MASTER

Improving the backorder performance by making use of advance demand information

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Improving the backorder performance by making use of advance demand information

Master thesis

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Abstract

This master thesis, conducted at Royal Philips N.V. , reviews the use of advance demand information (ADI) in the service part supply chain (SPSC) of Philips. Next to that, solutions are proposed that make use of ADI in the SPSC. These solutions are applicable to the forecasting of service part demand, the warehouse replenishment of service parts and the shipping of service parts. The overall aim of these solutions is to reduce the amount of backorders within the SPSC of Philips.

The ADI consists of information from orders placed long before the requested delivery date. Data analysis shows that the information of these orders is generally reliable. To use the ADI in the demand forecasting of service parts, a method is developed that makes use of ADI for forecasting intermittent demand. Comparing this method to the current service part demand forecasting method used by philips, shows that there is no significant difference between the current and proposed method regarding backorders, inventory costs and fill rate.

When using ADI, the replenishment of service parts is improved as well. When knowing that inventory will drop below the order level, proactive replenishment makes sure that backorders are avoided. This method shows to decrease backorders with over 10%, however it also increases inventory costs with about 10%. The method also shows that if inventory costs are kept the same, backorders are still reduced by 5%.

ADI is also used to optimize the shipping strategy, service parts that need to be delivered in the future can be shippped at an earlier stage. This leads to potential costs savings by batching orders or using slower shipments. Furthermore, this method shows to have no negative effect on the backorders, inventory costs and fill rate.

Keywords: Service parts, Inventory Control, Forecasting, Replenishment, Flexible delivery, Advance demand information

Executive Summary

This Master thesis is conducted at the Service Parts Supply Chain (SPS) department of Royal Philips N.V.. The SPS department is responsible for the total service parts supply chain from Philips factories and external suppliers to the customers, as well as the return flow of repairable service parts from the customer to the repair and back to the warehouse. The main aim of the SPS department is to maximize the service part availibity for its customers, while on the other hand minimzing the costs that are accompanying the service parts operations and costs that relate to the inventory of service parts. In order to provide service part availability, Philips maintains a worldwide service part distribution network. This network consists of Regional Distrubution Centers (RDC) that are supplied by external vendors and Philips business units. These RDCs supply both customers and several Local distribution centers (LDC) in the network, the LDCs also supply customers.

Orders for service parts come in at all times, most of the time these orders concern same business day or next business day delivery. However, for the Benelux market, 4.5% of the orders are placed at least 7 days before the requested delivery date, which is the date on which the part has to arrive at the customer. These orders contain valuable information for demand of service parts for the upcoming periods.

Currently the SPS department makes little use of advance demand information, the forecasts is independent of the future orders, unless the amount of future orders exceeds the forecasted value. Furthermore, future orders are handled at the moment the order has to be shipped, which often is one day before the requested delivery date. The stock level for the order and the way of shipping are reviewed just before shipping, which means that in a case of disruption there is no time to look for alternatives to fulfill the order.

The aim of this research is to make use of this advance demand information in the supply chain processes of Philips. First of all, it must be ensured that the orders placed in advance are reliable. To ensure the reliability of these orders a data analysis was performed. The amount of orders that are revoked by the customer before the requested delivery date are compared with the overall amount of orders. It turns out that over 98% of the placed orders were reliable.

Secondly, the forecasting of service part demand is reviewed. Literature on using ADI in forecasting exists, but mostly includes a continuous stream of demand. For the situation at Philips the demand shows to be intermittent, meaning the solutions from the literature can not be applied. For this reason a new forecasting method is developed that incorporates advance demand information to determine whether there will be demand in a certain period, and if so how much demand there will be. By using this method, the forecasting error is smaller compared to the current forecasting method. Furthermore, the simulation incorporated future orders has been implemented in the warehousing process. It turns out that the differences in terms of backorders, fill rate and relative holding costs are negligible, as can be seen in Table 1.

Method	Fillrate	Number of backorders	Holdingcosts
Current method	92.34%	1777	100%
Proposed method	92.28%	1792	99,44%
Smoothed method	92.36%	1774	100.35%

Table 1: Performance of the initial forecasting and two proposed forecasting methods

Next to the forecasting the way of replenishing is also reviewed. Currently advance demand information has no influence on the replenishment strategy. Replenishment is triggered when the inventory position, consisting of on hand stock and inventory in transit, drops below a certain reorder value. Advance demand information allows for proactive replenishment. For example, when it is known that the inventory level will drop below the reorder level next week because of an order known today, it is wise to trigger replenishment today already. For the presented solution the inventory position is calculated by subtracting future known demand from the former inventory position. When simulating this scenario, backorders show to decrease by at least 10%. The inventory relative holding costs show to increase, but

a note must be that less backorders will likely involve less overall costs as well, making up for the extra inventory costs. The overall result for proactive replenishment can be seen in Table 2. Next to this the method also shows that inventory costs can be kept the same, while backorders are reduced with 5%.

Method	Fillrate	Number of backorders	Holdingcosts
Without proactive replenishment	92.34%	1777	100%
With proactive replenishment	93.12%	1596	110.12%
Difference	+0.78%	-10.19%	+10.12%

Table 2: Performance of the proactive replenishment strategy using the original forecast

Lastly, the shipping method is reviewed. Currently future orders are shipped using the same shipment strategy that is also used for next business day shipping, meaning that shipping is done at the latest possible moment. When shipping at an earlier stage, the shipping costs can potentially be reduced. Furthermore, any disruptions involving the carrier have less effect on late arrival of the service part at the customer. To allow early shipment an algorithm is developed that aims to have no effect on the backorders, early shipping can lead to less inventory and therefore more backorders. When simulating the scenario for early shipment, it turns out that the amount of backorders are the same as in the situation without early shipping. The algorithm performs as desired in only sending parts that do not lead to backorders. Furhtermore, 67% to 85% of the parts known could be shipped early. As a result of this the method also showed to realise a minor cost reduction regarding inventory relative holding costs. All results obtained can be seen in Table 3, where ΔE represents the amount of days the parts are sent in advance.

ΔE	Backorders	relative holding costs	Fill rate	#Parts early sent	#Parts early known	% Early sent
0	1592	100%	93.13%	-	-	-
3	1580	97.40%	93.19%	3388	5009	67.64%
7	1562	99.80%	93.25%	698	878	79.50%
10	1596	98.38%	93.12%	535	652	82.06%
14	1552	99.92%	93.31%	385	453	84.99%

Table 3: Simulation results early shipment method for various values of ΔE

To conclude, this research provides three solutions to implement advance demand information in the supply chain processes. Two of them show to have the desired effect of reducing the amount of backorders and reduce late arrival of service parts. This shows the benefit of implementing ADI in the SPSC. As a result of this we recommend to implement the described replenishment strategy as the method only requires a change in calculation of inventory position, while at the same time a major backorder reduction is realized. Furthermore we recommend to investigate the advantages for Philips of early shipping. In case these advantages are significant, the early shipping algorithm can be implemented in the SPS processes. Latly, we recommend to make more use of ADI, as this research shows promising results, the increase of ADI can lead to an even better performance increase.

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ADI	Advanced demand information
FCO	Field change order
FSE	Field service engineer
FSL	Forward stocking location
KPI	Key performance indicator
LDC	Local distribution center
MCA	Software company providing supply chain tools
RDC	Regional distribution center
RDD	Requested delivery date
ROP	Reorder point
SAE	Sum of absolute errors
SPS	Service parts supply chain (Philips department)
SSE	Sum of squared errors
TSL	Target stock level

List of mathematical symbols

$D_{p,t}$	=	The demand for part p on day t
$BO_{p,t}$	=	The backorders for part p on day t
β_p	=	The fill rate for part p
p	=	The part number ranging from 1 to 3638
t	=	The day number ranging from 1 to 365
$OH_{p,t}$	=	The on hand inventory for part p at the end of day t
HC_p	=	The relative holding costs for part p
C_p	=	The price for part p
l_p	=	The leadtime for part p
rl_p	=	The repairtime for part p
$ORD_{p,t}$	=	Parts ordered at the supplier for part p for period t
$REP_{p,t}$	=	Parts sent in repair for part p for period t
cr	=	The percentage of the part costs that determines annual relative holding costs
$F_{p,t}$	=	The final forecast of part p for period t
$FA_{p,t}$	=	The initial forecast of part p for period t
$O_{p,t}$	=	The demand already placed in advance of part p for period t
$IP_{p,t}$	=	The inventory position of part p at time t
$OH_{p,t}$	=	The on hand inventory of part p at time t
$IT_{p,t}$	=	The inventory in transit to the warehouse of part p at time t
$TSL_{p,t}$	=	The target stock level of part p at time t
$ED_{p,t}$	=	The demand that is known at the moment the decision to send early is made position of part p at time t
$ES_{p,t}$	=	The demand that is actually send at an early stage of part p at time t

Chapter 1

Introduction

Currently, many industry business processes depend on the functioning of systems essential for the performance of the company. Downtime of these systems therefore lead to less functionality of the company resulting in direct costs like revenue loss and indirect costs like customer dissatisfaction. To make sure that the systems encounter as little downtime as possible, maintenance is of vital importance. During maintenance systems are restored to a functioning state, making sure that the systems can be used to its purpose by the companies. To perform maintenance activities, service parts are needed. These service parts need to be available quickly, to reduce system downtime. For this purpose service part networks are set up worldwide in which warehouses are used to stock the service parts. To operate such a network without having inventory costs going sky high, it is important to decide on the right stock levels for each warehouse in the network. The aim of the service part network is to fulfill all incoming orders as quickly as possible, leading to a minum of downtime for the essential systems.

This master thesis research is conducted at Philips. Philips wants to get insight in the way service part orders with a big difference between ordering date and requested delivery date are handled, meaning the orders are placed a long time ahead of the requested delivery date. Furthermore, Philips wants to improve its performance on these future orders, meaning a reduction of backorders and order handling costs for these order types.

In this chapter an introduction of the company and the research project will be given. First of all in §1.1 a short introduction of the company Philips is given. Secondly in §1.2 an overview of the service part supply chain department within Philips is given. Thirdly, in §1.3 a more detailed introduction of the Philips service part network is given as well as the decisions made to enable the service parts processes. Lastly an overview of the report is given in §1.4

1.1 Royal Philips

Royal Philips was founded in Eindhoven in 1891 by Frederik Philips and his son Gerard. Philips started as a light bulb factory producing carbon filament lamps. Gerard mainly focused on innovation and research, for this reason he established Natlab, a laboratory for research that is now known as the High Tech Campus. Together with the introduction of Frederik's other son, Anton, this led to a significant growth of the company Philips. Since then, Philips has broadened its focus on various fields in the electronic industry, making them responsible for some of the world's ground breaking innovations, e.g. the Compact Disc. Nowadays one of Philips main focal points lies within the development and realisation of medical devices like CT scanners, Cardiovascular systems and X-ray equipments.

Philips is not only responsible for providing these medical systems. Performing the maintenance on the machines they deliver is its responsibility as well. The medical systems provided by Philips are often essential for its customers, meaning that maintenance activities are crucial in case of a disruption or breakdown of the system. This maintenance strongly relies on the presence of service parts that are required during the repair.

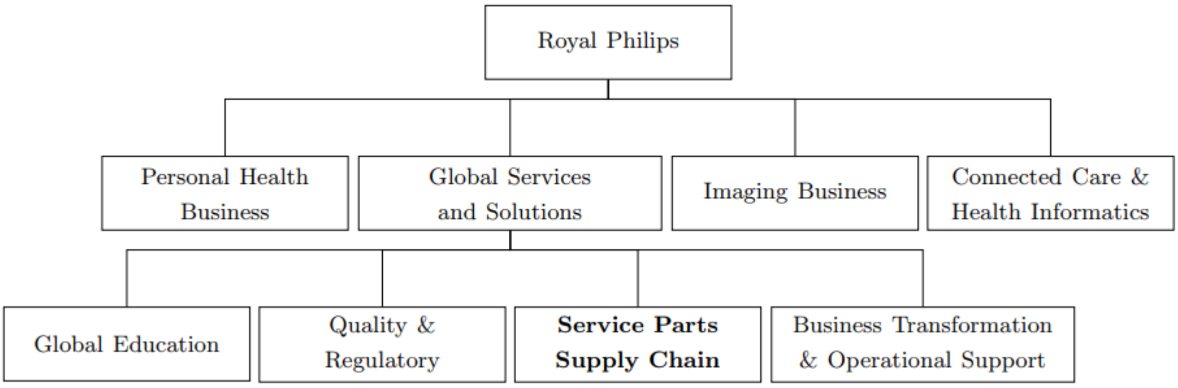

Figure 1: Place of the SPS department within Philips

1.2 Service parts supply chain department

Within Philips the Service Parts Supply chain (SPS) department is responsible for the whole process of providing service parts, starting at the vendor and ending at the customer. The main aim of the SPS team is to maximize the part availability while at the same time minimizing the costs accompanied with the transportation and inventory . In order to achieve the goals SPS has set, a solid working service part network is in place that transports all the service parts between the various warehouses worldwide. SPS is responsible for determining the optimal inventory levels for each of these warehouses as well as designing a replenishment strategy for the warehouses.

In its goal to maximize the service level while minimizing the costs, SPS works together with three main partners: Accenture, UPS and Sanmina. Accenture is responsible for the transactional activities of the service part system system. Accenture its activities consist of, but are not limited to, handling order requests and contacting customers in case of delay. Secondly, UPS is responsible for all warehousing activities of the service parts. UPS owns the warehouses with service parts and is responsible for stocking the parts and handing them to the shipment company. Lastly Sanmina is responsible for reintroducing used service parts in the system. Sanmina repairs service parts and test and pack them so they can be re-used as a service part. For all these three companies the SPS department is a direct partner. Meaning that SPS controls the relation between its partners and SPS, as well as being the party that gives the business orders for the other three parties. The three partners of SPS usually communicate with each other via the SPS team, only in sporadic cases the partners have a direct relationship with each other. For example in urgent situations where a quick response is demanded. An exact visualization of the division of the roles among the four parties can be found in Figure 2

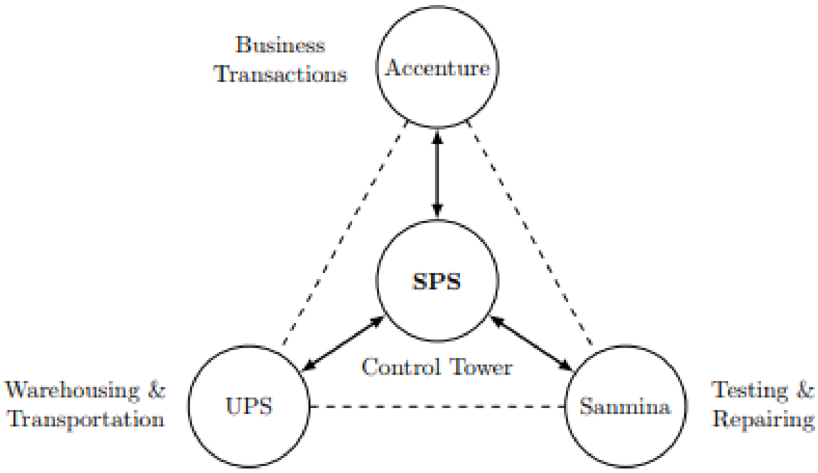

Figure 2: Visualization of the different roles and relationships between SPS and its partners (Borst, 2016)

1.3 Supply chain for service parts

In order to understand how service parts are delivered to Philips' customers, the supply chain of service parts is introduced in this section. A representation of the supply chain for service parts, as well as the material flow within this supply chain, is portrayed in Figure 3.

The first step in the service parts process is determining which service parts need to be used in the installed base. There are two ways to obtain the service parts. First of all there is the option to buy new service parts from the supplier. By doing so, a lead time has to be taken in account before the service parts can be stocked in the warehouse and are ready to be used. A second option to obtain service parts are the repair shops. Some of the parts that are replaced are considered repairable, meaning that they go to a repair shop and are brought back to an as good as new condition. Once the repair shop receives a part they will put it into repair and return it to the warehouse when the part has been repaired and tested. Sometimes the parts do not come from the supplier or repair vendor directly but go via a Philips business unit (BIU). A Philips business unit is responsible for the system as a whole and has therefore the knowledge on specific parts. They are also the department that determines what type of maintenance (corrective versus preventive) is needed on each specific part within the systems owned by Philips.

All new parts will be sent to one of the three main distribution centers (RDC) of Philips located in Roermond (NL), Louisville (USA) and Singapore. The parts are then redistributed to local distribution centers in the region. Stock is kept at both the RDC's and at the Local Distribution Centers (LDC). For some parts the decision can be made to only have stock at the main distribution centers. Whenever an order comes in, the logical aim is to fullfill the order from the LDC in the region of the installed base. In case the part is not in stock at this LDC there are two other options to quickly supply a service part to the desired location. First of all there is the possibility of a lateral transshipment, meaning that the order will be fulfilled from an LDC outside the region (Alfredsson and Verrijdt, 1999). A second option is an emergency transshipment, meaning that the order will be shipped from one of the main distribution centers to the customer directly (Van Houtum and Kranenburg, 2015). In case both these shipments are not possible and there is no part in stock, the part has to be bought new or has to come from the repair shop. Both these methods will take a lot of time and therefore lead to problems at the customer side. The aim of the SPS team is to fulfill as much demand as possible from the various distribution centers and thus limit the amount of backorders. Backorders lead to problems at the customer as their machines are not functioning over a longer period of time, meaning they can not help their clients. Next to RDC's and LDC's Philips also uses so called Forward Stocking Locations (FSL). An FSL essentially acts the same as a LDC, however there is less place for parts in comparison to an LDC.

Next to the forward flow of parts, there is a reverse flow of parts. repairable parts go to a so called Blue room. At the blue room a part's functionality is checked and the decision is made whether to discard, repair or reuse the part. In case the it is impossible or too expensive to repair the part, it is discarded. When the part still functions properly it is used as stock in the distribution centers. In all other cases the part goes to the repair shops in order to be repaired. A visualization of the service parts supply chain of Philips shows in Figure 3, together with the material flow. In this graph lateral and emergency shipments are not shown, as they follow the same path as the normal transshipments (from RDC or LDC to installed base).

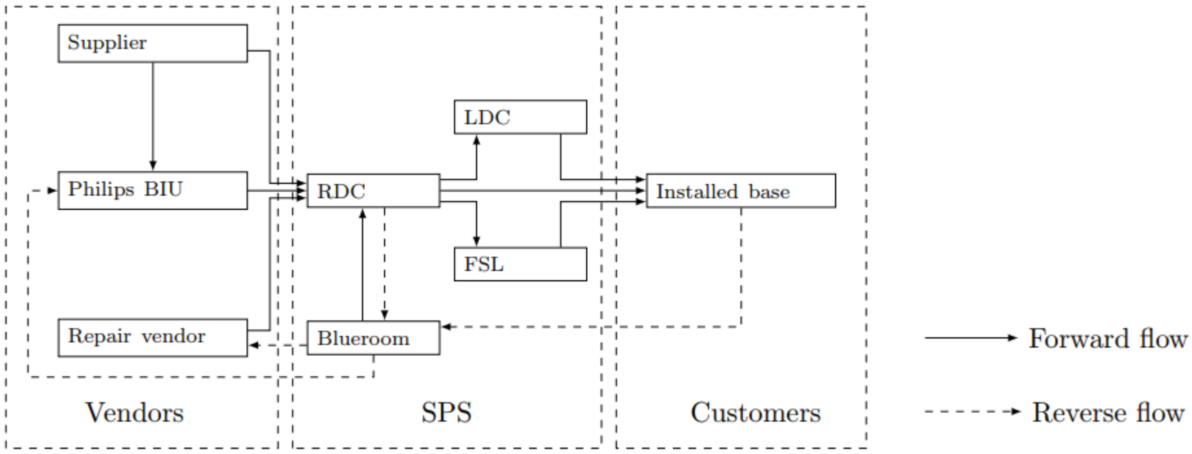

Figure 3: Service parts supply chain network of Philips (Borghouts, 2017)

1.3.1 Order process

A service part that is needed for maintenance can be ordered in various ways. The first and most likely option is that a Field Service Engineer (FSE) is performing maintenance and notices that a service part is needed to get the system in a proper state. A second possibility is that the customer notices a disruption or breakdown at the system and can diagnose the part that is needed itself. Consequently, the customer contacts Philips for requesting maintenance service as well as service parts. Lastly Philips also has a remote diagnostics department, in which irregularities at customer systems can be noticed and a service part along with an engineer can be directed towards the customer to perform maintenance. The remote diagnostics department can notice the disruption before the customer, so maintenance can be performed at an earlier stage. Leading to less downtime on the system, which is beneficial for the customer. The exact order process can be seen in Figure 4

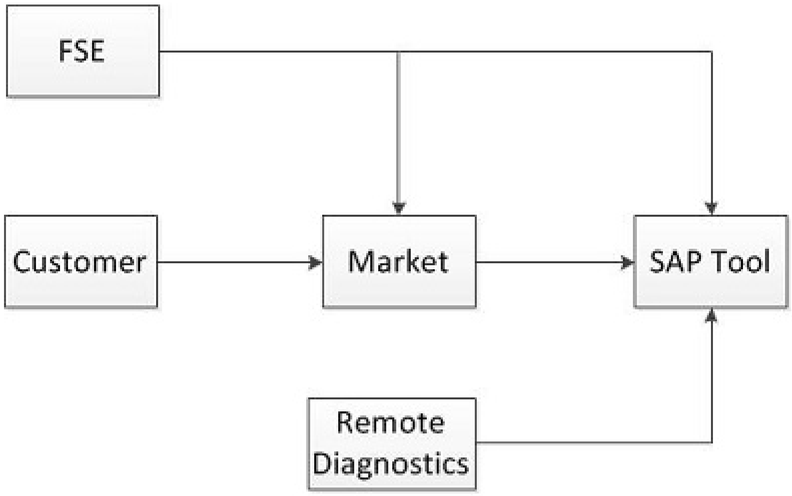

Figure 4: Graphical representation of the order process for service parts

Whenever an order for a service part comes in the order handling system (SAP Tool) checks whether the part is in stock at the accompanied LDC and determines the way of delivery. The way of delivery is based on various factors. First of all, the urgency for a service part, for each order the customer or FSE has to indicate the degree of urgency for the part. The urgency varies from very urgent (patient at risk) to not urgent (intermittent problem, meaning the system can still function). Another factor that plays a role in this is the promised service level that has been stated in the customers contract. Philips works with different types of service contracts that state that in case of a breakdown Philips needs to provide an engineer and part on site within 4-24 hours. The systems provided by Philips are essential for the processes performed at the customer, meaning that in case of a breakdown the systems need to be repaired as soon as possible. In order to perform repairs in time, the availability of service parts is of huge importance.

Whenever a part is available at the LDC the order handling system allocates the part to the order. In case the part is unavailable at the LDC the system looks for the best alternative (lateral or emergency transshipment), in order to fullfill the orders. Based on factors like urgency and service part availability the system also makes a decision on the delivery path. There are various options for the speed of delivery, in case of a highly critical part and a tight service contract the system will likely choose for a quick delivery e.g. by taxi to ensure same day delivery. When a part is not that critical the order handling system is more likely to opt for the cheaper parcel delivery that will ensure next day delivery. The reason for a difference in pricing lies within the fact that a same day delivery involves a taxi service in which the service part is the only item that is shipped. In parcel delivery there are loads of items delivered using a carrier, resulting in a lower costs per item compared to same day delivery.

1.3.2 Provisioning and replenishment strategy

In order to ensure that there is enough stock in place at the warehouses Philips makes use of forecasting to predict service part demand. The forecasting is done in a tool developed by the external company called MCA solutions, and is based on demand data over the last two years. In the tool the exponential smoothing method is used to smoothen the forecasted demand. The outcomes of this forecast determine the stock levels that are needed at the warehouses as well as giving the SPS department an indication of the amount of safety stock that is required.

Besides determining the stock levels the SPS team also determines a replenishment strategy, using an (S,s)-inventory policy. When a stock level drops below the reorder level s, an order is placed that will bring back the stock level to the target S. For LDCs this means that an order is placed at the RDC, when the stock level at the RDC drops below s, new parts will be ordered at the supplier. A RDC only delivers a part to a LDC if the part is not allocated to an order. Both LDCs and RDCs use the same replenishment strategy, the specific values for this strategy (S,s) can differ per warehouse of course.

1.3.3 Transportation

Next to the warehousing process, all goods need to be transported as well. This incorporates two flows, the transportation from either the vendor or the repair room to the warehouse, and the transportation from the warehouse towards the customer. Philips uses several carriers to perform this transportation. The decision on which carrier to use depends on the destination, size, weight and criticality of the part.

Every carrier has a different cutoff time, the time on which it collects its packages from the warehouse. This means that during the warehousing process the carrier which transports the part is taken into account when picking the orders. Furthermore, every carrier has a different speed of delivery and routing. For the Benelux market, Philips makes use of up to 12 different carriers every day to deliver service parts. Each of these carriers pick up the parts at the warehouse to deliver the parts on the same day. Furhtermore there is the possiblity of an emergency shipment, meaning that a carrier can pick up and deliver a package at any given moment. Note that in this case the carrier only ships a single part, making it a costly operation.

When looking at the transportation of the Philips service part network worldwide, there is not only transport from warehouses to customers, but also between warehouses. The goods are shipped between the three RDC's and also from RDC to LDC.

1.3.4 Future orders

The order handling system does not only handle orders that need a same day or next day delivery. For some orders a requested delivery date is attached that lies further away in the future, and even orders could be placed up to 200 days in advance. The reason that orders are placed this long in advance varies. One of the reasons is preventive maintenance on parts is performed. Preventive maintenance is planned in advance and therefore the order and requested delivery date will be known.

A second phenomena that occurs frequently is that the urgency of the order is relatively low. Occurring when a part is broken but the system still somehow functions as it should. In case this happens customers often prefer the part to be replaced at a time which is convenient for them. As customers schedule their patients on systems, there is no time in the near future to perform maintenance. Leading to corrective maintenance being planned, because the broken part needs to be replaced. Maintenance is performed 6 or 8 weeks after the disruption is noted, because the machine still functions without the broken part. Leading to the requested part and delivery date being known ahead.

When such a future order comes in the order handling system does not react immediately by allocating parts in stock to the order. This would result in parts being in the warehouse that cannot be used for more critical situations as they are already allocated to this less critical order. Currently the order is taken into consideration at the moment just before it needs to be shipped. At that point, parts in stock are allocated to the order and the shipment methods are defined. In case a part is unavailable the system starts looking for the possibilities to a lateral or emergency shipment of the part from other warehouses. In case this is not possible the order will result in a backorder, meaning that the part will not be delivered on time.

1.4 Outline of the report

The outline of the remainder of the report will be as follows. In Chapter 2 the research problem is introduced as well as the research questions and the scope. In Chapter 3 the definition of a future order is given and the reliability of future orders is determined. In Chapter 4 the Simulation model to obtain results is introduced. In Chapter 5 the use of advance demand information in forecasting is discussed. In Chapter 6 the replenishment decisions are combined with the use of advance demand information. In Chapter 7 the use of advance demand information in shipping is discussed. Laslty, the conlusions and recommendations are given in Chapter 8.

Chapter 2

Research question

2.1 Problem description

Future orders contain valuable information regarding demand forecasting, future stock levels and shipment methods (Chen, 2001). Currently none of this information is used by the SPS department. Future ordered are treated the same as any other order, associating them with relatively high shipping costs and a higher chance of backorders.

The fact that an order that is placed this far in advance results in a backorder is difficult to explain to the field service engineer and the customer. The field service engineer places the part order and plans the maintenance assuming the requested service part is there. Whenever the part does not arrive in time the engineer cannot perform the maintenance costing valuable time. Furthermore, unavailable parts frustrate the Field Service Engineer in its work. There are several occasions of engineers contacting their managers about, regularly used, parts being repeatedly unavailable.

For the customer the inconvenience is even bigger. The reason that the maintenance is planned is because of the fact that this fits its busy schedule. Whenever a part is unavailable at that time this means that the machine is reserved for maintenance (and not for patients) while actually no maintenance is performed. Furthermore, a new maintenance has to be planned, which will again be in several weeks because of the customer's busy schedule.

The aim of this project is to increase the spare part availability of future orders. The main target is to reduce the amount of backorders that result from future orders. The second aim is to find out if the information from future orders could be used to save costs. One can think of reductions in shipping and inventory costs. All these aims lead to the main research question formulated in §2.2, and split up into research questions in §2.3. Furthermore, the scope of the research is discussed in §2.4

2.2 Main research question

How can advance demand information be used to improve service part availability?

The overall goal of this research is to reduce backorders from future orders. To do so, future orders need to be handled in a different way, such that Philips can anticipate at an earlier stage. To make this change, the information from future orders is essential. Therefore this research focuses on how to make use of this type of advance demand information.

The thesis focuses on service parts availability, meaning that the analysis will be performed on the service parts handling and replenishment system. The thesis will therefore involve service part suppliers, warehouses, shipping companies and customers.

2.3 Research questions

In order to answer the main research question, several research questions are set up. The goal of these research questions is to answer an aspect of the main research question. The research questions are set up in a logical order. First of all insight in the process and characteristics of future orders are gathered. Afterwards possible improvements on the performance of these future orders are presented. Lastly, recommendations for the SPS department on how to handle these future orders are given.

Question 1 How reliable are future orders compared to the actual orders?

In order to make use of future orders, it has to be assessed first whether the future orders are reliable. A reliable order is an order that is not revoked by the customer before the requested delivery date. In case future orders turn out to be unreliable it makes no sense to propose solutions that incorporate these orders. In order to compute the reliability of future orders a quantitative data analysis is performed. In this data analysis the amount of reliable future orders are compared to the amount of unreliable future orders to obtain the future order reliability.

Question 2 How can the situation at Philips be modelled in a simulation?

To compute the results of scenario's that include the use of ADI, a discrete event simulation is built in the programming tool Matlab. The goal of this simulation is to recreate the situation at Philips relevant for this project. The effects of the proposed changes can then be measured by using this simulation model.

In order to build such a simulation, the inventory and warehousing model at Philips need to be recreated in the simulation. This concerns the ordering process of service parts ordered by Philips to create stock in its warehouses in particular. Furthermore the way the several calculations are performed at Philips needs to be replicated. This concerns the calculation of the reorder quantity, the stock level and the forecasting process.

To create input for the simulation, a data analysis will be performed on the historic order data. It is likely that this data needs cleaning before it can be used in the simulation. It has to be known how much parts are ordered each day and which parts are ordered at which frequency. Lastly part specific data is needed as well, which consists of the leadtime of the part, the chance of repair and the price of the part.

Question 3 How can the advance demand information be implemented in the service part demand forecast?

Question 3a What is the current forecasting method? In order to implement the advance demand information in the demand forecast an insight in the forecasting method needs to be gained first. Currently the forecast is done in an external tool called MCA (www.mcasolutions.com), the algorithm behind this forecast is not known in detail. However, the forecasting method is known, which is the exponential smoothing method. Furthermore, Philips developed a formula that replicates this forecast as closely as possible. This formula is used to test the implementation of advance demand information in forecasting. In order to adapt the demand forecast to the advance demand information, it has to be understood which part of the forecast is based on future orders. Currently the forecast is based on historical data over the last two years which is then smoothened using the exponential smoothing method. Simply adding the future orders to the existing forecast is unreliable, as part of the forecast is based on these orders. So this part has to be taken out of the forecast, and at the same time the future orders should be put in. In this process the current forecasting techniques of SPS will not be changed, the methods that are currently used for forecasting will remain. An extra element will be added to the input for forecasting.

Question 3b When can advance demand information be used in the forecasting method? In order to see which scope of orders can be regarded as future orders insight in the forecasting process is necessary. It needs to be known at which moment the forecasting is done as well as which orders are used in the forecasting process. Furthermore, the way of working in the forecast has to be known, the use of input parameters and how this affects the forecast.

Question 3c What are the currently known methods for implementing advance demand information in the forecasting method? To answer this question, we need current literature on using advance demand information in forecasting. A literature review is performed on how to incorporate (imperfect) advance demand information in a forecast. The aim of this literature review is to gain insight in how advance demand information is used in the forecast, and in what scenario's.

Question 3d How can the known methods be applied to the situation at Philips? The solutions that are presented in the literature, may not be suited for the situation present at Philips. To develop an enhanced forecasting method that will work for the situation at Philips the literature review is used as a start. The algorithms presented in literature can then be adjusted in order to have an optimal enhanced forecast that works for Philips. In order to monitor the performance of an enhanced forecast that includes advance demand information the simulation model will be used. By using simulation a comparison can be made between the forecast with and without advance demand information, giving an indication whether implementing advance demand information is actually beneficial.

Question 4 What will be the effect on inventory performance when incorporating advance demand information in the replenishment strategy?

A new replenishment strategy that accounts for future orders at an earlier stage in the replenishment process is introduced. The desired effect of this change is that stock will already be replenished at the moment it is sent towards the customer. The simulation will be used to compute the effects of the replenishment change on several relevant performance indicators

Question 5 How can shipping be optimized by using advance demand information?

Shipping parts at an earlier stage can increase the on time delivery. By doing so there is a smaller chance that the part arrives late at the customer. Furthermore, shipping at an earlier stage is a potential cost reduction, as faster shipping is often more expensive. The decision to ship early should be taken with care, it must not lead to fill rate problems or highly critical backorders. The simulation is used to determine the effects on the inventory performance of shipping several parts at an earlier stage.

2.4 Scope

To ensure that the project will not become too complex and results can be simulated in a reasonable amount of time the following scope is determined.

Geographical scope For this research project the Benelux market is taken into consideration. The Benelux market has one RDC, located in Roermond, and no LDC or FSL. This means that the market Benelux can be described as a single location system, reducing the complexity of modelling and computation. Furthermore the solution presented from this research will be based on the nature of the Benelux market. However, the aim is that the solution is applicable to other markets as well.

Supply chain scope This research project will focus on the Benelux, meaning an emergency shipment is not possible, however a lateral transhipment from one of the other two RDC's, outside the Benelux, can be possible in case of a stock out. The other two RDC's will not be taken into consideration, however a chance of p that an order can be fulfilled by lateral transhipment will be included in the model. In this way the model will not become too complex, but still be as close to reality as possible. Regarding the supply of parts, both the supplier and the repair vendor and their respective lead times will be taken into consideration in the model. To illustrate the supply chain scope, Figure 3 has been adapted to the scope (in thick red) and can be seen in Figure 5.

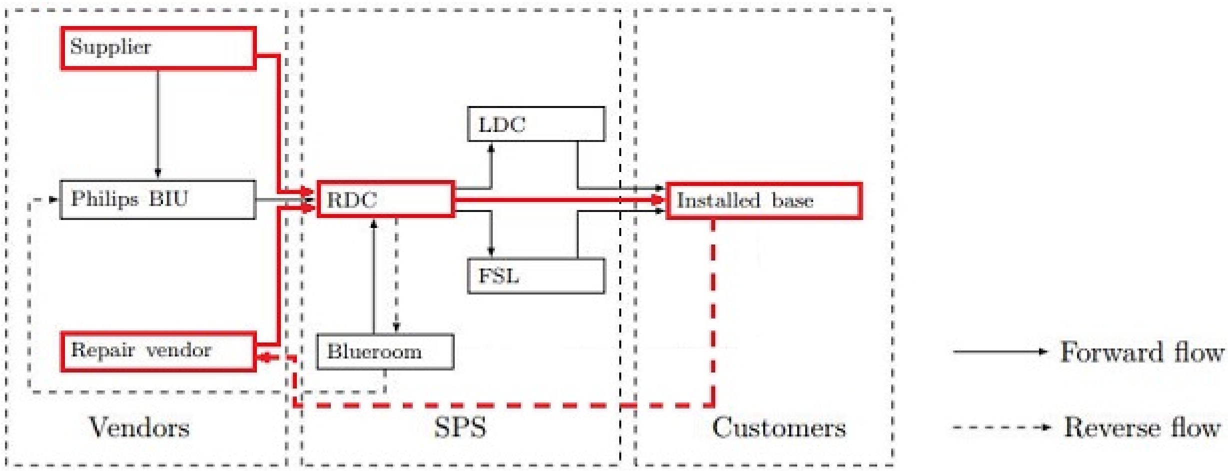

Figure 5: Project scope of the service parts supply chain network of Philips (in thick red)

Data scope Historical order data from the Benelux market of up to three years back will be used to analyse, meaning the years 2015, 2016 and 2017. Data of at least three years is needed as the forecast needs 24 months of input data. This data contains all orderlines for service parts for these three years. The parts within scope are all the service parts used for machines maintained by Philips healthcare, for both corrective and preventive maintenance. Field Change Order (FCO) will be left out of scope, as this demand has different characteristics compared to all other demand.

Department scope This research will be conducted within the SPS department at Royal Philips. More specifically the Customer Demand & Fulfillment team within the SPS department. This team is responsible for the demand planning and the replenishment strategy of the warehouses, as well as determining the stock levels.

Chapter 3

Definition of future orders

The first research question refers to the reliability of future orders. Before implementing future orders in the strategic decisions, it has to be exactly defined what future orders are and how they can be used. Whenever proposing a solution that uses future orders as an input, it must be ensured that this input is suited for the solution and that the input is reliable. For this reason this chapter takes a closer look at future orders. First of all future orders are defined, afterwards the reliability of future orders is calculated.

3.1 Service part orders

In order to get to future orders within the service part orders it is wise to look at the data on all service orders first. To do so, all data of orders that were placed during 2017 (1/1/2017-12/31/2017) has been retrieved from SAP. This data contains all orders that have been placed and sent as well. Orders that are revoked before the order is sent are not in this dataset. The dataset contains all relevant information on the order, the requested delivery date, the material (parts) requested, the order number, the customer number and the shipping method. When looking at the data for the market Benelux over 2017 it contains 18302 orderlines, these also include the FCO orders that are left out of scope for this project. When excluding the FCO orders 17098 orders remain, being about 60 orders per working day.

In order to compute the days in advance that an order is ordered, the difference between the Requested Delivery Date (RDD) and the date the order is put in the system is compared. In this process the data needs to be cleaned as well. 877 orderlines do not have a RDD and will not be taken into consideration. This means that 16421 orderlines remain. When looking at all orders it can be seen that most of the orders, about 75%, need to be delivered within 2 days. The reason for this is that most of Philips' maintenance activities are corrective, for which parts are needed right away. When looking orders that are placed further ahead we see that 559 orders are placed at least 10 days in advance, being about 3.4%. Although this might not look like being a lot, it still concerns more than 2 shipments per working day. Some more statistics about future ordering can be found in Table 4

Days in advance	Number of orders	Percentage
≤ 2	12472	76.0%
$[3, 6]$	3170	19.3%
$[7, 13]$	390	2.4%
$[14, 29]$	242	1.4%
≥ 30	147	0.9%

Table 4: Amount of calender days in advance the 16421 orders of 2017 were placed

3.2 Reliability of future orders

In order to make use of future orders and to make strategic decisions based on future orders, the reliability of future orders has to be ensured. When future orders can not be considered as being reliable it would not make sense to provide solutions based on future orders and to take future orders into account in replenishment decisions. In this section the reliability of future orders will be computed by comparing the amount of future orders realised to the amount of future orders revoked. This will be based on the historic demand data for the Benelux market over 2017.

By using the historic demand data of the realised orders, a problem emerges. Any orderlines that were revoked can not be found in this dataset, this data is needed to calculate the reliability of future orders. In order to get to know if there is a revoked order, we make use of missing orderline numbers. Whenever an order is placed, this order gets an order number and a line number. If an order contains multiple parts, each part gets the same order number and a different line number. In the dataset there are orders that do not have sequential orderline numbers, meaning that they do have the same order number, but some of the corresponding line numbers are missing.

Whenever a line number is missing in the sales data, this orderline number was either revoked, or used for other transshipments. In some cases the missing numbers correspond to an internal order handled at Philips, meaning that a part was shipped on the first line number between two warehouses and shipped to the customer on the second line number. All the missing orderline numbers were filtered out of the dataset and manually entered in SAP to get the information for these numbers. This information clearly indicates whether the orderline was an internal shipment or whether the order was revoked.

When detecting revoked orders in this way the assumption is made that whenever an order is revoked, a new order is placed on the same order number but a different line number. The reason for this is that usually one of the aspect of the orders changes which leads to revoking an order. The order will still take place, but with different aspects. In case the order is revoked but no new order is placed, the order can still be found when a different order on the same system is placed afterwards.

When looking at the historic order data, a total number of 104 missing order lines were found in the file for 2017. The information on these missing orderlines was then retrieved from the SAP system. Out of the 104 missing orderlines in the salesdata, 46 turned out to be actually revoked orders. The other missing orderlines correspond to internal transshipments or other non revoked orders. These 46 revoked orders do not only correspond to revoked future orders. Some of these orders are placed a day in advance and are immediately revoked, being out of our scope. For these calculations an order is categorized as a future order when the requested delivery date is at least ten days later than the date the order is put in the system. Out of the 46 orders, 9 turned out to be revoked future orders. In total the sales dataset contained 559 future orders, meaning that in the year 2017 nine out of 568 orders were revoked. This corresponds to 1.6% of all the orders being revoked for the year 2017.

	Reliable	Revoked	Reliability
Orders	559	9	98.4%

Table 5: Reliability of orders

To conclude, the data analysis shows that the majority of the service parts orders that are placed, can not be considered as future orders as they concern same day or next day shipment. However, about 559 service parts orders are placed at least 10 days in advance, meaning that there are enough future orders to be used in several solutions. When looking at the reliability of future orders, the conclusion can be drawn that the future orders show to be reliable as only a relatively small amount shows to be revoked. As the future orders can be considered reliable and as there are enough future orders to be taken in consideration, solutions can be created that make use of future orders.

Chapter 4

Simulating the service part supply network of Philips

The second research quesion that needs to be answered is how the SPSC of Philips can be simulated. A discrete event simulation will be performed to see whether the proposed solutions have the desired effect on the number of backorders and costs. In this chapter building of the simulation model will be explained, as well as the the assumptions that are used to create a feasible simulation. In §4.1 we will show the structure of the simulation model. In §4.2 the input of the simulation model is discussed. In §4.3 we will define the output of the simulation model.

4.1 Structure of the simulation model

First of all the warehouse needs to be modelled. In literature many variations of the inventory models for service parts exist (Basten and van Houtum, 2014); (Kennedy et al., 2002); (Paterson et al., 2011); (Strijbosch et al., 2000). Looking at the supply chain of Philips it can be seen that this is similar to the model of Van Houtum and Kranenburg (2015) given the two echelon network with lateral transshipments. However, as the scope is limited to the Benelux market, only one warehouse will be taken into consideration. And therefore the simulation model will be a single location model. This means that the basic multi item, single location inventory model can be used (Van Houtum and Kranenburg, 2015). As a result of this, the daily processes are modelled in the following order.

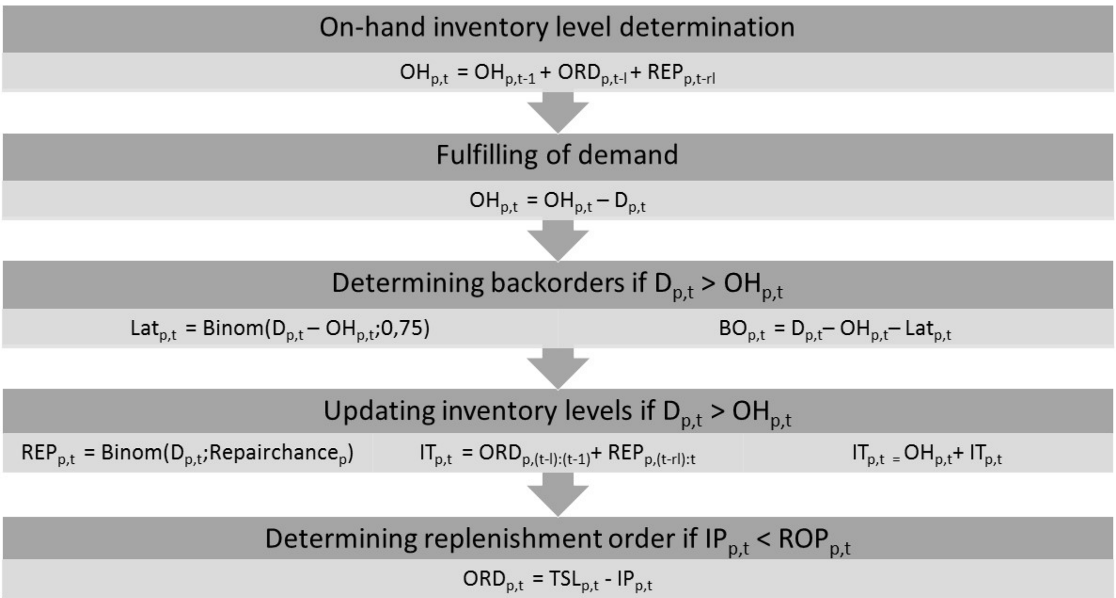

Figure 6: Order of daily processes in the simulation

Next to the warehousing process, the forecasting process is simulated in the simulation as well. Both the MCA forecast and Philips current forecast are simulated. For the forecasting process the demand must be known per month, meaning that the current daily demand data has to be converted to monthly data. Next to that demand that is known before the forecasting moment has to be labelled as such. To initiate the forecast, 2 years of demand data is needed, meaning that the forecasting process starts with the demand of 2015 and 2016, the MCA forecast uses this data to forecast for the upcoming periods.

For all demand the assumption is made that the part that is replaced, is ready to be repaired. All unique parts in the simulation have a repair rate, this indicates the chance that a part can be repaired after it is taken out of the system. Some parts are considered unrepairable and therefore have a repair rate equal to zero, this means that they will always be discarded after they have been used. For the parts with a repair rate higher than zero, a binomial random chance decides whether a part will go into repair or whether the part will be discarded. Next to a repair rate the parts also have a deterministic repair time, this indicates how long it will take for a part to get repaired. When a part is repaired it will go back in the warehouse as stock.

4.1.1 Execution of the simulation

The simulation will run the daily process for the period 1-1-2015 till 31-12-2017, the first two years are used as a setup phase. The performance of the simulation will therefore only be measured over 2017. Furthermore, each simulation is run 10 times to ensure reliability of the results. The average of the 10 runs is taken, meaning that extreme values from the binomial chances have less effect on the result.

4.1.2 Assumptions in the simulation model

For the simulation assumptions need to be made, in some cases because the part of the process can not be simulated without assumptions. In other cases the assumptions are implemented because it will reduce the complexity of the simulation and increase the simulation speed, while having a minor effect on the simulation results. As the assumptions make the simulation different to the model used at Philips it is important to list them. The following assumptions are made in the simulation process.

Assumption 1: Fill rate per part instead of fill rate for part set. Philips has a designated fill rate for each warehouse, this fill rate is not specified for each part but for the whole part set, meaning that individual parts can have a fill rate below the fill rate of the part set. The fill rate determines the target stock level, and accordingly the reorder point, for all parts. Because each individual part can have a different fill rate, there is a lot of complexity in the target stock level calculations, which are performed in the MCA tool. To reduce this complexity the target stock level in the simulation is based on the fill rate per part, meaning that every specific part in the part set has to reach the designated fill rate. As a result the majority of the TSL and ROP values will change. Furthermore, the inventory costs will be higher when achieving the same overall fill rate as a result of this assumption.

Assumption 2: Negative inventory and inventory costs. As is explained before, negative inventory will occur in case there are backorders. The inventory relative holding costs are based on the average inventory, which is influenced by the negative values. This means that in cases the inventory is negative, the relative holding costs are negative as well. Negative inventory will occur rarely though, and the average inventory will never be negative, meaning that the inventory relative holding costs will still be representative. Therefore, for computational reasons the decision is made to keep the simulation as such. As a result the inventory costs will be lower than in reality.

Assumption 3: Repair of parts. When parts are taken out of the system there is a chance that they can be repaired. Per part the decision is taken whether the part is repaired immediately to create stock in warehouses (push), or that the part is stored before there is a request for parts, and the part is then repaired (pull). In the simulation however, the decision is made to let all parts be pushed into repair so that they can be stocked in the warehouse afterwards. Furthermore, in reality some parts show to have no defects when they are taken out of the system, meaning that they are checked during the repair and no repair is needed. In the simulation this is not incorporated, the checking of the part takes time as well, it is assumed that the part will go through the repair cycle.

Assumption 4: Constant leadtimes. Philips orders its parts from its suppliers, each part has it's own leadtime. In the simulation these leadtimes are also specified per part. In some cases the part can not be delivered right away by the supplier, creating delay. This means that variance in the leadtime for a single part exists. In the simulation the leadtime is believed to be deterministic and thus constant, meaning that the supplier will always be able to deliver the part in the set leadtime.

Assumption 5: Chances have a binomial distribution and are uncorrelated. For several situations in the simulation there is a certain chance that something will happen. Examples of this are the chance that an unfulfilled order can be fulfilled via lateral transsshipment and the chance that a part can go into repair. These chances are assumed to be binomial, meaning that the simulation will compute the amount of parts binomial random based on the chance and amount of relevant parts. Furthermore the assumption is made that these chances are uncorrelated. The reason is that it is virtually impossible to simulate correlated chances, furthermore the most chances are truly uncorrelated.

Assumption 6: Sent and demand date of parts. In the current dataset two dates are available, the requested delivery date and the order creation date. This means that the send date, the date on which the part will go out of the warehouse towards the customer, is not available. The assumption is made that this date the same date as the requested delivery date. Usually the part will be taken out of the warehouse in the morning and delivered to the customer the same day. The reason is that all customers in the Benelux market can be visited within one day.

Assumption 7: Initial stock level in the simulation. The simulation runs for three years, the first two years are the initialization phase of the simulation, and the third year will be used to retrieve results. At the start of the three years the stock level will be equal to the target stock level. For most parts this normalizes after the two year initialization period because parts are frequently coming in and going out. There are other parts for which demand occurs only once in the three year period, in that case the part is in stock as the stock level is still equal to the targeted stock level. As a result, there will be no backorders on this part. This assumption does lead to a number of backorders could be slightly more positive than in reality. However, only a limited amount of parts are ordered so rare, meaning it only has a minor effect on the overall results.

4.2 Input

4.2.1 Data input for the simulation

The main data input for the simulation is the demand data for the Benelux over the years of 2015 to 2017. The data contains all orders for service parts for the Benelux market in this period. The data that is relevant for the simulation contains the following parameters: The order creation date, the requested delivery date, the order quantity and the part number, as can be seen in Table 6. The data is used for the forecasting process, and it determines the demand. Next to that the data specific for parts is used as input for the simulation as well. Per part the following aspects are specified: The part number, the part cost, the part leadtime, the chance that a part can be repaired and the repair leadtime, as can be seen in Table 7.

	Minimum	Maximum	Average
Requested Deliver Date (RDD)	1/9/2015	12/31/2017	-
Material number	1	3638	-
Creation date	1/8/2015	30/12/2017	-
Order quantity	1	100	1.40

Table 6: Data characteristics of orderdata

	Minimum	Maximum	Average
Material	1	3638	-
Leadtime	4	444	55.22
Repairtime	0	143	7.59
Repair chance	0	0.998	0.06
Costprice	0.02	72800	1101.82

Table 7: Data characteristics of partdata

4.2.2 Input parameters

Next to the data input there are some input parameters that are relevant to the simulation as well. Most of the input parameters come from the data as it is often part specific, such as leadtime and part costs. Some input parameters are generalized for the whole dataset and are therefore not extracted from the dataset, but are initiated at the start of the simulation. The input parameters can be found in Table 8.

Parameter	Description
Lateral chance	The chance that an order that can not be fulfilled by stock, can be fulfilled by a lateral transshipment, which is set to 0.75 in the simulation.
Forecast delay	The amount of days before the start of the month that the forecast is performed. When the forecast delay equals 7 this means that the forecast is performed 7 days before the start of the month. This is relevant for the orders that are already known at this date.
Designated fillrate	The desired fill rate for all individual parts, relevant for the calculation of the target stock level.
Holdingcostpercentage	Determines how high the annual inventory costs are relative to the part costs. When the relative holding cost percentage is 0.2 and the part price equals €100, the annual relative holding costs per unit are $100 \times 0.2 = 20$.
MCA alpha	The smoothing factor for the MCA forecast. For the simulation this factor is the same for all parts, in reality this can differ however. The factor lies between 0.1 for intermittent demand and 0.3 for smooth demand.

Table 8: Input parameters of the simulation

4.3 Output

To measure the effect of the proposed solutions, the simulation indicates the performance of the service parts supply chain. In order to have a clear image on how a solution performs, several Key Performance Indicators (KPI) are computed during the simulation. The performance of the various scenario's can be compared using these KPI's. The following KPI's are noted.

Fill rate. According to Sobel (2004), the fill rate is the percentage of demand which can be fulfilled directly from stock. As lost sales do not occur in our system, it means that this is all demand except for backorders. The fill rate is calculated per part, meaning that for each part it is noted whether or not the demand is fulfilled from stock for that part. The fill rate is determined by dividing the demand that was fulfilled directly from stock by all demand (Equation 4.1). To compute the overall fill rate, the fill rate of all parts are combined (Equation 4.2).

$$\beta_p = 1 - \frac{\sum_{t=1}^{t=365} BOo_{p,t}}{\sum_t D_{p,t}} \tag{4.1}$$

$$\beta_{total} = \sum_p \left(\frac{\sum_t (D_{p,t})}{\sum_{p,t} (D_{p,t})} \times \beta_p\right) \tag{4.2}$$

Where:

$D_{p,t}$	=	The demand for part p on day t
$BOo_{p,t}$	=	The amount of occurred backorders for part p on day t
β_p	=	The fill rate for part p
p	=	The part number ranging from 1 to 3638
t	=	The day number ranging from 1 to 365

Backorders. For each part the number of backorders are measured over the year, at the end of the year the total backorders for that part can be seen. By summing the backorders for all parts, the overall backorders can be calculated (Equation 4.3). The main goal of this research is to reduce the number of backorders.

$$BO = \sum_{p,t} BO_{p,t} \tag{4.3}$$

Inventory relative holding costs. An easy way to increase the performance of the KPI's mentioned above is to increase the amount of parts in stock, the downside of this is the costs of inventory will increase. For that reason the inventory relative holding costs are also computed. To compute the relative holding costs the average inventory is multiplied by the part price and the relative holding costs percentage (Equation 4.4). The relative holding cost percentage is a constant value that determines which percent of the part price determines the annual relative holding costs. At the end of the year the average inventory level, which is measured at the end of each day, is determined and used for these calculations.

$$HC_p = \frac{\sum_{t=1}^{t=365}(OH_{p,t})}{365} \times C_p \times cr \tag{4.4}$$

$$TotalHC = \sum_{p} HC_p \tag{4.5}$$

Where:

$OH_{p,t}$	=	The on hand inventory for part p at the end of day t
HC_p	=	The relative holding costs for part p
C_p	=	The price for part p
cr	=	The percentage of the part costs that determines annual relative holding costs

Conclusion

To conclude, the scope implies that the situation can be modeled as a Multi item, single location inventoy model. This model can be simulated, but needs some assumptions to account for specific situations. When these assumptions are included, as well as input parameters and data input are determinded, the simulation can be run. The simulation will return several KPI's, which can be used to measure the performance of a proposed solution.

Chapter 5

The use of advance demand information in forecasting

Philips uses historic demand data to compute an average amount of demand per period and to forecast the demand for the upcoming periods. In forecasts demand is often modelled as being stochastic. In case of advance demand information the forecast can be improved by implementing this deterministic information, like the exact moment of ordering and the order quantity. The reliability of the forecast will be improved when implementing advance demand information.

In this chapter an insight will be given in the way advance demand information can be used to improve the forecast. First of all a literature review on using ADI in forecasting is performed §5.1. Secondly a method for implementing ADI in forecasting is presented for the situation of Philips in §5.2. Lastly, the presented solution will be tested in a discrete event simulation to indicate its performance on backorders and costs in §5.3.

5.1 Advance demand information & forecasting

5.1.1 ADI and forecasting in literature

The advantages of using advance demand information in forecasting is also mentioned in the literature that is available on this topic (Dekker et al., 2013). A paper by Tan (2008) that is written specifically on this topic describes all the steps needed to implement advance demand information in the forecasting method. The paper handles imperfect advance demand information, meaning that the Advance Demand Information (ADI) can either be partly incorrect or partly unknown. despite the fact that the ADI is imperfect, it can still be used. Hence, we will first determine the characteristics of the ADI, before incorporating it in the forecast.

According to Thonemann (2002) there are several types of ADI to distinguish. First of all there is aggregated ADI, which is information given by customer that they will place an order at a certain time, but not what product it will be. Secondly there is detailed ADI, which does specify the product that will be ordered and the moment of ordering, but does not specify at which manufacturer the order will be placed. The chance that the order will be placed at manufacturer x will then be modelled as q_x. As Philips is the only supplier for service parts for the Philips systems, the situation can be described as detailed ADI with the certainty that the order is placed at Philips.

Whenever the type of ADI is determined, the decision has to be made on how to incorporate ADI in the forecasting procedure. To do so there are two main options, change the forecasting model to implement ADI, or add ADI to an existing forecasting model. In the paper of Abuizam, R. and Thomopoulos (2006) a solution is proposed in which the ADI is added to the forecasting model. A Bayesian technique is used to determine the forecasted value for a certain period, based on both the initial forecasted value and the known demand for the period. This technique is also one of the solutions presented by Tan (2008), which also adds ADI after the forecasting process, as can be seen in figure 7.

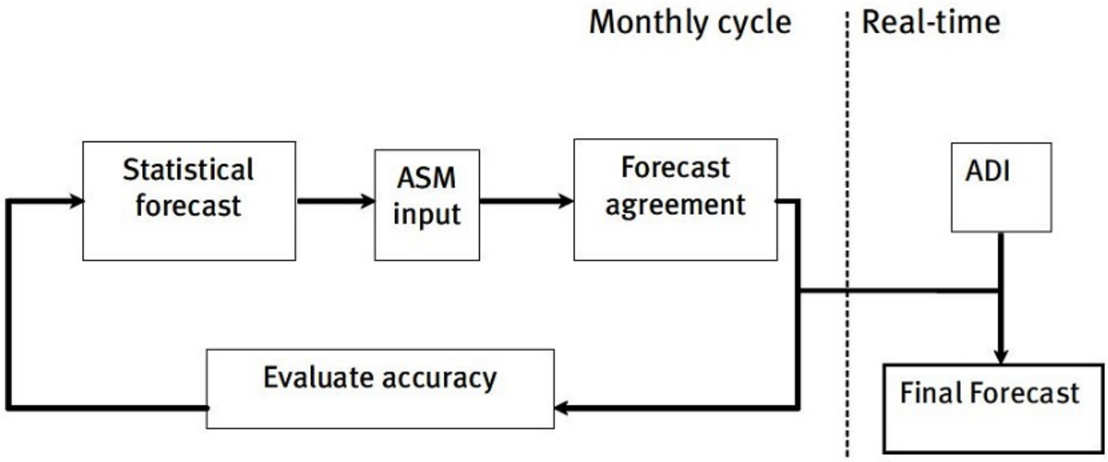

Figure 7: Methodology for implementing ADI in forecasting proposed by Tan (2008)

Tan (2008) presents four methods that add ADI to create an improved final forecast.

$$F_t = \max(FA_t, O_t) \tag{Method 1}$$

$$F_t = \max(FA_t, O_t + Q \sum_{i=NO_t}^{M} (i - NO_t)p_i) \tag{Method 2}$$

$$F_t = \begin{cases} O_t + \sum_{i=1}^{t-1} w_i(D_i - O_t)^+ & \text{if } O_t > cFA_t \\ FA_t & \text{otherwise} \end{cases} \tag{Method 3}$$

$$F_t = O_t + \sum_{i=1}^{t-1} w_i[(D_i - F_i) - (O_t - FA_t)]^+ \tag{Method 4}$$

Where:

F_t	=	The final forecast for period t
FA_t	=	The initial forecast for period t
O_t	=	The demand already placed in advance for period t
M	=	The maximum number of orders in the order history that have been placed for the same period in advance
D_t	=	The realized demand for period t
Q	=	The average historical order size t
NO_t	=	The number of orders that is placed in advance for period t
c	=	A positive constant value $(1 \geq c \geq 0)$
p_i	=	The probability of having i orders
w_i	=	The weighting factor used to differentiate between older and newer observations

The first, simple, method that is presented is the same method that is currently in use at Philips. In this method the forecasted value is the maximum of the initial forecasted value and the orders placed in advance. The second method is based on forecasting the number of orders and then multiplying it with the average order size. Again the final forecast is the maximum of this computation and the initial forecast. The third method that is presented is based on Karmarkar (1994), and is a right tail estimation method. In this method the adapted forecast is calculated by adding past demand realizations to the orders placed in advance. This value is only used if the demand placed in advance is close enough to the forecasted demand, determined by a constant value. In other cases the initial forecast is used as the final forecast. The disadvantage of the right tail estimation method is that it only works for stationary demand. This problem is tackled by the fourth method, known as the non-stationary right tail estimation method. In this method the observed demand is compared to past performances of forecasts instead of past demands.

In the paper of Tan (2008) all four methods are tested to a case for a dairy products company. The advance demand information is imperfect in their study, meaning that part of the order information is incorrect or unavailable. The fourth method (non-stationary right tail estimation method), which was applied with equal weights for all periods, proved to perform the best. As a result, required safety stock was reduced by 25%, showing the potential of using (imperfect) advance demand information in forecasting processes.

5.1.2 Current situation

In the current situation, forecasting is performed based on historic data using the sales data of the last 24 months as input. The forecast produces an average demand per month that is the same for all upcoming months, this is a result from smoothing the data. For forecasting an external tool called MCA is used, Philips provides the relevant data for this tool. The forecasts is used in many processes taking place within the service parts supply chain. It is the basis on which orders for new parts are placed. Furthermore it determines the stock levels for all parts at the warehouses. Lastly, the forecast is also used to re-allocate parts between warehouses. The forecasting process is frequently being evaluated, this can lead to parameter changes of the forecast for specific parts.

Currently Philips makes little use of advance demand information in their forecasting process. The forecasting results are only adapted in case the demand from future orders exceeds the forecasted demand. In that case the forecasted demand is replaced by the demand from future orders. This means that whenever the known future demand is not higher than the forecasted demand, the forecast will be the same. It is expected however, that in case the known future demand already equals the forecasted demand, the actual demand will be higher.

5.1.3 Scoping future orders for the forecast

First of all an insight will be gained in the future orders applicable for forecasting. The forecast process for service parts within Philips makes use of historic order data, this data is gathered monthly. Meaning that the input for the forecast is the total number of orders per month for the last 2 years. An order can be incorporated in the forecast when it is known before the moment of forecasting. As the the forecast is performed at a fixed moment in the month, and orders arrive throughout the month, the amount of time an order is placed ahead does not necessarily imply whether the order is taken into consideration in forecasting.

Instead, there has to be a point in time when an order needs to be known, to be implemented in the forecast. The forecast for the following months is made at a certain date, which means that the future order information has to be available on that date. As a result, it can happen that orders that are known 10 days in advance are implemented in the forecast, while orders that are known 30 days in advance are not. The reason for this is that the order has to be known before the forecasting date. A graphical representation can be seen in Figure 8

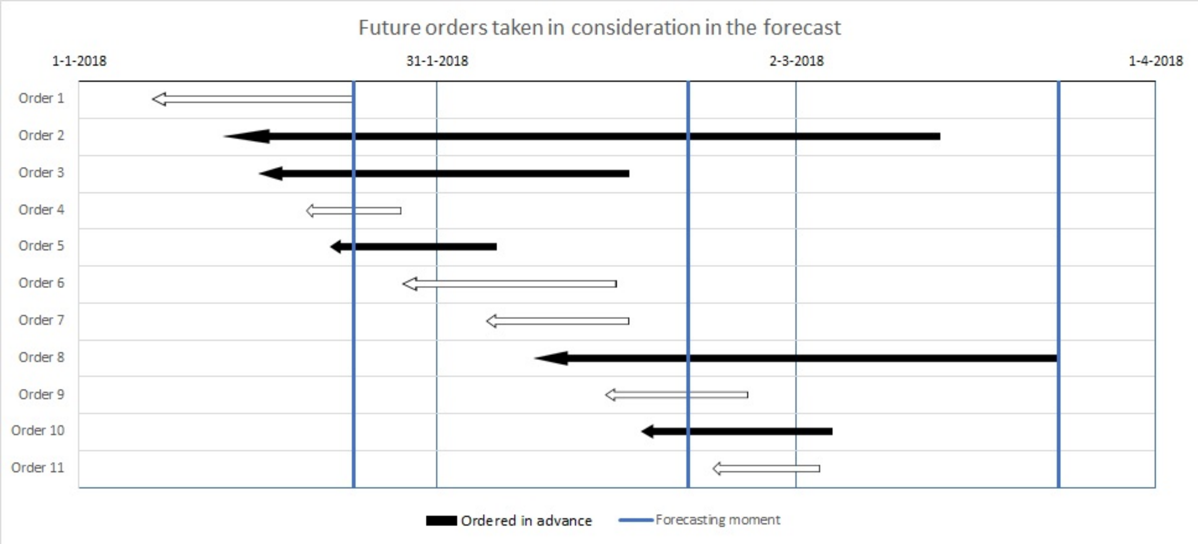

Figure 8: Orders implemented (filled) and not implemented (unfilled) in the forecast

As can be deducted from the figure a future order is only implemented in the forecast when it is known before the forecasting moment. This means that a future order for March has to be known before the forecasting moment at the end of February. The graph clearly visualizes that the length between ordering date and RDD is less relevant than the moment of ordering.

5.2 Implementing ADI in the forecasting process of Philips

As shown in §3.2 the advance demand information available at Philips shows to be generally reliable. Furthermore parts ordered are often ordered one or two a piece, so no bulk ordering. These phenomena make the situation different than the situation described in literature. The first remarkable difference is that for the majority of the parts in the Philips portfolio demand follows an intermittent pattern. This means that periods with demand are frequently followed by periods with no demand (Willemain et al., 2004).

The performance of the various ADI forecasts Tan (2008) presents are tested on 11 parts that are most frequently early ordered in 2017. To test the methods presented, the forecast is replicated and the final forecast is built for all months in 2017. To compute the performance of the methods, for each part the sum of squared errors (Equation 5.1), and the sum of absolute errors (Equation 5.2) is calculated. The results of the four methods are summarized in Appendix A.

$$SSE_p \text{ (sum of squared errors)} = \sum_{t=1}^{12} (F_{tp} - D_{tp})^2 \qquad \text{(Equation 5.1)}$$

$$SAE_p \text{ (sum of absolute errors)} = \sum_{t=1}^{12} |F_{tp} - D_{tp}| \qquad \text{(Equation 5.2)}$$

Where:

$F_{t,p}$	=	forecasted value for part p for period t
$D_{t,p}$	=	the actual demand for part p for period t
t	=	The month number $t \in [1, 2, ...12]$
p	=	The part number $p \in [1, 2, ...11]$

In order to compute the exact difference in performance of the various methods over the 11 parts, the relative error is calculated. Simply adding the values up is biased, as parts with high errors will have more influence. This is illustrated in the Appendix A, part 9 would have much more influence than part

3 on the final result. In order to calculate the relative error, method 1 is used as a reference. Method 1 is also the method that is used at Philips right now. The higher the percentage, the higher the relative forecasting error and thus the lower the performance. As can be seen in the table, the proposed methods has a lower error, meaning the forecast is most accurate. The calculations for the relative errors are presented in Equation 5.3 and Equation 5.4.

$$\text{Relative error on } SSE = \sum_{p=1}^{11} \frac{SSE_p^i}{SSE_p^{M1}} \times \frac{1}{11} \times 100\% \qquad \text{(Equation 5.3)}$$

$$\text{Relative error on } SAE = \sum_{p=1}^{11} \frac{SAE_p^i}{SAE_p^{M1}} \times \frac{1}{11} \times 100\% \qquad \text{(Equation 5.4)}$$

Where i is Method 1 to 4 and Proposed method 1.1 respectively.

Method	Relative error on SSE	Relative error on SAE
Method 1	100.0%	100.0%
Method 2	99.7%	101.5%
Method 3	100.8%	103.4%
Method 4	96.4%	97.1%

Table 9: Relative error of forecasting methods for all periods

5.2.1 Developing a forecast for intermittent demand using ADI

The methods described by Tan (2008) do not give the improvement in forecast error that is desired, as can be seen in the relative errors in Table 9, and the tables in Appendix A. The method that performs the best is method number four. This is mainly due to the good performance on part 6, 7 and 8. These three parts are strongly correlated, explaining the similar performance of the various methods on these three parts. Because of this, A new method is developed for the forecasting using ADI, applied to the situation at Philips. This method is designed to perform well in a intermittent demand situation. Next to that, the method should also perform in case there is no ADI, as well as perform in a non intermittent situation. To adapt the forecast for intermittency, the periods of zero demand need to be taken into account. Difficulty is that it is hard to predict if there will be demand in a certain period (Hua et al., 2007);(Wang, 2011). By using ADI, the chance of having demand in a certain period can be predicted. In case ADI already shows demand for a period you can be sure that there will be demand in the period. Following this belief, an interesting conclusion can be drawn. When there is no order placed in advance, the chance of demand will be lower than when computing the chance without making use of ADI. Which can be written as:

$$P(D_t = 0 \mid O_t = 0) > P(D_t = 0) \qquad \text{(Equation 5.5)}$$

In reality, the chance of having demand when no future orders are placed is unknown. For that reason it is computed by calculating the frequency this happened over the last 24 months. The probabilities that need to be computed are the probability that there will be demand, and the probability that there will be demand given no future orders. The probability of having demand given no future orders is

$$P(D_t \geq 1 \mid O_t = 0) = \frac{P(D_t \geq 1, O_t = 0)}{P(O_t = 0)} \qquad \text{(Equation 5.6)}$$

Next to the probability that demand occurs, the expected demand in case demand occurs needs to be known as well. To do so, the forecasted value is used. The formula for the MCA forecast can be seen in Equation 5.7, in this formula α is the smoothing factor. Note that the exact MCA forecasting formula is unknown, the formula presented is annotated by Philips to replicate the MCA forecasting formula.

$$FA_{t+1} = \begin{cases} \dfrac{\alpha \times D_t}{N_{t-1}+1} + (1-\alpha) \times FA_t & \text{if } D_t > 0 \wedge \sum_{j=1}^{5} D_{t-j} > 0 \\ FA_t & \text{otherwise} \end{cases} \qquad \text{(Equation 5.7)}$$

With $N_t - 1$ being

$$N_{t-1} = \begin{cases} 0 & \text{if } D_{t-1} > 0 \\ N_{t-2}+1 & \text{if } D_{t-1} = 0 \end{cases} \qquad \text{(Equation 5.8)}$$

Philips set the smooth factor $\alpha = 0.1$. the initial value of FA_t is the average demand over the last 24 months. Meaning that the overall results of the formula will be similar to the average demand as is portrayed in Equation 5.9.

$$FA_{t+1} \approx \frac{\sum_{j=1}^{24} D_{t-j}}{24} \qquad \text{(Equation 5.9)}$$

As:

$$P(D_t \geq 1) = \frac{\sum_{j=1}^{24} \mathbb{1}(D_{t-j} \geq 1)}{24} \qquad \text{(Equation 5.10)}$$

The average demand can be rewritten as:

$$\frac{\sum_{j=1}^{24} D_{t-j}}{24} = \frac{\sum_{j=1}^{24} D_{t-j}}{\sum_{j=1}^{24} \mathbb{1}(D_{t-j} \geq 1)} \times P(D_t \geq 1) \qquad \text{(Equation 5.11)}$$

In this formula $\frac{\sum_{j=1}^{24} D_{t-j}}{\sum_{j=1}^{24} \mathbb{1}(D_{t-j} \geq 1)}$ represent the expected demand in case $P(D_t \geq 1) = 1$, and $P(D_t \geq 1)$ represents the chance of having demand. This result is Equation 5.12

$$\frac{\sum_{j=1}^{24} D_{t-j}}{\sum_{j=1}^{24} \mathbb{1}(D_{t-j} \geq 1)} \approx \frac{FA_t}{P(D_t \geq 1)} \qquad \text{(Equation 5.12)}$$

Equation 5.12 represents the expected demand in periods with demand. Meaning a final forecast is developed that uses ADI to predict whether or not there will be demand.

$$F_t = \begin{cases} P(D_t \geq 1 \mid O_t = 0) \times \dfrac{FA_t}{P(D_t \geq 1)} & \text{if } O_t = 0 \\ \dfrac{FA_t}{P(D_t \geq 1)} & \text{otherwise} \end{cases} \qquad \text{(Proposed method 1.1)}$$

Where:

$$P(D_t \geq 1 \mid O_t = 0) = \frac{\sum_{j=1}^{24} [\mathbb{1}(D_{t-j} \geq 1) \times \mathbb{1}(O_{t-j} = 0)]}{\sum_{j=1}^{24} \mathbb{1}(O_{t-j} = 0)} \qquad \text{(Equation 5.11)}$$

When looking at the performance of this formula it can be seen that overall the method is far worse that the four methods Tan (2008) presents, as shows in Appendix A. The SSE is 86.3% higher than the current method, and the SAE is 33.2% higher than the current method. The main reason for this is that the formula presented mainly focuses on periods with no initial demand. When looking at the periods where $O_t = 0$, the method shows to perform better than the methods Tan (2008) presents (Table 10). In Tables 26 and 27 in Appendix A, the performance of all methods mentioned can be seen. It can be seen that the proposed method performs best in 8 out of 11 parts considered for $O_t = 0$.

Method	Relative error on SSE	Relative error on SAE
Method 1	100.0%	100.0%
Method 2	99.8%	100.1%
Method 3	100.0%	100.0%
Method 4	101.2%	97.3%
Proposed method 1.1	86.3%	90.2%

Table 10: Relative error of forecasting methods for periods with $O_t = 0$

Until now, the quantity of the future orders is not embedded into forecasting. However, the expected demand is equal or higher than the amount of future orders. In order to improve the formula, the amount of future orders will be taken into account. The actual demand will always be the same or more than the future ordered demand. In the new formula the forecasted value will be the amount future ordered parts plus the extra expected demand. The extra expected demand can be computed in several ways. First of all the coefficient between future orders and actual demand can be computed. The forecasted value can then be computed by multiplying this coefficient with the future ordered value. The second option is to calculate the average difference between future orders and actual demand. The forecasted value can then be calculated by adding the average difference to the future ordered value. Both the methods are evaluated in Appendix B, and the summation method shows to have the lowest forecasting error. The computation of the forecasted value can be seen in Equation Equation 5.12.

$$Option2 : O_t + \frac{\sum_{j=1}^{24}(D_{t-j} - O_{t-j}) \times \mathbb{1}(O_{t-j} \geq 1)}{\sum_{j=1}^{24} \mathbb{1}(O_{t-j} \geq 1)} \tag{Equation 5.12}$$

For clearness of the formulas, the equation will be renamed as can be seen in Equation 5.13.

$$\Delta DO_t = \frac{\sum_{j=1}^{24}(D_{t-j} - O_{t-j}) \times \mathbb{1}(O_{t-j} \geq 1)}{\sum_{j=1}^{24} \mathbb{1}(O_{t-j} \geq 1)} \tag{Equation 5.13}$$

This will then result in the final proposed method to be:

$$F_t = \begin{cases} P(D_t \geq 1 \mid O_t = 0) \times \dfrac{FA_t}{P(D_t \geq 1)} & \text{if } O_t = 0 \\ O_t + \Delta DO_t & \text{otherwise} \end{cases} \tag{Proposed method 1.2}$$

This formula already shows great improvements in the SSE, however there were a few notable cases in which the forecasted value is extremely high compared to the actual demand. This occurrs in cases where there are a few previous cases of future order and/or the difference between future orders and actual orders is relatively high. In order to limit the forecasted value, it can be no higher than the future orders plus the initial forecasted value. The result of this is Equation Proposed method 1.3. This excludes the extreme values, giving an extra improvement of the performance of the method.

$$F_t = \begin{cases} P(D_t \geq 1 \mid O_t = 0) \times \dfrac{FA_t}{P(D_t \geq 1)} & \text{if } O_t = 0 \\ O_t + \min(\Delta DO_t, FA_t) & \text{otherwise} \end{cases} \tag{Proposed method 1.3}$$

This proposed forecasting method returns the same values as the initial forecasts in case there are and have been no future orders. This means that for most parts that are forecasted, the values do not change. However, the forecast for the parts that do have future orders benefits from this method as shows in Tables 30 and 31 in Appendix A.

In case the proposed method is tested on all periods, there is a possibility that it will show a better performance because of the periods with $O_t = 0$. Table 10 shows that the proposed method performs better in periods with $O_t = 0$. To ensure that the method also performs in periods with initial demand, it is first tested in these specific periods. Next to Proposed method 1.3 and the method currently in place at Philips, the other proposed methods and the methods mentioned by Tan (2008) are portrayed as well, as can be seen in Tables 28 and 29 in Appendix A. The tables show there are parts for which the forecasting error is equal to zero, the reason for this is that there are very few periods with demand, and the forecasts is exactly right for these periods.

5.2.2 Evaluation of the proposed forecast

Usually the overall performance would be calculated by computing the relative performance, with the current method (Method 1) as the reference point. In this case Method 1 has a SSE (and thus a SAE) of zero in some cases, meaning this way of computing the overall performance can not be used. To estimate which method performs best, two other performance indicators are used. First of all we take a look at the unweighed sum of squared or absolute errors, although some parts might have more influence on the final value than others, this still gives an insight in how the method performs overall. Secondly, the amount of times a method performs best out of all available methods is noted. In case multiple methods perform best they will all be counted as the best method, the computation of this method can be seen in Figure 9.

SSE: Part:	1	2	3	4	5	6	7	8	9	10	11	∑	SAE:	1	2	3	4	5	6	7	8	9	10	11	∑
Method 1	✓		✓							✓	✓	4		✓		✓						✓	✓	✓	5
Method 2	✓		✓									2		✓		✓						✓			3
Method 3												0										✓			0
Method 4			✓		✓	✓	✓	✓				5				✓		✓	✓	✓	✓				5
Proposed Method 1.1												0													0
Proposed Method 1.2	✓	✓	✓	✓						✓	✓	6		✓	✓	✓	✓						✓	✓	6
Proposed Method 1.3	✓	✓	✓	✓					✓	✓	✓	7		✓	✓	✓	✓						✓	✓	6

Figure 9: Methods who perform best in SSE and SAE per part

In Table 11 the performance of the sum of squared and absolute errors as well as a summary of Figure 9 can be found.

Method	$\sum_p SSE$	$\sum_p SAE$	Performs best (SSE)	Performs best (SAE)
Method 1	191.04	33.39	4	5
Method 2	189.60	34.27	2	3
Method 3	190.52	35.64	0	1
Method 4	205.48	34.84	5	5
Proposed method 1.1	1183.46	92.21	0	0
Proposed method 1.2	757.78	67.83	6	6
Proposed method 1.3	155.69	36.77	7	6

Table 11: Performance of the seven methods in periods with initial demand

As can be seen Proposed method 1.3 performs best in 3 out of 4 performance indicators, giving enough reason to believe that overall this method performs best in the cases it was tested on. Given the fact that the proposed method performs best in both cases with initial demand and cases without initial demand, it must perform best in the situation in which both cases occur. The fact that Proposed method 1.2 Has such a high sum of squared errors, whilst it still performs best in 6 cases is because of its bad performance for part 9. Table 28 in Appendix A shows that for the other 10 parts, the performance of Proposed method 1.2 is similar to the other methods.

The performance of all methods in all periods can be found in Tables 30 and 31 in Appendix A . As can be seen the proposed method performs better than the current method in 8 of the 11 cases. Furthermore, in these 8 cases the proposed method performs the best of all the methods reviewed. In the three other cases the method performs worse than the current method. When looking at the total performance, which is the average of all 11 cases, we see that the proposed method performs the best of all methods. The proposed method shows to reduce the SSE with 8.5% compared to the current method, and reduces the SAE with 4.3% compared to the current method.

Method	Relative error on SSE	Relative error on SAE
Method 1	100.0%	100.0%
Method 2	99.7%	101.5%
Method 3	100.8%	103.4%
Method 4	96.4%	97.1%
Proposed method 1.1	186.3%	133.2%
Proposed method 1.2	107.0%	101.1%
Proposed method 1.3	91.4%	95.7%

Table 12: Relative error of forecasting methods for all periods

5.2.3 Selecting the optimal timespan for proposed method 1.3

Currently the chances for demand, as well as the expected demand in case o demand are computed using data over the last 24 months. In order to ensure that a timespan of 24 is optimal, an analysis is performed that uses various timespans in the same forecast. The details of this analysis are found in Appendix C, a summary of the results is portrayed in Table 13.

Timespan	$n = 24$	$n = 18$	$n = 23$	$n = 25$	$n = 30$
Relative error on SSE	100%	102.59%	102.03%	100.36%	100.06%
Relative error on SAE	100%	100.38%	100.24%	100.23%	99.95%
Average	100%	101.49%	101.13%	100.30%	100.01%

Table 13: Performance of the various timespans for 11 frequently early ordered parts

As expected, the differences between the various timespans are very small. When looking at both the SSE and the SAE it can be seen that the 24 month timespan performs best in all cases except for the SAE for the 30 month timespan. When looking at the average of the SAE and SSE it can be seen that the 24 month timespan performs best overall. As a result of this, we will use proposed method 1.3 with a timespan of 24 months in the simulation. Proposed method 1.3 is referred to as the proposed forecast from now on.

5.3 Simulation results of the proposed forecast

When simulating the effect of the change in forecast method, four KPI's are revised, Fill rate, Backorders, Order fulfillment and Inventory relative holding costs. When simulating for all parts in the dataset, the new method showed to have no significant impact on the KPI's as can be seen in Table 14. The reason could be because only a minor percentage of all parts have orders placed thus far in advance that they are taken into account in forecasting. In order to get a more reliable result the simulation will be run again only considering the parts that are affected by the new forecasting method. Out of the total 3638 parts, 238 are affected by the new forecasting method. When looking at the results of the simulation for these 238 parts again there is no dramatic difference in performance on the KPI's as can be seen in Table 15.

This is surprising as the forecasting accuracy was increased. The reason for the performance may be long lead times for the relevant parts. Although the forecast was more accurate, the resulting change in inventory position came 2 to 3 months later, at this point the forecast was no longer relevant to the performance. To tackle this problem, a third forecast is introduced, which is a smoothed varaint of the proposed forecast. The exact calculations on this forecast can be found in Appendix D. When applying this formula, results show a minor difference compared to the current method and proposed method 1.3.

The exact performance can be found in Table 14, as can be seen the number of backorders is similar for all three methods, with it being the highest for the proposed method and the lowest for the smoothed method. Regarding the fill rate, the performance is roughly the same for all three methods with a maximum difference of only 0.08%. The same can be said when looking at the relative holding costs. All in all, there is a very small difference in the performance of all three methods, meaning that there seems to be no improvement when applying the presented forecasting techniques.

Method	Fillrate	Number of backorders	Holdingcosts
Current method	92.34%	1777	100%
Proposed method	92.28%	1792	99.44%
Smoothed method	92.36%	1774	100.35%

Table 14: Performance of the three methods in simulation for all 3638 parts

The reason for the fact that the performance differences are so small could be because of the fact that only a minor fraction of the parts is affected by the newly introduced forecasting method. To have a better idea of what the effect will be of the new forecasting method we will simulate the situation again, but now only taking into consideration the parts that are influenced by the new method. The results of these simulation can be seen in Table 15.

Method	Fillrate	Number of backorders	Holdingcosts
Current method	93.62%	237	100%
Proposed method	93.47%	241	101.89%
Smoothed method	93.58%	234	99.38%

Table 15: Performance of the three methods for the parts for which the forecast changes

As can be seen in the table, the difference between the three methods remains very small. With that being said, in this scenario there is one method which performs best on all three criteria, being the smoothed method. When looking at the improvements of the smoothed method compared to the current method, it can be seen that these are very small. For the fill rate there is no difference, and for the relative holding costs there is just a 0.6% decrease. The smoothed method reduced the amount of backorders by 3, being a 1.3% decrease. With that being said we can conclude that the new forecasting method shows some potential, but there is not enough evidence to be an improvement for the Philips scenario.

5.4 Sensitivity analysis of the proposed forecast

For the sensitivity analysis, the sensitivity of all three methods has been tested. To do so the relevant input parameters are varied to see what effect this has on the simulation result. For the simulation the following five input parameters were used: *Lateralchance, Designfillrate, Holdingcostpercentage, Forecastdelay* and *MCAalpha* as can be seen in Table 8 It would make no sense to vary the relative holding cost percentage, as this has only influence on the final calculations and not on outcomes during the simulation and the decisions made in the simulation. The same can be said of the lateral chance, This will only affect the backorders and will therefore have the same linear result for all three simulated methods. The value of MCAalpha is fixed and is determined by the SPS department of Philips, therefore the decision has been made to not perform a sensitivity analysis on this value.

As a result, only two values remain on which a sensitivity analysis will be performed, the Designfillrate and the Forecastdelay. The initial input values of these parameters were 0.99 for the Designfillrate and 6 for the Forecastdelay. During the sensitivity analysis the value of the Designfillrate is varied over $[0.980, 0.985, 0.990, 0.995, 0.999]$ and the value for the Forecastdelay is varied over $[4, 5, 6, 7, 8]$. The result of the simulations for these variables can be seen in Tables 16 and 17.

As can be seen in the sensitivity analysis on the designfillrate, an increase in the designfillrate leads to less backorders and higher inventory costs and fill rate. For all five values of the designfillrate, the performance of all three methods is very similar. On each performance indicator all methods perform roughly the same, which is the same conclusion that could be drawn from Table 14.

When looking at the forecastdelay, There seems to be no correlation between the forecastdelay and the performance of the simulation. This is surprising as a lower forecastdelay would mean that the moment of forecasting is later, increasing the amount of advance demand information. This means changing the moment of forecasting, will have no effect on the performance on backorders. When comparing the three methods, again the conclusion can be drawn that all three perform similar on the various values of forecastdelay.

Current method					
Designfillrate	**0.98**	**0.985**	**0.99**	**0.995**	**0.999**
Current method	2001	1902	1789	1614	1311
Holdingcost	87.45 %	90.53%	100 %	115.16%	145.47%
Fillrate	91.37%	91.79%	92.28%	93.04%	94.35%
Proposed method					
Designfillrate	**0.98**	**0.985**	**0.99**	**0.995**	**0.999**
Backorders	2008	1843	1775	1591	1296
Holdingcost	86.46%	90.36%	100%	112.02%	144.29%
Fillrate	91.35%	92.05%	92.34%	93.14%	94.41%
Smoothed method					
Designfillrate	**0.98**	**0.985**	**0.99**	**0.995**	**0.999**
Backorders	2019	1868	1734	1599	1311
Holdingcost	85.41%	87.92%	100%	110.99%	141.38%
Fillrate	91.29%	91.94%	92.52%	93.09%	94.34%

Table 16: Sensitivity analysis of the designfillrate for the three methods

Current method					
Forecastdelay	**4**	**5**	**6**	**7**	**8**
Backorders	1772	1783	1749	1770	1802
Holdingcost	101.74%	101.01%	100%	100.29%	100.38%
Fillrate	92.35%	92.30%	92.45%	92.36%	92.22%
Proposed method					
Forecastdelay	**4**	**5**	**6**	**7**	**8**
Backorders	1754	1801	1761	1782	1767
Holdingcost	101.00%	99.89%	100%	98.36%	101.39%
Fillrate	92.43%	92.22%	92.41%	92.31%	92.38%
Smoothed method					
Forecastdelay	**4**	**5**	**6**	**7**	**8**
Backorders	1759	1801	1814	1815	1795
Holdingcost	101.58%	100.02%	100%	98.99%	99.99%
Fillrate	92.42%	92.23%	92.17%	92.17%	92.25%

Table 17: Sensitivity analysis of the Forecastdelay for the three methods

Overall, we can draw several conclusions from the sensitivity analysis. First of all, the designfillrate has the expected effect on the performance of the simulation. An increase of the designfillrate leads to an increase of the actual fill rate and an increase of inventory costs, furthermore it leads to a decrease in backorders. Secondly, the forecastdelay shows to have no effect on the performance of the simulation of all three methods. As a result of this, it means that there is no advantage to change the moment of forecasting, Forecasting at an earlier or later stage will not lead to a reduction of backorders. Lastly, the three forecasting methods have no sensitivity advantage over each other.

Conclusion

To conlcude, a new forecasting method has been developed which is designed specifically for the forecasting of intermittent demand while using advance demand information. The aim of this forecasting method is to forecast when there will be demand, and in case of demand how much demand there will be. The forecasting mehod shows to have a lower forecasting error compared to the current forecasting method. In the simulation the difference is neglectable however, even when the forecast is smoothed in regard to the part leadtime.

Chapter 6

Advance demand information in replenishment decisions

Next to forecasting, there are several other fields in which a reduction of backorders can be realised using advance demand information. One of these fields is the replenishment of service parts. Usually service parts are replenished at the moment the inventory level drops below a certain value, an order to replenish will be placed and the new stock will come in after the lead time. In some cases the the demand may be known already because of advance demand information (ADI). In this case it is wise to replenish in a proactive manner, to reduce the chance of being out of stock.

In this chapter this change in replenishing will be presented. First of all, a literature review on advance demand information in replenishing is performed in §6.1. Secondly, a new replenishment strategy is introduced in §6.2. Lastly, the performance of this strategy is reviewed in §6.3.

6.1 Replenishment and advance demand information

6.1.1 Replenishment and advance demand information in literature

Although sparse, literature exists on using advance demand information in replenishment decisions. Gallego and Özer (2003) show that the use of advance demand information in replenishment decisions lead to less inventory relative holding costs. Furthermore, this effect shows to increase as customers place their orders longer in advance (Gallego and Özer, 2001). Next to a reduction of inventory costs, the use of advance demand information in replenishment decisions can also lead to backorder reductions (Karaesmen et al., 2004). Futhermore, the use of advance demand information leads to having the same performance under lower base stock levels. Next to that, Topan et al. (2016) show that imperfect demand information can be used in replenishment decisions as well. Lastly, Basten and Ryan (2015) apply the using of ADI to the replenishment of spare parts in maintenance situations. Following the literature on advance demand information in replenishment decisions, the conclusion is that using advance demand information increases the performance of the service parts supply chain.

6.1.2 Current Situation

Currently, the decision to replenish, and the replenishment size, is determined by calculating the inventory position. The inventory position is calculated using Equation 6.1

$$IP_{p,t} = OH_{p,t} + IT_{p,t} \qquad \text{(Equation 6.1)}$$

Whenever the inventory position drops below the reorder point ($ROP_{p,t}$), a replenishment order will be triggered, the size of this replenishment order will be as shown in Equation 6.2

$$Ordersize = TSL_{p,t} - IP_{p,t} \qquad \text{(Equation 6.2)}$$

Where:

$IP_{p,t}$	=	The inventory position of part p at time t
$OH_{p,t}$	=	The on hand inventory of part p at time t
$IT_{p,t}$	=	The inventory in transit to the warehouse of part p at time t
$TSL_{p,t}$	=	The target stock level of part p at time t

The performance of this method, which is the current situation at Philips can be found in Table 19.

6.1.3 Scope

When looking at the order replenishment strategy, there is no fixed amount of days the order should be known in advance, for that reason all future orders can be incorporated in the strategy. It is questionable however, at which time point it is wise to implement the order in the replenishment strategy. Whenever the replenishment system starts taking into account the future order, it will trigger a replenishment process to make sure that the stock level will be sufficient to full fill demand. In case the demand lead time is equal to the lead time of service parts this would give a perfect timing. However, when the future order is known at an earlier stage in time it will create extra stock, which first of all has extra costs and secondly increases the chance that the stock level will exceed the maximum stock level. This could mean that service parts are ordered but there is no place in the warehouse to stock them. In reality the on hand stock, even with the new replenishment, never exceeds the TSL value, meaning that no extra constraint is needed to prevent overstocking and exceeding warehouse capacity. This will mean that in some cases parts will be ordered too early, leading to extra relative holding costs. These relative holding costs can partly be prevented when optimizing the replenishment by taking leadtimes into account.

6.2 Implementing a proactive replenishment method

To anticipate towards future orders and replenish in time, a new variable is introduced and added to the inventory position calculation. This variable is defined as future demand (futdem), and is calculated as seen in Equation 6.3.

$$Futdem_{p,t} = O_t \text{ with } RDD > t > Orderdate \qquad \text{(Equation 6.3)}$$

Where RDD represents the requested delivery date, and the Orderdate represents the date the order is submitted towards SPS. Future demand is then all demand that has a requested delivery date at least 1 day ahead, and is ordered in the past. The calculated future demand can be used to calculate the adapted inventory position, and if necessary the replenishment order size.

$$IP_{p,t} = OH_{p,t} + IT_{p,t} - Futdem_{p,t} \qquad \text{(Equation 6.4)}$$

Whenever the adapted inventory position drops below the reorder point ($ROP_{p,t}$), a replenishment order will be triggered, the size of this replenishment order will be as shown in Equation 6.5

$$Ordersize = TSL_{p,t} - IP_{p,t} \qquad \text{(Equation 6.5)}$$

6.3 Simulation results of the proactive replenishment method

As a result of the adapted inventory position calculation, replenishment will be triggered at an earlier stage. This reduces the chance of backorders, and increase the fill rate. On the other hand it increases the average inventory on hand, which will increase the inventory costs. To see what the exact effects are on the performance of the system, a simulation is run on all three forecasting methods using the new replenishment strategy. The results of these simulations can be seen in Table 18, and can then be compared with the results in Table 19, where the former replenishment strategy is used.

Method	Fillrate	Number of backorders	Holdingcosts
Current method	93.12%	1596	100%
Proposed method	93.17%	1584	100.57%
Smoothed method	93.18%	1582	99.76%

Table 18: Performance of the three methods using the proactive replenishment strategy

Method	Fillrate	Number of backorders	Holdingcosts
Current method	92.34%	1777	100%
Proposed method	92.28%	1792	99.44%
Smoothed method	92.36%	1774	100.36%

Table 19: Performance of the three methods without the proactive replenishment strategy

Method	Fillrate	Number of backorders	Holdingcosts
Current method	+0.78%	-10.19%	+10.12%
Proposed method	+0.89%	-11.61%	+11.36%
Smoothed method	+0.82%	-10.82%	+9.46%

Table 20: Difference in performance comparing the new and old replenishment strategy

In Table 20 the percentual difference for the three methods between the old and new method can be seen. As expected the fill rate and relative holding costs increases and the amount of backorders decreases. When looking at the absolute values of the specific methods in Table 18 it can be seen that the smoothed method performs best on all three criteria. When looking at the overall performance it can be seen that the new replenishment strategy strongly reduces the amount of backorders with at least 10%. Furthermore, the fill rate increases in all cases with at least 0.78%. Overall, it can be concluded that it is worthwile to introduce the new replenishment strategy to reduce backorders and increase the fill rate.

6.4 Sensitivity analysis of the proactive replenishment method

As the previous sensitivity analysis has shown that the value for forecastdelay does not influence the result of the simulation, this will not be taken in consideration in this sensitivity analysis. To ensure that the forecastdelay has no influence on the replenishment, the simulation will be run for one of the methods. In case the results are still the same for the various values of forecastdelay, we will assume that the forecastdelay has no influence on the other two methods either.

Forecastdelay	4	5	6	7	8
Fillrate	93.27%	93.25%	93.33%	93.23%	93.12%
Backorders	1563	1567	1549	1569	1597
Holdingcosts	99.68%	99.31%	100%	99.39%	99.12%

Table 21: Sensitivity analysis for Forecastdelay with the new replenishment strategy

Table 21, with the varied value in bold and the initial simulation value in dark grey, shows that the Forecastdelay has no influence on the performance of the method. This means that the sensitivity analysis will be performed on the variable Designfillrate only. Again, this value will be varied over $[0.98, 0.985, 0.99, 0.995, 0.999]$.

Current method					
Designfillrate	**0.98**	**0.985**	**0.99**	**0.995**	**0.999**
Backorders	1704	1686	1592	1402	1193
Holdingcost	87.76%	92.08%	100%	112.17%	139.29%
Fillrate	92.66%	92.73%	93.12%	93.96%	94.86%
Proposed method					
Designfillrate	**0.98**	**0.985**	**0.99**	**0.995**	**0.999**
Backorders	1795	1642	1569	1434	1159
Holdingcost	88.06%	92.42%	100%	112.73%	139.06%
Fillrate	92.27%	92.92%	93.24%	93.82%	95.01%
Smoothed method					
Designfillrate	**0.98**	**0.985**	**0.99**	**0.995**	**0.999**
Backorders	1724	1713	1582	1447	1174
Holdingcost	86.45%	90.29%	100%	110.55%	140.43%
Fillrate	92.57%	92.62%	93.18%	93.76%	94.93%

Table 22: Sensitivity analysis of the three methods using the new replenishment strategy

The results of the sensitivity analysis in Table 22 show a change in designfillrate has a direct effect on the fill rate, amount of backorders and the holdingcosts. The fill rate and relative holding cost increase while the designfillrate increases, at the same time the amount of backorders decreases. Furthermore, the methods perform similarly for each value of the designfillrate, there is no method that performs best in every case. For this reason the conlcusion can be drawn that the different forecasting methods have no effect on the performance of the new replenishment method.

Secondly, another interesting conclusion can be drawn. When looking at the relative holding costs of the replenishment change for a designfillrate of 0.985, it is similar to the performance on the method without the replenishment change for a designfillrate of 0.99. Also the fill rate seems to be relatively the same for the two cases. When looking at the amount of backorders however, it can be seen that the backorders for the scenario with procative replenishment are seriously lower than the amount of backorders without proactive replenishment.

Current forecast method	Current replenishment method	New replenishment method	Difference
Designfillrate	**0.99**	**0.985**	+0.005
Backorders	1777	1686	-5.12%
Holdingcost	100%	100.64%	+0.64 %
Fillrate	92.34%	92.73%	+0.39 %

Table 23: Comparison of the current method with the proactive replenishment strategy

Overall, this means that the amount of backorders is strongly reduced using the new replenishment strategy while at the same time the costs are only increased by a relative small amount. Together with the results of Tables 18 and 20, this provides strong support for the effectiveness of the new replenishment strategy.

To conclude, the proposed replenishment strategy leads to a backorder reduction of at least 10%. Furthermore, the fill rate is increased as well. The relative holding costs show to increase as well, however the extra costs for inventory could be saved by having less, costly, backorders. The costs of backorders are not taken into consideration in this research. Next to that, a backorder reduction can also be realised, whilst having no cost increase, in this case the backorders will be reduced with about 5%. All in all the proposed replenishment strategy shows to have the desired effect by reducing the amount of backorders.

Chapter 7

The use of advance demand information in shipping

A recurring problem in the service parts logistics is that the requested part is not delivered in time. When this occurs the service engineer has to wait for the part to arrive before he can start the maintenance on the system. To prevent this from happening the part could be sent at an earlier stage, which means that the part will be stored at the customer for a short while until the service engineer arrives. Meaning that shipping at an earlier stage leads to a lower chance of late arrival of the parts. Next to that the early shipment of parts enables to use a slower, and possibly cheaper shipment. For the Benelux market this makes a minor or even no difference, but it can be wise to research what the effect is of early shipping on the fill rate, back orders and relative holding costs. For other markets it can then be interesting to switch to shipping at an earlier stage in case the demand is known.

In this chapter a method will be presented on how to decide whether it is wise to ship at an earlier moment, and what the effect will be on the overall supply chain performance. To do so, the current situation will be sketched and the scope of the orders to which the method applies is defined in §7.1. Afterwards, the method to ship parts at an early stage is developed in §7.2. Lastly, the effect of the method on the supply chain performance is presented in §7.3..

7.1 Advanced demand information and variable shipping

7.1.1 Literature on advanced demand information and variable shipping

In literature very little information can be found on combining advanced demand information with variable, or early, shipping. The only research that makes use of flexible shipping with advance demand information shows that this can lead to a cost reduction of 14% (Wang and Toktay, 2008). This indicates that using early shipping in combination with advance demand information can be beneficial.

7.1.2 Current situation

For the Benelux market currently all orders are processed to be shipped on the day that the part is requested. Whenever there is a last minute order with high criticality, or when a part has not arrived in time, an express shipment is used. For an express shipment a courier usually transports just the single part, meaning it involves higher shipping costs. For the Benelux market all service parts are delivered using road transportation, several carriers are used to deliver the parts within the Benelux. Parts are picked up from the RDC at a daily basis, and delivered to the customers or engineers at the same day.

7.1.3 Scope

Regarding the early shipments of future orders, orders should at least be known before the designated shipping date. Furthermore, the decision has to be taken whether or not the part should be shipped early, or should be shipped using a normal shipment to maintain stock levels. For this reason, the order has to be known at the moment the early shipment will take place, meaning the scope will be all orders that have a difference between the order date and the requested delivery date that is bigger than the early shipment time.

7.2 Obtaining an anticipating shipping method

A first condition, to enable an early shipment is that stock has to be available to ship at an early stage. Whenever there is no stock available at the moment a part is intended to ship early, there is no possibility to ship early.

A part that can possibly be shipped early, has to be shipped eventually. meaning that it will make no difference on the backorders if the part is shipped early or at normal timing, unless there will be a replenishment of the parts between the early shipment date and the normal shipment date. In case there will be no replenishment between these times, the part can be shipped early without affecting backorders. The difference in this scenario could be that a backorder will occur on a different order compared to a situation without early shipment. Therefore, it will make no difference to the performance of the model which order will result in a backorder.

In case there is replenishment between the early shipment date and the normal shipment date, the decision to ship the part early is more difficult. It needs to be based on the stock at hand, the incoming goods in the period, the known demand in the period and the expected demand in the period. In case there is a future order to be fulfilled before the replenishment, and stock is currently 1, it is unwise to ship at this stage. In order to ship early, it has to hold that there will be no avoidable backorders between the early shipment date and the normal shipment date. This means that for each day t between these two dates it has to hold that

$$\forall t \in [t_e, t_n] : OH_t + REP_t \geq D_t \qquad \text{(Equation 7.1)}$$

With REP_t being the replenishment of parts on that day. As the demand for period t is unknown at this stage, it should be estimated by using the known demand and expected demand.

$$OH_t + REP_t \geq O_t + F_t \qquad \text{(Equation 7.2)}$$

The values for OH_t, REP_t, O_t are integers, whereas as F_t is any positive number. Furthermore, the value of F_t is an estimation. In order to be more certain that the demand cannot exceed the inventory, there should be a certainty to accompany this demand. This can be obtained using the inverse Poisson probability. By using a Poisson probability it can be assured with a certain degree of certainty that the demand will not exceed a certain value, given the expected demand. As the aim of the algorithm is to lead to no extra backorders, the decision is made to be 99% sure that the demand will not exceed stock.

$$OH_t + REP_t \geq O_t + \bar{C}^{-1}(F_t, 0.99) \qquad \text{(Equation 7.3)}$$

Where $\bar{C}^{-1}(F_t, 0.99)$ results in a value that will be lower than the demand with a 99% certainty.

In case Equation 7.3 holds for all days t between the early shipment date and the intended shipment date, it can be considered that it is safe to ship the part early. The change of backorders occurring that were avoidable is thus small that it does not weigh heavier than the benefits of early shipment. The expected demand for the period needs to be accounted for all days between the calculated date and the early shipment date. Meaning it becomes

$$\forall t \in [t_e, t_n] : OH_t + REP_t \geq O_t + \bar{C}^{-1}\left(\sum_{y=x+1}^{t} (F_y), 0.99\right) \qquad \text{(Equation 7.4)}$$

Where x is the early shipment date. The decision to ship early on day x is taken after the normal demand is fulfilled on this day. As a result of this the incoming and outgoing stock of day x does not need to be calculated. Furthermore, the part has to be shipped on the normal shipment day, meaning that the incoming and outgoing stock of the normal shipment day does not need to be calculated as well.

After obtaining all the formulas, the algorithm that can decide whether it is wise to ship early can be computed as follows.

Algorithm 1 Early sending algorithm

For all parts p and all days t
for all orders with $RDD_{p,t} = t + \Delta E$ **and** $Creationdate_{p,t} \leq t$ **do**
  $ED_{p,t} = D_{p,t}$
  if $OH_{p,t} \geq ED_{p,t}$ **then**
    if $\sum_{y=t+1}^{t+\Delta E-1} ORD_{p,y-l} + REP_{p,y-rl} = 0$ **then**
      $ES_{p,t} = ED_{p,t}$
    else if for all x in $[t + \Delta E, t]$, $OH_{p,x} + REP_{p,x} \geq O_{p,x} + \bar{C}^{-1}(\sum_{t+1}^{x}(F_{p,x}), 0.99)$ **then**
      $ES_{p,t} = ED_{p,t}$
    else
      $ES_{p,t} = 0$
    end if
  else
    $ES_{p,t} = 0$
  end if
end for

Where:

$ED_{p,t}$ = The demand that is known at the moment the decision to send early is made position of part p at time t
$ES_{p,t}$ = The demand that is actually send at an early stage of part p at time t

The algorithm constraints that need to be met for an early shipment to take place are described before. The algorithm works according to the all or nothing principle. It selects the amount of orders that can be shipped early (in other words, that are known at the moment of early shipment). For these orders it checks whether the early shipment will not lead to possible backorders, in case this is negative it will ship all demand early. In case the early shipment could lead to possible backorders it will ship none of the demand early. Using this algorithm there are two shipment methods, the early shipment method which is ΔE days before the normal shipment method. Or the normal shipment method. It is not possible to ship in between these two dates, if an order is not shipped early, it will be shipped at the normal shipment date. The value of ΔE can be varied of course depending on the characteristics of the order.

7.3 Simulation results of the anticipating shipping method

The method is tested using the previously build simulation. The value of ΔE is varied over $[3, 7, 10, 14]$. The reason for this is that any value greater than 14 would lead to a very small sample size, as only a few orders are ordered more than 14 days in advance. Furthermore, it would not make sense to let the value of ΔE get smaller than 3, as sending one or two days in advance is creating extra complexity for a minor improvement. The main objective of the algorithm is to avoid an increase of backorders, while at the same time sending a proportion of the demand at an earlier stage. Next to the usual performance indicators (backorders, relative holding costs & fill rate), the simulation also returns the number of parts known ΔE days before the RDD and the number of parts send ΔE days before the RDD. When having both these values, the percentage of sendable parts that is actually sent at an early stage can easily be computed.

ΔE	Backorders	relative holding costs	Fill rate	Early sent	Early known	%
0	1582	100%	93.18%	-	-	-
3	1595	97.06%	93.12%	3390	5009	67.68%
7	1554	99.47%	93.30%	697	878	79.38%
10	1570	99.68%	93.24%	531	652	81.44%
14	1580	99.85%	93.19%	387	453	85.43%

Table 24: Simulation results method using the smoothed forecast

ΔE	Backorders	relative holding costs	Fill rate	Early sent	Early known	%
0	1592	100%	93.13%	-	-	-
3	1580	97.40%	93.18%	3388	5009	67.64%
7	1562	99.80%	93.26%	698	878	79.50%
10	1596	98.38%	93.11%	535	652	82.06%
14	1552	99.92%	93.31%	385	453	84.99%

Table 25: Simulation results using the intial Philips forecast

As can be seen in Tables 24 and 25, there is no major change in the amount of backorders because of the early sending of parts. At the same time, there seems to be a little decrease in the fill rate. Which makes sense, as parts exit the warehouse at an earlier stage, increasing the chance of having no stock at the warehouse. Furthermore, the inventory relative holding costs also show to decrease, this can also be explained by the fact that parts leave the warehouse earlier.

When looking at the differences between the several values of ΔE, it can be seen that the highest decrease of relative holding costs is obtained for $\Delta E = 3$. This is quite surprising as for the other mtehods, the warehouse is send out of the warehouse at an even earlier stage. The reason that the saving is the highest for the value of $\Delta E = 3$ is because much more parts can be taken into account when sending three days before the RDD. This can also be seen in the fifth column of Table 24.

A second interesting finding is about the percentage of sendable parts that is actually send at an early stage. These values are higher than expected. Furthermore the value increases as ΔE increases, this is surprising as the calculations for a high value of ΔE are done for a longer period, meaning that more conditions need to be met in order to allow the parts to be send early.

Another advantage of sending early, that does not come out of the simulation and can not be expressed in a numerical value is the early arrival of the part at the customer. By sending the part early, the chance that the part arrives late at the customer, e.g. because of external factors like carrier issues, is strongly reduced. Leading to more satisfaction at the customer and the field service engineer that needs the part to perform maintenance.

When evaluating the algorithm, we can conclude that the algorithm performs as desired. It leads to no increase in backorders, while at the same time sending the majority of the parts at an early stage. This leads to a decrease in inventory costs, and likely an increase in customer satisfaction. The algorithm could be further improved by adding more possible send dates. Currently the method only allows to send ΔE days before the RDD or on the RDD. When more sending options are included in between these days the inventory costs can be reduced even more. A note must be that for this step no major costs reduction can be obtained, as the differences between the inventory relative holding costs are relatively small for the scenario's with $\Delta E = 7, 10, 14$ and the scenario without early sending.

7.4 Sensitivity analysis of anticipating shipping method

For the early sending algorithm a sensitivity anaylis is performed as well. Similar to the previous sensitivy analyses, the value of Designfill rate will be varied. Next to that, along with the introduction of the sending algorithm, A new value was introduced. This value is to determine if the parts can be send early in case there will be a replenishment between the normal and early sending date as can be seen in Equation 7.5.

$$OH_{p,x} + REP_{p,x} \geq O_{p,x} + \bar{C}^{-1}(\sum_{t+1}^{x}(F_{p,x}), \mathbf{0.99}) \qquad \text{(Equation 7.5)}$$

The value that is bold faced was kept equal to the designfillrate in the previous simulations. For the sensitivity analysis, both values will be varied separately. The sensitivity analysis will only be run for the values of $\Delta E = 3$ and $\Delta E = 14$, as this will give representative results for all values of ΔE. .

As can be seen in the Tables in Appendix E, the value of the algorithm, referred to as Sendfillrate, does not influence the KPI's of the various simulations. This is surprising as a lower value of Sendfillrate should relax the algorithm, leading to more parts being send early and possibly more backorders and a lower fill rate. When looking furher in the simulation results it can be seen that the majority, more than

90%, of the early sended parts are allowed because of the fact that no replenishment occurs between the early sending date and the normal sending date. This means that changing the Sendfillrate will have a minor to no effect on the algorithms performance.

When looking at the Designfillrate it can be seen that the effect on the performance of the algorithm is similar to the effect on the other two solutions. When the designfillrate increases the fill rate and relative holding costs increase as well and the amount of backorders decrease. Regarding the early sending algorithm it can be seen the the amount of parts being send early increase as the Designfillrate increases.

Lastly, it can be seen that the performance for $\Delta E = 3$ and $\Delta E = 14$ is similar, meaning there is no reason to perform a sensitivity analysis for the other values of ΔE.

Conclusion

To conclude, the Algorithm for sending parts at an early stage performs as desired. The amount of backorders stay the same, while at the same time the majority of the orders are shipped at an earlier stage. As a result of this there is a minor decrease in the relative holding costs. Next to this measurable effect, it is also expected that less orders arrive late at the customer. Increasing the customer satisfaction and the speed of maintenance actions. The early sending algorithm proofs that sending parts at an earlier stage does not necessarily lead to backorders. This provides opportunities for batching orders or shipping at a lower speed.

Chapter 8

Conclusion, Recommendations, Limitations & Future research

In this chapter a conclusion is given by answering the formulated research questions in §8.1.. Furthermore, recommendations for Philips are given on how to interpret the outcomes of this research and how the research can be used to increase performance in §8.2. Lastly, the limitations of the research are mentioned.

8.1 Conclusion

The main objective of this research was to increase the backorder performance on parts where the order date was far ahead of the requested delivery date. These type of orders, referred to as future orders, are scarcely used in the service part supply chain processes going on at Philips, while they contain valuable information. This section presents the conclusions for the research questions that are formulated in §2.3.

In order to make use of future orders, it must be ensured that these orders are reliable. Historical data analysis shows that 9 out of 568 orders were unreliable, corresponding to 1,6%. Meaning the conclusion can be drawn that future orders are generally reliable.

A discrete event simulation is set up that replicates the warehousing processes for three years, using historical order data. The multi item, single location model is used as a basis of this simulation model. In order to compare the current situation and the proposed solutions the simulation presents three performance indicators, the amount of backorders, the fill rate and the relative holding costs.

The first solution that is proposed, makes use of advance demand information in forecasting. A new forecasting formula is presented that's uses ADI in a case of intermittent demand. Simulation shows that there was no serious difference on backorders, relative holding cost and fill rate between the current method and the proposed method.

The second solution that is presented in this thesis, aims to improve the replenishment by making use of advance demand information. Compared to the current situation, the amount of backorders is reduced with at least 10%, but the relative holding costs increase with about 10% as well. Furthermore, there is an increase in the fill rate of about 0.8%. The sensitivity analysis reveals that in case the relative holding costs are kept equal, the new method reduces the backorders with 5.1%.

Lastly, the third solution combines advanced demand information with shipping options. The simulation shows that this algorithm performed as desired, the amount of backorders is kept the same, while 67% to 85% of the possible orders are sent at an early stage. This leads to a decrease in relative holding costs, albeit a minor decrease.

Overall this research shows the positive effects of using advance demand information in strategic decisions in the field of service parts. By using advance demand information, companies can optimize their inventory model and reduce backorders, relative holding costs, or increase fill rates. Advance demand information shows to be beneficial at several stages in the supply chain, from forecasting to delivery.

8.2 Recommendations

In this section an indication will be given on how Philips can benefit from the proposed solutions that are presented in this thesis.

First of all, although the current method of forecasting makes little use of advance demand information, it does perform no worse than other methods that do make extensive use of advance demand information. For that reason, we recommend to keep using the current method of forecasting as this method is also easy to oversee. In case the amount of future orders show an enormous increase, it can be wise to review the method of forecasting once again. If necessary the method of forecasting can then be changed to make more use of future orders.

Secondly, we recommend to implement advance demand information when making replenishment decisions. This procedure does not increase the complexity of the calculations but creates a strong backorder reduction. A note must be that it also leads to an increase of relative holding costs. If the increase of relative holding costs is undesired the method can also be implemented in such a way that the relative holding costs remain the same, while the backorders are still seriously reduced.

Furthermore, we recommend to make use of early shipments. The benefits of early shipment can be found throughout the whole supply chain, likely also increasing the customer satisfaction. When making use of the early shipping algorithm, there are no negative side effects of early shipment as the amount of backorders stays the same and the inventory relative holding costs are slightly reduced.

Lastly, this thesis shows the value of advance demand information. Therefore, we recommend to make more use of the information that comes with future orders. Also it would be wise to encourage customers, field service engineers and markets to place an order as soon as the order specifications are known. When the proportion of future orders increases, the performance of the presented methods increases as well, leading to more backorder reductions.

8.3 Limitations

Because of the assumptions made and the scope selected for this research, there are some limitations that need to be taken into account when interpreting the results of this research. First of all the assumptions made make a simplified version of the real world scenario. It could be that issues occur when implementing the presented solutions in the Philips situation. Secondly, this research was conducted for the Benelux market, For other markets, the scenario should work in a similar way bu factors like leadtime instability could influence the results. Lastly, the simplifications also create a gap between the actual scenario and the ideal scenario, an example of this is the worrying big difference between the designated fill rate and the actually realized fill rate.

8.4 Future research

This research gives new insight in using ADI in forecasting intermittent demand, as well as using ADI in replenishment strategies. However, there are some parts that need more future research to obtain extra results. More research on the effect of the forecast on the stock levels when using ADI can create a forecast that does increase the inventory model performance. Secondly, extra research in the anticipating shipping method can be performed to look for more applications of the algorithm. Currently the method is only used for shipping parts to the customer, but it can be imagined that shipping within the supply chain can benefit from early sending as well.

References

Abuizam, R. and Thomopoulos, N. T. (2006). Adjusting a forecasting model when some future demands are known in advance; A Bayesian technique. *Journal of Business & Economics Research*, 4(7):85–96.

Alfredsson, P. and Verrijdt, J. (1999). Modeling Emergency Supply Flexibility in a Two-Echelon Inventory System. *Management Science*, 45:1416–1431.

Basten, R. J. I. and Ryan, J. K. (2015). Inventory Management with Two Demand Streams : A Maintenance Application Inventory. *Beta Working Paper*, 480(August).

Basten, R. J. I. and van Houtum, G. J. (2014). System-oriented inventory models for spare parts. *Surveys in Operations Research and Management Science*, 19(1):34–55.

Borghouts, E. V. (2017). Effects of configurations in a service network with lateral transshipments and emergency shipments. *Master thesis.*

Borst, R. (2016). Evaluate the Effect on Logistics Costs by Comparing different Service Parts Distribution Networks. *Master thesis.*

Chen, F. (2001). Market Segmentation, Advance Demand Information, and Supply Chain Performance. *Manufacturing and Service Operations Management*, 34(August 2016):482–499.

Dekker, R., Pinçe, Ç., Zuidwijk, R., and Jalil, M. N. (2013). On the use of installed base information for spare parts logistics: A review of ideas and industry practice. *International Journal of Production Economics*, 143(2):536–545.

Gallego, G. and Özer, Ö. (2001). Integrating Replenishment Decisions with Advance Demand Information. *Management Science*, 47(10):1344–1360.

Gallego, G. and Özer, Ö. (2003). Optimal replenishment policies for multiechelon inventory problems under advance demand information. *Manufacturing & Service Operations Management*, 5(2):157–175.

Hua, Z. S., Zhang, B., Yang, J., and Tan, D. S. (2007). A new approach of forecasting intermittent demand for spare parts inventories in the process industries. *Journal of the Operational Research Society*, 58(1):52–61.

Karaesmen, F., Liberopoulos, G., and Dallery, Y. (2004). The Value of Advance Demand Information in Production/Inventory Systems. *Annals of Operations Research*, 126(1-4):135–157.

Karmarkar, U. S. (1994). A robust forecasting technique for inventory and leadtime management. *Journal of Operations Management.*

Kennedy, W. J., Wayne Patterson, J., and Fredendall, L. D. (2002). An overview of recent literature on spare parts inventories. *International Journal of Production Economics*, 76(2):201–215.

Paterson, P., Kiesmuller, G. P., Teunter, R., and Glazebrook, K. (2011). Inventory models with lateral transhipments: a review. *European Journal of Operational Research*, 2(210):125–136.

Sobel, M. J. (2004). Fill Rates of Single-Stage and Multistage Supply Systems. *Manufacturing & Service Operations Management*, 6(1):41–52.

Strijbosch, G., Heuts, J., and Van Der Schoot, M. (2000). Combined forecast - inventory control procedure for spare parts. *Journal of the Operational Research Society*, 51(10):1184–1192.

Tan, T. (2008). Using imperfect advance demand information in forecasting. In *IMA Journal of Management Mathematics*.

Thonemann, U. W. (2002). Improving supply-chain performance by sharing advance demand information. *European Journal of Operational Research*.

Topan, E., Tan, T., and van Houtum, G. J. (2016). Using imperfect advance demand information in lost- sales inventory systems Using Imperfect Advance Demand Information in Lost-Sales Inventory Systems. *Beta Working Paper*.

Van Houtum, G.-J. and Kranenburg, B. (2015). *Spare parts inventory control under system availability constraints*, volume 227. Springer.

Wang, T. and Toktay, B. L. (2008). Inventory Management with Advance Demand Information and Flexible Delivery. *Management Science*, 54(4):716–732.

Wang, W. (2011). A joint spare part and maintenance inspection optimisation model using the Delay-Time concept. *Reliability Engineering and System Safety*, 96(11):1535–1541.

Willemain, T. R., Smart, C. N., and Schwarz, H. F. (2004). A new approach to forecasting intermittent demand for service parts inventories. *International Journal of Forecasting*, 20(3):375–387.

Young, P. C. (2011). *Recursive Estimation and Time-Series Analysis.* Springer Science & Business Media.

Appendices

Appendix A

Forecasting errors of the discussed methods

Part:	1	2	3	4	5	6	7	8	9	10	11
Method 1	11.287	19.979	1.364	151.808	48.238	12.835	11.410	11.825	332.462	4.680	4.726
Method 2	11.287	19.979	1.364	151.808	48.238	12.835	11.410	11.825	332.462	4.680	4.639
Method 3	11.287	19.979	1.364	151.808	48.238	12.835	11.410	11.825	332.462	4.680	4.726
Method 4	11.146	21.409	1.329	164.221	57.087	7.861	6.635	6.790	663.004	5.236	4.507
Proposed method 1.1	10.603	18.424	1.031	150.492	48.229	9.777	8.427	9.097	250.685	4.502	4.248
Proposed method 1.2	10.603	18.424	1.031	150.492	48.229	9.777	8.427	9.097	250.685	4.502	4.248
Proposed method 1.3	10.603	18.424	1.031	150.492	48.229	9.777	8.427	9.097	250.685	4.502	4.248

Table 26: SSE over 11 parts for periods with $O_t = 0$

Part:	1	2	3	4	5	6	7	8	9	10	11
Method 1	8.286	11.68	2.165	31.33	21.41	10.7	10.11	10.29	50.59	5.598	5.734
Method 2	8.286	11.68	2.165	31.33	21.41	10.7	10.11	10.29	50.59	5.598	5.766
Method 3	8.286	11.68	2.165	31.33	21.41	10.7	10.11	10.29	50.59	5.598	5.734
Method 4	8.163	12.17	2.307	34.08	22.65	7.985	7.235	7.344	69.8	5.436	5.394
Proposed method 1.1	8.006	11.41	1.364	31.12	21.42	9.319	8.585	8.973	44.37	5.444	5.27
Proposed method 1.2	8.006	11.41	1.364	31.12	21.42	9.319	8.585	8.973	44.37	5.444	5.27
Proposed method 1.3	8.006	11.41	1.364	31.12	21.42	9.319	8.585	8.973	44.37	5.444	5.27

Table 27: SAE over 11 parts for periods with $O_t = 0$

Part:	1	2	3	4	5	6	7	8	9	10	11
Method 1	0.000	7.969	0.000	51.943	18.742	0.109	0.047	0.063	112.170	0.000	0.000
Method 2	0.000	6.066	0.000	51.943	18.742	0.222	0.170	0.170	112.170	0.016	0.103
Method 3	0.236	6.476	0.007	51.943	18.742	0.199	0.174	0.174	112.170	0.090	0.313
Method 4	0.124	4.843	0.000	30.100	11.535	0.065	0.039	0.041	158.592	0.044	0.093
Proposed method 1.1	3.190	2.723	9.358	44.427	14.403	3.776	3.903	3.321	1093.850	1.046	3.459
Proposed method 1.2	0.000	0.396	0.000	25.000	16.000	5.340	5.340	5.340	700.361	0.000	0.000
Proposed method 1.3	0.000	0.396	0.000	25.000	16.000	4.099	3.683	3.804	102.703	0.000	0.000

Table 28: SSE of the seven methods for periods with $O_t \geq 1$

Part:	1	2	3	4	5	6	7	8	9	10	11
Method 1	0.000	5.442	0.000	7.207	4.329	0.443	0.278	0.328	15.358	0.000	0.000
Method 2	0.000	4.838	0.000	7.207	4.329	0.667	0.583	0.583	15.358	0.208	0.493
Method 3	0.667	5.025	0.083	7.207	4.329	0.629	0.583	0.583	15.358	0.417	0.750
Method 4	0.456	4.255	0.000	5.486	3.396	0.349	0.276	0.284	19.626	0.319	0.396
Proposed method 1.1	2.866	2.947	4.920	6.665	3.795	3.088	3.089	2.992	57.007	1.726	3.109
Proposed method 1.2	0.000	1.244	0.000	5.000	4.000	3.917	3.917	3.917	45.833	0.000	0.000
Proposed method 1.3	0.000	1.244	0.000	5.000	4.000	3.487	3.314	3.366	16.358	0.000	0.000

Table 29: SAE of the seven methods for periods with $O_t \geq 1$

Part:	1	2	3	4	5	6	7	8	9	10	11
Method 1	11.287	27.948	1.364	203.751	66.980	12.944	11.458	11.888	444.632	4.680	4.726
Method 2	11.287	26.045	1.364	203.751	66.980	13.057	11.581	11.996	444.632	4.696	4.742
Method 3	11.523	26.455	1.371	203.751	66.980	13.033	11.584	11.999	444.632	4.771	5.039
Method 4	11.270	26.252	1.329	194.321	68.622	7.926	6.674	6.831	821.597	5.280	4.600
Proposed method 1.1	13.792	21.147	10.390	194.918	62.631	13.553	12.330	12.418	1344.535	5.548	7.707
Proposed method 1.2	10.603	18.820	1.031	175.492	64.229	15.117	13.767	14.437	951.046	4.502	4.248
Proposed method 1.3	10.603	18.820	1.031	175.492	64.229	13.876	12.109	12.901	353.388	4.502	4.248

Table 30: SSE of the seven methods for all periods

Part:	1	2	3	4	5	6	7	8	9	10	11
Method 1	8.286	17.120	2.165	38.540	25.736	11.145	10.393	10.619	65.950	5.598	5.734
Method 2	8.286	16.516	2.165	38.540	25.736	11.368	10.698	10.874	65.950	5.807	6.260
Method 3	8.953	16.704	2.249	38.540	25.736	11.331	10.698	10.874	65.950	6.015	6.484
Method 4	8.620	16.421	2.307	39.568	26.047	8.334	7.511	7.628	89.425	5.755	5.790
Proposed method 1.1	10.873	14.357	6.284	37.785	25.217	12.407	11.675	11.965	101.374	7.170	8.379
Proposed method 1.2	8.006	12.654	1.364	36.120	25.422	13.236	12.502	12.889	90.200	5.444	5.270
Proposed method 1.3	8.006	12.654	1.364	36.120	25.422	12.806	11.900	12.339	60.725	5.444	5.270

Table 31: SAE of the seven methods for all periods

Appendix B

Multiplication versus summation of the forecast

$$Option1 : \times \frac{\sum_{j=1}^{24} D_{t-j} \times \mathbb{1}(O_{t-j} \geq 1)}{\sum_{j=1}^{24} O_{t-j}} \qquad \text{(Multiplication variant)}$$

$$Option2 : O_t + \frac{\sum_{j=1}^{24} (D_{t-j} - O_{t-j}) \times \mathbb{1}(O_{t-j} \geq 1)}{\sum_{j=1}^{24} \mathbb{1}(O_{t-j} \geq 1)} \qquad \text{(Summation variant)}$$

When comparing the results of these two measures, the summation variant shows to perform better as can be seen in Table 32. In 10 out of eleven parts the summation variant performs better than the multiplication variant. Furthermore the average performance of the multiplication variant is 18% or 51% worse compared to the summation variant, depending on which measure you refer to.

Part	Type	SSE	SAE	ΔSSE	ΔSAE
1	Multiplication	11.2869	8.28616	+6%	+3%
	Summation	10.60281	8.006499073		
2	Multiplication	21.7057	14.29528928	+15%	+13%
	Summation	18.81961	12.65447514		
3	Multiplication	1.363897	2.165333333	+32%	+59%
	Summation	1.0314	1.36442236		
4	Multiplication	152.808	32.3324374	-13%	-10%
	Summation	175.4917	36.11958256		
5	Multiplication	66.97992	25.73627464	+4%	+1%
	Summation	64.22872	25.4222632		
6	Multiplication	30.18513	16.83240037	+100%	+27%
	Summation	15.11735	13.23562144		
7	Multiplication	28.76088	16.24581963	+109%	+30%
	Summation	13.76703	12.50200764		
8	Multiplication	29.17586	16.42179386	+102%	+27%
	Summation	14.43722	12.88928039		
9	Multiplication	2764.88	125.1248713	+191%	+39%
	Summation	951.0464	90.20032425		
10	Multiplication	4.680377	5.598166667	+4%	+3%
	Summation	4.502281	5.444192262		
11	Multiplication	4.726194	5.733525	+11%	+9%
	Summation	4.247917	5.269860611		
			Average	+51%	18%

Table 32: Forecasting error of the multiplication method relative to the summation method

Appendix C

Selecting optimal timespan for the forecast

In this part we will take a look at the effect changing the amount of months has on the performance of the forecast. The performance of the forecast is measured using the sum of squared errors and the sum of absolute errors. As the value of 24 has already been tested, the performance for using 18, 23, 25 and 30 months will be tested. The test is only applied to Proposed method 1.3 as analysis shows that this method performs best.

In order to get the performance for the other timespan, the 11 parts that are most frequently ordered are used to test on. The expectation is that the differences will be extremely small, especially between using 23, 24 or 25 months. In most cases the values will be the same for all three timespans. As data is only available from the first of January 2015 onwards, the cases of 25 and 30 months cannot be tested for the whole of 2017. To compute the correct values for these cases an initialization phase that is the size of the number of months is needed. This means that for 25 months the test is performed on the last 11 months of 2017 and for 30 months the test will be performed on the last six months of 2017. To have a fair comparison the results will be compared to the performance of the 24 month timespan for the same months. In mathematical terms this will look like the following formula:

$$F_t = \begin{cases} \dfrac{\sum_{j=1}^{n} \mathbb{1}(D_{t-j} \geq 1) \times \mathbb{1}(O_{t-j} = 0)}{\sum_{j=1}^{n} \mathbb{1}(O_{t-j} = 0)} \times \dfrac{\sum_{j=1}^{n} D_{t-j}}{\sum_{j=1}^{n} \mathbb{1}(D_{t-j} \geq 1)} & \text{if } O_t = 0 \\ O_t + \min\left(\dfrac{\sum_{j=1}^{n} (D_{t-j} - O_{t-j}) \times \mathbb{1}(O_{t-j} \geq 1)}{\sum_{j=1}^{n} \mathbb{1}(O_{t-j} \geq 1)}, FA_t\right) & \text{otherwise} \end{cases} \qquad \text{(Summation variant)}$$

Where $n = 18, 23, 24, 25, 30$

Timespan:	24	18	23	24	25	24	30
Part: 1	10.603	10.656	10.570	10.263	10.376	1.535	1.665
2	18.820	20.211	18.629	17.916	17.740	7.625	7.654
3	1.031	1.034	1.032	1.031	1.031	0.030	0.029
4	175.492	215.232	214.607	167.782	168.192	146.052	138.607
5	64.229	64.383	64.162	64.072	64.094	33.817	33.861
6	13.876	13.783	14.004	12.892	12.993	6.655	6.679
7	12.109	11.863	12.143	11.195	11.314	6.037	6.050
8	12.901	12.746	12.927	11.926	12.019	6.284	6.295
9	353.388	365.263	354.794	319.242	317.918	164.697	157.397
10	4.502	4.553	4.506	4.362	4.402	0.956	0.992
11	4.248	4.116	4.229	4.074	4.094	0.804	0.820

Table 33: SSE for several timespans for proposed method 1.3

Timespan:	24	18	23	24	25	24	30
Part: 1	8.006	8.072	8.011	7.423	7.502	2.354	2.435
2	12.654	12.318	11.877	11.100	11.007	4.648	4.621
3	1.364	1.380	1.366	1.364	1.363	0.330	0.321
4	36.120	39.295	39.129	33.343	33.398	24.340	23.580
5	25.422	25.449	25.408	25.026	25.017	13.609	13.610
6	12.806	12.688	12.852	11.813	11.858	6.255	6.290
7	11.900	11.723	11.907	10.940	10.999	5.892	5.949
8	12.339	12.180	12.337	11.350	11.393	6.063	6.096
9	60.725	61.999	60.882	54.882	54.735	30.555	29.743
10	5.444	5.477	5.446	5.069	5.109	1.951	1.989
11	5.270	5.110	5.249	4.853	4.874	1.792	1.810

Table 34: SAE for several timespans for proposed method 1.3

After the computation of the sums of squared errors and the sum of absolute errors, a comparison is made for the overall performance. To do so the performance of the 24 month period is used as a reference and the performance of the different timespans is compared to this. The sum of squared errors and the sum of absolute errors are found in Tables 33 and 34 in the appendix. As can be seen the timespan of 24 months is computed three times, the first one is for the 12 month period to be compared with the 18 and 23 month timespan. The second one is for the 11 month period to be compared with the 25 month timespan. The third one is for the 6 month period to be compared with the 30 month timespan.

As can be seen in both tables, the differences between the various timespans are extremely small. For most cases FA_t is exactly the same, and when it differs there is only a minor change. In order to compute the overall performance, the 24 month timespan is used as a reference point.

Appendix D

Smoothing the proposed forecast

The fact that the currently used method performs better, is because of the smoothing which makes for a stable forecast. The new method has a more volatile forecast though which increases and decrease the target stock level. This phenomenon is visually represented in Figure 10.

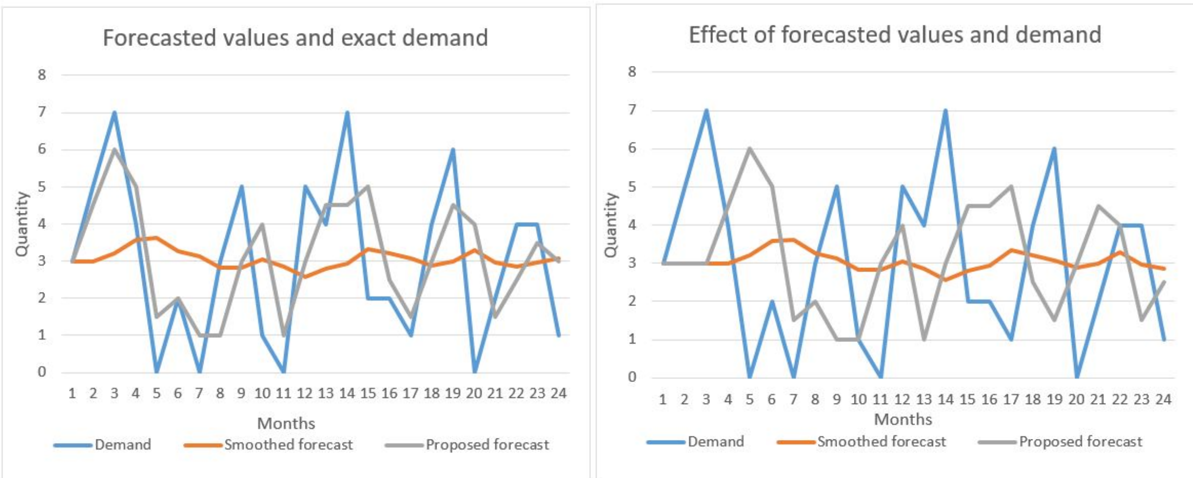

Figure 10: Effect of the forecast values on the inventory position with a 0 month lead time (left) and a 2 month lead time (right)

In order to increase the performance of the system, the forecast should be more volatile for parts with a short lead time, and smoother for parts with a long lead time. To achieve such an effect, the forecasted value should be in the middle between the proposed forecast F_t, which is very volatile, and the original forecast FA_t, which is very smooth and stable. Short lead time parts should lean towards F_t, while long lead time parts should lead to FA_t. A way to achieve this can be seen in Equation 5.7

$$FF'_t = \alpha_p * F'_t + (1 - \alpha_p) * FA'_t \qquad \text{(Summation variant)}$$

Where FF'_t is the new updated forecast value and α is dependant on the leadtime of part p. In case the leadtime is low, α should be high and vice versa. As can be seen the formula is very similar to the formula that is used for exponential smoothing in forecasting, with the only difference that FF'_t is not recurring in the formula. Instead the initial forecast FA'_t is in it's place.

As mentioned before α needs to be low in case the lead time is high and vice versa. Furthermore, the change in alpha has to be rapid. When the leadtime is over a month a relative low alpha is desired, and when the leadtime is under a month a relative high alpha is desired. Therefore a linear relation between the leadtime and alpha is not likely to give the desired results. When reviewing literature on this subject a formula that is mentioned several times is the so called time constant (Young, 2011). This formula can be seen in Equation 5.8. In this formula ΔT is the fixed time interval and τ is the variable time. Adapted to our case ΔT would be 1 month, or 30.42 days, and τ would be the leadtime for the part in days.

$$\alpha_p = 1 - \exp\left(\frac{-\Delta T}{\tau}\right) \qquad \text{(Summation variant)}$$

Appendix E

Sensitivity analysis of the early sending algorithm

ΔE	Sendfillrate	Backorders	relative holding costs	Fill rate	Early sent	Early known	%
3	**0.5**	1557	99.58%	93.29%	3370	5009	67.28%
3	**0.6**	1553	99.52%	93.31%	3374	5009	67.36%
3	**0.7**	1601	100.75%	93.09%	3386	5009	67.60%
3	**0.8**	1594	100.30%	93.14%	3406	5009	68.00%
3	**0.9**	1590	100.65%	93.12%	3398	5009	67.84%
3	**0.99**	1595	100%	93.11%	3390	5009	67.68%

Table 35: Sensitivity analysis of the Sendfillrate for the early sending algorithm

ΔE	Sendfillrate	Backorders	relative holding costs	Fill rate	Early sent	Early known	%
14	**0.5**	1586	100.16%	93.15%	388	453	85.65%
14	**0.6**	1580	99.09%	93.19%	389	453	85.87%
14	**0.7**	1610	99.65%	93.06%	389	453	85.87%
14	**0.8**	1564	99.80%	93.24%	388	453	85.65%
14	**0.9**	1573	100.00%	93.21%	388	453	85.65%
14	**0.99**	1580	100%	87.67%	387	453	93.19%

Table 36: Sensitivity analysis of the Sendfillrate for the early sending algorithm

ΔE	Designfillrate	Backorders	relative holding costs	Fill rate	Early sent	Early known	%
3	**0.98**	1722	88.21%	92.57%	3195	5009	63.79%
3	**0.985**	1677	92.30%	92.76%	3269	5009	65.26%
3	**0.99**	1575	100%	93.21%	3379	5009	67.46%
3	**0.995**	1396	113.61%	93.97%	3525	5009	70.37%
3	**0.999**	1187	142.36%	94.88%	3793	5009	75.72%

Table 37: Sensitivity analysis of the Designfillrate for the early sending algorithm

ΔE	Designfillrate	Backorders	relative holding costs	Fill rate	Early sent	Early known	%
14	**0.98**	1745	87.82%	92.48%	373	453	82.34%
14	**0.985**	1671	90.56%	92.80%	375	453	82.78%
14	**0.99**	1562	100%	93.26%	387	453	85.43%
14	**0.995**	1422	110.67%	93.87%	396	453	87.42%
14	**0.999**	1193	139.13%	94.85%	405	453	89.40%

Table 38: Sensitivity analysis of the Designfillrate for the early sending algorithm