileage to the usage of the truck and not to the single part number.

Table E: Total population.

Part Number	Population	Ø Mileage per week	Ø Mileage per day	Demand
A	129 956	2 018 km	403 km	7 611
B	117 001	2 089 km	417 km	6 992
C	87 830	2 243 km	448 km	5 691
D	12 954	1 326 km	265 km	564
E	12 950	1 326 km	265 km	752
F	10 962	1 125 km	225 km	638
G	3 801	1 488 km	297 km	635
Total	**129 990**	**2 018 km**	**403 km**	**22 883**

The above executed analysis has been done for each service part number and is shown in the following sections. It has been found out that part number F has the same combination as the previous one and is only built-in with the two most populated parts.

Table F: Part number F and its combinations.

Part Number	Population	Ø Mileage per week	Ø Mileage per day	Demand
F	10 962	1 125 km	225 km	638
B	10 930	1 125 km	225 km	6 992
A	10 962	1 125 km	225 km	7 611
Total	**10 962**	**1 125 km**	**225 km**	**15 241**

Part number E is different and is showing another correlation. The connection exist also with A, but instead of being built-in with the second highest populated part it is connected to part D, which has beside four parts the same population as the selected part itself. That leads to the result that those two parts are only built- in together.

Table G: Part number E and its combinations.

Part Number	Population	Ø Mileage per week	Ø Mileage per day	Demand
E	12 950	1 326 km	265 km	752
D	12 950	1 326 km	265 km	564
A	12 950	1 326 km	265 km	7 611
Total	**12 950**	**1 326 km**	**265 km**	**8 927**

Looking at it the other way around and selecting first part number B proofs the previous analysis that those two part numbers are only built-in as a combination together with the highest part in the population. Comparing the average mileage per week in those two cases shows that they are the same with a slightly difference from 0.1 km due to the four single combination of part number A and D. The four chassis which have those two parts integrated were driving on an average a bit more per week.

Table H: Part number D and its combinations.

Part Number	Population	Ø Mileage per week	Ø Mileage per day	Demand
E	12 950	1 326 km	265 km	752
D	12 954	1 326 km	265 km	564
A	12 954	1 326 km	265 km	7 611
Total	**12 954**	**1 326 km**	**265 km**	**8 927**

The next observed part number C has the connection to the two highest populated parts as well. Nevertheless, the average mileage per week is almost double as the previous analyzed parts. This leads to the assumption that the truck type, with this part number built-in, is different than the other once.

Table I: Part number C and its combinations.

Part Number	Population	Ø Mileage per week	Ø Mileage per day	Demand
C	87 830	2 243 km	448 km	5 691
B	87 830	2 243 km	448 km	6 992
A	87 830	2 243 km	448 km	7 611
Total	**87 830**	**2 243 km**	**448 km**	**20 294**

The analysis with the part number B and its population of 117 001 shows the return path to the numbers which has been calculated in the previous procedures. Furthermore, this gives the total connection to the service part A with the highest population. When the part number is deselected the population of chassis dropped down by two to 116 999. That means that two chassis have B as a single part built-in. This leads to the assumption that this part is, beside two trucks, never built-in alone.

Table J1: Part number B and its combinations.

Part Number	Population	Ø Mileage per week	Ø Mileage per day	Demand
B	117 001	2 089 km	417 km	6 992
A	116 967	2 089 km	417 km	7 611
C	87 830	2 243 km	448 km	5 691
F	10 930	1 126 km	225 km	638
G	3 801	1 488 km	297 km	635
Total	**117 001**	**2 089 km**	**417 km**	**21 567**

Table J2: Part number 21 983 655 cross-checking.

Part Number	Population	Ø Mileage per week	Ø Mileage per day	Demand
A	116 967	2 089 km	417 km	7 611
C	87 830	2 243 km	448 km	5 691
F	10 930	1 126 km	225 km	638
G	3 801	1 488 km	297 km	635
Total	**116 699**	**2 089 km**	**417 km**	**14 575**

In the final step, the last part number A has been evaluated and is given the output, which is seen in the following table and goes in line with the previous findings. Nevertheless, from the total population 129 956 for this part number only three trucks having that part as a single part built-in.

Table K1: Part number A and its combinations.

Part Number	Population	Ø Mileage per week	Ø Mileage per day	Demand
A	129 956	2 018 km	403 km	7 611
B	116 967	2 089 km	417 km	6 992
C	87 830	2 243 km	448 km	5 691
D	12 954	1 326 km	265 km	564
E	12 950	1 326 km	265 km	752
F	10 962	1 125 km	225 km	638
G	3 801	1 488 km	297 km	635
Total	**129 956**	**2 018 km**	**403 km**	**22 883**

Table K2: Part number A cross-checking.

Part Number	Population	Ø Mileage per week	Ø Mileage per day	Demand
B	116 967	2 089 km	417 km	6 992
C	87 830	2 243 km	448 km	5 691
D	12 954	1 326 km	265 km	564
E	12 950	1 326 km	265 km	752
F	10 962	1 125 km	225 km	638
G	3 769	1 487 km	297 km	635
Total	**129 953**	**2 018 km**	**403 km**	**15 272**

The next picture shows the amount of combinations with the first five part numbers 115 515. That leads to the result that 14 438 (129 953 - 115 515) chassis are having only built-in the combination of the two service parts with the highest population. In general it can be seen that the last part number has a connection to every other part number. Whereas the second last one has no connection to part number D & E and got replaced by them, since they are connected to each other.

Table K3: Part number A.

Part Number	Population	Ø Mileage per week	Ø Mileage per day	Demand
C	87 830	2 243 km	448 km	5 691
D	12 954	1 326 km	265 km	564
E	12 950	1 326 km	265 km	752
F	10 962	1 125 km	225 km	638
G	3 801	1 488 km	297 km	635
Total	**115 515**	**2 033 km**	**406 km**	**8 280**

Appendix V. Dealer sales

The figures below are showing the comparison of the demand and the dealer sales per period. The trend curves within each figure are similar in their increase. On the one hand, the service part B and C are having an exponential increase and reaching dealer sales of more than 700 parts per month. On the other hand, the trend curves from the one other service parts are having a smaller increase as well as a more fluctuate demand curve over the whole time. This goes in line with the analyzed demand curves for the service parts in chapter 5.2. It has to be considered that the demand in the latest period in 2017 is lower since the data was extracted before the end of the period, where it was not completed and that is the reason for the drop. In general in can be seen that the direct dealer sales are lower than the central demand out of Gent, which might underline the assumption that the dealers are stacking up their inventory. As is was analyzed in chapter 5.3.

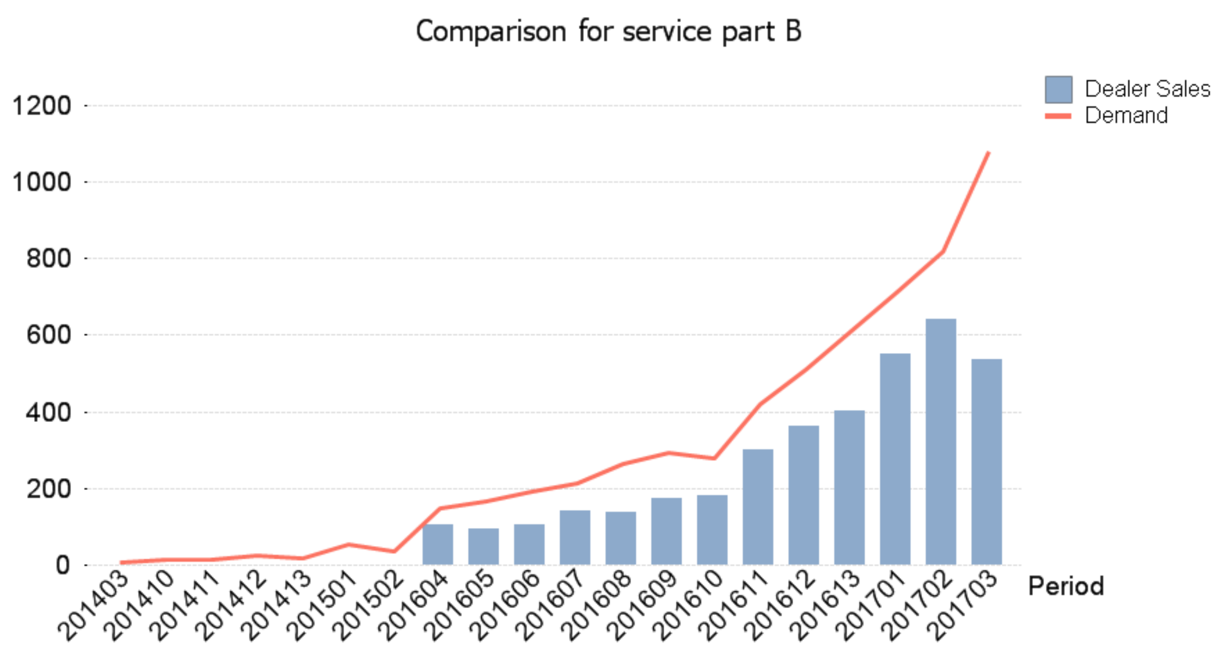

Figure A1: Comparison of demand and dealer sales from service parts B.

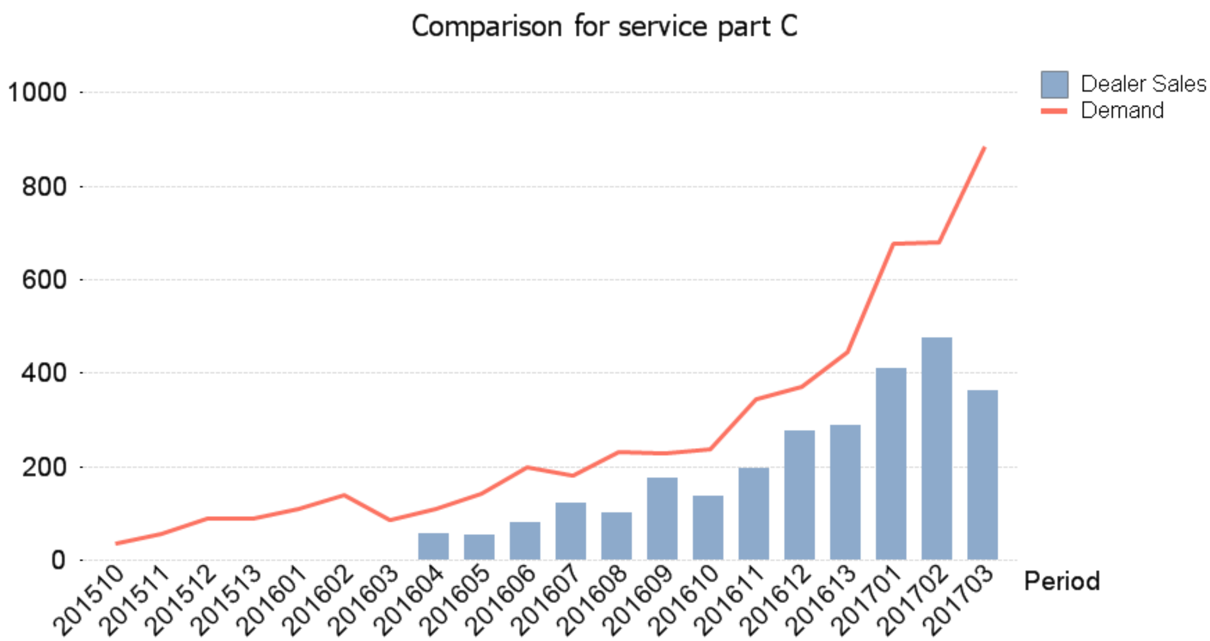

Figure A2: Comparison of demand and dealer sales from service parts C.

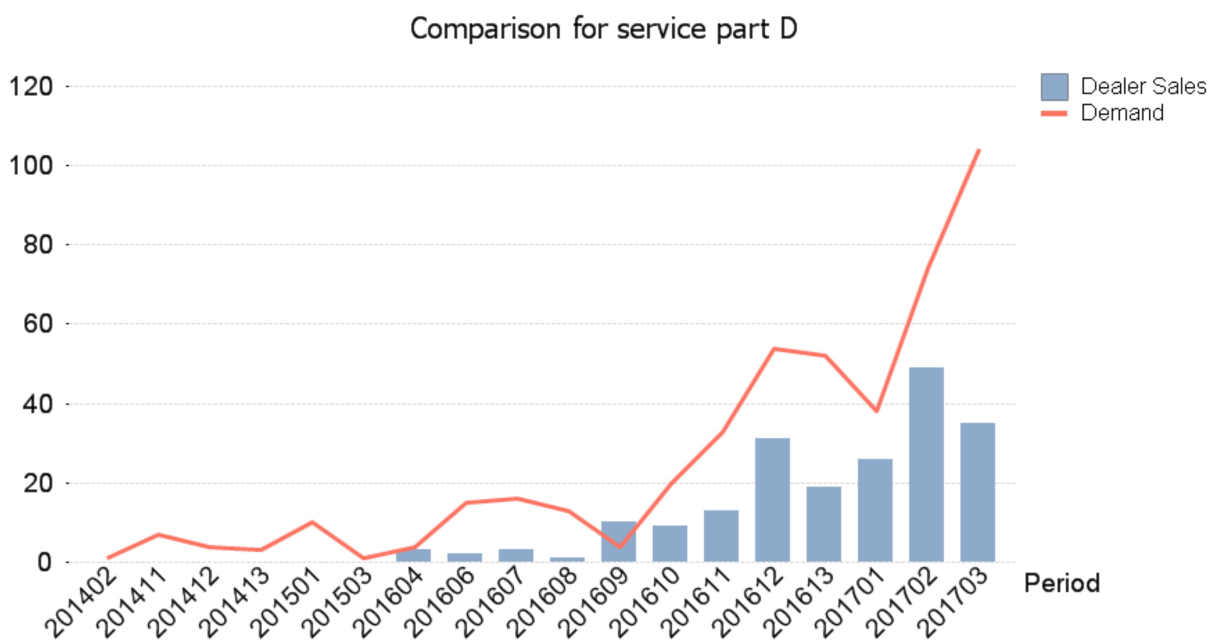

Figure A3: Comparison of demand and dealer sales from service parts D.

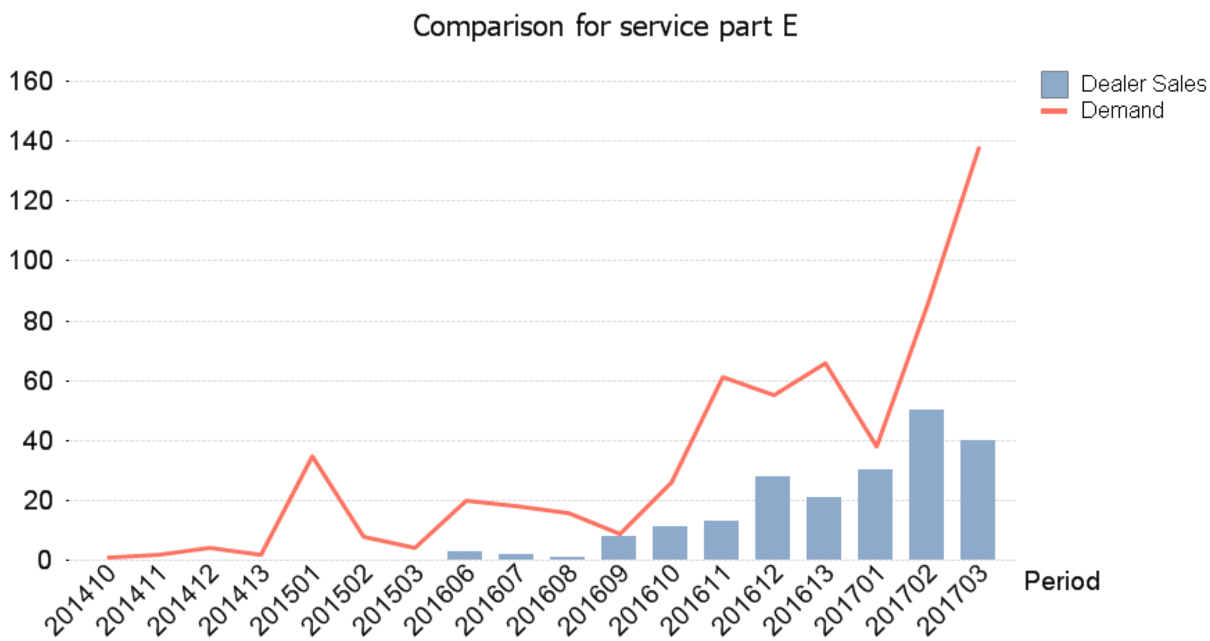

Figure A4: Comparison of demand and dealer sales from service parts E.

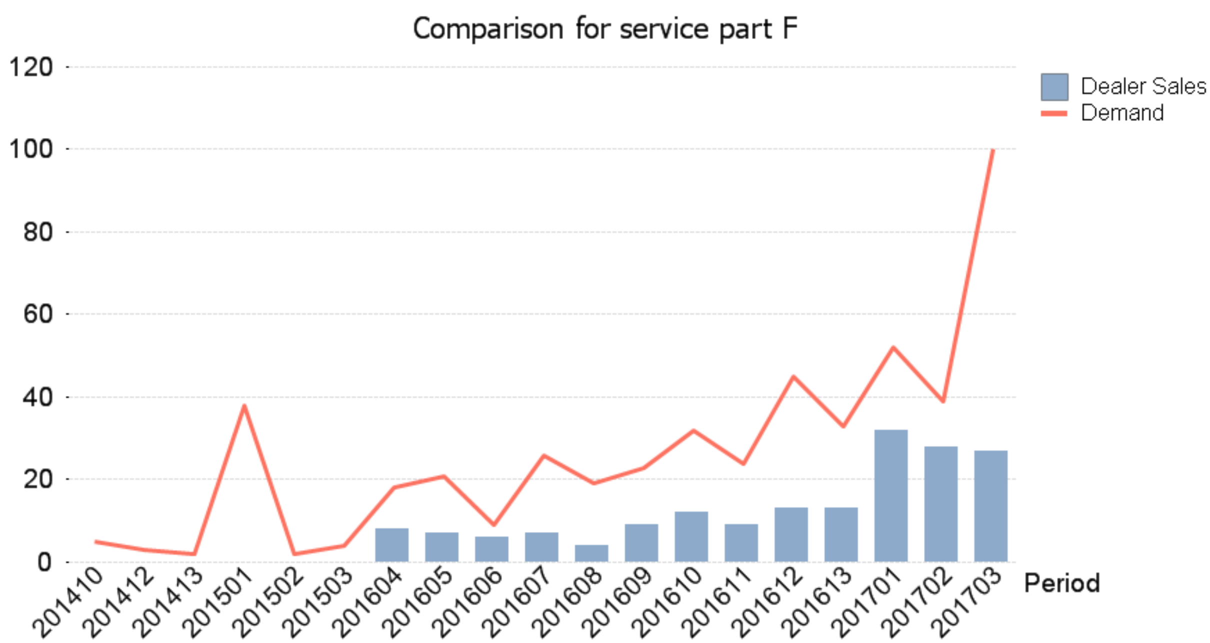

Figure A5: Comparison of demand and dealer sales from service parts F.

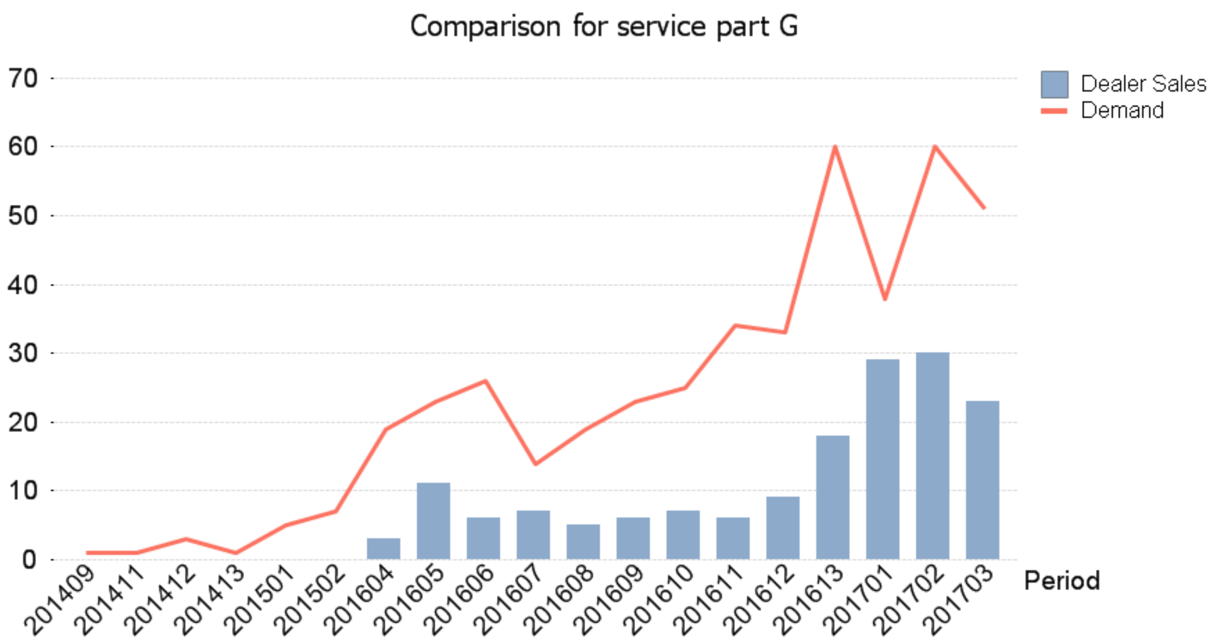

Figure A6: Comparison of demand and dealer sales from service parts G.

Appendix VI. Testing the method

Using the method in practice

A Qlikview tool was created for the DIP team in order to operationalize the method. The software uses the mileage data as an input. This can be updated on a weekly basis in order to use the most recent readings. In the next step the software calculates the number of trucks that will reach 500 000 km in the next periods. Further, this number is adjusted to estimate the real number of trucks and a forecasted number of demand is displayed. This can be done on part number level.

Description how to do:

Using the average mileage per part number is helping to foresee the mileage which the trucks should drive in the upcoming periods. Based on the total average of 2 000 km per week the chosen mileage interval is 8 000 km, which is a month. This is due to the lead time of around 21 days and the time frame until an order hit is introduced. For the lower average mileage of 1 400 km could be a mileage interval of 5 000 km be chosen, to provide a more accurate result.

The whole calculation will be on a part number level. After detecting the total amount of trucks which have reached the critical mileage interval, it will be translated for the next periods how many parts are needed.

This method will be first tested with historical data, and then will be observed how accurate the forecast was, compared to the real one from DIP. After this was successful, it will be tried out for the real next periods (June, July and August) as the first step.

Calculating the adjustment coefficient of 1.21. As mentioned, 83% of all trucks send telematics data. This was found by dividing the total number of trucks to the number of trucks with readings. This was 129 990 and 157 288.

Appendix VII. Forecasted mileage in relation to driven mileage

Figure B: Difference between real mileage and forecasted mileage.

In the figure above, the differences between real and forecasted mileage is presented per chassis for a couple of weeks. The forecasting was done by average mileage per truck. Y axis is mileage and X axis is weeks. As seen, two trucks had significant difference. After investigating the cause, it was concluded that this was due reading error. In other words, for these trucks the mileage was very low in the reading weeks while the average mileage was high.

Appendix VIII. Comparison for the other service parts

The figures presented in this appendix are showing the different service parts within the scope, the number of trucks that have reached the service interval as well as the demand and the forecast.

In general it can be seen that the demand is shifted to the left until 2017 compared to the number of trucks that would need the service part replaced, by reaching the service interval. A reason can be that dealers were stacking up their inventory and this increased the demand out of Gent. The number of trucks that needs a part replaced becomes higher than the demand from the end of 2016 for all service parts. This gap is continuously growing on. In other words, the previously built stocks in inventory were consumed.

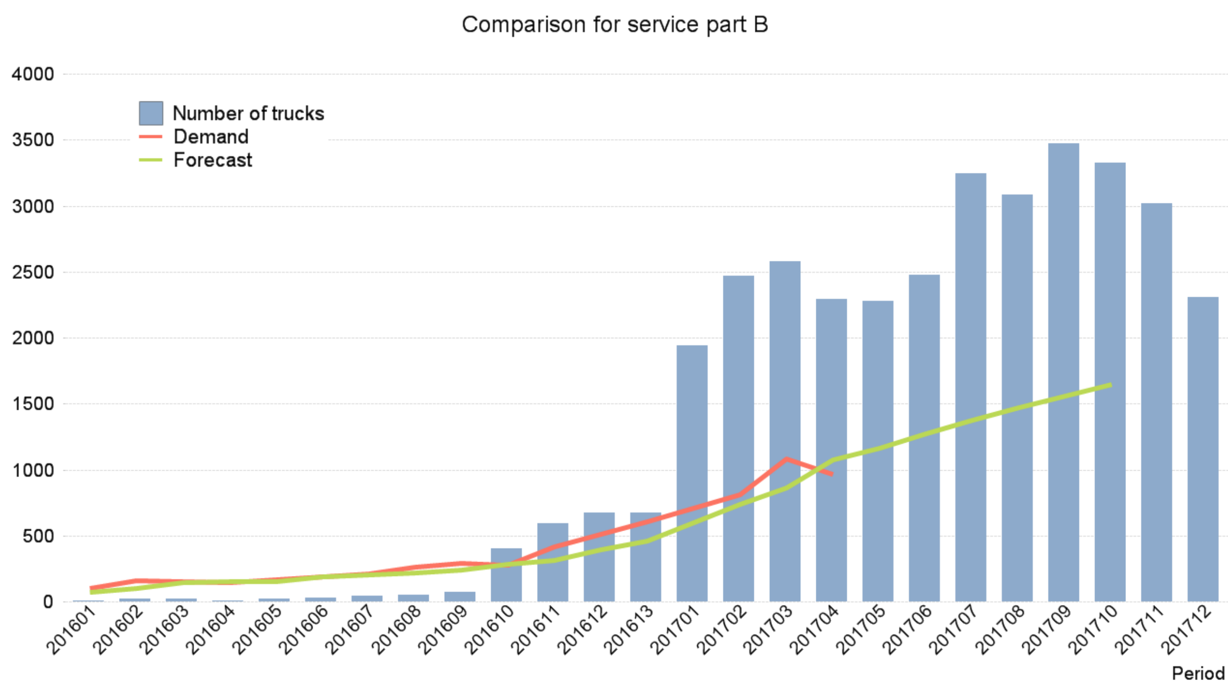

Figure B: Number of trucks that need service part B replaced.

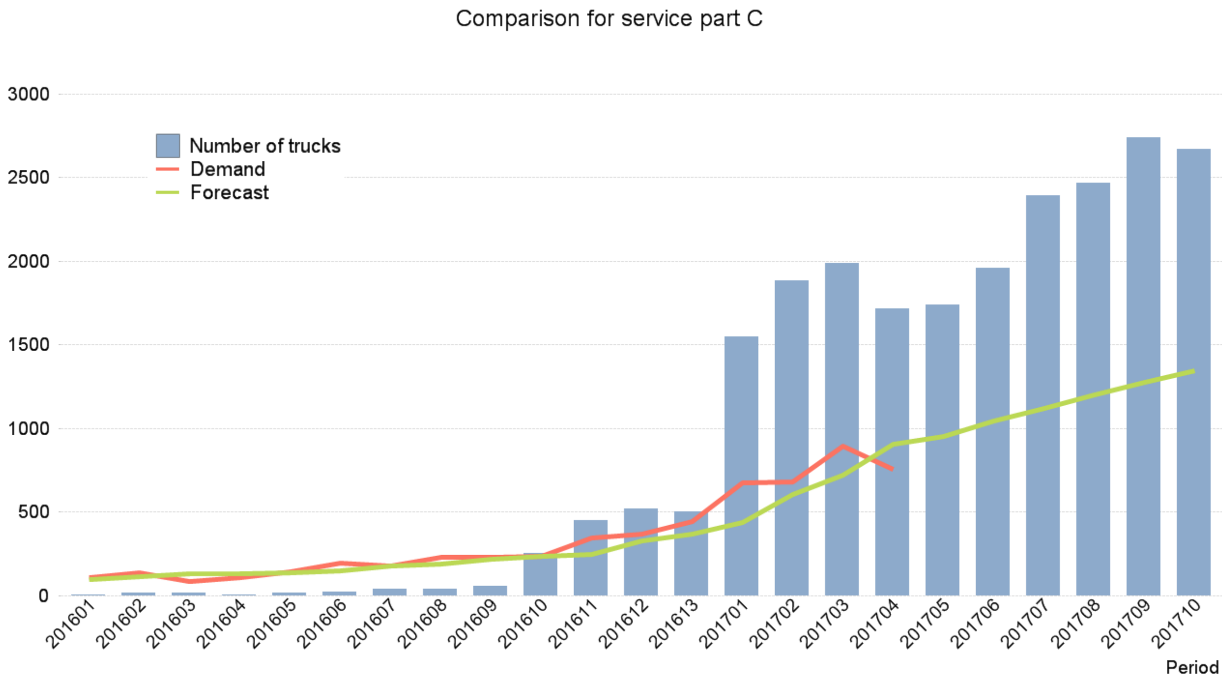

Figure C: Number of trucks that need service part C replaced.

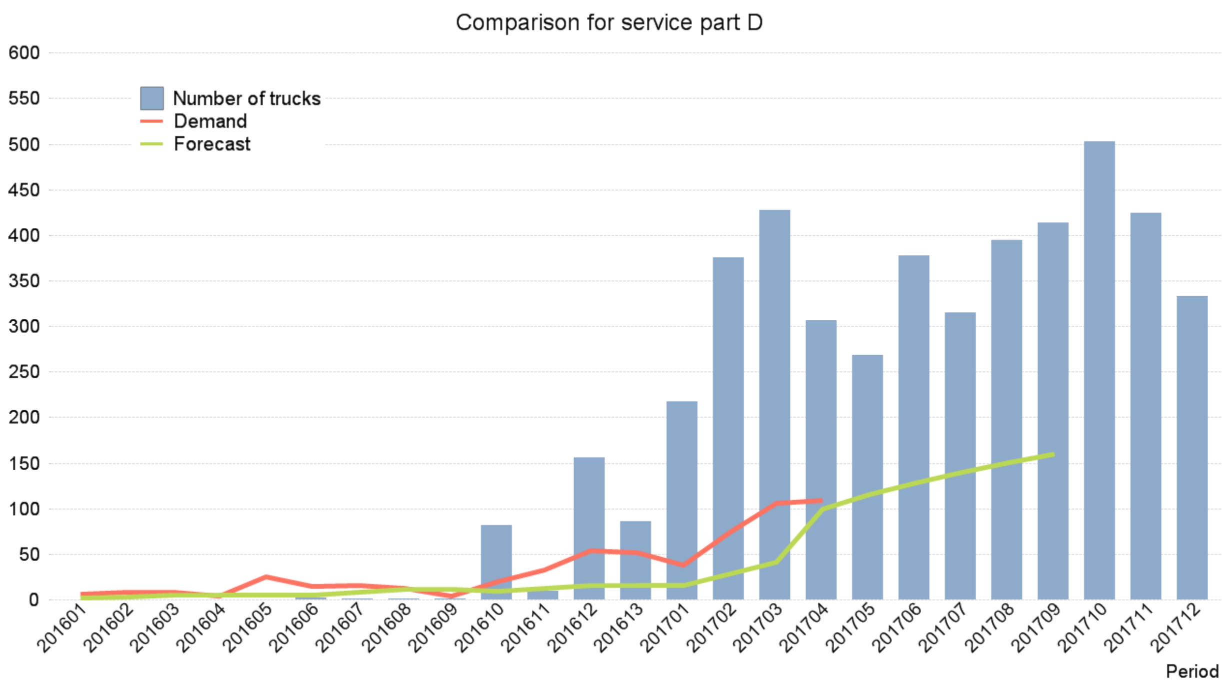

Figure D: Number of trucks that need service part D replaced.

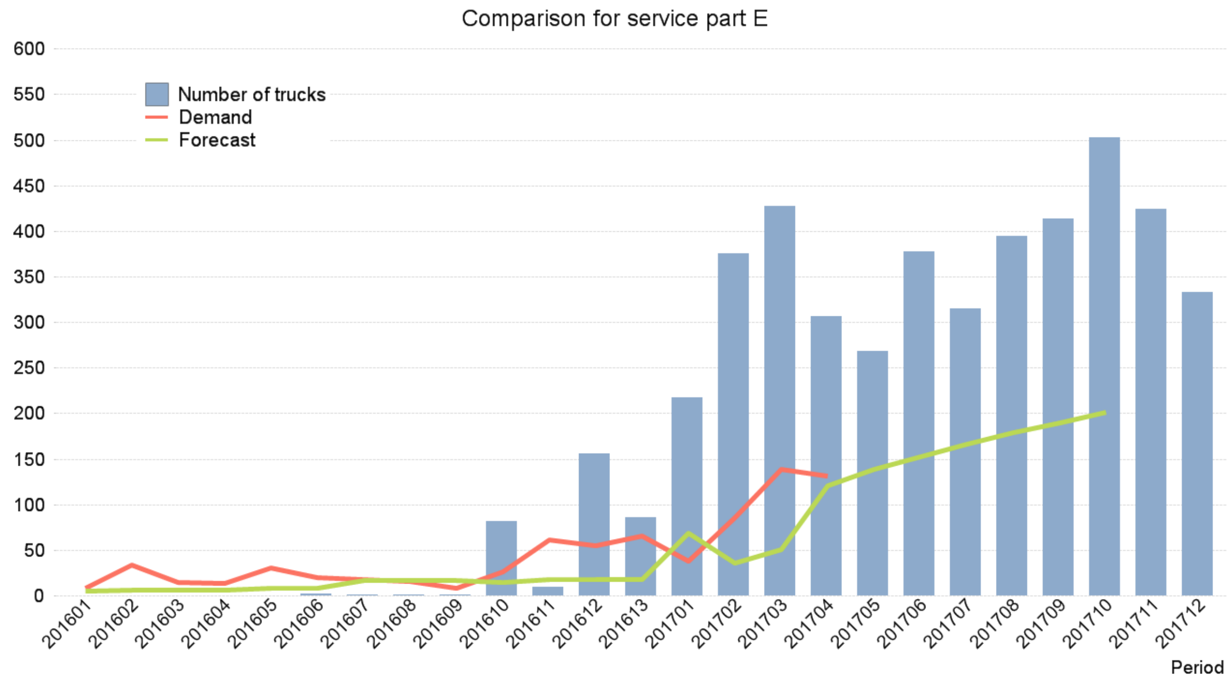

Figure E: Number of trucks that need service part E replaced.

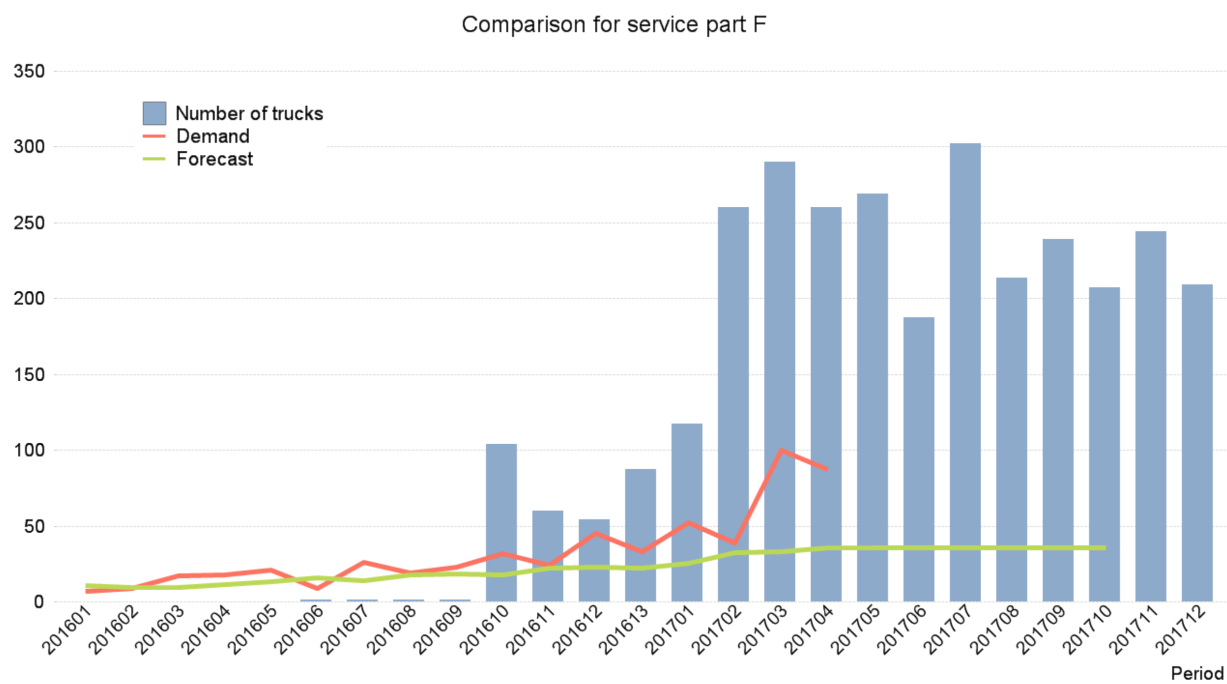

Figure F: Number of trucks that need service part F replaced.

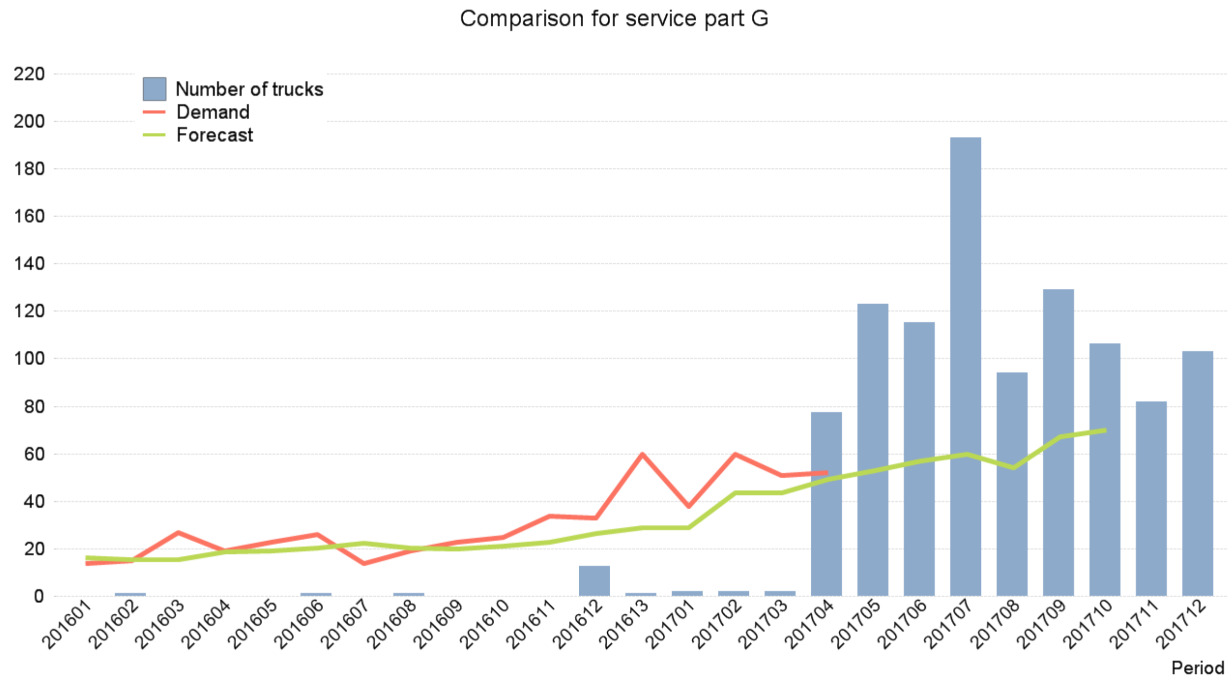

Figure G: Number of trucks that need service part G replaced.

Appendix IX. Mape analysis and regression forecasting

Currently the company forecasts on part number level so in order to make this possible, the number of trucks reaching 500 000 km or 3 years are studied in relation to the actual forecast and demand. A Mape analysis was performed to understand the effects of these variables. The result is presented on the table below.

Table L: Relation of forecast and number of trucks for all periods.

Service parts	MAPE Forecast	MAPE Regression
A	15.95	18.24
B	14.39	21.84
C	16.49	20.58
D	58.17	60.13
E	51.77	46.8
F	36.14	36.28
G	20.67	39.49

Table H: Relation of forecast and number of trucks for all periods from 201611 onwards.

Service parts	MAPE Forecast	MAPE Regression
A	19.14	15.87
B	16.56	15.33
C	17.63	9.26
D	55.09	33.99
E	58.3	40.78
F	41.1	29.75
G	23.87	24.61

In the figures below are the current forecast compared with the regression based forecast for each service part.

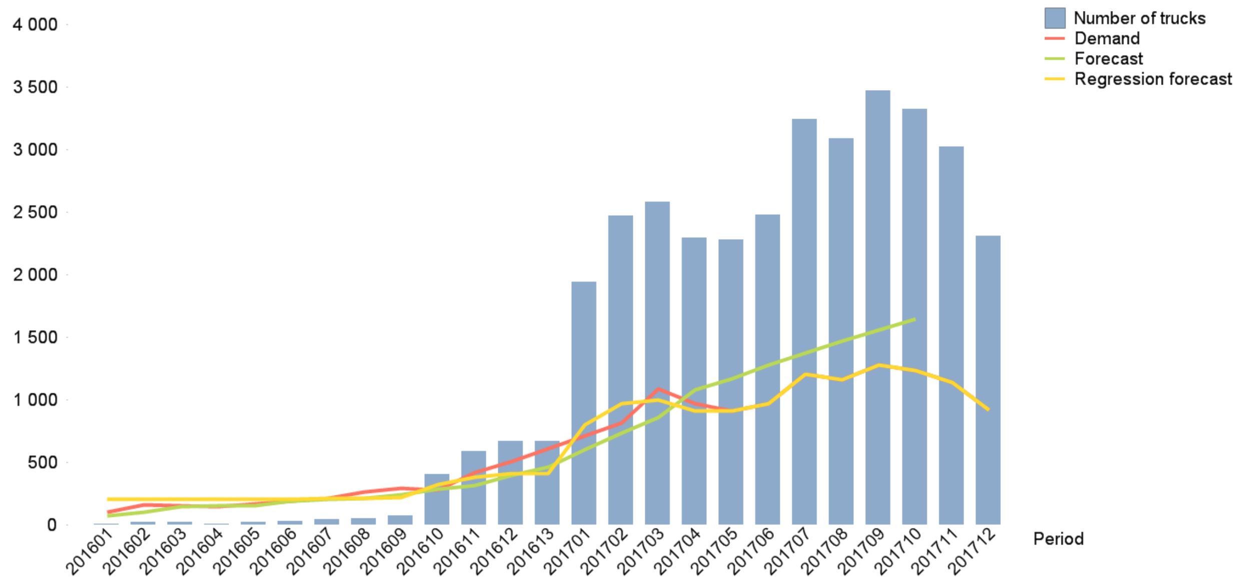

Figure H: Regression based forecast for service part B.

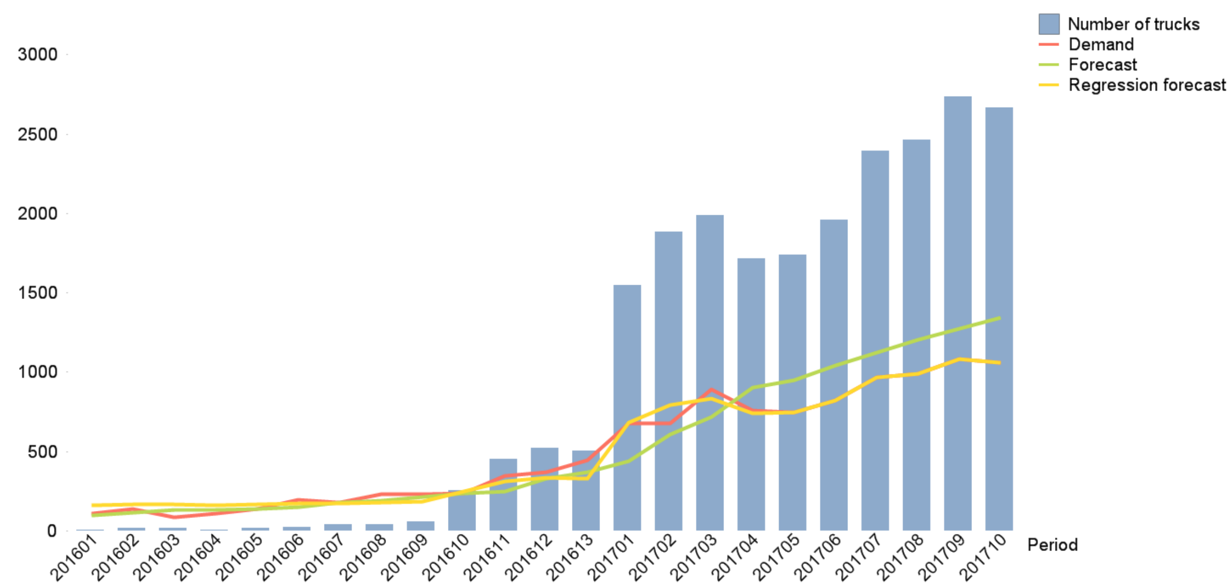

Figure I: Regression based forecast for service part C.

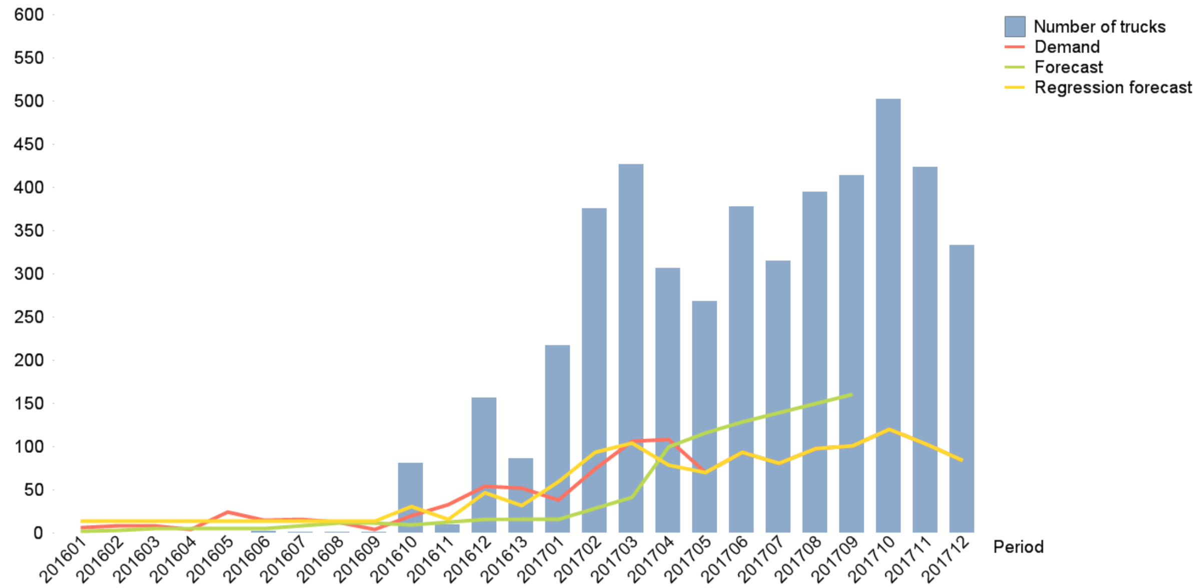

Figure J: Regression based forecast for service part D.

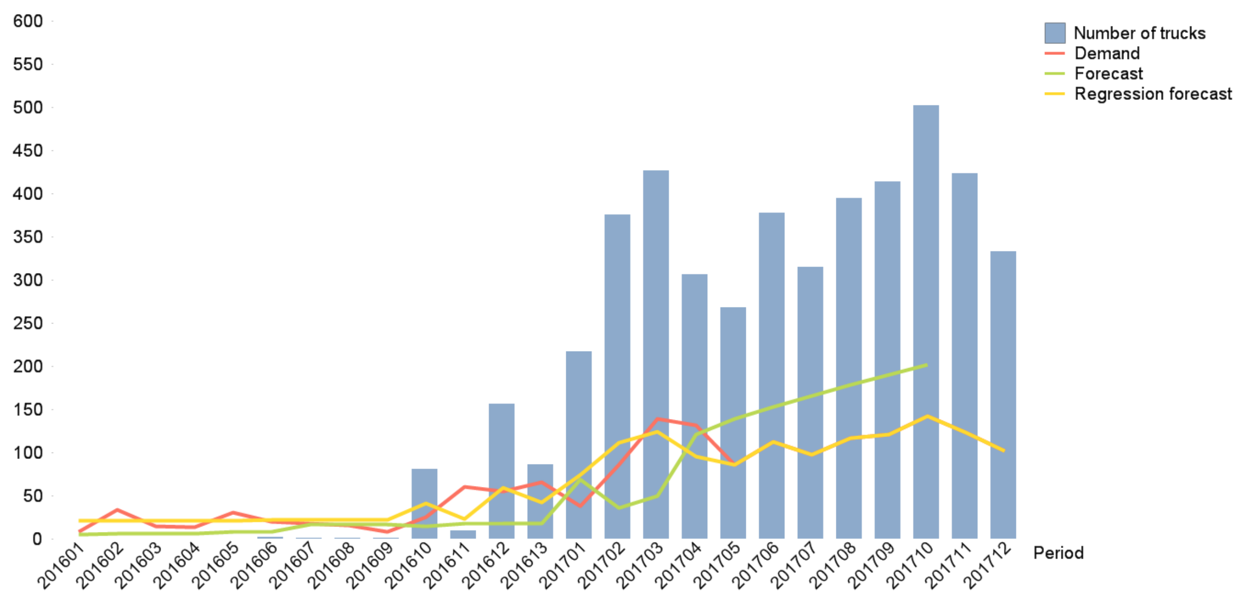

Figure K: Regression based forecast for service part E.

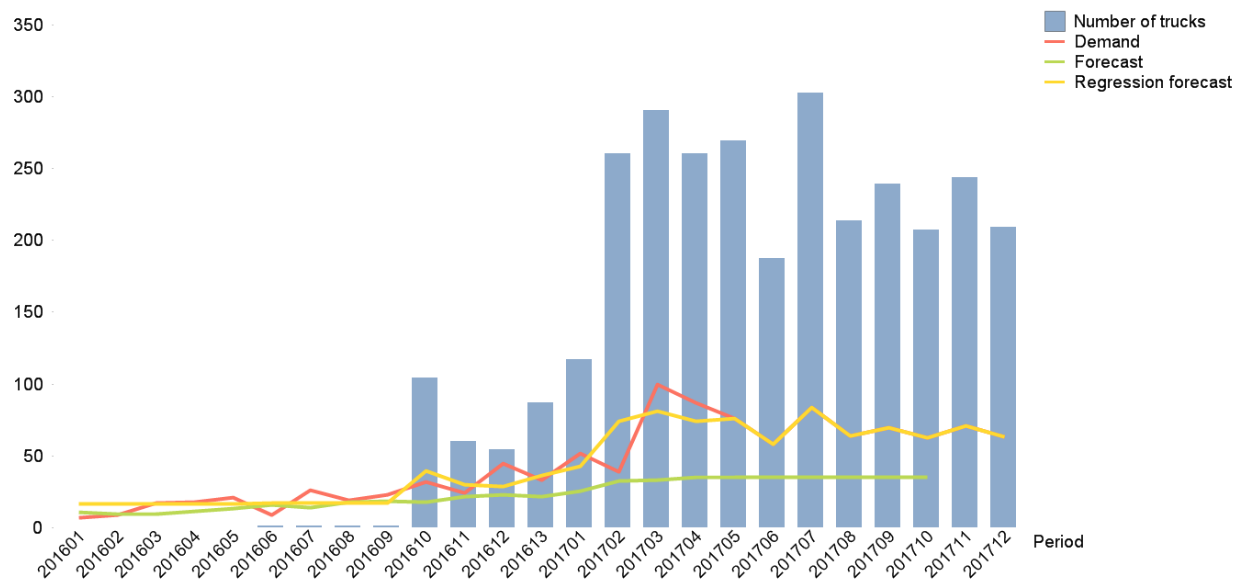

Figure L: Regression based forecast for service part F.

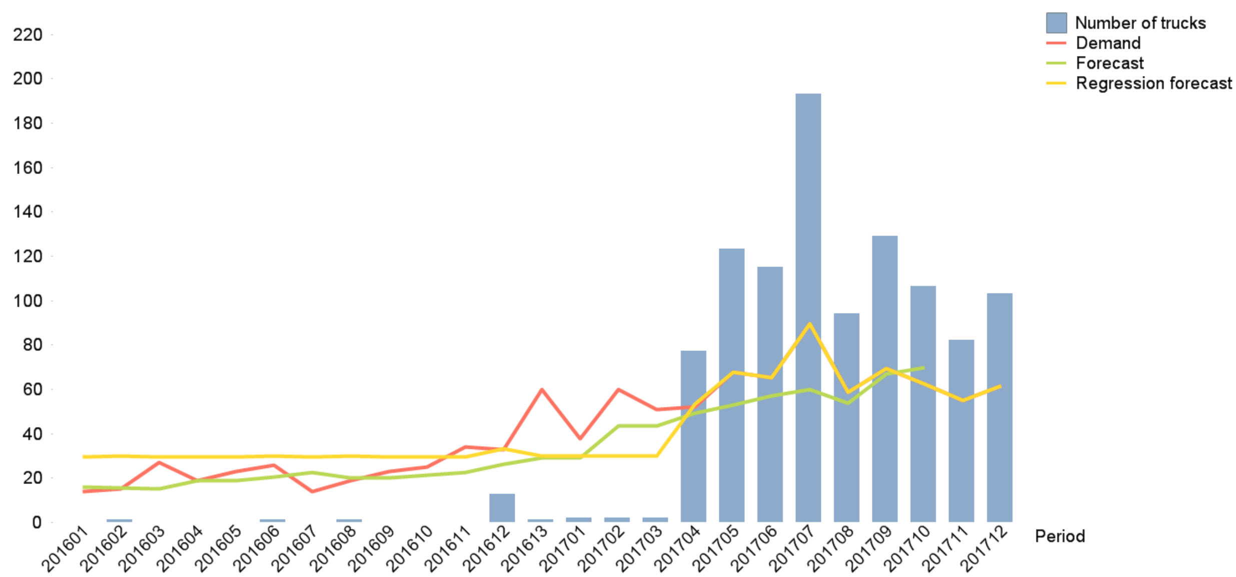

Figure M: Regression based forecast for service part G.