MASTER

Creating insights and predicting the future of demand in order to plan capacity for a distribution center of a sportswear retailer

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Creating insights and predicting the future of demand in order to plan capacity for a distribution center of a sportswear retailer

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"It is difficult to make predictions, especially about the future"

- Neils Bohr

Preface

As I am writing these last words of my master thesis and putting in the last effort for fulfilling my graduation of the Master of Science in Operations Management and Logistics, the end to my student life comes near. Those 5.5 years have gone by faster than I could have ever Imagined, even though at times it felt like that I still had such a long journey ahead. However, I can honestly say that I have enjoyed being on this journey, but at times I also wished to be done with it as quickly as possible. I knew especially when I chose to follow this master program that it wouldn't be an easy road. But I know for sure that life will have many more difficult paths with different obstacles ahead, that I will gratefully face head on. With putting in the time and effort I made this dream and will make those other dreams a reality, "*rep by rep*". I feel proud to have achieved this final state and looking back to it I am happy to say that I have come this far.

It was a privileged experience to be able to do my master thesis for such a great company, NIKE. I would like to personally thank Ricky Glinski for taking me in and giving me this opportunity to start my graduation project on a real business problem from NIKE. Many thanks to Bert Beirinckx for stepping up as my manager and guiding me through the journey. Giving me the personal time and space to develop myself and coming up with new insights within the Goods Flow Planning department. I would like to thank Nico Dellaert from the TU/e for being my supervisor during my whole period as a master student. Thank you for being so hospitable and even letting me have appointments at your personal address after office hours.

Furthermore, I want to thank the many friendly and helpful people at NIKE, that helped me making this all possible. Providing me with all the essential background information, insights and time. Especially Tuba, a personal thank you too you for all the sparring and brainstorm sessions that I could bother you with. I need to say I was privileged to get to know so many nice people along the way, that I got to call my friends as well. You all made the time at NIKE an unforgettable and amazing experience.

Lastly and most importantly, I want to thank my family for being there for me no matter what and always being supportive, loving and caring. Therefore, from the bottom of my heart thank you, Cees, Linda, Lotte and Lieke.

Thank you all and enjoy reading my master thesis!

Cees Bijleveld

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Management Summary

The research project is executed within a large international distribution center from NIKE, INC. in Belgium, named the European Logistics Center (ELC). The distribution center stores and delivers sportswear products to customers all over the EMEA region. Distribution Centers deliver labor-intensive services to customers. Personnel capacity drives the service performance of these facilities and therefore the delivered customer quality value of a business. In order to guarantee the customer order distribution in a timely way, forecasting is needed to predict the upcoming workload and capacity planning. Therefore, reliable and accurate forecasts are required to support distribution center supervisors in determining the required number of workforces. This project mainly concentrates on the first step of personnel capacity planning, more specifically forecasting the amount of workload based on empirical data.

Deciding on the weekly required amount of production staff in order to meet the incoming demand is perceived as a difficult process by distribution managers and planning personnel. Currently there are forecasts in place to aid the distribution managers and planners in this process, however they are perceived to be deviating too much from the experienced demand. Currently it is not clearly known how well the existing forecasts are actually performing. Hence, this also needed to be evaluated. This resulted in the following main research question:

How can NIKE ELC improve the demand forecasting for the value-added services in order to better align the staffing capacity?

Hence, the objective of this research project is applying analytics to create insights into the capacity forecasting problem and to determine a good forecasting method (that is able to perform better compared to the current forecasts) in order to better anticipate on the demand that can be expected for value added services (VAS[1]) in the APP12 DC. This way the project strives to reducing excess capacity or improving the lack of capacity for the VAS process of APP12 and ultimately bring extra value to the customer by elevating NIKE's service.

This research project provides insights into how the historical and current VAS labor demand data behaves from the empirical data of FY14-FY19[2]. Important patterns and behaviors were discovered that served as valuable inputs for the forecasting models. Furthermore the current forecasting performances were evaluated and it was seen that indeed the current weekly forecasts were deviating significantly from the actual VAS labor demand in FY19. The performances resulted in: on average per week an absolute deviation(MAE) of 420.85 hours for the Retail VAS, 502.51 hours for the Wholesale VAS and a combined result with the total VAS demand of a MAE of 668.22 hours per week. This means that the forecasts accuracies have on average 16.47% absolute deviation per week for Retail and 24.91% for Wholesale. Consequently this comes down to an 14.87% average absolute deviation every week for the total VAS forecast. This has a big impact on the staffing levels and therefore also affects the productivity and operations costs within the DC due to moments of idle or overexploited capacity.

[1] The VAS activities represent hanging, tagging and labelling of the products.
[2] Each FY starts at the 1st of June and ends at the 31st of May.

The current forecast method along with an exponential smoothing method are used as benchmarks for the evaluation of the provided forecasting model of this research project. This research project provides a general linear forecasting method that accurately and reliably predicts the demand workload for the upcoming week. The data of FY14-FY18 are used for the training of the forecasting model and the data of FY19 for the validation of the forecasting model. As a result of this study the forecasting performance improved for Retail VAS forecasting to predicting 160.20 hours on average more accurate per week (based on the MAE) which gives an improvement by 41.37% based on the MAPE. The Wholesale forecast predictions are an absolute 123.56 hours more accurate per week (based on the MAE) which resulted in an 8.43% accuracy improvement in terms of the MAPE. Lastly, the Total VAS forecasting performance is improved with 30.93% in terms of the MAPE, making the forecasts 216.86 hours per week more accurate in absolute terms, compared to the currently used forecasting method

This clearly shows the added value of this research study in practice. Resulting in avoiding unnecessary high labor costs of either overestimated or underestimated forecasting by reducing at least 5 FTE's on average per week. The results of this study show that predicting the total amount of labor VAS that is needed in the upcoming week can be forecasted in a more accurate way. This new forecasting method possibly also saves costs outside the operations department in FTE's. As the current way of forecasting is very labor intensive. Since it needed many applied estimations and different analytics from the responsible goods flow planning analysts.

In addition to help the operations managers plan the required number of workforces on a weekly basis, two different capacity planning tools are provided for the determination of the operations workforce capacity for a certain service level. Capacity planning model 1 is a very intuitive but effective model that makes use of the assumption that the total VAS demand values are normally distributed. This way the model looked at the historical actuals and determines with which probability the computed total VAS demand prediction will meet the demand. Model 2 uses the deviations from the actuals relative to the total VAS predictions of the two best VAS forecasting models combined. The model makes use of the assumption that the deviations from the actual demand and forecasts relative to the predictions are normally distributed. Hence, the probabilities denote the certainty level of covering the demand by taking the deviations from the prediction models into account. Together these models give insightful support for the capacity planning decision of the distribution managers and planners with deciding on to optimally plan the right amount of capacity with a certain probability. This results in making the labor force planning less reliant on the availability of skilled operations planning personnel.

Table of Contents

List of figures

List of tables

Acronyms

Abbreviation	Meaning
ACF	Autocorrelation Function
ANN	Artificial Neural Network
APLA	Asia Pacific and Latin America
APP	Apparel
APP12	Apparel 1 and 2 (Distribution Center)
APP3	Apparel 3 (Distribution Center)
DC	Distribution Center
DRS	Direct Shipments
DTC	Direct to Customer
EHQ	European Head Quarters
ELC	European Logistics Campus
EMA	Exponential Moving Average
EMEA	Europe, Middle – East and Asia
E2E	End-to-End
EQP	Equipment
FTE	Full Time Employee
FTW	Footwear
FY	Fiscal Year
GFP	Goods Flow Planning
GLM	General Linear Model
IDP	Integrated Delivery Planning
MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MDP	Marketplace Distribution Planning
ME	Mean Error
MPE	Mean Percentage Error
MPO	Market Place Operations
MSE	Mean Squared Error
MTO	Make to Order
MTS	Make to Stock
PE	Product Engine (=Different distribution centers e.g. Wings, APP12 etc.)
TU/e	Technische Universiteit Eindhoven (Eindhoven University of Technology)
VAS	Value Added Services

1. Introduction

This research is conducted as a Master thesis project, in order to finalize the Master Operations Management and Logistics at the Eindhoven University of Technology. The project is conducted within the biggest sportswear company in the world, NIKE, Inc., and focuses on creating insights and predicting the future of demand for a distribution center and aligning this with the right amount of capacity.

The following subsections will illustrate the outline of the project, starting with the introduction of the general problem context in section 1.1, thereafter a description of the company will be given in section 1.2 and its organizational structure will be described in section 1.3. Lastly, in section 1.4 the chapters of the remainder of the project report will be clarified.

1.1 Problem introduction

Nowadays, consumers demand more choice, always available, fast delivery, personal services and experiences with their purchases. In order for companies to strive in those marketplaces, they must be able to serve the customers when, where and how they want it. Therefore, businesses need to constantly improve their processes in pursuance to deliver the extra value demanded from their customers. For this, the supply chains of businesses need to depend on efficient and effective logistical systems to fulfill these customer orders. A distribution center (DC) is a warehouse that serves as a facility that enables the activities of receiving, storing, order picking and shipping of products. DC's form critical parts of supply chains, and therefore it is crucial that their operations are performing in an efficient and effective way (Jinxiang, Goetschalckx & McGinnis, 2007). Typically, those DC's are dealing with highly seasonal demand patterns of fluctuating customer orders.

Distribution centers can apply diverse strategies for fulfilling these customer orders. One strategy could be to fill orders through already finished goods from the firms stocked inventory. This strategy is referred to in the literature as a make-to-stock (MTS) policy. Another strategy for firms is where all manufacturing and order fulfillment processes are initiated on an order only after it has been demanded by the customer. Such a strategy is introduced in the literature as a make-to-order (MTO) policy (Chen, Mestry, Damodaran & Wang, 2009). MTS and MTO items can be either direct inputs into the production process or the end product itself (Robinson, Sahin & Gao, 2005). The biggest difference between the MTS and MTO policies is that the MTS policy produces non-specific products with standardized processes, which are not available for the MTO specific demand at the time of the capacity planning. When using the MTS policy firms hold finished products in the inventory as a buffer to deal with variations in customer demand. However, with the MTO policy firms must hold spare capacity in order to deal with the variance of customer demand (Barut & Sridharan, 2004). This research will be focused on the MTO approach. The effective and efficient use of the available capacity therefore forms the most important aspect when using the MTO strategy. Consequently, an operation manager needs to be cautious with holding excessive capacity since unutilized capacity results in a deficiency in profit. Therefore, an organization needs to ensure to hold the right amount of capacity for its processes to meet the incoming customer demand (Chen et al., 2009).

Anticipating on the customer's demand in sufficient time before its occurrence is the most fitting solution to this complicated problem. As a result, forecasting the labor demand forms a key challenge in deciding the needed amount of production staff (De Koster, Le-Duc & Roodbergen, 2007). Good forecasting models that predict, as accurately as possible, the trends and fluctuations of the customer demand are essential for having good anticipation on this incoming demand (Hamiche, Abouaissa, Goncalves & HSU, 2018). Forecasting is the computation of analyzed patterns on the firm's growth patterns to interpret the impact on the business processes (Haines, 2006). The better a firm identifies its customers buying behaviors, the more precise its demand forecasts will be. This in turn will help with more efficiently planning and executing of supply chain operations (Boone, Ganeshan, Jain & Sanders, 2019). Forecasts have always served as the basis for planning and executing supply chain activities such as sourcing, manufacturing and supplying products and services to customers. The globalization of supply chains, the explosion of product variety and the increasingly competitive markets have made forecasting more difficult, though its well-functioning more important than ever (Boone et al., 2019).

The output of these forecasting model(s), which is thereafter communicated to all relevant stakeholders, forms the basis of the capacity plans. Capacity planning is the reaction to forecasts that subsequently needs to make sure that the business processes are coherent with the predicted future demands (Haines, 2006). Benefits resulting from better planning are more precise capacity determination of factories, warehouses, and transport systems, and logistics-oriented product and packing design (Knolmayer & Zeier, 2002). By providing supporting optimization algorithms or heuristics, this decision making with respect to available employees, capacities or for short-term adjustments of capacities can be improved (Knolmayer & Zeier, 2002).

1.2 Company Background

A company that needs to deal with all these aspects and decision-making processes is NIKE, Inc.. NIKE, Inc. is a leading international brand and company (including Converse, Hurley and Jordan brands) that operates in the market of sportswear and apparel products. With a mission to *"Bring inspiration and innovation to every athlete*[3] *in the world"* (NIKE, 2018). The company was founded in 1964 as Blue-Ribbon Sports by Bill Bowerman and Phil Knight and later became NIKE, Inc. in 1971. NIKE's world headquarters (WHQ) is based in Portland, Oregon and its European headquarters (EHQ) in Hilversum, The Netherlands. The multinational corporation is involved in the design, marketing, development, manufacturing and supply of footwear, apparel, equipment, accessories and services for a wide variety of sports and fitness activities (NIKE, 2018). NIKE sells the products through their NIKE-owned retail stores (392 in the US and 790 all over the world) and through digital platforms, to retail accounts and a mix of independent distributors, licensees and sales representatives in virtually all countries around the world (NIKE, 2018).

In this report the terms "NIKE", "Company", "Organization" and "Business" are all referring to NIKE, Inc and its predecessors, subsidiaries and affiliates, collectively, unless the report indicates otherwise.

1.3 Organizational structure

NIKE is organized over four semi-autonomous geographies, namely North America, Europe, Middle East and Africa (EMEA), Greater China and Asia Pacific and Latin America (APLA). This is more clearly illustrated

[3] If you have a body, you are an athlete.

in Figure 1. Centrally led decisions are driven globally such as strategy alignments since this concerns all the regions. This thesis graduation project is conducted within the EMEA geography. More specifically within the Goods Flow Planning department within the European Logistics Center (ELC) at Laakdal, Belgium.

Figure 1: NIKE geographies

1.3.1 European Logistics Center (ELC)

In order to supply the customers within EMEA the ELC has been established in Laakdal, Belgium in 1994. Nike is a growth company, and in order to continually serve customers on a global scale, the ELC with currently around 4700 employees has been expanded many times since it first started operating in 1994, see Figure 2 below. Today, the campus is at the heart of a huge network of factories, transporters, retail stores and customers, shipping hundreds of thousands of units of the latest Nike products every single day. It receives their products from 620 different factories situated in 42 different countries, in order to supply the consumers around Europe, Middle-East and Africa.

Figure 2: NIKE ELC

As soon as the products are manufactured, which is mainly done in Asia, they are transferred to consolidation centers. Here a split is being made in the way NIKE supplies its customers. The first shipment method is the Direct Flow, also called DRS (Direct Shipments), where NIKE directly delivers the big customers which represent the big whole sale retailers such as JD, Footlocker and Decathlon. The DRS flow is illustrated in Figure 3 below. The other supply method follows the products through the DC flow which stands for the Distribution Centers of the NIKE ELC, as shown in Figure 4 below. This NIKE DC flow represents approximately 75% of the whole supply of NIKE products. Here the products for the NIKE stores, online NIKE.com customers but also again the big whole sale retailers get their products and NIKE services delivered from.

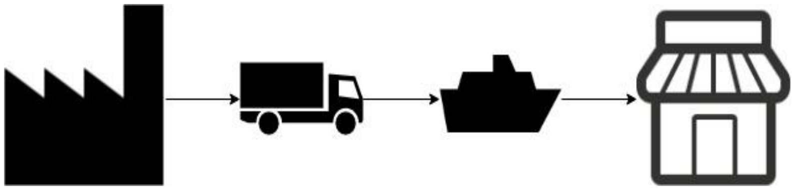

Figure 3: NIKE Direct Shipment Flow

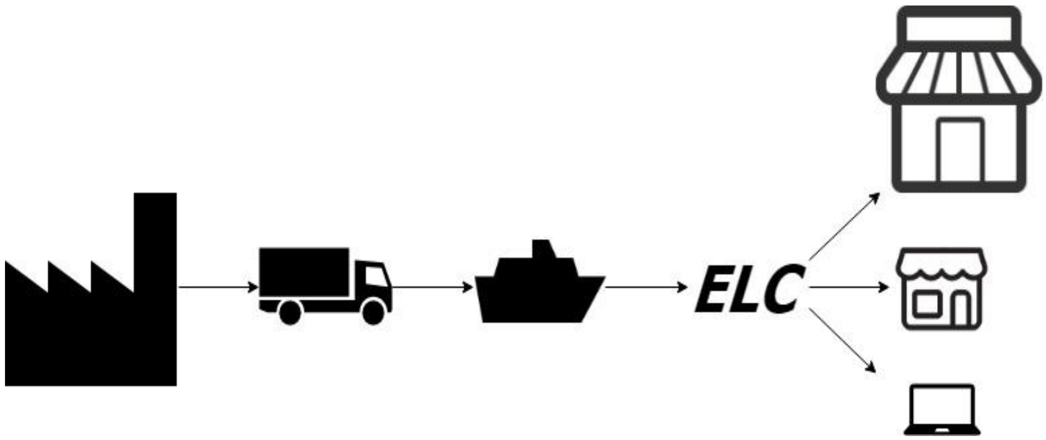

Figure 4: NIKE DC Flow

The ELC is divided in multiple DC's where the separation is based on Product Engine level (PE's); Footwear (FTW), Apparel (APP) and Equipment (EQP). This means that some DC's only store footwear products (FTW1/2), others store equipment (Herentals), others store apparel products (APP1/2 and APP3), and others that store a combination of products (The court and Wings). Summing this up the ELC currently consists of 6 different NIKE DC's listed below, with each their specific code of abbreviation used in systems;

- FTW12;1065
- APP12;1060
- APP3;1067
- Herentals;1164
- Wings;1064
- The Court; 1264

1.3.2 Goods Flow Planning

Within the ELC there are different departments that work together to reach and optimize the strategic goals of the organization. The department that is responsible for the optimal flow of goods is the Goods Flow Planning (GFP) department. It takes care of every process stage of the products, from the moment that they leave the factories, until they reach the end customer with the aim of maximizing the consumer experience. This happens in two major segments; on the one hand, the planning and flow from the factories to the DC's and on the other hand, the distribution planning within the DC's. Where the first segment falls under the responsibility of the End-to-End team (E2E) and the second segment is the responsibility of the Marketplace Distribution Planning team (MDP). These 2 teams also form the two main pillars within the GFP department. To support these two teams there is in addition a Reporting and Insights team, a Process Transformation team and several outcome groups within the GFP department.

This research project is focused on the distribution planning within the DC's, where the products have already arrived at the inventory so that they can be scheduled for shipment to the customer, and therefore will be mostly involved with the MDP team.

1.4 Thesis structure

The remainder of the project will be conducted in a step-by-step approach referred to as the problem-solving cycle (Van Aken, Berends & Bij, 2012). Figure 5 illustrates these steps.

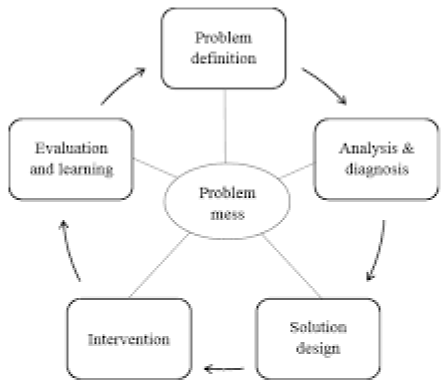

Figure 5: The problem-solving cycle (Van Aken et al., 2012)

The problem-solving cycle is an effective approach for analyzing business problems (Van Aken et al., 2012). First the problem mess that the business is facing needs to be identified and structured. This is done by formulating the problem definition in chapter 2. The following step is executing the analysis and diagnosis where the context of the problem is analyzed firstly by giving a literature review in chapter 3. Thereafter, the causes of the problem are analyzed more in depth in chapter 4 by giving an approach to tackle the forecasting and capacity planning process. Chapter 5 and 6 continue the approach of chapter 4, where afterwards a solution is designed that improves the current problem. The implementation of this solution design is discussed in the conclusion. The fifth and last step of the problem-solving cycle is the learning and evaluation step. This step represents the evaluation of the implemented solution where the learning outcomes are addressed. These will be given in the management summary where the whole result of the problem-solving cycle is summarized.

2. Problem definition

Section 1.1 has introduced the importance of a good forecasting process in order to anticipate on the incoming customer's variable demand with the right amount of capacity. The business problem that the NIKE ELC faces with regards to this topic is described in this chapter of the research report. Firstly, the business problem is discussed in section 2.1, secondly the scope and aim of the project is stated in section 2.2 and thirdly the research questions that the project will answer are given in section 2.3.

2.1 Business problem

The problem definition is a crucial part of the project. *"Where in general, a problem can be defined as a state of affairs in the real world with which important stakeholders are dissatisfied, while believing that things can be improved"* (Van Aken et al., 2012, p. 53). In order to formulate the right business problem expert interviews have been held with several managers, analysts and distribution planners who are knowledgeable about the business problem. The problems have been discussed with these individuals during individual in depth interviews to capture the strategic relevance of the problem from the perspective of the business.

In context of the NIKE ELC some important customers from NIKE are getting a priority treatment and their demand must be always met within their given planned goods issue date. Due date feasibility is a critical issue within MTO operations. Making sure the MTO due date is met is more than optimizing an objective, because of the character of this demand. Since, multiple orders are competing for the resources of a company, due date feasibility depends on the availability of the time-phased resource capacity (Knolmayer & Zeier, 2002). Therefore, it is extremely important for NIKE to have a well aligned forecasting model and demand planning where, the forecasting output builds a solid foundation for the capacity planning of the distribution centers. The ability to increase forecasting accuracy will result in lower costs and higher customer satisfaction because of less moments of capacity discrepancies and more on-time deliveries (Carbonneau, Laframboise & Vahidov, 2008).

Every customer demand order requires several different operations and each distribution center handles different types of customer demand orders. The different distribution centers each have a specific capacity, cost and production plus distribution/handling lead time. To make the ELC production process perform optimally, the right balance must be found for each DC in the expenses of allocating too much capacity, which can result in having idle production staff, with the expenses of allocating too little capacity, which can result in overtime charges or in the worst-case: unsatisfied demand (Olivares, Terwiesch & Cassorla, 2008).

2.1.1 Value-Added Services process

One important process that the NIKE DC's perform is the Value-Added Services (VAS) process. This is a service that NIKE provides to the big and important wholesale customers (referred to as IDP customers = integrated delivery planning customers) and also implements for its NIKE-owned stores (referred to as Retail or DTC = Direct to Customer customers). In other words, all VAS customers are IDP and/or DTC orders and these IDP and DTC orders are prioritized over NON-IDP orders. NON-IDP customers never require VAS however they could ask for so much demand, that some production staff would probably shift temporarily to another operation of APP12 (like order picking). However, this extreme situation is very rare and is therefore left out of the scope.

An important aspect of the VAS process is that this is an MTO operation, since every customer needs different VAS and products can't have VAS treatment before it is ordered by a certain customer. The activities that are carried out for these orders and referred to as the VAS are: hanging, tagging and labeling of the products. In short, hanging is applying clothing hangers onto the products, tagging stands for applying security tags onto the products and labeling referrers to adding the price tag and product information onto the products. These VAS activities are mostly the same at every DC. However, they do differ in the way they are handled at Product Engine (PE) level. As an example; shoe labeling requires less VAS treatment than the hanging, tagging and labeling of an apparel product. Therefore, this VAS process plays a bigger role within certain DC's with PE's that require more VAS treatment such as the apparel responsible DC, APP12.

There is an Marketplace Distribution Planning (MDP) team in every DC, taking care of their own flow. They all work a little bit different depending on the DC because the DC's run on different warehouse management systems (WMS's)[4], but they all have the same goal and put customer service as top priority. A very important difference within each DC is the work-structure itself. The work structure refers to the way the product flow is handled within the DC. In the newer DC's (the Court and Wings) one production staff employee handles both the order picking and the VAS process. Therefore, this gives more flexibility and results in less idle capacity of the production staff. In APP12 this process is however split up and there are different departments that handle the different stages of the product handling and distribution within the DC. This means that the production staff is mostly specialized and trained for one of the processes in the DC (as an example, either VAS processing or order picking). As a consequence the switch from VAS to non-VAS activities is difficult for the production staff, since most people aren't cross functionally trained/prepared for multiple processes in APP12. In addition, it takes some training time before an employee understands the VAS processing activities. Also, the processes are conducted at different locations within the APP12-DC, therefore, the exchange of production staff from one process to the other is not efficient for the VAS production and distribution process. The switch from VAS to non-VAS activities or vice versa, can happen when there is more urgency for either one of the activities. For APP12 the VAS capacity is limited due to a capacity constraint of work places and therefore needs to be well managed. The normal work capacity is divided into three shifts of 7.5 hours, with each shift normally containing approximately 40 to 45 people to handle the VAS activities simultaneously. However, the maximum capacity of available VAS stations is 84 work places within APP12. Due to the difficulties and constraints of the VAS process for APP12, a bad capacity and forecasting alignment can have a bigger impact on the performance than within another DC. Therefore, the project will focus specifically on the APP12 DC VAS forecasting and capacity management.

2.1.2 VAS Forecasting and capacity management

The MDP team maintains the VAS capacity tables on a monthly, weekly and daily basis to make the VAS process run smoothly. These VAS capacity tables are representing the daily production time capacity in hours[5]. The purpose is to act as proactively as possible. Therefore, they open capacity upfront so that orders can be planned in. The target for their capacity plan initially comes from the monthly goalsetting. On a monthly basis the goals for the next coming 3 months are set. In this step, GFP also works together with Market Place Operations (MPO) as they give the monthly VAS forecast (in hours) where they also take the budgets into consideration. Budgets are determined at the beginning of every fiscal year (FY)[6] in

[4] The legacy DC's: APP12 and FTW12 work with DS400 and APP3 works with XPDS. The newer DC's: Herentals, Wings and the Court are running on Manhattan.

[5] Therefore, in this project when referred to VAS, the amount, demand and forecast is always in hours

[6] Each FY starts at the 1st of June and ends at the 31st of May.

cooperation with the finance team from the ELC. This monthly forecasting file is called the "*DC*" VAS FY "*XX*"[7] file and contains the forecast for the next 3 months, see Appendix A for an example of this file. Here the monthly VAS forecast is given in hours for retail (DTC) and wholesale (non-DTC). The monthly VAS demand forecast is also given for each week of the current month in order to give more detail for the expected VAS demand, see Appendix A. So, in summary in the "*DC*" VAS FY "*XX*" file the forecast of the current month and the next two months is displayed. For the current month, the forecast is on month and week level while the next two months are on month level (*e.g. forecast of September: weekly buckets of September and monthly forecast of October and November).* For wholesale this is the latest and smallest aggregated forecast that is provided to the distribution planners. This means that currently the capacity that is planned for wholesale on a daily basis is literally the weekly forecast (that is rolled out once per month) split up evenly over the working days of that week, resulting into a flat daily average for the wholesale VAS. For DTC there is a forecast rolling out every week for the daily DTC VAS hours. In this forecast file, called the "*DTC forecast day level*", the conversion of weekly forecasts is given in daily forecasts, see Appendix A.

In summary, the VAS capacity management and planning is starting off with a monthly VAS staffing plan, based on the monthly forecasts for wholesale and retail. Initially the daily VAS capacity tables are opened-up by the rolled-out predictions for that month. Therefore, the planned staffing levels at that moment are aligned with the opened-up VAS capacity in the SAP tables. From that moment the capacity can be booked in by the customers. These monthly staffing levels for every day VAS production are not yet set in stone. The real scheduled daily staffing levels for the next week are always determined on each Thursday the week before. Staffing can be planned differently on each day of that next week depending on the number of predicted hours at each day, that are given by the DTC day level forecasts and the wholesale *1060 VAS FYXX* forecasts. Therefore, daily targets are used for the staffing plans that are finally confirmed the day before at 06:00 AM taking into account sick leave and holiday leave to guarantee the opened-up capacity for the next day. However generally the distribution managers try to level out the staffing for the whole week as much as possible. Therefore most accurate weekly forecasts are preferred so that this weekly total can be split up evenly over the shifts of the week.

2.1.3 The Business Problem

According to several managers, analysts and distribution planners that have been approached for the individual depth interviews, the current weekly VAS forecasts are deviating too much at times from the actual demand. Based on the experiences of these experts, it is a recurring event that there is a significant gap between the forecasts and the actual occurring VAS demand. Consequently, these deviations from the forecasts with the real experienced demand are causing trouble for the capacity planning of the VAS process. This has a big impact on the staffing levels and therefore also affects the productivity within the DC due to moments of idle or overexploited capacity. Therefore, the experts have the idea that the current forecasting approach could be improved. However, it is not yet clearly known how well the current forecasts are performing and therefore this also needs to be evaluated and investigated.

[7] For APP12 this would be for example: 1060 VAS FY19

At the moment, with a given demand forecast, there is also no clear optimal capacity target known. So, there is no model available to guide the distribution planners with deciding on to optimally plan the right amount of capacity with a certain probability. Meaning that the capacity planning is currently more a reactive process. This is a missed opportunity to reduce excessive or insufficient capacity levels. Therefore, an analytic approach can be used to support decision making on proactively applying these targets, to align the supply (staff hours) in a better way and prevent excess and lack of capacity as much as possible.

Currently temporary solutions are applied at times when capacity issues arise. As an example: if capacity issues, like expected excessive capacity, can be foreseen on time, often the decision is made to try and pull demand forward, instead of producing it at the initial planned day. However, implementing temporary interventions is not the solution to the problem.

NIKE is continuously evolving to always serve the customer, while trying to maintain the maximum efficiency. Therefore, this business problem needs to be analyzed in order to gain insights and a better understanding of the current process and ultimately improve NIKE's performance.

2.2 Scope and aim of the project

Forecasting plays a central role in the operations function of a firm, where the production department needs to use forecasts mostly for operations planning decisions. The goal of aggregate planning is to determine aggregate production quantities and the levels of resources required to achieve the production goals. It is assumed that there exists a forecast of demand for that specified planning horizon. If future demands turn out to be very differently from the forecasts, then decisions indicated by the capacity planning could be incorrect (Nahmias, 2015).

In context of this project this translates to finding the number of workers that should be employed in order to produce the required forecasted demand in each of the planning periods with a certain probability. This means that a balance needs to be found by changing the levels of production with the workforce levels in order to meet demand as closely as possible by taking into account the fluctuating disruptive demand.

The scope of this master thesis project will focus on the two first steps of the Production Planning Decisions hierarchy. The availability of inventory is left out of the scope because for the VAS process the products are always already in stock at the APP12 DC. Below in Figure 6 the position of the forecasting and capacity planning can be seen within a schematic illustration of the hierarchy of production planning decisions.

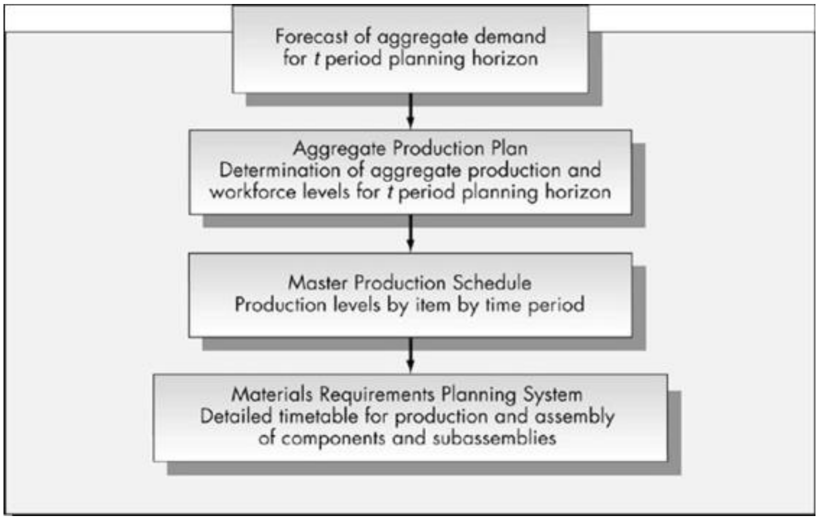

Figure 6: Hierarchy of Production Planning Decisions (Nahmias, 2015)

In conclusion, the objective of this master thesis project is:

Applying analytics to create insights into the capacity forecasting problem and to determine a good forecasting method (that is able to perform better compared to the current forecasts) in order to better anticipate on the demand that can be expected for value added services (VAS[8]) in the APP12 DC. This way the project strives to reducing excess capacity or improving the lack of capacity for the VAS process of APP12 and ultimately bring extra value to the customer by elevating NIKE's service.

2.3 Research Questions

The research project is focused on the particular business problem that the managers want to solve and has therefore an applied research approach. This means that the research is conducted in order to reveal insights to specific questions related to the business problem and its performance (Cooper & Schindler, 2011). Therefore, the business problem needs to be translated into the relevant management question that then will be split up into multiple research questions in order to proceed with the research process.

The introduction stresses the importance for the business to have a well aligned forecasting and demand planning, from which the output builds a solid foundation for the capacity planning of the distribution center. The problem definition in section 2.1 gives an indication that an improvement is needed for NIKE's VAS forecasting and demand planning. In order to fully grasp the impact of the current problem, in addition further analysis need to be implemented. This is a complex process, which requires a well formulated methodological approach. Therefore, the main research question of this project is:

How can NIKE ELC improve the demand forecasting for the value-added services in order to better align the staffing capacity?

In order to answer the main research question, the question is split up into multiple sub-research questions:

[8] The VAS activities represent hanging, tagging and labelling of the products.

1. *What does the historical and current time series of VAS labor demand data look like?*

2. *How is the current VAS forecasting process performing for APP12?*

3. *What predictive model performs the best to forecast the VAS demand for APP12?*

4. *How is the forecasting accuracy with weekly aggregation level on real data?*

5. *Given the forecast demand prediction, what is the ideal amount of workforce capacity that needs to be planned for a certain service level?*

These research questions will be answered over the following chapters of the research report.

3. Literature Review

This chapter serves as the exploratory research phase. Here, background information is gathered on the topic of the research question(s) in order to expand the understanding of the business problem. The exploration is particularly useful to further develop concepts and operational definitions to improve the research design of the project (Cooper & Schindler, 2011). The chapter is split up into three subsections where, the results of Demand Forecasting section 3.1 and Capacity Planning section 3.2 are described. In the last subsection 3.3 the literature gap of demand forecasting and capacity planning within a distribution center environment is discussed.

3.1 Demand forecasting

Demand forecasting serves as a crucial part for supply chain decision making. In addition, it forms the first step in response to customer demand with respect to applying a fitting activity planning (Hamiche et al., 2018). In order to predict the unknown future for supporting decision making today. Usage of a simple forecasting method has been shown to help reduce safety stock in half in comparison with not using any forecasting methods for customer demands, which results in significantly decreasing the operating costs for the respective company (Courtois, Martin-Bonnefous, Pillet & Pillet, 2003). It is also beneficial for the firm to have predictable work hours since, this is a key driver for employee satisfaction and consequently their productiveness. Different methods and techniques can be used for the forecasting models. Even though there are many circumstances that call for forecasts, there are only two main type of forecasting techniques: qualitative methods and quantitative methods.

Qualitative forecasting techniques are based on subjective human judgment and opinions from experts. Some of these methods are: sales force composites, customer surveys or the Delphi Method. These techniques can be suitable in situations where ad hoc or local decision making is needed and there is little to no available historical data to build a forecasting model on. Other than that, they are not that accurate and very fault sensitive due to biases of the certain experts. Therefore, qualitative forecasting methods are not further elaborated in this literature study (Montgomery, Jennings & Kulahci, 2015).

Quantitative forecasting methods are objective forecasting techniques that are making use of actual historical information structured time series and try to extrapolate, recognize and model the patterns found in these historical data. Time series are time-focused on a historical sequence of observations from a variable of interest (Montgomery et al., 2015). A time series is just a collection of past values of the variable that is being predicted. The goal is to develop a mathematical relationship between the demand factors and isolate patterns in this historical data such as:

- Trend
- Seasonality
- Cycles
- Randomness

A trend represents a gradual, long-term up or downward movement of demand. Seasonal patterns are oscillating movements in demand that occur periodically. Seasonality is often weather related; however, this can also occur on a daily or weekly basis. Cycles illustrate an up-and-down movement in demand that repeats itself over a lengthy time span. Random variations are movements that are not predictable and follow no pattern (Nahmias, 2015).

Forecasts are often seen as a particular value that serves as the best estimate for the predicted future value of a certain variable of importance. This is called a point estimate or a point forecast by statisticians (Montgomery et al., 2015). Often these forecasts are not a 100% accurate and hence a forecasting error is typically experienced. Therefore, to improve this sole forecasting value it is of great importance when in addition an estimate of this forecasting error is provided. This can be done by accompanying the point forecast with providing a prediction interval (Montgomery et al., 2015). This prediction interval can be much more beneficial in decision-making than a single forecasting value as it then serves as a range of values for the future value prediction. Other meaningful aspects of forecasting are the forecast interval and the forecast horizon. The forecast interval stands for the regularity of preparing and rolling out new forecasts. The forecast horizon is the length of the periods that need to be forecasted and depends on the nature of the process. In other words, it depends on the time that is required to plan or modify the operations and activity schedules. The accuracy of a forecast however erodes as we go further into the future (Montgomery et al., 2015).

Looking at the modeling point of view different methods haven been developed in order to best predict future behavior based on time series. These are regression techniques, smoothing techniques, statistical or neural techniques (Montgomery et al., 2015). However, developing a great and an exact mathematical forecasting model is a challenging process, because certain phenomena cannot be taken into account (Lafont, Balmat, Pessel & Fliess, 2015). As stated by statistician George Box: “All models are wrong. Some are useful” (Box & Draper, 1987, p. 74). Within the literature the exponential smoothing also called an exponentially weighted moving average (EWMA) and ARIMA models are the two most studied techniques for demand forecasting models, and present complementary concepts to the forecasting objective. The exponential smoothing is based on interpreting the trend and seasonality in the data, ARIMA models interpret the autocorrelations in the data.

The process of using different forecasting methods for the analyses is illustrated below in Figure 7. The standard criterion for measuring which method provides the best forecast is generally the mean squared error (MSE) (Montgomery et al., 2015). Forecasting with time series models is more often stated within the literature that fitting the right model can be perceived as a combination of science and art which is learned the best way with practice and experience. It is also not uncommon that a time series data set which includes a trend, is possible to be forecasted well by multiple techniques such as an EWMA approach and an ARIMA model. In these situations, it is valuable to use multiple forecasts as the combination of two methods can be superior than either forecast alone with respect to the forecast error (Montgomery et al., 2015). Therefore, it would be unwise to ignore information from the insights gained from the different applied methods. For this reason, multiple models will be possibly applied for the forecasting process in chapter 5 and will there be discussed into more detail.

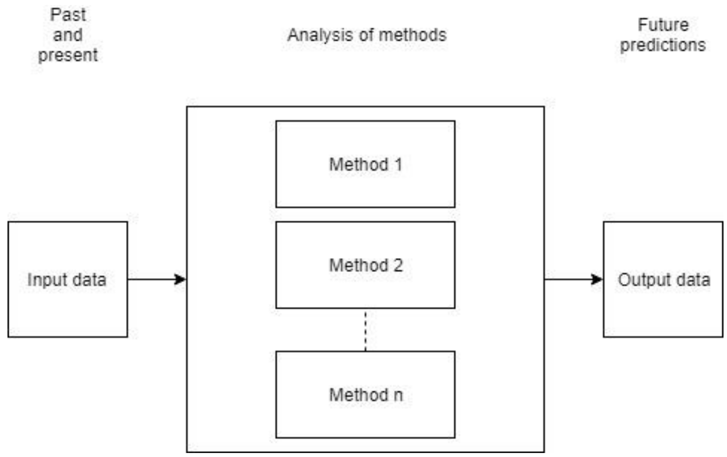

Figure 7: Forecasting methods analysis (Debnath & Mourshed, 2018)

3.2 Capacity planning

Due to fluctuating demands, increasing expenses, new innovative technologies and increasing delivery lead-times, corporations are forced to thoughtfully plan their capacity. Having too much capacity results in useless expenditures, whereas having too little capacity results into loss of revenue (Huh & Roundy, 2003). Manufacturers also prefer to have only a limited number of finished goods waiting in inventory because fashionable products face declining prices and may stay unsold. Therefore, a good capacity planning process is important to determine the required amount of capacity for an organization in order to sustain a given demand during a planning horizon. Capacity decisions depend greatly on the length of the planning period, as well as the cost of capacity and the demand uncertainty in the course of the planning horizon. Since, once the capacity is chosen it stays unchanged during the planning horizon (Wu, Erkoc & Karabuk, 2005).

Based on the planning horizon, capacity planning is divided into three different classes of capacity planning within the literature. The long-term capacity planning is classified as dealing with the resource's requirements of factories and its divisions of new and current production processes depending on demand forecasts and financial assets availability on a strategical yearly or longer time basis (Wu et al., 2005). Decisions are made for the locations and capacities of the plants, the strategical supplier plans and vertical integrations, implementing new production technologies (processing or automation systems) and production methods (Chen, et al., 2009). The medium-term capacity planning is classified as dealing with resource requirements for a monthly to a quarterly planning horizon. Decisions are made for the workforce level, the amount of raw materials and inventory policies for each product class and business unit. Depending on the demand forecasts, production capacity plans are created for the amount of the labor-employment (layoffs, hiring, recalls, vacations, overtime and part-timer), the inventory policies, utility conditions, facility adjustments, outsourcing and other supply contracts (Chen, et al., 2009). Lastly the short-term capacity planning is classified as dealing with resource requirements on a daily or weekly basis. Decisions are made about the resource's availability and the capacity requirements for the production plan at the operational work level (Chen, et al., 2009). On operational level, capacity planning represents the decision-making models that are developed and support specific operational environments (Wu et al., 2005).

In order to assure a smooth production for an MTO operation a suitable planning approach is needed of matching demand with the level of capacity during the planning horizon. An MTO operation cannot build up on inventory, as every order requires customization. Hence, the production capacity varies each time period to meet the forecasted demand for that time period, by hiring and firing/laying-off production staff. However, in order to serve the customers in a satisfying manner, the organization will need to maintain a certain production capacity level as well. Generally, these type of operations therefore keep a minimum level of production capacity and relies on overtime labor, part time labor, temporary labor, subcontracting, backlogging and firing/laying-off production to regulate its capacity and to handle demand fluctuations. Where, in addition an MTO production manager constantly needs to decide whether to accept or reject a customer order into the production given the available capacity at that moment in time (Chen, et al., 2009). To make the ELC production process perform optimally, the right balance has to be found for each DC in the expenses of allocating too much time, which can result in having idle production staff, with the expenses of allocating too little time, which can result in overtime charges or in the worst-case: unsatisfied demand (Olivares et al., 2008).

The objective for capacity planning is to minimize the sum of cost for lost sales and capital cost, where each is a function depending on the cost of increasing and decreasing capacity (Huh & Roundy, 2003). A decision must be made before demand occurs and unless with a lot of luck, it is almost impossible to perfectly match supply with demand (Cachon & Terwiesch, 2008). The approach to balance this supply and demand, is to forecast the short term workload (Van Gils, Ramaekers, Caris & Cools, 2017). Thereafter, a decision tool is needed to make the best tradeoff in this challenging situation. The more specific literature of the applied decision tool will be discussed in chapter 6.

3.3 Literature gap

This subsection aims to establish the current literature gap of demand forecasting and capacity planning within a distribution center environment. It addresses the problems that are not yet (adequately) researched and studied in the current literature.

Workforce related research studies have been conducted in manufacturing environments before, but comparable studies in distribution center environments are scarce. This scarcity has also been stated by Davarzani and Norrman (2015). In addition, it is a shared conclusion in recent literature reviews that most research studies treat demand as a given within warehouse planning and ignore the forecasting and determination of the amount of workforce (Davarzani & Norrman 2015; De Koster et al., 2007; Jinxiang et al., 2007; Rouwenhorst, Reuter, Stockrahm, van Houtum, Mantel, & Zijm 2000). The only research that deals with a similar type of environment and settings is the article of Van Gils et al. (2017). They are predicting order pickers' workload in a warehouse which has similarities with the business process of this study. In their article Van Gils et al. (2017) even stated that "To the best of our knowledge, we are the first to forecast order pickers' workload in a warehouse".

So, in conclusion it can be said that none of the articles found in the literature took all the critical and essential elements into account for the workforce demand forecasting of a distribution center. In addition, there is a lack of approaches and solutions that can aid the distribution managers in their capacity planning decisions, in which the solutions are considering that demand forecasts are never making 100% accurate predictions. In this research study a contribution is made to the above recognized gap in the existing scientific literature. The primary contribution this research project will bring to the current literature is to display a proof of concept of the effect that forecasting methods have on a distribution center. More specifically on a labor intensive process in a DC from the world's biggest sportswear retailer, in order to efficiently and effectively manage the workforce capacity. This research project provides managerial insights and an integrated solution for labor forecasting and the capacity planning of a distribution center's labor intensive process.

4. Project methodology

The research project is not a purely theoretical approach but a real-world applied problem analysis. Therefore, it is more performance focused which means that the actual performance improvement is the primary objective of the project and that the analysis and design are a means to that end. With this approach it is not the beauty of the analysis or the sophistication of the solution that counts (however desirable these may be), but the potential for performance improvement created by the analysis and design for the company in question (Van Aken et al., 2012). In order to achieve this goal, the project approach is discussed here.

4.1 The forecasting process approach

The forecasting process, for the quantitative forecasting methods, is normally executed in the subsequent activities (Montgomery et al., 2015):

1. Problem definition
2. Data collection
3. Data analysis
4. Model selection and fitting
5. Model validation
6. Forecasting model deployment
7. Monitoring forecasting model performance

As can also be seen in Figure 8 that illustrates the steps within the forecasting process.

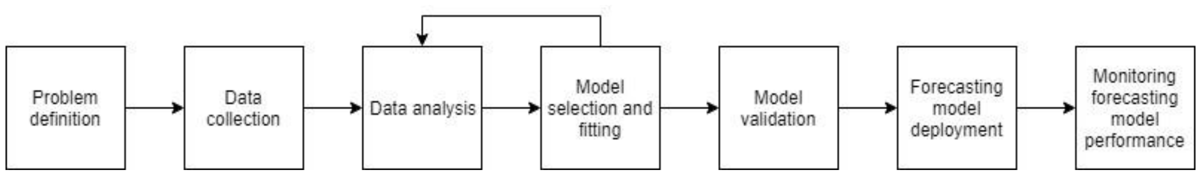

Figure 8: The forecasting process (Montgomery et al., 2015)

The problem definition activity covers the determining and defining of the forecasting components. Here alignment needs to be made with what the desires and expectations of the forecast user(s) are and how the forecast will be going to get used. In the data collection step relevant historical values of the variables that are going to be forecasted need to be obtained, as well as historical data from other obtainable possible predictor variables. Here it is often also necessary to deal with data-related problems that have occurred in the past such as potential outliers or even missing values. Thereafter follows the data analysis which forms a crucial step prior to the forecasting model selection. During the data analysis the historical data should be organized and visually inspected for pattern recognition like trends and seasonality. This information normally indicates which quantitative forecasting methods need to be examined. Then these selected models can be applied and fitted to the data in the next step. In the fifth step the models need to be validated by analyzing the forecasting errors in order to get the “best” functioning model. In this step it is important to keep in mind that selecting the model that gives the best fit to historical data does not necessarily result in a forecasting method that also produces the best forecast for future data (Montgomery et al., 2015). After having identified the right applicable model it is important to initiate the deployment of the forecasting model. This activity consists of making sure that the user(s) of the forecast model understand(s) how to apply and continuously generate timely forecasts as a routinely ongoing process. The last step, monitoring of the forecasting model performance is a crucial activity because of the fact that businesses grow, evolve and their conditions change over time. This means that the models' performance may decline after having performed well before and there needs to be ensured that these models keep on performing adequately. Consequently, monitoring of forecast errors is needed for a valuable forecasting system design. The last two steps of the forecasting process will not be described in this thesis report. However, this project report can be seen as the needed input for delivering the forecasting model deployment.

4.2 Capacity planning approach

One effective heuristic way for deriving the optimal usages of the capacity is by using the classic "newsvendor" model (also called the newsboy problem). This model can be considered as one of the stepping stones for decision making in Operations Management (Olivares et al., 2008). In this model the newsvendor has to decide what amount of a specific asset (in this case newspapers) he needs to buy at a fixed price per unit. In this problem-state, only the probabilistic forecast of the demand is known of the specific asset which is sold for a fixed price. This newsvendor problem can also be applied in many other settings.

When a firm faces a situation like the newsvendor problem it can control, but not prevent, the probability of a demand-supply mismatch: leftovers for having too much capacity, but plan too little and incur the opportunity cost of lost sales. So, an organization always has to deal with this problem since it commits to the supply before demand occurs. A firm has the opportunity to react to early demand (forecast) information by implementing reactive capacity. It can considerably decrease but never dispose the mismatch cost that occur in the newsvendor's situation. The MTO is an extreme situation to the newsvendor. An MTO process is also not unaffected to the problems of demand-supply mismatches since it functions as a queueing system. Consequently, customers have to wait before their demand is fulfilled and the extent of their waiting time is related to the amount of available capacity (Cachon & Terwiesch, 2008).

The problem can be seen as the optimal trade-off between the costs that arise with missing revenue by not having capacity available, and the costs of having capacity available that is in the end not utilized within a DC. The newsvendor model will therefore serve as an inspirational approach and starting point for the capacity planning tool that will be presented in chapter 6.

5. The forecasting process

In this chapter the forecasting process is executed. For this, the subsequent steps of the forecasting process approach of section 4.1 are followed. In that order section 5.1 first defines the problem definition step, section 5.2 covers the data collection step, the data analyses are performed in section 5.3. The performance measurement metrics, that are used in the following sections, are introduced in Appendix E. The model validation step of the current forecast's performance is determined in section 5.4. In section 5.5 the exponential smoothing method and the general linear forecasting model are introduced. Lastly in section 5.6 all the performance evaluations from the different forecasts are summarized in a clear overview.

5.1 Problem definition

Defining the forecasting problem forms the most crucial part of the forecasting process. It requires a thorough understanding of the way the forecast will be utilized, who requires the forecasts, and how the forecasting fits the needs and requirements within the organization. Hyndman and Athanasopoulos (2018) also state: "*A forecaster needs to spend time talking to everyone who will be involved in collecting data, maintaining databases, and using the forecasts for future planning*". This follows from looking back at the business problem that is discussed in chapter 2. Expert interviews have been held with several managers, analysts and distribution planners who are knowledgeable about the forecasting problem, in order to collect the right information and formulate the right forecasting elements. These aspects are described below.

Forecast horizon: The forecast horizon is the length of the periods that need to be forecasted and depends on the nature of the process. In other words, it depends on the time that is required to plan or modify the operations and activity schedules. Different types of setups and models are also necessary, depending on what the forecast horizon is set too (Hyndman & Athanasopoulos, 2018). With respect to the current work flow, the forecast horizon needs to be 1 week. Therefore, the project is focused on short-term forecasting which is needed for the capacity of production personnel of the VAS process the next week. More specifically the forecasts needs to be made no later than the Thursday for the total amount of hours of the whole week thereafter. This results into that only information that is known on and before that Thursday can be used in order to predict the whole amount of VAS hours for the next week in total.

Forecast interval: The forecast interval stands for the regularity of preparing and rolling out new forecasts. Currently the business process makes use of a weekly forecast interval, therefore the forecast interval of this project is also on a weekly schedule, since this research project is driven by improving this current weekly forecast performance. As stated above the forecasts need to be rolled out every Thursday for the coming week. Consequently the forecast interval will remain the same.

What level of accuracy: Since the project is focused on a performance improvement, the level of accuracy that needs to be obtained is at least performing on par and preferably even better than the current forecasting accuracy. Therefore, the current forecasting performance needs to be analyzed first, this is evaluated in subsection 5.4.

What level of product aggregation: NIKE currently makes a differentiation between retail and wholesale for the VAS process, therefore the forecasting aggregation is split up into retail and wholesale labor hours. Another type of aggregation the forecasts could be split into are the product categories (e.g. footwear, apparel and equipment). However, the forecasts in this project will be aggregated on DC level, due to business needs and requirements. More specifically the forecasts are produced for one DC, the APP12 DC. This brings some extra challenges into the forecasting problem, since there has been some movement of product categories from one DC to another over the years. There is data available for indications of what the product transfers are in future situations these are also assumed to be 100% correct, however in practice this isn't always the case. Since all this data wasn't easily available for the project due to time restrictions a different approach has been incorporated in the prediction model to take this phenomenon into account. This will be explained in more detail in section 5.2.

5.2 Data collection

Now that it has been determined what the forecasts requirements are, the next step is to find and collect the data on which the forecasting model will be build. In the data collection step relevant history values of the variable that is going to be forecasted need to be obtained, as well as historical data from possible predictor variables. Gathering the right data for developing a suitable forecasting method forms a large part of the forecasting process. The model that can be used in forecasting and the way in which it can be used is also heavily depending on the available data and resources (Hyndman & Athanasopoulos, 2018). Therefore, the first step is to collect data that is consumable (usable). Different type of data variables have been collected over time, where along the project additional useful variables have been obtained.

The first and most important data source that is collected, is the historical daily VAS labor hours. The data that could be collected is the data from the time period FY14-FY19. This data can be found within the daily process management (DPM)[9] files. The actual VAS processed labor hour data are not representing the perfect demand data due to slight capacity management influences on a daily basis. However, it does give a representable reflection of the real experienced demand. Especially since NIKE always strives to fulfill the customer demand needs. It is assumed that specifically on the higher weekly and monthly aggregation levels of the VAS DPM data, the VAS labor hours reflects the real demand patterns, since these values wouldn't be affected by the slight alteration of capacity management influences on the daily level. The historical VAS demand data will be analyzed in section 5.3.

The second source of data that is collected are the historical monthly forecasts. These are the "*1060 VAS FYXX*" (FY14-FY19) files. This data is needed in order to create insights to find out how the current forecasting is and was performing on a monthly level. In addition the third source of data that is collected are the, currently used, most detailed forecasts. The detailed forecasts data of FY19 is collected, however data of prior years is sadly not available any longer. Therefore, the accuracy analysis of how the current most detailed forecasting is performing will be limited to only FY19. AS stated in section 2.1.2, the most detailed forecasts are the combination of the monthly forecasts from wholesale on a weekly aggregation (from the "*1060 VAS FYXX*" files) and the weekly rolled out "*DTC forecast day level*" for retail.

[9] DPM is an integrated file reporting on all operational fields on a shipping point (DC) level. The data from these files are used for operational decisions throughout the organization.

The above-mentioned data sources were provided in many Excel files. The DPM files contain loads of different data from the APP12 DC besides the VAS labor hours. Data from FY14 until FY19 was collected from 72 monthly Excel files. The relevant historical hourly VAS labor data is extracted from these Excel files by using Alteryx[10]. The Alteryx workflow that has been constructed in order to extract the relevant daily VAS data from these monthly DPM files is illustrated in Figure 9.

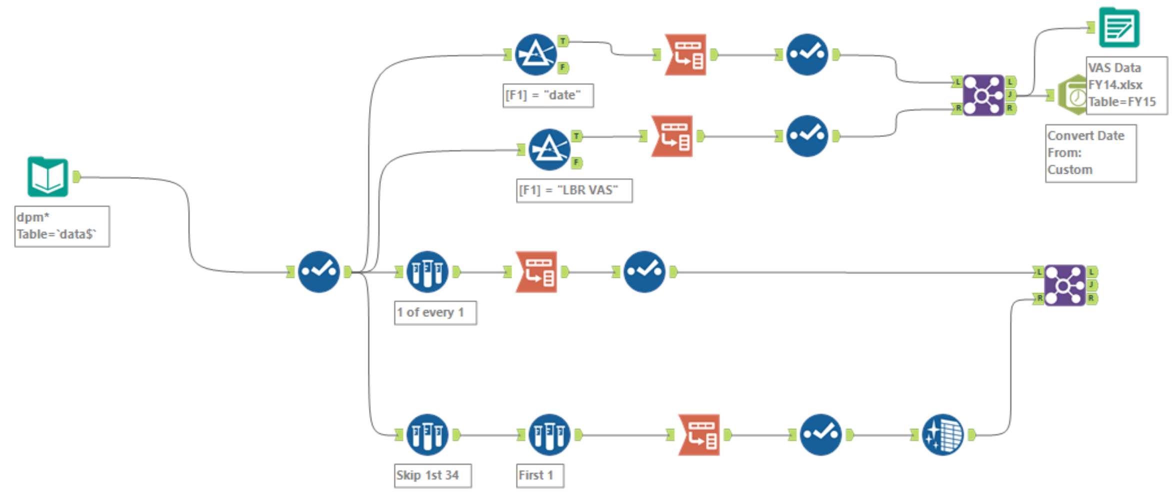

Figure 9:Alteryx data collection workflow

Here the data was imported into the workflow from the DPM files. The DPM files were imported per FY in order to extract the data from multiple monthly DPM's at the same time. After importing, the relevant columns are selected for the data for each day in the month. Afterwards the unwanted data of the DPM's is filtered so that the VAS data and the dates from that data are getting extracted, transposed and, in the end, joined together. The end of the workflow writes down the data into a new and all including usable Excel file. The detailed forecasts data from FY19 were provided into 52 different Excel files. In order to put these data files into one useable "database" the workflow of Figure 9 was slightly altered for this data extraction. The same was done for putting the historical monthly forecasts (the "*1060 VAS FYXX*" files) for FY14-FY19 together that were acquired from a cloud drive. After extracting, constructing and cleaning up the data, followingly the data analysis can be performed in section 5.3 and the existing forecasting performance evaluated in section 5.4.

To make predictions of a variable of interest there can be more important variables and factors that can have an influence, rather than only its own **historical values**, **trends** and **seasonality's**. Capturing these important variables and factors lays the foundation of creating a good functioning forecasting model. A useful explanatory forecasting model can be developed with incorporating information about other variables. Therefore one should ask the question:

" What other variables and factors affect the too be predicted weekly VAS labor hours? "

---

[10] Alteryx is a leader in data science and self-service analytics with a platform that can prep, blend, enrich, and analyze data.

There are several useful predictors that affect the needed amount of VAS labor hours, these have been collected over time. The variables that will be used within this project are listed below.

- **The amount of working days in the week within the DC;** this is obviously a key driver for the amount of VAS labor hours in a week, since less working days results immediately in less available working hours that week. In addition, in case of a fully lost working day, it is rather difficult to incorporate these lost hours in the working hours of the rest of the work week due to capacity limitations and the availability of production personnel. Hence it is an important factor that needs to be taken into account. The amount of working days in the week can be affected by holidays, offside days and other major events that turn a normal workday into a "free" day.
- **The amount of public holidays in the week within the DC;** this relates to the amount of working days in the week, however not every non-working day is necessarily a public holiday and therefore this variable is similarly taken into account.
- **The amount of commercial days in the week;** whether or not there are commercial days in a week, influences the amount of demand heavily. Consumers start to buy more products in these periods and these shopping periods form a major source of revenue for companies and retailers (Swilley & Goldsmith, 2013). Therefore dates of the commercial days such as black week (Cyber Monday and Black Friday), Christmas, Sinterklaas, Valentine's Day, good Friday and Easter are arranged and taken into account, in the forecasting model in section 5.5. This variable is also taken as a **lag** and **lead** variable since it is often the case that a major part of demand is already felt in the week before, due to wholesale orders and supplying the products of their own retail stores. The period afterwards can also be still containing some aftereffects of these demand influxes and is therefore also included as a potential predictor variable.
- **The week number within the year;** with forecasting the aim is to predict how the sequence of observations will extend into the future. Often seasonal patterns play a big role since high and low demand periods often fall into the same period over the years. Therefore it is useful to also take into account this indication of which week number within the year would need to be predicted. The presence and effects of trends and seasonality in the VAS demand data will be analyzed in section 5.3.
- **The month number within the year;** for the same reasons mentioned above it is useful to incorporate which month number of the year the predictions need to be made into the dataset. This has to do with highly seasonal patterns in the retail sector (Alon, Qi & Sadowski, 2001).
- **The year number;** there can be changes within in every fiscal year and therefore it is important to add this indicator as well into the dataset. Since even over the years there can be forms of seasonality present in the data.
- **the amount of PGI[11] VAS units in the week (sales orders);** this variable is an indicator of how much VAS units are planned at a specific date and therefore represents a good predictor for the amount of needed VAS labor hours. These units however are the sales orders that are planned and can be made a long time ago. Therefore the ultimate end date that these VAS units need to

[11] PGI, is the abbreviation for planned goods issued. This is the **planned** date on which the **planned** unit(s) must be ready to be shipped at the latest in order to be on time as the customer had requested.

be shipped at the latest in order to be on time, as the customer's[12] request, can still change. This variable also doesn't contain all the VAS units yet that in the end actually are requested by the customer. Since predictions need to be made on Thursday for the week after, only the data that is known up to that time can be taken into account. Additional PGI sales orders can still come in after this time period, this information however cannot be taken into account. This variable is compared with the actual VAS units and examined in more detail in section 5.3.3.

- **the amount of PGI VAS units in the week (delivery documents);** this variable is another indicator of how much VAS units are planned at a specific date. The difference with the sales orders is that this is the delivery document that is made for the customer's sales orders request. This is an even more accurate indicator of how much VAS units are planned at a specific date in order to be shipped on time for the customer, since these delivery documents are made on a later date closer to the actual PGI date of the VAS units. For this variable again holds that predictions need to be made on Thursday for the week after, therefore only the data that is known up to that time can be taken into account. Still additional VAS units can be requested after this time period, however this additional information cannot be taken into account for the PGI delivery documents to serve as a predictor variable. The PGI delivery documents variable is also compared with the actual VAS units and examined in more detail in section 5.3.3.
- **the amount of AGI[13] VAS units in the week (lagged values);** this variable represents the actual amount of VAS units that have been made ready to be shipped on a specific issued date. The actuals obviously can't be used as a predictor variable at the moment of making predictions since this is not happened yet. However this variable holds valuable information of the past and can be used to look back on what actually has been the amount of VAS units in a specific week before. Then in a **lagged** manner this information can be taken into account for making predictions of the future. In subsection 5.3.3 the AGI VAS units will be compared to the PGI sales orders and PGI delivery documents.
- **APP3 AGI VAS units; this variable represents the actual amount of VAS units of APP3 that have been made ready to be shipped on a specific issued date.** As stated in section 5.1, there has been some movement of product categories from one DC to another over the years. When the DC of APP3 opened up in June 2017 some stock-transfers have taken place. Since the forecasting model will be created on DC level it is important to take this factor into account. In order to see what effect this movement had on the amount of VAS labor hours in the APP12 DC, the APP3 AGI VAS units data are collected. When APP3 opened up there is a distinct downward trend seen in the VAS labor hours of APP12. Followingly in section 5.3 in the data analysis this effect is exemplified.

5.3 Data analysis

This step will answer the first research question, "*What does the historical and current time series of VAS labor demand data look like?*", by analyzing the historical data of the VAS labor hours. During the data analysis the historical VAS labor data (FY14-FY19) is organized and visually inspected for pattern

[12] The customer refers to the IDP customers that can be either an important wholesale customer or a NIKE owned retail store.

[13] AGI, is the abbreviation for actual goods issued. This is the **actual** date on which also all the **actua**l unit(s) must be ready to be shipped at the latest in order to be on time as the customer had requested.

recognition like trends and seasonality. This information needs to be examined as it gives indications for which important factors need to be considered with the quantitative forecasting method(s). Then these selected models can be applied and fitted to the data in subsection 5.5. The data is analyzed on monthly and weekly aggregation level as the total amount of VAS, Retail VAS and wholesale VAS. The data is analyzed by using the free software and programming language R.

The goal is to isolate patterns in this historical data such as:

- Trend(s)
- Seasonality
- Cycles
- Randomness

In order to do any data analysis, the first step that is executed is plotting the data. The graphs enable visual observations of the VAS pattern changes over time. The features that are seen in the plots of the data will later be incorporated, as much as possible, into the forecasting methods to be used in section 5.5. Just as the type of data determines what forecasting method to use, it also determines what graphs are appropriate and therefore some additional special graphs are given in subsection 5.3.1 and 5.3.2. The data will be plotted against the individual years in which the data were observed. This enables to discover the underlying seasonal patterns to be seen more clearly, and also enables to identify any significant deviations from the usual seasonal patterns (Hyndman & Athanasopoulos, 2013).

In addition, the autocorrelations are measured with the autocorrelation function (ACF). Correlations measure the intensity of linear relationships between two different variables, autocorrelation estimates the linear relationship of lagged values of a time series. The lag stands for the time interval between the observed data values (Montgomery et al., 2015). The lags within the data can't be ignored. Due to the fact that current demand values are affected by the values of the demand in the past. The problem with making predictions without lags, is that the relationship through time is ignored to be taken into account. As a consequence the relationship between the dependent and independent variables wouldn't be correct (Hyndman & Athanasopoulos, 2013).

When the data has a trend, the autocorrelations from the small lags are usually positively large. When the data has seasonality, the autocorrelations should show to be larger at the seasonal lags (e.g., 12 and probably 24, 36, … for reoccurring yearly seasonality in monthly data). When both are present within the data, there should be a combination seen of these two effects in the ACF. In order to compute the ACF function the autocorrelation coefficient at lag k is measured with Equation 1 (Montgomery et al., 2015; Hyndman & Athanasopoulos, 2013):

$$r_k = \frac{\sum_{t=k+1}^{T}(y_t - \mu)(y_{t-k} - \mu)}{\sum_{t=1}^{T}(y_t - \mu)^2} \tag{1}$$

here T is the length of the time series. In order to get a reliable estimate of the ACF at least 50 observations are required to be included (Montgomery et al., 2015). This rule of thumb is always respected in the ACF calculations in this research report. Significant relations found in the ACF's are then later taken into account for the forecasting model in section 5.5.

5.3.1 Monthly VAS demand data

In this subsection the plots of the historical VAS data are illustrated on a monthly aggregation level, in order to discover the trend(s), seasonality cycles and randomness on a higher aggregation level first. This gives an easier overview at first to discover the broader lines of the data. Firstly, the total amount of VAS labor hours on a monthly basis from FY14-FY19 is visualized and can be seen in Figure 10. It can be seen that until the beginning of 2017 there was an upward trend in the total amount of VAS. Thereafter in FY18 and FY19 the amount of VAS labor dropped back into the same ranges as it was from FY14-FY16. This decline is mainly caused by the opening up of another apparel DC APP3. The APP3 DC went live at June 2017 (the start of FY18). However, it took some time before it became fully operational and therefore, slowly more demand transferred to this DC over time. For this reason the VAS demand values in Figure 10 are seen to drop back after FY17. From the graph also some seasonality patterns can be seen, such as peaks at the 6th month of the year and troughs at the 2nd month of every year. But in order to get a better look at these seasonality indications in the data, a seasonality plot is constructed and can be seen in Figure 11. In addition, in order to inspect seasonality another variant of seasonal plots is constructed, here the time axis is circular rather than horizontal in Figure 12. These graphs are representing exactly the same data as Figure 10, however now the data of each year represents a new line in the plot. This way these two graphs show clear patterns that can be perceived within the data. It is clear that there is a trough every year in February, April/May and November. In addition, distinct peaks are seen in March, July and December/January. However, an interesting finding that can be seen in Figure 11 is that also since the opening of the APP3 DC in FY18 (June 2017) the seasonality patterns seem to behave differently. The peaks and troughs are less consistent and deviate more in comparison with the years before.

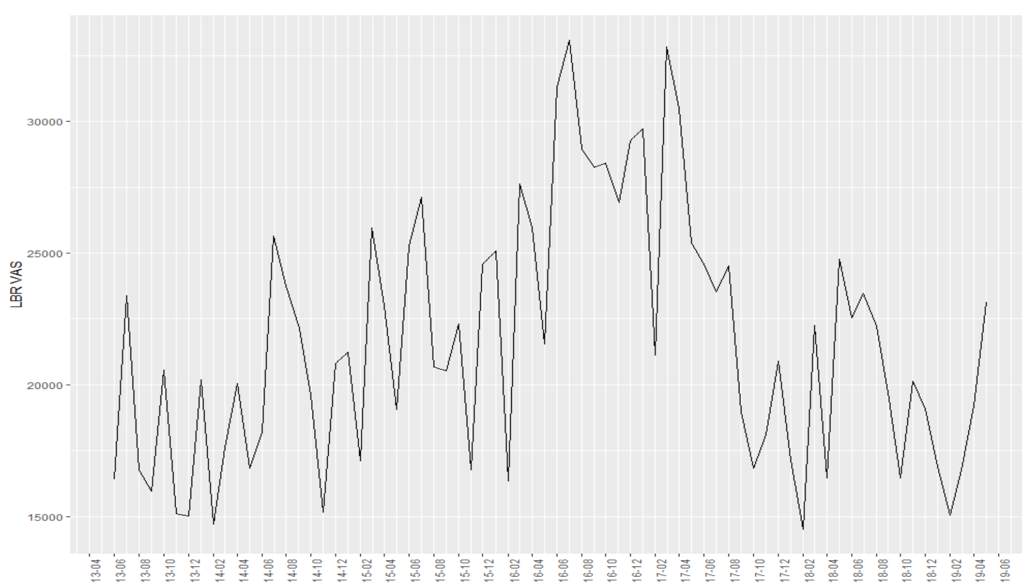

Figure 10:Total actual VAS labor hours aggregated per month for FY14-FY19

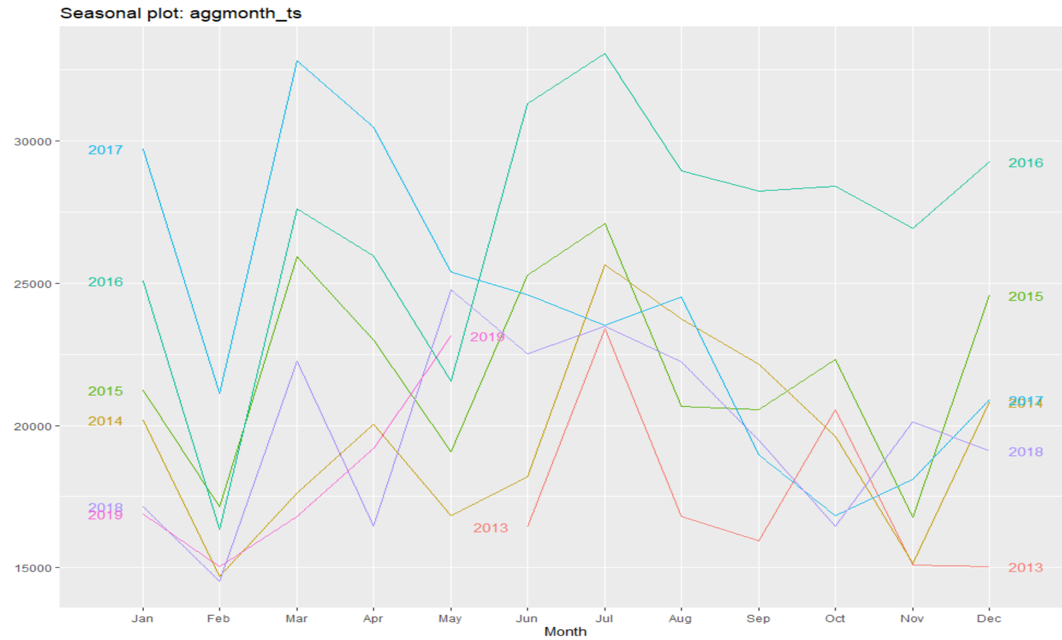

Figure 11: Total actual VAS labor hours aggregated per month for FY14-FY19 illustrated per calendar year

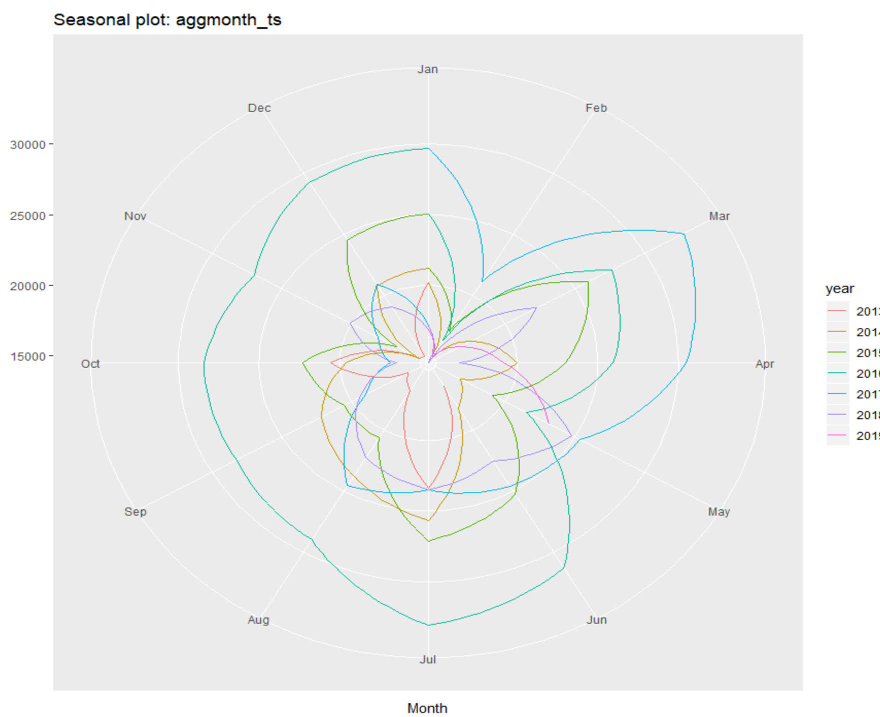

Figure 12: Total actual VAS labor hours aggregated per month for FY14-FY19 polar representation

In order to get an even better understanding of the trends and seasonality present in the data the autocorrelations are quantified with the ACF of equation 1. The results of this ACF for the monthly total actual labor of VAS for FY14-FY19 are plotted in the correlogram in Figure 13. In the graph it can be seen that the small lags r_1 and r_2 are large and positive due to the trend in the data. The lag of r_3 is higher than the other lags. This is due to the seasonal pattern in the data, from returning quarterly effects, the peaks and troughs tend to be a quarter of a year apart from each other. This is a logical seasonal phenomenal that is present in the retail sector, due to the 4 weather seasons that are occurring through the changing weather conditions. The first three lags seem to weaken over time as the same pattern can be seen in the lags of r_4, r_5 and r_6. Where r_4 and r_5 are again caused by the trend and r_6 due to the seasonal effect again that also reappears at r_9 and r_{12}. Which shows that the quarterly, half- and yearly patterns peak at the seasonal lags. The lags underneath the dashed blue lines indicate the correlations that are not significantly and represent the randomness in the data. In conclusion the ACF values of Figure 13 quantifies the relations and confirms the trend and pattern recognitions that were first indicated by analyzing the demand data in Figure 10, 11 and 12.

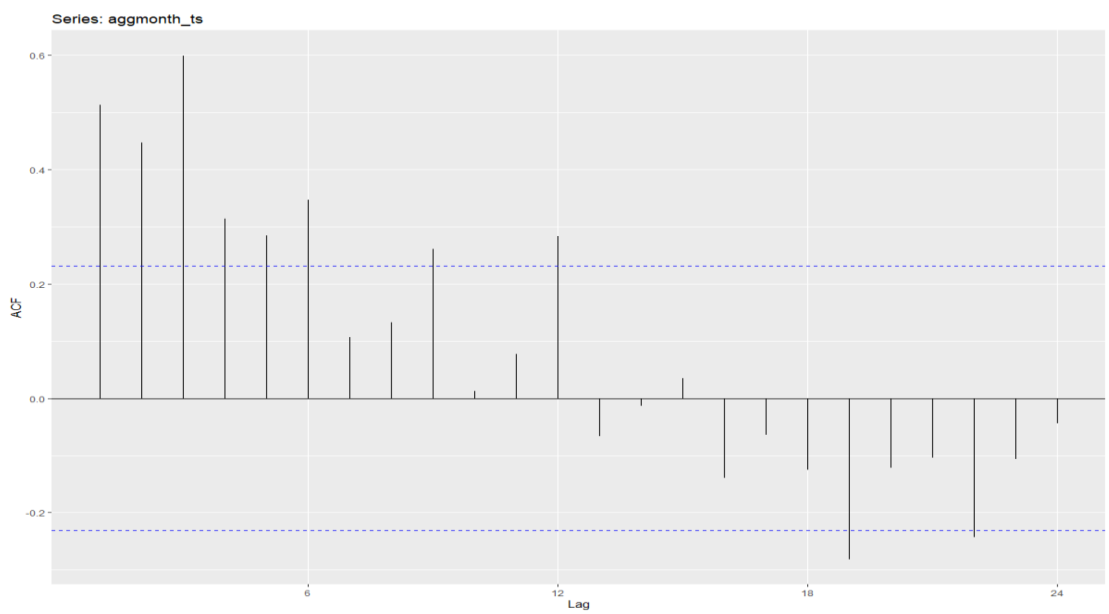

Figure 13: Correlogram ACF of monthly total actual labor hours of VAS for FY14-FY19

5.3.1.1 Monthly Retail VAS demand data

Since Nike executes the VAS process for Retail customers and Wholesale customers it is important to look at these data sets separately. The graphs are presented in Appendix B1.1. In Figure 43 the amount of Retail VAS on a monthly basis from FY14-FY19 is visualized. The graph shows similarities with Figure 10 of the total combined amount of VAS. Again it can be seen that until the beginning of 2017 there was an upward trend in the total amount of VAS. Thereafter in FY18 and FY19 the amount of VAS labor dropped back into the same ranges as it was from FY14-FY16. This again is caused by the opening from the APP3 DC and the stock-transfers to this DC. So it can be concluded that the Retail VAS individually was also effected by the opening of the APP3 DC.

Figure 44 and 45 visualize the seasonality more clearly. Here it can be seen that the Retail monthly VAS data shows less strong seasonal patterns in comparison with the total monthly VAS data before. The monthly Retail demand data displays to be more erratic. This could indicate that the Wholesale monthly VAS causes the main contribution of the seasonality seen in the Total monthly VAS before. Again there is a trough every year in February. Less present is the trough in May and November. The peak in March is again seen however the peaks in July and December/January are less evident. It can be concluded without a doubt that the Retail demand shows different patterns than the combined Total VAS data. Looking at the ACF graph in Figure 46, it can be seen that the significance from the lags decreases quickly after the first couple of lags. Which means that only the first 6 lagged months only have a significant influence on any specific current month. So no perfectly reoccurring seasonality is present in the demand data on a monthly level. In the ACF graph r_1 and r_2 show the presence of the trend in the data again whereas r_3 is large again due to the seasonal pattern in the data. Lag r_4 and r_5 follow the trend pattern again whereas r_6 shows a small and almost neglectable significance of the present half yearly seasonality of the Retail demand.

5.3.1.2 Monthly Wholesale VAS demand data

The graphs of this section are presented in Appendix B1.2. In Figure 47 the amount of Wholesale VAS on a monthly basis from FY14-FY19 is visualized. The graph shows similarities with Figure 10 of the total combined amount of VAS. Again it can be seen that until the beginning of 2017 there was an upward trend in the total amount of VAS. Thereafter in FY18 and FY19 the amount of VAS labor dropped back into the same ranges as it was from FY14-FY16. This again is caused by the opening from the APP3 DC and the stock-transfers to this DC. So it can be concluded that also the Wholesale VAS individually was effected by the opening of the APP3 DC. Figure 47 again shows that every February there are troughs as well as in May and November. Furthermore peaks in March, July, October and December/January are identified. Figure 48 and 49 visualize the seasonal plots and confirm these findings. However, it can be seen that after June 2017 the before so evident patterns start to deviate. The peak in October before the trough in November is not present in 2017 and 2018. In addition the peak in June/July is also less evident in 2017 and 2018 as well as the peak in March in 2019 in contrast to the years before.

In comparison with the combined and the Retail VAS, the Wholesale demand data shows more distinct recurring patterns which were more evident prior to the opening of the APP3 DC. The ACF is plotted in Figure 50 and confirms the stated findings. The lags which show the most significance are the ones that are caused by the seasonal pattern in the demand data. This can be seen in r_3, r_6, r_9 and r_{12}. This validates the assumption that the monthly Wholesale VAS was the main contributor for the seasonality patterns that were seen in the Total combined monthly VAS data.

5.3.2 Weekly VAS demand data

In this subsection the plots of the historical VAS data are illustrated on a weekly aggregation level. Since the forecasting horizon is on a weekly level and the forecasting interval also needs to be on a weekly schedule it is of importance to also specifically look at the trend(s), seasonality, possible cycles and randomness of the weekly VAS demand data. First, the total amount of VAS on a weekly basis from FY14-FY19 is visualized and can be seen in Figure 14. In this graph the upward trend until the beginning of 2017 in the total amount of VAS labor hours is even more visible in comparison with the graph in Figure 10, that showed the VAS labor hours on a monthly level. In addition, the same holds for the downward trend thereafter in FY18 and FY19 in Figure 14, here it is clearly shown that exactly after the opening of the APP3 DC at June 2017 the amount of VAS labor started to decline. The seasonality patterns from the graph in Figure 14 are more difficult to conclude on a weekly level due to the high fluctuating values. Therefore, in order to get a better look at these seasonality indications in the data, again seasonality plots are constructed and can be seen in Figure 15 and Figure 16. It is clear that there is a trough every year in the weeks of February, April/May and November. In addition, distinct peaks in the weeks of March, July and December/January. The most noticeable pattern is the sudden big increase (seen as a peak) after every lowest trough. Since, after every trough there is a big increase from three/four weeks that is getting lower afterwards in a step-wise manner in the weeks that follow. So, it can be concluded that there is a clear sign of seasonality in the VAS total labor hours.

To confirm and get an even better understanding of the trends and seasonality present in the total actual VAS labor hours aggregated on a weekly level, the weekly autocorrelations are quantified with the ACF of equation 1. The results of the weekly ACF for the total amount of VAS labor from FY14-F19 are seen in Figure 17. The decrease in the ACF as the lags increase represents the trend in the data. Therefore, the lags from r_1 up to r_{10} decrease. The up and down scalloped shape seen in the correlogram is due to the seasonality in the VAS demand data. For this reason the lags start to increase again around r_{12}, r_{13} and r_{14}. Afterwards the same effect extends towards to lag r_{25} and r_{26} where the ACF peaks again due to the seasonality that is occurring at a 12/13 week period. The same reason holds for the lags at r_{38}/r_{39} and r_{52}/r_{53} where the seasonal effect reappears and the latter one shows the high autocorrelation at the yearly lags. The lags underneath the dashed blue lines indicate the autocorrelations that are not significantly and represent the randomness in the data. In conclusion the ACF values of Figure 17 verify the trend and pattern recognitions that were first indicated in Figure 14, 15 and 16. In addition it quantifies these important relations within the data.

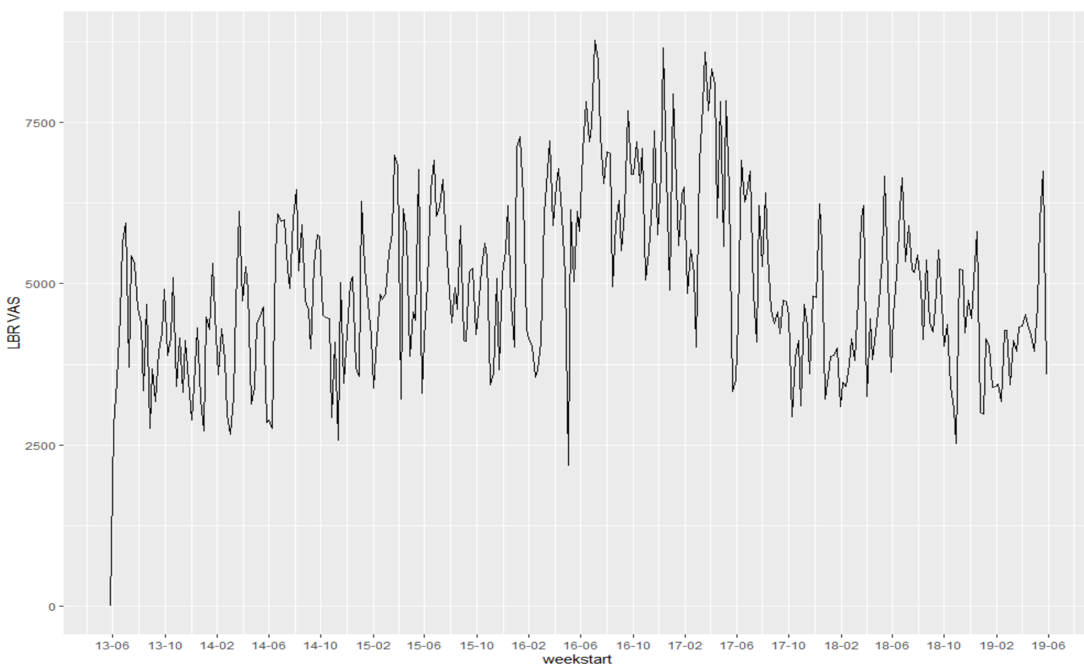

Figure 14:Total actual VAS labor hours aggregated per week for FY14-FY19

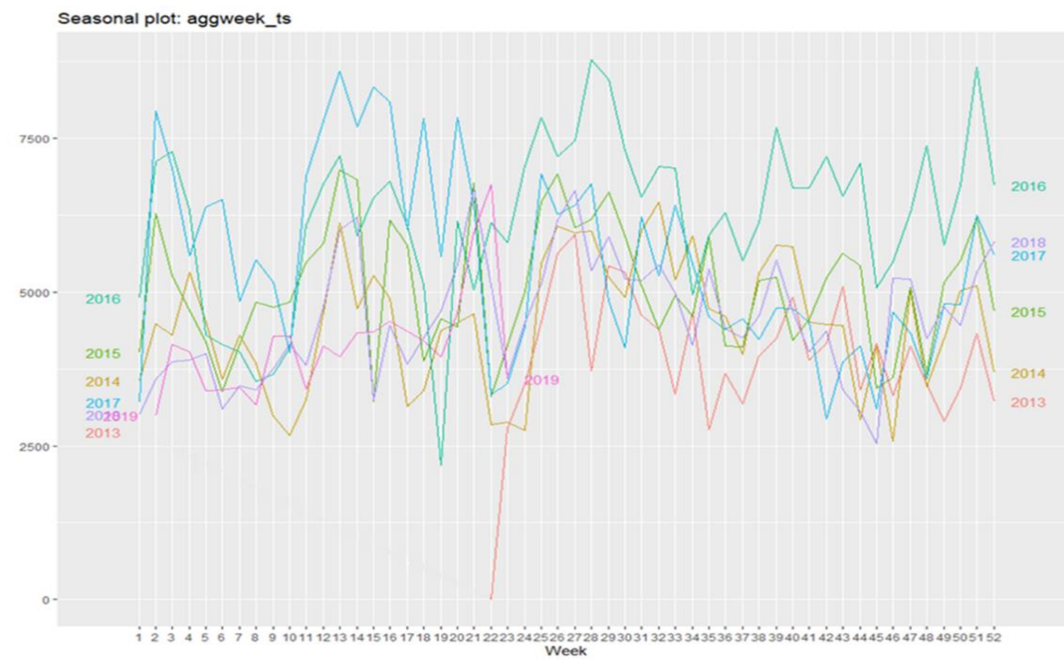

Figure 15:Total actual VAS labor hours aggregated per week for FY14-FY19 illustrated per year

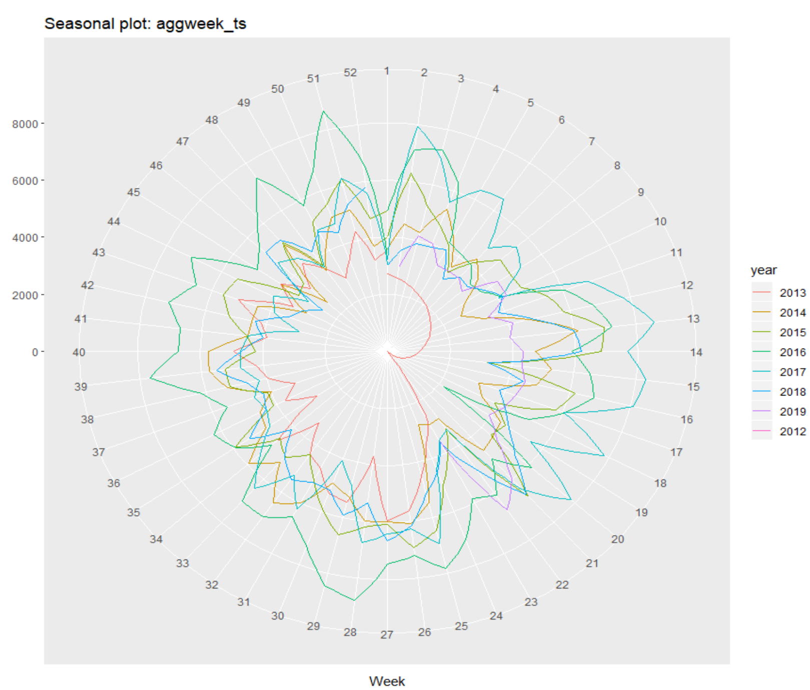

Figure 16:Total actual VAS labor hours aggregated per week for FY14-FY19 polar representation

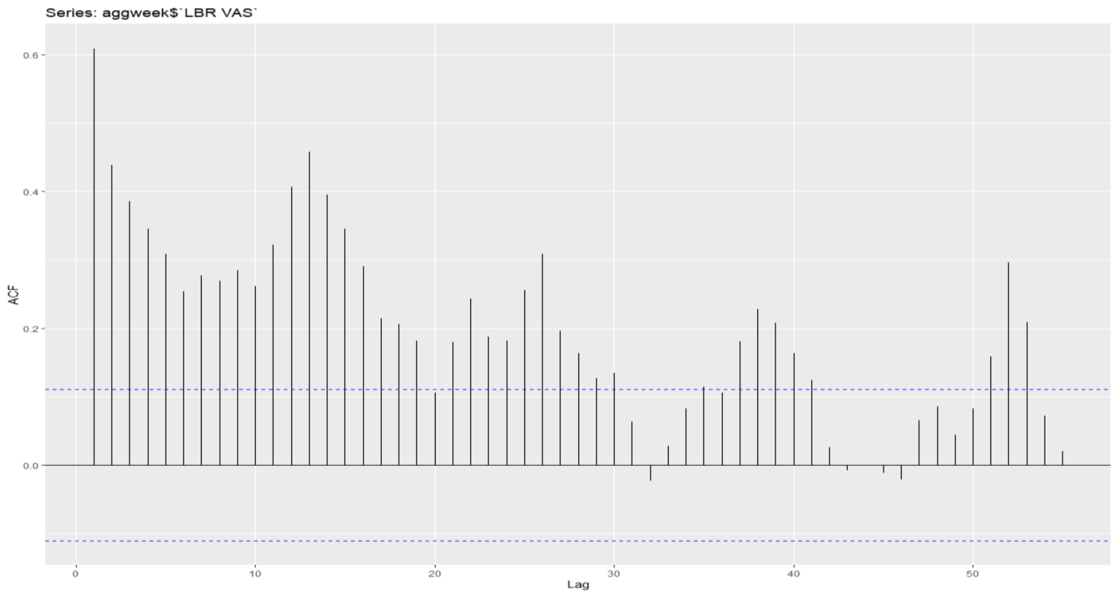

Figure 17: Correlogram ACF of weekly total actual labor hours of VAS for FY14-FY19

5.3.2.1 Weekly Retail VAS demand data

Since Nike executes the VAS process for both Retail customers and Wholesale customers it is important to look at these data sets also separately again on a weekly level. The graphs of this section are presented in Appendix B2.1. Looking at Figure 51 the amount of Retail VAS on a weekly basis from FY14-FY19 is visualized. The demand data demonstrates to behave highly erratic by showing many fluctuations. Here it can be seen more clearly that also until the beginning of 2017 there was an upward trend in the amount of Retail VAS labor hours. Thereafter in FY18 and FY19 the amount of VAS labor dropped back again as the same ranges from FY15 and FY16. As stated before also the Retail VAS drop is affected by the opening from the APP3 DC as the demand data starts to drop after June 2017. Looking at the graph for seasonality it is difficult to verify any clear seasonality patterns. Even plotting the data against the individual years in the seasonality graphs of Figure 52 and 53 it is still hard to discover any underlying seasonal patterns. The only real observation that can be established from these graphs is that the peaks and troughs roughly follow each other every 12/13 weeks. The ACF graph is created again to better understand and estimate the linear relationships of the data values. Figure 54, shows indeed minor signs of the seasonality pattern by showing higher values at the lags r_{13}, r_{26} and r_{52} compared to the surrounding lags. The other significant lags show the importance and presence of the trend in the data. The smaller lags are the most related to any current weekly value. Especially the values of demand from one week before any other week seem to show big significant relations as can be seen by the high value of r_1.

5.3.2.2 Weekly Wholesale VAS demand data

The graphs of this section are presented in Appendix B2.2. For the data analyses of the weekly Wholesale VAS, Figure 55 visualizes the graph from the total actual demand of Wholesale VAS labor hours aggregated per week for FY14-FY19. It can be seen that the slope of the upward trend until the beginning of 2017 is not as big in comparison with the weekly Retail VAS demand increase of that same period, in Figure 51. Again it can be perceived that roughly around the opening date of the APP3 DC the weekly wholesale demand data for the APP12 DC started to decline in FY18 and FY19. The seasonality patterns in the VAS demand data are difficult to identify in Figure 55, hence as before seasonality graphs are illustrated in Figure 56 and 57.

The seasonality graphs display distinct seasonality patterns over the years. As most of the peaks and troughs fall in the same weeks year after year. This can be seen by the overlying lines in the seasonality graphs in roughly the same weeks. This results in that the seasonality pattern follows a similar path over the years. With distinct peaks in weeks 1 to 4 followed by a trough in weeks 5 to 11. Thereafter the next big influx of demand is shown in the graph from weeks 12 to 16 with a steep fall of demand in the weeks right after. Then roughly in between the weeks 19 to 22 a small peak of demand increase is seen over the years with a sudden trough in weeks 23 and 24. Followed by again a big demand increase afterwards in approximately week 25. The weekly VAS demand levels are decreasing in the weeks after until around week 38 to 43 where again an increase of demand is observed. This demand peak is followed by the last trough of all the years in weeks 44 to week 48 where after the demand start to rise again to the last weeks of the year. The above stated weekly demand pattern over the year holds for most of the years. However, FY18 and FY19 start to deviate from the clearly overlapping patterns from the years prior to the opening of the APP3 DC. Especially the before so evident peak in weeks 1 to 4 is where the biggest deviation is seen from the seasonality pattern.

In order to confirm the mentioned seasonal demand pattern and get a better understanding of the autocorrelations in the wholesale VAS weekly hours, the correlogram is demonstrated in Figure 58. The autocorrelation coefficients of the ACF indeed illustrate a strong seasonal pattern with the scalloped shape. The higher lags around r_{13}, r_{25}, r_{38} and r_{52} than the other lags are due to the seasonal pattern in the data; where the peaks tend to be roughly 13 weeks apart and the troughs tend to be also roughly 13 weeks apart. The lower negative lags at r_{20}, r_{32}, r_{45} and r_{58} are showing negative coefficients because the troughs tend to be around 8 weeks behind the peaks. The lags underneath the dashed blue lines indicate the correlations that are not significant. In conclusion the ACF values of Figure 58 confirm the trend and pattern recognitions that were first indicated in Figure 55, 56 and 57. These patterns, trends and relations in the data are taken into account with the implementation of the forecasting model in section 5.5.

5.3.3 Additional variable analysis

In this section additional analysis are implemented to get a better understanding from some of the prediction variables before using them in the forecasting process. For the definitions of these variables the reader is referred to section 5.2. As stated in section 5.2 the AGI VAS units will be compared to the PGI sales orders (PGI SO) and PGI delivery documents (PGI DD). To show the differences between the variables the data of FY14-FY19 is compared, as this is also the data that will be used for the forecasting in section 5.5.

First the difference between the dates of the PGI SO, PGI DD and the date of the AGI VAS is analyzed. Since in section 5.2 it was already highlighted that the PGI SO are made at a longer time period before the actual PGI(thus the AGI) date compared with the PGI DD. What kind of effect this has at the amount of difference in days between the AGI and the PGI SO expressed in amount of VAS units can be seen in Figure 18 and 19. Figure 18 shows the amount of difference in days between the AGI and the PGI SO VAS amounts in percentages. Whereas, Figure 19 displays the amount of difference in days between the AGI and the

PGI SO VAS amounts in units. The days with a negative sign refer to the amount of days that the AGI date is later than the original PGI SO date. In Appendix C a list is given with potential reasons for deviations between the PGI and AGI dates. In the graphs it can be seen that the major part of the AGI date is indeed also executed at the original PGI SO date. This is illustrated by the biggest peak in the graph of 14.0%. However, this means that 86.0% of the AGI VAS is not happening at the original PGI SO date. Looking at a time span of a difference within a week it can be seen that 39.3% of the AGI VAS from the original PGI SO date is completed. Therefore, it can be concluded that this variable gives a good indication for the expected amount of VAS units in a week however more information is needed to come up with good forecasts.

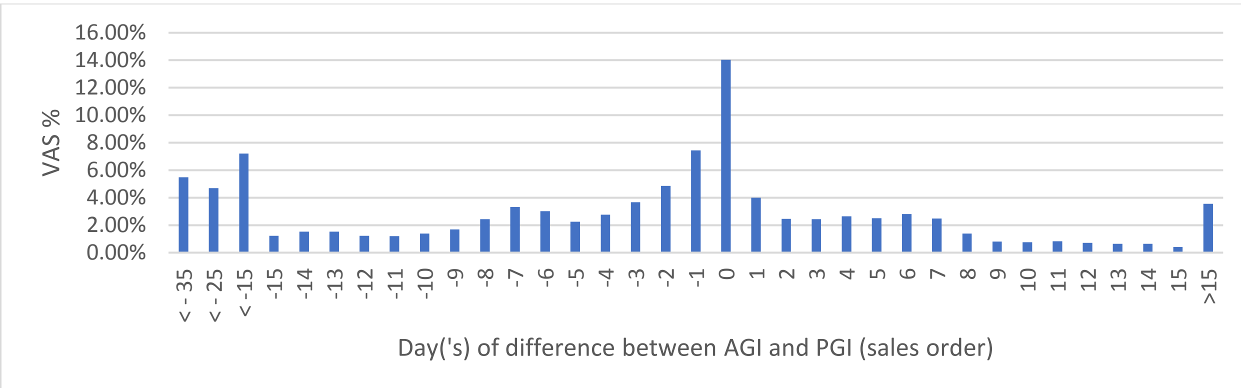

Figure 18: Amount of difference in days between the Actual and the sales order Planned VAS amount (in percentage)

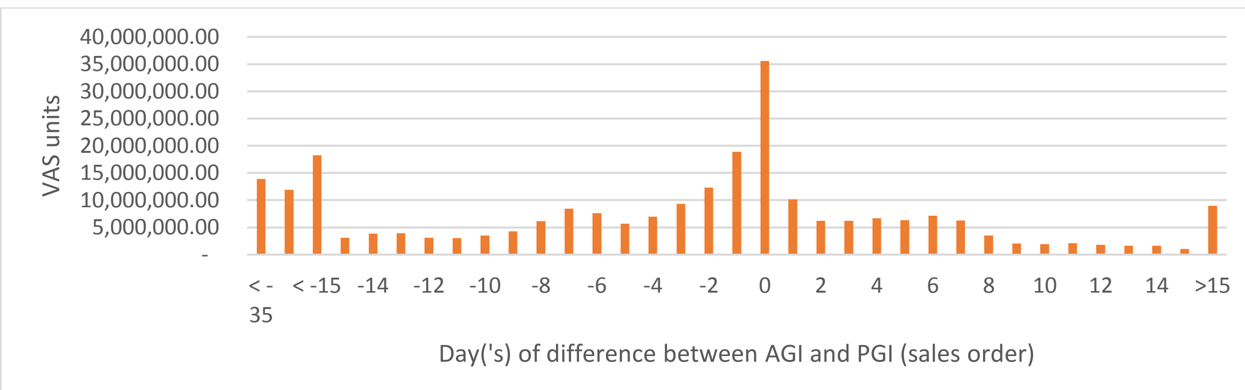

Figure 19: Amount of difference in days between the Actual and the sales order Planned VAS amount (in units)

The PGI DD dates are requested and made from the earlier sales orders with the customers at a nearer date towards the actual planned date. Therefore this is a more accurate indicator of how much VAS units are planned at a specific date in order to be shipped on time for the customer. Figure 20 and 21 indicate what kind of effect this has at the amount of difference in days between the AGI and the PGI DD in amount of VAS units. Figure 20 shows the amount of difference in days between the AGI and the PGI DD VAS amounts in percentages. Figure 21 displays the amount of difference in days between the AGI and the PGI DD VAS amounts in units. The days with a negative sign refer to the amount of days that the AGI date is later than the original PGI DD date. In Appendix C a list is given with potential reasons for deviations between the PGI and AGI dates. Looking at the amount of difference in days between the AGI and the PGI

DD in amount of VAS units, it can be concluded that indeed the PGI DD are much more consistent with the AGI date. As can be seen within the graph that 79.2% is indeed also executed at the PGI DD date. Looking at a time span of a difference within a week it can be seen that 90.3% of the AGI VAS from the original PGI DD date is performed. Hence it can be concluded that this gives a useful indication for the amount of VAS units that can be expected to be requested in a week.

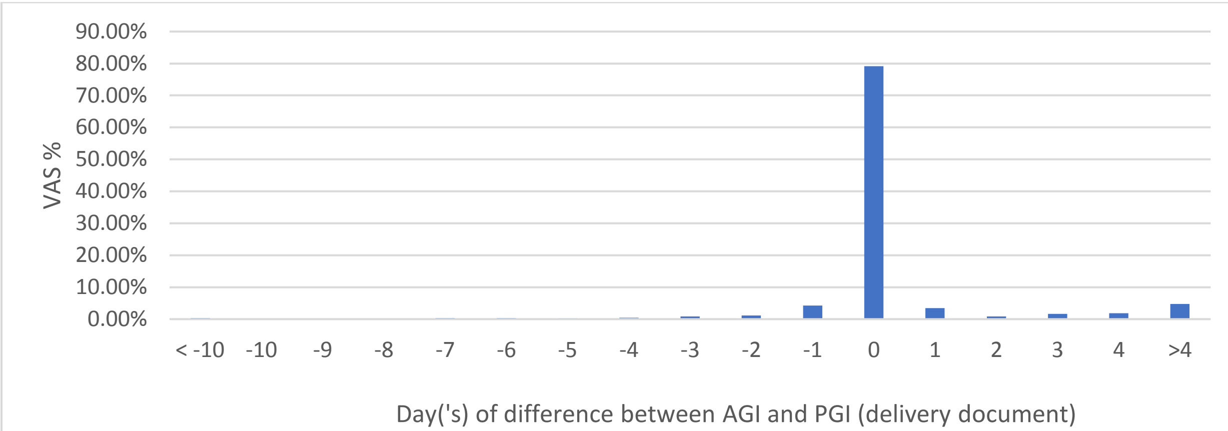

Figure 20: Amount of difference in days between the Actual and the Planned (delivery documents) VAS amount (in percentage)

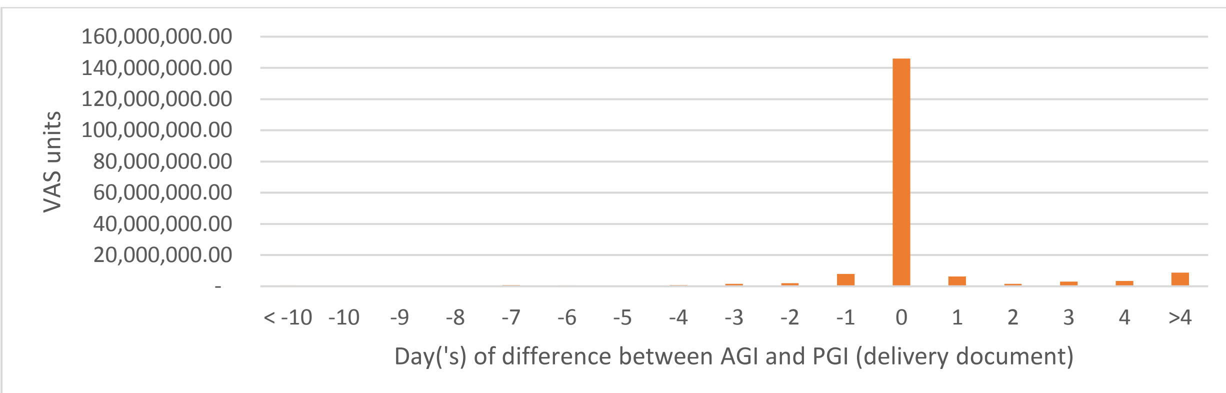

Figure 21: Amount of difference in days between the Actual and the Planned (delivery documents) VAS amount (in units)

Besides analyzing the differences in days between the AGI and the PGI SO and DD, it is important to see what the differences are in the VAS units. These differences can be seen in Figure 59 to Figure 86 that are included in Appendix D. In these graphs only the information of the PGI SO and the PGI DD VAS amounts known on and before the Thursday when forecasts need to be made for the upcoming week are taken into account. Since this is the information that can be used as input for the forecasting model. The graphs show the differences between the AGI VAS units, the PGI SO and the PGI DD for Retail Figure 59-70 and Wholesale Figure 71-82 for every FY, from FY14 to FY19. In Figure 83 to Figure 86 these differences are made more explicit in the graphs where only the line of the differences between the Actual VAS units and the planned VAS units is illustrated. This is demonstrated only for FY19 to just aid in making the differences clear between the variables, in order to perceive this discrepancy more visibly. From these graphs it can be seen that there are indeed bigger differences between the AGI and the PGI SO compared to the differences between the AGI and the PGI DD. This holds for both wholesale and retail. Therefore these graphs show that these two variables contain valuable information for the amount of VAS units that can be predicted in a week. However these variables alone are not the solution, nonetheless useful indicators of what can be expected. Hence they can serve as valuable input as prediction variables for the forecasting model.

In addition to the earlier data analysis a correlation matrix with scatterplots is generated, to show the correlation between the demand of VAS hours, the PGI SO, the PGI DD and the amount of VAS at APP3. The matrices in Figure 22 and 23 help to visualize the relationship between the variables. This is beneficial as it indicates a predictive relationship that can be exploited for forecasting. On the diagonal each variable is represented. The matrix is symmetrical with the correlation shown above being a mirror image to the scatterplots below the diagonal variables. The correlation coefficient only measures the strength of the linear relationship, also called the Pearson correlation coefficient (r) (Hyndman & Athanasopoulos, 2018; Moore & Kirkland, 2007). Here the correlation between variables x and y is given by:

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

Where n is the sample size, x_i and y_i are the individual sample points with i as index, $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$ which is the sample mean (this holds analogously for $\bar{y}$. The bigger the illustrated number of the coefficient the greater the statistical significance of that correlation. In addition the number of stars indicates the significance level. Each significance level is associated to a symbol:

$$p - values(0, 0.001, 0.01, 0.05, 0.1, 1) \Leftrightarrow symbols\ (\text{“ *** ”, “ ** ”, “ * ”, “.”, “ “})$$

The p-value shows the probability of the correlation coefficients, the probability that the relationship between two variables is equal to zero (null hypotheses; no relationship). Where correlations with low p-values have a strong correlation, since the probability that the variables do not have a relationship is pretty low. In the literature correlations are usually statistically significant when the p-value is lower than 0.05 (Moore & Kirkland, 2007).

In the wholesale scatterplot in Figure 38, it can be seen that the relation between the demand of VAS labor hours(LBR Wholesale) and the PGI SO VAS units(Wholesale planned SO) is positively strong, with a correlation coefficient of 0.32. The relationship between the PGI DD VAS units and the VAS labor hours seems to be stronger, as can be seen by the higher correlation coefficient of 0.54. This confirms the earlier stated relation, that the PGI DD VAS units give a better indication for the amount of VAS labor demand compared to the PGI SO VAS units. Lastly, it can also be seen that indeed the APP3 DC causes the weekly Wholesale demand data for the APP12 DC to decline. This can be seen by the negative coefficient for the LBR Wholesale and the amount of Wholesale VAS percentage at APP3, that shows a significantly strong negative relationship.

The Retail variables show also strong significant relationships which the demand of Retail VAS labor. Where it can be seen in Figure 39 that the Retail VAS labor hours(LBR Retail) has a positively strong relationship with the PGI SO(Retail Planned SO) of 0.63, with in addition a high significance. For the Retail PGI DD(Retail Planned DD) also holds that it is has a stronger relationship with the VAS labor demand in comparison with the PGI SO, as can be seen by the correlation coefficient of 0.82. Therefore for Retail it also holds that the PGI DD VAS units give a better indication for the amount of VAS labor demand compared to the PGI SO VAS units. Also the strong negative correlation coefficient for the LBR Retail and the amount retail percentage at APP3, confirms the relationship that the APP3 DC causes the weekly Retail demand data for the APP12 DC to decay. The correlation coefficient is lower compared to the Wholesale correlation coefficient. Therefore it is likely that the APP3 DC affects the Retail labor demand at the APP12 DC differently than the Wholesale labor demand. Stock transfers from the DC's are on category level and division. It is possible that the product categories for Retail orders are mainly located in APP12. Retail customers offer primarily lifestyle and regular sport products, while Wholesale customers offer most of the time more specific categories (e.g. Golf and Tennis products).

In conclusion the findings in the exploratory data analysis step serve as useful inputs for the next step in the forecasting process, the forecasting model selection and fitting. The gathered information gives indications for which important factors need to be considered with the quantitative forecasting method(s). Then these selected models can be applied and fitted to the data in section 5.5.

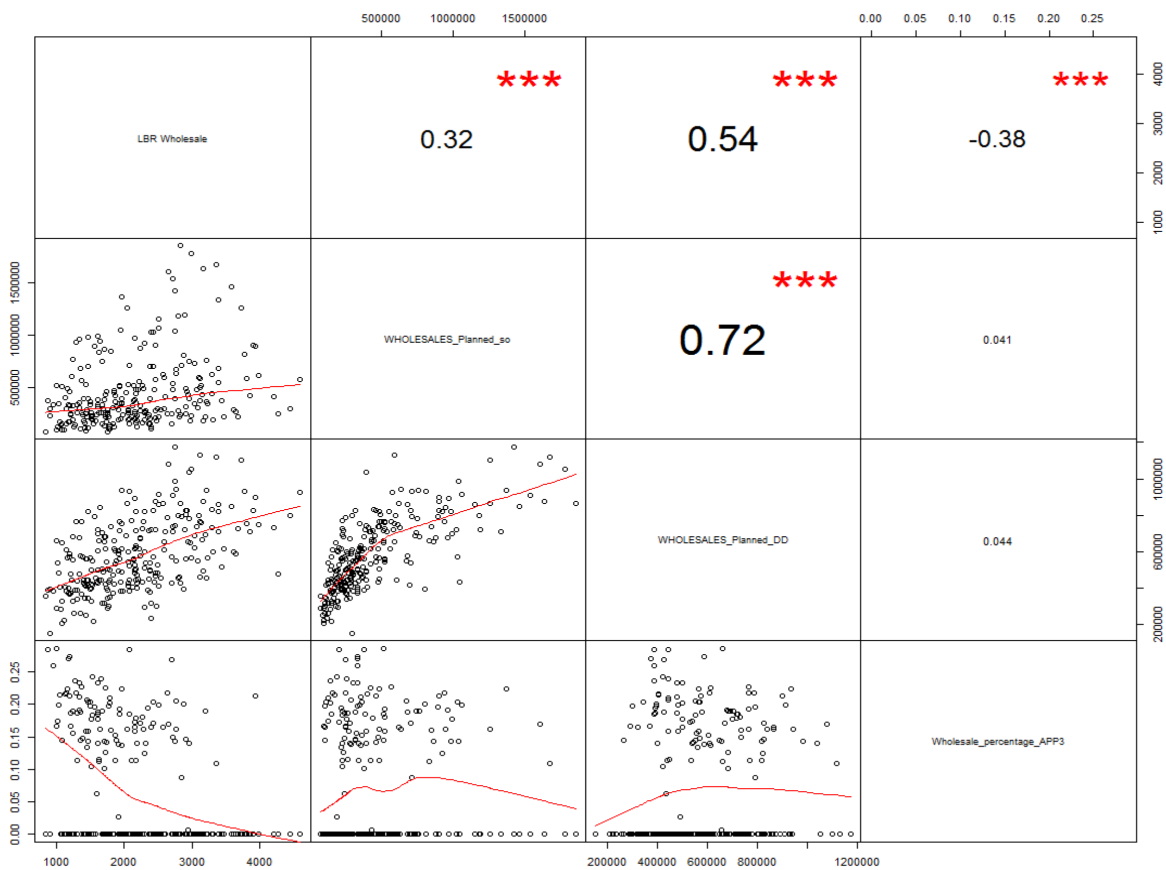

Figure 22: Scatterplot matrix with correlations of the Wholesale variables

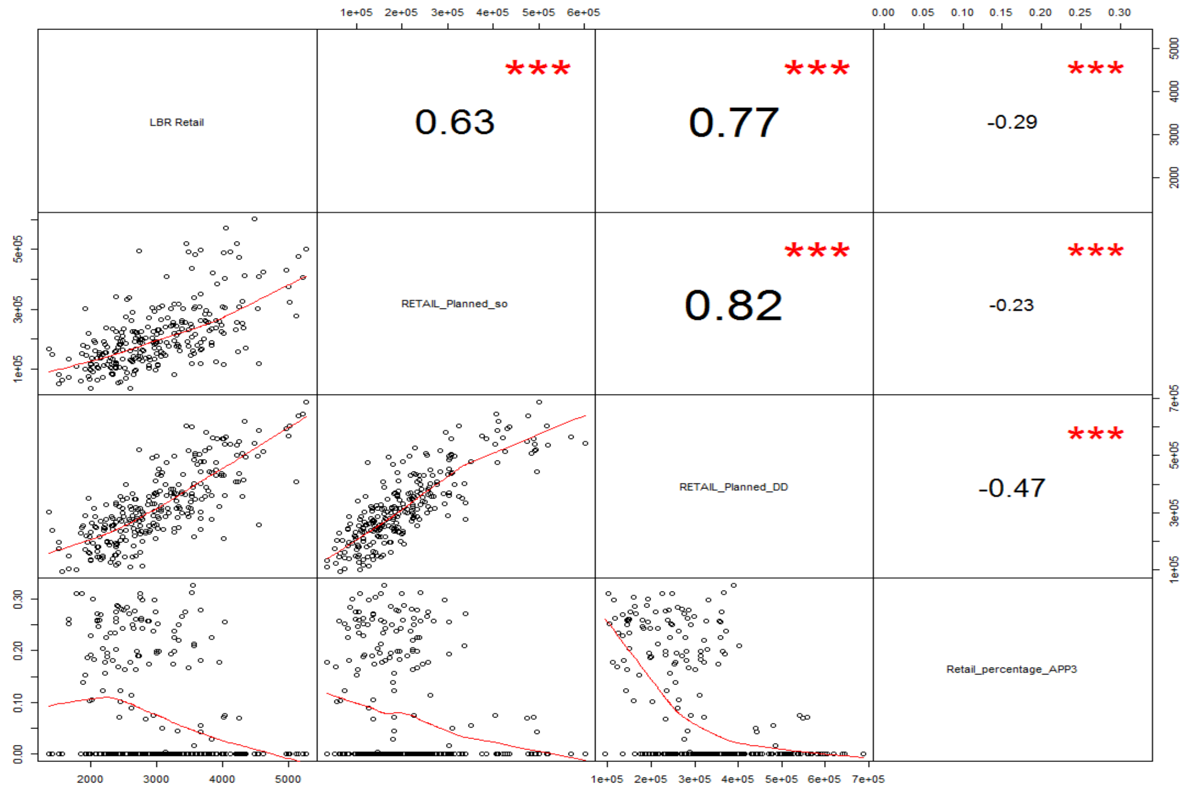

Figure 23: Scatterplot matrix with correlations of the Retail variables

5.4 Current forecasting performance

Currently there are no clear insights into how the current forecasting process is performing. Hence the second research question in section 2.3 stated: "*How is the current VAS forecasting process performing for APP12?*" Therefore, in this section it is investigated where the forecasts deviate the most from the actual VAS labor demand. This means that it needs to be identified what the performance (accuracy) of the current forecasting situation is on each aggregation level. This is also important in order to set the bar for trying to obtain better results with the improved forecasting model that will be constructed within this project in section 5.5. Resulting in comparing the monthly and weekly actual VAS amounts of retail, wholesale and the total combined amount against the current forecasted amounts from FY14-FY19. For each of the forecasting levels a summary of the performances will be given with the performance metrics (from Appendix E): ME, RMSE, MAE, MPE and the MAPE. The statistical software program that is used for the performance analysis of the forecasts is the programming language R.

5.4.1 Monthly forecasting performance

In this subsection the monthly total, Retail and Wholesale forecasting performances are examined. In order to test the forecasting performances, the monthly forecasts from the "*1060 VAS FYXX*"(see section 2.1.2) files are used. These forecasts are provided during the goalsetting meeting at the beginning of the month. In the meeting the forecast of the current month and the next two months are received. The most recent monthly forecast of each month is taken for the comparison of the forecasting performance with the actual demand values.

The monthly VAS forecasting results of the total combined, Retail and Wholesale forecasting values from FY14-FY19 can be seen in Figure 24, 87 and 88 respectively (Figure 87 and 88 are presented in Appendix F). These graphs display the comparison of the monthly total combined, Retail and Wholesale VAS demand (labeled as "Actual") and their forecasted (labeled as "FC") values in the past. The results of the monthly total combined forecasting accuracies for FY14-FY19 are given in Table 1. In addition the result of the monthly forecasting accuracy for only FY19 can also be seen in Table 1, for comparison reasons. It can be seen that the forecasts were less accurate in the final year, as the actual demand exceeded most of the forecasted monthly VAS values, hence also the high ME. The corresponding monthly forecasting performances of the Retail and Wholesale VAS from FY14-FY19 are also displayed in Table 1. From the ME it can be concluded that on average the forecasting values from the combined and Wholesale VAS have been lower over the years than the actual VAS demand. Whereas the negative ME in the Retail VAS forecasts indicates that the forecasts have been slightly exceeding the demand over the years. The MAE results of the Retail and Wholesale forecasts are fairly close, however this doesn't indicate that they also perform as good. The Retail VAS consists of higher demand and forecasting values. Therefore, looking at the MAPE, it can be seen that the Retail forecasts have been performing better than the Wholesale forecasts, with a difference of 3.93% in the MAPE. Figure 87 and 88 also show that the Wholesale forecasts have more deviating demand and forecasting values than the Retail forecasts.

In the individual depth interviews, that have taken place in the problem definition phase, it was revealed that the stakeholders at NIKE haven't perceived the monthly forecasts to be causing significant trouble. It can also be concluded that these forecasts are performing decent with having a MAPE of 10.39% for the monthly total VAS forecasts. Nevertheless, the result is that on average the actual demand and the forecasted demand have an absolute deviation of 2171.02 hours per month, for the combined total monthly VAS.

Model	ME	RMSE	MAE	MPE	MAPE
Monthly Total VAS Forecast FY14-FY19	391.67	2697.49	2171.02	1.06	10.39
Monthly Total VAS Forecast FY19	2571.81	3135.71	2606.69	12.91	13.12
Monthly Retail VAS Forecast FY14-FY19	-78.37	1796.82	1384.19	-2.52	11.82
Monthly Wholesale VAS Forecast FY14-FY19	470.04	1760.79	1401.35	4.75	15.75

Table 1: Forecasting performance monthly total combined, Retail and Wholesale VAS forecasts for FY14-FY19

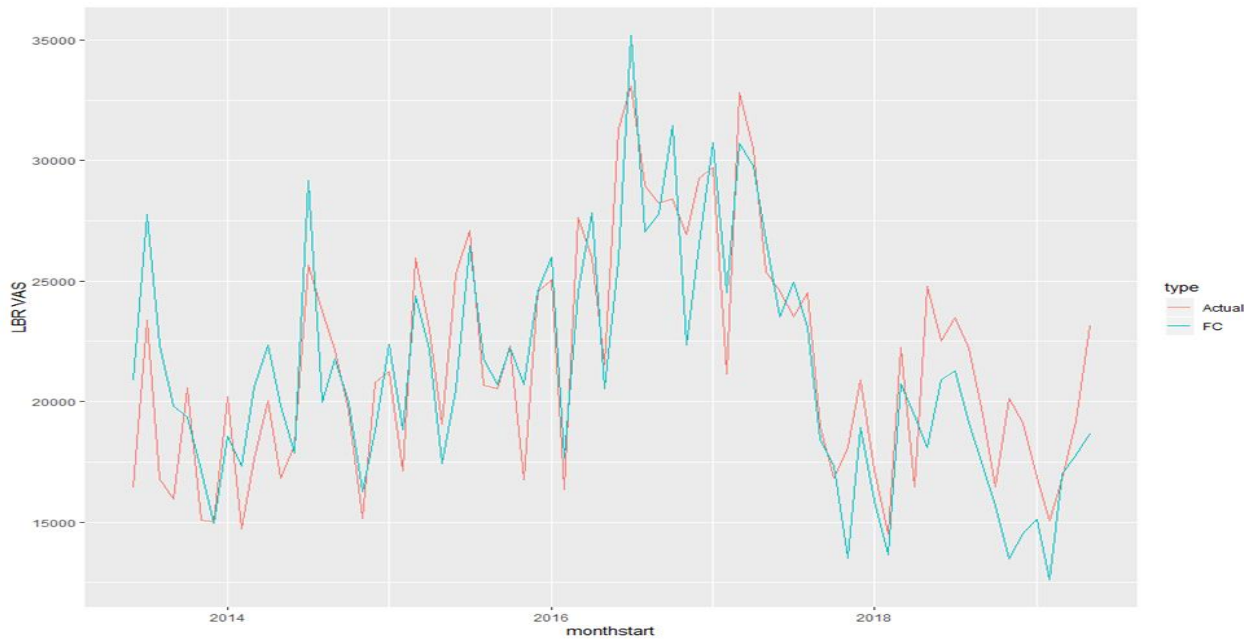

Figure 24: Total monthly forecasted and actual labor demand of VAS per month for FY14-FY19

5.4.2 Weekly forecasting performance

In this subsection the weekly forecasting performance is examined for the total, Retail and Wholesale VAS forecasts. According to several managers, analysts and distribution planners that have been approached for the individual depth interviews, the current weekly VAS forecasts are deviating too much at times from the actual demand. Based on the experiences of these experts, it is a recurring event that there is a significant gap between the forecasts and the actual occurring VAS demand. Consequently, determining these forecasting performances is vital for possible further improvements. These forecasting performances are then used as benchmarks for evaluating the proposed forecasting models of this research project in section 5.5. As the objective of this master thesis project is to determine a good forecasting method, that is able to perform better compared to the current forecasts, in order to have a better anticipation on the demand that can be expected.

For comparison on the weekly and most detailed forecasts, only data of FY19 is used, due to data availability. This detailed forecast is the combination of the monthly forecasts from wholesale on a weekly aggregation (from the "*1060 VAS FYXX*" files) and the weekly rolled out "*DTC forecast day level*" for retail. The weekly VAS forecasting results of the total combined, Retail and Wholesale forecasting values from FY19 can be seen in Figure 25, 26 and 27 respectively. The graphs compare the forecasts(characterized as "Current Prediction") with the weekly total combined, Retail and Wholesale VAS demand (characterized as "Actual"). The corresponding forecasting performances are presented in Table 2.

Model	ME	RMSE	MAE	MPE	MAPE
Weekly Total VAS Forecast FY19	330.37	961.97	668.22	5.90	14.87
Weekly Retail VAS Forecast FY19	-166.47	560.40	420.85	-7.39	16.47
Weekly Wholesale VAS Forecast FY19	452.45	728.33	502.51	20.29	24.91

Table 2: Forecasting performance weekly total combined, Retail and Wholesale VAS forecasts for FY19

It can be seen that the forecasts are indeed deviating significantly from the actual demand. With on average per week an absolute deviation of 420.85 hours for the Retail VAS and 502.51 hours for the Wholesale VAS. Combining the forecasts and comparing it with the total VAS demand results in a MAE of 668.22 hours per week. Looking at the MAPE the forecast accuracies result in an average 16.47% absolute deviation per week for Retail and 24.91% for Wholesale. Consequently this comes down to an 14.87% average absolute deviation every week for the total VAS forecast. This has a big impact on the staffing levels and therefore also affects the productivity within the DC due to moments of idle or overexploited capacity. This validates the concern of the experts and therefore section 5.5 is focused on creating forecasting improvements, with the goal to diminish excess capacity and improving the lack of capacity for the VAS process of APP12, through developing more accurate forecasting models.

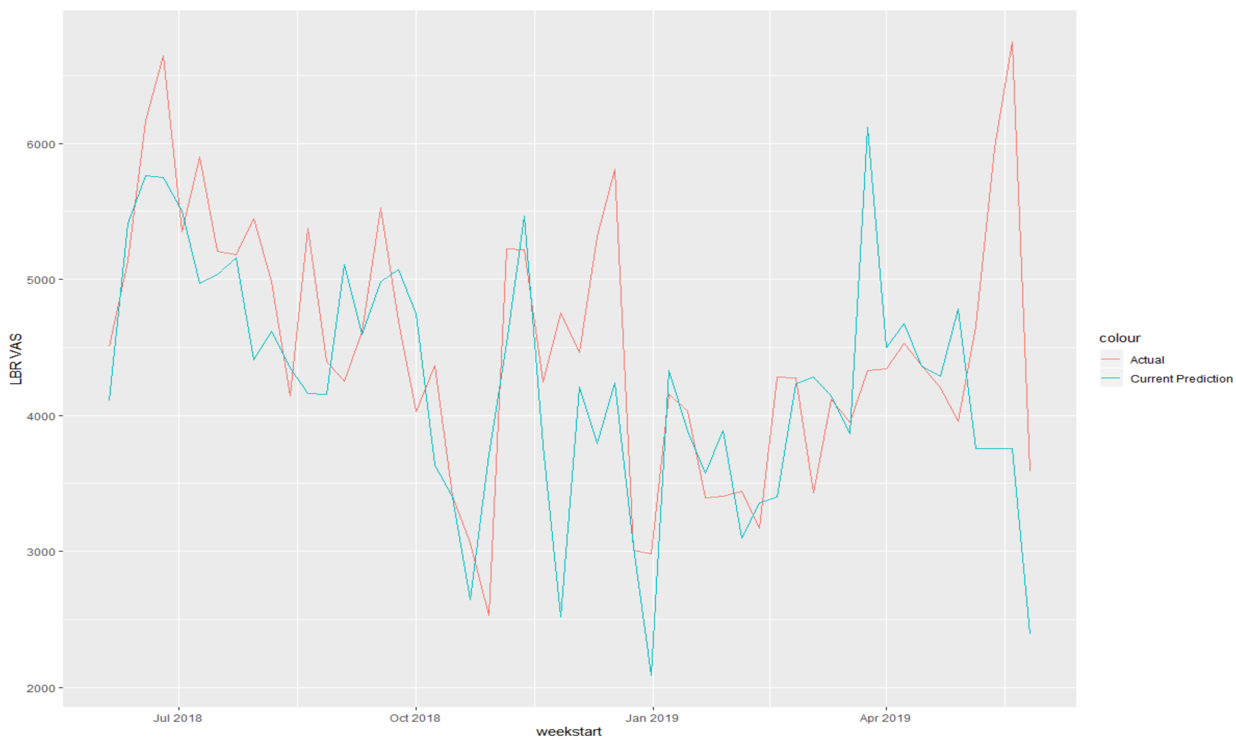

Figure 25: Total weekly forecasted and actual labor demand of VAS per week for FY19

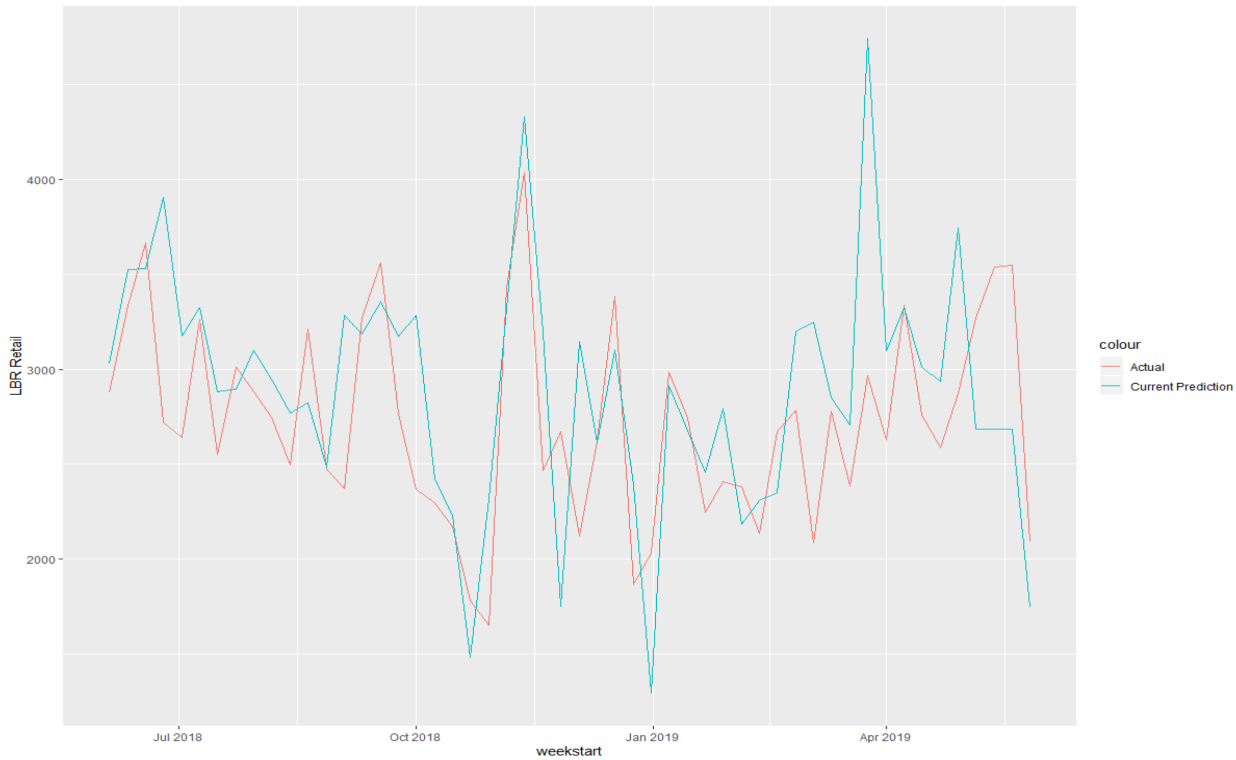

Figure 26: Total weekly forecasted and actual labor demand of Retail VAS per week for FY19

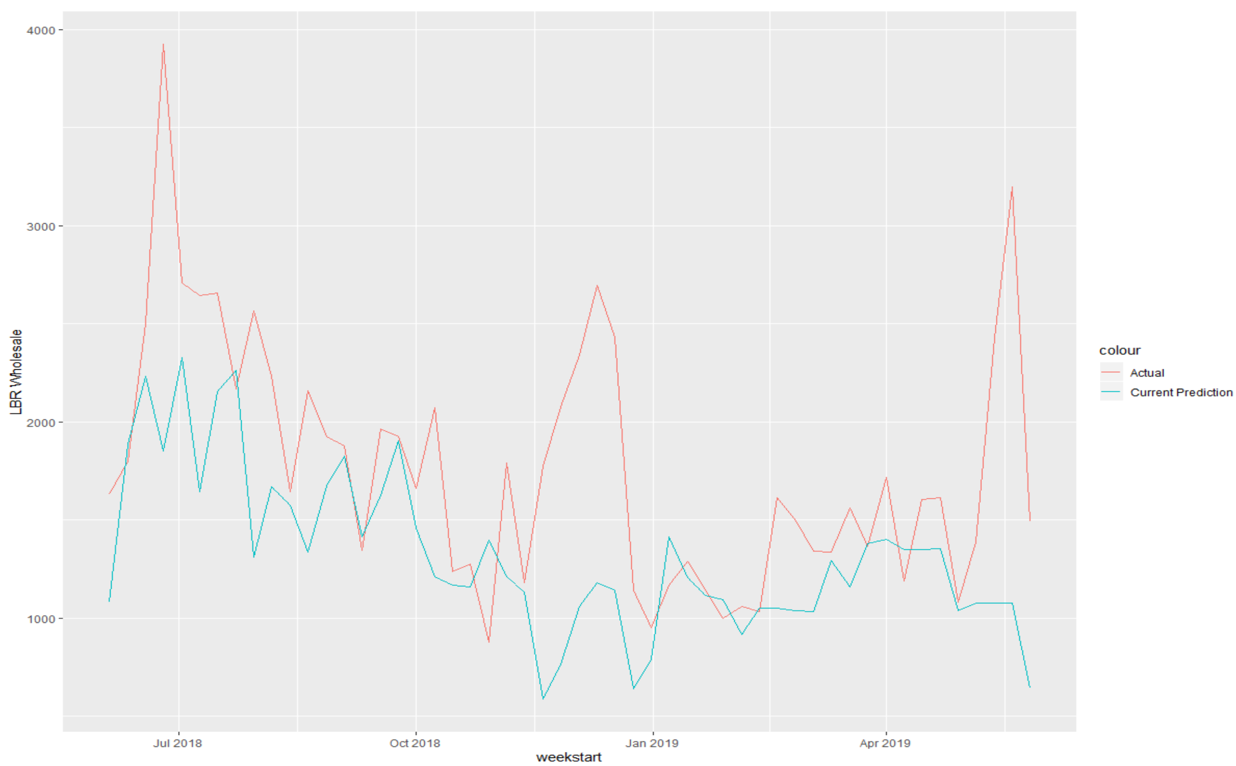

Figure 27: Total weekly forecasted and actual labor demand of Wholesale VAS per week for FY19

5.5 Model selection and fitting

In this section the model selection and fitting of new forecasting methods is realized. The foundation will be made to start answering the third research question: *"What predictive model performs the best to forecast the VAS demand for APP12?"*. For the model fitting(training) the historical VAS data of prior years' FY14-F18 will be used. The data of FY19 will be used as the test set. Hence, the rule of using around 80% of the available data for the training set and 20% for the test set to evaluate the performance is satisfied (Hyndman & Athanasopoulos, 2018). The test set is not used in any way for the development and construction of the models. Instead it is only used for establishing the forecast accuracy of the constructed forecasting models. The training set is used to estimate the forecasting parameters of the forecasting models, whereas the forecasts are made for the test set for accuracy evaluation. This provides important indications on how the forecasting model performs when it is applied to new data. Since most often forecast errors are bigger than the fitting errors, and therefore show reliable information on which forecasting models perform the best (Montgomery et al., 2015).

Which model performs the best depends on different factors such as, historical data availability, the significance of the relation between the prediction variables and the forecast variable, and in which manner the forecasts need to be utilized (Montgomery et al., 2015; Hyndman & Athanasopoulos, 2018). In addition to this, every model is based on different assumptions and will (always) have room for improvement. Therefore this section will discuss different models that will be applied to the data. Subsection 5.5.1 handles exponential smoothing and subsection 5.5.2 general linear models. These subsections will also include the more specific literature part of the forecasting method that is discussed.

5.5.1 Exponential Smoothing forecasting

In the data analysis section it is discovered that there is a strong autocorrelation between the to be predicted week of VAS demand and the previous week of demand. Hence more recent data gives a more important indication of the demand than the older observations. The simple exponential smoothing is a fairly simple method, but it will form a good starting point and extra benchmark for the comparison with the forecasting methods of section 5.5.2.

The exponential moving average(EMA) method is a data smoother and is called the single/simple or first order exponential smoothing forecasting method (Montgomery et al., 2015; Nahmias, 2015; Hyndman & Athanasopoulos, 2018). The important characteristic of the EMA is the responsiveness each forecasting model illustrates to alterations in the input data that is used for calculating the forecast. The EMA assigns the newest observed data with higher weightings. In other words, the weighting decreases exponentially with each older observation. This makes the EMA more reactive to the most recent data changes, as can be seen in the formula here below in Equation 3 (Montgomery et al., 2015; Nahmias, 2015; Chen, Drezner, Ryan & Simchi-Levi, 2000b; Holt, 2004; Ma, Weng, Che, Huang & Xu, 2013):

$$\hat{y}_{t+1|t} = \alpha y_t + \alpha(1-\alpha)y_{t-1} + \alpha(1-\alpha)^2 y_{t-2} + \cdots, \quad t = 1,2,\dots,T \qquad (3)$$

Which can also be written shortly as:

$$\hat{y}_{t+1|t} = \alpha y_t + (1-\alpha)\,\hat{y}_{t|t-1}, \qquad where\ 0 \le \alpha \le 1 \qquad (4)$$

Where $\hat{y}_{t|t-1}$ is the previous forecasted demand value, $\hat{y}_{t+1|t}$ the next predicted value, y_t the current observed demand and α the smoothing parameter, which determines the relative weight assigned to the current observation of demand. Generally, α is small for creating stability of the forecasts. If α is large, then more weight is placed on the more recent observation of demand and less on past observations. To start the exponential smoothing process a first fitted value is needed for the recursive calculations. This value will be noted as $\hat{y}_0$ and needs to be estimated along with the smoothing parameter α. After these values are known the forecasts can be calculated. The parameters are estimated by minimizing the sum of squared errors (SSE) with the following expression (Montgomery et al., 2015; Hyndman & Athanasopoulos, 2018):

$$SSE = \sum_{t=1}^{T} (y_t - \hat{y}_{t|t-1})^2 = \sum_{t=1}^{T} e_2^t \tag{5}$$

where R is used as computation tool to solve this optimization. The forecasts that are made are one step ahead forecasts.

The estimated parameters for the total VAS EMA are estimated to be: $\alpha = 0.4896$ and $\hat{y}_0 = 1802.822$. Hence the EMA model for making the forecasts for the total VAS results into:

$$\hat{y}_{t+1|t} = 0.4896 y_t + (1 - 0.4896)\ 1802.822$$

Estimating the EMA parameters for the Retail VAS forecasting gives: $\alpha = 0.2597$ and the initial state parameter $\hat{y}_0 = 1291.5213$. The corresponding initial EMA model for making the forecasts for the Retail VAS is then as follows:

$$\hat{y}_{t+1|t} = 0.2597 y_t + (1 - 0.2597)\ 1291.5213$$

For the Wholesale EMA the parameters are estimated to be $\alpha = 0.5969$ and the initial state parameter $\hat{y}_0 = 830.7733$. This results into the Wholesale EMA equation of:

$$\hat{y}_{t+1|t} = 0.5969\ y_t + (1 - 0.5969\ )830.7733$$

The graphs of the above fitted EMA models on the trainings data from FY14-FY18 can be found in Appendix G. The corresponding performance values of the fitted models on the trainings data are displayed in Table 3.

Model	ME	RMSE	MAE	MPE	MAPE	AIC
Weekly fitted EMA for the Total VAS on FY14-FY18	28.57	1123.12	885.98	N.A.	N.A.	5124.797
Weekly fitted EMA for the Retail VAS on FY14-FY18	26.60	690.49	550.76	N.A.-	N.A.	4870.861
Weekly fitted EMA for the Wholesale VAS on FY14-FY18	9.06	688.94	531.81	N.A.	N.A.	4869.691

Table 3:EMA forecasting performance weekly total combined, Retail and Wholesale VAS forecasts for fitted trainings data FY14-FY18

The created forecasting models, by the model fitting, deliver the following forecasted values that can be seen in Figure 28, 29 and 30. It can be seen that the forecasts are performing better for the Total VAS and the Wholesale VAS compared to the Retail VAS. The EMA model shows to have difficulties to deal with the highly fluctuating pattern of the Retail VAS. The EMA model functions as a data smoother and this is clearly seen in the forecasts graphs. The resulting forecasting performances of the simple exponential smoothing models are presented in Table 4.

Model	ME	RMSE	MAE	MPE	MAPE
Weekly Total EMA VAS Forecast FY19	-25.78	902.65	691.06	-3.788	16.30
Weekly Retail EMA VAS Forecast FY19	-13.79	546.29	450.50	-4.038	17.11
Weekly Wholesale EMA VAS Forecast FY19	-8.10	554.89	408.95	-6.914	24.50

Table 4: EMA forecasting performance weekly total combined, Retail and Wholesale VAS forecasts for test data FY19

The EMA method could be more effective in situations that deal with less fluctuating demand levels. Since it is a method that only uses old values, which doesn't give actual indications of future unknown demand. However, it still gives a good extra benchmark that even comes close to the current forecasting performances seen in section 5.4.2. Since it even has a better forecasting accuracy for the Wholesale VAS.

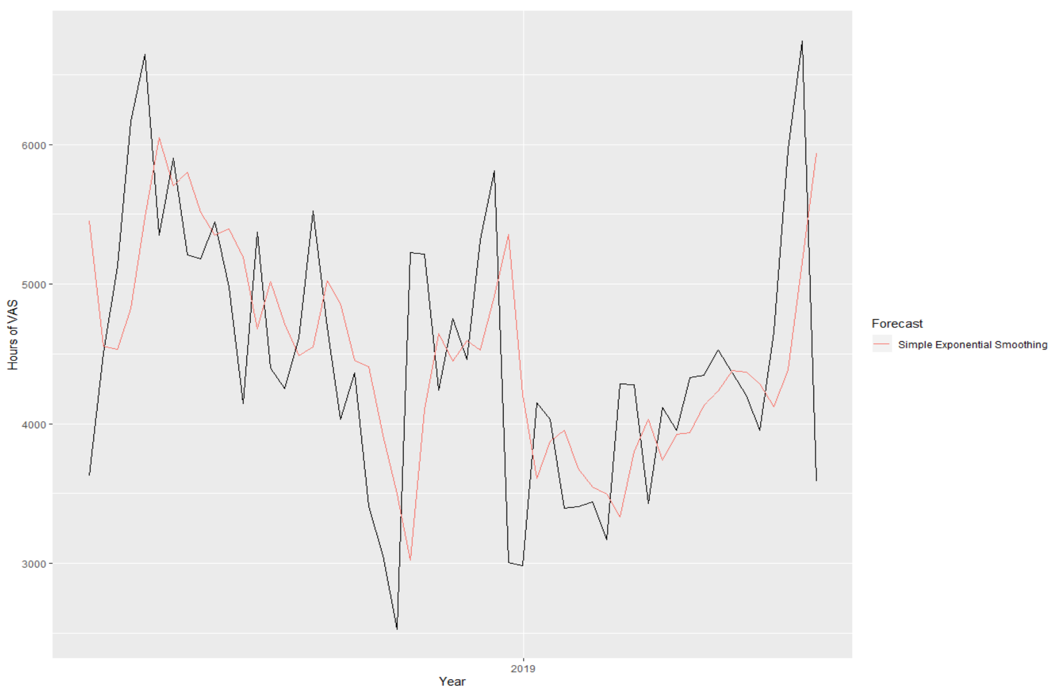

Figure 28: Total weekly EMA forecast generated values and actual labor demand of VAS per week for FY19

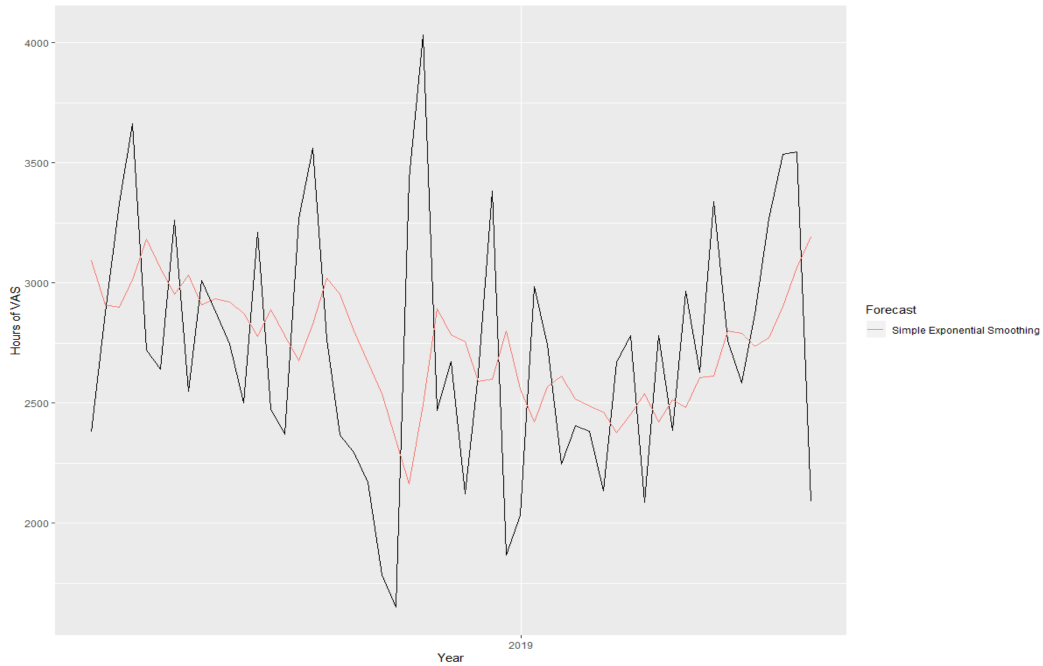

Figure 29: Retail weekly EMA forecast generated values and actual labor demand of VAS per week for FY19

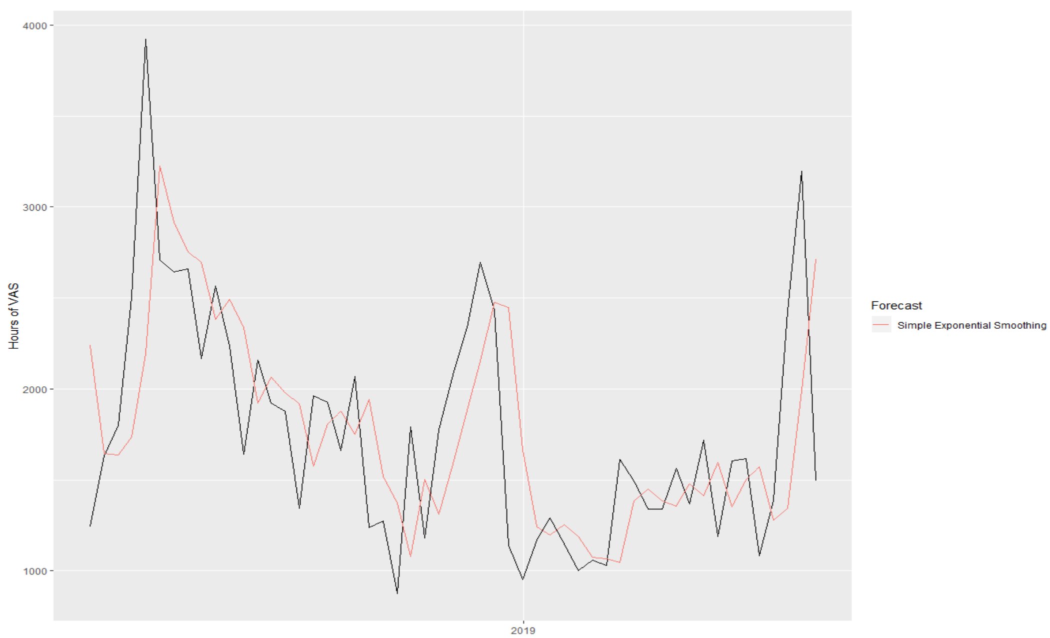

Figure 30: Wholesale weekly EMA forecast generated values and actual labor demand of VAS per week for FY19

5.5.2 General linear model forecasting

The forecasting model that will be constructed needs to take multiple predictor variables, trends and seasonality into account, since these elements have shown to be important in the data analysis. This means that the findings of section 5.3 need to be incorporated in the forecasting model. In addition it needs to incorporate the predictor variables of the historical data and the historical demand values.

Therefore, the forecasting model that will be used is a generalized linear model (GLM) with the H2O package from Nykodym, Kraljevic, Hussami, Rao & Wang (2019) for the statistical software tool R. GLMs are an extension of the traditional linear models. It is a statistical analysis technique that indicates, that the output variable vector y depends linearly on its own preceding values and its corresponding predictor vector x. In other words, it can be used to investigate the relationships between an outcome or response variable and k multiple predictor or regressor variables. The linear regression model with multiple predictor variables is defined as (Montgomery et al., 2015; Nahmias, 2015; Nykodym et al., 2019):

$$\hat{y}_t = \beta_0 + \beta_1 x_{t1} + \beta_2 x_{t2} + \cdots + \beta_k x_{tk} + \varepsilon_t, \quad t = 1,2, \dots, T \tag{6}$$

Here $\hat{y}_t$ stands for the response variable or in other words the predicted value, β_0 represent the intercept term, $\beta_1, \beta_2, \dots, \beta_k$ are the unknown parameters also called the regression coefficients , the vector x represents the different predictor variables (may be continuous, categorical or a mixture), the ε is an error term and $t = 1,2, \dots, T$ is used to denote the number of observations where T then suggest the last possible observation. The regression coefficients $\beta_0, \beta_1, \beta_2, \dots, \beta_k$ are determined by solving the least squares method to establish each predictor's contribution to predicting the dependent variable $\hat{y}_t$.

Usually the response variable $\hat{y}_t$ is normally(Gaussian) distributed with $\hat{y}_t \sim N(x^T\beta_k + \beta_0, \sigma^2)$. The GLM relaxes this assumption and provides a more general regression framework to consider various types of response distributions. More specifically the response distribution of the exponential family of distributions. Since we are trying to predict continuous non-negative outcomes the Gamma distribution and the Gaussian distribution are used (Nykodym et al., 2019).

In conclusion, a GLM in this project consists of the following components:

- A dependent variable $\hat{y}_t$ that has a probability distribution function from the exponential family, that corresponds either to a Gamma distribution or the Gaussian(normal) distribution. Because we are dealing with a response variable that is numeric and always has positive values (since demand for labor hours can't be negative).
- A methodical component that incorporates (linear predictor model) η: $\eta = X\beta$, where X is the matrix of all predictor vectors $x_k$and the unknown parameters β.
- A link function $g: E(\hat{Y}) = \mu = g^{-1}(\eta)$. Since we are interested in building the best predictive model different link functions will be used in combination with the two distributions. The link functions that are used in combination with the two distributions are the identity, inverse and log link function. The link functions are behaving as: the Identity link function as: $X\beta = \mu$, the Inverse link function as: $X\beta = \mu^{-1}$ and the log link function as: $X\beta = \ln(\mu)$

The GLM forecasting models are fitted to the data by solving the following log-likelihood optimization problem with regularization parameters:

$$max_{\beta,\beta_0}(GLM\ Loglikelihood - Regularization\ Penalty) \tag{7}$$

The regularization penalty is performed by the elastic net penalty. Where the elastic net regularization penalty is the weighted sum of the combined penalties of the Lasso (l_1) and Ridge regression (l_2). These penalties are used in order to prevent over-fitting with the creation of the forecasting model. The Lasso penalty leads the optimization problem to a sparse solution with a sufficiently large tuning parameter. By increasing the value for λ, all coefficients are turned to zero. By setting the coefficients to zero the usage of the Lasso penalty removes them from the model. This way the model only makes use of a smaller number of variables that have a crucial interpretability to the forecasting model. The Ridge regression keeps all the predictors in the model but shrinks them proportionally without setting any of them to zero. This provides greater numerical stability and is computed more easily and faster.

The elastic net regularization penalty is defined as:

$$Regularization\ penalty = \lambda\left(\alpha\left\|\beta\right\|_1 + \frac{1}{2}(1-\alpha)\left\|\beta\right\|_2^2\right) \tag{8}$$

The elastic net parameter α specifies the regularization distribution between the l_1 penalty and the l_2 penalty. The parameter α can be set to any value in the range of [0, 1], if $\alpha = 0$ the equation is solved by using ridge regression, if $\alpha = 1$ the Lasso penalty is used. λ specifies the regularization penalty strength, from which the resulted fitted model is based on the optimal value of λ with the fitting process. The parameter can have any positive value until the smallest λ for which the solution results in all zeros. Note that there is no penalty on the intercept term β_0.

The Gaussian model is fitted by determining the best solution to the least squares problem, which is equal to solving the following likelihood maximization for:

$$max_{\beta,\beta_0} - \frac{1}{2\,N}\sum_{i=1}^{N}({x_i}^T\beta + \beta_0 - y_i)^2 - \lambda\left(\alpha\left\|\beta\right\|_1 + \frac{1}{2}(1-\alpha)\left\|\beta\right\|_2^2\right) \tag{9}$$

The gamma model is fitted by solving the following likelihood maximization problem:

$$max_{\beta,\beta_0} - \frac{1}{N}\sum_{i=1}^{N}\frac{y_i}{{x_i}^T\beta + \beta_0} + log({x_i}^T\beta + \beta_0) - \lambda\left(\alpha\left\|\beta\right\|_1 + \frac{1}{2}(1-\alpha)\left\|\beta\right\|_2^2\right) \tag{10}$$

The value of α is set at 0.5 to have the combination of both regularization penalties. The value of α is later changed to fine tune the best performing forecasting model. The combination of the l_1 penalty and the l_2 is beneficial because the l_1 penalty promotes sparsity and the l_2 penalty gives stability and computation speed.

In the next section the results of the forecasting models on the trainings data and the test data will be provided. The performance values of the different distributions (Gamma and Gaussian) and link functions are compared with one another to find out what works the best in this forecasting situation for Retail and Wholesale VAS. Therefore, answering the third research question that was initiated in this section: *"What predictive model performs the best, to forecast the VAS demand for APP12?"*.

5.6 Model validation

In this section the forecasting methods are evaluated on their performance. For the Retail and Wholesale VAS forecasting, both the results of the training data (FY14-FY18) and the test data (FY19) are discussed.

This will answer the third(mentioned above in section 5.5) and the fourth research question: “*How is the forecasting accuracy with weekly aggregation level on real data?”.*

Both for Retail and Wholesale the different data frames that are used as input for the GLM forecasting models contained of a total of 285 predictor variables. These predictor variables consist of the variables that are described in the data collection process in section 5.2. Therefore, information that is used for the prediction models is split up in 3 main components and can be defined as:

Historical data and trends;

- Actual amount of hours VAS labor Retail/Wholesale
- AGI VAS units Retail/Wholesale
- PGI (sales orders) VAS units Retail/Wholesale
- PGI (delivery documents) VAS units Retail/Wholesale
- APP3 AGI VAS units

Planned data (that is known at Thursday the week before);

- PGI (sales orders) VAS units Retail/Wholesale
- PGI (delivery documents) VAS units Retail/Wholesale

Meta data;

- time based: week number, month number, year number
- Commercial days indicator (e.g. black week)
- work day and/or public holiday

FY14 is lost as the trainings data input due to using predictor variables also in a lagged manner and having no availability of lagged values in that year from FY13. Resulting into that the final trainings data set consists of the data input from FY15, FY16, FY17 and FY18. Whereas the historical VAS data of FY19 is used, as the test data set used for validating the forecasting models. This can provide useful insights on how the forecasting method(s) will perform when it will possibly be implemented in the company and start to be exposed to new data. The measures that are implemented to evaluate the forecast accuracy are the performance measuring metrics Appendix E. In the performance evaluation the results from the current prediction computed in section 5.4, the performances found by applying the EMA of section 5.5.1 and the corresponding performances of the forecasting models of section 5.5.2 are compared. Answering the third research question that was initiated in section 5.5: *“What predictive model performs the best to forecast the VAS demand for APP12?”*.

5.6.1 Retail forecasting model validation

The results of the fitted models for the Retail forecasting are displayed in Table 5. Not all values could be computed and are therefore noted as N.A.(not available) values. In the table it can be seen that the GLM forecasting models are performing much better compared to the fitted simple exponential smoothing method of section 5.5.1.

Model	ME	RMSE	MAE	MPE	MAPE	MSE	AIC	R^2
Current forecast	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.

Simple exponential smoothing	26.60	690.49	550.76	N.A.	N.A.	N.A.	4870.86	N.A.
GLM Gaussian - identity	N.A.	450.35	361.62	N.A.	N.A.	202810.1	3654.04	0.7070
GLM Gaussian - log	N.A.	423.83	331.62	N.A.	N.A.	179635.5	3182.81	0.7405
GLM Gaussian - inverse	N.A.	430.67	332.04	N.A.	N.A.	185478.1	3185.46	0.7321
GLM Gamma - identity	N.A.	465.33	364.45	N.A.	N.A.	216530	N.A.	0.6872
GLM Gamma - log	N.A.	416.98	325.80	N.A.	N.A.	173872.9	N.A.	0.7488
GLM Gamma - inverse	N.A.	428.32	330.44	N.A.	N.A.	183461.3	N.A.	0.7350

Table 5: Retail fitted forecasting performances on trainings data of FY15-FY18

The GLM models perform not that differently from each other. Resulting in the worst MAE of 364.45 hours with the Gamma-identity model combination and the best fitted performance with the Gamma-log model scoring a MAE of 325.80 hours. The Gamma-log model scores the best at all the performance metrics, having the lowest RMSE, lowest MAE, lowest MSE and highest scoring R^2. Indicating that it is the best fitted forecast model, based on the trainings data. This does not necessarily mean that it is also going to be the best performing forecasting model.

Evaluating these Retail forecasting models on the test data of FY19, results into the forecasting performances that are displayed in Table 6. Based on these performance metrics it can be stated that indeed the best fitted model on the trainings data does not give the best forecasting performances on new data. The best performing forecast method is the GLM with the combination as the Gaussian-log model. As it scores the best on the most crucial performance metrics, having the lowest RMSE, MAE, MPE, MAPE, MSE and highest R^2 value. The Gamma-log model also performs very good, so looking back at the training metrics, the two best fitted models yield also the best forecasting results.

Based on the performance evaluation results of Table 6, it can also be seen that the newly constructed forecasting models of this research study result in better forecasting performances. The models demonstrate to be superior to the current forecasting model that is deployed in the company. Therefore, the models will supply more accurate forecasting values for the business process of making Retail VAS predictions. Figure 31 illustrates the forecasts, from all the produced GLM forecasting models on the test data. The black line in the graph represents the actual demand of VAS labor per week, the different forecasting models are highlighted with separate colors. The graph demonstrates that the GLM forecasting values are fairly close to each other every week and would therefore all produce reliable and more accurate forecasting values than the current forecasts.

To evaluate, the current forecasts for the Retail VAS process of predicting the amount of labor VAS that is needed the upcoming week, was on average deviating 420.85 hours per week from the real demand. The corresponding MAPE forecasting accuracy of this forecasting method is equal to 16.47%. The simple exponential smoothing forecasting model came close to these forecasting performances, having a MAE of 450.50 hours and a MAPE of 17.11%. That way the EMA formed a good benchmark of how the current forecast method was holding up to such a simple and effective method. The best performing GLM forecast shows to be a great improvement with having a MAE of 262.48 hours and a MAPE accuracy of 9.73%. Resulting in an improvement of on average predicting 158.37 hours more accurately per week for the Retail VAS process. This improves the current forecasts by $40.92\% \left(1-\frac{9.73\%}{16.47\%}\right)$ in terms of the MAPE. That means that, on average the weekly amount of either overestimated or underestimated number of full time production personnel could have been reduced by at least 4[14] FTE’s (Full Time Employee).

Model	ME	RMSE	MAE	MPE	MAPE	MSE	AIC	R^2
Current forecast	-166.47	560.40	420.85	-7.39	16.47	314049.1	N.A.	N.A.
Simple exponential smoothing	-13.79	546.29	450.50	-4.04	17.11	N.A.	N.A.	N.A.
GLM Gaussian - identity	-31.87	380.12	328.44	-3.13	12.38	144490.9	1302.099	0.4593
GLM Gaussian - log	34.72	320.89	262.48	-0.31	9.73	102971.7	838.145	0.6147
GLM Gaussian - inverse	-3.40	329.67	276.17	-2.07	10.53	108682.7	837.005	0.5933
GLM Gamma - identity	-41.57	386.93	338.14	-3.57	12.79	149711.7	N.A.	0.4398
GLM Gamma - log	49.28	323.50	265.54	0.35	9.76	104655.1	N.A.	0.6084
GLM Gamma - inverse	18.02	330.17	275.65	-1.15	10.38	109012	N.A.	0.5921

Table 6: Retail validation forecasting performances on test data of FY19

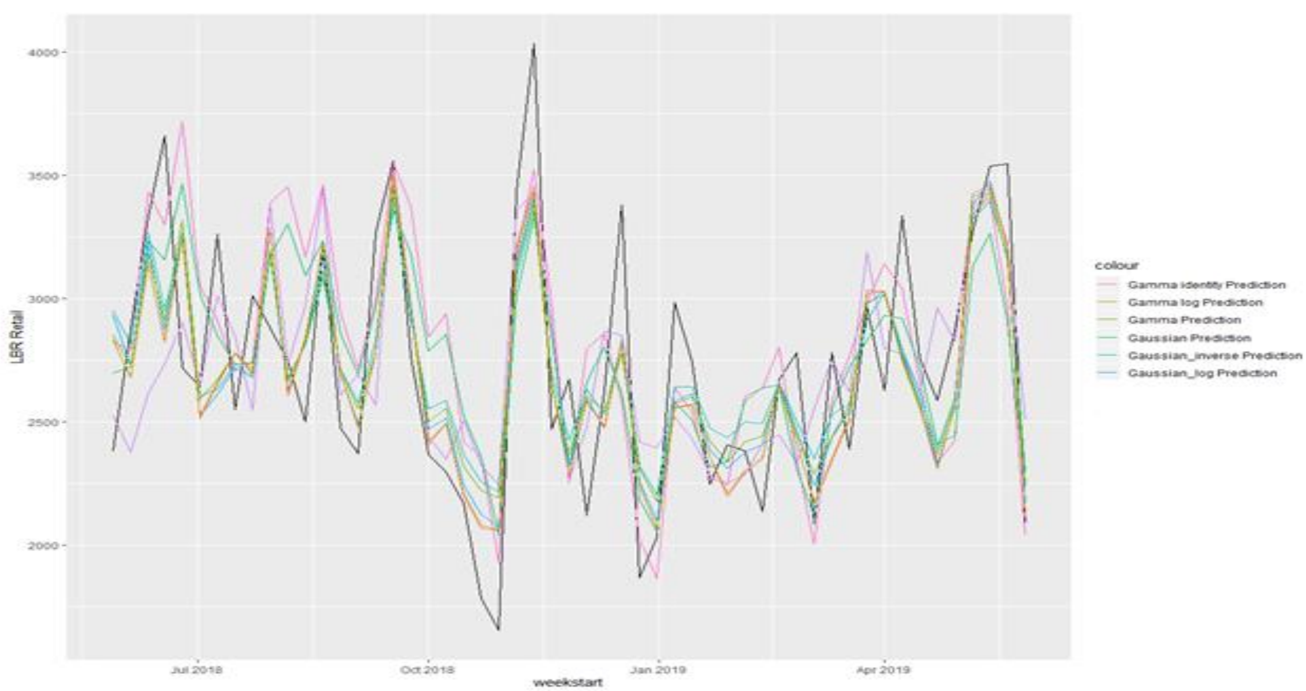

Figure 31: Retail weekly GLM forecast generated values and actual labor demand of VAS per week for FY19

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[14] Based on a 40 hour work week for a full time employee.

5.6.2 Wholesale forecasting model validation

The results of the fitted models for the Wholesale forecasting are displayed in Table 7. The fitted GLM models of section 5.5.2 show to perform well on the trainings data set. Comparing the fitting performances of the simple exponential smoothing model with the GLM performances, it can be seen that the GLM models have a significant improved RMSE and MAE. The GLM models are performing pretty similar to each other, with the MAE ranging between the values of 330.92 and 309.18 hours of deviation per week. The best fitted model on the trainings data set is the Gaussian-inverse model. The Gaussian-inverse model scores the best at all the performance metrics, having the lowest RMSE, lowest MAE, lowest MSE and highest scoring R^2.

Model	ME	RMSE	MAE	MPE	MAPE	MSE	AIC	R^2
Current forecast	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
Simple exponential smoothing	9.05	688.94	531.81	N.A.	N.A.	N.A.	4869.691	N.A.
GLM Gaussian - identity	N.A.	405.92	318.99	N.A.	N.A.	164773.7	3626.843	0.7248
GLM Gaussian - log	N.A.	415.88	326.98	N.A.	N.A.	172952	3184.918	0.7111
GLM Gaussian - inverse	N.A.	396.97	309.18	N.A.	N.A.	157583	3171.562	0.7368
GLM Gamma - identity	N.A.	424.95	328.91	N.A.	N.A.	180583.1	N.A.	0.6984
GLM Gamma - log	N.A.	425.09	330.92	N.A.	N.A.	180699.9	N.A.	0.6982
GLM Gamma - inverse	N.A.	409.21	320.41	N.A.	N.A.	167450.1	N.A.	0.7203

Table 7: Wholesale fitted forecasting performances on trainings data of FY15-FY18

Validating the Wholesale forecasting models on the test data of FY19, results into the forecasting performances that are displayed in Table 8. Looking at the validation performances it can be concluded that again the best fitted model on the trainings data does not give the best forecasting performances on new data. The model with the least fitted forecasting performances on the trainings data, performs the best evaluated forecasting performances on test data of FY19. The Gamma-log model is the best performing forecast model as it has the lowest RMSE, MAE, MAPE and MSE, and highest R^2 value.

Comparing the fitted forecasting performances and the validation performances, there can be seen that the forecasting model performances were better on the trainings data. This means that the models are overfitting on the older data, since the least fitted model now performs the best forecasts for new data that has altered seasonality patterns. In subsection 5.3.2.2 of the data analysis it was discovered that the seasonal pattern was deviating in FY18 and FY19 from the reoccurring pattern from the years before. The strong seasonality patterns that are in the data from FY14-FY17 are weighing heavy in the trainings data since the optimization problem only has FY18 to take the new altered pattern into its computations. Therefore the models are trained and fitted to these strong seasonality patterns that are suddenly not there anymore in the new test data. Figure 32 illustrates the forecasts, from all the produced GLM forecasting models on the Wholesale test data. The black line in the graph represents the actual demand of Wholesale VAS labor per week, the different forecasting models are highlighted with separate colors. In the graph it can be seen that all models predict a high demand value in the first weeks of January 2019.

As this high demand peak was so evident in all the years before, as can be seen in Figure 56 from Appendix B 2.2.

Evaluating the forecast improvements compared to the current forecasts for the Wholesale VAS process of predicting the amount of labor VAS that is needed the upcoming week. The current forecast had on average an absolute deviation of 502.51 hours per week from the real demand. The corresponding MAPE forecasting accuracy is equal to 24.91%. The simple exponential smoothing method forms already a good improvement having a MAE of 408.95 hours and a forecast accuracy in terms of the MAPE of 24.50%. The best performing GLM forecast model improves the forecasting performances further with having a MAE of 379.90 hours and a MAPE accuracy of 22.89%. Resulting in an improvement of on average predicting in absolute terms a 122.61 hours more accurately per week for the Wholesale VAS process. Which improves the current forecasts by $8.11\% \left(1 - \frac{22.89\%}{24.91\%}\right)$ in terms of the MAPE. That means that, on average the weekly amount of either overestimated or underestimated number of full time production personnel could have been reduced by at least 3[15] FTE's.

Model	ME	RMSE	MAE	MPE	MAPE	MSE	AIC	R^2
Current forecast	452.45	728.33	502.51	20.29	24.91	530461.5	N.A.	N.A.
Simple exponential smoothing	-8.10	554.89	408.95	-6.91	24.50	N.A.	N.A.	N.A.
GLM Gaussian - identity	-160.62	522.85	428.86	-16.39	27.30	273373.1	1351.893	0.3020
GLM Gaussian - log	-13.27	496.08	391.02	-8.40	23.36	246098.6	894.3223	0.3716
GLM Gaussian - inverse	-15.88	518.63	410.92	-9.69	24.94	268977	905.0337	0.3132
GLM Gamma - identity	-137.08	519.24	422.80	-15.04	26.66	269609.9	N.A.	0.3116
GLM Gamma - log	-35.20	482.99	379.90	-9.39	22.89	233279.8	N.A.	0.4044
GLM Gamma - inverse	-0.07	508.25	398.76	-8.41	23.83	258317.4	N.A.	0.3404

Table 8: Wholesale validation forecasting performances on test data of FY19

[15] Based on a 40 hour work week for a full time employee.

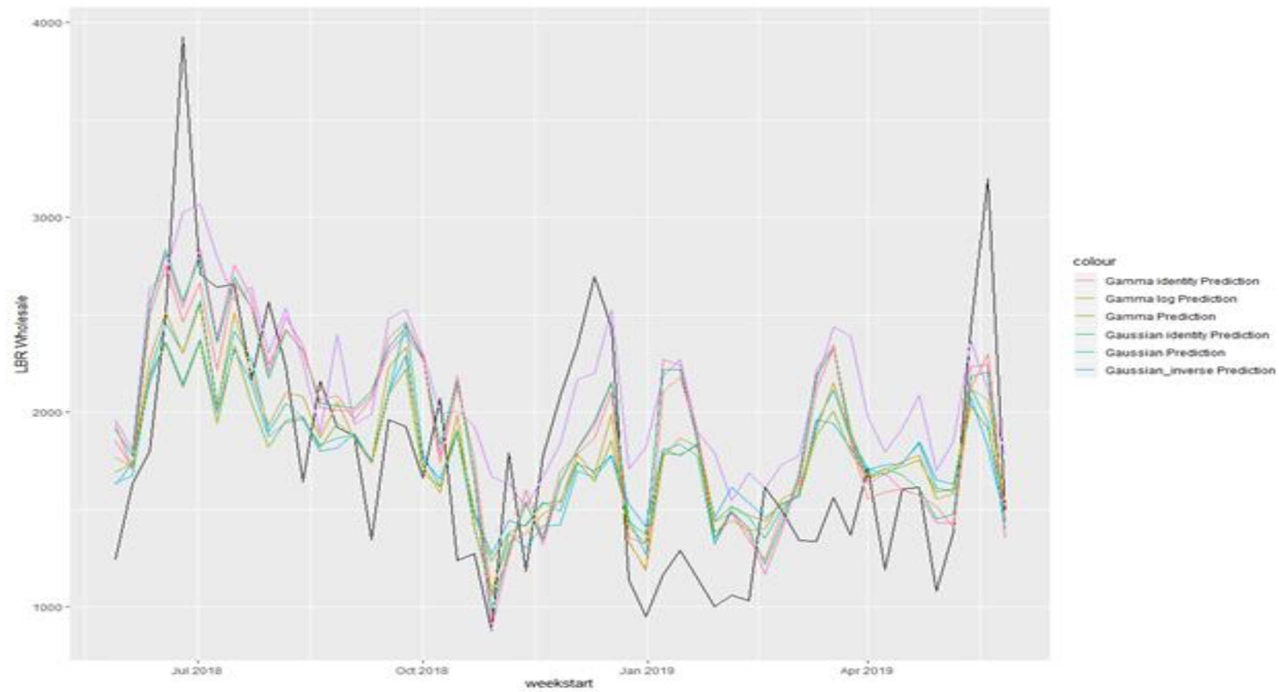

Figure 32: Wholesale weekly GLM forecast generated values and actual labor demand of VAS per week for FY19

5.6.3 Final forecasting results

The elastic net parameter α specifies the regularization distribution between the l_1 penalty and the l_2 penalty. The parameter α can be set to any value in the range of [0, 1], if $\alpha = 0$ the equation is solved by using ridge regression, if $\alpha = 1$ the Lasso penalty is used. Therefore fine tuning the best performing forecasting models of Retail and Wholesale by performing a grid search over alpha results in the performances realized in Table 9 and 10 respectively. Using the Lasso penalty by setting $\alpha = 1$ gives slightly improved forecasting results. This way the model only makes use of a smaller number of variables that have a crucial interpretability to the forecasting model. Nevertheless it does increase the computation time of the forecasting model. However this extra computation time can be ignored since it doesn't have any significant impact on the business.

Resulting in the final forecasting performance of Retail VAS predicting the amount of labor VAS that is needed the upcoming week with a MAE of 260.65 hours per week and a forecasting accuracy based on the MAPE of 9.66%. For Wholesale VAS forecasting the best result has a MAE of 378.95 hours per week and a forecasting accuracy with a MAPE of 22.81%.

This brings the final forecasting improvements from Retail forecasting to predicting 160.20 hours on average more accurate per week (based on the MAE) which gives an improvement by 41.37% $\left(1-\frac{9.66\%}{16.47\%}\right)$ based on the MAPE. For Wholesale forecasting the prediction is an absolute 123.56 hours more accurate per week (based on the MAE) and resulting in a 8.43% $\left(1-\frac{22.81\%}{24.91\%}\right)$ accuracy improvement in terms of the MAPE.

GLM Gaussian - log	ME	RMSE	MAE	MPE	MAPE	MSE	AIC	R^2
Alpha = 0.0	-38.61	385.26	335.16	-3.57	12.75	148425.9	1355.523	0.4446
Alpha = 0.2	31.48	324.96	266.86	-0.51	9.91	105595.8	841.4783	0.6049
Alpha = 0.4	34.44	321.64	263.19	-0.33	9.76	103453	836.3917	0.6129
Alpha = 0.5	34.72	320.89	262.48	-0.31	9.73	102971.7	838.1446	0.6147
Alpha = 0.6	35.12	320.34	261.89	-0.28	9.71	102615.5	835.9609	0.6160
Alpha = 0.8	35.61	319.63	261.13	-0.25	9.68	102165.4	835.7279	0.6177
Alpha = 1.0	35.90	319.21	260.65	-0.23	9.66	101895.1	835.5875	0.6187

Table 9: Retail final forecasting performances on test data of FY19 with Alpha grid search

GLM Gamma - log	ME	RMSE	MAE	MPE	MAPE	MSE	AIC	R^2
Alpha = 0.0	-129.87	520.019	422.05	-15.36	26.89	270419.5	N.A.	0.3095
Alpha = 0.2	-37.43	483.94	381.88	-9.48	22.99	234194.2	N.A.	0.4020
Alpha = 0.4	-36.18	482.93	380.50	-9.46	22.94	233222.5	N.A.	0.4045
Alpha = 0.5	-35.20	482.99	379.90	-9.39	22.89	233279.8	N.A.	0.4044
Alpha = 0.6	-34.62	483.07	379.54	-9.35	22.86	233359	N.A.	0.4042
Alpha = 0.8	-34.00	483.21	379.12	-9.30	22.83	233491.9	N.A.	0.4038
Alpha = 1.0	-33.67	483.34	378.95	-9.28	22.81	233619.7	N.A.	0.4035

Table 10: Wholesale final forecasting performances on test data of FY19 with Alpha grid search

Combining these two best performing forecast methods for Retail and Wholesale, the results of the new total weekly forecast are given in Table 11. The corresponding forecasting results compared to the weekly demand values are illustrated in the graph of Figure 33. The new constructed forecast values shows a predicted pattern that is coming very near to the actual demand values. The results of this study show that the VAS process of predicting the total amount of labor VAS that is needed in the upcoming week can be forecasted in a more accurate way. Improving the forecasting performances with $30.93\% \left(1 - \frac{10.27\%}{14.87\%}\right)$ in terms of the MAPE accuracy. Predicting in absolute terms 216.86 hours per week more accurate on the total VAS requirements per week compared to the current forecasting method. This clearly shows the added value of this research study in practice. Resulting in avoiding unnecessary high labor costs of either overestimated or underestimated forecasting by reducing at least 5[16] FTE's on average per week. Based on a salary costs of DC operation personnel of € 30.00 per hour of labor and the data of FY19, this could bring possible savings of € $344{,}808$ per year for the APP12 DC operations costs. This new forecasting method possibly also saves costs outside the operations department in FTE's, as the current way of forecasting was very labor intensive, since it needed many applied estimations and different analytics from the responsible goods flow planning analysts.

Model	ME	RMSE	MAE	MPE	MAPE	MSE
Current weekly total VAS Forecast FY19	330.37	961.97	668.22	5.90	14.87	N.A.
New weekly total VAS Forecast FY19	-0.48	569.47	451.36	-2.12	10.27	324294.4

Table 11: Final forecasting performances comparison on test data of FY19 for the total VAS process

[16] Based on a 40 hour work week for a full time employee.

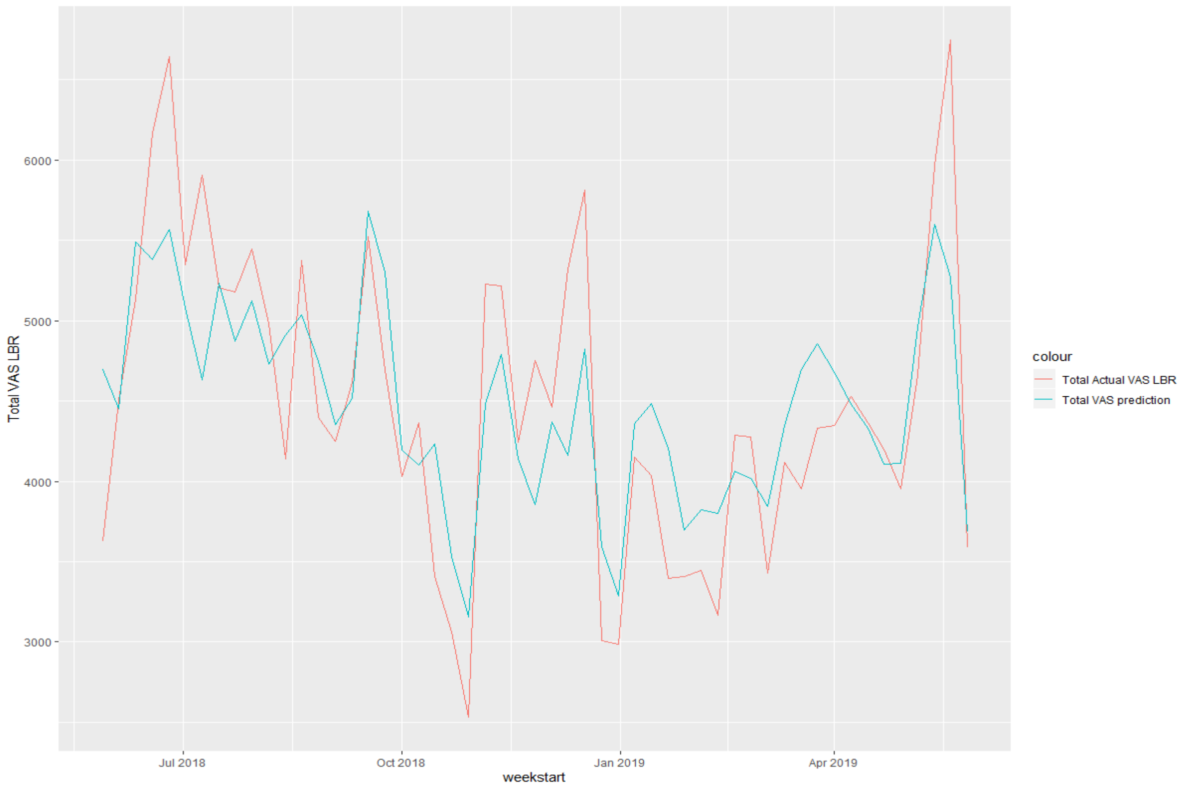

Figure 33: Total weekly GLM forecast generated values and actual labor demand of VAS per week for FY19

6. Capacity planning

The capacity planning is the process, that follows on the forecasts, determining the operations capacity utilization that is needed for a specific business process to meet the incoming demand in order to ensure the integrity of the business process (Haines, 2006). Therefore, with the given best performing demand forecasts values from section 5.6.3, in this chapter it will be analyzed what the optimal amount of workforce capacity is for that weekly planning horizon with a certain service level. By doing so this answers the last research question: "*Given the forecast demand prediction, what is the ideal amount of workforce capacity that needs to be planned for a certain service level?".* This section will also include the more specific literature part of the capacity planning method that will be used.

At the moment, with a given demand forecast, there is no clear optimal capacity target known. So, there is no model available to guide the distribution planners with deciding on to optimally plan the right amount of capacity with a certain probability. Meaning that the capacity planning is currently more a reactive process. This is a missed opportunity to reduce excessive or insufficient capacity levels. By providing supporting optimization algorithms or heuristics, this decision making with respect to the number of available employees can be improved (Knolmayer & Zeier, 2002). Therefore, an analytic approach can be used to support decision making on proactively applying these targets, to align the supply (staff hours) in a better way and prevent excess and lack of capacity as much as possible. As stated in section 4.2, one effective heuristic way for deriving the optimal usages of the capacity that will be used is the classic "newsvendor" model (also called the newsboy problem)(Olivares et al., 2008). The approach of the newsvendor problem can be applied in many different settings. In this situation the newsvendor model is used in order to investigate with what probability the given forecast can be met with enough capacity. So that there is a well thought through trade-off of determining a certain amount of capacity with a given forecast. The newsvendor model will therefore serve as an inspirational approach and starting point for the capacity planning tool.

Two different capacity models have been created for the determination of the operations workforce capacity for a certain service level. Both models make use of the characteristics of the normal distribution. The normal probability distribution curve is based on the parameters mean and standard deviation of the variable. The higher the standard deviation, the more variability there is in the data. The z-score or z-value indicates how many standard deviations a score is deviating off the average. It is the expected value of a normal distribution with a known standard deviation, expressed in units of the standard deviation. These z-scores then are converted into areas under the normal distribution curve and therefore display the probabilities or percentages of having enough capacity for that given number of employees. All the probabilities together from the total area under the curve sum up to 100%, thus forming all the values that the variable can take. This allows for effective estimating of how likely it is what the value is going to be. The z-score is calculated as followed (Montgomery et al., 2015; Nahmias, 2015):

$$z = \frac{x - \mu}{\sigma} \tag{11}$$

Here x represents the specific observation, μ the mean of the dataset and σ for the standard deviation of the dataset.

Capacity planning model 1

Model 1 (illustrated in Figure 34) is a very intuitive but effective model that makes use of the assumption that the total VAS demand values are normally distributed, with x as the “Total VAS Prediction in hours”, μ as the “Mean Total VAS Actuals” and σ as the “Standard deviation from Total VAS Actuals”. Where the μ and σ are calculated from the distribution function by Maximum-likelihood fitting of the Normal distribution in R. This way the model looks at the historical actuals and determines with which probability the computed total VAS demand prediction will meet the demand. So with a total demand prediction of 5000 hours, historically in 70.71% of the weeks this would have covered the demand. Hence, this gives also a probability indication that this will also cover the demand of next week with a 70.71% probability, denoted in the right column of the capacity planning tool.

# FTE workers planned	(+/-) # FTE workers to prediction	(+/-) # FTE hours to prediction	x-u	z-score	p-value cumulative
115	-10	4600	111.5283	0.118823333	0.547292339
116	-9	4640	151.5283	0.161439721	0.564126458
117	-8	4680	191.5283	0.204056108	0.580845174
118	-7	4720	231.5283	0.246672496	0.597419153
119	-6	4760	271.5283	0.289288884	0.613819841
120	-5	4800	311.5283	0.331905272	0.630019605
121	-4	4840	351.5283	0.37452166	0.645991878
122	-3	4880	391.5283	0.417138048	0.661711282
123	-2	4920	431.5283	0.459754436	0.677153754
124	-1	4960	471.5283	0.502370824	0.692296651
125	0	5000	511.5283	0.544987212	0.707118844
126	1	5040	551.5283	0.5876036	0.721600803
127	2	5080	591.5283	0.630219988	0.735724668
128	3	5120	631.5283	0.672836376	0.749474304
129	4	5160	671.5283	0.715452764	0.762835341
130	5	5200	711.5283	0.758069152	0.775795207
131	6	5240	751.5283	0.80068554	0.788343142
132	7	5280	791.5283	0.843301928	0.800470198
133	8	5320	831.5283	0.885918316	0.812169227
134	9	5360	871.5283	0.928534704	0.823434863
135	10	5400	911.5283	0.971151092	0.834263478
Total VAS Prediction in hours =	5000				
number of hours an FTE works =	40				
Standard deviation from Total VAS Actuals =	938.60606				
Mean Total VAS Actuals =	**4488.4717**				

Figure 34: Total VAS Capacity planning model 1

Model 1 can be used with the prediction value from any forecasting model as it only considers the distribution of the historical VAS values. This makes it a very simple and straightforward to use capacity planning tool, however it does not reflect the most reliable probabilities as it does not take into account how accurate the forecasted values are. For example, with a low forecasted value (e.g. of 2000 hours) the model would indicate a low probability of covering the incoming demand, even though it is very credible to assume that indeed the demand is going to be low as is predicted. Therefore it does not give the most relevant probabilities in all situations and it only gives the probabilities from an instinctive point of view. This makes it a model that can always be used without the well-functioning of a forecasting model, provided that the actual historical demand values are normally distributed.

Capacity planning model 2

Model 2 (illustrated in Figure 35) uses the deviations from the actuals relative to the total VAS predictions of the two best forecasting models combined of section 5.6.3. The model makes use of the assumption that the deviations from the actual demand and forecasts relative to the predictions are normally distributed, with x as the "Relative deviation", μ as the "Mean Total VAS Relative deviation" and σ as the "Total VAS Standard deviation" from the $\frac{Actuals-Predictions}{Predictions}$. The average deviation of the predictions compared to the actuals was found to be close to zero, calculated from the distribution function by Maximum-likelihood fitting of the Normal distribution in R. Hence, the forecasts almost forms the middle of the normal distribution curve in this situation. The probabilities in the right column denote the certainty level of covering the demand by taking the deviations from the prediction models into account.

Total # FTE workers planned	(+/-) # workers to prediction	(+/-) # hours to prediction	x-u	z-score	p-value cumulative
115	-10	4600	-0.074586409	-0.591682209	0.277031706
116	-9	4640	-0.066586409	-0.528219472	0.298673508
117	-8	4680	-0.058586409	-0.464756734	0.321052837
118	-7	4720	-0.050586409	-0.401293997	0.344101841
119	-6	4760	-0.042586409	-0.33783126	0.367745176
120	-5	4800	-0.034586409	-0.274368523	0.391900715
121	-4	4840	-0.026586409	-0.210905786	0.416480395
122	-3	4880	-0.018586409	-0.147443049	0.441391164
123	-2	4920	-0.010586409	-0.083980311	0.466536043
124	-1	4960	-0.002586409	-0.020517574	0.491815246
125	0	5000	0.005413591	0.042945163	0.517127376
126	1	5040	0.013413591	0.1064079	0.542370637
127	2	5080	0.021413591	0.169870637	0.567444063
128	3	5120	0.029413591	0.233333374	0.592248728
129	4	5160	0.037413591	0.296796111	0.616688913
130	5	5200	0.045413591	0.360258849	0.640673215
131	6	5240	0.053413591	0.423721586	0.664115565
132	7	5280	0.061413591	0.487184323	0.686936143
133	8	5320	0.069413591	0.55064706	0.709062179
134	9	5360	0.077413591	0.614109797	0.730428613
135	10	5400	0.085413591	0.677572534	0.750978617
Total VAS Prediction in hours =	5000				
number of hours an FTE works =	40				
Total VAS std deviation (Actual-Pred)/Pred =	0.126058225				
Mean Total VAS (Actual-Pred)/Pred =	**-0.005413591**				

Figure 35: Total VAS Capacity planning model 2

Model 2 reflects more reliable probabilities for covering the demand compared to model 1, as it takes the accuracy of the forecasting models into account (in this case the forecasting models of section 5.6.3). Therefore in extreme cases (of e.g. low and high predicted demand) it gives relevant probability indications of having enough capacity in that specific situation. This makes model 2 the more appropriate type of capacity planning tool, provided that the used prediction values, from the forecasting models, have deviations from the actual demand relative to the predictions that are normally distributed.

6.1 Normality test of data

To show that these models are constructed in the right manner it first need to be shown that the variables used in the models indeed follow a normal distribution, this will be proven in this section. In the literature there is considerable empirical evidence that the distribution of variables can be approximated by a normal distribution(Montgomery et al., 2015). However it is not academically correct to assume that the variable follows a normal distribution without any analysis.

The first model assumes that the historical actual demand values are following a normal distribution. The second model assumes that the deviations from the actual demand from the forecasts relative to the predictions are normally distributed.

The first step to understanding the goodness of fit of the normal distribution is by using plots (Thode, 2002). In the literature of academic research one often used plot is the quantile-quantile plot also referred to as the Q-Q plot. These plots provide insights in the evaluation of normality and the possible deviation from this normality. The Q-Q plots of the first and second model variables are given in Figure 38 and 39 respectively. In the graphs the sample data is plotted against a theoretical normal distribution in such a

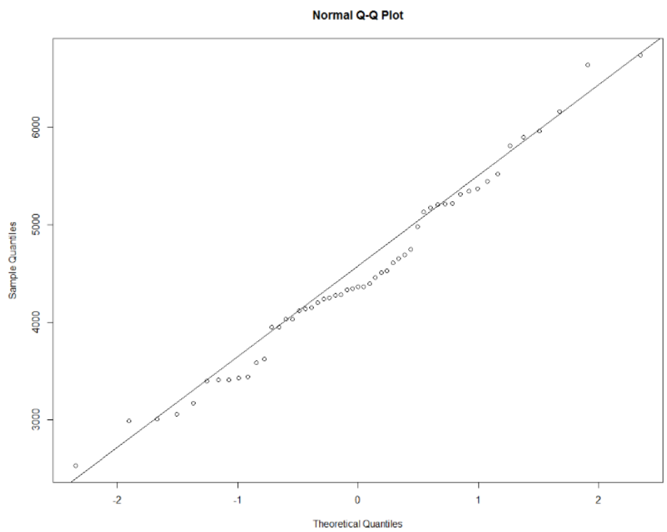

Figure 36: Q-Q normal probability plot for model 1: Historical demand values

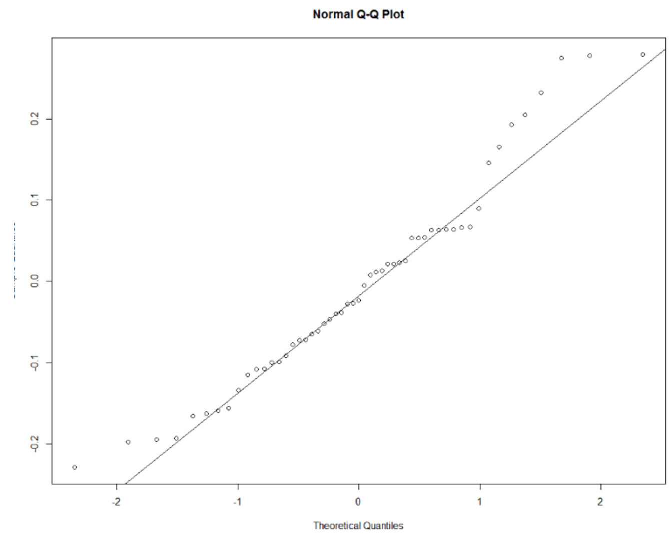

Figure 37: Q-Q normal probability plot for model 2: Deviations from the demand from the forecasts relative to the predictions

way that the points should form a straight line.
Deviations from this straight line indicate divergence from normality (Filliben, 1975). In both of the graphs it can be seen that the data forms a nearly linear pattern, indicating that the normal distribution could be a good model for the two data sets.

To determine whether or not the data fits a normal distribution and it is realistic to assume that the sample data follows a normal distribution, normality test have to be performed. When testing for normality the tests consist of testing two hypothesis where the null and alternative hypotheses are:

H_0 : The sample data is normally distributed

H_A : The alternative hypothesis is that the sample data is not normally distributed

For the first hypothesis to be accepted with testing the distributions on normality the p-value needs to be at least of a significance level above 0.05 to qualify as a normal distribution (Montgomery et al., 2015). The rest rejects the normality hypothesis when the p-value is less than 0.05, thus a normal distribution may not be assumed. The higher the p-value the more the distribution follows the normal distribution.

Multiple normality tests are used to certify the assumptions of normality:

- The Shapiro-Wilk test (Shapiro & Wilk, 1965)
- The Shapiro-Francia test (Royston, 1993)
- The Anderson-Darling test (Stephens, 1974)

- The Cramer-von Mises test (Stephens, 1974; Thode, 2002)
- The Lilliefors (Kolmogorov-Smirnov) test (Stephens, 1974; Thode, 2002)

Computing these tests in R, gives the following results presented in Table 12.

Normality test	**Model 1**		**Model 2**	
The Shapiro-Wilk test	W = 0.98047	p-value = 0.5334	W = 0.95991	p-value = 0.0728
The Shapiro-Francia test	W = 0.98289	p-value = 0.552	W = 0.96587	p-value = 0.1192
The Anderson-Darling test	A = 0.38368	p-value = 0.3837	A = 0.55476	p-value = 0.1453
The Cramer-von Mises test	W = 0.070452	p-value = 0.2705	W = 0.071558	p-value = 0.2615
The Lilliefors test	D = 0.086716	p-value = 0.4105	D = 0.11409	p-value = 0.08248

Table 12: Normality test computation results

The H_0 hypothesis is never rejected on all the tests, as all the p-values are above 0.05. Thus for both the variables it can be assumed that the data follow the normal distribution. Since it can be assumed that the normal distribution can represent the data, the parameters need to be estimated for the functioning of the capacity models. The parameter estimation is realized by the maximum-likelihood fitting of the normal distribution on the sample data of the variables (NIST, 2013). Computing this in R gives the "Mean Total VAS Actuals" $\mu = 4488.472$ and "Standard deviation from Total VAS Actuals" $\sigma = 938.61$ for model 1. For model 2 the "Mean Total VAS Relative deviation" as $\mu = -0.005413591$ and the "Total VAS Standard deviation" as $\sigma = 0.126058225$. To evaluate the goodness of fit from these estimated normal distribution parameters, the normal distribution graph is presented together with the line of the corresponding probability density functions. These are illustrated in Figure 38 and 39. In these graphs it can be seen that the probability density functions indeed almost exactly follow a normal distribution.

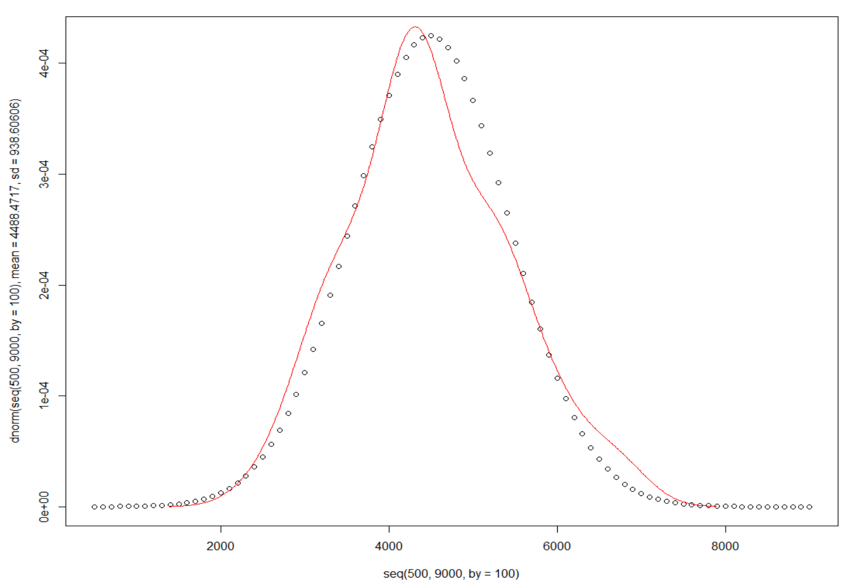

Figure 38: The normal distribution graph with the probability density function of historical actual demand values

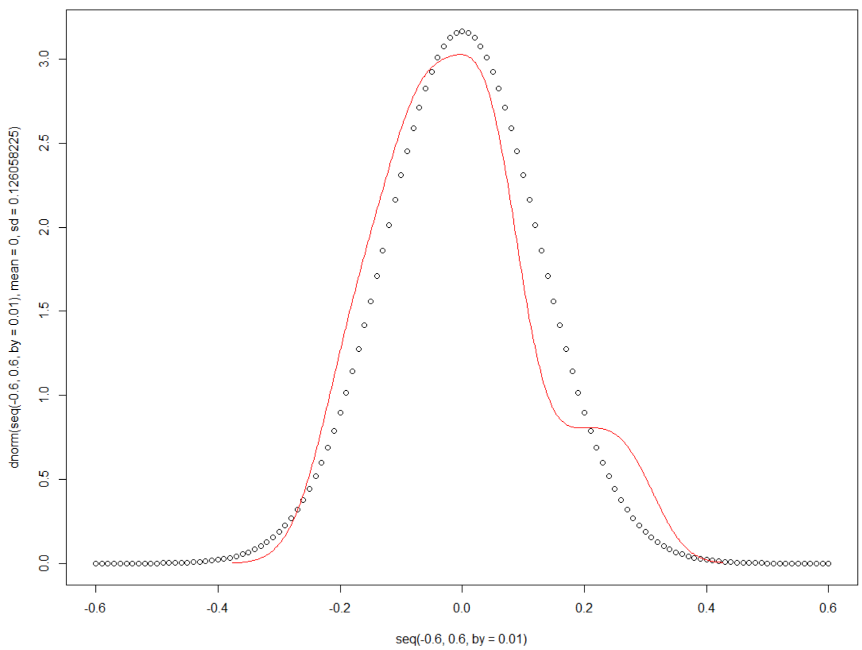

Figure 39: The normal distribution graph with the probability density function of deviations from the actual demand from the forecasts relative to the predictions

Conclusion

In this final chapter, concluding answers are provided to the research questions that are formulated in section 2.3 of this research study. In addition recommendations are given for the management team within NIKE's Goods Flow Planning department, specifically for the Marketplace Distribution Planning team of the APP12 DC. Furthermore, the contribution of this research study to literature is presented. Lastly, the limitations of this research project are discussed along with directions for possible future research.

The introduction of this report stressed the importance for the business to have a well aligned forecasting and demand planning where, the output builds a solid foundation for the capacity planning of the distribution center. The problem definition in section 2.1 gives an indication that an improvement is needed for NIKE's VAS forecasting and demand planning. In order to fully grasp the impact of the current problem, in addition further analyzes needed to be instigated. Therefore, the main research question of this project was stated as:

How can NIKE ELC improve the demand forecasting for the value-added services in order to better align the staffing capacity?

This resulted in the objective of this research project of applying analytics to create insights into the capacity forecasting problem and to determine a good forecasting method (that is able to perform better compared to the current forecasts) in order to better anticipate on the demand that can be expected for the VAS in the APP12 DC. So, that also the right amount of capacity is planned for supplying this demand. With the goal to reduce excess capacity or improving the lack of capacity for the VAS process of APP12 and ultimately bring extra value to the customer by elevating NIKE's service.

In order to answer the main research question and fulfill this research objective, the main research question was split up into multiple sub-research questions:

1. *What does the historical and current time series of VAS labor demand data look like?*

In section 5.3.2 the weekly VAS demand data was analyzed and visually inspected. It is was clearly seen that exactly after the opening of the APP3 DC at June 2017 the amount of VAS labor started to decline. This influenced the Retail and Wholesale VAS demand, and therefore also the total amount of VAS labor. The Retail demand data demonstrated to behave highly erratic by showing many fluctuations. Looking at the graph for seasonality it was difficult to verify any clear seasonality patterns. Even plotting the data against the individual years in the seasonality graphs of Figure 52 and 53 it was still hard to discover any underlying seasonal patterns. The ACF analyses demonstrated that the lag values of more recent demand data showed significant relations with the upcoming week. For the Wholesale VAS the seasonality graphs displayed very distinct seasonality patterns over the years. As most of the peaks and troughs fell in the same weeks year after year. However, FY18 and FY19 started to deviate from the clearly overlapping patterns from the years prior to the opening of the APP3 DC. Especially the before so evident peak in weeks 1 to 4 is where the biggest deviation is seen from the seasonality pattern. The autocorrelation coefficients of the ACF confirmed a strong seasonal pattern with having the larger autocorrelations at the seasonal lags.

Additional data analysis were realized for possible important predictor variables. The correlation coefficients and scatterplots revealed that the PGI DD VAS units give a better indication for the amount of VAS labor demand compared to the PGI SO VAS units, but both are good inputs for the forecasting model. Also the demand for Wholesale and the amount of Wholesale VAS percentage at APP3, showed a significantly strong negative relationship. These relations were also established for the Retail VAS demand.

2. *How is the current VAS forecasting process performing for APP12?*

In section 5.4 it was indeed discovered that the current forecasts were deviating significantly from the actual demand. With on average per week an absolute deviation of 420.85 hours for the Retail VAS and 502.51 hours for the Wholesale VAS. Combining the forecasts and comparing it with the total VAS demand resulted in a MAE of 668.22 hours per week. Looking at the MAPE the forecast accuracies had an average 16.47% absolute deviation per week for Retail and 24.91% for Wholesale. Consequently this comes down to an 14.87% average absolute deviation every week for the total VAS forecast. This has a big impact on the staffing levels and therefore also affects the productivity and operations costs within the DC due to moments of idle or overexploited capacity.

3. *What predictive model performs the best to forecast the VAS demand for APP12?*

The EMA model showed to have difficulties to deal with the high fluctuating pattern of the Retail VAS. However, it still gives a good extra benchmark that even comes close to the current forecasting performances seen in section 5.4.2. As it even has a better forecasting accuracy for the Wholesale VAS. Based on the performance evaluation results of Table 6 and 8, it can be concluded that the newly constructed GLM forecasting models of this research study result in better forecasting performances. The models demonstrate to be superior to the current forecasting model that is deployed in the company. Therefore, the models will supply more accurate forecasting values for the business process of making Retail and Wholesale VAS predictions.

4. *How is the forecasting accuracy with weekly aggregation level on real data?*

The best forecasting performance of Retail VAS predicting the amount of labor VAS that is needed the upcoming week had a MAE of 260.65 hours per week and a forecasting accuracy based on the MAPE of 9.66%. For Wholesale VAS forecasting the best result has a MAE of 378.95 hours per week and a forecasting accuracy with a MAPE of 22.81%. This brings the final forecasting improvements from Retail forecasting to predicting 160.20 hours on average more accurate per week (based on the MAE) which gives an improvement by 41.37% based on the MAPE. For Wholesale forecasting the prediction is an absolute 123.56 hours more accurate per week (based on the MAE) and resulting in an 8.43% accuracy improvement in terms of the MAPE. Combining these two best performing forecast methods for Retail and Wholesale improved the Total VAS forecasting performances with 30.93% in terms of the MAPE accuracy. Predicting in absolute terms 216.86 hours per week more accurate on the total VAS requirements per week compared to the current forecasting method. This clearly shows the added value of this research study in practice. Resulting in avoiding unnecessary high labor costs of either overestimated or underestimated forecasting by reducing at least 5 FTE's on average per week. The results of this study show that the VAS process of predicting the total amount of labor VAS that is needed in the upcoming week can be forecasted in a more accurate way. This new forecasting method possibly also saves costs outside the operations department in FTE's. As the current way of forecasting was very labor intensive. Since it needed many applied estimations and different analytics from the responsible goods flow planning analysts.

5. *Given the forecast demand prediction, what is the ideal amount of workforce capacity that needs to be planned for a certain service level?*

In addition to help the operations managers plan the required number of workforces on a weekly basis two different capacity models have been created for the determination of the operations workforce capacity for a certain service level. Together these models give insightful support for the capacity planning decision of the operations managers and planners with deciding on to optimally plan the right amount of capacity with a certain probability. Making the labor force planning less reliant on the availability of skilled operations planning personnel.

Both models used the characteristics of the normal distribution. Capacity planning model 1 (illustrated in Figure 52) is a very intuitive but effective model that makes use of the assumption that the total VAS demand values are normally distributed. This way the model looked at the historical actuals and determines with which probability the computed total VAS demand prediction will meet the demand. So for example, with a total demand prediction of 5000 hours, historically in 70.71% of the weeks this would have covered the demand. Hence, this gives also a probability indication that this will also cover the demand of next week with a 70.71% probability. Model 2 (illustrated in Figure 53) uses the deviations from the actuals relative to the total VAS predictions of the two best forecasting models combined of section 5.7.3. The model makes use of the assumption that the deviations from the actual demand and forecasts relative to the predictions are normally distributed. Where the probabilities denote the certainty level of covering the demand by incorporating the deviations from the prediction models into the model. This makes model 2 the more appropriate type of capacity planning tool, as it takes the accuracy of the forecasting models into account from section 5.6.3 and therefore reflects more reliable probabilities for covering the demand.

Contribution of this research study to the literature

The models and results of this research study contributes to both academical as well as applied research. The primary contribution this research project has brought to the current literature is presenting a proof concept, of the effect that forecasting methods have on a distribution center. More specifically on a labor intensive process in a DC from the world's biggest sportswear retailer, in order to efficiently and effectively manage the workforce capacity. This project has resulted into delivering a good solution in this field of research. In addition it has brought the company of interest an improvement into their existing forecasting and capacity planning process. This research project provided managerial insights and an integrated solution for labor forecasting and the capacity planning of a distribution center's labor intensive process.

Limitations and future research

Recall, as stated by statistician George Box: "All models are wrong. Some are useful" (Box & Draper, 1987, p. 74). It is impossible to find the perfect model that fits to the data with having a 100% accuracy. It is always a challenge to get the best and most useful model. As forecasting is more often stated within the literature that fitting the right model can be perceived as a combination of science and art which is learned the best way with practice and experience.

Hence there will always be room for improvement even for the constructed forecasting method in this research study. Even though it has been shown to improve the current forecasting performance and forecast in a highly accurate way. The forecasting models are largely dependent and therefore limited by the available data that can be used as input for making the predictions. Putting bad data and prediction variables in, will most likely also result in getting bad predictions out of the constructed forecasting models. The Retail VAS demand data showed no clear seasonality patterns in the data analysis of section 5.3.2 and showed higher autocorrelation values for smaller lags. Hence, the Retail GLM forecasting models of section 5.6.1, showed less dependency on older data and showed to rely more on recent data from the prediction variables. The data analysis of the Wholesale VAS demand showed the opposite by having strong seasonality patterns. Hence having high autocorrelation on the seasonal lags and having less strong relations with the smaller lags. Starting from FY18 the behavior of the seasonality started to differ and this deviation continued in FY19. As a result the Wholesale GLM forecasting models of section 5.6.2 were for a big part on depending the first so evident seasonality's in the data, by being fitted and trained to the data of these years. Therefore, the Wholesale GLM forecasting performance most likely will improve over time when the model has more data available and consequently giving less relevance towards older seasonal patterns. Resulting in giving more value towards newer data as these seasonal patterns start to differentiate more and more from the earlier patterns. This shows as the least fitted model now performs the best forecasts for newer data that contains this altered seasonality patterns.

Another phenomenon that can be improved specifically for situations of dealing with multiple DC's, since this also causes fluctuations in demand for the amount of labor in each DC. Normally this data would most likely be known upfront of which exact stock transfer is taking place and therefore can serve as an upfront input to the forecasting model. This way it would give a potential better forecasting result in contrast to looking backwards at historical data of how much demand has shifted. Which was the case in this specific business case.

Other potential options to improve the forecasting performances is to include other useful predictors that could possibly effect the demand of VAS labor hours. Such as: including which season of the year the prediction needs to be made (summer, fall, winter and spring), in which week number within the season, the size of the relevant product catalog of that specific season, relevant competitor activities, advertising/promotional campaign expenditure of relevant product articles residing in that specific DC, including data from big labor strikes and system outages. All of this would however take a lot of time, finding the correct and relevant information from this data, that one needs to ask the question if it is worth it to put in the time and effort for the potential gain that it can deliver.

The capacity planning models use the theoretical assumption that the data from the variables are normally distributed. However these data samples are not perfectly normally distributed and in practice this will also almost never be the case. Hence, the models will not give 100% correct probability values for having enough capacity in the distribution center with the corresponding planned labor values for the operations process in the upcoming week.

This research project was limited to labor demand forecasting of an activity in the outbound operations process within a distribution center. This same type of study could be applied to other operations within a distribution center such as activities in the inbound operations. These solutions could also be tested even further on how portable the research is to different distribution centers or warehouses, to contribute to the general conclusions of this research project.

In addition to improving above mentioned limitations, future research could also be focused on other workforce related research of the capacity planning steps from the in Figure 6 mentioned hierarchy of Production Planning Decisions (Nahmias, 2015). Such as simulating a “production run” with the models presented in this report serving as the input, for the planning and determination of employees on a longer period of time, in order to analyze the effects on the production quantity and the lead/backlog on the planned work schedule.

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Appendix A: Examples of current forecasting files

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
49	HOURS		Apparel FY15 budget hours												
50			June	July	August	September	October	November	December	January	February	March	April	May	Total
51		Franchise	1,250	1,359	884	1,220	1,062	680	986	963	563	1,137	1,373	1,075	12,552
52	DtC	Factory Stores	6,786	10,563	9,129	7,459	8,719	7,668	13,241	8,154	8,473	10,231	10,890	11,015	112,327
53		Inline	3,438	4,063	3,359	3,594	3,584	2,297	2,653	3,177	2,542	3,077	4,284	2,981	39,048
54		SDI	721	1,038	473	1,014	961	793	1,212	967	765	1,625	1,789	1,111	12,468
55		Harrods	208	271	181	244	18	13	271	94	64	366	244	195	2,167
56		JD	472	512	876	386	433	468	286	369	404	627	544	526	5,903
57	UK	Lifestyle	632	831	623	903	1,264	190	686	646	251	837	465	186	7,512
58		Shopdirect (Homeshopping)	354	57	793	496	510	248	623	430	297	362	315	204	4,689
59		Next (Homeshopping)	424	623	482	496	453	330	634	765	385	544	344	19	5,499
60		Argos (Homeshopping)	0	0	0	0	0	0	0	0	0	0	0	0	0
61		Office	0	0	0	0	0	0	0	44	27	18	44	27	160
62		ECI	994	563	578	794	523	419	939	477	260	647	376	415	6,985
63	Iberia	FC Barcelona	2,994	1,374	824	1,573	906	650	1,055	359	220	264	198	815	11,233
64		Sprinter	113	168	38	120	116	61	144	71	51	56	6	35	979
65		Sportzone	230	701	220	248	173	63	237	326	263	205	164	86	2,916
66		Karstadt	551	1,235	1,594	493	1,544	701	3	2,253	762	871	1,906	1,562	13,475
67	AGS	Kaufhof	317	1,167	955	803	803	444	10	1,748	957	1,027	2,262	775	11,267
68		Kastner & Oelher													0
69		Intersport Germany	289	425	273	241	237	188	303	487	223	179	184	210	3,239
70		Intersport Sweden	214	163	17	87	57	31	159	121	66	25	333	53	1,326
71		Intersport Finland	0	12	7	0	16	0	74	19	10	6	10	5	159
72		Stockman	30	49	4	22	17	5	34	29	10	26	3	1	229
73		Aktiesport	14	81	0	0	146	5	3	208	37	122	68	37	722
74		Brantano	0	47	0	0	9	0	0	5	0	0	0	0	62
75	NE	Perry	6	60	0	0	102	30	14	595	199	414	477	372	2,268
76		Primo	1	69	0	9	32	1	51	365	81	300	91	55	1,054
77		Ellos	0	40	3	0	0	0	0	21	19	28	5	3	119
78		Scapino	0	0	0	0	0	0	0	0	0	0	0	0	0
79		Bijenkorf	1	46	32	50	33	4	2	0	0	0	0	0	168
80		United Brands	83	83	0	83	68	21	45	9	3	87	12	0	494
81		Stadium	0	0	0	262	226	68	508	144	49	2	67	23	1,349
82	Footlocker	Footlocker	149	162	203	160	107	170	215	117	111	199	168	194	1,953
83		Cisalfa	325	350	193	154	204	50	58	367	117	192	275	125	2,410
84	Italy	Bata													0
85		Athletes world	0	0	0	0	0	0	0	0	0	0	0	0	0
86		Pittarello													0

Budget FY16 | Forecast | Actuals | data | tracking | Weekly FC | Weekly Act | DIFFERENCE | weekly act units | weekly act hours

Figure 40:Apparel(1060) VAS FY XX monthly forecast file

50-51	HOURS		Sep W36	Sep W37	Sep W38	Sep W39	Sep W40	Oct W40	Oct W41	Oct W42	Oct W43	Oct W44
52	DtC	Franchise	146	159	366	354	195	42	276	276	255	212
53		Factory Stores	975	1,993	1,786	1,870	836	1,557	1,717	1,794	1,785	1,867
54		Inline	467	395	1,078	1,078	575	143	896	1,004	824	717
55	UK	SDI	203	203	203	203	203	209	209	209	209	209
56		Harrods	49	49	49	49	49	25	25	25	25	25
57		JD	91	91	71	71	61	140	140	140	140	140
58		Lifestyle	181	181	181	181	181	318	318	318	318	318
59		Shopdirect (Homeshopping)	99	99	99	99	99	37	37	37	37	37
60		Next (Homeshopping)	99	99	99	99	99	106	106	106	106	106
61		Argos (Homeshopping)	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS
62		Office	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS
63	Iberia	ECI	79	108	188	144	274	0	91	149	120	163
64		FC Barcelona	36	637	365	244	291	6	192	283	283	141
65		Sprinter	8	7	9	33	62	36	14	8	25	33
66		Sportzone	74	74	50	37	12	69	52	26	17	9
67	AGS	Karstadt	493	0	0	0	0	488	370	459	163	64
68		Kaufhof	265	145	185	169	40	265	145	185	169	40
69		Kastner & Oelher	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS
70		Intersport Germany	0	7	112	10	112	47	2	0	188	0
71	NE	Intersport Sweden	0	14	29	22	22	11	11	11	11	11
72		Intersport Finland	0	0	0	0	0	0	0	7	4	4
73		Stockman	0	0	12	10	0	0	4	10	1	2
74		Aktiesport	0	0	0	0	0	47	34	23	33	9
75		Brantano	0	0	0	0	0	0	0	0	9	0
76		Perry	0	0	0	0	0	6	69	13	8	5
77		Primo	3	0	1	1	3	2	11	6	6	6
78		Ellos	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS
79		Scapino	0	0	0	0	0	0	0	0	0	0
80		Bijenkorf	0	0	0	46	4	11	12	4	3	3
81		United Brands	0	9	12	31	31	31	0	37	0	0
82		Stadium	0	37	70	101	54	45	36	40	50	56
83	Footlocker	Footlocker	113	18	9	13	7	4	6	15	45	35
84	Italy	Cisalfa	54	33	25	21	21	17	29	67	50	42
85		Bata	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS
86		Athletes world	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS
87		Pittarello	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS	NO VAS

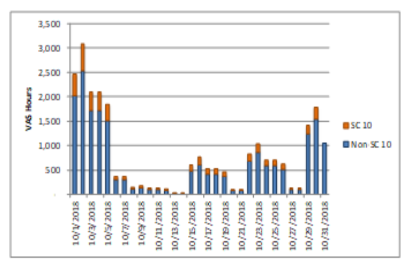
Budget FY16 / Forecast / Actuals / data / tracking / Weekly FC / Weekly Act / DIFFERENCE / weekly act units / weekly act hours

Figure 41:Apparel(1060) VAS FY XX weekly forecast file

APPAREL

			PGI - VAS Hours											PGI - Units		
			Inline		Partners		NFS		NFS Russia							
Date	Weeknum	Weekday	Non-SC 10	SC 10	Non-SC 10	SC 10	Non-SC 10	SC 10	Non-SC 10	SC 10	Non-SC 10	SC 10 forecast	Total Retail	Non-SC 10	SC 10 forecast	Total Retail
1-Oct	40	Monday	64	193	15	131	1,919	122	24	-	2,022	447	2,469	129,000	17,000	146,000
2-Oct	40	Tuesday	81	242	18	164	2,398	153	30	-	2,527	559	3,086	129,000	17,000	146,000
3-Oct	40	Wednesday	55	164	12	112	1,631	104	20	-	1,718	380	2,098	129,000	17,000	146,000
4-Oct	40	Thursday	55	164	12	112	1,631	104	20	-	1,718	380	2,098	129,000	17,000	146,000
5-Oct	40	Friday	48	145	11	98	1,439	92	18	-	1,516	335	1,851	129,000	17,000	146,000
6-Oct	40	Saturday	10	29	2	20	288	18	4	-	303	67	370	129,000	17,000	146,000
7-Oct	40	Sunday	10	29	2	20	288	18	4	-	303	67	370	129,000	17,000	146,000
8-Oct	41	Monday	6	18	1	11	99	6	1	-	107	35	142	129,000	17,000	146,000
9-Oct	41	Tuesday	7	22	1	13	124	8	1	-	134	44	177	129,000	17,000	146,000
10-Oct	41	Wednesday	5	15	1	9	84	5	1	-	91	30	121	129,000	17,000	146,000
11-Oct	41	Thursday	5	15	1	9	84	5	1	-	91	30	121	129,000	17,000	146,000
12-Oct	41	Friday	4	13	1	8	74	5	0	-	80	26	106	129,000	17,000	146,000
13-Oct	41	Saturday	1	3	0	2	15	1	0	-	16	5	21	129,000	17,000	146,000
14-Oct	41	Sunday	1	3	0	2	15	1	0	-	16	5	21	129,000	17,000	146,000
15-Oct	42	Monday	17	69	4	35	459	24	3	-	483	128	610	129,000	17,000	146,000
16-Oct	42	Tuesday	22	86	5	43	573	30	4	-	603	160	763	129,000	17,000	146,000
17-Oct	42	Wednesday	15	59	3	29	390	21	2	-	410	109	519	129,000	17,000	146,000
18-Oct	42	Thursday	15	59	3	29	390	21	2	-	410	109	519	129,000	17,000	146,000
19-Oct	42	Friday	13	52	3	26	344	18	2	-	362	96	458	129,000	17,000	146,000
20-Oct	42	Saturday	3	10	1	5	69	4	0	-	72	19	92	129,000	17,000	146,000
21-Oct	42	Sunday	3	10	1	5	69	4	0	-	72	19	92	129,000	17,000	146,000
22-Oct	43	Monday	15	61	5	44	659	27	8	-	688	133	821	129,000	17,000	146,000
23-Oct	43	Tuesday	19	77	6	55	824	34	11	-	860	166	1,026	129,000	17,000	146,000
24-Oct	43	Wednesday	13	52	4	38	560	23	7	-	584	113	698	129,000	17,000	146,000
25-Oct	43	Thursday	13	52	4	38	560	23	7	-	584	113	698	129,000	17,000	146,000
26-Oct	43	Friday	12	46	4	33	494	21	6	-	516	100	616	129,000	17,000	146,000
27-Oct	43	Saturday	2	9	1	7	99	4	1	-	103	20	123	129,000	17,000	146,000
28-Oct	43	Sunday	2	9	1	7	99	4	1	-	103	20	123	129,000	17,000	146,000
29-Oct	44	Monday	19	76	6	57	1,194	50	19	-	1,238	183	1,421	129,000	17,000	146,000
30-Oct	44	Tuesday	24	94	8	72	1,492	62	24	-	1,548	228	1,776	129,000	17,000	146,000
31-Oct	44	Wednesday	16	64	5	49	1,015	42	16	-	1,053	-	1,053	129,000	17,000	146,000

Buffer perweek				
40	41	42	43	44
0%	0%	0%	0%	0%



Required actions in the IDP capacity table (SAP)
- Open **non-SC 10 forecast** in the beginning of the month
- Each evening: add **SC 10 forecast** for PGI today+2
+ maximize with available capacity

Figure 42: DTC Month forecast on day level

Appendix B: Demand data analysis graphs from section 5.3

Appendix B 1.1: Monthly Retail VAS demand data graphs from section 5.3.1.1

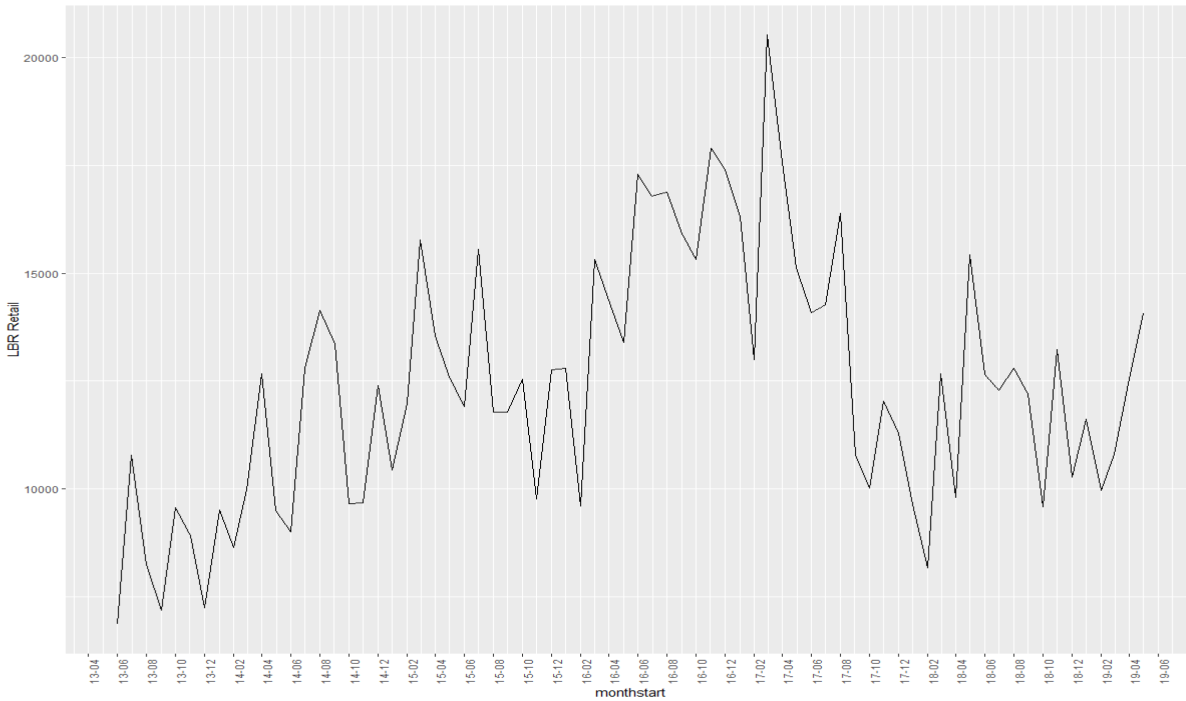


Figure 43: Total actual of Retail VAS labor hours aggregated per month for FY14-FY19

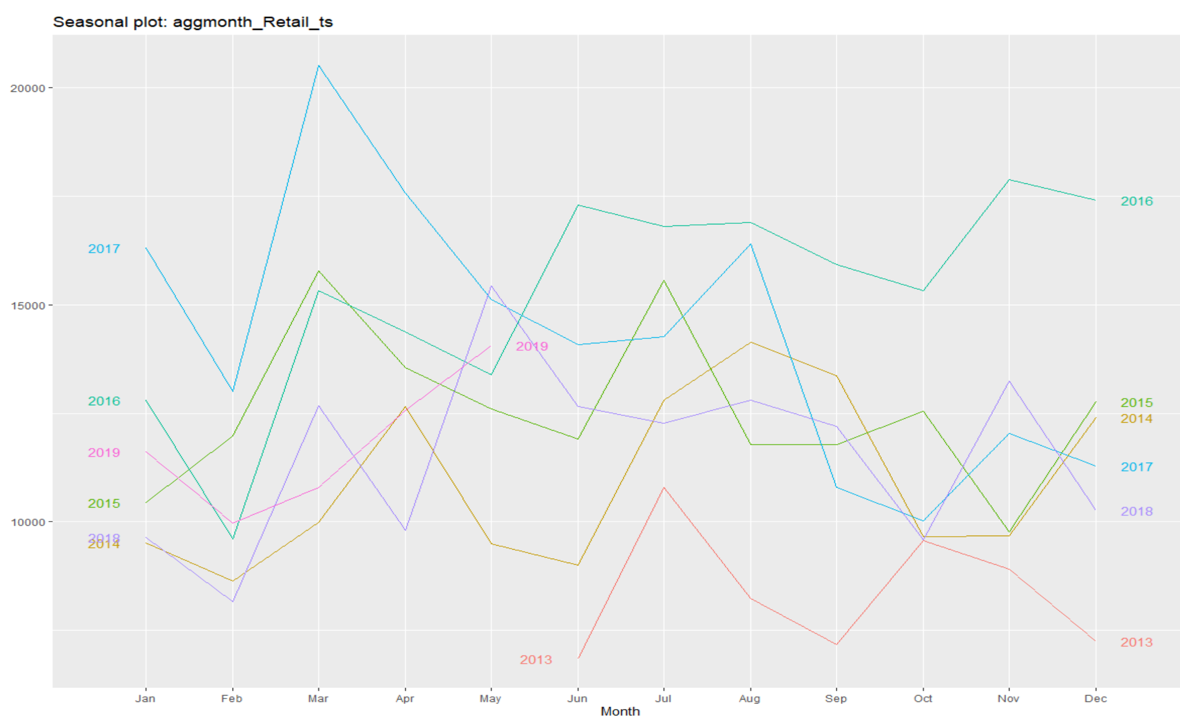


Figure 44: Total actual of Retail VAS labor hours aggregated per month for FY14-FY19 illustrated per calendar year

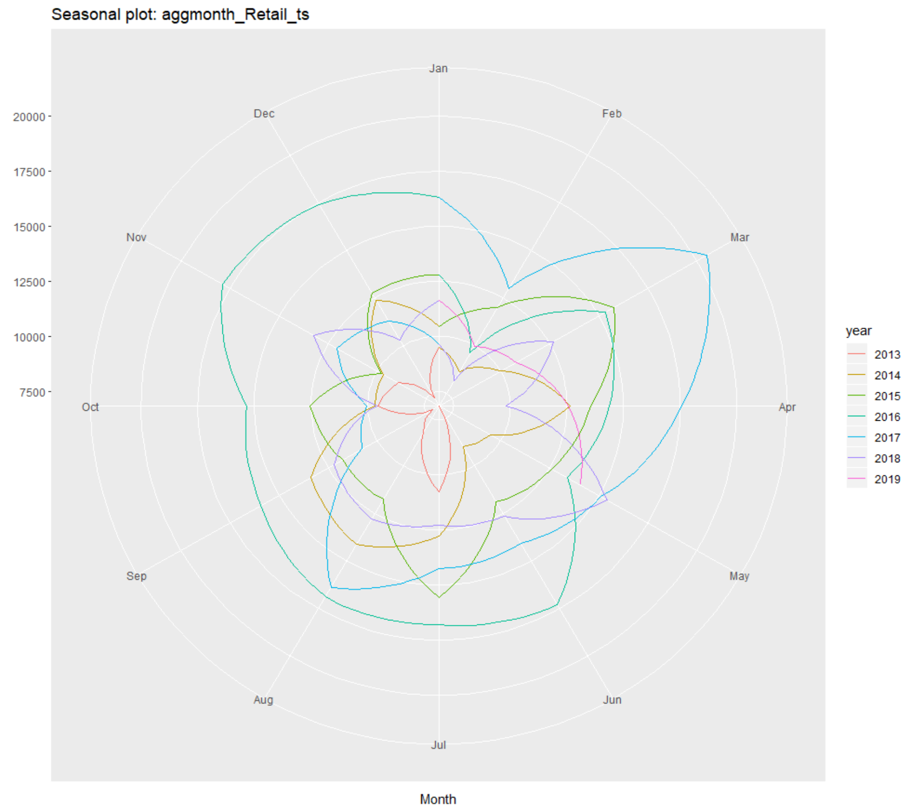


Figure 45: Total actual of Retail VAS labor hours aggregated per month for FY14-FY19 polar representation

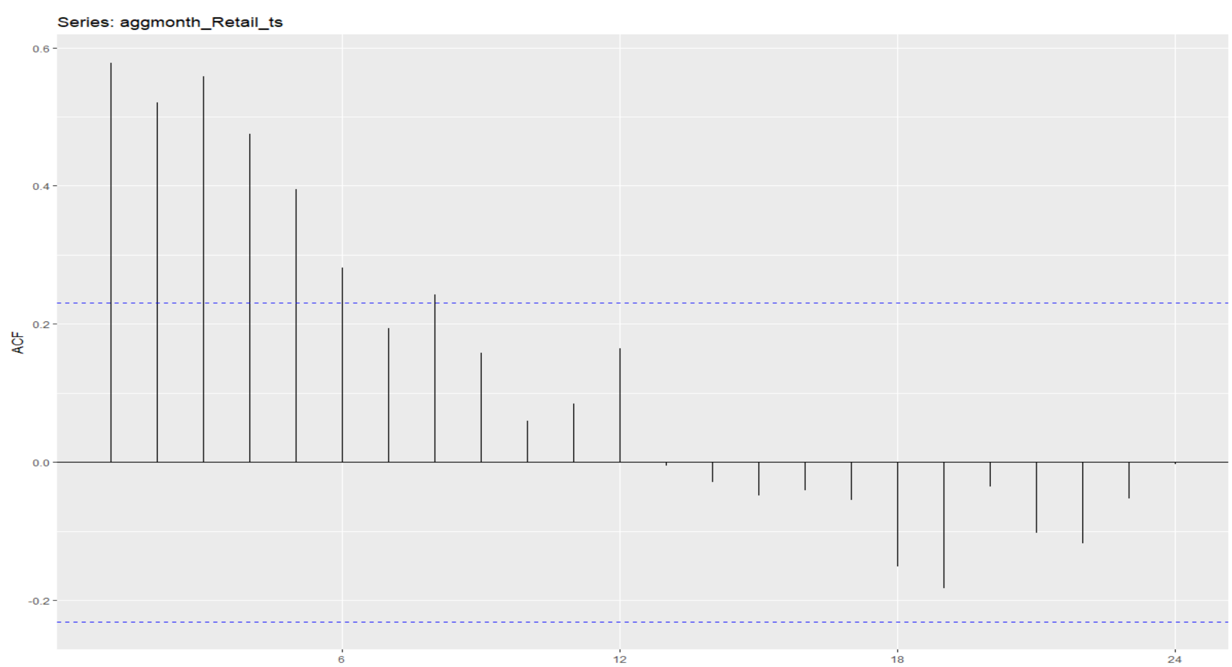


Figure 46: Correlogram ACF of monthly actual labor hours of Retail VAS for FY14-FY19

Appendix B 1.2: Monthly Wholesale VAS demand data graphs from section 5.3.1.2

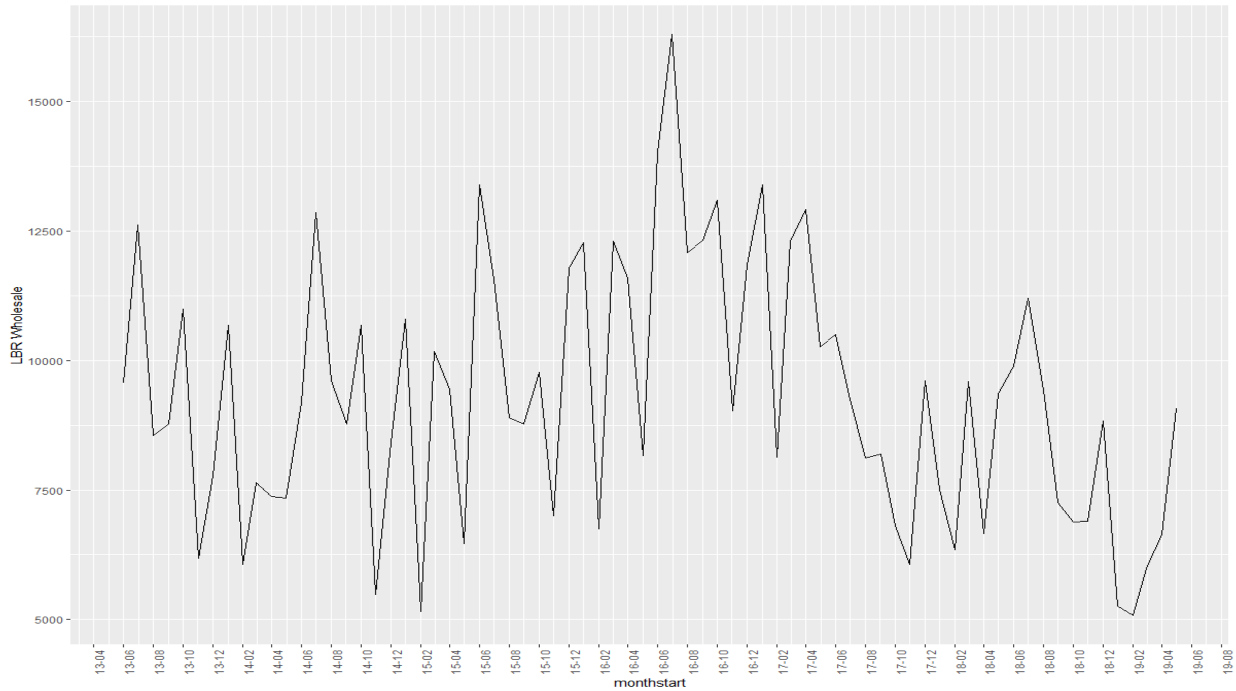


Figure 47: Total actual of Wholesale VAS labor hours aggregated per month for FY14-FY19

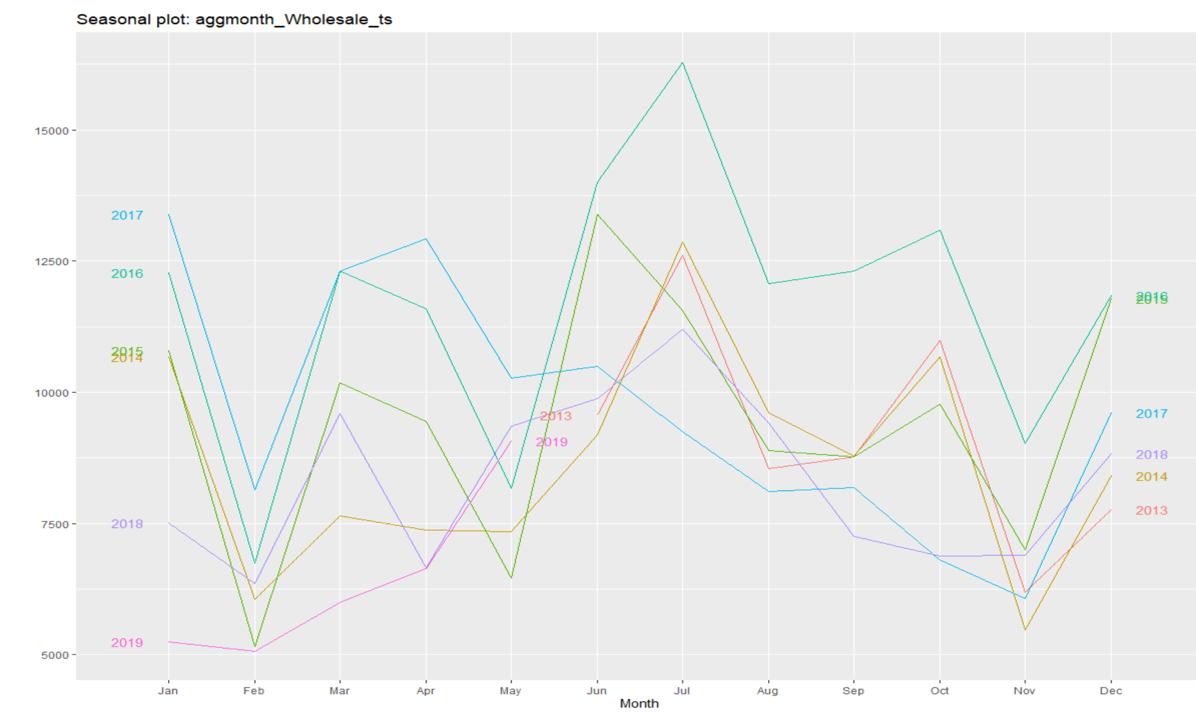


Figure 48: Total actual of Wholesale VAS labor hours aggregated per month for FY14-FY19 illustrated per calendar year

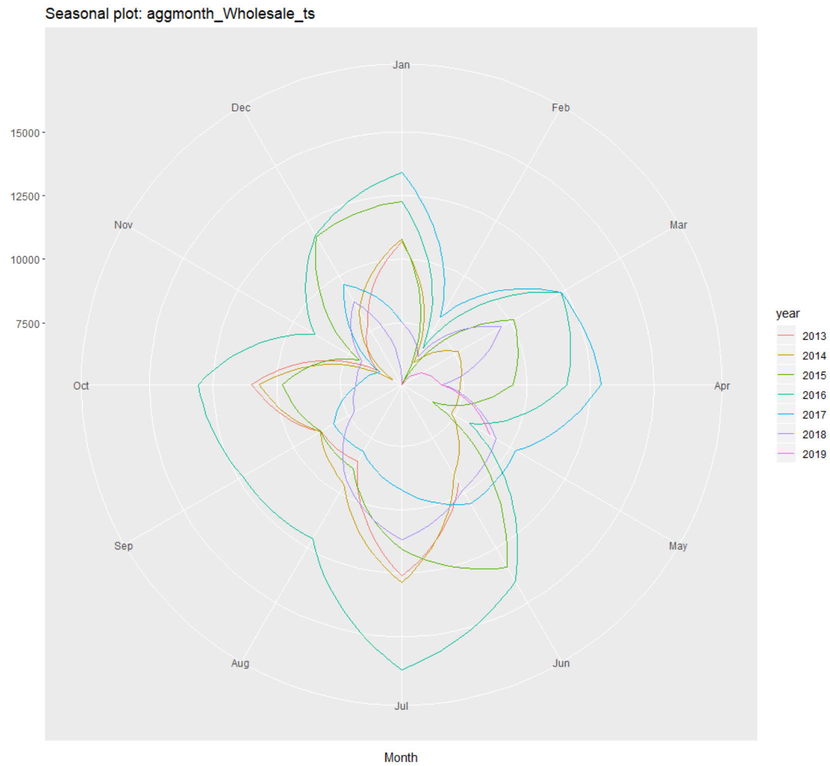


Figure 49: Total actual of Wholesale VAS labor hours aggregated per month for FY14-FY19 polar representation

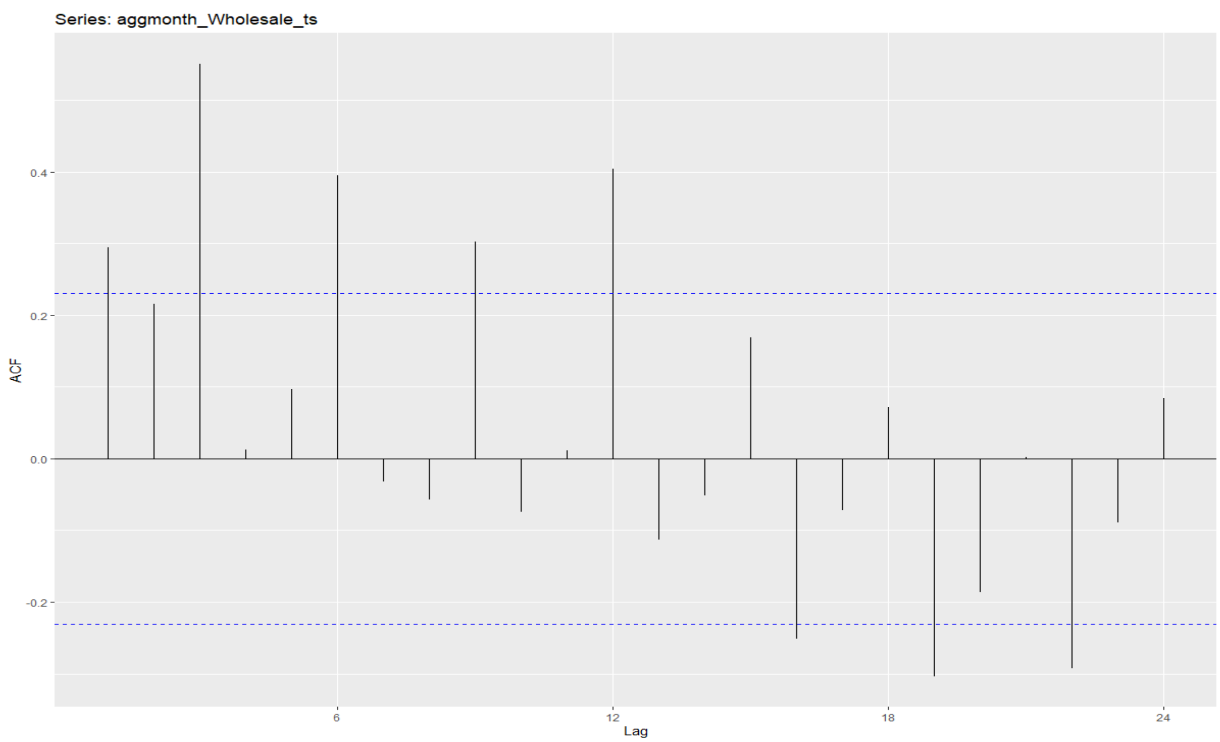


Figure 50: Correlogram ACF of monthly actual labor hours of Wholesale VAS for FY14-FY19

Appendix B 2.1: Weekly Retail VAS demand data graphs from section 5.3.2.1

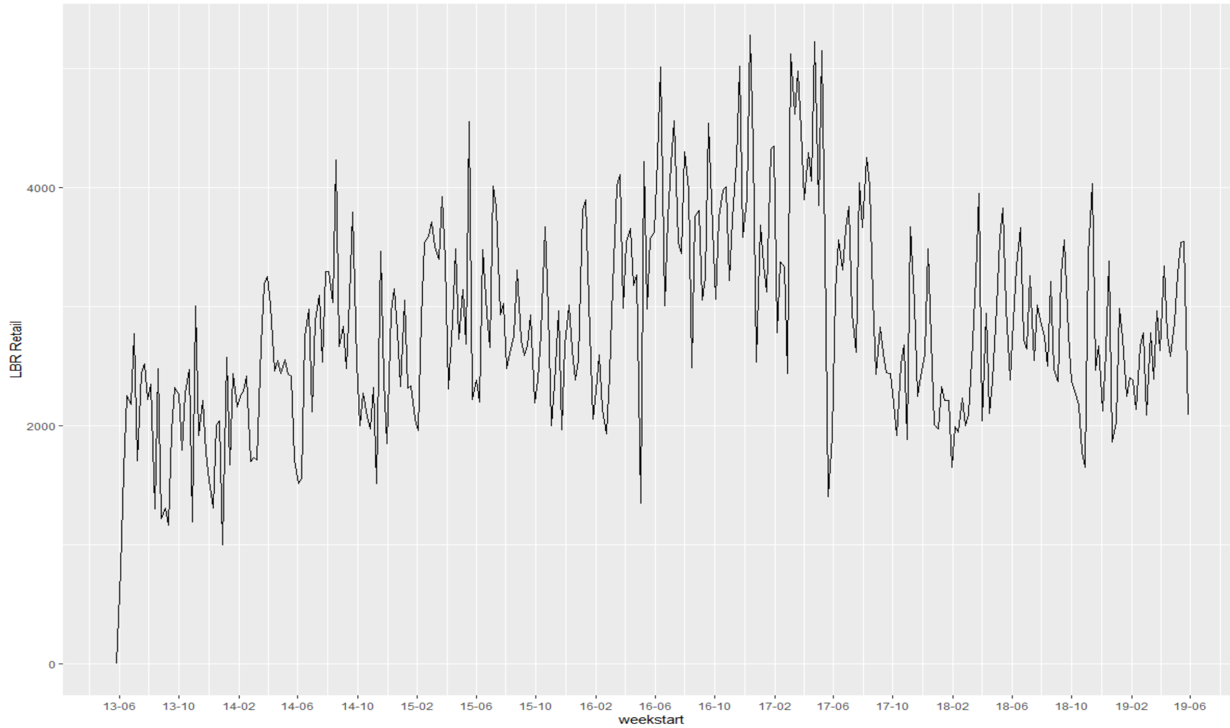


Figure 51: Total actual of Retail VAS labor hours aggregated per week for FY14-FY19

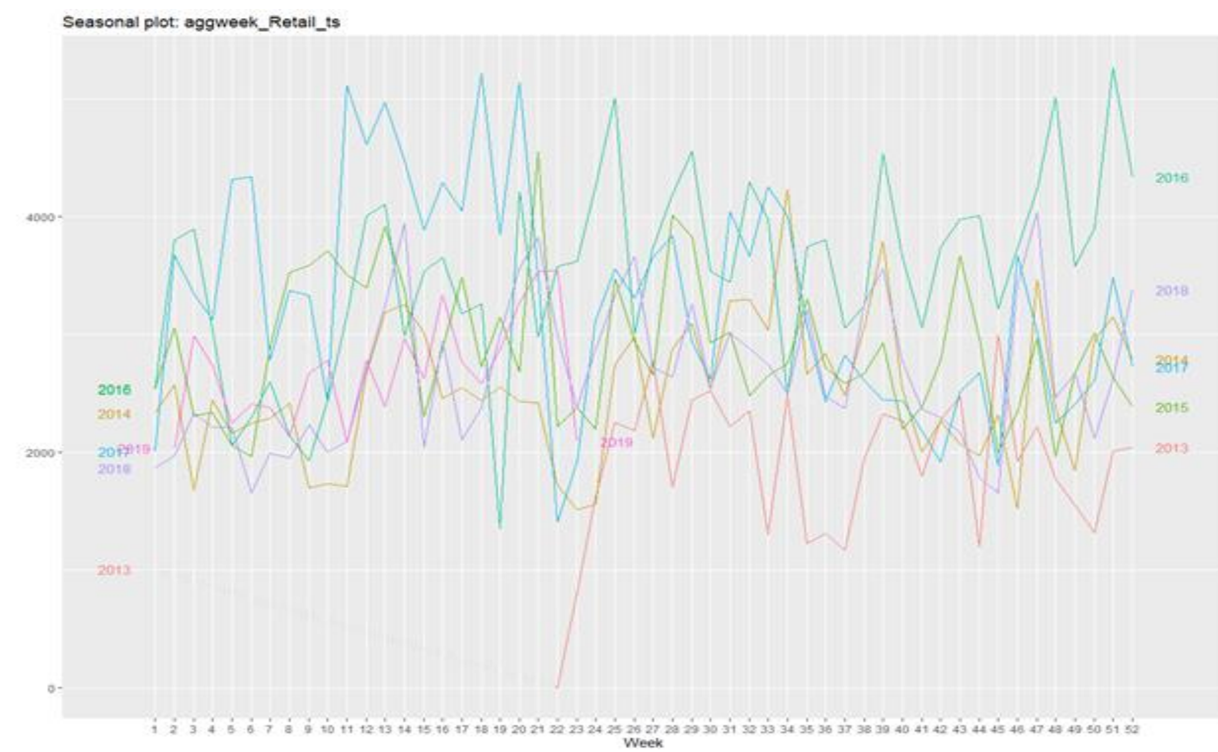


Figure 52: Total actual of Retail VAS labor hours aggregated per week for FY14-FY19 illustrated per year

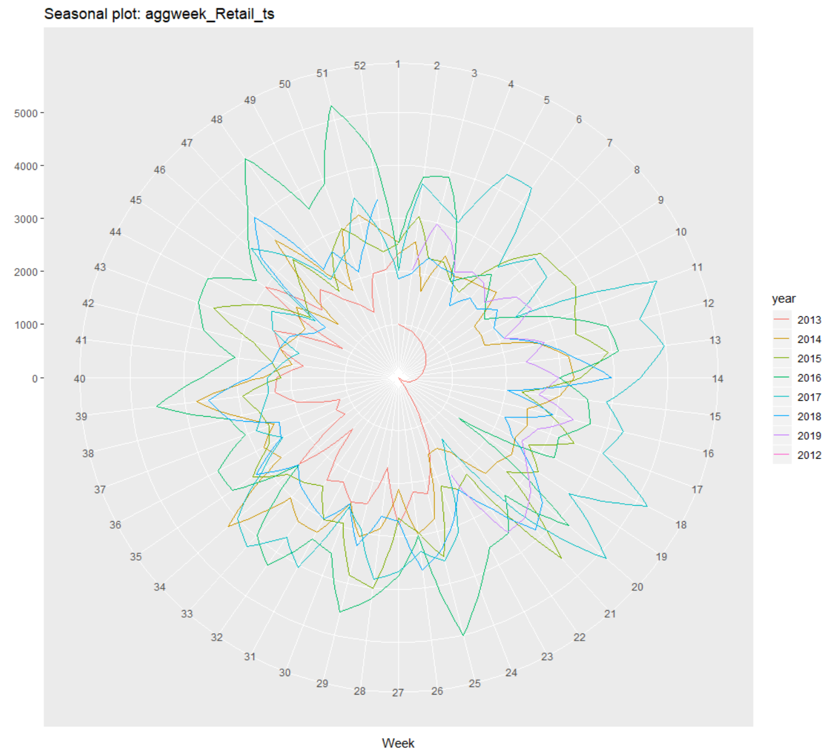


Figure 53: Total actual of Retail VAS labor hours aggregated per week for FY14-FY19 polar representation

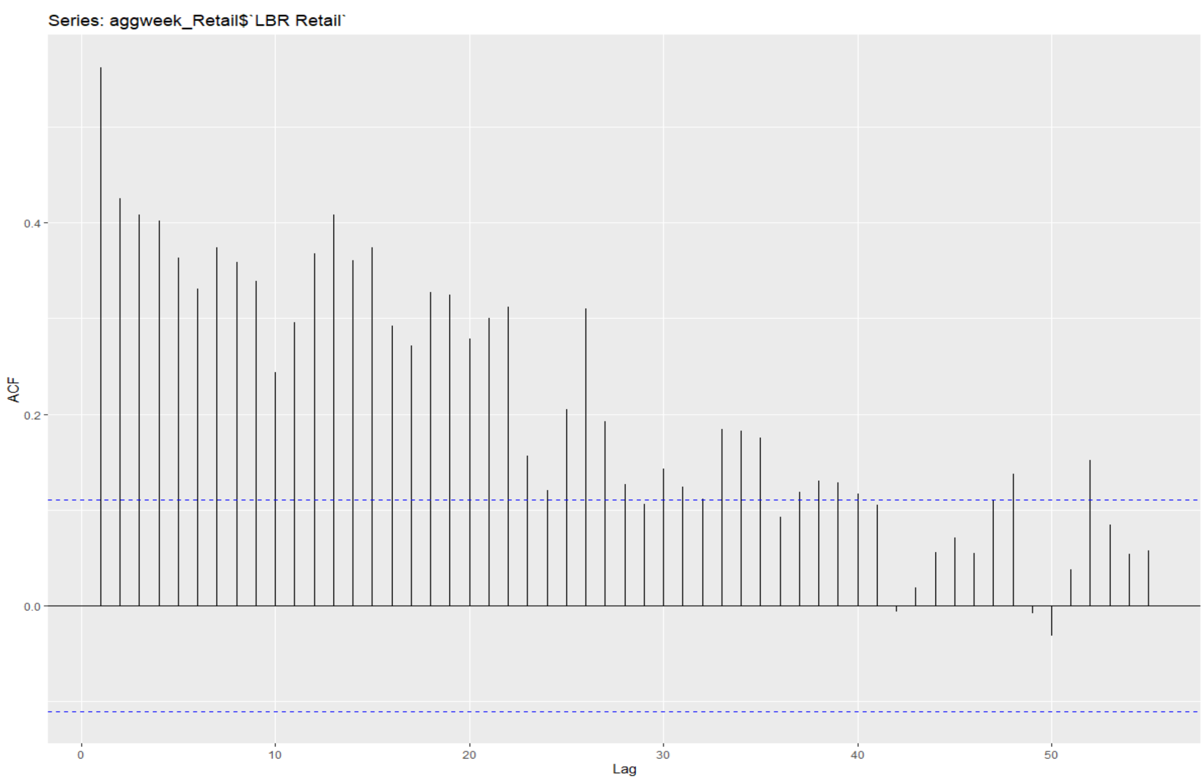


Figure 54: Correlogram ACF of weekly actual labor hours of Retail VAS for FY14-FY19

Appendix B 2.2: Weekly Wholesale VAS demand data graphs from section 5.3.2.2

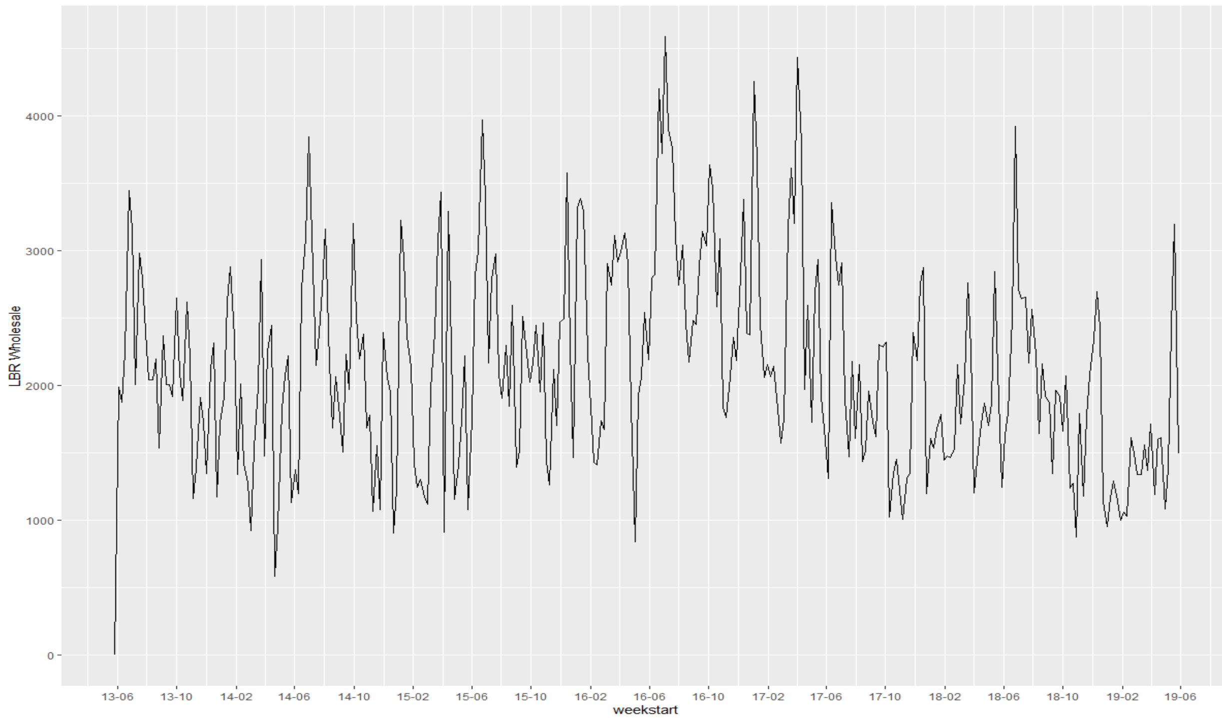


Figure 55: Total actual of Wholesale VAS labor hours aggregated per week for FY14-FY19

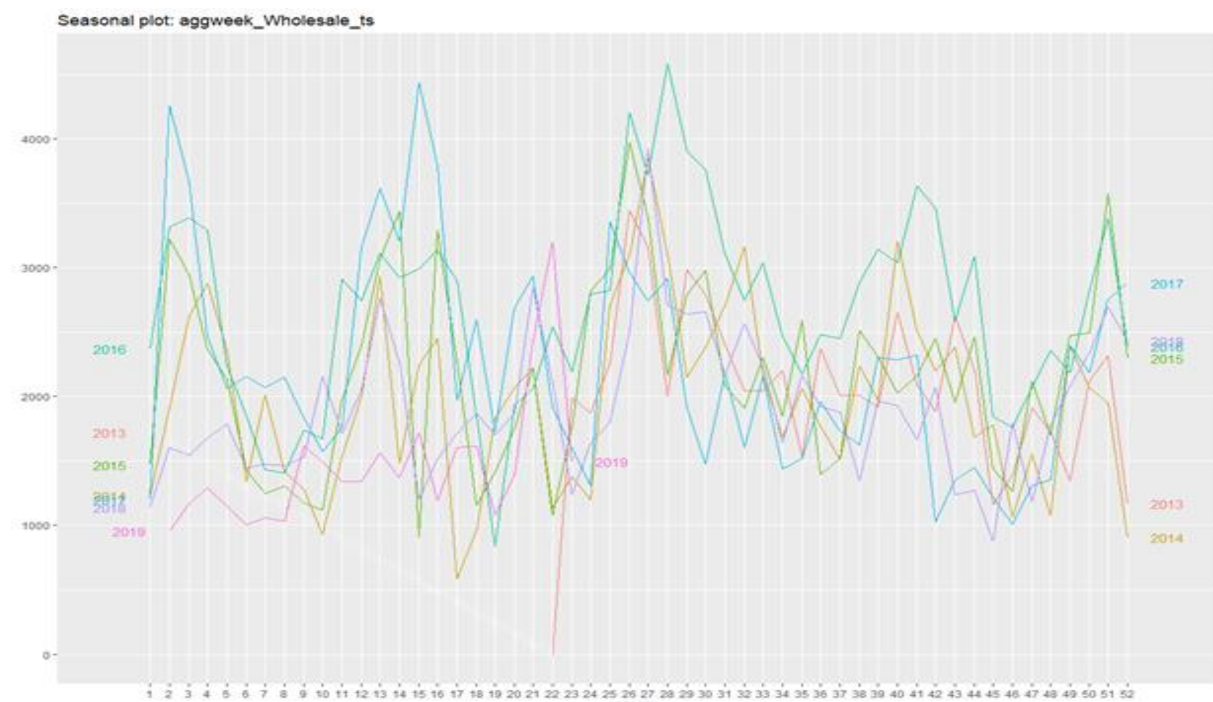


Figure 56: Total actual of Wholesale VAS labor hours aggregated per week for FY14-FY19 illustrated per year

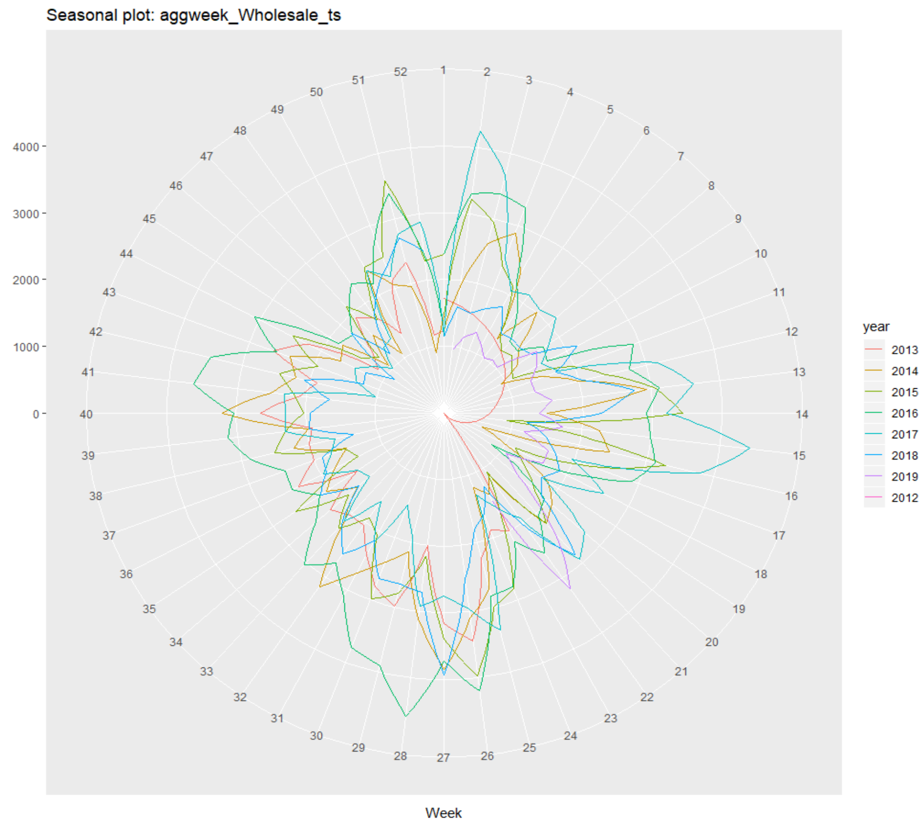


Figure 57: Total actual of Wholesale VAS labor hours aggregated per week for FY14-FY19 polar representation

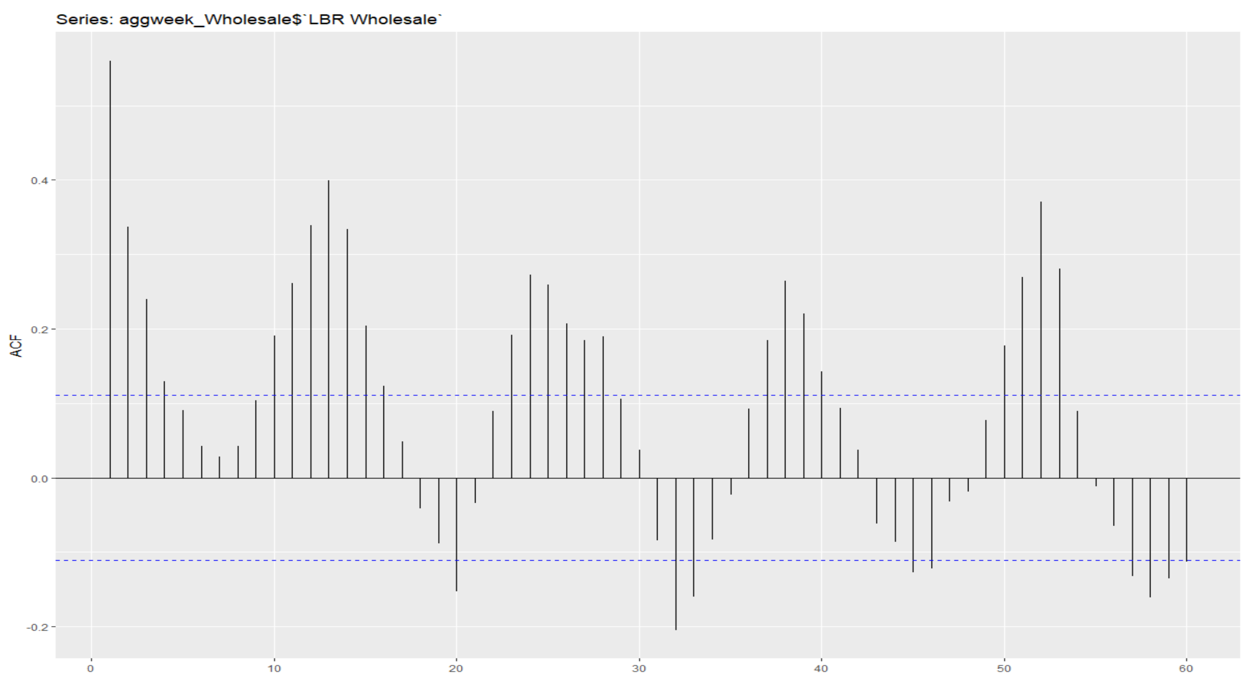


Figure 58: Correlogram ACF of weekly actual labor hours of Wholesale VAS for FY14-FY19

Appendix C: List of potential reasons of deviating PGI and AGI date

Below follows a list with possible reasons why the PGI and the AGI date are deviating from each other.

1. The VAS handling contains a launch product that the customer has requested earlier than the first agreed upon launch date. Therefore these products are not allowed to be processed yet.

2. The definitive customer order hasn't been received on time in order to be planned in time for the PGI date.

3. The customer order belongs to a long distance carrier (e.g. Russia, Turkey and Israel). These are IDP-orders that are saved up to leave in full trailers because otherwise it is not cost efficient to distribute these units to the customers.

4. The order is considered as a direct drop. These orders are distributed in trailers that are going directly to a specific customer. This holds for customers with such a big order for a same shipping address with a certain PGI date. In these situations it is more cost efficient to fill up an entire trailer that is going directly to this customer, instead of consolidating first with other customer orders that afterwards have to be sorted out again in a hub. Therefore direct drops can leave a day later because the order is distributed directly to the customer.

5. Caused by human error while planning, which results into not including the orders on their PGI date.

6. System errors and issues; failures in SAP or in the warehouse management system.

7. Orders are stopped because of mistakes on the delivery documents. These orders have to be adjusted by sales representatives and are therefore processed again at another time.

Appendix D: PGI SO, PGI DD and AGI data analysis from section 5.3.3

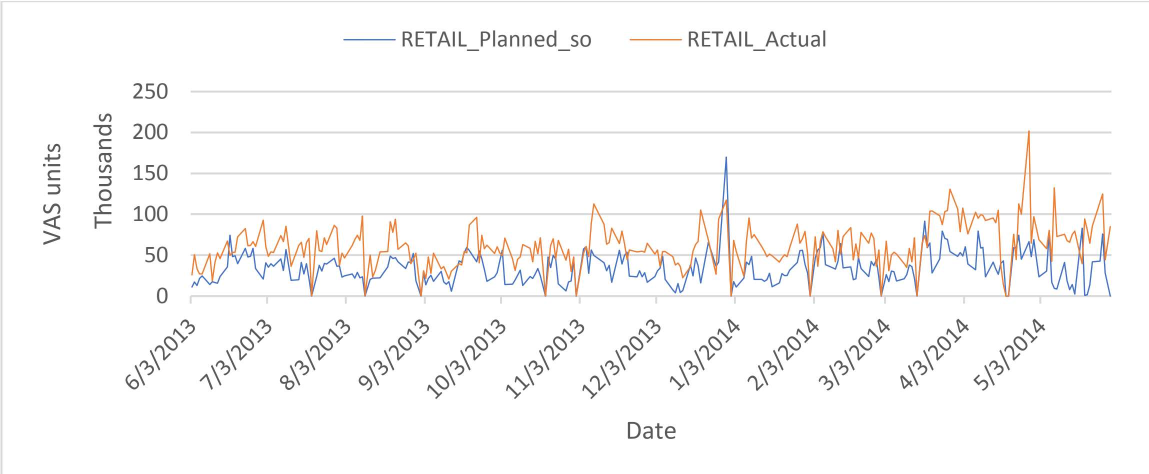


Figure 59:The difference between the PGI SO and the AGI Retail VAS units for FY14

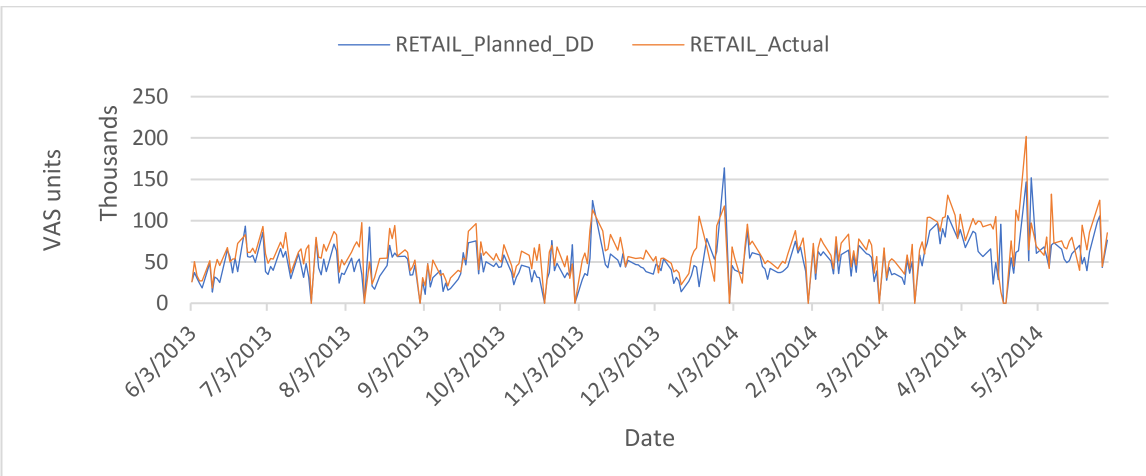


Figure 60:The difference between the PGI DD and the AGI Retail VAS units for FY14

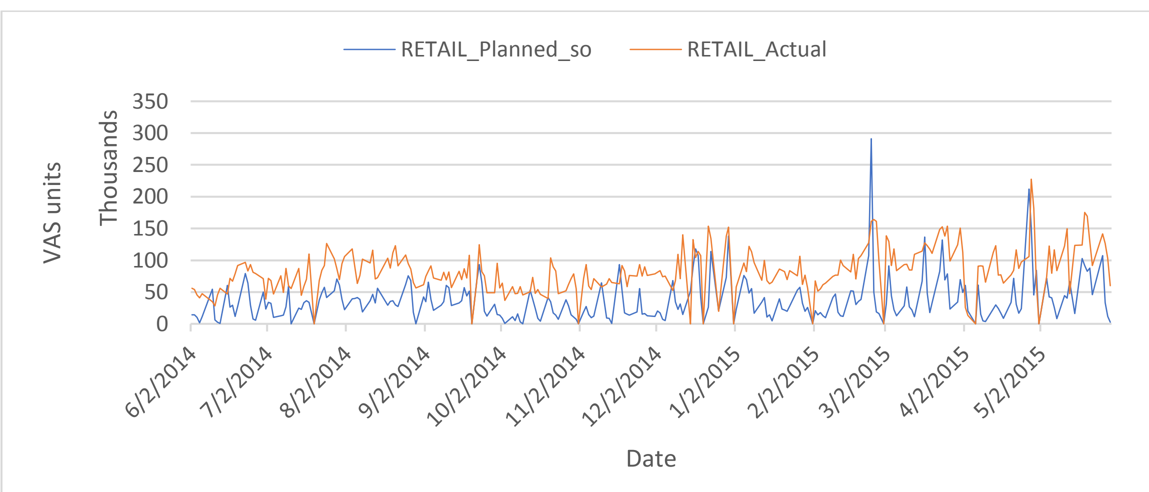


Figure 61:The difference between the PGI SO and the AGI Retail VAS units for FY15

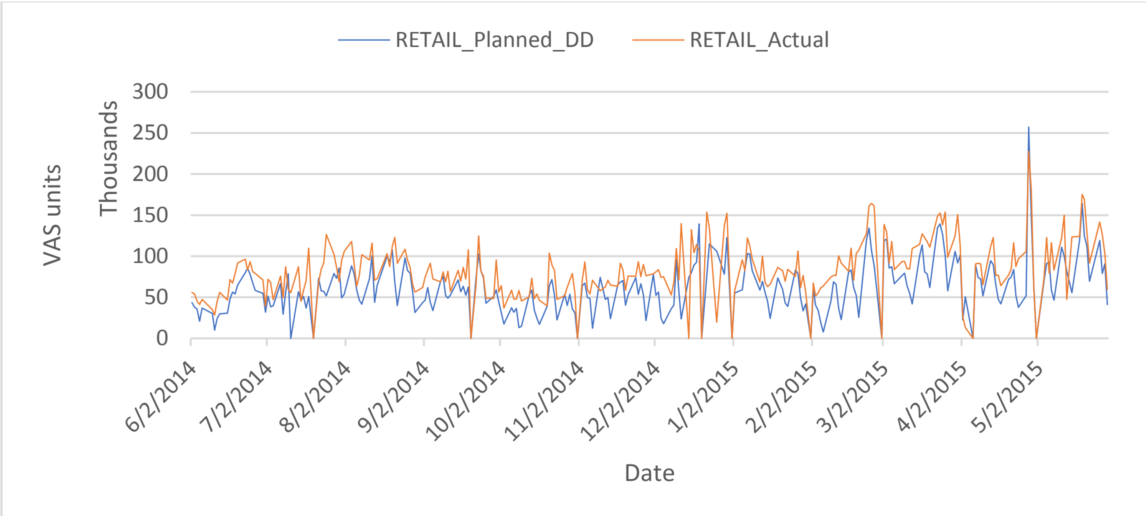


Figure 62: The difference between the PGI DD and the AGI Retail VAS units for FY15

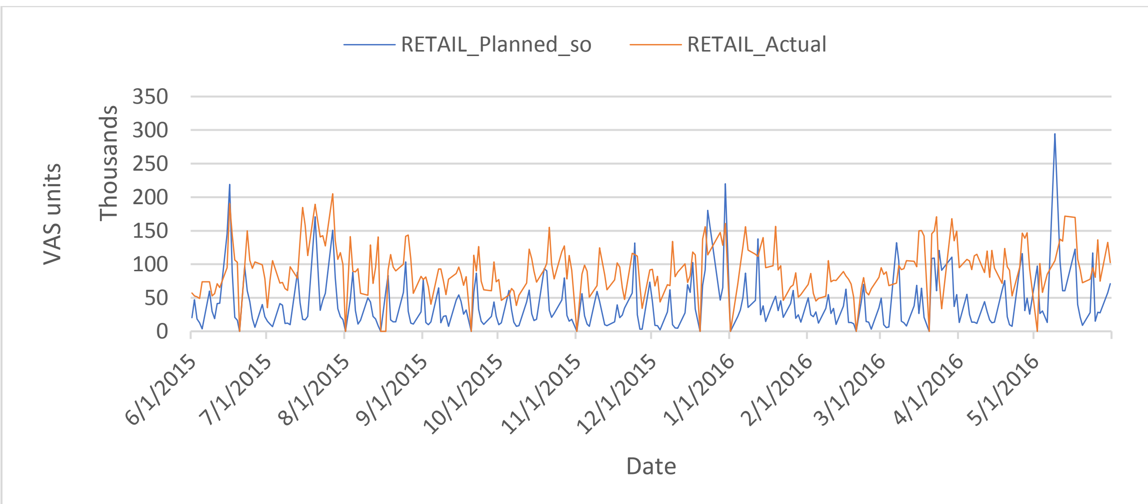


Figure 63:The difference between the PGI SO and the AGI Retail VAS units for FY16

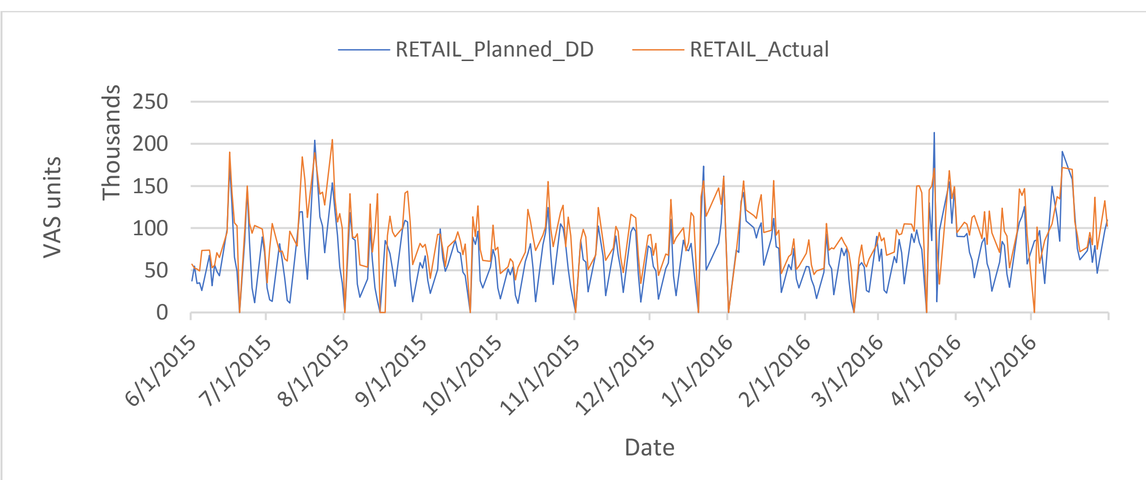


Figure 64:The difference between the PGI DD and the AGI Retail VAS units for FY16

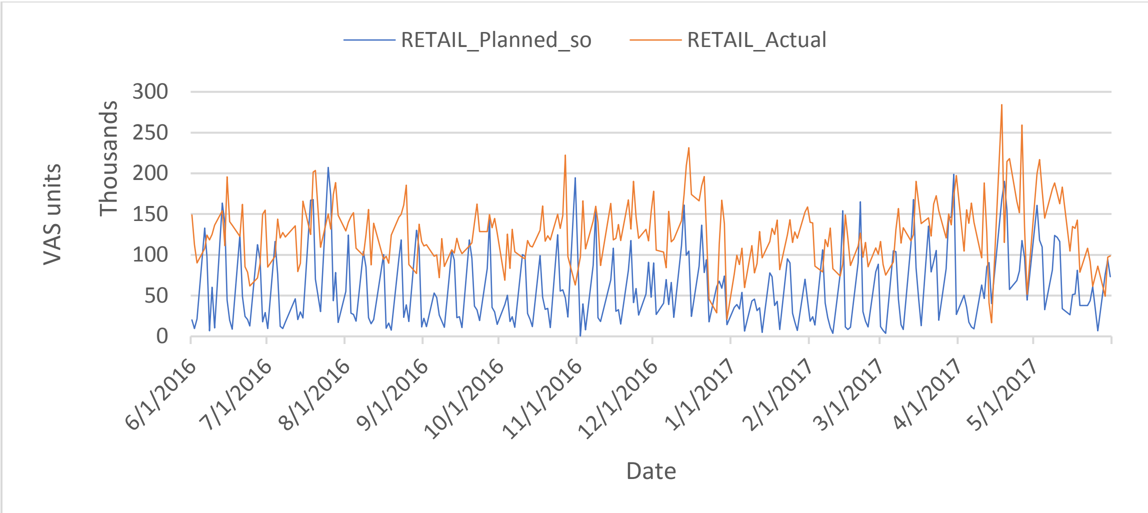


Figure 65: The difference between the PGI SO and the AGI Retail VAS units for FY17

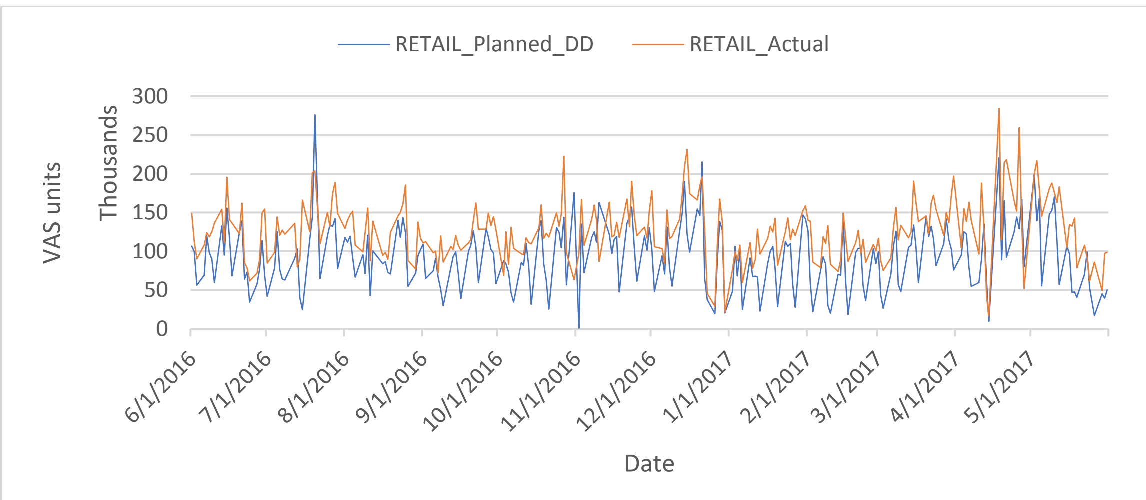


Figure 66: The difference between the PGI DD and the AGI Retail VAS units for FY17

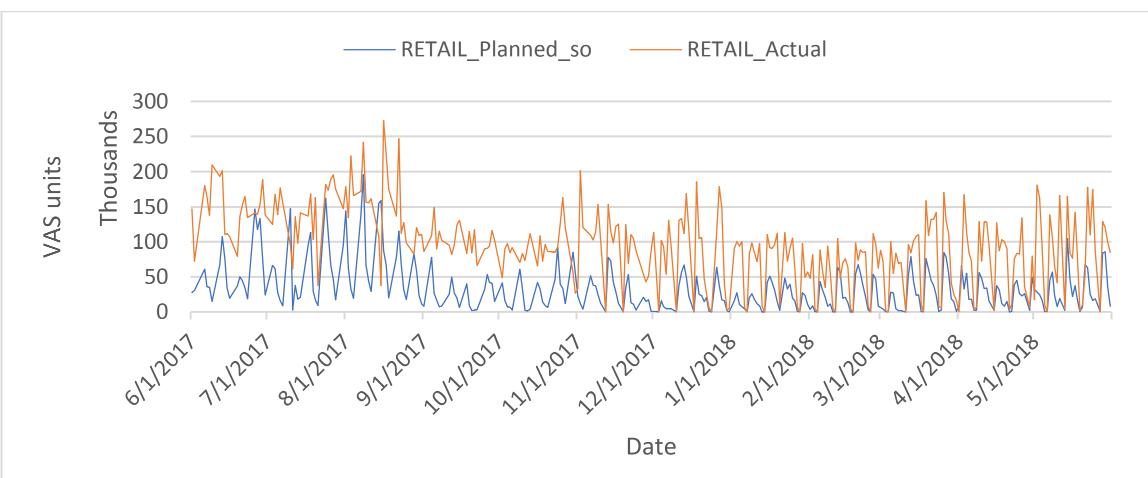


Figure 67: The difference between the PGI SO and the AGI Retail VAS units for FY18

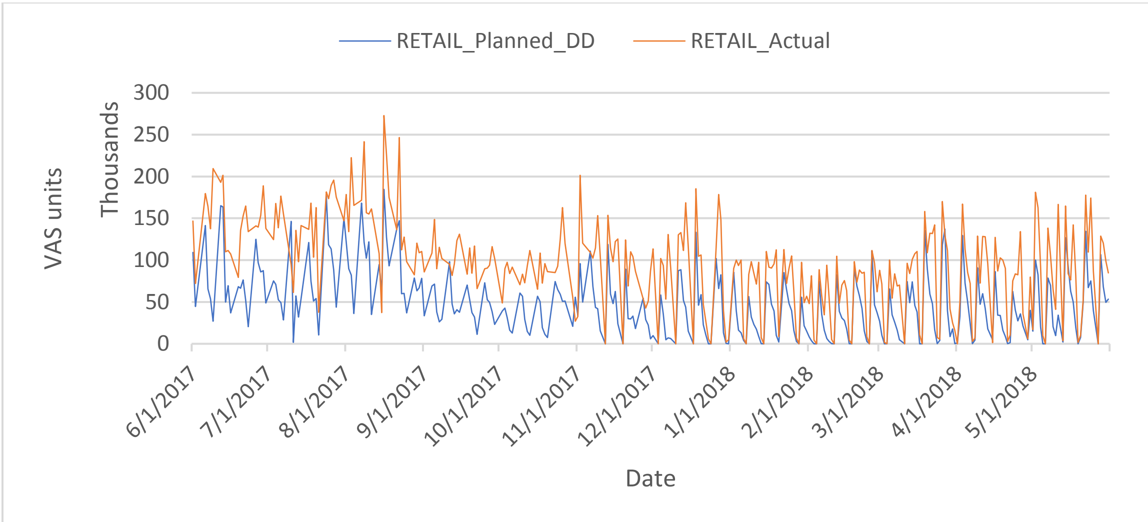


Figure 68: The difference between the PGI DD and the AGI Retail VAS units for FY18

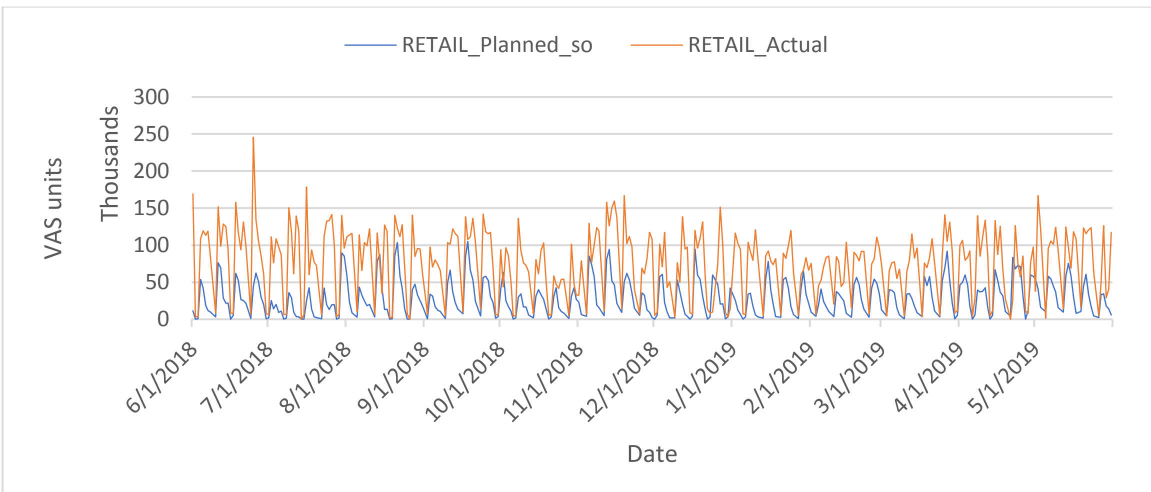


Figure 69: The difference between the PGI SO and the AGI Retail VAS units for FY19

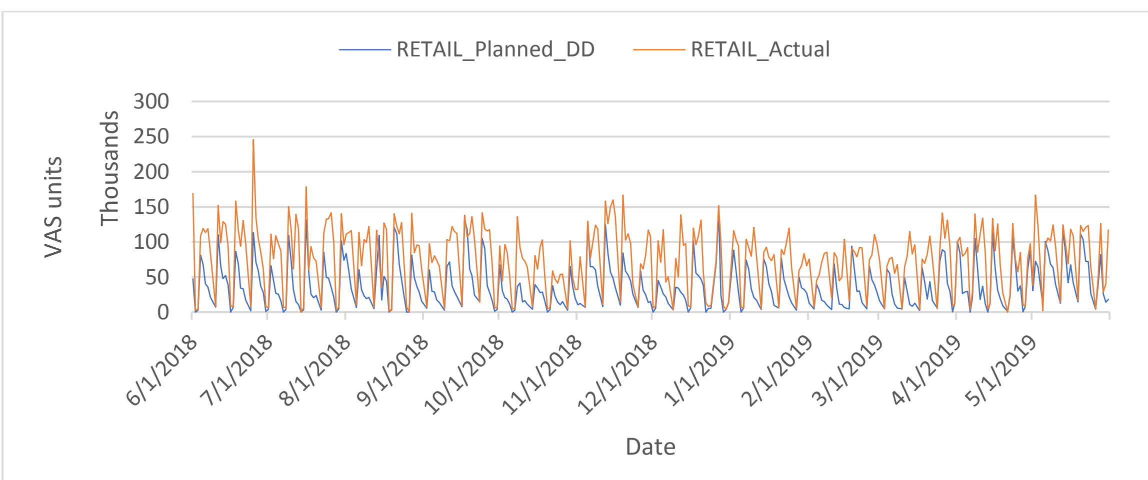


Figure 70: The difference between the PGI DD and the AGI Retail VAS units for FY19

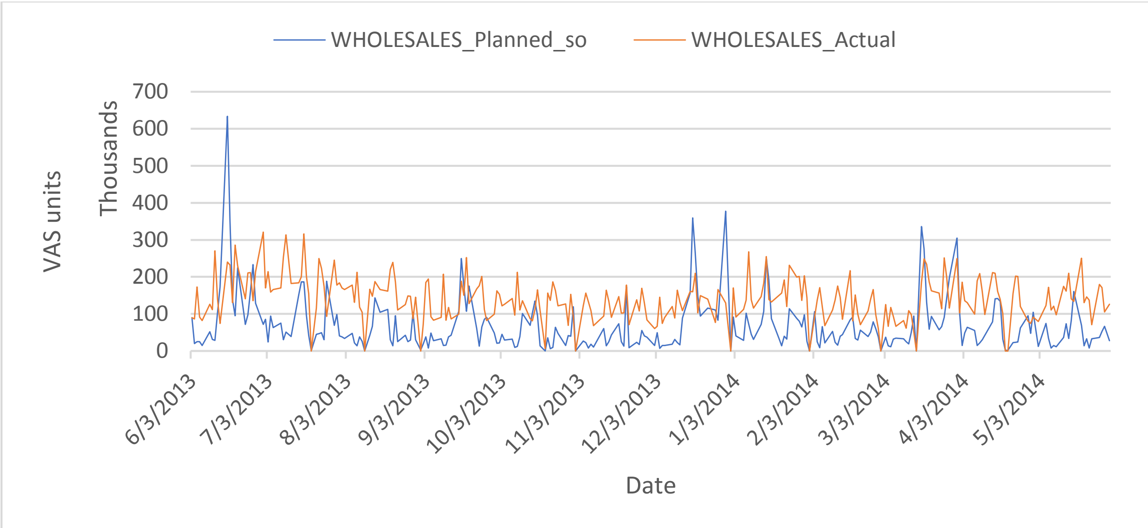


Figure 71: The difference between the PGI SO and the AGI Wholesale VAS units for FY14

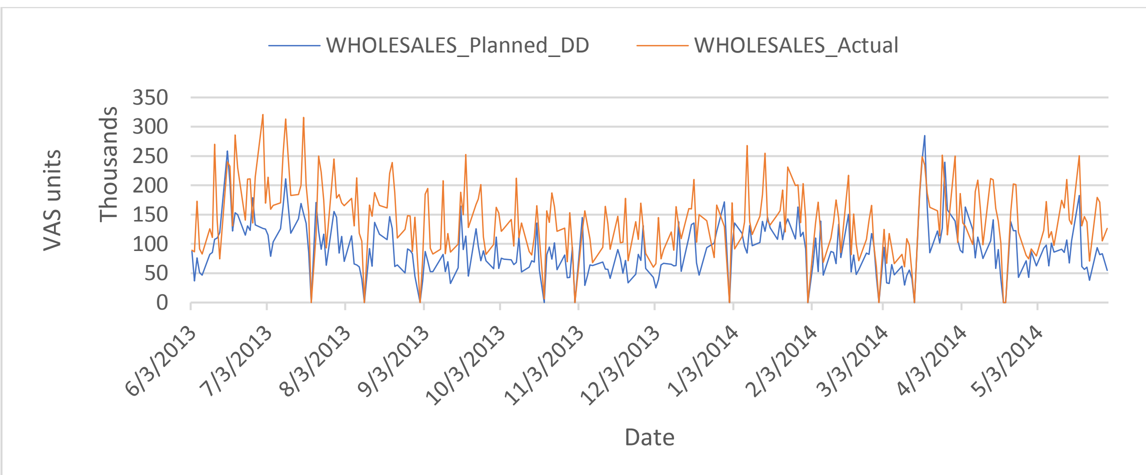


Figure 72: The difference between the PGI DD and the AGI Wholesale VAS units for FY14

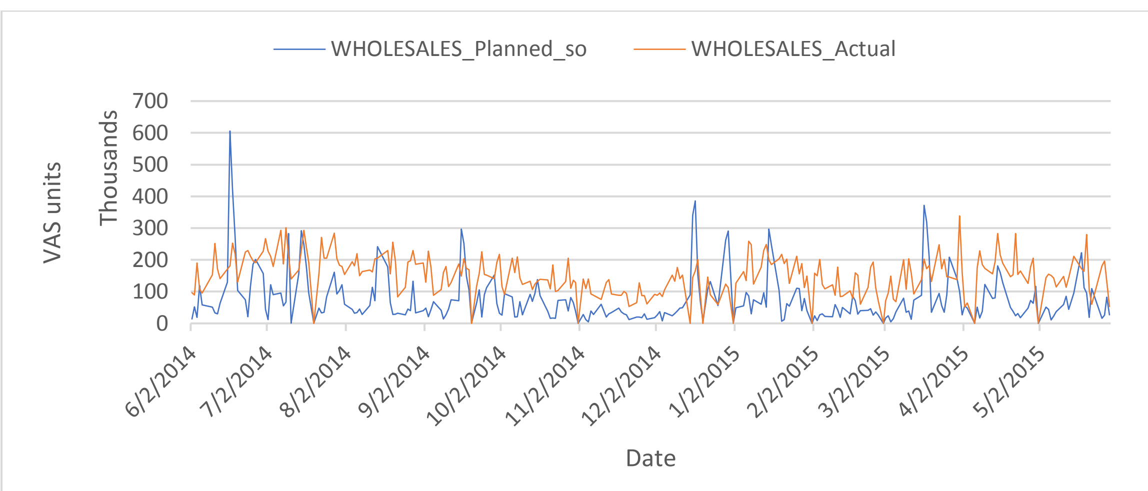


Figure 73: The difference between the PGI SO and the AGI Wholesale VAS units for FY15

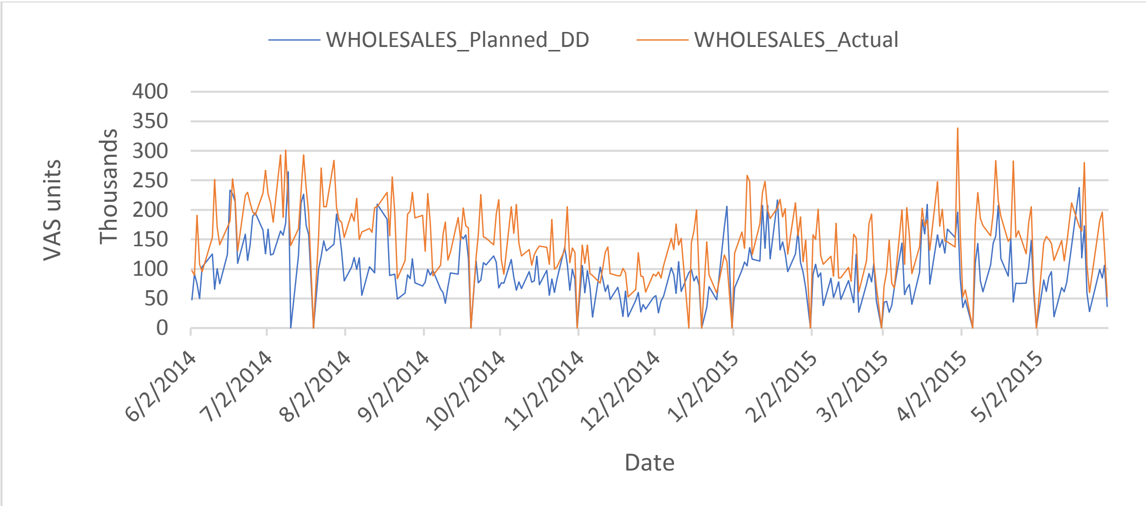


Figure 74: The difference between the PGI DD and the AGI Wholesale VAS units for FY15

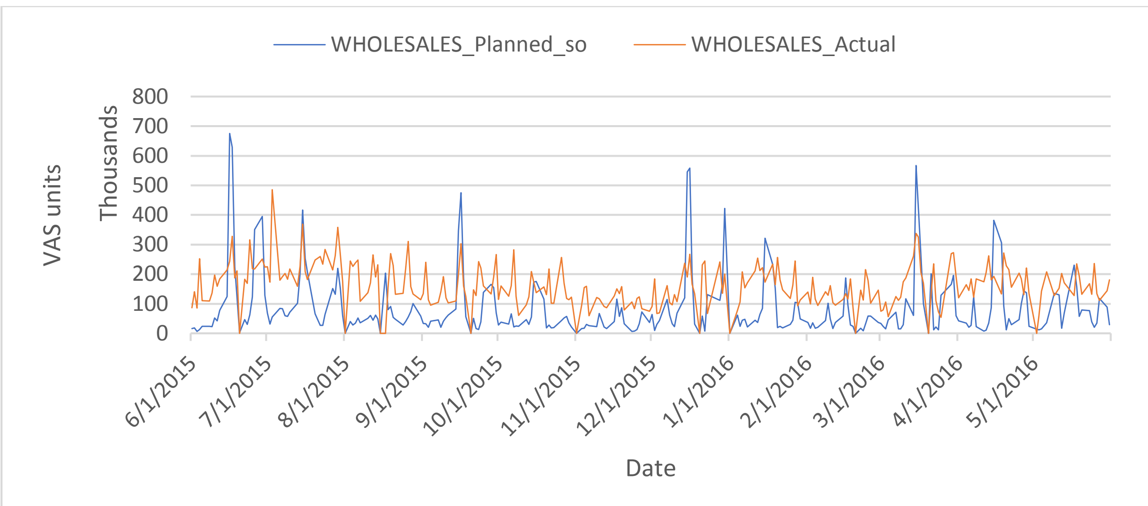


Figure 75: The difference between the PGI SO and the AGI Wholesale VAS units for FY16

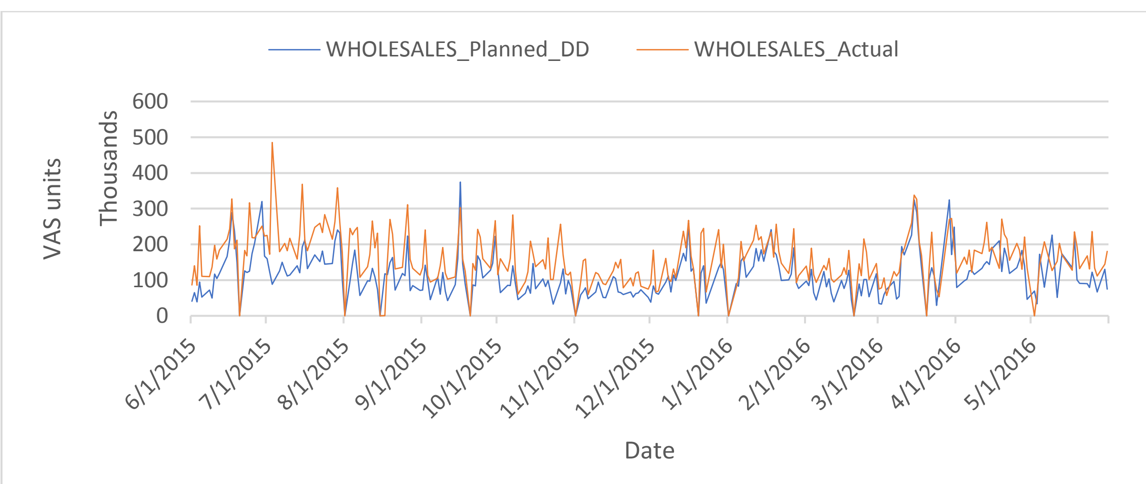


Figure 76: The difference between the PGI DD and the AGI Wholesale VAS units for FY16

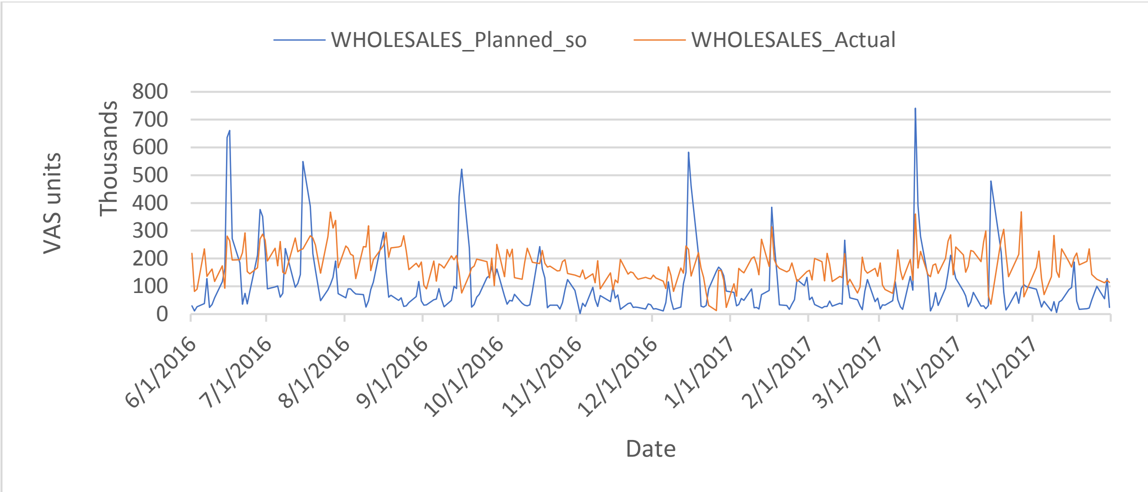


Figure 77: The difference between the PGI SO and the AGI Wholesale VAS units for FY17

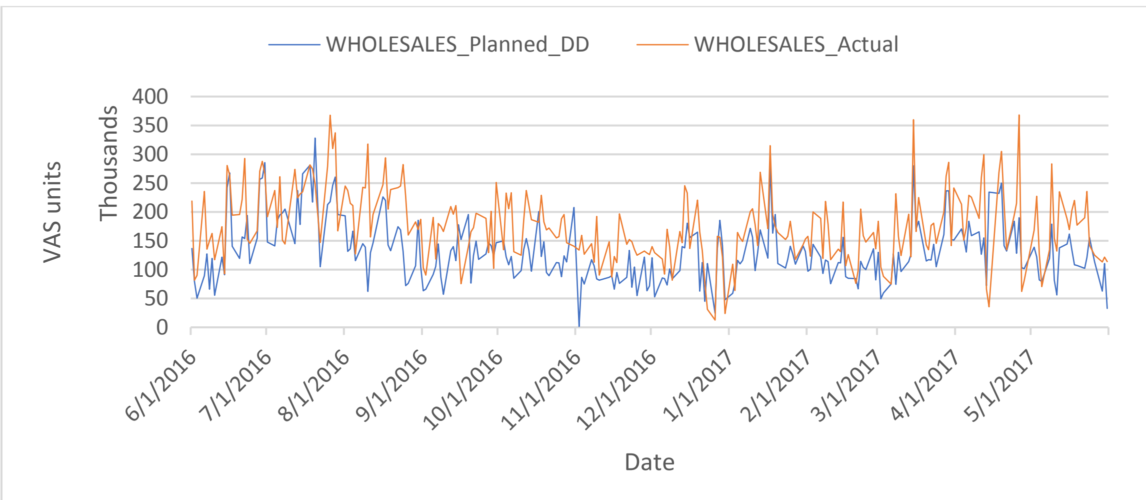


Figure 78: The difference between the PGI DD and the AGI Wholesale VAS units for FY17

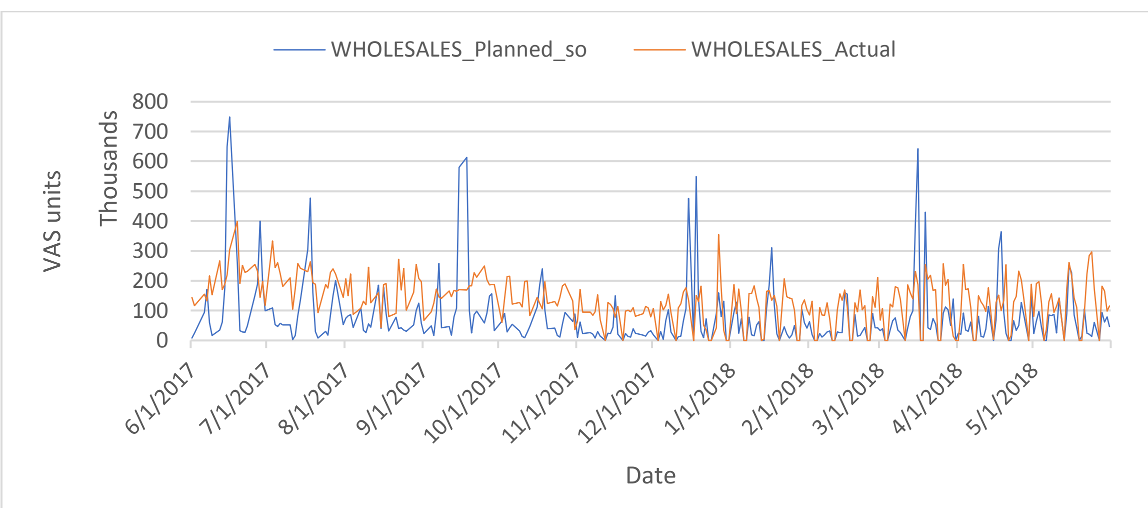


Figure 79: The difference between the PGI SO and the AGI Wholesale VAS units for FY18

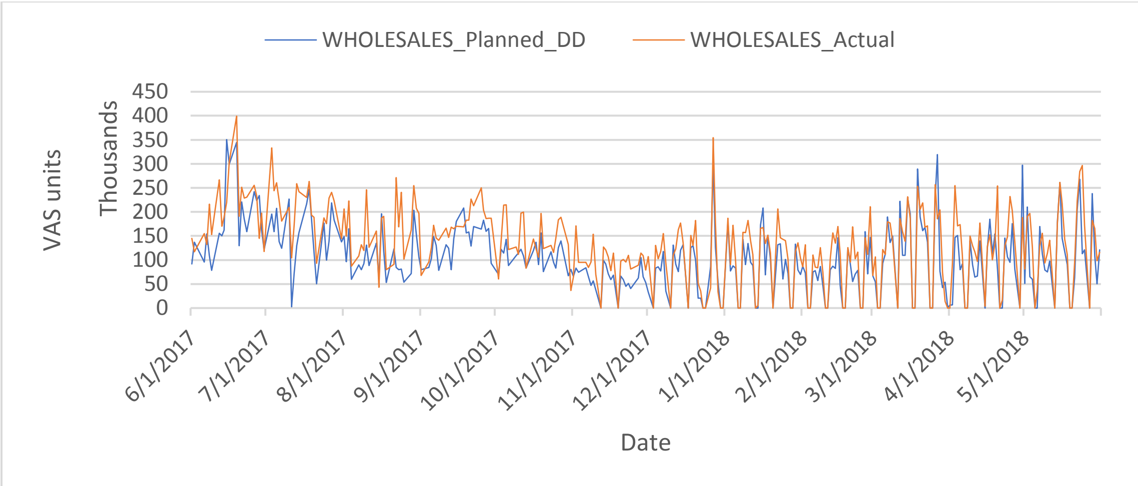


Figure 80: The difference between the PGI DD and the AGI Wholesale VAS units for FY18

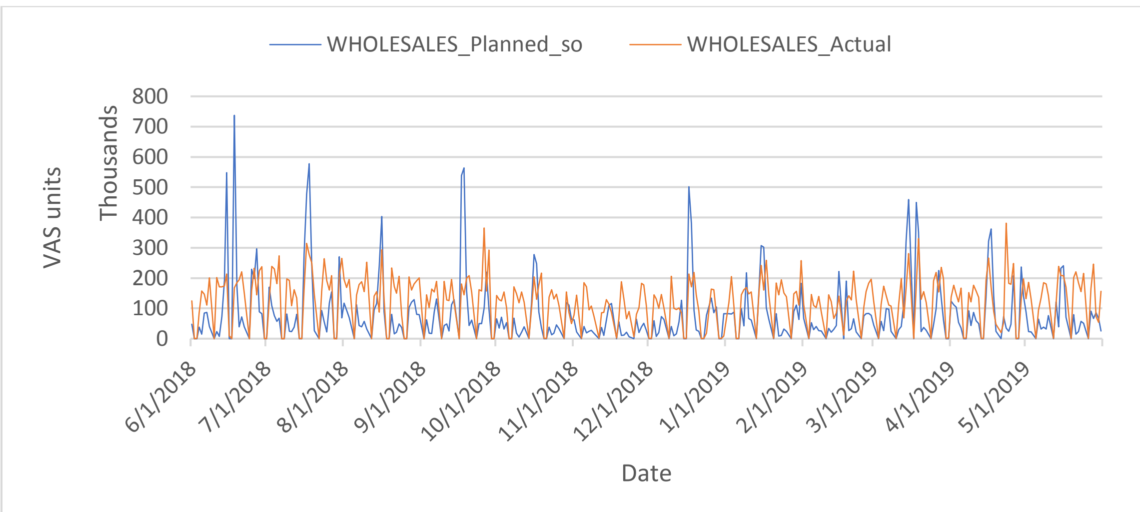


Figure 81: The difference between the PGI SO and the AGI Wholesale VAS units for FY19

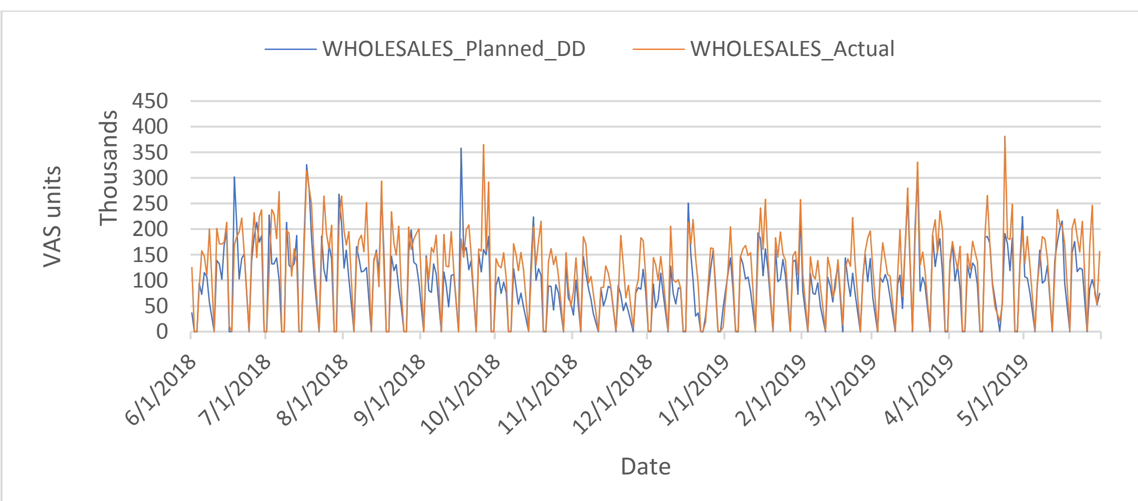


Figure 82: The difference between the PGI DD and the AGI Wholesale VAS units for FY19

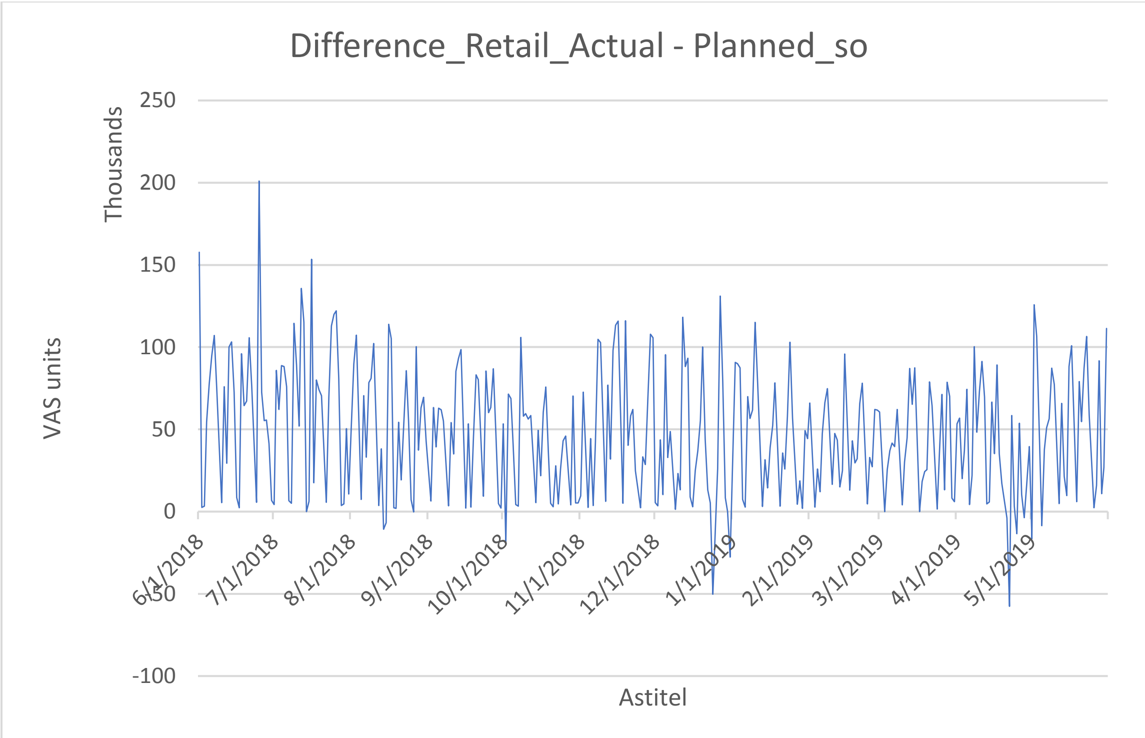


Figure 83: The difference between the AGI Retail VAS units and the PGI SO VAS units for FY19

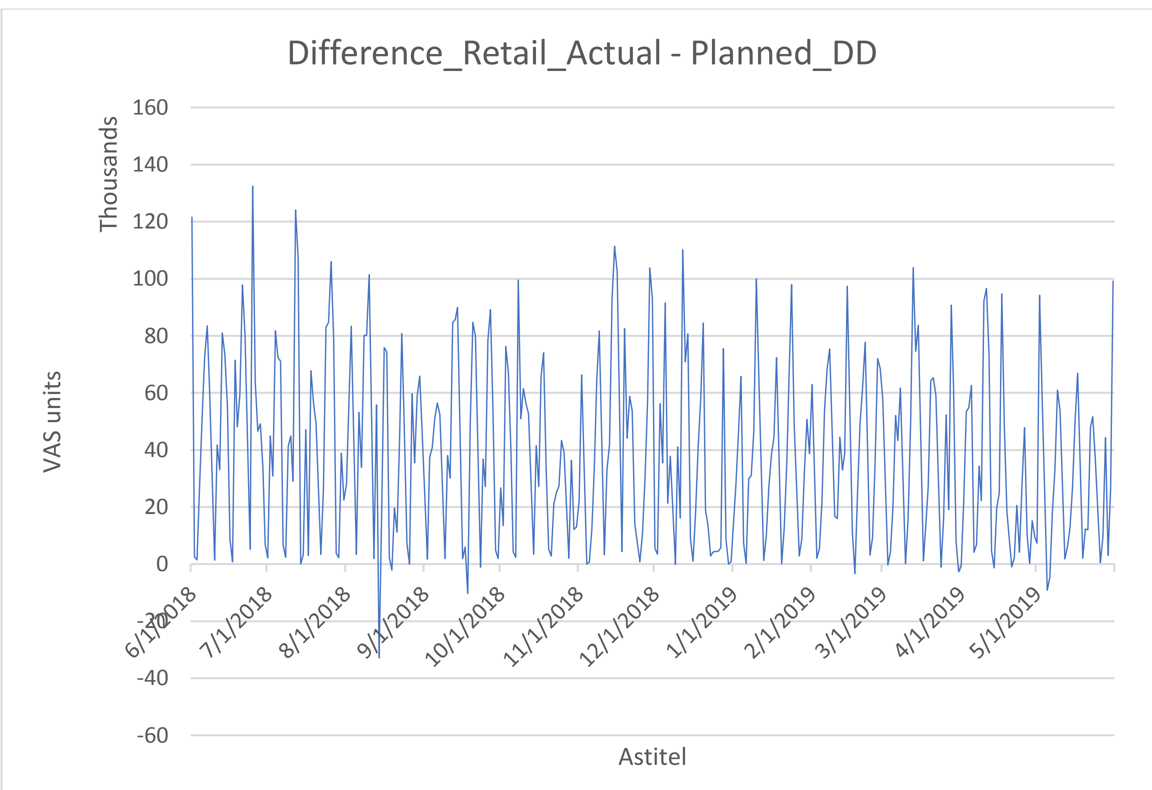


Figure 84: The difference between the AGI Retail VAS units and the PGI DD VAS units for FY19

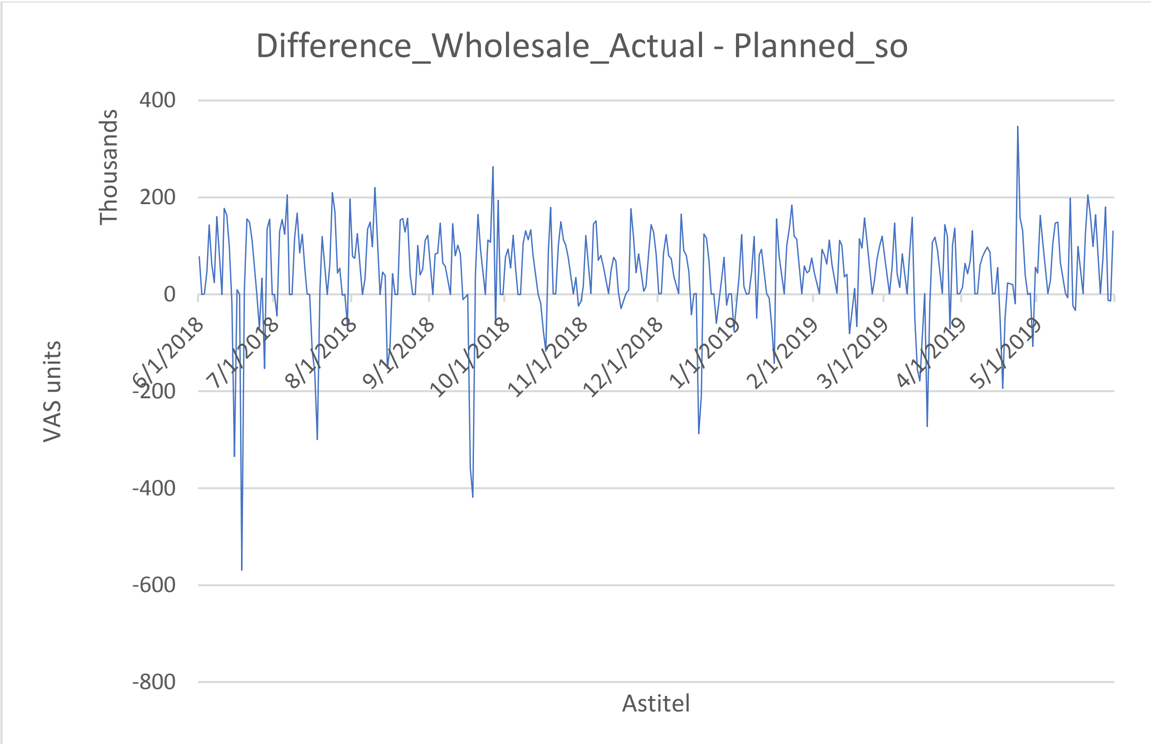


Figure 85: The difference between the AGI Wholesale VAS units and the PGI SO VAS units for FY19

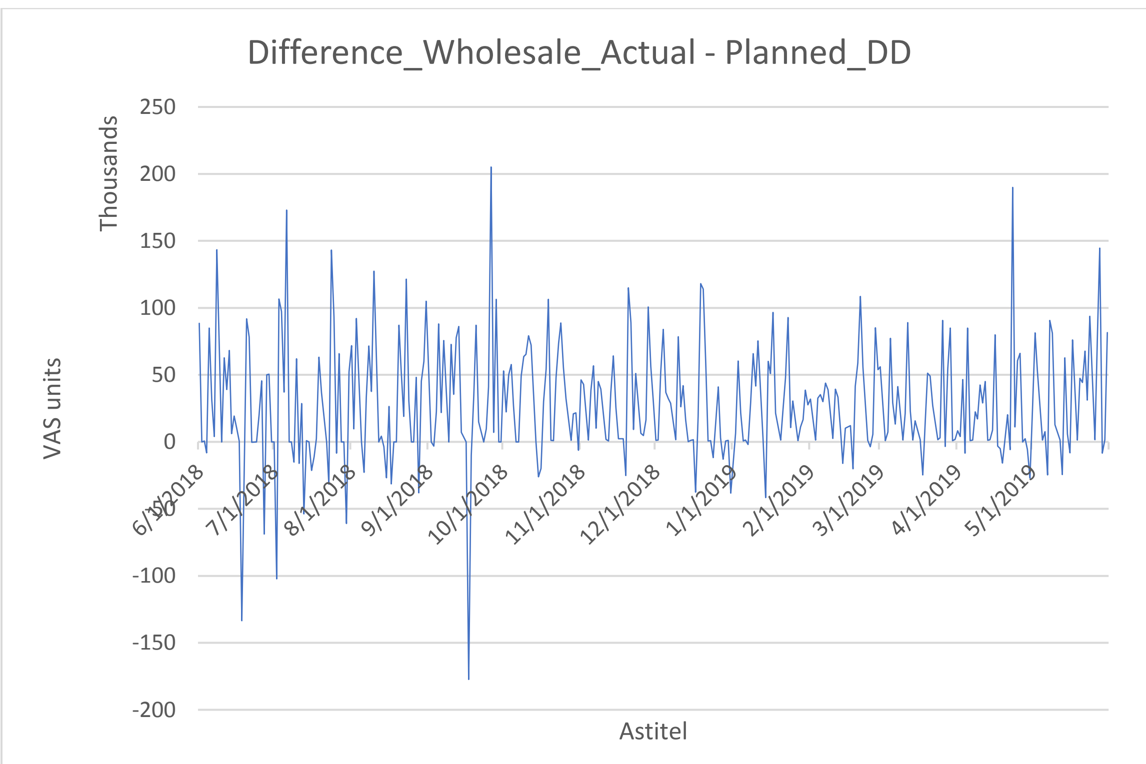


Figure 86: The difference between the AGI Wholesale VAS units and the PGI DD VAS units for FY19

Appendix E: Performance measuring metrics

In this section different ways to measure the accuracy of the "best" fitting and performing forecasting models are introduced. To decide how the current forecasting method is performing in section 5.4 and to consider which of the forecasting models is the most accurate later in section 5.5 and 5.6.

Measuring of the forecasting model performance should always be performed since this serves as the forecast validation step (step 5 of the forecasting process approach, see section 4.1). Forecast accuracy can be measured in different ways by summarizing the forecasts errors on various mathematical metrics. The forecast error is defined as the difference between the observed value and the forecast (Montgomery et al., 2015):

$$e_t = y_t - \hat{y}_t(t-1) \tag{12}$$

here $\hat{y}_t(t-1)$ is the forecast that was made the period prior for the actual observed value of y_t. The performance of the forecasts is evaluated on multiple statistical measures. These forecast accuracy measures can be used to discriminate between different competing forecasting models (Montgomery et al., 2015). Therefore, the same accuracy metrics will also be used in section 5.4 for the current forecasting and section 5.6 to validate the forecasting model that is created in section 5.5. The useful measures that are implemented to evaluate the forecast accuracy are as followed (Montgomery et al., 2015; Nahmias, 2015; Hyndman & Athanasopoulos, 2018):

The mean error (ME):

$$ME = \frac{1}{n}\sum_{t=1}^{n} e_t \tag{13}$$

The mean squared error (MSE):

$$MSE = \frac{1}{n}\sum_{t=1}^{n} (e_t)^2 \tag{14}$$

The root mean squared error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} (e_t)^2} \tag{15}$$

The mean absolute error (MAE):

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |e_t| \tag{16}$$

The ME is a measure of the average forecast error, which would ideally be (close to) zero, that way the forecasting method makes unbiased forecasts. If the ME would deviate from zero when the forecasting method is in use, it could be an indication that the underlying time series has changed, whereas the forecasting method hasn't integrated this change, and therefore now generates biased predictions (Montgomery et al., 2015). Both the MSE and the MAE measures the variability in the forecast errors. With the MSE metric the errors are weighted exponentially, therefore larger errors give bigger MSE's. When comparing forecast methods that are applied to the same time series with the same units, the MAE is a very easy to use and interpret as an error metric. By minimizing the MAE, it will cause the forecasts closer to the median. With minimizing the RMSE the forecasts will direct more to the mean. The above mentioned metrics are all scale-dependent forecast accuracy measures. Metrics that measure by means of a relative forecast error follow below. Here the re_t represents the relative forecast error (in percent) as (Montgomery et al., 2015; Nahmias, 2015; Hyndman & Athanasopoulos, 2018):

$$re_t = \left(\frac{y_t - \hat{y}_t(t-1)}{y_t}\right) * 100 \tag{17}$$

The mean percentage error (MPE):

$$MPE = \frac{1}{n}\sum_{t=1}^{n} re_t \tag{18}$$

The mean absolute percentage error (MAPE):

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} |re_t| \tag{19}$$

The percentage errors have the advantage of being unit-free and are therefore useful to compare the forecast performances of the data sets (Hyndman & Athanasopoulos, 2018). However, a disadvantage of these measures is that a relatively large forecast error e_t can be canceled out by a large observation y_t, giving a possible false representation of a good forecasting performance.

Another metric that gives a good measure for the quality of the fitted forecasting model is the Akaike information criterion (AIC), defined as (Montgomery et al., 2015; Hyndman & Athanasopoulos, 2018; Nykodym, Kraljevic, Hussami, Rao & Wang, 2019):

$$AIC = \ln\left(\frac{\sum_{t=1}^{T} e_t}{T}\right) + \frac{2k}{T} \tag{20}$$

where T represent the periods of data that is used to fit a model given a set of number of parameters k that are included in the model. The AIC compares the fit qualities of different models with respect to one another for a given dataset. This gives an indication to selecting the optimal one, which is the model with the lowest AIC score. The value of AIC cannot always be generated by the software and does not give a complete measure of the quality of the models. But it does prevent from obtaining forecasting models that are overfitting the data, which is not considered in the other performance metrics. Because it takes the number of parameters that are included in the model into account, which increases the penalty as the number of parameters increases (Montgomery et al., 2015; Nykodym et al., 2019).

The last metric that is used is the R-squared statistic, given by (Montgomery et al., 2015; Nykodym et al., 2019):

$$R^2 = 1 - \frac{MSE}{\sigma_y^2} \tag{21}$$

The model that maximizes R^2 , is similar to selecting the model that minimizes the sum of the squared residuals. Therefore, a larger value for R^2 indicates a better fit to the given dataset.

The results of the ME, RMSE, MAE, MPE and MAPE of the current forecasting are discussed in section 5.4. The other performance metrics are used in addition in section 5.5 to the fitted models. All the performance metrics are used in the final comparison of all the forecasting methods in in section 5.6.

Appendix F: Current forecasting performance graphs from section 5.4.1

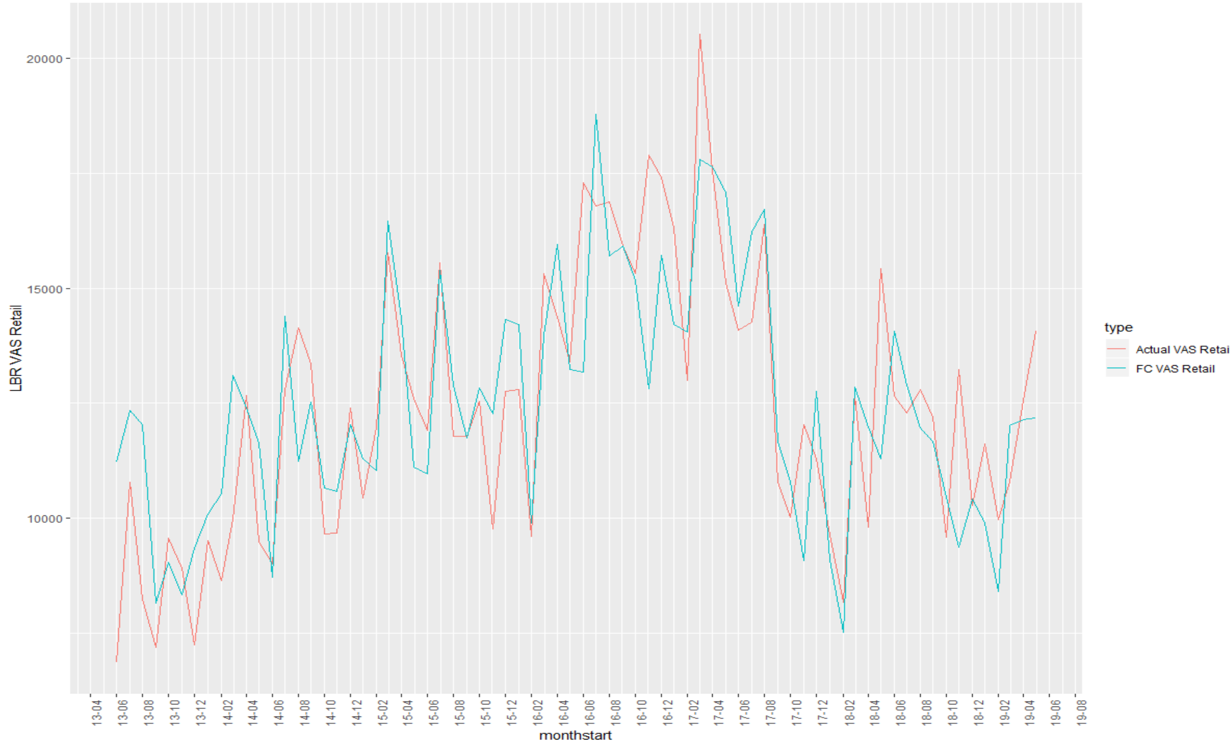


Figure 87: Total monthly forecasted and actual labor demand of Retail VAS per month for FY14-FY19

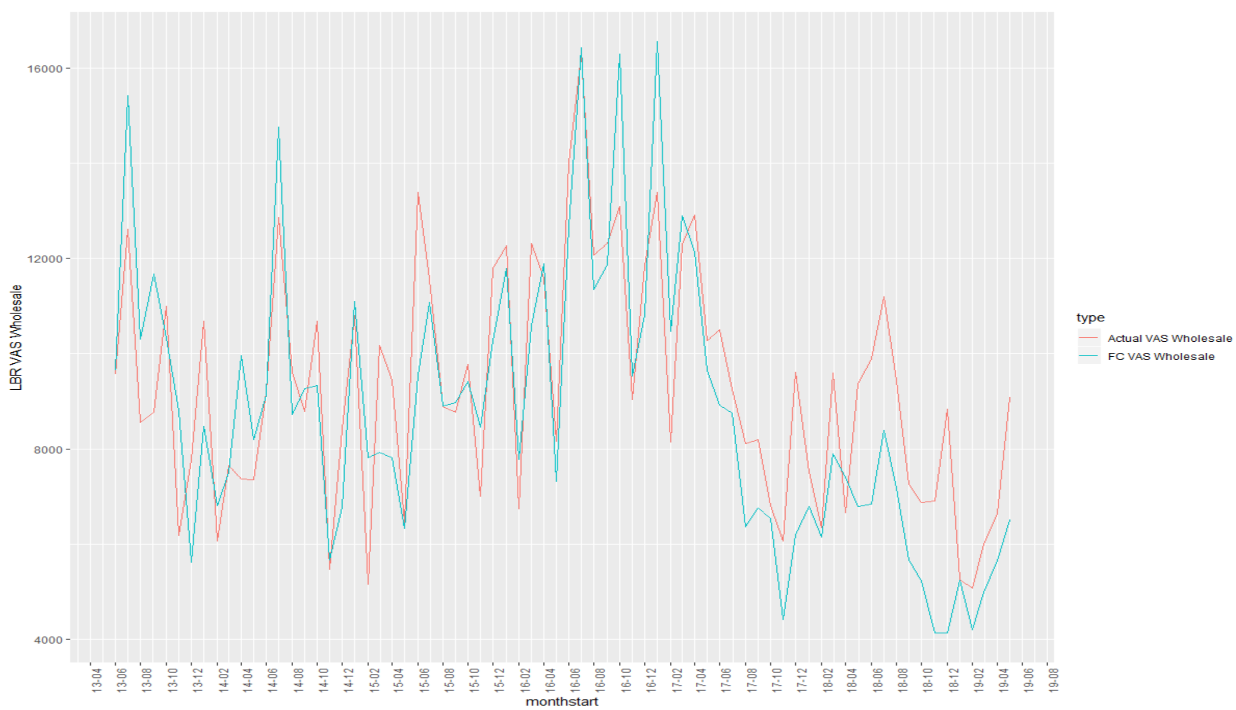


Figure 88: Total monthly forecasted and actual labor demand of Wholesale VAS per month for FY14-FY19

Appendix G: Exponential smoothing fitted models from section 5.5.1

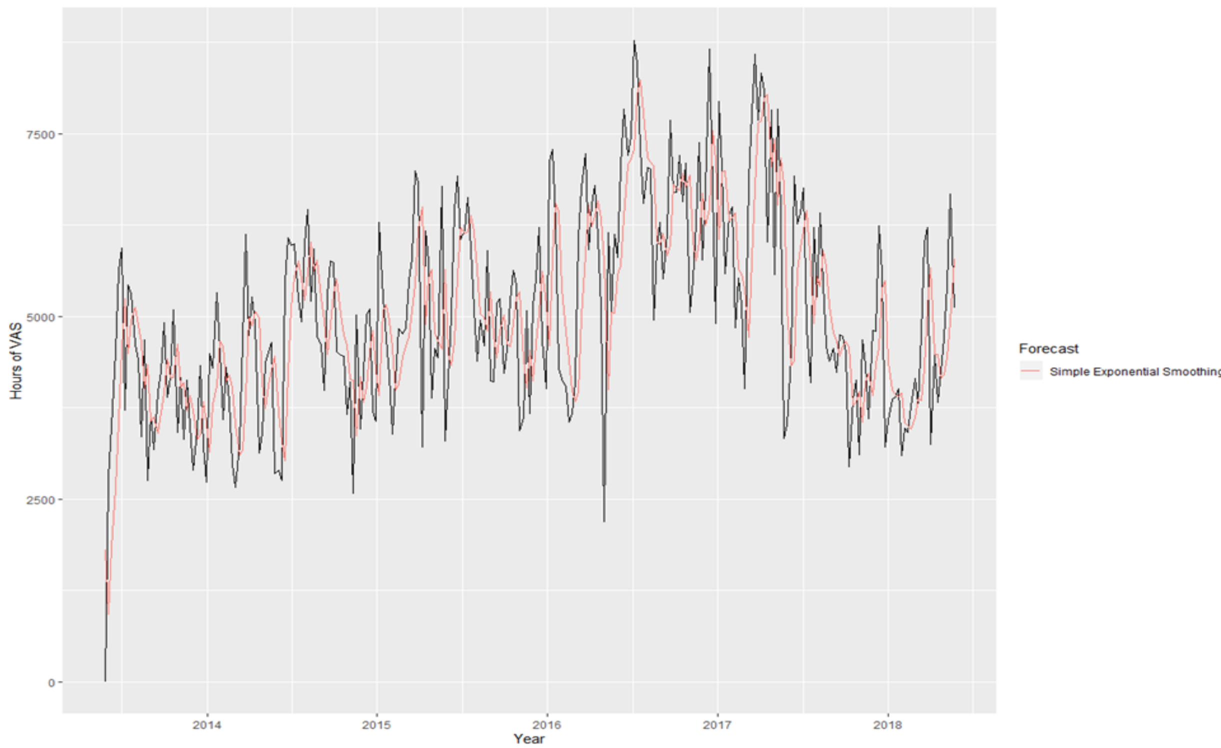


Figure 89: The fitted EMA model for the Total VAS on the trainings data FY14-FY18

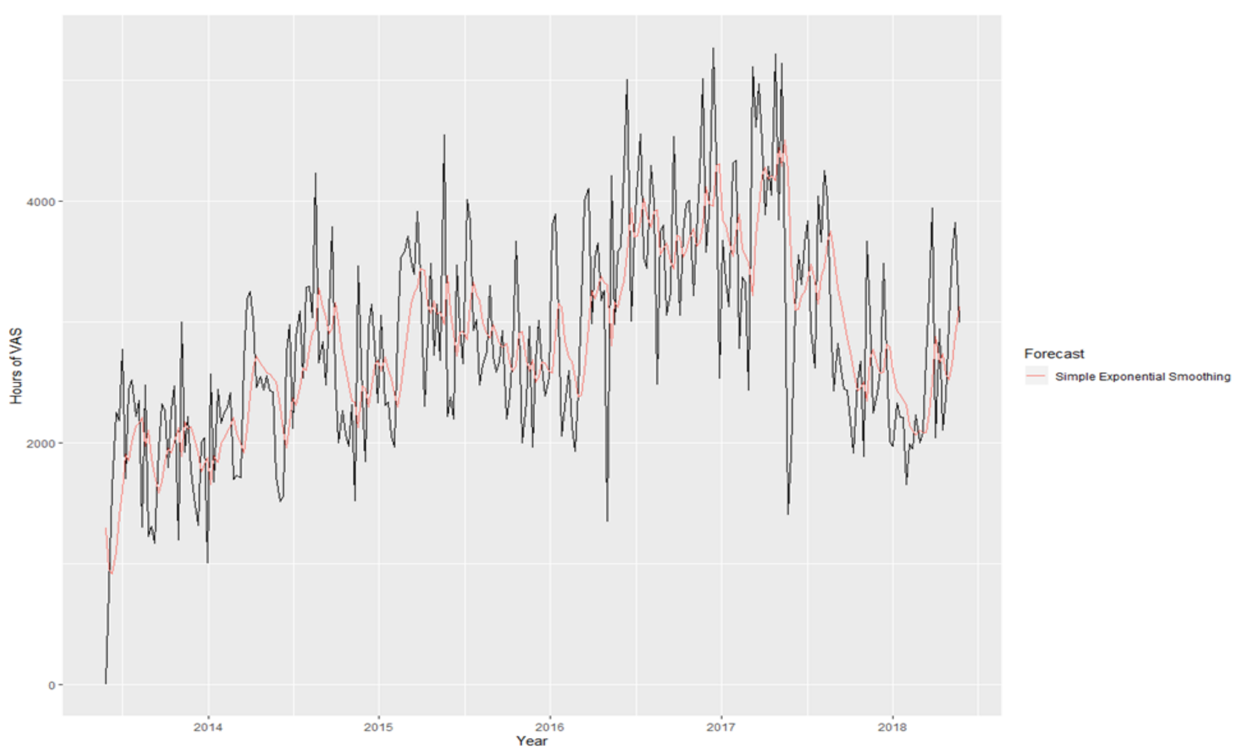


Figure 90:The fitted EMA model for the Retail VAS on the trainings data FY14-FY18

Figure 91:The fitted EMA model for the Wholesale VAS on the trainings data FY14-FY18