MASTER

Redesign of the inventory control model for the least performing SKUs in a reselling environment

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Redesign of the Inventory Control Model for the Least Performing SKUs in a Reselling Environment

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I. Abstract

This research concerns improving the inventory control model for the least performing items, for one of the main resellers of office supplies. It presents how performance can be measured, which items are the least performing items, and how the performance can be improved. Performance of items planned with a specific inventory control model, can be measured by the achieved service level and the amount of human intervention needed to achieve this service level. When considering human intervention in the case of the reseller, it is found that intervening on the least important items is not needed to achieve the overall targeted service level. Besides, it is found that hiding a specific amount of items from the replenishment system as form of human intervention, in response to demand uncertainty, is not useful. Only doing the useful interventions leads to a decrease in expected annual costs. At the reseller of office supplies, the worst inventory performance is found for items with long lead times, items with a seasonal demand pattern and low value density items. For low value density items, it is found that the space-dependent part of the holding cost percentage has to increase, to realize a cost decrease. The space-dependent part of the holding costs is determined based on comparing the costs of space used and the annual inventory holding costs. Another finding is that at the reseller, order quantities are rounded, while this is not considered in the reorder level determination. This is why a simple heuristic is given to include order quantity rounding in a replenishment system which determines the reorder levels based on achieving a targeted service level. For the reseller of office supplies, including the actual used order quantities in fill rate calculations means targeting on an average service level of 99,1% instead of 99,4%. This is closer to the actual target of 99,0%. This leads to a decrease in expected annual costs. Finally, it was found that allowing planners to review less than once a week for specific items, leads to a decrease in expected annual costs.

II. Preface and Acknowledgements

This report is the result of my final act as a student. It is the final requirement to become Master of Science in Operations Management and Logistics. After five years of hard work at the Eindhoven University of Technology, this is the end of my time as a full time student. In this part of the thesis, I would like to thank people that helped me. Not only with this project, but with getting me where I am today.

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III. Executive Summary

This research is about the inventory control model for the least performing items in a reselling environment. This research is performed at Office Depot Europe, one of the main resellers of office supplies. The current inventory control model is not managing all items, or is not able to manage items effectively. The management team wants to know which items are not planned with the current model and which items are planned with the current model, but are not performing well. The performance is measured in terms of stock holding costs, order costs, service level achievement and the amount of human intervention. Effectively managed items do achieve the targeted service level, without needing human intervention. When it is known which items are not – or not effectively managed with the current model, an improved inventory control model can be fit to those items. The main research question is given below and split up in eight sub questions. The sub questions are given and answered below.

Main Research Question:
Which inventory control model is improving the performance in terms of stock holding costs, incoming order lines, service level achievement and human intervention for SKUs which are not – or not effectively managed in the current model?

What are the characteristics of the current inventory control model?

The current model is based on the (R,s,S) logic, which means periodic reviewing *R*, ordering when the inventory position is below the reorder level *s*, and ordering up to the order-up-to level *S*. The review periods per subvendor and targeted service levels per class of items are determined by a solver function, which minimizes the expected annual costs. The reorder levels per item are determined based on achieving the targeted service levels. The optimal order quantity without undershoot or rounding is determined to be the maximum of the expected demand during review period and the calculated economic order quantity. The economic order quantity is a trade-off between costs of ordering and costs of holding. Order costs are fixed, and holding costs are determined by a fixed holding cost percentage. The demand during a specific future period in time is always derived from the forecasted demand during one arbitrary future period in time, which means that a stationary demand approach is used. The actual order quantity is rounded twice after determining the optimal order quantity and the expected undershoot. The first rounding is based on the number of units which fit on/in full pallets, layers or cartons, and second rounding is based on by-vendor required minimal- and incremental order quantities.

Which SKUs are not planned with the current inventory control model and why?

Items are not planned with the inventory control model when planners have a grounded reason to use another method. The first group of items not planned with the model, are items which contain contracted planning actions. Planners state that the model is not able to process contracted planning actions. The second group of items not planned with the model, are items of the company's own brands. Planning these items needs a model which allows difficulties like long lead times and multiple echelons, because these items are produced in China. The third group of items not planned with the model, are low value density items. Ordering based on simple fixed economic order quantity calculation leads to overfull distribution centers. Seasonal items are the last items which are not planned with the currently used model because proper forecast methods for seasonal items are not used in this model.

Which SKUs are not effectively planned with the current inventory control model?

The most striking results are found when looking at the lead time classification. Long lead time items have the highest average deviation between the targeted- and actual service levels when the targeted service level is higher than the actual service level, but also when it is the other way around. Furthermore, it can be seen that on average, long lead time items need more human intervention per item.

What are the characteristics of the total assortment in scope?

Of all items, 63,6% is in the scope of this thesis. Items which are not in scope are non-mature items and items using multiple echelons. When looking at the scope of this thesis, 83,3% of all items are planned with the current inventory control model. Of all items in scope, 76,1% has a review period of five workdays and 59,2% has a targeted service level of 99,0%. A review period of five workdays is the maximum value in the review period determination used in the current inventory control model, and a targeted service level of 99,0% is the starting value of the targeted service level determination.

What are the characteristics of the SKUs that are not – or not effectively managed in the current inventory control model?

The answer to the second sub question shows that the characteristics of the items which are not managed in current inventory control model, are the following: 1) items with contracted planning actions, 2) own brand items, 3) low value density items, and 4) seasonal items. The answer to the third sub research question shows that characteristics of the items which are not effectively managed in the current inventory control model, are items with a long lead time. Besides, it is proven that seasonal items show worse performance than non-seasonal items.

What is an effective way of categorizing the inventory?

The reseller of office supplies classifies inventory based on: 1) importance, 2) forecastability, and 3) purchase price. The advantage of classifying based on importance is that more effort can be put into the items which are considered to be the critical few, instead of focusing on the trivial many. Classifying importance based on the weekly average sales value is effective and commonly used. The addition of the price classification is useful to avoid that cheap items with a high sales volume are always handled the same as expensive items with a lower sales volume. Another commonly used and more modern method of determining importance is a multi-criteria classification. However, data about other characteristics is hard to gather in this case. This is why this thesis does not focus on a multi-criteria importance classification. A forecastability classification is also commonly used. The advantage of classifying based on forecastability is that a simple forecasting method can be used for unforecastable items, while forecastable items can use more complex methods. Classifying forecastability based on the coefficient of variation of demand is an often-used method when demand shows a stationary pattern, or demand can be converted to a stationary pattern. In the case of the office supplies reseller, demand is not stationary and no attempt has been made to convert the demand pattern to a stationary pattern.

Which inventory control model with which parameters fits the SKUs that are not – or not effectively managed in the current inventory control model?

The used inventory control model can fit to all items which are not- or not effectively managed in the current inventory control model, the way of determining different parameters does make a difference. First of all, the expected demand during one future arbitrary time period is used in calculating different parameters. This thesis proves that seasonality can be seen in the total demand of the reseller of office supplies, and that items which show more seasonality perform worse than stable items. It is also shown that long lead time items perform worse than items with medium or short lead time. When forecastable patterns are taken into consideration while forecasting demand, own brand items and seasonal items can be planned with the current inventory control model. Besides, long lead time and seasonal items will perform better. There is no optimal forecasting method given in this thesis, because of time restrictions. Although, using demand during a specific lead time or review period as input, would be an improvement. Doing this, allows the replenishment logic to look at expected demand of this specific days of a year, which allows taking seasonality into account.

When looking at the characteristics of the total assortment, it can be seen that most items have a review period of five workdays. A review period of five workdays is the maximum value in the review period determination of the current inventory control model. When also considering review periods longer than five workdays per subvendor, a reduction in expected annual costs of 0,34% is shown.

Human intervention was used for 93,0% of all items. The usefulness of human intervention was tested by simulating the current inventory control model for all scoped items with the actual demand of 2018. It can be seen that the baseline performance of items on the current inventory control model is better than the baseline performance of items which are planned differently. Given this, it can be concluded that reasons to not plan items on the inventory control model are well-grounded. When looking at the performance, it can be seen that human intervention on the least important items was not needed and using demand adjustments is the only right way to correct for demand uncertainty. This leads to a decrease of 40,10% of all human interventions and a decrease of 5,56% in expected annual costs. When including human intervention in expected annual costs, the decrease is between 5,64% and 5,67%.

Different types of items considered as low value density items are: office paper, chairs, continuous paper, lever arch files and hygiene paper. The new holding costs percentage for these items is 42,64%, because the space-dependent part of the holding cost percentage increased with 164,55%. These calculations are based on the amount of pallet locations needed per item. Using this new holding cost percentage for these different types of items, leads to a decrease of 4,86% in expected average stock value and an increase in expected order lines of 49,98%. In total, a decrease in expected annual costs of 4,75% is realized. Note that most of these items need to be reviewed more often, otherwise these items get out of stock before the next moment of reviewing.

Before this thesis, reorder levels were calculated based on the optimal order quantity plus undershoot, while for 82,1% of all items on the current inventory control model, the order quantity is rounded. A new heuristic is given in this thesis, to calculate reorder levels based on the rounded order quantities. The reorder level calculations are based on the (R,s,S,nQ) logic. Calculations for all other parameters can still be based on (R,s,S) logic. This heuristic is determining the expected rounded order quantity based on the two types of rounding, and uses the rounded order quantity as input for the calculation of the expected service level. The average expected service level decreases from 99,4% to 99,1%, which is closer to the targeted service level of 99,0%. This decrease in expected service level leads to a decrease in average annual inventory value of 4,5%, while the amount of expected order lines stays the same. In total, the change in reorder level determination leads to a decrease of 3,8% of expected annual costs.

Retained items are also not planned with the inventory model. No improvement is needed for these items, when management wants to plan these items with the inventory control model. However, different types of contracted planning actions can be determined to add constraints in the replenishment system.

How is the recommended model performing for all other SKUs?

With the improvement of the reorder level determination, it can be stated that the currently used inventory control model is still a (R,s,S) model, but when order quantities are rounded, it is converted to a variant of the (R,s,S,nQ) model. However, most parameters stay the same. Parameters that are changing, change because specific items did not perform well, like the holding cost percentage for low value density items. There are also some processes which can be changed after this thesis. These processes change because it is cost efficient to do it in the new way, like not placing hideout quantities because of demand uncertainty, not using human intervention for the least important items, allowing planners to review less than once a week for specific items, or determining the reorder levels on the actual ordered quantities (rounded).

IV. Table of Contents

V. List of Abbreviations

Abbreviations used in this thesis are given in full for the first time, after which the abbreviation follows in [brackets]. The following list is a list of all abbreviations used in this thesis.

AFR	-	Achieved Fill Rate
AOQ	-	Actual Order Quantity
BENELUX	-	Belgium, the Netherlands and Luxembourg
BO	-	Back Order
CDC	-	Central Distribution Center
DC	-	Distribution Center
CLP	-	Carton-, Layer- and Pallet Quantity
DACH	-	Germany, Austria and Switzerland
EOQ	-	Economic Order Quantity
GOH	-	Großostheim
IOH	-	Inventory On Hand
IOQ	-	Incremental Order Quantity
IP	-	Inventory Position
ITM	-	Inventory Transaction Model
LT	-	Lead Time
MOQ	-	Minimal Order Quantity
NES	-	Never Ending Store
OB	-	Own Brand
OEM	-	Original Equipment Manufacturer
OL	-	Order Line
OQ	-	Order Quantity
RDC	-	Regional Distribution Center
RP	-	Review Period
RQ	-	Research Question
SKU	-	Stock Keeping Unit
SOQ	-	Suggested Order Quantity
TFR	-	Targeted Fill Rate
UCLP	-	Usable Carton-, Layer-, or Pallet Quantity

VI. List of Figures

VII. List of Tables

VIII. List of Equations

1. Introduction

In this chapter, an introduction to this thesis is presented. In the first part, the company is introduced. In the second part of this chapter, an introduction to the inventory control model of Office Depot follows.

1.1 Office Depot Europe

This part provides a quick overview of Office Depot Europe. The name of the company is Office Depot Europe, but Office Depot is used in the remaining of this thesis. This chapter provides insights in the main businesses, the history, the size, the assortment and the organization structure of the company.

1.1.1 Main Businesses

Office Depot is a reseller of office supplies. The company sells nearly everything needed in offices. A general overview of the assortment categories is provided in chapter 1.1.4. Next to reselling products, Office Depot also offers office solutions. One concept is called the Never Ending Store [NES], which is by Office Depot managed inventory at the customer site, with essential office supplies. Another solution Office Depot offers is helping with the layout and design of a customers' new office. Office Depot is active in the business-to-business and business-to-consumer markets, but most of the revenues come from the business-to-business way of selling. The company sells via two main brands, Viking and Office Depot Europe. Vikings' target customer segment is the smaller customers. The brand Office Depot Europe focusses on bigger customers. For Viking customers, Office Depot wants the customer acquisition online. The resell prices of the office supplies are consistent and transparent to Viking customers. For Office Depot customers, acquisition is offline. The service levels are relationship-based and the pricing is bespoke and via contracts.

1.1.2 History

In 1986, Office Depot Inc. was found by F. Patrick Sher, Stephen Doughtery and Jack Kopkin. Office Depot Inc. started to operate on the European market in 1990. The United Kingdom was the first market to enter, after which Office Depot became bigger around Europe by merging with Viking Direct in 1998. At the start of 2015, Staples, Office Depot Inc.'s biggest competitor, offered 6,3 billion dollars to buy Office Depot Inc.. The Federal Trade Commission of the United States of America did not allow this deal, because the two companies together would become to influential and there would not be a fair competition anymore (Financieel Dagblad, 2016). Just after this judgement in 2016, Office Depot Europe was sold by Office Depot Inc. to AURELIUS, a European investors group. This investors group acquires, restructures and eventually sells companies in special situations, like corporate spin-offs, succession issues, disputes among shareholders or obvious optimization potential. Office Depot Europe still belongs to AURELIUS group today.

1.1.3 Size

Office Depot had annual sales of approximately 1,5 billion euros and 5500 employees in 2017. The company serves customers in thirteen countries via three different channels. The thirteen different countries are shown in Appendix 1. As stated above, the two main channels for customers to purchase from Office Depot are: 1) order online, and 2) offline (via call centers, by phone and mail). The third channel Office Depot uses to sell products are retail stores. This channel is only offered in France and Sweden. There are about 160 retail stores spread over those two countries, which together generate about 14% of the total revenues.

1.1.4 Assortment

The total assortment can be split over three main categories, 1) Facility Management, 2) Office Administration and 3) Printing & Technology. These three categories contain several different product groups. Figure 1 provides an overview of all product groups, divided over the three main categories.

Facility Management

- Cleaning & Hygiene
- Food & Catering
- Furniture

Office Administration

- Filling & Solutions
- GOS & Mailing
- Writing & Machines

Printing & Technology

- Paper & Labels & Envelopes
- Ink & Toner
- Printers & Technology
- Presentations

Figure 1: Product assortment Office Depot

Within the three categories, Office Depot sells different brands in two main brand categories: Original Equipment Manufacturer [OEM] and Own Brand [OB]. OEM means that the company is a reseller of brands, OB are private brands, branded and designed by themselves. Manufacturing activities for OB products is always outsourced. Currently, the private brands that Office Depot sells are: Office Depot, Viking, Niceday, Foray, Realspace, Workpro, Highmark and Ativa. All brands play a role in the total portfolio of Office Depot, which is determined by strategical positioning of these brands.

1.1.5 Inventory and Planning Structure

This thesis is written for the inventory and planning department of Office Depot. This department can be split up in five parts. The first three parts are the categories, which aligns with the assortment categories in Figure 1. Category 1 is 'Facility Management', category 2 is 'Printing & Technology' and category 3 is 'Office Administration'. The third category operates from the United Kingdom, the other two in the Netherlands. The company works with Scrum teams. Each team consists of demand planners, supply planners, product managers and procurement employees. Employees work in seven different Scrum team, divided over the three categories. The demand- and supply planners are representing the inventory and planning department over the Scrum teams.

The fourth part of the inventory and planning department is 'Own Brand', which deals with OB products. These private brands are distributed over the Scrum teams. However, the demand- and supply planners are not working in Scrum teams, they are a stand-alone team. The product management and procurement are executed by the Scrum teams, for the specific product groups only.

The last part of the company is called 'Retained', which has their own Scrum team. They deal with large customers, who can ask for their own assortment. For example, paper with the customers' logo on it, or selling pens per single unit instead of per box, because it is agreed upon with the customer. Demand for retained Stock Keeping Units [SKUs] is never fulfilled with OB products. Figure 3 shows an overview of the five parts of inventory and planning.

The organizational structure is shown in Figures 2 and 3. In the organization chart in Figure 2 is visible that regarding to this thesis, the researcher has to report to the Director Supply Chain Optimization. This thesis is performed for the Inventory and Planning department (orange rectangles in Figure 2). The dotted lines mean that these managers have to report to the Director Inventory and Planning, but are not part of my scope. More information about the scope is presented in chapter 4.1.

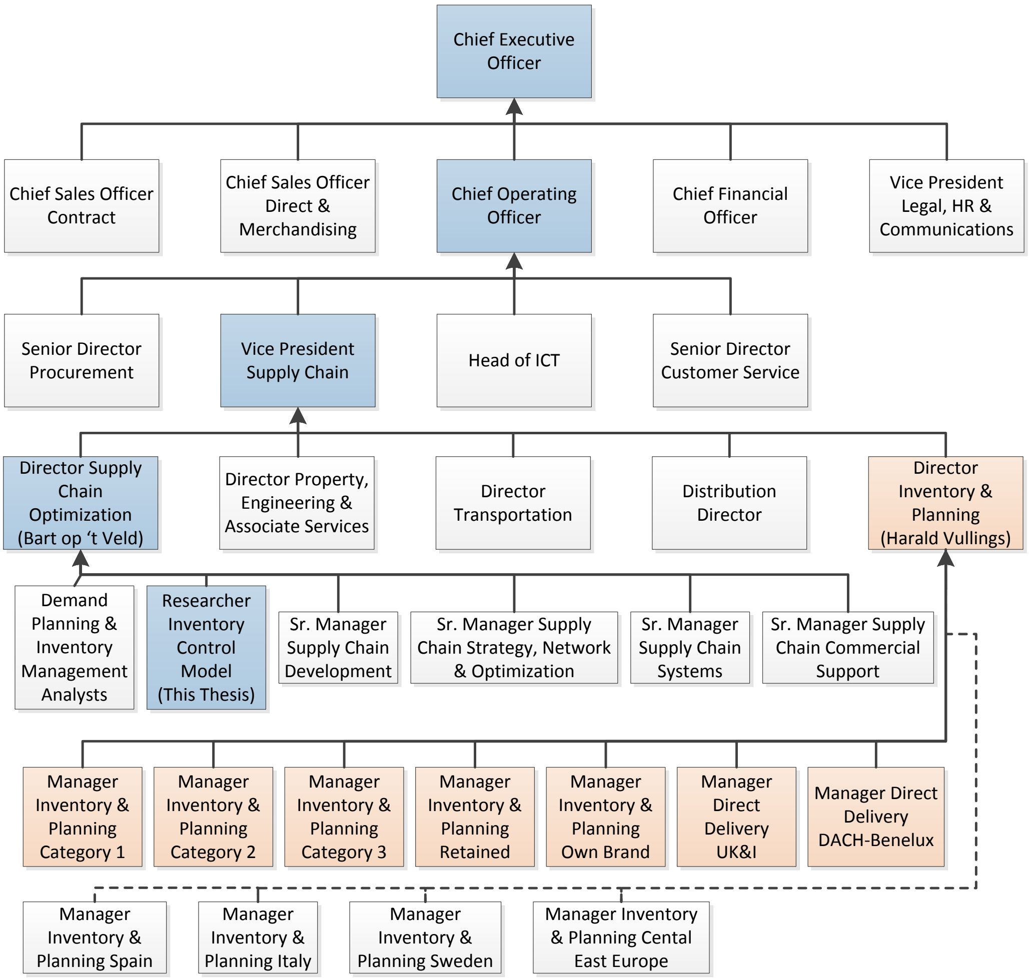

Figure 2: Organization chart

1.2 Inventory Control

Office Depot used two different models to make replenishment decisions, 1) Prime One of software supplier Demand Soft, and 2) SAP. Prime One and SAP both use a variant of the can-order policy to make the replenishment decision (Vargas Suavita, 2012). In the Master Thesis of Op 't Veld (2016) was determined that a policy with periodic review, reorder level and order-up-to level would outperform the can-order policy, as implemented in Prime One, for most SKUs. Therefore, Office Depot decided to implement this periodic review and lotsizing system, calling it the 'Inventory Transaction Model' [ITM]. ITM is implemented for almost the whole assortment, but not for every SKU. Reasons for not implementing follow in paragraph 5.2 of this thesis. The original ITM gave the option to choose between using the (R,s,S) logic or the (R,s,nQ) logic. Management decided to only use the (R,s,S) logic, because the calculated parameters resulted in less inventory on hand. Later on, rounding Order Quantities [OQs] became a business requirement to reduce workload at the Distribution Center [DC]. This means that the currently used model is a (R,s,S) model converted to a variant of the (R,s,S,nQ) model.

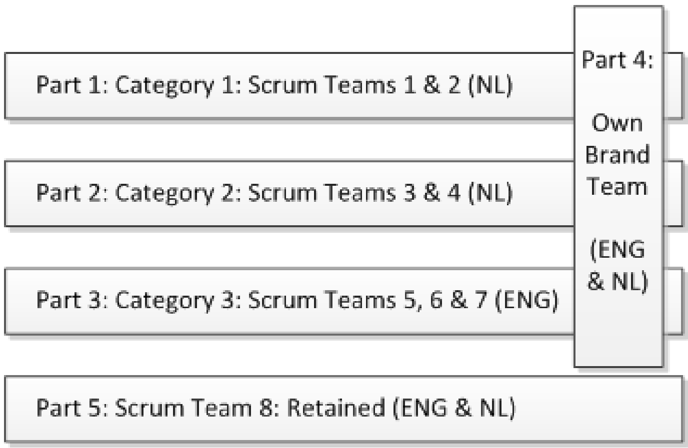

Figure 3: Overview inventory and planning department Office Depot

2. Problem Definition

In this part of the thesis, the origin and the relevance of the thesis is explained in more detail. Office Depot believed that performing a Master Thesis in their company would be useful, this chapter explains 1) why the management team thinks this is needed, 2) what the objectives of this research are, 3) what the research questions are, and 4) what gap in the literature is filled by performing this thesis. The first three subchapters are about the companies view on the problem definition, and the fourth is about the literature view on the problem definition.

2.1 Management Dilemma

The current inventory control model uses the (R,s,S) logic, which means periodic reviewing *R*, ordering when the Inventory Position [IP] is below the reorder level *s*, and ordering up to the order-up-to level *S*. This model is not able to manage all SKUs, or is not able to manage SKUs effectively. The management team wants to know which SKUs are not planned with ITM and which SKUs are planned with ITM, but are not performing well. The performance is in terms of stock holding costs, order costs, service level achievement and amount of human intervention. Effectively managed SKUs do achieve the targeted fill rate, without needing human intervention. When it is known which SKUs are not – or not effectively managed with the current inventory control model, an new or improved model can be fit to those SKUs. This provides the following management dilemma:

Management Dilemma:
Several SKUs are not – or not effectively managed with the current inventory control model.

2.2 Research Objectives

The thesis of Op ‘t Veld (2016) resulted in the implementation of the currently used inventory control model, but with restrictions regarding the software application in which this model had to be implemented. Since the implemented inventory control model was a (R,s,S) model, the phrase *‘current (R,s,S) model’* is used in the remaining of this thesis, despite the OQ rounding. With the implementation of the (R,s,S) model, the replenishment calculations are executed by this model instead of the software application itself (Prime One or SAP). For most SKUs, the input parameters are interfaced from the software application to the (R,s,S) model, after which the calculations are executed in the (R,s,S) model and the outcomes of these calculations are interfaced from this model to the software application. This means that for most SKUs, the software application is only used for the actual ordering. The management team is currently re-evaluating the software application. They want the performance of the (R,s,S) model for the effectively managed SKUs, but want the software application to calculate the parameters on itself. When this is known which SKUs are not – or not effectively managed with the current inventory control model, they want to know which inventory control model outperforms the (R,s,S) model for SKUs which are not – or not effectively managed with this model. This information can be used as input for the selection of a new software application.

2.3 Research Question

With the background information given above, the management dilemma can be translated into the main research question of this thesis:

Main Research Question:
Which inventory control model is improving the performance in terms of stock holding costs, incoming order lines, service level achievement and human intervention for SKUs which are not – or not effectively managed in the current model?

The goal is to minimize total costs, but Office Depot does not want to increase the workload for the warehouses. This means that the amount of incoming Order Lines [OLs] have to remain the same. The targeted service has to be achieved. The service level is measured as annual fill rate per SKU. The total target is 99,00% for all SKUs, which means that the target is to fulfill 99,00% of all demand directly out of stock. The term ‘fill rate’ is used in the remaining of this thesis and means the unit fill rate over a year. The main research question can be split up in multiple smaller Research Questions [RQs]. By combining the answers of the RQs, the main research question is answered. The RQs are the following:

- **RQ 1.** What are the characteristics of the current inventory control model?
- **RQ 2.** Which SKUs are not planned with the current inventory control model and why?
- **RQ 3.** Which SKUs are not effectively planned with the current inventory control model?
- **RQ 4.** What are the characteristics of the total assortment in scope?
- **RQ 5.** What are the characteristics of the SKUs that are not – or not effectively managed in the current inventory control model?
- **RQ 6.** What is an effective way of categorizing the inventory?
- **RQ 7.** Which inventory control model with which parameters fits the SKUs that are not – or not effectively managed in the current inventory control model?
- **RQ 8.** How is the recommended model performing for all other SKUs?

The first six RQs can be answered after the diagnosis and analysis phase of this thesis. The seventh and eighth RQs can be answered after finding, testing and validating a new/improved inventory control model, which is in de the design phase of this thesis. The answers to all these RQs combined, leads to an answer on the main RQ of this thesis, which is presented in the conclusion.

2.4 Contribution to the Literature

According to literature, the most important SKUs should get the most attention. Literature states that it is more useful to focus on the critical few instead of the trivial many and that it might not be valuable to put effort in the least important SKUs (Juran, 1954) (Silver, Pyke, & Peterson, 1998) (Nahmias & Olsen, 2015). To prevent putting useless effort in unimportant items, it is suggested to use an importance classification. The importance classification used at the reseller of office supplies is based on the Pareto rule (Pareto, 1971). Besides, human intervention is done for all classes of importance. Hence, an empirical test follows on the usefulness of human intervention per importance classification. It is empirically tested how useful human interventions per importance class is, and whether or not to do human interventions on the least important SKUs at all. Empirically testing whether human intervention on the least important items is needed in a reselling environment has never been done before.

The inventory control model of the reseller of office supplies works with the (R,s,S) logic. Though, rounding OQs is applied to reduce the workload at the DCs. Replenishment logics working with periodical review and rounding OQs are the (R,s,nQ) logic and the (R,s,S,nQ) logic (Van Donselaar & Broekmeulen, 2015) (Hill, 2006). The used inventory control model works with rounded order quantities, while not using a replenishment logics based on rounding OQs. The (R,s,S,nQ) model is explained in research of Hill (2006). In this research is stated that after an order is placed, the IP never exceeds the order-up-to level *S*. This is stated, because the reorder level *s* and order-up-to level *S* are restricted to be multiples of the batch size *Q* (Hill, 2006). By making a simple adjustment in the (R,s,S) logic, a new variant of the (R,s,S,nQ) will be tested, where the reorder level *s* and order-up-to level *S* do not have to be multiples of the batch size *Q*. This means that the IP can exceed the order-up-to level *S* when an order is placed. Testing the impact of adjusting a (R,s,S) model to a variant of the (R,s,S,nQ) model on the reorder levels has never been done before.

3. Methodology

In this chapter, the approach on which this thesis is build is explained. This approach functions as a backbone of this thesis. A commonly used approach for a Master thesis in which a problem needs to be solved is the Regulative Cycle, by Van Strien (1997), which can be found on the left side of Figure 4. This iterative approach is used for continuous improvement within companies, but can also be used as a guide to solve a single problem (Van Strien, 1997). This chapter explains each part of the regulative cycle and links it to the chapters of the thesis. After this, an overview is presented in the last part of this chapter.

3.1 Stage 1: Problem Definition

The problem definition was given to the writer of this thesis in the form of a problem description. After accepting this problem and collecting relevant literature, the definition is broken down to a management dilemma, research objectives, a main research question, sub RQs and a contribution to the literature. This can be found in chapter 2 of this thesis. The methodology of how to tackle this problem is given in this chapter of the thesis, chapter 3.

3.2 Stage 2: Diagnose and Analyze

In this stage of the thesis, data is gathered to diagnose and analyze the problem. In chapter 4 of this thesis, the diagnosis is given. Chapter 4 explains which data is needed, how this data is gathered and how this data is processed. In chapter 5 of this thesis, the data is processed and the analysis is given. With completing the analysis, the first six RQs of this thesis are answered.

3.3 Stage 3: Solution Design

Based on the findings in stage 2, an inventory control model needs to be redesigned. What design is needed for each specific topic, is explained in stage 3 of the thesis. This is given in chapter 6 of this thesis, the design.

3.4 Stage 4: Intervention

After redesigning the inventory control model, the change in the model is tested based on historical data of the SKUs which are not – or not effectively managed in the (R,s,S) model. The tests of the possible improvements are compared with the old way of using the (R,s,S) model, in such a way that the best performing option can be chosen. This happens in chapter 7 of this thesis, the results. In the intervention stage is determined what interventions are needed and what the consequences of these interventions are. In chapter 8, the conclusion of this thesis is given, which is an advice regarding the implementation of the interventions.

3.5 Stage 5: Learning and Evaluation

Learning and evaluation is the last stage of the regulative cycle of Van Strien (1997). Chapter 9 shows the discussion of this thesis, where the evaluation of the used methods is given.

3.6 Method Overview

In Figure 4, a summary of the thesis is presented. The regulative cycle of Van Strien (1997) is stated on the left side, and on the right side the chapters and answers to specific RQs of this thesis can be found.

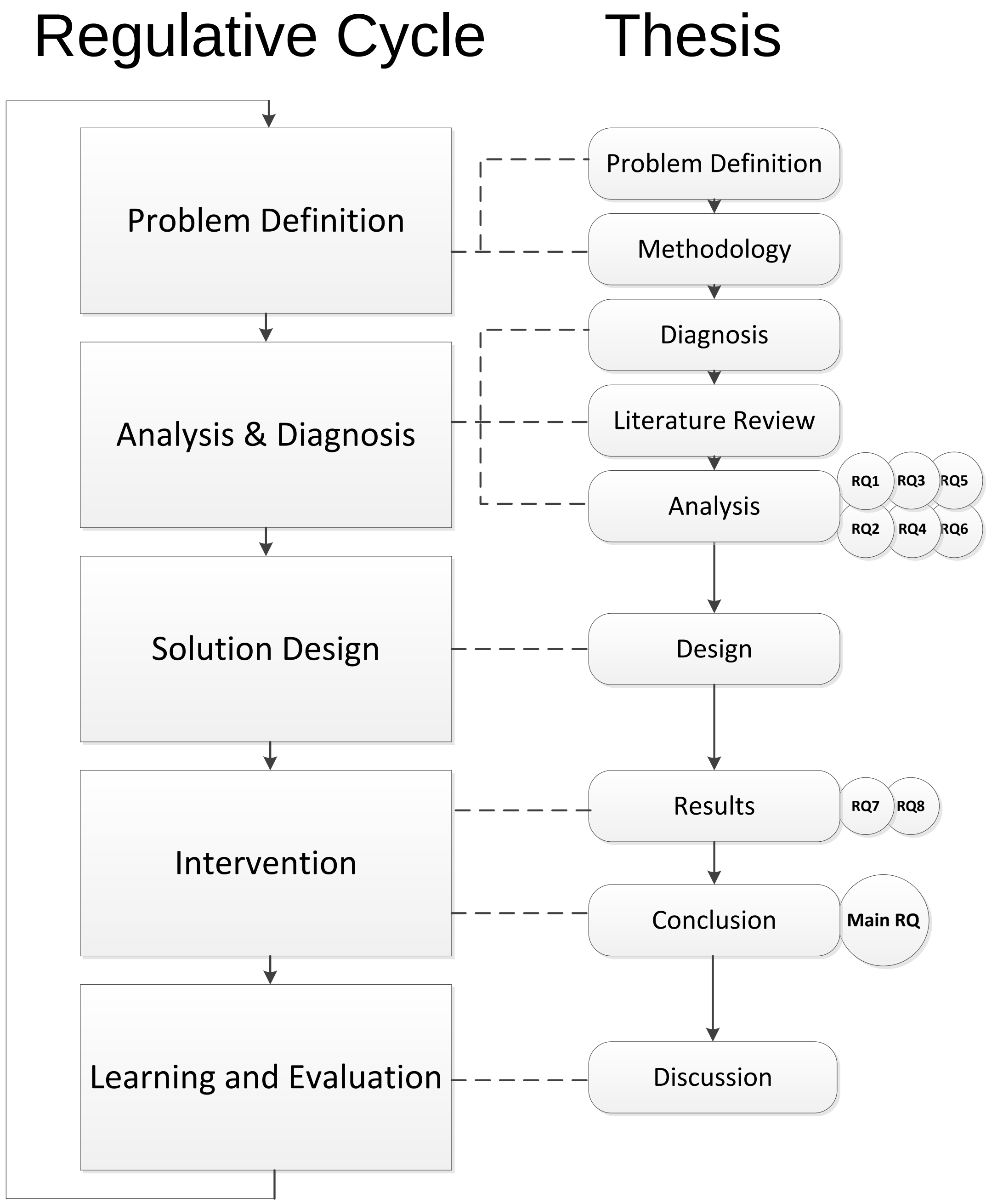

Figure 4: Regulative cycle and this thesis

4. Diagnosis

In this chapter, a diagnosis of what has to be done with which kind of data is described. This corresponds to the first part of stage 2 of the regulative cycle of Van Strien (1997). To diagnose the problem, data has to be collected. First, the scope of this thesis is explained to come up with the right data. After this, the explanation about which data is used and why follows. Data which is needed for this thesis is divided into two groups: 1) Qualitative data and 2) Quantitative data.

4.1 Scope

In this part of the thesis, the scope is specified. The first part provides the geographical and DC scope, and the second part explains the scope regarding SKUs.

4.1.1 Geographical and DC Scope

This thesis uses data of the Regional Distribution Center [RDC] located in Großostheim [GOH]. This RDC fulfills demand for the regions Germany, Austria and Switzerland [DACH] & Belgium, the Netherlands and Luxembourg [BENELUX]. There is also a Central Distribution Center [CDC] to collect OB products produced in China. These products have two ways of transportation to the RDCs: 1) Indirect shipment, via the CDC located in Zwolle (the Netherlands), or 2) direct shipment to the RDCs. The choice between direct or indirect shipment depends on quantities that need to be shipped. The scope of this thesis is the inventory planning in the DC of GOH, with other words a single echelon model. SKUs coming to the RDC via the indirect flow can be added to the improved inventory control model for RDCs, when unlimited supply from the CDC is assumed. Before doing this, it is recommended to perform an allocation project of OB SKUs from the CDC to all RDCs, as explained in chapter 9.2.

4.1.2 SKU Scope

Data of all SKUs stored in the DC is gathered. The kind of data gathered, is explained in paragraph 4.2. To work with this data, historical data of the SKUs is needed. This is why only mature SKUs are taken into the scope of this thesis, which means SKUs with more than one year of sales data. This means that ‘Phase In’ and ‘Phase Out’ SKUs are excluded from the scope. Non-mature SKUs can be planned with the improved inventory control model, when demand forecasts are based on other data than historical data of the SKU itself. This is why it is recommended to perform a forecasting project of non-mature SKUs of Office Depot, as explained in paragraph 9.3.3 of this thesis.

4.2 Qualitative Data

Qualitative data is used to make the problem definition clear and also to answer RQs. Qualitative data is gathered in four different forms: 1) company information, 2) observations, 3) conversations with employees, 4) interviews with employees and 5) literature related to this thesis.

4.2.1 Company Information, Observations and Conversations With Employees

To get a clear overview of what the current inventory control model looks like, internal company documents were reviewed. A list of names of all these documents is presented in Appendix 2. Besides, observations were made while working with people, and there were conversations with colleagues regarding to topics of this thesis.

4.2.2 Interviews

Interviews are the fourth form of qualitative data gathered. Questions of the semi-structured interview can be found in Appendix 3. Interviews are performed for several reasons. The first reason is to get clear which types of models and software are used for which SKUs, and why they use different models. The researcher is working at the Supply Chain Optimization department, which is heavily involved in the

(R,s,S) model. Some SKUs are not performing well with this model, planners of these SKUs use other models or own excel files to plan their own demand and supply. The second reason to perform an interview is to get another view on the performance of the total inventory control as it is now, which means the (R,s,S) model, but also all other models that Office Depot is working with. To avoid a one-sided view, supply- and demand planners, the European Supply Planning Managers and the European Director of Inventory and Planning are interviewed. The last reason for the interview is to get a first idea of SKUs which are not- or not effectively managed by the (R,s,S) model.

4.2.3 Literature

The last type of qualitative data needed for this thesis is literature. Literature is needed to find the different available inventory control models and to find the best fit between an inventory control model and the characteristics of the assortment. A systematic literature review is conducted as a part of this thesis. The literature review is a document on itself and cannot be found in this document, but references to related literature are placed when literature is used.

4.3 Quantitative Data

Quantitative data is needed to see which SKUs not effectively managed by the (R,s,S) model, to redesign the inventory control model, and to test the redesigns. To find SKUs that are not performing well, look at the performance in 1) inventory value, 2) fill rates and 3) the amount of human intervention.

4.3.1 Grouping SKUs

SKUs need to be grouped to find SKUs which are not- or not effectively managed by the (R,s,S) model. SKUs are grouped based on the following characteristics: 1) Lead Time [LT], 2) importance, 3) forecastability, 4) purchase price, and 5) subvendor. The way the reseller of office supplies divides all SKUs over different classes in the first four product characteristics, is explained in part 5.1 of this thesis. SKUs are also grouped by subvendor, to avoid planning SKUs from the same subvendor on different dates. A subvendor is a subclass within a vendor, because vendors can use different LTs for different products, for example when one vendor has multiples DCs. Grouping by subvendor reduces incoming orders at the DC and creates a clear reviewing schedule for supply planners. The currently used categories are based on prior research at Office Depot by Kaplan (2015) and Op ‘t Veld (2016).

4.3.2 Raw Data

Different types of raw data needed in specific parts of the thesis, is given per part. Appendix 4 gives an overview of all raw data needed for this research. The newest data is always used.

4.3.3 Determine Poor Performance

After grouping the SKUs, groups which are not planned effectively on the (R,s,S) model can be found. This can be not effectively in three dimensions: 1) human intervention is needed, 2) the average inventory value is higher than needed, and 3) the TFR is not achieved. Human intervention in the (R,s,S) model are used in three different forms. Explanations about these forms follows in part 5.3.2 of this thesis. The TFRs per product group can be compared with the Achieved Fill Rates [AFRs] per product group, to find which SKUs are performing poor on this dimension.

4.3.4 Redesign

After finding which SKUs are not – or not effectively managed in the (R,s,S) model, those SKUs are selected to find a new better fitting model. It can be the case that different product characteristics for different SKUs, need different models or redesigns for better performance. The models are compared based on expected inventory value, expected fill rates and expected incoming OLs, by simulating the selected SKUs with the new (re)designed model.

5. Analysis

This chapter corresponds to the second part of stage 3 of the regulative cycle of Van Strien (1997). The gathered qualitative and quantitative data is presented in this chapter of the thesis, after which an analysis about this data follows. An improved model is also made based on literature. The first six RQs are answered in this chapter of the thesis.

5.1 Current Inventory Control Model

Most SKUs are planned with the (R,s,S) model, this is why in this chapter is explained what the characteristics of the (R,s,S) model are and how the parameters are calculated. The (R,s,S) model is implemented and adjusted by the Supply Chain Optimization team, after Op 't Veld (2016) concluded in his thesis that this was a better performing inventory control model for Office Depot. Professor A.G. de Kok guided him during his thesis, this is why most of the current inventory systems equations are based on (De Kok A. G., 2004). This subchapter is the answer to RQ1, *'What are the characteristics of the current inventory control model?'*.

5.1.1 Demand Distribution

The current (R,s,S) model uses a gamma demand distribution. There are too many SKUs and the average demand is too high to use a discrete demand distribution, so a continuous demand distribution is needed (Van Donselaar & Broekmeulen, 2015). The gamma distribution is preferred over the normal distribution because of the following reasons: 1) the gamma distribution is commonly used in practice (De Kok A. G., 2004), 2) the gamma distribution only has positive output, where the normal distribution can also have negative output (Silver, Pyke, & Thomas, 2017), and 3) gamma distributed demand models and normal distributed demand models behave similar in case of normal distributed demand, but not similar in case of gamma distributed demand (De Kok A. G., 2004).

5.1.2 Item Classification

The currently used classification method is explained in this paragraph. Based on the item classification, the Review Periods [RPs] and TFRs are determined. This process is explained in the part 5.1.3 of this thesis. A combination of an importance classification, a forecastability classification and a price classification is used at Office Depot. Combining these three classifications, provides the total item-classification. For example, an 'AZ1' SKU is an important SKU (A), which is hard to forecast (Z) and has a low purchase price (1). There are 27 combinations possible.

The first classification is the importance classification (A-B-C), where class 'A' is used for a small percentage (about 5-10%) of the SKUs which cause 80% of the average weekly sales value. The average weekly sales value is the item purchase price multiplied by the average weekly demand (based one year of weekly sales data). SKUs causing 80-95% of the average weekly sales value are classified as 'B' SKUs, and the SKUs causing the last 5% of the average weekly sales value are classified as 'C' SKUs. This classification is based on the 80-20 rule (Pareto, 1971) and theory of benefiting from the top SKUs (Juran, 1954).

The second classification is the forecastability classification (X-Y-Z), which is determined according to the coefficient of variation of the specific SKU. The coefficient of variation can be calculated by dividing the standard deviation of the weekly demand of last year by the average weekly demand of last year. When the coefficient of variation is lower than 0,4, a SKU is classified as easy-to-forecast (X). Coefficient of variation between 0,4 and 1,0: medium-to-forecast (Y), and a coefficient of variation higher than 1,0: the SKU is hard-to-forecast (Z). This classification is based on forecasting- and stock control policy theories (Boylan, Syntetos, & Karakostas, 2008) (Syntetos, Boylan, & Croston, 2005).

The last classification of SKUs is based on the purchase price (1-2-3). 80% of the SKUs with the lowest purchase price is classified as ‘1’, 15% of the SKUs with a medium purchase price is classified as ‘2’ and the 5% highest priced SKUs is classified as ‘3’. This classification is used as an addition to the importance classification, to avoid that SKUs with a high sales volume and low purchase price always have the same TFR as SKUs with a lower sales volume and high purchase price. This classification is based on the 80-20 rule (Pareto, 1971) and theory of benefit from the top SKUs (Juran, 1954).

5.1.3 Review Period and Targeted Fill Rate Determination

Based on the item classification, the RPs and TFRs are determined. The RPs are determined per subvendor and the TFRs per item classification. The first step in determining the RPs is giving every SKU a TFR of 99,0%. With this TFR, three model modifications of one model are made, to compare costs. The first one is a modification with RP 5, which means reviewing once a week, the second uses RP 3 (reviewing twice a week) and the last uses RP 2 (reviewing every other day). The minimal expected annual costs with different RPs per subvendor are determined. This RP is used for every SKU within the same subvendor. The equation for the expected annual costs is based on annual holding costs (25% of the average inventory value), costs per order (20 euros) and costs per order line (5 euros). The equation is given and explained in Appendix 5.

After the first RP determination, the fill rates per item classification are determined. Ten different model modifications are made, where the fill rates differ from 95,0% till 99,0% (steps of 1,0%) and from 99,1% till 99,5% (steps of 0,1%). A solver function is used with two restriction: 1) the average fill rate over all SKUs has to be at least 99,0%, and 2) the targeted fill rate per item classification has to be one of the ten options (so not 99,44%, but 99,4% or 99,5%). This objective is to minimize the expected inventory value. An evolutionary solver is used, and when there is no improvement in 1800 seconds of calculations, the solver stops running and the output is used. The computer on which the solver runs, is not used for 30 minutes. In most cases, the solver found the output already. When it did not, the solver function is stopped and the output is used. This gives new TFRs per item classification.

The last part of the RP and TFR determination is to determine the RPs per subvendor, like the first step of this process, but with the new TFRs. This process is executed every quartile.

5.1.4 Reorder levels

Reorder levels per SKU are based on the TFR per SKU. In the paragraph before is explained how the TFRs per item classification are found. The TFRs are used as input for the reorder level determination. Determining the reorder level happens once every four weeks, or when a demand adjustment is placed by a planner. More about demand adjustments in part 5.3.2 of this thesis. To determine the reorder levels s, the expected fill rate P_2 of a SKU is calculated based on the iterating reorder level of a SKU. The starting values of the reorder level used to compare the calculated expected fill rate with the TFR, are given in Equation 1. In Equation 2, there are terms which are not explained before. The explanations and calculations of these terms can be found in Appendix 6.

$$s = \frac{s_{max} + s_{min}}{2}, where\ the\ starting\ value\ of\ s_{max} = 10 * E[D_L]\ and\ of\ s_{min} = 0$$

Equation 1: Calculation of the reorder level

This reorder level is used in Equation 2, to calculate the expected fill rate (De Kok A. G., 2004).

$$P_2 = 1 - \frac{(E[D_L] + E[U_R]) * \left(1 - F\left(s; \alpha_{E[D_L]+E[U_R]}; \beta_{E[D_L]+E[U_R]}\right)\right) - s * \left(1 - F\left(s; \alpha_{E[D_L]+E[U_R]} - 1; \beta_{E[D_L]+E[U_R]}\right)\right)}{Q_{opt} + E[U_R]} + \frac{(E[D_L]) * \left(1 - F\left(s + Q_{opt}; \alpha_{E[D_L]}; \beta_{E[D_L]}\right)\right) - s * \left(1 - F\left(s + Q_{opt}; \alpha_{E[D_L]} - 1; \beta_{E[D_L]}\right)\right)}{Q_{opt} + E[U_R]}$$

Equation 2: Calculation of the expected fill rate

When the starting value of the reorder level gives as output that the TFR is lower than the calculated fill rate, the old s is used as s_{max} in the new iteration. When the TFR is higher than the calculated fill rate, the old s is used as s_{min} in the new iteration. Doing this iteration multiple times causes the values of s_{min} and s_{max} to get close to each other, just like the values of the calculated fill rate and TFR. This iteration is based on different articles which provide a way to use the fill rate as input for calculating the optimal reorder level s (De Kok A. G., 2004) (Viswanathan, 1997). The actual reorder level can be higher when extra safety stock is added. This extra safety stock added is in workdays of average demand, which means $SSDays_{extra}$ multiplied by the expected daily demand. Management asked for the addition to the model. The calculation for the final reorder level s_{actual} is stated in Equation 3.

$$s_{actual} = (1, s + SSDays_{extra} * E[D_1])^+$$

Equation 3: Calculation of the actual used reorder level

5.1.5 Expected Demand, Lead Time and Variances

This paragraph explains how the expected demand and its variance is used as input in the currently used (R,s,S) model. In all calculations, the forecasted demand during one arbitrary future time period is used. This means the expected demand during each arbitrary future workday is expected to be the same. The forecasted demand during one week in this (R,s,S) model is equal to the cleansed moving average of 13 weeks demand before the period in time that the calculations is executed. This means that the average of the actual weekly demand of the past 13 weeks, when all 13 values are within 2σ-boundaries. When one of the thirteen data points of weekly demand exceeds one of the boundaries, this value is excluded and the forecasted demand is the average over the other 12 data points. The forecasted demand during one arbitrary future time period is calculated by dividing the cleansed average of last 13 weeks by five (workdays in one week). The demand variance per period is calculated over the same data as the expected demand per period. It can also be the case that the forecasted demand during one arbitrary future time period is adjusted. In this case, the demand variance does not change. Changing the forecasted demand during one arbitrary future time period, is one of the three ways of intervening in the model. Human intervention is explained in detail in part 5.3.2 of this thesis.

When it was decided to use this method of forecasting, other forecasting methods were tested. The other forecasting methods which were tested are the moving average of the last year and last half year. Updating the forecasted demand every week is considered, but using 13 weeks and updating the value once every four weeks is determined to be a cost efficient method on average, when every SKU planned with the (R,s,S) model uses the same forecasting model (Op 't Veld, 2016). The cost equation given in Appendix 5 is used for this calculation. When the forecasted demand and the variance of a fixed amount of periods in time (K) needs to be calculated, the equations on the left side of Equation 4 and 5 are used (De Kok A. G., 2004). $E[D_1]$ and $\sigma^2[D_1]$ are the expected demand and demand variance of one period in time, calculated as explained above. The left side of Equation 4 is used to calculate the expected demand during RP. LT is not fixed, so the expected demand during LT has to be calculated differently. When it is given that LT is an integer number of periods, the forecasted demand and the variance of the demand during LT, can be calculated with the equations given on the right side of Equation 4 and 5 (De Kok A. G., 2004).

$$E[D_K] = K * E[D_1] \quad \& \quad E[D_L] = E[D_1] * E[L]$$

Equation 4: Calculations of expected demand during multiple time periods

$$\sigma^2[D_K] = K * \sigma^2[D_1] \quad \& \quad \sigma^2[D_L] = E[L] * \sigma^2[D_1] + \sigma^2[L] * E[D_1]$$

Equation 5: Calculations of demand variance during multiple time periods

5.1.6 Actual Order Quantity

When not considering undershoot, literature states that the optimal OQ is *S-s*, which is often predetermined by an EOQ calculation (Silver, Pyke, & Peterson, 1998). Undershoot is the amount of SKUs the IP gets under the reorder level. Undershoot is caused by periodic reviewing or OQs higher than one (Nahmias & Olsen, 2015). Office Depot uses the maximum of the EOQ or the expected demand during RP as optimal OQ. When accounting for undershoot, the expected undershoot can simply be added to this, which makes the optimal OQ $S\text{-}s\text{+}E[U]$. Office Depot also has a business requirement to reduce the workload for their DCs, which means that it can be beneficial to order a SKU in an order size which is equal to the amount of SKUs that fit in a full carton, layer or pallet.

The CLPs are given, but may not be useful because the data is unreliable. Office Depot is working on making this data more useful. Before starting the process of rounding the AOQ to CLPs, a check takes place whether the quantities are usable. When the single unit quantity < carton quantity < layer quantity < pallet quantity, and the CLPs are not 0 or 999, the quantities can be used. The rule of thumb given by the business, is that when the cost variance of ordering in full pallets instead of $S\text{-}s\text{+}E[U]$ is less than eight percent, full pallets are ordered instead. When this is not the case, the cost variance of ordering in full layers are considered in the same way. When this is also not the case, the cost variance of ordering in full cartons is also considered. When this is also not the case, a new rule of thumb based on the value of a full carton is used. When the costs of one full carton is 300 euros or less, the OQ is rounded up to full cartons. When this is also not the case, the optimal OQ $S\text{-}s\text{+}E[U]$ is ordered. Equations for this process can be found in Appendix 7.

When the undershoot and the CLP rounding is done, the AOQ can still be a different value because of constraints by the vendor. Vendors can dictate a by-vendor required MOQ (MOQ_{VR}) and a by-vendor required IOQ (IOQ_{VR}). When Office Depot wants to place an order for a specific SKU, which exceeds the MOQ_{VR} by x, and an IOQ_{VR} is in place, the AOQ is:

$$AOQ = MOQ_{VR} + \left\lceil \frac{x}{IOQ_{VR}} \right\rceil * IOQ_{VR}$$

Equation 6: Calculation of the actual ordered quantity

In most cases, the by-vendor required MOQs and IOQs are one of the CLPs, or multiples. For 82,1% of all SKUs planned with the (R,s,S) model and stored in GOH, OQs are rounded. When taking both kinds of rounding into account, for 34,3% of all SKUs planned with the (R,s,S) model and stored in GOH, the SOQ is deviating more than 25% from the $Q_{opt} + E[U]$. For 17,9% of all SKUs planned with the (R,s,S) model and stored in GOH, there is no OQ rounding used.

5.1.7 Conclusion RQ1

In this part of the paragraph, a summary of how the current (R,s,S) model works is presented, which provides a summarized answer to RQ1. The previous parts of paragraph 5.1 together are the full answer to RQ1, this part only provides a quick overview.

RQ1. What are the characteristics of the current inventory control model?

The current model uses a gamma demand distribution. The RP per subvendor and TFR per item classification are determined by a solver function, which minimizes the expected annual costs. Classification is done by looking at three different product characteristics, which are the following: 1) the importance of SKUs, determined based on the average weekly sales value per SKU, 2) the forecastability of SKUs, determined based on the coefficient of variation of the cleansed demand of last 13 weeks, and 3) the purchase price per SKU, in euros. The reorder levels per SKU are determined based on achieving the TFRs per SKU. An extra safety stock in workdays can be added to the reorder level, when there are incentives that this extra safety stock is needed. The optimal OQ without undershoot or rounding is determined to be the maximum of the demand during RP and the calculated EOQ. The EOQ is a trade-off between costs of ordering and costs of holding items. Order costs are fixed, and holding costs are determined by a fixed holding cost percentage. The demand during a specific future period in time is always derived from the forecasted demand during one arbitrary future period in time, which means that a stationary demand approach is used. The OQ is rounded twice after determining the optimal OQ, first based on the CLPs, after which a second rounding is based on by-vendor required MOQs and IOQs. These two types of rounding the OQ are not considered when determining the optimal reorder level.

5.2 SKUs Not Planned with (R,s,S) Model

This paragraph provides an overview of which SKUs are not planned with the current (R,s,S) model. The information in this paragraph provides an answer to RQ2, *'Which SKUs are not planned with the current inventory control model and why?'*. First, an overview of reasons to not plan a SKU on the current (R,s,S) model is given. After this, a summarized answer to RQ2 is presented.

5.2.1 Reasons to not use the (R,s,S) model

Most of the SKUs are planned with the (R,s,S) model, because the company wants to plan all SKUs on one model. The other SKUs are either planned manually or via an alternative model (e.g. Prime One or SAP), because the planners thought that the performance of these specific SKUs would be worse on the (R,s,S) model. According to planners, SKUs which can perform worse on the (R,s,S) model than on other models are:

1. SKUs which have contracted planning actions, this is the case for SKUs under category 'Retained' (Fifth part of the company in Figure 3). It can be the case that a contract between Office Depot and a customer states that a fixed amount has to be ordered when the IP or the Inventory On Hand [IOH] of this specific SKU in Office Depot's DC has decreased to a specific amount.
2. SKUs under category 'OB' (fourth part of the company in Figure 3). These SKUs are sourced in Asia, where there is a consolidation center. These products can be shipped directly to a RDC, or first to the CDC, after which the products are allocated to the different RDCs. Planning these SKUs requires a more complex form of the (R,s,S) model.
3. SKUs which are considered to have a low value density, because the (R,s,S) model is currently not set up to handle with this problem, which can cause overfull DCs.
4. SKUs which are considered to be seasonal, because proper forecast tools for seasonal SKUs are not used in the current (R,s,S) model.

These reasons are the only reasons not to plan a SKU via the current (R,s,S) model. Table 1 shows how many SKUs are planned with the (R,s,S) model and how many are not. Table 1 is a snapshot made on November the 27th of 2018. It concerns all inventory stored in GOH, which is used to deliver in the DACH & BENELUX regions. The average weekly sales are based on one full year of data (week 48, 2017 – week 47, 2018).

Planning method	% of SKUs	% Average weekly sales	% Inventory value
(R,s,S)	71,3	72,5	59,5
Other	28,7	27,5	40,5
Total GOH	**100,0**	**100,0**	**100,0**

Table 1: Amount of (R,s,S)-planned SKUs

Reason not on (R,s,S)	% of SKUs	% Average weekly sales	% Inventory value
Retained	33,3	16,7	37,4
Own Brand	25,5	12,5	19,7
Low v. dens.	0,7	58,4	28,3
Seasonality	40,5	12,4	14,6
Total not (R,s,S)	**100,0**	**100,0**	**100,0**

Table 2: Reasons to not plan on the (R,s,S) model

Of the SKUs not planned with the (R,s,S) model, the amount of SKUs can be split up per reason. Of all SKUs not planned with the (R,s,S) model, the first three reasons can be quantified. Parts of a unique item key show SKUs that can be considered as 'retained' or 'Own Brand'. Furthermore, there are two item groups which are not planned with the (R,s,S) model because of the low value density. When a SKU is not planned with the (R,s,S) model, without being labeled as retained, OB or low value density, planners chose to not use the (R,s,S) model with seasonality as reason. The amount of SKUs, average weekly sales value and percentage of inventory value per reason not to plan on the (R,s,S) model, can be found in Table 2. More detailed explanations per reason is stated in the next five subparagraphs.

5.2.2 Retained SKUs

SKUs under the category 'retained' have contracted planning actions, which can be for example paper with a logo on it, but also selling pens per single unit instead of per box, because it is stated in a contract. Most of the retained SKUs are not planned with the (R,s,S) model, because of contracted rules. Some SKUs under 'retained' are currently planned with the (R,s,S) model, which is shown in Table 3.

Retained Planning	% of SKUs	% Average weekly sales	% Inventory value
(R,s,S)	10,3	33,3	14,5
Other	89,7	66,7	85,5
Total Retained	**100,0**	**100,0**	**100,0**

Table 1: Planning logic retained SKUs

From the interviews can be subtracted that the amount of SKUs with contracted planning actions which can have influence on the way of planning are neglectable. Interviewees give contracted planning actions as reason to not plan retained SKUs on the currently used (R,s,S) model. However, interviewees also state that for most retained SKUs, the planning actions needed can be implemented in the current (R,s,S) planning method. For this reason, retained SKUs can be used in the scope of this thesis.

5.2.3 Own Brand SKUs

OB products can be divided over two main categories: 1) Indirect shipment, so via the CDC located in Zwolle (The Netherlands), or 2) direct shipment to the RDCs. The choice between direct or indirect shipment depends on quantities that need to be shipped.

Own Brand	% of SKUs	% Average weekly sales	% Inventory value
OB direct	58,4	68,7	80,4
OB indirect	41,6	31,3	19,6
Total OB	**100,0**	**100,0**	**100,0**

Table 2: Own brand SKUs

Table 4 shows the amount SKUs in the two OB categories. The indirect item flow of OB SKUs is not considered in this thesis, because it uses multiple echelons. The direct flow of OB SKUs can be used in the scope of this thesis, because these SKUs are single echelon, only with long LT (>20 workdays). Planners still chose to not plan these SKUs on the (R,s,S) model, because long LT SKUs are expected to perform worse than SKUs with shorter LTs on the (R,s,S) model.

5.2.4 Low Value Density SKUs

Low value density SKUs which are not planned with the (R,s,S) model can be divided over two item groups, 1) manual paper, and 2) sealed air. These groups are not planned with the (R,s,S) model, because doing this causes overfull DCs. This can be explained by not using the same EOQ calculation for all SKUs, which uses the holding cost percentage. Table 5 shows the amount of SKUs in the two low value density product groups. For this thesis, keeping the EOQ calculation the same is not a constraint, which means that low value density SKUs can be used in the scope. At this moment, the (R,s,S) model calculates the EOQ based on a holding cost percentage of 25% of the value of each SKU. This percentage is used for all SKUs, while for some SKUs, the costs of storing this SKU might be higher than 25% of its value. When OQs are determined based on this inventory holding costs for all SKUs, the warehouse gets full with low value density SKUs, because of high OQs. When adjusting the holding cost percentage for SKUs which are considered low value density SKUs, these SKUs can also be planned with the (R,s,S) model.

Low value density	% of SKUs	% Average weekly sales	% Inventory value
Manual Paper	71,4	99,8	99,8
Sealed Air	28,6	0,2	0,2
Total Low Value Density	**100,0**	**100,0**	**100,0**

Table 3: Low value density SKUs

5.2.5 Seasonal SKUs

When a SKU is not planned with the (R,s,S) model, without being labeled as retained, OB or low value density SKUs, the only reason left to not plan this SKU on the (R,s,S) model is that planners labeled this SKU as seasonal. When looking at the forecastability class of those SKUs, it can be seen that only 0,5% of the SKUs considered seasonal are labeled easy-to-forecast, while 48,6% is labeled as medium forecastable and 50,9% of those SKUs are hard-to-forecast.

5.2.6 Conclusion RQ2

The final part of this paragraph provides a summarized answer to RQ2. SKUs which are not planned with the current (R,s,S) model, with the reason to not plan on this model, are given in the following enumeration. A more extended answer is given in the prior parts of paragraph 5.2.

RQ2. Which SKUs are not planned with the current inventory control model and why?

1) Retained SKUs, because there can be contracted planning actions which the currently used (R,s,S) model is not able to process.
2) OB SKUs, because planning these SKUs need an inventory control model which allows difficulties like long LTs and multiple echelons.
3) Low value density SKUs, because when the logic of the currently used (R,s,S) model would be followed, the DCs get overfull with low value density SKUs because of high OQs.
4) Seasonal SKUs, because proper forecast methods for seasonal SKUs are not used in the current (R,s,S) model.

5.3 SKUs Not Effectively Planned with (R,s,S) Model

This paragraph states how the performance is measured of all SKUs on the current (R,s,S) model. By determining the performance per SKU in different ways, it can be seen which SKUs are not effectively planned with the (R,s,S) model. This helps to answer RQ3, *'Which SKUs are not effectively planned with the current inventory control model?'*. In the ideal situation, effectively planning means that the TFR is equal to the AFR. Another way of looking at how effective a SKU is planned, is looking at the amount of human intervention. In the ideal situation, no human intervention is needed to correct OQs. Determining the performance regarding to the fill rates is done in part 5.3.1, and determining the performance regarding to the amount of human intervention is done in part 5.3.2.

5.3.1 Targeted vs. Achieved Fill Rates

In this paragraph, the TFRs and AFRs are compared. This shows which SKUs get too much inventory (when the AFR is higher than the TFR) and which SKUs do not achieve the TFR (when the AFR is lower than the TFR). It has to be said that achieving the TFR exactly is almost impossible with fluctuating demand patterns, but looking at average deviations can give useful insights. The historical value of the TFR is saved since June 2018. TFR data is gathered from the 4th of June till the 9th of December of 2018. The AFR is calculated by using the historical values of the weekly total Back Orders [BOs] and total weekly demand per SKU. The total fill rate over the given time period is calculated and compared with the weighted average of the weekly TFR.

Of all SKUs, 71,4% has a higher AFR over the given time period than weighted average of the weekly TFR of the given time period. This means that most of the SKUs achieve a higher fill rate than targeted, so the inventory value is higher. For these SKUs, the average percentage of deviation is 1,33%. The average percentage of deviation when the AFR is higher than the TFR can considered high, when the determination of TFRs wants an overall average unit fill rate of 99,0%. This might be this high because of the rounding. In many cases, rounding OQs causes that the amount of SKUs per OL is higher, which can lead to less stockouts than targeted.

For the other 28,6% of the SKUs, the TFR is not achieved over the given time period. For these SKUs, the average percentage of deviation is 10,13%. The average percentage of deviation is higher for these SKUs than the average percentage of deviation of SKUs with a higher fill rate than targeted, because of a few reasons: 1) it is not possible to reach a higher AFR of 100%, 2) when a big order for a specific SKU is placed, while it is not expected, all these demanded SKUs are backordered and the deviation can get to 100%. Appendix 8 shows that for almost 75% of all SKUs, the AFRs deviates less than 2% of the TFR, which can be explained by the reasons above.

By comparing those values per SKU, the absolute percentage deviation of the TFR and AFR achieved over the given time period can be calculated per SKU. These values in combination with the characteristics of the total assortment (RQ4), gives insights in the performance in terms of fill rates per characteristics. Detailed results of this performance is given in part 5.5 of this thesis.

5.3.2 Human Intervention

In this paragraph, the amount of human intervention per SKU is determined. Human intervention is used in three different ways at Office Depot. The different ways are: 1) adjusting the expected demand during one arbitrary future time period by placing a 'demand adjustment', 2) fill in a hideout quantity in the replenishment system, and 3) not ordering the SOQ by the (R,s,S) model. An explanation and quantification per type of human intervention follows in this paragraph. All tables and figures in this paragraph are based on all SKUs planned with the (R,s,S) model.

5.3.2.1 Demand Adjustments

The first way of human intervention is placing a demand adjustment. A demand adjustment means adjusting the forecasted demand during one arbitrary future period in time, which is input for the current (R,s,S) model. The demand adjustments file is used for this, where a planner can upload the expected demand for one arbitrary future time period, which overrules the forecasted demand. In short, the way of forecasting demand is calculating cleansed average of demand of 13 weeks before. A more detailed explanation can be found in part 5.1 of this thesis. The uploaded value is used in further calculations. The demand adjustment files of all workdays in 2018 till the end of October are gathered and combined into one file. This time period is used, because the historical values of daily demand adjustments are not saved before the first of January 2018. For this reason, the same time period is used for all other types of human intervention. The amount of demand adjustments per workday and per SKU is determined. Out of all human intervention, 64,7% is demand adjustments.

For all SKUs planned with the (R,s,S) model, there are on average 412 OLs placed per workday. When determining the average amount of demand adjustments per workday, outliers had to be removed. The reason for this and how the outliers are removed, can be found in Appendix 9. Without the outliers, the average amount of demand adjustments per workday is 204,0. The amount of demand adjustments per SKU is determined, to determine the amount of human intervention per SKU and use this value as performance meassure. The performance of specific groups of SKUs are explained in detail in part 5.3.3.

5.3.2.2 Hideout Quantities

Hideout quantities are the second form of human intervention. Hideout quantities are quantities which are hidden in the system after entering. When a hideout quantity is active in the replenishment system, an order can be triggered while the actual IP is not below the reorder level. The order is triggered because the IP minus the hideout quantity is below the reorder level. Uploading or updating this quantity counts as one human intervention. Out of all human intervention, 13,1% is hideout quantities. All hideout quantities of the time period 01-01-2018 till 30-10-2018 are gathered. This period is used, because it is the same period as used for the demand adjustments, which means that those values can be combined. The amount of hideout quantities per workday and per SKU are determined.

For all SKUs planned with the (R,s,S) model, there are on average 412 OLs placed per workday. Appendix 10 shows three different figures; 1) the absolute quantity hidden in the system, divided over all SKUs planned with the (R,s,S) model, 2) the percentage of SKUs planned with the (R,s,S) model with a hideout quantity in the system per workday, and 3) the total demand per period over the same period and same SKUs as the hideout quantities. It can be seen that all figures show the same peaks in the same periods of the year. The first two show a peak period which starts just before September, which can be explained by the peak period in demand in September. On average, 41,3 hideout quantities are added per workday.

Hideout quantities are added 9.325 times in 226 workdays, while this form of human intervention is only used for 23,3% of the SKUs planned with the (R,s,S) model. This means that 76,7% of the SKUs planned with the (R,s,S) model never use a hideout quantity. Before the implementation of the (R,s,S) model, there were only two forms of human intervention possible; 1) hideout quantities, and 2) not following the SOQ. Now that the (R,s,S) model is implemented, the amount of hideout quantities for SKUs planned with this system dropped, because using a demand adjustment is the preferred way of human intervention. This explains why for this time period and scope, for 76,7% of all SKUs do not have hideout quantities at all. Hideout quantities are still used for 23,3% of all SKUs planned with the (R,s,S) model, which is higher than expected because demand adjustments are the preferred form of human intervention for SKUs planned with this model. Adding a hideout quantity for a specific SKU can be more useful than using a demand adjustment, when a SKU has a promotion. The amount of promotions per period is showing a stable pattern, while the amount of sales differs per period, with a peak season in September. Appendix 10 shows that most hideout quantities are added because of demand uncertainty, and not because of the amount of promotions. This can be seen because the pattern of hideout quantities per workday follows the demand pattern per workday. This is in line with the qualitative information gathered from interviews.

The amount of hideout quantities per SKU is determined, to determine the total amount of human intervention per SKU and use this value as performance meassure. The performance of specific groups of SKUs is explained in detail in part 5.3.3.

5.3.2.3 SOQ versus AOQ

OQ adjustments are the last form of human intervention. This form of human intervention can be measured by a difference between SOQ and AOQ. When these values differ, the planner decides to not use the SOQ while ordering a specific SKU. Planners are free to do so, because they are responsible for the performance of their SKUs. In this part of the analysis, the AOQ of every OL is checked and compared with the SOQ. The historical size of every OL is stored, and the historical amount of BOs per SKU can be combined with the historical amount of demand and inventory per SKU, to get to the SOQ for every SKU at every workday in history. All information is stored per workday. Out of all human intervention, 22,2% is OQ adjustments.

All OQ adjustments of the time period 01-01-2018 till 30-10-2018 are gathered. This period is used, because it is the same period as used for the demand adjustments and hideout quantities, which means that those values can be combined. The amount of OQ adjustments per workday and per SKU is determined. For all SKUs planned with the (R,s,S) model, there are on average 412 OLs placed per workday. Appendix 11 provides more details in the way of determining when an OQ is adjusted. When determining the average amount of QO adjustments per workday, outliers had to be removed. The reason for this and how it is executed, can be found in Appendix 11. Appendix 11 shows that at 17,0% of the OLs has a different AOQ than the SOQ, which means that on average 70,0 OLs are adjusted per workday. When the OL is adjusted by a planner, in 62,7% of the cases more the AOQ is higher than the SOQ. In 37,3% of all adjusted OLs, the AOQ is less than the SOQ.

The amount of times changing the OQ per SKU is determined, to determine the total amount of human intervention per SKU and use this value as performance meassure. The performance of specific groups of SKUs are explained in detail in part 5.3.3.

5.3.3 Conclusion RQ3

The final part of this paragraph provides a conclusion to RQ 3. Now it is known what the deviation between the TFRs and AFRs per SKU is, and what the amount of human intervention per SKU over a period of ten months is, different groups of SKUs can be compared.

RQ3. Which SKUs are not effectively planned with the current model?

The most striking results are found when looking at the LT classification. SKUs can be considered as long LT SKUs when the quoted LT is higher than 20 workdays, short from 1 to 10 workdays (maximum of two workweeks), and everything between can be considered as medium LT SKUs.

LT Class	% of SKUs	Average deviation TFR<AFR	Average deviation TFR>AFR	SKUs average amount of demand adjustments	SKUs average amount of hideout quantities	SKUs average amount of OQ adjustments	SKUs average total amount of human interventions
Short	74,3	1,34%	9,95%	9,33	0,62	2,20	12,15
Medium	24,1	1,30%	11,08%	13,64	0,82	2,01	16,47
Long	1,6	1,38%	13,46%	14,33	1,06	2,23	17,62
Total	100,0	1,33%	10,13%	9,97	0,65	2,17	12,80

Table 4: Lead time classification performance (R,s,S)

In Table 6 can be seen that on average, long LT SKUs have the most average deviation when the TFR is higher than the AFR, but also when it is the other way around. Furthermore, it can be seen that on average, long LT SKUs have more human intervention per SKU of all human intervention categories.

5.4 Characteristics of Total Assortment in Scope

This paragraph summarizes the characteristics of the total assortment of Office Depot and explains which part is in the scope of this thesis. This answers RQ4, *'What are the characteristics of the total assortment in scope?'*. The first part of this paragraph explains which parts of the total assortment of GOH is in scope. After this, different characteristics of the total assortment in scope follows. The last part of this paragraph provides an answer to RQ4.

5.4.1 Scoped SKUs

The total assortment can be divided over five parts, which is explained in paragraph 1.1.5. The scope of this thesis does not contain SKUs which fall under the indirect flow of OB SKUs. Furthermore, this thesis focusses on mature products only, so SKUs which are e.g. phase-in or phase-out, are all removed. Reactivated SKUs are also removed. Reasons for scoping this way can be found in paragraph 4.1 of this thesis. To get a view on how many percent of the total SKUs stored in GOH fall in the scope of this thesis, SKUs are removed from scope reason by reason, so that overlap is eliminated. First OB indirect is removed from, after which the non-mature SKUs are removed. In Table 7 can be seen what is in- and out of scope.

In/Out Scope SKUs in GOH	% of SKUs	% Average weekly sales	% Inventory value
In scope	63,6	74,3	74,5
Out of scope	36,4	25,7	25,5

Table 5: SKUs in- and out of scope

Percentages in this part of the thesis differ from prior tables, because this paragraph focusses on only scoped SKUs and not all SKUs on the (R,s,S) model. Again, the snapshot of November the 27th of 2018 is used for the inventory value and the average weekly sales value, both in euros.

5.4.2 Planning Method Scoped SKUs

Now that the SKUs which are included in the scope are known, an insight needs to be given how many of these SKUs are planned with the (R,s,S) model. This is provided in Table 8.

Planning method	% of SKUs	% Average weekly sales	% Inventory value
(R,s,S) planned	83,3	71,8	59,5
Other	16,7	28,2	40,5

Table 6: (R,s,S) planned in- and out of scope

Table 8 shows that 83,3% of the SKUs in scope are planned with the (R,s,S) model. As said before, of all SKUs stored in GOH, 71,8% is planned with the (R,s,S) model. The difference can be explained, because most of the mature SKUs are planned with the (R,s,S). With this reason, the relatively high inventory value compared to the percentage of SKUs not planned with the (R,s,S) model can be explained. Furthermore Table 8 shows that although only 16,7 percent is not planned with the (R,s,S) model, the percentage of average weekly sales is 28,2 percent. An explanation for this is that paper is not planned with the (R,s,S) model, but is one of the main businesses for Office Depot. This can also be seen in Table 5. This also explains why the percentages of inventory value are closer to each other than the percentage of SKUs. Another reason for that is that OB SKUs use a safety stock calculation that results in higher safety stock value than for (R,s,S) planned SKUs.

5.4.3 Review Period Scoped SKUs

Table 9 presents the percentage of SKUs, average weekly sales value and inventory value for SKUs planned with specific RP.

RP	% of SKUs	% Average weekly sales	% Inventory value
<5 & not (R,s,S)	0,7	0,2	0,9
2	2,4	7,5	2,6
3	13,5	29,5	23,5
5	76,1	60,6	65,0
6-10	3,2	0,3	1,7
>10	4,1	1,8	6,2

Table 7: SKUs in scope review periods

Table 9 is also shown in Appendix 12, but in Appendix 12, all RPs are given separately. With '<5 & not (R,s,S)' all SKUs with RPs 0, 1 and 4 are given, because only RPs 2, 3 and 5 are an option for RPs in the (R,s,S) model. Table 9 shows that 76,1% of all SKUs have a RP of 5, which means reviewing once a week. This is the highest value in the RP determination process. A high percentage for this RP might be caused by the settings of the RP determination process, because higher values of the RP are not considered. When only looking at (R,s,S) planned SKUs in the scope, 83,1% of the SKUs have a RP of 5.

5.4.4 TFR Scoped SKUs

Table 10 shows that no SKUs have a TFR of 95%, while this is one of the ten options in the TFR determination process. The other nine options are given in Table 10. The category 'other' means that the TFR is not one of the ten options used in the (R,s,S) model. This category includes values of 97,1%, 97,5%, 98,5%, 98,9% and 99,9%, only for SKUs not planned with the (R,s,S) model.

% Targeted fill rate	% of SKUs	% Average weekly sales	% Inventory value
96,0	7,7	2,1	9,2
97,0	0,2	0,1	0,3
98,0	11,8	7,8	11,9
99,0	59,2	20,1	29,2
99,1	6,7	13,4	12,1
99,2	5,6	39,7	24,2
99,3	0,0	0,6	0,3
99,4	5,2	15,1	8,3
99,5	0,8	0,6	2,7
Other	2,8	0,5	1,8

Table 8: SKUs in scope TFRs

The amount of SKUs, the average weekly sales value and inventory value per TFR for all TFRs used, can be found in Appendix 13. It can again be noticed that the biggest amount of SKUs are targeted on the start value of the TFR determination process. The start value is 99,0% and 59,2% of the SKUs use this TFR. This might again be caused by the settings of the solver function. The solver function gives the output after 1800 seconds without improvements. When only looking at (R,s,S) planned SKUs in the scope, a TFR of 99,0% is used for 67,3% of the SKUs.

5.4.5 Lead Time Scoped SKUs

The quoted LT for a SKU varies from 1 to 120 workdays, 49% of all SKUs have 5 workdays LT (one workweek) and the average LT is 10,6 workdays. SKUs can be considered as long LT SKUs when the quoted LT is higher than 20 workdays, short from 1 to 10 workdays (maximum of two workweeks), and everything between can be considered as medium LT SKUs.

LT (workdays)	% of SKUs	% Average weekly sales	% Inventory value
Long (>20)	7,6	16,7	27,2
Medium (11-20)	12,6	19,1	17,8
Short (<10)	79,8	64,2	55,0

Table 9: SKUs in scope lead time classification

Table 11 shows the amount of SKUs in the different LT classes. Most SKUs have a short LT. For 79,8% of all SKUs, there is a short LT, but they cause only 64,2% of the average weekly sales value and 55,0% of the average inventory value. Long LT SKUs are only 7,6% of all SKUs, but cause 27,2% of the total inventory value. This might be explained by the safety stock needed to protect the company from stockouts. The percentage of long LT SKUs is higher than in Table 6, which can be explained by including OB direct SKUs in the scope.

5.4.6 Item Classification Scoped SKUs

In Table 12, the amount of SKUs, the average weekly sales value and the inventory value per importance classification is given. As expected, A-SKUs have around 80% of the average weekly sales value, B-SKUs around 15% and C-SKUs around 5%. Although the most important SKUs are only 14,4% of the SKUs, they cause 60,9% of the inventory value. According to the literature, the most important SKUs should get the most attention (Juran, 1954) (Silver, Pyke, & Peterson, 1998) (Nahmias & Olsen, 2015). Getting more attention should not only mean less stockouts, but getting as close as possible to the TFR, which leads to less inventory value. This is why it might be useful to look at the amount of human intervention per classification. Details of this can be found in part 5.5 of this thesis.

Item class	% of SKUs	% Average weekly sales	% Inventory value
A	14,4	81,3	60,9
B	27,5	14,3	21,0
C	58,1	4,4	18,1

Table 10: SKUs in scope importance classification

Item class	% of SKUs	% Average weekly sales	% Inventory value
X	12,1	55,2	33,9
Y	39,9	33,6	37,3
Z	48,0	11,3	28,8

Table 1312: SKUs in scope forecastability classification

Item class	% of SKUs	% Average weekly sales	% Inventory value
1	80,3	66,3	70,1
2	14,4	20,9	18,2
3	5,3	12,8	11,7

Table 1411: SKUs in scope price classification

Table 13 shows the amount of SKUs, the average weekly sales value and inventory value per forecastability classification. The coefficient of variation over the demand of the last year determines which forecastability classification a SKU gets. It can be seen that only 12,1% of all SKUs in scope are classified as 'easy-to-forecast', but that these SKUs still cause 33,9% of the inventory value. Literature states that forecastability can be tested based on the coefficient of variation when the demand is stationary (Boylan, Syntetos, & Karakostas, 2008), which is almost never the case. Forecastable patterns (e.g. seasonality or trend) can cause a high coefficient of variation, so SKUs are classified as 'hard-to-forecast', while these patterns are forecastable.

Table 14 shows the amount of SKUs, the average weekly sales value and inventory value per price classification. As expected, 1-SKUs have around 80% of the total SKUs, 2-SKUs around 15% and 3-SKUs around 5%. Furthermore, it can be noticed that only 5,3% (classified 3) of the total SKUs cause 11,7% of the total inventory value, which can be explained by the given that these SKUs are the most expensive SKUs. The total amount of SKUs and the average weekly sales value and inventory value per classification used (combination importance, forecastability and price) can be found in Appendix 14.

5.4.7 Conclusion RQ4

The final part of this paragraph provides a conclusion to RQ4. This is a summary, a more extended answer is given in the prior parts of paragraph 5.4.

RQ4. What are the characteristics of the total assortment in scope?

Of all SKUs stored in GOH, 63,6% is in the scope of this thesis. Most of the SKUs which are not in scope are SKUs which are not mature, for example dead stock, phase in- and phase out SKUs or reactivated SKUs. Other SKUs which are not taken into the scope of this thesis are the OB indirect SKUs, because multiple echelons are used. When looking at the scope of this thesis, 83,3% of the SKUs are planned with the (R,s,S) model. Of all SKUs in scope, 76,1% has a RP of 5 and 59,2% has a TFR of 99,0%. A RP of 5 is the maximum value in the RP determination for (R,s,S) planned SKUs and a TFR of 99,0% is the starting value of the TFR determination. When only looking at (R,s,S) planned SKUs in scope, these values are relatively 83,1% and 67,3%. The LT for a SKU varies from 1 to 120 workdays, 49% of all SKUs have 5 workdays LT (one workweek) and the average LT is 10,6 workdays. These are the results from the analyses of the characteristics of the total assortment of Office Depot in scope of this thesis, more can be found in the other parts of paragraph 5.4.

5.5 Characteristics of SKUs Not- or Not Effectively Planned with (R,s,S)

This paragraph summarizes the characteristics of SKUs which are not- or not effectively planned with the currently used (R,s,S) inventory control model. This answers RQ5, *'What are the characteristics of the SKUs that are not – or not effectively managed in the current inventory control model?'*. First, the performance per SKU classification is determined. After this, the performance per LT classification is determined. Furthermore, a split is made between seasonal and non-seasonal SKUs to compare the performance of these two groups. At the end of this paragraph, an answer to RQ5 is presented.

5.5.1 Performance per Item Classification

In part 5.4 of this thesis, the conclusion is drawn that only 12,9% of the SKUs, the most important SKUs, cause more than 50% of the current inventory value. Literature states that A-class SKUs need to be watched closely (Juran, 1954) (Silver, Pyke, & Peterson, 1998) (Nahmias & Olsen, 2015). This is why the amount of human intervention per importance class is shown in Table 15. The amount of human intervention per SKU for every SKU in the (R,s,S) model is determined in part 5.3.2 of this study, to determine the performance of the (R,s,S) model.

Importance class	% of SKUs	% Average weekly sales	% Inventory value	Human intervention per SKU (over 10 months)	% of Human intervention
A	14,4	81,3%	60,9%	18,45	23,6
B	27,5	14,3%	21,0%	13,37	32,6
C	58,1	4,4%	18,1%	8,51	43,8
Total	100,0	100,0%	100,0%	11,28	100,0

Table 13: Amount of human intervention per importance classification

The amount of human intervention per SKU is higher for more important SKUs. On average, 11,28 human intervention over the first 10 months of 2018 per SKU are performed, where the average for the class A SKUs is 18,45. The amount of human intervention per SKU for class C SKUs is still 8,51. Literature states that it might not be valuable to put effort in human intervention for the least important SKUs (Silver, Pyke, & Peterson, 1998).

Literature also states that it might not be valuable to put effort in human intervention for the least forecastable SKUs, because these SKUs show an inexplicable pattern (Van Donselaar & Broekmeulen, 2015). Inexplicable patterns are all patterns caused by unpredictable activities, so all patterns except from a seasonality or trends. This is why the amount of human intervention per forecastability classification are shown in Table 16.

Forecastability class	% of SKUs	% Average weekly sales	% Inventory value	Human intervention per SKU (over 10 months)	% of Human intervention
X	12,1	55,2%	33,9%	17,55	18,8
Y	39,9	33,6%	37,3%	13,41	47,5
Z	48,0	11,3%	28,8%	7,92	33,7
Total	100,0	100,0%	100,0%	11,28	100,0

Table 14: Amount of human intervention per forecastability classification

On average, 11,28 human intervention over the first 10 months of 2018 per SKU are performed, where the average for the class X-SKUs is 17,55. The amount of human intervention per SKU for Z-SKUs is still 7,92. Because of the amount of human intervention, it is expected that the performance regarding the fill rate might be better for class A products. The exact numbers can be found in Table 17.

Importance class	Absolute deviation % Achieved Fill Rate 2018 vs Weighted Average of TFR
A	2,1
B	2,9
C	4,9
Total	3,9

Table 15: Absolute deviation percentage fill rates per importance classification

Table 17 shows that on average, the worst performing SKUs are the least important SKUs. This means that the important SKUs are performing better than the average SKU, which is a good thing and can mean the human intervention for A class SKUs is useful. Human intervention is done by the planners. The main target of the planners is achieving the TFR. This is why in Table 17, the amount of times that the AFR is higher than the TFR is compared with the other way around for the importance classification.

Importance class	% of SKUs	% Average weekly sales	% Inventory value	% SKUs with AFR > TFR	% SKUs with TFR > AFR
A	14,4	81,3%	60,9%	69,4	30,6
B	27,5	14,3%	21,0%	69,7	30,3
C	58,1	4,4%	18,1%	72,5	27,5
Total	100,0	100,0%	100,0%	71,3	28,7

Table 16: Targeted- or achieved fill rate higher, per importance classification

In Table 18 can be seen that on average, in 71,3% of the cases, the AFR is higher than targeted. The more important SKUs are, on average, the bigger the percentage of times that the TFR is higher than the AFR.

5.5.2 Performance per Lead Time Classification

The current (R,s,S) model uses the forecasted daily demand for an arbitrary future time period as input to calculate the expected demand over a longer period. This means that a stationary future demand pattern is expected, but it is explained above, that there is no stationary demand pattern. This indicates that the performance of SKUs with a long LT (>20 workdays) perform worse than SKUs with a short LT. Table 19 shows that this is true for the LT classification used by Office Depot.

Lead Time Class (workdays)	Absolute deviation % Achieved Fill Rate 2018 vs Weighted Average of TFR
Long (>20)	5,41
Medium (11-20)	4,31
Short (<10)	3,73
Total	3,93

Table 17: Absolute deviation percentage fill rates per lead time classification

Table 20 shows the amount of human intervention per LT classification, which can be used to check whether there are more human intervention per SKU for the long LT classification. This can be expected because these SKUs show the worst performance of all LT classes regarding to the deviation of the fill rate. Furthermore, more demand adjustments can be expected for SKUs with a long LT, because the demand during LT is determined by the input of the expected demand for one future time period.

LT class (workdays)	% of SKUs	% of human intervention	Average human intervention per SKU	% of demand adjustments	Average demand adjustments per SKU
Long	7,6	2,8	4,12	1,6	2,07
Medium	12,6	17,5	15,72	18,0	14,30
Short	79,8	79,7	11,26	80,4	10,08
Total	100,0	100,0	11,28	100,0	10,01

Table 18: Amount of human intervention per lead time classification

Table 20 shows that the amount of human intervention is the largest for medium LT classified SKUs and the least amount of human intervention are used for long LT SKUs, for which even less demand adjustments per SKU were needed.

5.5.3 Performance for Seasonality

In the last part of this paragraph, the forecastability classification is checked. The forecastability classification is based on a coefficient of variation, but without removing forecastable patterns, like seasonality or trend. These patterns can be forecasted, but when determining the coefficient of variation without removing these forecastable patterns, the coefficient of variation can still be high. This is why it is checked whether a forecastable pattern can be found at first sight by looking at the total weekly demand pattern of the scoped SKUs, from the first week of 2016 till the 44th week of 2018.

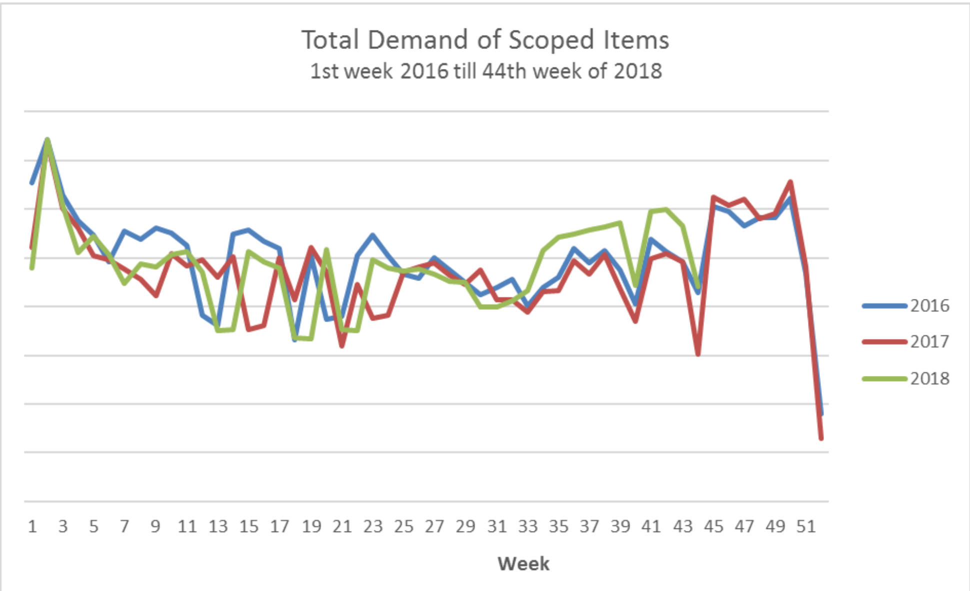

Figure 5: Total demand of scoped SKUs

A seasonal pattern can be suspected when looking at Figure 5, which shows the total demand of GOH stored SKUs in different years. In the last weeks of a year, the demand drops, because most customers are closed. Customers did not order, or did order less, in these weeks. This explains that the demand goes up in the first weeks of the year.

The next step is to find which SKUs can be considered seasonal and what the performance of these SKUs is, compared to less seasonal SKUs. This can be done by finding the index for one week of demand per product group of scoped demand, which is calculated for every week of the year. Because of having only two full years of data at the date of determining the indices, a higher aggregation level is needed. This is why the seasonal indices per product group are determined instead of per SKU. A product group can for example be 'paper' or 'cold drinks'.

Determining an index for one week per product group is done with the following logic: First, the average sales per week for the two full years of data (2016 and 2017) is determined. When there is no demand for a full year, or the SKU was not in assortment in all weeks of 2016 or 2017, the SKUs cannot be considered. In total, 63,7% of all SKUs can be used in this calculation. These SKUs are divided over 193 product groups, out of the 204 product groups that are active at Office Depot. By dividing the sales of a specific week in a specific year by the average weekly sales of that specific year, the index of that week in that specific year is calculated for a SKU. Averaging the index per SKU per week of the two years apart provides the usable index for a SKU in a specific week. Averaging the indices per SKU of all SKUs in a specific product group in one specific week gives the usable index for a product group for that given week. Applying this logic makes sure that all SKUs within one product group are equally weighted. The average indices of all product groups also shows a seasonal pattern, which can be seen in the Figure 6.

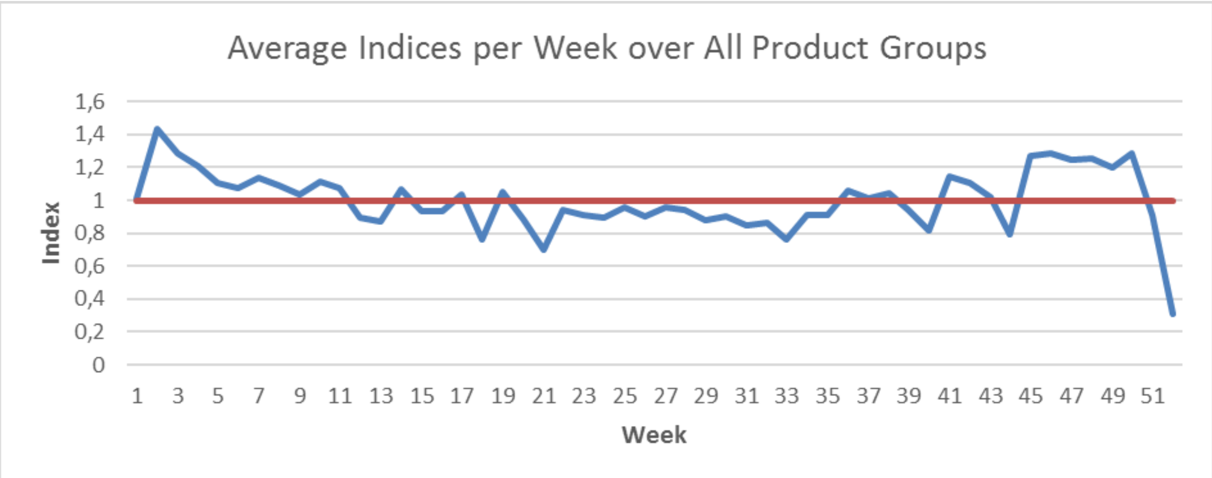

Figure 6: Average indices per week over all product groups

Now that is known that there is a seasonal pattern, product groups which cause seasonality can be identified. The average indices per week of all product groups are known, and peak periods can be seen in the second and third week of every year, and the 45th till the 50th weeks. The average index of all product groups of these weeks is 1,25. To figure out whether or not seasonality is an issue, the researcher considered all product groups with an average index of this same period above 1,25 as seasonal, and all other product groups as not seasonal. Of the product groups left in scope, 66,7% is considered not seasonal and 33,3% is considered seasonal.

These two groups can be compared based on the average percentage of deviation of the TFR and AFR. The total average deviation is presented in Table 21, but is also split into 1) when the average percentage deviation when the TFR is higher than the AFR, and 2) when the average percentage deviation when the TFR is smaller than the AFR.

	Total average % of deviation				Average % of deviation when TFR > AFR			Average % of deviation when AFR > TFR		
Lead Time	**Long**	**Medium**	**Short**	**Total**	**Long**	**Medium**	**Short**	**Long**	**Medium**	**Short**
Not Seasonal	3,7	3,7	2,7	2,9	8,9	9,7	6,0	1,9	1,6	1,4
Seasonal	4,5	2,1	3,7	3,4	10,5	5,7	8,6	2,3	1,0	1,2

Table 19: Seasonal vs. not-seasonal

In Table 21 can be seen that on average, the performance based on the average percentage of deviation between the TFR and AFR is worse for seasonal SKUs, in specific seasonal SKUs with a long LT.

5.5.4 Conclusion RQ5

The final part of this paragraph provides a conclusion to RQ5.

> **RQ5.** What are the characteristics of the SKUs that are not – or not effectively managed in the current inventory control model?

The answer to RQ2 shows that the characteristics of the SKUs which are not managed in the (R,s,S) model are the following: 1) retained SKUs, 2) OB SKUs, 3) low value density SKUs, and 4) seasonal SKUs. The answer to RQ3 shows that the characteristics of the SKUs which are not effectively managed in the (R,s,S) model SKUs with a long LT. This is shown again in the prior part of paragraph 5.5. Furthermore, this paragraph explains that seasonal SKUs also show a performance which is not as good as non-seasonal SKUs.

5.6 Categorizing Inventory

This paragraph provides an advice on how to categorize the current inventory. The current item classification is used to determine the TFR, which means that indirect item classification is also used to determine the reorder level. It is also used to determine the RP, which means that indirect item classification might be used to determine the optimal OQ, which is the maximum of the demand during RP and the EOQ. In other words: Categorizing SKUs is important in the current (R,s,S) model. Based on this categorization, SKUs can be more efficiently planned.

The current item classification is based on three characteristics; 1) the importance, 2) the forecastability, and 3) purchase price (in euros) per SKU. In the first part of this chapter, the different ways of categorizing SKUs is given and related to literature. The coming paragraphs relate the way of categorizing used to the way of categorizing advised by literature. The last paragraph is a summarized answer to RQ6, *'What is an effective way of categorizing the inventory?'*.

5.6.1 Importance Classification

Literature states that the main reason of carrying out item classification is to determine the level of attention that different SKUs deserve (Lolli, Ishizaka, Gamberini, Balugani, & Rimini, 2017). The inventory control model can be determined per item classification when looking at the importance (Silver, Pyke, & Peterson, 1998). Office Depot wants the (R,s,S) planning technique for every SKU, independent of the item classification. Silver, Pyke and Peterson (1998) state that the (R,s,S) model is a model which uses a lot of labor, and is used a lot for the most important SKUs, while the least important

SKUs can for example use an (R,S) or an (s,Q) model, which need less labor. Literature also states that nowadays the computational time is faster than it used to be, so more SKUs can be planned as important or of medium importance, or in a more labor intense way (Silver, Pyke, & Peterson, 1998).

When the firm wants to determine the level of attention that different inventory SKUs deserve, this determination is executed based on importance. According to literature, there are many different ways of determining the importance of a SKU. One of the ways is called the A-B-C classification, which means focusing on the ‘critical few’ (A-SKUs) instead of the ‘trivial many’ (C-SKUs) (Juran, 1954). Silver, Pyke and Peterson (1998) use the percentage of total annual dollar usage to classify SKUs, which is comparable with the way of working of Office Depot. Office Depot uses the average weekly sales value (over the last year) of a specific SKU. According to literature, this is the most commonly used inventory classification based on importance (Silver, Pyke, & Peterson, 1998) (Nahmias & Olsen, 2015). The critical few can get more attention by using another replenishment method, but also by tracking these SKUs more often, which happens at Office Depot. Office Depot uses the average weekly sales value (over one year). Literature also states that an ABC analysis can be executed by a multi-criteria approach by considering more SKU characteristic (Zhang, Zhao, & Li, 2017) (Millstein, Yang, & Li, 2013). Flores and Whybark (1986;1987) started with developing a multi-criteria ABC analysis, annual dollar usage, but also criticality. Other characteristics are identified as important in management of maintenance inventories, these are: 1) obsolescence, 2) LT, 3) availability, and 4) substitutability (Flores, Olsen, & Dorai, 1992) (Ramanathan, 2006). Office Depot is known with the fact that more effective planning is possible when these product characteristics are known, but determining unique item keys is done in different ways in the history of Office Depot, which makes it hard to find data about most of these characteristics.

5.6.2 Forecastability Classification

As stated above, the main reason of carrying out item classification is to determine the level of attention that different SKUs deserve. According to (Lolli, Ishizaka, Gamberini, Balugani, & Rimini, 2017), forecasting, inventory control and inventory classification represent strictly interrelated fields of research. This, because when dealing with a huge amount of SKUs, firms are often interested in grouping them with the aim of simplifying the management regarding to inventory control and forecasting. Each class is managed by means of either the same inventory control system or the same forecasting technique. Office Depot also categorizes inventory based on its forecastability, which is a commonly used method when management wants to categorize inventory with the aim of simplifying the forecasting method (Lolli, Ishizaka, Gamberini, Balugani, & Rimini, 2017). This is not the aim of the forecastability categorization at Office Depot. At Office Depot, the advice is given to planners to not put effort in unforecastable SKUs and the forecastability classification is used as one of the three different classifications to make the TFRs and RP different from other classes. The forecastability analysis lead to three different classes; 1) easily forecastable SKUs, 2) medium forecastable SKUs, and 3) SKUs which are hard to forecast. This method can be used to determine whether SKUs are forecastable, but only under stationary demand (Nahmias & Olsen, 2015). Demand at Office Depot is not stationary. Deviations from a stationary pattern can be forecasted, but the current method considers all deviations from the average as unforecastable. When deviation from the average shows a pattern, for example trend or seasonality, the deviation might also be forecastable (Nahmias & Olsen, 2015). Forecastable patterns can be taken out of the demand pattern, after which the coefficient of variation can be used to determine whether a SKU is forecastable or not.

Literature states that firms are often interested in grouping SKUs with the aim of simplifying the forecasting (Lolli, Ishizaka, Gamberini, Balugani, & Rimini, 2017). It might for example be the case that for a specific group of SKUs the sales always increase from the start of September, or sales always decrease at the end of December. Reason for this is the increase in workload at customers after summer holidays, or the workload at customers decreases at the end of the year. It might also be the case that sales of products increase or decrease when temperature is increasing or decreasing. When for a specific event, all SKUs are in one item classification, it might be easier to intervene when a triggering event happens. Forecasting methods based on item classification might also be useful to implement. The current (R,s,S) model does not effectively deal with long LT SKUs, which can be explained when looking at how demand during LT and demand during RP are defined. The demand during LT or RP is calculated by first calculating the expected demand during one arbitrary time period in the future, then extending this to the demand during multiple time periods. How these calculations work, can be found in paragraph 5.1. The expected demand during one arbitrary period in time is calculated by a forecasting method, which is the same for all SKUs. This way of calculating the demand during multiple periods is useful when demand is stationary, which is often not the case.

5.6.3 Price Classification

The last type of item classification executed by Office Depot is based on the item purchase price. This classification is in use with as main reason that cheap SKUs with a high sales volume might end up in the same class as expensive SKUs with a lower sales volume, when only considering the importance classification. This is a useful addition to the importance classification, because unless that Office Depots' importance classification is commonly used, other literature states that it might be valuable to only look at the amount of units sold instead of the value (Silver, Pyke, & Thomas, 2017). With also using the price classification, it is avoided that cheap SKUs with a high sales volume are handled the same as expensive SKUs with a lower sales volume.

5.6.4 Conclusion RQ6

The final part of this paragraph provides a conclusion to RQ6. This is answered per type of classification.

RQ6. What is an effective way of categorizing the inventory?

An importance classification is the most used way of classifying SKUs. The advantage of doing this, is that more effort can be put into the SKUs which are considered to be the critical few, instead of focusing on the trivial many. The way that the importance classification is determined at Office Depot, is effective and commonly used. The addition of the price classification is useful to avoid that cheap SKUs with a high sales volume are always handled the same as expensive SKUs with a lower sales volume. Another commonly used and more modern method of determining the importance of SKUs, is a multi-criteria classification, which means that the importance is based on more product characteristics than only the average weekly sales value. Data about these other characteristics is hard to gather at Office Depot, which is why this thesis does not focus on a multi-criteria importance classification.

A forecastability classification is also commonly used. Determining the coefficient of variation is an often used method when demand shows a stationary pattern, or demand can be converted to a stationary pattern. At Office Depot, demand is not stationary and it is not tried to convert the demand pattern to a stationary pattern, which is a possible improvement for the company. The advantage of classifying based on forecastability is that for unforecastable SKUs can use a simple forecasting method, while forecastable SKUs can use a more complex one. Furthermore, human intervention works counterproductive in most cases for unforecastable SKUs. This means that no effort has to be put into unforecastable SKUs, and more effort can be put into forecastable SKUs. More complicated forecasting methods can be considered for SKUs which are classified as forecastable. This advantage can be used by Office Depot, when correction for forecastable patterns is executed.

6. Design

In this chapter, possible improvements are presented after which a design is made for the chosen topics. This corresponds to stage 3 of the regulative cycle of Van Strien (1997). In the first part of this chapter, all possible improvements which follow from the analysis are presented. The end of paragraph 6.1 gives an overview of the possible improvements. For every possible improvement is explained why or why not to focus on this possible improvement in the remaining part of this thesis. A method on how to continue this possible improvement follows in part 6.2.

6.1 Scope of the Design Phase

In this part of the chapter, all possible improvements are presented. After all topics are given, a priority list to rank the importance follows. The importance is based on how many SKUs are influenced by these topics, what the average weekly sales values are, what the inventory values of these SKUs are, and what the expected impact of a change in this topic is.

6.1.1 Expected Demand During One Future Arbitrary Time Period

Despite of using the expected LT and its variability in all calculations, the performance of long LT SKUs is still worse than the performance of SKUs with an average- or short LT. According to interviews, this is the reason to not plan direct OB SKUs on the (R,s,S) model, but part 5.5 of this thesis also shows that SKUs which are planned with the (R,s,S) model and are in the long LT classification (>20 workdays) have the worst average performance of all LT classes. The bad performance of long LT SKUs can be explained by the way of forecasting future demand. The forecasting method is taking the average of weekly demand of the last 13 weeks, cleansed at two-sigma. Dividing the outcome by five (workdays) gives the *expected demand during one future arbitrary time period*, which is the input value for the (R,s,S) model. Using this forecasting method and the way of determining the demand during LT and RP, means that a stationary demand pattern is assumed. In part 5.5 of this thesis is shown that the total demand is not stationary, which is particularly caused by one-third of all product groups. The average performance of SKUs in the seasonal product groups is worse than the average performance of SKUs in the other product groups. Seasonality is also a reason to not plan SKUs on the current (R,s,S) model.

Future demand can be forecasted more precise by taking forecastable patterns like seasonality and trend into consideration. When forecastable patterns are taken into consideration, a better forecast of the expected demand during LT and RP can be made. Using this as input instead of expected demand during one future arbitrary time period for forecastable SKUs is an improvement for the model. When the forecasted demand is improved, long LT SKUs (e.g. OB direct SKUs) and seasonal SKUs probably perform better on the (R,s,S) model. For unforecastable SKUs, taking the cleansed average of the last 13 weeks might be a better forecasting method. Note the current forecastability classification is not considering forecastable patterns, so the forecastability classification needs to be adjusted.

Finding out for which SKUs it might be valuable to use a different forecasting method, and finding the optimal forecasting method for these SKUs, is a project which requires and deserves more time than available for this project, which is why it is decided not to focus on this potential improvement.

6.1.2 Amount of Human intervention

For all SKUs planned with the (R,s,S) model, there are on average 412 OLs placed per workday. On average 204,0 demand adjustments, 41,3 hideout quantities and 70,04 OQ adjustments are added per workday. It can be said that the amount of human intervention is high. It might be the case that this amount of effort spend on intervening in the replenishment process is not needed. This is why the supervisors and the writer of this thesis want to know what the impact of all these human interventions is. It is decided to focus on this potential improvement, to find out whether intervening the system is useful at all, and for which SKUs it might be the most valuable to do which kind of human intervention.

6.1.3 Low Value Density SKUs

The current (R,s,S) model works with the same order costs and holding cost percentage for all SKUs, but when the holding costs are determined based on the value of a product, and the value density is low, the optimal OQ (when following the rules used at this moment) is high. In part 5.2 of this thesis can be found that the amount of SKUs not planned with the (R,s,S) model, based on low value density, is not high. However, the percentage of average weekly sales and inventory value caused by these SKUs are high. This is why it is chosen to focus on this potential improvement.

6.1.4 Reorder Level Determination

The reorder levels are determined based on the optimal OQ $S\text{-}s+E[U]$, which is the maximum of the demand during RP and the EOQ, plus the undershoot. Rounding the OQ happens for 82,1% of all (R,s,S) planned SKUs stored in GOH, but the reorder levels are based on the unrounded OQs. As explained in part 5.1 of this thesis, 34,3% of the AOQ is more than 25% deviating from the SOQ because of the two types of rounding. Finding a way to determine the reorder levels which takes the rounding into account is an improvement for the current (R,s,S) model, because at this moment safety stock is kept based on the reorder levels calculated with unrounded OQs. The AOQs are rounded, which can be seen as extra safety stock. Calculating reorder levels might cause a decrease in average inventory value. Because of the high amount of SKUs for which OQs are rounded and the potential decrease in inventory, it is decided to focus on this potential improvement, and look at how the right reorder levels can be calculated with rounded OQs.

6.1.5 Review Period & Targeted Fill Rate Determination

When looking at the characteristics of the total assortment, it can be seen that most SKUs have a RP of 5 and a TFR of 99,0%. A RP of 5 is the maximum value in the RP determination for (R,s,S) planned SKUs and a TFR of 99,0% is the starting value of the TFR determination. It might be cost efficient to not review groups of SKUs at least every week. It might also be the case that the solver for the TFR determination needs other settings and a longer running time. Because this potential improvement can easily be tested and has impact on the outcomes of the (R,s,S) model, it is decided to focus on this potential improvement. More RPs are used as options and settings of the solver of the TFR determination is changed.

6.1.6 Retained SKUs

Retained SKUs are not planned with the (R,s,S) model, because these SKUs can have contracted planning actions. For 33,3% of all SKUs not planned with the current (R,s,S) model, SKUs are marked as retained SKUs. The contracted planning actions can be used in a (R,s,S) model, so this does not have to be a reason for not planning on the current (R,s,S) model. Contracted planning actions can be used as constraint in the replenishment system, so the (R,s,S) logic can still be used. This means that no improvement is needed for these SKUs. A next step can be checking all the contracts to see which of the retained SKUs do have contracted planning actions, after which the different types of contracted planning actions can be determined to see which constraint is needed. This is a time consuming activity, but after doing this, all SKUs without contracted planning activities can start using the (R,s,S) model. For SKUs with contracted planning actions, the follow up is to add the constraints to the (R,s,S) model, after which these SKUs can also start using the (R,s,S) model. Checking all contracts is a time consuming activity, which is why the supervisors and the writer of this thesis chose not to focus on this potential improvement.

6.1.7 Summary

With the information elaborated in the paragraphs above, Table 22 is created with all topics, sorted by importance. Per topic is stated on which percentage of the SKUs this might have an impact, for all SKUs planned with the (R,s,S) model and SKUs not planned with the (R,s,S) model. The expected impact of improvement is presented, the rank of the topic (based on importance) and whether this topic is in scope in the remaining part of the design phase. The weekly average sales value and inventory value of these SKUs are also used in determining the importance. Importance is determined with the help of the Senior Manager Demand Planning & Inventory Management. Importance rank 1 is the most important, while importance rank 6 is the least important.

Topic name	% SKUs influenced (not on (R,s,S) model)	% SKUs influenced (on (R,s,S) model)	Expected impact of improvement	Ranking on importance	Scoped yes/no?
Forecasting and way of using	65,9	Not known*	High	1	**No**
Determination RP & TFR	Not known	100,0	Average	2	**Yes**
Human intervention	Not known	93,0	Average	3	**Yes**
Reorder levels with rounding	0,0	82,1	Average	4	**Yes**
Low value density SKUs	0,1	Not known**	Average	5	**Yes**
Retained SKUs	33,3	0,0	Low	6	**No**

** = Total demand is showing a seasonal pattern, so probably impacts a big part of the SKUs*

*** = Making a redesign by changing inventory holding costs can also influence SKUs already planned with the (R,s,S) model*

Table 20: Summary (re)design topics

6.2 Plan for Improvement

In chapter 6.1, the scope of the design phase is explained. There are four topics for which a (re)design is made to come up with an improved inventory control model. All topics within the scope are explained in the subparagraphs below.

6.2.1 Determination Review Period and Targeted Fill Rate

In this part of the thesis is discussed what happens if a RP above 5 is allowed, and what happens when the solver of the TFR determination runs until the optimal solution is found. This process of the RP and TFR determination consists of three steps, which can be found in part 5.1.3 of this thesis. The RP is determined per subvendor. Part 5.4 of this thesis states that the RPs for almost all subvendors is 5. This can be the case because the optimal RP is higher, while this is not an option in the RP determination. It might be valuable to look at higher RPs. RPs above five have to be a multiple of five, because otherwise fixed order- and delivery dates cannot be followed. This is why three extra options are added to the determination process: Reviewing once every two weeks (RP = 10), once every three weeks (RP = 15) and once every four weeks (RP = 20). A longer RP is not considered for the simple reason that in practice too many things change in a month.

An evolutionary solver is used to determine the TFR. When there is no improvement in 1800 seconds of calculations, the solver stops running and the output is used. The computer on which the solver runs, is not used for 30 minutes. In most cases, the solver found the output already. When it did not, the solver function is stopped and the output is used. In the redesign, other settings are used to find the TFR. It is tested what the difference is when not setting a time limit without improvements, and whether more than 30 minutes is needed to find the optimum of the solver. This is tested for two cycles.

6.2.2 Total Human Intervention Needed

The performance of the (R,s,S) model without human intervention is simulated for all SKUs in scope. A simulation tool is created, to analyze how the replenishment system would perform in the year 2018, when there was no human intervention at all and when all scoped SKUs followed the logic of the (R,s,S) model. Based on how the current (R,s,S) model works and the daily demand data of all SKUs in scope from week 40 of 2017 till the last week of 2018, a simulation is made for the IP, IOH, placed orders and inbound orders of every workday in 2018. Based on this information, the expected annual costs and AFRs are calculated. When the performance of the (R,s,S) model without any kind of human intervention is known, types of human intervention can be added in this tool, and the performance of this system with intervention can be compared with the performance of the system without intervention. Furthermore, from this tool can be analyzed what the effect of human intervention per classification is. In this way can be checked whether it was useful to do human intervention for unforecastable SKUs and the least important SKUs.

In part 5.3 of this thesis can be found that there are three types of human intervention. Demand adjustments and hideout quantities can be added into the tool, because the historical data of the date of setting, the date of removing, and the quantity used per intervention are all known. The third type of human intervention is not following the SOQ. This type of human intervention cannot be tested with this simulation tool, because the SOQ of the simulation can differ from the historical SOQ, which is not stored by Office Depot. This means that the SOQ of a clean dataset cannot be compared with the AOQ.

6.2.3 Reorder Level with Rounded Order Quantities

In this part of the thesis, a plan is stated to find the impact of adding the OQ rounding to the reorder level calculations in the currently used (R,s,S) model. This means that the reorder levels are calculated based on the real OQ, instead of the calculated optimal OQ. It is checked what the effect of rounding is on the reorder levels and the expected annual costs, while the (R,s,S) replenishment logic with the current way of determining the reorder levels, based on literature of (Viswanathan, 1997), is still used. This is done with a simple heuristic, which is using the AOQ (rounded for 82,1% of all SKUs) in determining the calculated expected fill rate instead of the calculated optimal OQ $S\text{-}s+E[U]$. The reorder levels calculated this way are compared to the reorder levels calculated in the DoBr-tool (Van Donselaar & Broekmeulen, 2019). This tool contains exact calculations for reorder levels, based on the used TFR, for SKUs when the quoted LT, RP, average demand per period, standard deviation of demand per period, IOQ, MOQ and TFRs are known.

6.2.4 Low Value Density SKUs

In the current (R,s,S) model, the inventory holding cost percentage is 25% for every SKU. When OQs of low value density SKUs are determined by the (R,s,S) model, it looks cost efficient for the model to place large OQs, while it uses a lot of pallet locations. This means that inventory holding costs used in the EOQ calculation should be higher for low value density SKUs. With the dimensions of all standard packs of every SKU, the units per standard pack, the purchase price per SKU and the dimensions of pallet locations, the value density of all SKUs can be determined. Product groups which contain low value density SKUs is searched for, and the holding cost percentage is changed. These product groups are determined based on the value density in combination with the percentage of the total amount of pallet locations used by specific SKUs. The changed holding cost percentage is determined based on the percentage of pallet locations used by the SKUs considered to be low value density SKUs. A detailed plan in how to the determine the new holding cost percentage and for which SKUs, follows in paragraph 7.4 of this thesis.

7. Results

In this part of the thesis, the results are presented. This corresponds to the first part of stage 4 of the regulative cycle of Van Strien (1997). At first, the results per topic are presented. After this, all remaining RQs are answered.

7.1 Determination Review Period and Targeted Fill Rate

The determination of the TFRs runs with the determined RPs following from the cycle update of 08-12-2018, which means $R \leq 5$ when SKUs are planned with the (R,s,S) model. How the determination runs, is explained in paragraph 5.1. The solver is still evolutionary, because this heuristic is asked for by the management of the Supply Chain Optimization Team. There is no time limit set for time without improvement, and after every time period of 5 minutes is checked whether the optimal TFRs are found. The optimization is not stopped after 30 minutes. Less than five minutes was needed to find the optimal TFRs for the cycle update of 08-12-2018 and there was no difference from the results with the maximum time without improvements. One more cycle update is tested, which is the cycle update of 4 weeks before (09-11-2018). Again, the new settings were used, less than 5 minutes were needed and there was no improvement.

As it might be cost efficient to not review a SKU at least every week, RPs of 10, 15 and 20 are added to the RP determination process. RP = 1 is also added as an option. In Figure 7, two charts can be found, where the percentage of SKUs and subvendors with a specific RPs are given. These RPs are the optimal RPs before the three new options were added to the process. When also considering the new RP options for the cycle update on the 8th of December of 2018, only 35,9% of all subvendors still have a RP of 5 after. This can be seen in Figure 8. These subvendors still have 65% of all SKUs. The determination method explained in paragraph 5.1 is applied for the execution of this chapter.

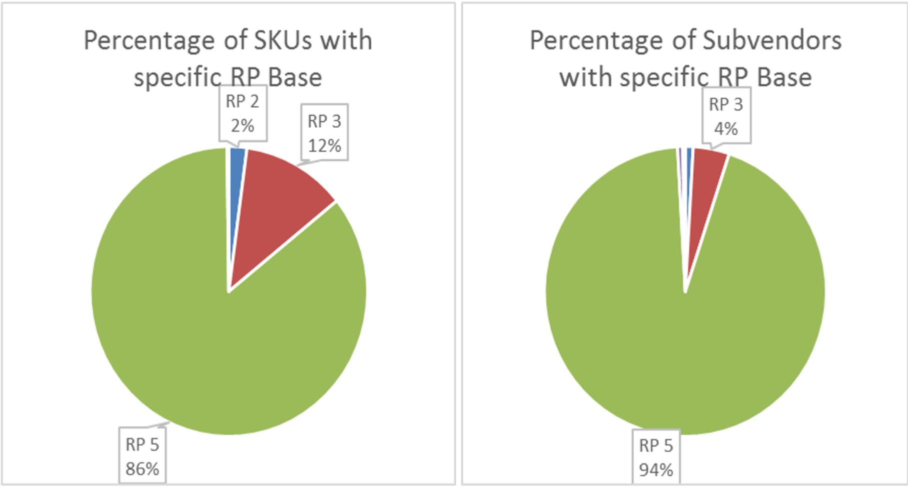

Figure 7: Percentage of SKUs / subvendors per review period

When using the new RPs per subvendor in the (R,s,S) model, it causes a reduction of 1,41% in expected annual OLs, while the expected average inventory value over a year only increases with 0,01%. In total there is 0,34% reduction of the expected annual costs. The equation used for the expected annual costs can be found in part 5.1 of this thesis. When the determination for the TFR was running with the new optimal RPs, again less than 5 minutes were needed to find the optimum. Given this, it can be concluded that it is valuable to add R=10, R=15 and R=20 as options for the RP and that running the determination for the TFRs for the maximum time of 30 minutes is probably enough to get the optimal output from the solver, and a maximum of 1800 seconds without improvement gives the same value as running till the optimum is found.

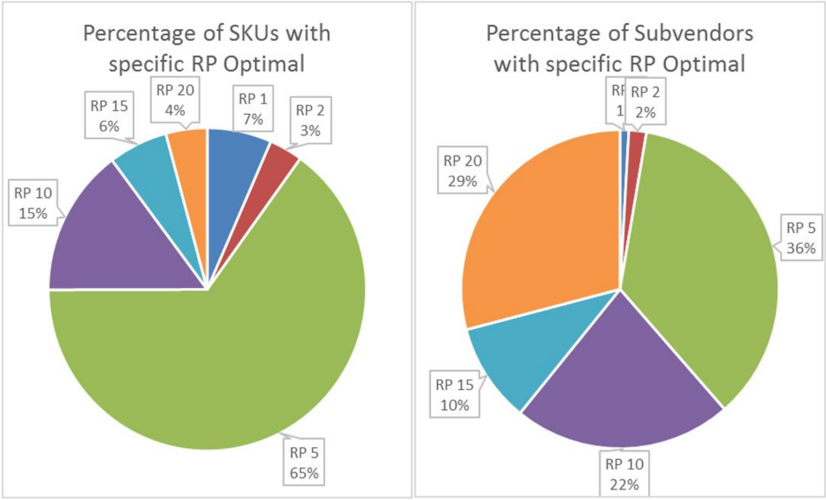

Figure 8: Percentage of SKUs / subvendors per review period (new)

7.2 Total Human Intervention Needed

At this moment, three ways of human intervention are possible at Office Depot. In this part of the thesis, a simulation model is used to check how the system would perform without any form of human intervention. This is considered the baseline performance, to which the performance of the human intervention is benchmarked. Two out of three types of human intervention are added to the simulations, which are: 1) Demand adjustments, and 2) hideout quantities. An overview is given in Figure 9.

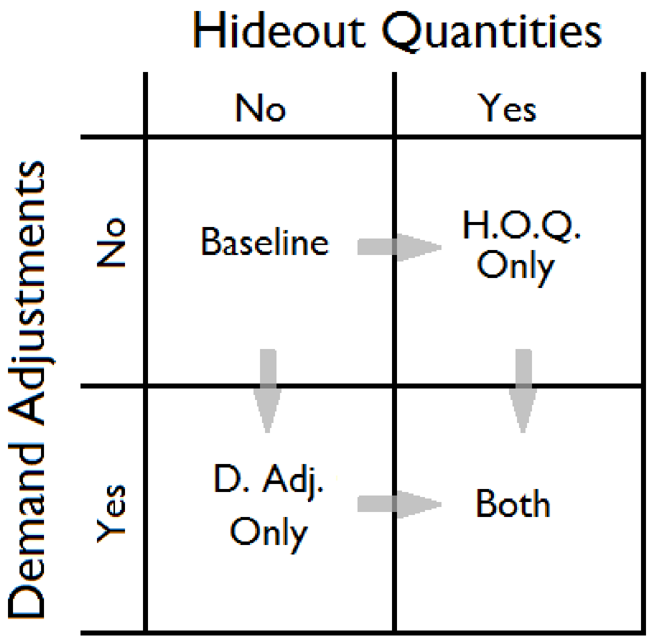

Figure 9: Human intervention matrix

Adjusting the SOQ cannot be tested with this simulation tool, because of two reasons: 1) the SOQ which follows from the simulation can differ from the historical SOQ, and 2) the changed SOQ has a significant impact on the order cycle, which consequently changes the OQ for the next periods. This means that the SOQ of a clean dataset cannot be compared with the AOQ. Simulations of the (R,s,S) model without human intervention (baseline), with only demand adjustments, with only hideout quantities and with both types of human intervention are compared. Part 7.2.1 explains the used simulation input, part 7.2.2 explains how the simulated output is calculated, and part 7.2.3 describes the results of the simulations in detail.

7.2.1 Input Simulations

The first simulation shows how the replenishment system would perform in the year 2018, when there was no human intervention at all. The input needed to simulate the (R,s,S) model without human intervention, are the following things: 1) demand data per SKU per workday, 2) The LT per SKU (simulated), 3) the reorder levels per SKU per workday, 4) the order-up-to levels per SKU per workday, 5) the minimum order quantities per SKU per workday, 6) the incremental order quantities per SKU per workday, and 7) the order days per subvendor. When simulations with human intervention have to run, these are added as input in different ways. Per type of input, an explanation and the needed assumptions are explained. All assumptions made for the simulations are summed up in Appendix 15. The first assumptions is that there are no promotions, because data about promotions is not accessible. Simulations are made for all scoped SKUs, the scope is explained in paragraph 4.1.

7.2.1.1 Daily demand data

The demand data per SKU per workday of all workdays of 2018 is the first type of input needed. This historical data is stored by the company. Some weekend days showed demand, the assumption is made that this demand is added to the demand the Monday after. This assumption is based on comparing weekly demand data with daily demand data.

7.2.1.2 Lead Time

The LT input for the simulations is a simulation on itself. Based on delivery data of all subvendors of 2018, the average LT per SKU and standard deviation of the LT are calculated. The average LT and standard deviation of the LT are used in a gamma distribution to calculate the scale- and shape parameters, to simulate the amount of workdays after ordering the order arrives. This is done for all potential order workdays of all subvendors. By determining the average LT and the standard deviation based on data of a whole year, it is assumed that the subvendors performance is about the same through a year. When for a specific OL the LT is known, the LT is added to that specific day. In this way, the date of the order delivery is known for every workday and for every SKU. An assumption needed is that all OLs are always fully delivered.

7.2.1.3 Reorder Levels, Order-Up-To Levels, MOQs and IOQs

Demand data of the end of 2017 is needed to calculate the forecasted demand during one future arbitrary time period for the first cycle update at the 5th of January 2018. It is assumed that the reorder levels, order-up-to levels, MOQ and IOQ calculated in the first cycle update, are also used in the first week of January. Week 51 and 52 of 2017 and week 1 of 2018 are not used in calculating the forecasted demand. Three earlier weeks are used instead. This assumption is also used by the Supply Chain Optimization team, which is responsible for performing the cycle updates of the (R,s,S) model. The forecasted demand during one future arbitrary time period is the cleansed average of 13 weeks demand. The standard deviation of demand is calculated based on the same weeks. A more extended explanation about these calculations can be found in paragraph 5.1. The forecasted demand and standard deviation are the input in the (R,s,S) model, which determine the reorder levels, order-up-to levels, MOQ and IOQ. After every cycle update, the new forecasted demand and its standard deviation can be implemented in the (R,s,S) model, after which the model recalculates the reorder levels, order-up-to levels, MQO and IOQ. In this way, these parameters per SKU per workday are known. The (R,s,S) model calculates these values not only based on forecasted demand, other parameters used in these calculations are: 1) TFR, 2) RP, 3) CLPs, 4) fixed order days, 5) item purchase price in euros, 6) by-vendor required MOQs, and 7) by-vendor required IOQs. These historical values are not stored by Office Depot through 2018, which leads to the assumption that the latest values of these parameters are correct and used through the whole year.

Another assumption had to be made regarding the forecasted demand. A DC in Zwolle was closed on the 10th of August 2018, after which the demand in the BENELUX was fulfilled from the DC in GOH. The assumption needed: The forecasted demand and its standard deviation are calculated based on the weekly demand data for the DC in GOH for weeks 1 till 31, and week 45 till the last week of 2018. For the weeks 32 till 44, the forecasted demand and its standard deviation are calculated based on the weekly demand data for the DC in GOH and in Zwolle. These time intervals are based on the closure of the DC in Zwolle and the planning of the cycle updates, which can be found in Appendix 16. The problem only exists with forecasted demand, as the DC switch correctly allocates sales data.

7.2.1.4 Hideout Quantities

Hideout quantities can be added into the build simulation tool, because the historical values of total quantity hidden from the system per SKU per workday of 2018 is stored by Office Depot. Only for five workdays, this data is missing. It is assumed that the quantity hidden on these days is the same as the workday before.

7.2.1.5 Demand Adjustments

Demand adjustments can be added into the tool, because the historical data of the date of setting, the date of removing, and the quantity used per demand adjustment are all known. From this data can be subtracted which demand adjustment was in place per SKU per workday. Based on this data, the (R,s,S) model can calculate a new reorder level, order-up-to level, MOQ and IOQ per SKU per workday, which is used as input. This input is used from the day after updating a demand adjustment. These output values stay the same till a new demand adjustment is placed, or till a new cycle update. When a demand adjustment is placed within a week before a new cycle update, the output values are based on the latest demand adjustment instead of the cycle update.

7.2.2 Output Simulations

Based on the input described above and the starting values (based on the 1st of January 2018) of the IP, IOH, inventory on order and amount of BOs, a simulation is made for 1) the IP, 2) IOH, 3) the amount of BOs, 4) the placed orders, and 5) the inbound orders of every workday in 2018. Per type of output, an explanation of the calculations and needed assumptions are presented. All assumptions made for the simulations are summed up in Appendix 15.

7.2.2.1 Inventory Position

To determine the IP at the end of a specific day, an assumption has to be made about the RP. When a RP is higher than 5, the assumption is made that counting workdays to see whether or not reviewing is needed starts on the 1st of January 2018. This assumption does not harm the simulations because comparing the performance of different time periods is not the cause of the simulation. This means that when the RP is 15 and the fixed order day is Monday, the third week on Monday is the first review moment of 2018. The IP for a specific SKU on a specific day can be calculated as follows:

When it is not an order day, or it is an order day but the IP is not below the reorder level, the IP is equal to the IP of the day before, minus the hidden quantity on that day, plus the hidden quantity on the day before, minus the demand on that day. When it is an order day and the IP is below the reorder level, the IP is equal to the same formula, but plus the OQ placed that day. The OQ is determined as explained in part 5.1 of this thesis. When it is the 1st of January, the IP of the day before can be replaced by the starting value of IP, and the same equations can be used.

7.2.2.2 Inventory On Hand

The IOH for a specific SKU on a specific day can be calculated as follows: The maximum of zero and the IOH of the day before, minus the demand on that day, plus the inbound quantity on that day. There is no historical data available about when the on order inventory at the 1st of January 2018 would arrive. This is why the assumption is made that the IOH at the 1st of January 2018 is equal to the IP at that date.

7.2.2.3 Back Ordered Quantity

The BO quantity for a specific SKU on a specific day can be calculated as follows: The absolute value of the minimum of zero and the IOH of the day before, minus the demand on that day, plus the inbound quantity on that day.

7.2.2.4 Suggested Order Quantity

The determination of the OQ based on the order-up-to level, MOQ and IOQ are already considered in the equations for the IP, which is why the SOQ for a specific SKU on a specific day can be calculated as follows: The IP on that day, minus the IP of the day before, plus the demand on that day, plus the hidden quantity on that day, minus the hidden quantity on the day before. For the first of January, the SOQ is calculated differently: The maximum of zero and the IP of that day, minus the starting value of the IP, plus the demand on that day.

7.2.3 Validation of the Simulation Tool

To check the validity and reliability of the tool, some test items were put into the tool before the actual simulations for this thesis started. First, the baseline input and output is tested. After this, tests follow per type of human intervention. This paragraph explains one test as example. However, multiple tests with different numbers and looking at different dates are performed. Finally, an expert test is performed.

7.2.3.1 Baseline Tests

In the example, a stationary demand pattern of 10 pieces every day was used. The LT is one week, RP is once a week, fixed order day is Wednesday, the reorder level is 100, and order-up-to level is 200. The start IP is 100 at 01-01-2018. The IP at the end of the 2nd of January is 80, because of two days demand and not ordering (no order day). The 3rd of January is an order day, and the IP is below the reorder level. This means that the IP at the end of this day is 190, which is the order-up-to level minus the demand at that day. The IOH at the end of that day is 70, and placed OQ is 120 pieces. When looking at the inbound tab, it can be seen that at the 10th of January, an order of 120 pieces arrives and the IOH on that day goes up with 120 pieces. When changing the MOQ to 125, the simulation shows that the OQ also changes to 125. When also changing the IOQ to 10, the simulation shows that the OQ changes to 130. These values are all as expected, when looking at paragraph 5.1.

7.2.3.2 Adding Hideout Quantities

When a hideout quantity of 30 is added to simulation from the 2nd of January till the 5th of January, it can be seen that the IP of the 2nd of January goes down with 30 pieces. The IP at the 3rd of January stays the same, because it is an order day. However, the OQ goes up with 30 and the IOH of the 3rd of January also goes down with 30. At the 6th of January, when the hideout quantity is not in place anymore, both the IP and IOH go up with 30. This is as expected and how this type of human intervention works.

7.2.3.3 Adding Demand Adjustments

When a demand adjustment is added, the newly calculated reorder level, order-up-to level, MOQ and IOQ are put into the system. These are the input parameters that can change, because of a change in forecasted demand. The values of these parameters are calculated by using the new forecasted demand into the inventory control model, which is how it is done in the simulations. When a demand adjustment is placed, the new determined reorder level can be put into the simulation and has to overwrite the old reorder level. This is why an adjusted reorder level of 60 and an adjusted order-up-to level of 250 are put into the system. It can be seen that no order is placed on the 3rd of January, because although the IP is below the reorder level, it is not below the adjusted reorder level. One week later, the IP is below the adjusted reorder level and the IP goes up to 240, because of the adjusted order-up-to level. The SOQ is also adjusted to 220, because the IP has to go up to a higher order-up-to level. When using an adjusted MOQ of 230, it can be seen that the OQ also changes to 230. When also using a normal MOQ of 100, it can be seen that the simulation still follows the adjusted MOQ of 230. When removing the adjusted MOQ and using a normal IOQ of 18 and an adjusted IOQ of 30, the OQ changes to 240, which is a multiple of the adjusted IOQ. This is as expected and how this type of human intervention works.

7.2.3.4 Expert Tests

The simulation tool can be useful for the company, which is why the Supply Chain Optimization team offered to help developing this tool. The management asked to a Demand Planning & Inventory Management Analyst to help validating and testing the tool. Besides, this employee was closely involved in the development of this tool. After the tool was finished, it was tested and compared to the real performance of randomly picked SKUs by the expert. Testing for different SKUs was executed for a couple of hours. After this, a few adjustments were needed and it was decided that the simulation tool is valid and reliable. Finally, it is checked whether results given in paragraph 7.2.4 does not give notable differences per planner. In this case, results may be skewed by a wrong way of using human interventions by one specific planner. Notable differences among planners were not found.

7.2.4 Results Simulations

In this subchapter, the results of the simulations are presented and discussed in detail. Because of the assumption that the start IOH is equal to the IP given, results after the 100th workday are compared, which is the maximum LT + RP. The first results are the overall results of the simulation, where the outcomes of the simulation without human intervention are compared with outcomes of simulations with human intervention. After this, it is concluded which human intervention was the most useful and which human intervention was not needed. Expected annual costs in euros in the results are based on inventory holding costs and incoming order line costs.

7.2.4.1 Overall Results Simulations

Table 23 shows the performance of the simulations without human intervention, only hideout quantities, only demand adjustments, and a combination of both forms of human intervention. The actual daily demand per scoped SKU in 2018 is used for the simulations.

Performance human intervention	Average fill rate	% Deviation in OLs	% Deviation in IOH value	Total human intervention	% Deviation in total costs
Baseline	95,69%	Baseline	Baseline	0	Baseline
Hideout Quantities	96,32%	-0,89	4,65	5.332	4,20
Demand Adjustments	97,76%	-35,05	206,50	23.251	186,92
Both	97,89%	-35,30	210,68	28.583	190,75

Table 21: Performance simulations

In Table 23 can be seen that without any form of human intervention, the average fill rate would be 95,69%, while adding both forms of human intervention leads to an increase in fill rate to 97,89%. Please note that this includes the entire scoped assortment, and not only the (R,s,S) managed SKUs. This is not equal to the TFR, which has different reasons. The first reason is that the third form of human intervention is not considered. It is expected that this type of human intervention does have a positive impact on the average fill rate. The second reason is that the simulation is done according to the (R,s,S) model, while not all SKUs in scope are actually planned with this model. Some SKUs are planned with a planners' own procedure, which means these SKUs are micro managed. There were reasons to not use the current (R,s,S) model for all SKUs, simulating all SKUs in scope on the (R,s,S) model probably leads to a lower average fill rate. This is tested and explained later in this paragraph. The third reason is that assumptions had to be made. Assumptions have influence on the performance.

It can be seen that the amount of demand adjustments used in 2018 for the scoped SKUs is more than four times higher than the amount of hideout quantities used. The reason is that demand adjustments are the preferred way of human intervention for (R,s,S) planned SKUs and most of the scoped SKUs are planned with the (R,s,S) model. The performance improvement by human intervention of (R,s,S) planned SKUs and SKUs planned with other methods are compared in Table 24.

Planning Method	% SKUs	Form of human intervention	Average Fill Rate	% Deviation in OLs	% Deviation in IOH value	Total human intervention	% Deviation in total costs
(R,s,S) planned	83,83	Baseline	96,06%	Baseline	Baseline	0	Baseline
		Hideout quantities	96,93%	-0,89	6,34	4744	5,48
		Demand adjustments	99,21%	-39,00	347,46	23251	301,58
		Both	99,31%	-39,17	353,00	27995	306,44
Not (R,s,S) planned	16,17	Baseline	94,98%	Baseline	Baseline	0	Baseline
		Hideout quantities	95,15%	-0,92	2,27	588	2,20

Table 22: Performance simulations by planning method

In Table 24 can be seen that as expected, the performance of the simulations is better for (R,s,S) planned SKUs, also without human intervention. Furthermore, it can be seen that with only the preferred form of human intervention (demand adjustments), the (R,s,S) model would reach its TFR for SKUs in the scope of this thesis.

7.2.4.2 Usefulness Human Intervention

In this part of the results is checked whether all human intervention were useful regarding to the service levels. This is done by comparing the amount of SKUs for which the fill rates increase due to human intervention. Table 25 provides the output for this.

Type Intervention	Compared to baseline	% SKUs without human intervention	% SKUs with human intervention
Hideout Quantities	Equal	75,08	14,89
	Higher		8,37
	Lower		1,66
Demand Adjustments	Equal	42,60	26,47
	Higher		29,84
	Lower		1,10
Both	Equal	36,08	29,72
	Higher		32,65
	Lower		1,55

Table 23: Effect of human intervention

In Table 25 can be seen that for all SKUs in scope, only 24,92% have hideout quantities. Of these SKUs with hideout quantities, 33,59% of all SKUs get a higher fill rate because of the hideout quantity, 59,75%

of the SKUs with hideout quantities do not change in service level, and 6,66% results in a worse fill rate. Of all SKUs in scope, 57,40% have demand adjustments. Of these SKUs, 51,99% get a higher fill rate because of the demand adjustment, 46,10% do not change in service level, and 1,91% gets a worse fill rate. Of all SKUs in scope, 63,92% have one or both forms of human intervention. Of these SKUs, 51,08% get a higher fill rate because of the interventions, 46,50% of the SKUs do not change in service level, and 2,42% gets a worse fill rate. To check which human intervention are the most useful ones, the value added per classification and product group is calculated. This is done by calculating the percentage of less BOs caused per adjustment per classification or product group. According to the literature, it might be the case that C-SKUs or Z-SKUs do not need any form of human intervention. Table 26 provides the average percentage less BOs caused per human intervention per classification. In Appendix 17, the same table but with the combined importance- and forecastability classes can be found.

	Hideout Quantities		**Demand Adjustments**		**Both**	
Classification	Average interventions per SKU	Average less BOs per intervention	Average interventions per SKU	Average less BOs per intervention	Average interventions per SKU	Average less BOs per intervention
A	1,07	0,00609%	3,66	0,00560%	4,73	0,00451%
B	0,55	0,00094%	2,74	0,00071%	3,29	0,00068%
C	0,19	0,00040%	0,91	0,00041%	1,09	0,00039%
X	1,08	0,00573%	3,05	0,00516%	4,13	0,00403%
Y	0,52	0,00159%	2,93	0,00141%	3,45	0,00125%
Z	0,16	0,00098%	0,51	0,00081%	0,67	0,00077%

Table 24: Percentage less backorders caused by human intervention

In Table 26 can be seen that the most useful interventions are done for A-SKUs and X-SKUs, and the least useful intervention for C-SKUs and Z-SKUs, which is in line with the literature. To be more specific, the usefulness per hideout quantity for A-SKUs is on average 15,2 times more useful than for C-SKUs, with demand adjustments this is 13,7 times more useful and for both kinds of human intervention together, this is 11,6 times more useful. The usefulness per hideout quantity for X-SKUs is on average 5,8 times more useful than for Z-SKUs, with demand adjustments this is 6,4 times more useful and for all human intervention together, this is 5,2 times more useful.

In Appendix 17 can be seen that for the combination of the importance- and forecastability classes, intervention on A-SKUs combined with all forecastability classes has more impact than intervention on B-SKUs, and both classes combined with all forecastability classes has more impact than intervention on C-SKUs. For the forecastability classification can be seen that intervention on X-SKUs is not always more useful than intervention on Z-SKUs, which is not in line with literature. For example, human intervention on BZ-SKUs has more impact than human intervention on BX-SKUs. This can be explained by how the forecastability classification is made at Office Depot, because when SKUs are classified as unforecastable, it might be the case that the SKU is forecastable. The results of this simulations are in line with the conclusion of RQ6, which can be found in paragraph 5.6.4 of this thesis.

Now that it is known that the impact of human intervention on C-SKUs is less than the impact of human intervention on all other SKUs, there is tested what the average fill rate, expected OLs, average IOH, total human intervention and expected costs in euros would be when there is no human intervention on C-SKUs. This is compared to the case where all human intervention stays as it was in 2018. The same is done for only (R,s,S) planned SKUs, to see whether the TFR is still reached. This is presented in Tables 28 and 29.

Performance human intervention	Average Fill Rate	% Deviation in OLs	% Deviation in IOH value	Total human intervention	% Deviation in total costs
Human intervention As it was in 2018	97,89%	Baseline	Baseline	Baseline	Baseline
Only demand adjustments Only on A- and B-SKUs	97,76%	8,99%	-4,03%	-27,32%	-3,80%

Table 25: Performance without human intervention on C-SKUs

In Table 27 can be seen that when there was no human intervention on C-SKUs in 2018, the performance in fill rate would be 0,13% worse. The amount of order lines would increase with 8,99%, while the average expected IOH value would decrease with 4,03%. This can be explained by the amount of adjustments These two together would lead to a decrease in expected annual costs in euros of 3,80%. From the simulations cannot be concluded whether Office Depot can afford it to not intervene on C-SKUs, because the simulated fill rate is lower than the AFR for 2018 with all forms of human intervention. Reasons for that are given in part 7.3.3.1 of this thesis.

Performance human intervention (R,s,S) only	Average Fill Rate	% Deviation in OLs	% Deviation in IOH value	Total human intervention	% Deviation in total costs
Human intervention as it was in 2018	99,31%	Baseline	Baseline	Baseline	Baseline
Only demand adjustments Only on A- and B-SKUs	99,11%	10,64%	-4,70%	-27,39%	-4,43%

Table 26: Performance without human intervention on C-SKUs, (R,s,S) planned withly

In Table 28 can be seen that when the same comparison is made for only (R,s,S) planned SKUs, the performance would be 0,20% worse, but still higher than the TFR. No human intervention on C-SKUs would have saved 27,39% of all human intervention and 4,43% in expected annual costs, while the TFR would still be reached. When costs related to human interventions are included as calculated in Appendix 18, the decrease in expected annual costs is between 4,48% and 4,50%. In Table 29 can be seen that when only the preferred form of human intervention was used for A- and B-SKUs, and no human intervention was used for C-SKUs, the TFR would still be reached for (R,s,S) planned SKUs, with an average simulated fill rate of 99,03%. This would have saved 40,10% of all human intervention and 5,56% in expected annual costs. When human intervention is included in the costs calculations as explained in Appendix 18, this would lead to a decrease between 5,64% and 5,67% in expected annual costs.

Performance human intervention (R,s,S) only	Average Fill Rate	% Deviation in OLs	% Deviation in IOH value	Total human intervention	% Deviation in total costs
Human intervention As it was in 2018	99,31%	Baseline	Baseline	Baseline	Baseline
Only demand adjustments Only on A- and B-SKUs	99,03%	10,78%	-5,85%	-40,10%	-5,56%

Table 27: Performance with only demand adjustments for A- and B-SKUs, (R,s,S) planned withly

A comparable table is made for all product groups, and the ten product groups with the most useful interventions are given in Appendix 19. Product groups which showed worse performance with human intervention were ‘Stretch Film & Strapping’, which are packaging accessories, ‘Suspension File Boxes’, and ‘Vital’, which are products from retained with specific prints on it. Of these product groups, only the suspension file boxes are planned with the (R,s,S) model. Product groups which showed no improvement while there was human intervention and are planned with the (R,s,S) model are: webcams, storage components, pointers and presenter, transparent film foil, message pads and typewriters. Product groups which showed no improvement while there was human intervention in the (R,s,S) simulation, but are not (R,s,S) planned, are: office papers, rubber bands, cutting instruments and display books.

7.3 Reorder Level with Rounded Order Quantities

At this moment, the reorder levels are determined based on the TFRs. With the determination, the process looks at with which reorder level for a specific SKU the calculated expected fill rate is getting the nearest to the TFR, as described in part 5.1 of this thesis. This part of the thesis elaborates on the effect of rounding is on the reorder levels and the expected annual costs. The (R,s,S) replenishment logic with the current way of determining the reorder levels, based on literature of (Viswanathan, 1997), is still used. At this moment, rounding the OQ is applied on 82,1% of all SKUs, to decrease the workload at the DC in GOH. The calculations for the AFRs do not use the rounded OQs. The effect of rounding the OQ and not using those rounded values in further calculations, is that the AFR is expected to be higher than the TFR. This might explain that in chapter 5 is found that for 71,4% of the SKUs, the AFR is on average 1,3% higher than the TFR.

A simple heuristic is used to check the effect of ordering the rounded OQ and not including this into the reorder level determination. The reorder level which follow from the process as described in paragraph 5.1, is used as input in the equation for the calculated expected fill rate, which can also be found in paragraph 5.1. However, this time with the rounded OQs instead of the optimal OQ $S\text{-}s+E[U]$. Including the rounded OQs in the reorder level determination is executed with a simple heuristic, where the optimal OQ in the equation for the calculated expected fill rate is replaced with the rounded OQs. The average of all TFRs in scope is 99,0%. When the rounded OQs are used in the equation for the calculated expected fill rates, it can be seen that over all SKUs, the average expected fill rate is 99,4% for all SKUs planned with the (R,s,S) model (based on the total expected BOs and the total expected demand). The average expected fill rate is higher than the targeted. When reorder levels are determined based on optimal OQs without rounding, but OQs are rounded, there are orders which cause the IP to get above the order-up-to level, which means that on average there is less probability for BOs. By using the rounded OQs, it is tried to reach the optimal reorder level where TFRs match with the expected fill rate. When changing the way of determining the reorder levels as explained before, it can be seen that the average reorder level decreases with 4,3%. The reorder level decreases for all 82,1% of the SKUs which use rounding.

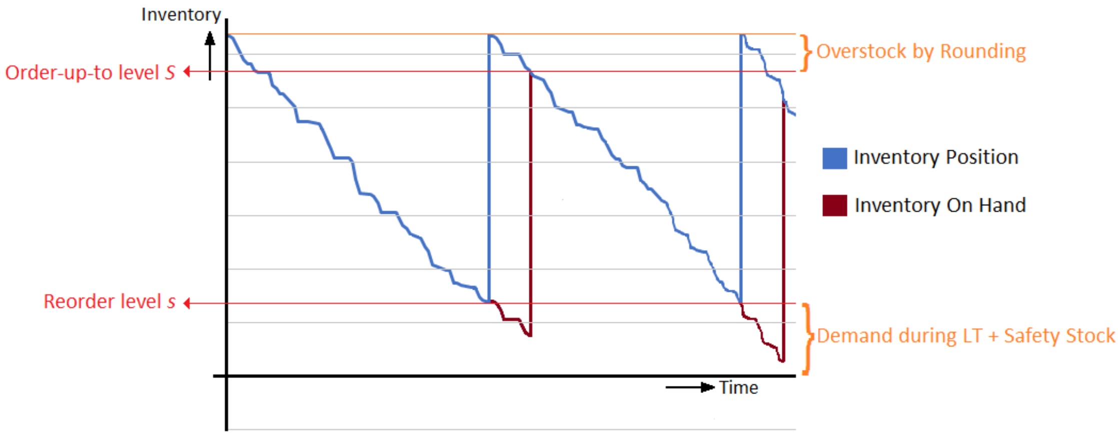

Figure 10: Inventory position and inventory on hand with unrounded order quantities

The decrease in reorder levels causes a decrease of the average calculated expected fill rate to 99,1%, which is closer to the TFR of 99,0%. This decrease leads to a decrease in average annual inventory value by 4,5% and the amount of OLs stays the same. In total, the change in reorder level determination leads to a decrease of 3,8% of expected annual costs. The decrease in expected fill rate and in reorder levels can be explained with comparing the two situations, as shown in Figure 10 and Figure 11. Both show a graph of the inventory (IP & IOH) in time. The difference is that Figure 10 shows the situation in which reorder levels are determined based on the optimal OQ $S\text{-}s+E[U]$, and Figure 11 shows the situation which reorder levels are determined based on the actual OQs (rounded). With setting the average TFR below 100,0%, it is targeted to have BOs. When setting the reorder levels based on the optimal OQ without rounding, while ordering more because of rounding, there is less chance of getting BOs. This can be seen in Figure 10, where there are no BOs and the reorder level is higher than in Figure 11. In Figure 11, where the actual OQ is used, can be seen that there are BOs and the reorder level is lower than in Figure 10.

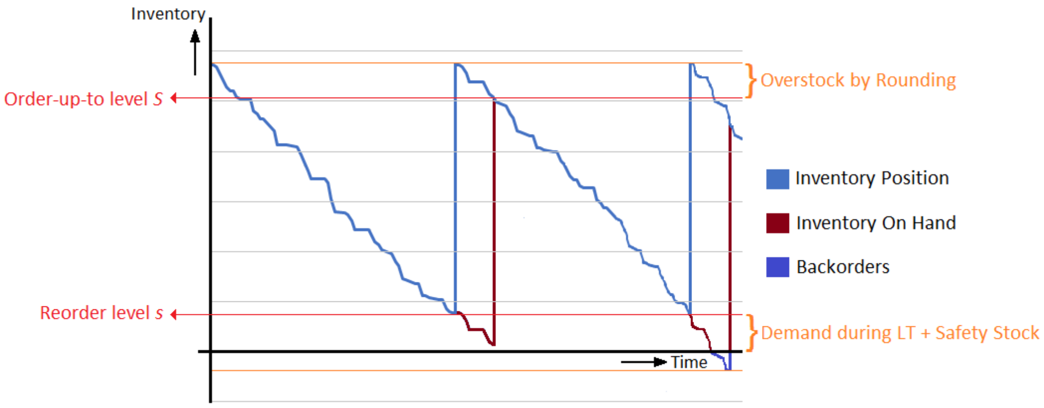

Figure 11: Inventory position and inventory on hand with rounded order quantities

As explained in part 6.2.3 of this thesis, the new heuristic is compared with the DoBr-tool (Van Donselaar & Broekmeulen, 2019). The tool uses the following logic: The IOQ and MOQ determine the type of inventory control system. With an IOQ≥1 and MOQ≤IOQ, the (R,s,nQ) logic is used, when IOQ=1 and MOQ>1, the (R,s,S) logic is used. When the IOQ>1 and MOQ>1, the (R,s,S,nQ) logic is used. In this case, the MOQ has to be an integer multiple of the IOQ (Hill, 2006). Reorder levels following from the simple heuristic and the DoBr-tool can be compared. The input parameters needed to calculate the reorder level based on TFR in the DoBr-tool are: TFR, LT, RP, average demand per period, standard deviation per period, IOQ and MOQ per SKU. The average LT per subvendor is used as input parameter. This is how the subvendors performance is expected to be, which is why it is preferred to the quoted LT. The standard deviation per period has to include the standard deviation of demand per period and the standard deviation of the LT. This is why an adjusted standard deviation is made, to use as input for the DoBr-tool. The adjusted standard deviation includes the standard deviation of demand during LT and RP (Van Donselaar & Broekmeulen, 2019). The calculation is shown in Equation 7.

$$\sigma'_{d,1} = \sqrt{\frac{\sigma^2_{d,LT+RP}}{LT + RP}}$$

Equation 7: Calculation of the adjusted standard deviation for DoBr-tool

This means that the new standard deviation of demand during one period is the square root of the variance of demand during LT plus RP, divided by the LT plus RP. The variance of demand during LT plus RP includes the standard deviation of LT and the standard deviation of demand during one period, which is explained in paragraph 5.1. All other input parameters are known. With the knowledge that a BO situation is in case at Office Depot, the DoBr-tool can determine the minimal reorder level that satisfies a given TFR with stationary demand. Including the standard deviation of the LT, as explained before, is a way of including uncertainties which are not considered when only demand variance is included.

Of all SKUs in scope, 5,84% has a reorder level calculated by the heuristic that differs more than 100% from the reorder levels calculated by the DoBr-tool. Of these SKUs, 51,72% has a negative reorder level when the calculations of the DoBr-tool are used. As explained in paragraph 5.1, the current inventory control model gives a minimum reorder level of 1, which is also used in the heuristic. This is why the by DoBr-tool calculated reorder levels are also set to have a minimal reorder level of 1. Still, 2,82% of the reorder levels differ more than 100%. This can be explained by the low values of the reorder levels. Of these SKUs, 46,4% use a reorder level of 1 and 100% uses a reorder level equal to or below 10.

When comparing the values of the reorder levels calculated with the DoBr-tool with the reorder levels calculated with the heuristic, it can be seen that 8,7% of the SKUs have a lower reorder level with the DoBr-tool, 20,8% of the SKUs give the same reorder levels in both calculations, and 70,5% give a higher reorder level with the DoBr-tool. The average deviation of reorder levels of SKUs with a lower value than the DoBr-tool, is 6,1%. The average deviation of reorder levels of SKUs with a higher value than the DoBr-tool, is 16,8%. This deviation can be explained by the logic that the DoBr-tool uses. The DoBr-tool uses the calculations as explained in the research of Hill (2006). This calculations are based on a reorder level *s* and order-up-to level *S* that have to be multiples of the batch sizes for the (R,s,S,nQ) model. This is why for most SKUs, the reorder level is higher with the DoBr-tool calculations.

According to the comparison above, the reorder levels calculated with the new heuristic in the current (R,s,S) model and with the DoBr-tool provide comparable values. Based on this, it can be concluded that the heuristic used to go from the (R,s,S) model to the (R,s,S,nQ) model is ready for implementation.

7.4 Low Value Density SKUs

The holding cost percentage of all SKUs is the same, 25%. This means that Office Depot states that 25% of the value of a SKU is used to determine the annual holding costs. This percentage includes multiple components, one of these components is space-dependent. Using the same percentage for all SKUs in the EOQ calculations, means that value density is not considered. Not considering value density in these calculations can lead to overfull DCs. To avoid this, the holding cost percentage is adjusted for low value density SKUs. The value density per SKU is calculated and the space-dependent part of the holding cost percentage is adjusted. The first step is to find the space-dependent part of the holding cost percentage.

7.4.1 Space-Dependent Part of Holding Cost Percentage

The total amount of pallet locations in the DC is known and the fixed monthly costs per pallet location is six euros. According to the Network Analyst of Office Depot, the monthly costs per pallet location are based on the regional norm for these costs, and includes electricity, rent and supervision for the DC. By multiplying the fixed annual costs per pallet location by the amount of pallet locations in the DC, the expected annual costs for the DC are calculated. The average inventory value over the last quartile of 2018 is calculated. An average is used instead of a snapshot, because of the high differences in inventory value per day. The last quartile is used, because the closure of the Zwolle DC was finished at the start of this quartile. The expected annual costs for the DC are 42,89% of the average inventory on hand costs of the last quartile of 2018. The latter is 25% of the average inventory value of the last quartile of 2018. This means that the space-dependent part of the holding cost percentage is 42,89% of 25%, which is 10,72%. The other 14,28% is value-dependent, which means that this percentage is fixed in the remaining part of this paragraph.

7.4.2 Low Value Density SKUs

The value density of all SKUs is determined. These values are determined based on the value which could practically fit on a pallet. For a pallet location, the retrieved dimensions from the DC in GOH are used, which are: length of 1.200 millimeters, width of 800 millimeters and height of 1.300 millimeters. The amount of SKUs which would practically fit on a pallet are determined in the following way: The dimensions of all standard packs of each SKU are known, based on these values the amount of SKUs which can fit on a pallet are determined. The amount of SKUs which could practically fit on a pallet are multiplied by their purchase prices, which gives the total value which could practically fit on a pallet. These dimensions of a standard pack are used instead of the CLPs, because data about dimensions is more reliable than data about the CLPs. Products with the highest value density in the scope of this thesis are SD cards, and products with the lowest value density are paper and lever arch files.

When using the dimensions of the standard packs in combination with the average inventory per SKU over the last quartile of 2018, the average amount of cubic meters used to store a specific SKU can be determined. In the last quartile of 2018, 84,81% of all SKUs in scope only needed one pallet location on average. These SKUs are not considered anymore, because the main cause of this chapter is to reduce the amount of used pallet locations. For the SKUs which needed more cubic meters, the value density is considered. It is found that 0,52% of all scoped SKUs need one third of the total cubic meters storage used by all scoped SKUs. Out of these SKUs, it can be seen that 81,25% falls under four different product groups with a low value density, which are the following: 1) 'Paper', with 39,06%, 2) 'Chairs', with 18,75%, 3) 'Files and Binders', with 17,19%, and 4) 'Hygiene Paper', with 6,25%. More specific, all these SKUs in 'Files and Binders' are lever arch files. A solution is found for SKUs which are in product classes paper, hygiene paper and chairs, and for lever arch files. For now, it can be seen that most of these SKUs are not planned with the current (R,s,S) model (51,92%), because of the low value density. Besides, it can be seen that for SKUs which are planned with the (R,s,S) model, 76% is paper or lever arch files. In Appendix 19 can be seen that the most useful human intervention were placed for these product groups.

This means that using a higher holding cost percentage for the following product groups is useful: 4 different types of Chairs (Operator-, Executive-, Draughtmans- and Occasional-Chairs), all 5 different types of Office Paper (Business-, Color-, Everyday-, Tinted- and Green-Segment), Continuous Paper, Standard Lever Arch Files, Special Lever Arch Files, Hand Towels, Toilet Paper and Hygiene Paper.

7.4.3 Adjusted Space-Dependent Part of Holding Cost Percentage

The space-dependent holding cost percentage can be determined by the total costs of holding the SKUs divided by the average inventory of these SKUs. When dividing the total costs of holding all SKUs except from lever arch files or SKUs in product groups paper, hygiene paper or chairs, (based on the total pallet locations needed in the last quartile of 2018) by the inventory value of the same SKUs, the space-dependent holding cost percentage is 10,29%. This is close to the 10,72% which is calculated earlier. When determining the space-dependent holding cost percentage for lever arch files, paper, hygiene paper and chairs in the same way, the outcome is 28,36%. Adding up the value-dependent holding cost percentage, which is still 14,28%, the holding cost percentage of these SKUs is determined to be 42,64%.

7.4.4 Results New Holding Cost Percentage

When running the (R,s,S) model with the new holding cost percentage for the low value density SKUs, it can be seen that the expected decrease in average stock is 0,09%. This causes an increase in expected OLs of 4,30%, which in total gives an increase in expected costs of 0,01%. The difference is relatively low, which can be explained by the determination of the optimal OQ. The optimal OQ without undershoot S-s is determined to be the maximum between demand during RP and the EOQ. Most of the low value density SKUs are ordered based on demand during RP (65,38%). When forcing to order based on EOQ for low value density SKUs, and comparing this to the old situation, it gives the following outcomes: a decrease of 4,86% in expected average stock, an increase in expected OLs of 49,98%, which in total gives a decrease in expected costs of 4,75%. The decrease in expected costs of the low value density SKUs, despite of the large increase in expected OLs for these SKUs, can be explained. Outcomes which are given, are only for the low value density SKUs. The inventory of this few SKUs uses about one third of the total pallet locations needed in the last quartile of 2018, while the expected amount of OLs for these SKUs was only 11,43%. This means that a smaller decrease for a large percentage of the total IOH weights more than a bigger increase for a small percentage of the total OLs. Note that forcing to order based on the EOQ means that these SKUs have to be reviewed more often, because otherwise these SKUs are out of stock before the next moment of reviewing.

7.5 Conclusions RQ7 and RQ8

The final part of this chapter provides a conclusion to RQ7 and RQ8, based on all results. Answers are presented under each RQ. The answer to RQ7 is more detailed, since this RQ is close to the main research question.

RQ7. Which inventory control model with which parameters fits the SKUs that are not – or not effectively managed in the current inventory control model?

Conclusions to this question are given per subject, for all subjects explained in part 6.1 of this thesis. After this, a paragraph follows about the performance of the new model with all (re)designs, for SKUs which were performing well already.

7.5.1 Expected Demand During One Future Arbitrary Time Period

A model which uses the (R,s,S) logic can fit to all SKUs not- or not effectively managed in the current (R,s,S) model. The way of determining different parameters does make a difference. First of all, the expected demand during one future arbitrary time period is used. The expected demand is calculated based on the cleansed average of last 13 weeks demand, once every four weeks. In chapter 5, it is proven that seasonality can be seen in the total demand of the company, and that SKUs which show more seasonality perform worse than stable SKUs. It is also shown that long LT SKUs perform worse than SKUs with medium or short LT. When forecastable patterns are taken into consideration, and the expected demand during LT and RP is forecasted and used as input instead of expected demand during one future time period, OB direct SKUs and seasonal SKUs can be planned with a (R,s,S) model. For the problems above, no further research was performed, because of time restrictions.

7.5.2 Review Period & Targeted Fill Rate Determination

When looking at the characteristics of the total assortment, it can be seen that most SKUs have a RP of 5 and a TFR of 99,0%. A RP of 5 is the maximum value in the RP determination for (R,s,S) planned SKUs and a TFR of 99,0% is the starting value of the TFR determination. When also using RPs of 1, 10, 15 and 20 per subvendor in the (R,s,S) model, a reduction of 1,41% in expected total annual OLs is realized, while the expected average inventory value over a year only increases with 0,01%. In total there is 0,34% expected annual costs reduction. When not letting the TFRs solver run for the time the solver needs, without a maximum of 1800 seconds without improvement, a difference in output is not found.

7.5.3 Amount of Human intervention

Human intervention was used for 93,0% of all SKUs in scope. The usefulness of human intervention was tested, by simulating the (R,s,S) model for all scoped items over 2018. It can be seen that the baseline performance of SKUs on the (R,s,S) model is better than the baseline performance of SKUs which are planned differently. Given this, it can be concluded that reasons to not plan SKUs on the

(R,s,S) model are well-grounded. When looking at the performance of (R,s,S) planned SKUs in scope of the simulation, it can be seen that human intervention on C-SKUs was not needed. Furthermore, it can be concluded that using hideout quantities to correct for demand uncertainty are not needed.

7.5.4 Low Value Density SKUs

The different types of SKUs considered as low value density SKUs are office paper, chairs, continuous paper, lever arch files and hygiene paper. The new holding costs percentage for these SKUs is 42,64%, since the space-dependent part of the holding cost percentage went up with 164,55%. This was determined based on the amount of pallet locations needed to store 0,52% of the SKUs which showed a low value density. Using this new holding cost percentage for these different types of SKUs leads to a decrease of 4,86% in expected average stock, an increase in expected OLs of 49,98%, which in total gives a decrease in expected costs of 4,75%. Note 65,38% of these SKUs need to be reviewed more often, since otherwise these SKUs are out of stock before the next moment of reviewing.

7.5.5 Reorder Level Determination

Reorder levels were calculated based on the expected optimal OQ $S\text{-}s\text{+}E[U]$, while for 82,1% of all (R,s,S) planned SKUs in GOH the OQ is rounded. A new heuristic is given in this thesis, to calculate reorder levels based on the rounded OQs. This heuristic is determining the expected rounded OQ based on the two used types of rounding, and using this as input for the calculation of the expected fill rate. Reorder level determination is still the same, based on achieving the TFR. For all (R,s,S) planned SKUs for which the OQ is rounded, the reorder level decreases. The average calculated expected fill rate decreases from 99,4% to 99,1%, which is closer to the TFR of 99,0%. This decrease leads to a decrease in average annual inventory value by 4,5% and the amount of OLs stays the same. In total, the change in reorder level determination leads to a decrease of 3,8% in expected annual costs.

7.5.6 Retained SKUs

Retained SKUs are also not planned with the (R,s,S) model. No improvement of the method is needed for these items, when management wants to plan these items with the (R,s,S) model. However, all contracts have to be checked to see which of the retained items do have contracted planning actions. After this, the different types of contracted planning actions can be determined to see which constraint is needed.

7.5.7 Performance of Currently Well-Performing SKUs

This paragraph gives the answer to RQ8.

RQ8. How is the recommended model performing for all other SKUs?

With the improvement of the reorder level determination, it can be stated that ITM is still a (R,s,S) model, but converted to a (R,s,S,nQ) model with a simple heuristic, when OQs had to be rounded. However, most parameters stay the same. Parameters that are changing, change because specific SKUs did not perform well, like the holding cost percentage for low value density SKUs. There are also some processes which can be changed after this thesis. These processes change because it is cost efficient to do it in the new way, like not placing hideout quantities because of demand uncertainty, not using human intervention for the least important items, considering RPs of 1, 10, 15 and 20 in the RP determination, or determining the reorder levels on the actual ordered quantities (rounded).

8. Conclusion

In this part of the thesis, a conclusion about this research is given. This corresponds to the second part of stage 4 of the regulative cycle of Van Strien (1997). The conclusion of this thesis is an answer to the main RQ, given in the first paragraph. After this, the contribution to the literature is given.

8.1 Conclusion to the Main Research Question

The conclusion to the main RQ follows in this paragraph. This conclusion is stated right after the RQ.

Main Research Question:
Which inventory control model is improving the performance in terms of stock holding costs, incoming order lines, service level achievement and human intervention for SKUs which are not – or not effectively managed in the current model?

The recommended model is not a change for the model itself. With the improvement of the reorder level determination, it can be stated that ITM works like a (R,s,S) model, but combined with a (R,s,S,nQ) model. The performance in terms of stock holding costs, incoming order lines and service level achievement for the SKUs which are not- or not effectively managed in the (R,s,S) model can be improved by undertaking the following actions:

1. Allowing planners to review less than once a week for specific items.
2. Not intervening in SKUs which are classified as least-important.
3. Not using hideout quantities as form of human intervention for demand uncertainty.
4. Using a holding cost percentage of 42,64% for low value density SKUs.
5. Determining reorder levels based on a newly determined heuristic, which includes rounding.

A quantification per improvement can be found in part 7.5 of this thesis. SKUs which can be considered low value density SKUs are stated in chapter 7.4 of this thesis. The newly determined heuristic for reorder level calculation is explained in more detail in part 8.2 of this thesis, the contribution to the literature.

8.2 Contribution to the Literature

The contribution to the literature consists of two parts. The first part states the usefulness of human intervention, while the second part gives a simple heuristic of adjusting reorder level calculations because of OQ rounding.

8.2.1 Empirical Test of Human Intervention

As explained in part 2.4 of this thesis, this research fulfills a literature gap. The first gap in the literature is an empirical test of the usefulness of human intervention per class of importance. Literature states that it is more useful to focus on the critical few instead of the trivial many and that it might not be valuable to put effort in the least important SKUs (Juran, 1954) (Silver, Pyke, & Peterson, 1998) (Nahmias & Olsen, 2015). This is tested with empirical data of one of the main resellers of office supplies. The used importance classification is performed based on the average weekly sales value and the Pareto rule (Pareto, 1971). The used data to test this is the same as used in paragraph 7.2 of this thesis. Table 26 shows that the most valuable human interventions are done for the most important SKUs, and the least valuable human interventions are done for the least important SKUs. It shows that interventions on the most important SKUs are 11,6 times more useful than interventions on the least important SKUs. Besides, Table 29 shows that hiding a specific amount of SKUs from the replenishment system, is not the right form of human intervention to prepare for demand uncertainty. Table 30 shows that when not doing human intervention on the least important SKUs, the targeted fill rate of 99,0% would still be reached, while 27,4% of all human interventions is not needed anymore.

Human intervention Per class of importance	Average Fill Rate	% Human intervention less needed	% Less SKUs with human intervention
Human intervention on all SKUs	99,3%	0,0	0,0
No Human intervention on A-SKUs	96,7%	30,9	15,8
No Human intervention on B-SKUs	98,8%	41,7	30,3
No Human intervention on C-SKUs	99,1%	27,4	53,9

Table 28: Usefulness of human intervention per class of importance

From the observations above can be concluded that intervening for the least important SKUs is not useful. Besides, it can be concluded that hiding a specific amount of SKUs from the replenishment system to prepare for demand uncertainty, is not a useful way of human intervention.

8.2.2 Rounding Order Quantities with a (R,s,S) Model

The second part of the contribution to the literature is a heuristic to determine the reorder level based on rounded OQs in a (R,s,S) environment. This can be seen as converting a variant of a (R,s,S) model to a variant of a (R,s,S,nQ) model. MOQs and IOQs are determined based on two different requirements: 1) A by-vendor required MOQ and IOQ: MOQ_{VR} and IOQ_{VR}, and 2) a percentage of cost variance a company is willing to order extra for DC workload reduction, $\%_{CV}$. The value of a new introduced variable '*Usable Carton-, Layer-, or Pallet Quantity*' [UCLP] is determined by the $\%_{CV}$. The UCLP can take on the following values: the specific amount of SKUs which can fit on a pallet, on a layer, or in a carton. The UCLP can be determined in the following way: When the cycle costs of the OQ rounded by (a) full pallet(s) causes a higher percentage of cycle costs, which is lower than $\%_{CV}$, the UCLP is the amount of SKUs which fit on a pallet. When this is not the case, but the cycle costs of the OQ rounded by (a) full layer(s) causes a higher percentage of cycle costs, which is lower than $\%_{CV}$, the UCLP is the amount of SKUs which fit on a layer. When this is also not the case, but the cycle costs of the OQ rounded by (a) full carton(s) causes a higher percentage of cycle costs, which is lower than $\%_{CV}$, the UCLP is the amount of SKUs which fit on a carton. When everything stated above is not true, the UCLP is 1. The MOQ is the maximum value of the MOQ_{VR} and the UCLP and the IOQ is the maximum value of the IOQ_{VR} and the UCLP. The AOQ is based on the MOQ and IOQ.

Hill (2006) shows exact calculations for a (R,s,S,nQ) model, when demand is stationary. This research states that the batch size may be of any size. In this thesis is shown how to come up with batch sizes based on the percentage of cost variance a company is willing to order extra, combined with by-vendor required MOQs and IOQs. Besides, Hill (2006) states that after an order is placed, the IP may not exceed the order-up-to level *S*. This is stated, because the reorder level *s* and order-up-to level *S* are restricted to be multiples of the batch size *Q* (Hill, 2006). In this thesis, the reorder levels and order-up-to levels do not have to be multiples of the batch size. This can result in an IP that exceeds the order-up-to level. Paragraph 7.3 shows that the heuristic from this thesis gives comparable reorder levels as the exact calculations from literature (Hill, 2006), used in the DoBr-tool (Van Donselaar & Broekmeulen, 2019). From the observations above can be concluded that the simple heuristic as advised in this thesis, gives usable values of reorder levels, when rounding is implemented in a variant of the (R,s,S) model. This adjusted inventory control model is a combined variant of the (R,s,S) model and the (R,s,S,nQ) model.

9. Discussion

In this part of the thesis, the thesis itself is discussed. Furthermore, an advice is presented how to implement parts of this thesis, and which topics need future research. This corresponds to stage 5 of the regulative cycle of Van Strien (1997). At first, the limitations of this thesis are presented. In the second part, an advice about implementation is given. Finally, an advice is given regarding future research.

9.1 Limitations

This part of the thesis states what the limitations of this research are. The limitations of this research are given in the scope of this thesis and assumptions that are made. First of all, this research is performed for the DC in GOH only, because of time limitations. The improvements can be tested for other DCs with the help of the build simulation tool. Second, this research gives an advice regarding the inventory control model for the least performing SKUs, while the performance of non-mature SKUs is not considered. This means that the group of non-mature SKUs is not included in the final advice. Non-mature SKUs can be planned with the improved model, when the forecasted demand for those items is determined based on other characteristics than historical demand of this specific SKU. This is why it is recommended to perform a forecasting project of non-mature SKUs at Office Depot at the marketing department. Other limitations can be found in assumptions that needed to be made. Some limitations are caused by unreliable or missing data for specific topics. This is why in the simulations the assumptions had to be made that there were *no promotions* and that the *input parameters retrieved at the day of starting with the simulations were the same as during the whole year 2018*, because historical values of this parameters were not stored by Office Depot. When promotion data per SKU and all input parameters for the simulations per SKU are stored daily, the simulation would give the most reliable output. This is why it is recommended to store this data from now on. The last limitation is that changing the SOQ as form of human intervention could not be simulated, while in chapter 5.3 it is concluded that changing the SOQ by the planners is 22,2% of all human interventions.

9.2 Implementation

This part of the thesis gives an advice about the implementation. First of all, it is advised to allow planners to review less than once a week for specific items, not intervene in SKUs which are classified as least-important, not use hideout quantities to prepare for demand uncertainty, use the new holding cost percentage of 42,64% for the specified low value density SKUs, and include rounded OQs in reorder level determination. These adjustments lead to a decrease in costs.

The second advice is to not prohibit hideout quantities. The process might not be useful to prepare for demand uncertainty, but it can still be a useful form of human intervention for promotions. More about this is stated in part 9.3.3 of this thesis. Furthermore, it is advised to store historical data about promotions.

The third advice is to check the optimal holding cost percentage for low value density SKUs over time. All calculations are explained in part 7.4 of this thesis. Checking and adjusting if necessary can be done in line with the cycle updates.

Finally, the simulation tool can be used for multiple causes. When it is considered to use the inventory control model for a new group of items, the performance can be tested with the simulation tool. Besides, when future research states that different ways of determining specific input parameters is useful, tests with newly determined input parameters can be performed with the simulation tool. Furthermore, it is advised to store historical data about all input parameters used in the simulation tool. Using the right data at the right days, gives the most reliable output.

9.3 Future Research

This part of the thesis states possible subjects to do future research on. Three subjects for future research resulting from this thesis are: 1) searching for the SKU allocation from the CDC to the RDCs for OB SKUs, 2) searching for the right input regarding the expected demand, and 3) searching for the right method for forecasting demand of non-mature SKUs and forecasting during promotions, and using this forecast as input.

9.3.1 OB SKU Allocation

Indirect OB SKUs can be planned with the (R,s,S) model, by using the LT from the CDC to the RDCs. By doing this, it is assumed that the CDC has enough stock to fulfill the demand from the RDCs. However, in practice this might not be the case. This is why a future research project is to optimize the replenishment logic used for the CDC. This includes ordering from to the manufacturers in China , and determining the optimal allocation for the received SKUs in the CDC to all different RDCs.

9.3.2 Expected Demand

Paragraph 6.1 concludes that forecasting and the way of using the forecasted demand in the inventory control model, is the topic with the highest expected impact. At this moment, the forecasted demand during one future arbitrary time period is used as input for the inventory control model. The forecasted demand is determined by the cleansed average of last 13 weeks demand. This means that a stationary demand pattern is expected. Chapter 5 concludes that the demand pattern is not stationary. This means that Office Depot could use a different way of forecasting demand and another way of using the expected demand as input. It is also shown that the total demand pattern shows a seasonal pattern, particularly caused by one third of all product groups. This is why the inventory control model at Office Depot could use expected demand during RP and LT, which considers the period of the year. However, as stated in paragraph 5.6 of this thesis, it might not be useful to find a more complex way of forecasting for unforecastable SKUs. Defining for which SKUs it might be valuable to use a different (more complex) forecasting method, and finding the optimal forecasting method for these SKUs, is a project which requires and deserves more time than available for this project. This is why this topic is chosen to be future research material.

9.3.3 Non-Mature SKUs and Promotions

Non-mature SKUs and promotions are not considered in this thesis. Forecasting demand for non-mature SKUs needs other parameters than historical demand data for this specific SKU. This is why determining the way of forecasting needs marketing research, to see what the expected demand will be for a new product on the market. Historical demand during promotion periods of specific SKUs is not data that is stored by Office Depot at this moment. Forecasting demand during promotions also needs more data than historical data of the demand without promotions. For example, it might be useful to know the demand pattern during past promotions of this SKU or the demand pattern during past promotions of comparable SKUs. This is why it is recommended to perform a forecasting project of non-mature SKUs and promotion periods of SKUS, at the marketing department.

The forecasted demand of non-mature SKUs can be used in the replenishment system in the same way as forecasted demand of mature SKUs. When forecasted extra demand because of promotions can be determined, the forecasted extra demand can be put into the replenishment system with the use of hideout quantities.

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11. Appendices

Appendix 1: Countries Office Depot Europe Operates In

The countries that Office Depot Europe is operating in, are the following:

1. Austria
2. Belgium
3. Czech Republic
4. France
5. Germany
6. Ireland
7. Italy
8. Slovakia
9. Spain
10. Sweden
11. Switzerland
12. The Netherlands
13. The United Kingdom

Appendix 2: Office Depots' Intern Documents Used

The following intern documents of Office Depot are used to gather information about the company and inventory control model:

- The Demand Exceptions File
- Work instructions and Training Manuals
- Introduction to Office Depot September 2018
- Inventory Planning CDC Own Brand Overview
- ITM Planner Presentation
- Overview Planners
- Planner Checklist
- Planner Presentation
- Prime One Training V2
- Re-Order Policy exceptions
- Review Period & Fill rate Goal optimization
- Work Instruction Demand Adjustment File ITM
- ITM

Appendix 3: Interview (Dutch)

Voorstellen:

Hallo, mijn naam is dus Sil. Ik zit hier voor mijn Masters Thesis vanuit mijn studie Operations Management and Logistics, aan de Technische Universiteit van Eindhoven. Voor het afronden van mijn studie moet ik een onderzoek doen, dat dus hier plaats vind.

Ik ga hier een onderzoek doen naar het voorraadbeheersing systeem dat jullie gebruiken, ITM. Bart kwam met zijn thesis uit op dit model, echter wel door een aantal restricties. Het model moest goed presteren binnen de restricties van dit bedrijf. Zo moest het implementeerbaar zijn in de huidige software, dus compatible met Prime One. Men denkt hier dat het nieuwe voorraadbeheersing systeem niet beter werkt voor een aantal productgroepen. De vraag aan mij is: Welke productgroepen presteren niet goed onder de nieuwe inventory policy en wat voor inventory systeem zou je ons aanraden voor deze productgroepen, wanneer deze restricties er niet zijn?

Ik heb al deels kennisgemaakt met ITM en Prime One, er zijn me een aantal dingen verteld, maar alleen door de afdeling Supply Chain Optimization. Ik zou ook graag een andere kant van het verhaal horen, daarom kom ik bij jullie met een aantal vragen. De antwoorden worden gebruikt om mij te oriënteren, ze zullen niet terug te vinden zijn in mijn thesis.

Vragen:

- Wat is je naam en je functie binnen Office Depot?
- Hoofdtaken van jouw functie?
- Hoe steekt het huidige voorraadbeheersing systeem in elkaar?
- Met welke systemen werk jij? En welke Excel files?
- Hoe vind je het huidige voorraadbeheersing systeem presteren?
- Wat zijn de voor- en nadelen van ITM ten opzichte van Prime One?
- Wat is het risico wat het huidige voorraadsysteem met zich mee neemt?
- Wat heeft jullie ertoe doen besluiten om definitief op ITM over te gaan?
- Waarom duurde het een jaar voor UK&I live ging?
- Waren er problemen met de implementatie van ITM? Welke?
- Achteraf blij dat het geïmplementeerd is? Verbetering?
- Mis je opties in het voorraadbeheersing/forecasting systeem die jouw werk makkelijker zouden maken?
- In welke productcategorieën verwacht jij dat het systeem niet goed presteert?
- Heb je nog tips voor mij in mijn verdere onderzoek?

Appendix 4: Overview Raw Data Needed

Data over multiple years is required to check whether or not seasonality can be found. At the moment of writing this, the last two full years of weekly sales data (2016 – 2017) will be gathered, because this is suitable for the purpose of finding demand patterns in through a year. These years were used because from 2016, Office Depot started storing the full weekly sales data. Weekly and daily sales data of 2018 will also be used, but since this research also started in 2018, it cannot be stated in this chapter which time periods will be used in which chapters of the thesis. This will be stated in the chapters itself. The newest data will always be used. Specific quantitative data needed in this thesis is given in Table 31.

Quoted LT per subvendor	Deviation of LT per delivery	Unique item key per SKU
Actual daily/weekly demand per SKU	Fulfilled daily/weekly demand per SKU	Demand variation per SKU
Vendor and subvendor per SKU	Actual inventory units / value per SKU	AOQ per SKU per order
By-vendor required IOQ per SKU	By-vendor required MOQ per SKU	The CLPs per SKU
Demand adjustments per SKU / day*	Hideout quantities per SKU/ day*	TFRs per SKU
Purchase price in euros per SKU	Fixed order day per subvendor	

** = Term explained in part 5.3.2 of this thesis*

Table 29: Specific quantitative data needed

Appendix 5: Expected Annual Costs Equation

The following expected annual costs equation is used at Office Depot Europe:

$$C_y = E[O_y] * C_O + E[OL_y] * C_{OL} + E[X_y] * C_h$$

Equation 8: Calculation of the total annual costs

In Equation 8, the order costs C_O are €20, order line costs C_{OL} are €5 and the holding costs C_h is equal to the value of a SKU multiplied by holding cost percentage, which is 25 percent. The expected number of orders *E[O]*, order lines *E[OL] and* expected average stock *E[X]* are all annual (*y*).

Appendix 6: Equations & Explanations of Reorder Level Determination

The equations and explanations needed in reorder level determination are given in the following equations: (De Kok A. G., 2018) (De Kok A. G., 2004)

$$E[U_R] = \frac{(\alpha+1)}{2\lambda}, where\ \alpha = \frac{E^2[D_R]}{\sigma^2[D_R]}\ and\ \lambda = \frac{\alpha}{E[D_R]}$$

Equation 9: Calculation of the expected undershoot

$$\sigma^2[U_R] = E[U_R^2] - E^2[U_R] = \frac{(\alpha+1)*(\alpha+2)}{3\lambda^2} - \left(\frac{(\alpha+1)}{2\lambda}\right)^2, where\ E[U_R^2] = \frac{(\alpha+1)*(\alpha+2)}{3\lambda^2}$$

Equation 10: Calculation of the variance of the undershoot

$$\sigma[D_L + U_R] = \sqrt{\sigma[D_L]^2\ \sigma[U_R]^2}$$

Equation 11: Calculation of the standard deviation of D_L and U_R

$$E[D_L + U_R] = E[D_L] + E[U_R]$$

Equation 12: Calculation of expected demand during LT plus undershoot

$$\alpha_{E[D_L]+E[U_R]} = \frac{1}{\left(\frac{\sigma[D_L+U_R]}{E[D_L+U_R]}\right)^2} + 1$$

Equation 13: Calculation of shape parameter of expected D_L and U_R

$$\beta_{E[D_L]+E[U_R]} = E[D_L + U_R] * \left(\frac{\sigma[D_L+U_R]}{E[D_L+U_R]}\right)^2$$

Equation 14: Calculation of scale parameter of expected D_L and U_R

$$\alpha_{E[D_L]} = \frac{1}{\left(\frac{\sigma[D_L]}{E[D_L]}\right)^2} + 1$$

Equation 15: Calculation of shape parameter of expected D_L

$$\beta_{E[D_L]} = E[D_L] * \left(\frac{\sigma[D_L]}{E[D_L]}\right)^2$$

Equation 16: Calculation of scale parameter of expected D_L

P_2 is the fill rate. $E[U_R]$ is the expected undershoot in a periodic reorder model, which is calculated this way when demand is gamma distributed. $E[D_K]$ is the expected demand during K periods of time. For calculations of the demand and variance during a specific period, see chapter 5.2.4. $F(x;\alpha;\beta)$ is the cumulative gamma distribution function, with input parameters x, α, and β. The first input parameter x is the value at which the distribution is evaluated to. The other two parameters are the shape parameter α and the scale parameter β. These values can be calculated in excel, using the function '*=GAMMADIST(…)*'. Q_{opt} is the optimal OQ without considering undershoot, which is the maximum value of expected demand during RP $E[D_R]$ or the EOQ. The *EOQ* calculation can be found in Equation 20.

$$EOQ = \sqrt{\frac{2 * E[D_y] * C_O}{C_h}}$$

Equation 17: Calculation of the EOQ

Where C_O is the costs of ordering this SKU and C_h is the costs of holding one piece of this SKU on stock for one period. Order costs per SKU are 5 euros and holding costs are 25% of the value of the SKU.

Appendix 7: Equations CLP Rounding

The following equations are used when the first type of rounding is performed:

$$CostVar_{pallet\ rounded} = \frac{CC_{Q_{Pallet\ Rounded}}}{CC_{Q_{opt}+E[U_R]}} - 100\%$$

Equation 18: Calculation of the cost variance by pallet rounding

$$CC_{Q_{Pallet\ Rounded}} = \frac{Q_{Pallet\ Rounded}}{2} * C_h + \frac{E[D_y]}{Q_{Pallet\ Rounded}} * C_{OL}$$

Equation 19: Calculation of the cycle costs by pallet rounding

$$Q_{Pallet\ Rounded} = \left\lceil \frac{Q_{opt} + E[U]}{Units\ per\ Pallet} \right\rceil * Units\ per\ Pallet$$

Equation 20: Calculation of the order quantity by pallet rounding

The same equations can be made for rounding based on ordering full layers of full cartons.

Appendix 8: Deviation Targeted- and Achieved Fill Rates

Percentage Deviation	**Percentage of SKUs**
<1	23,2
1-2	51,3
2-3	7,3
3-4	3,0
4-5	1,8
5-10	4,9
10-25	5,5
25-50	2,2
50-100	0,8

Table 30: Percentage of SKUs per percentage of deviation of fill rates

Appendix 9: Demand Adjustment Cleansing

A cycle update happens every week on Friday, after which the new calculated expected demand during one arbitrary future time period is uploaded in a demand adjustment file. These files are not used in determining the human intervention, because updating the expected demand during one arbitrary future time period is part of how the model functions. Figure 12 shows how many adjustments are done per workday for inventory stored in GOH. Figure 12 shows extreme outliers. The Supply Chain Optimization team found out that the seven largest outliers were caused by cycle updates which were done on another workday than Friday, which is why these values are removed from the dataset.

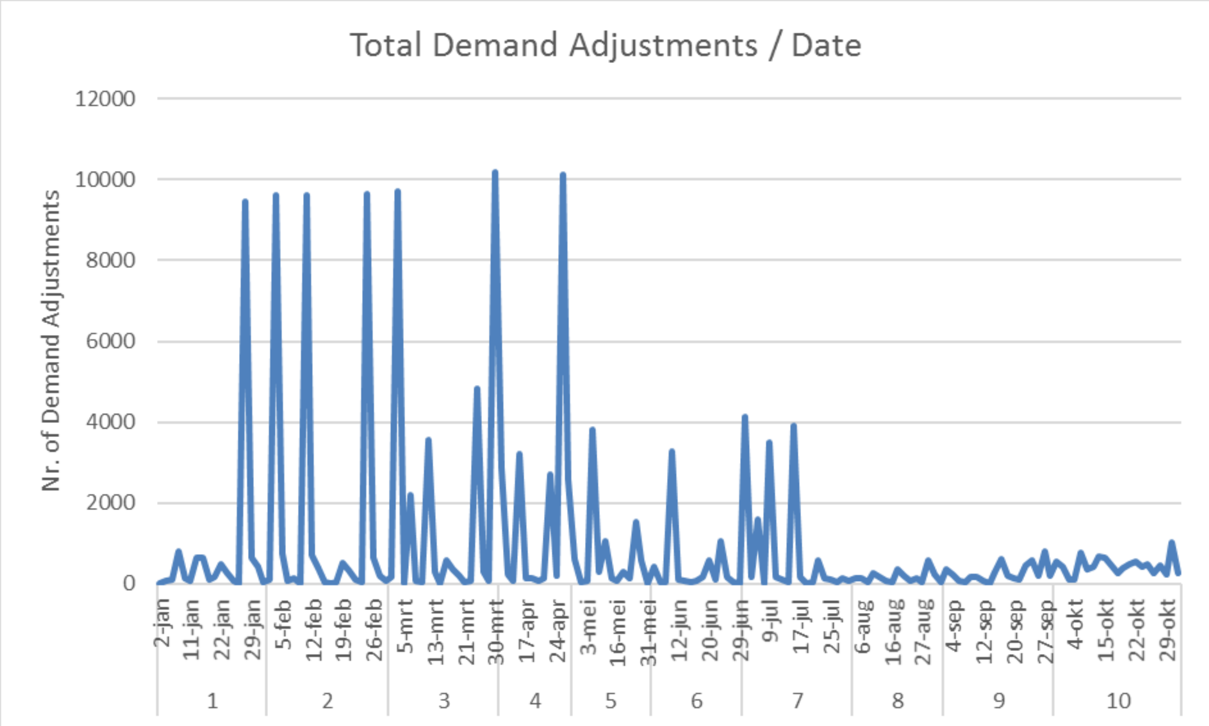

Figure 12: Total demand adjustments per workday with cycle updates.

On average, there are 377 demand adjustments per workday without the seven removed data points. There are 14.287 SKUs planned with the (R,s,S) model, with on average 412 OLs of these SKUs per workday. This given, it can be stated that the amount of demand adjustments per workday is relatively high. A note has to be made that besides the seven removed outliers, the average amount of demand adjustments per workday still includes the peaks. These peaks can have the following reasons:

1. In the months March, April and May, a planner who uses another way of forecasting was planning a group of SKUs planned with the (R,s,S) model, because of absence of the planner who is responsible for those SKUs. He planned hundreds of SKUs with this forecasting method, so had to use the demand adjustments file more than other planners.
2. The Supply Chain Optimization team tried a different forecasting method in March and April, which caused in higher amount of demand adjustments.
3. A warehouse closure happened this year, all inventory had to be shipped from Zwolle to GOH before the start of August. Before this period, demand which was fulfilled from Zwolle was manually added to the demand which was already fulfilled from the warehouse in GOH.

Because of these reasons, Figure 13 shows the amount of demand adjustments without outliers above 1000 demand adjustments per workday. Removing these outliers means that again 15 days were removed. The 15 removed dates together caused 51% of the total demand adjustments over the given period, without the earlier removed days. The new average amount of demand adjustments per workday is 204, which is still almost half the average amount of OLs per workday.

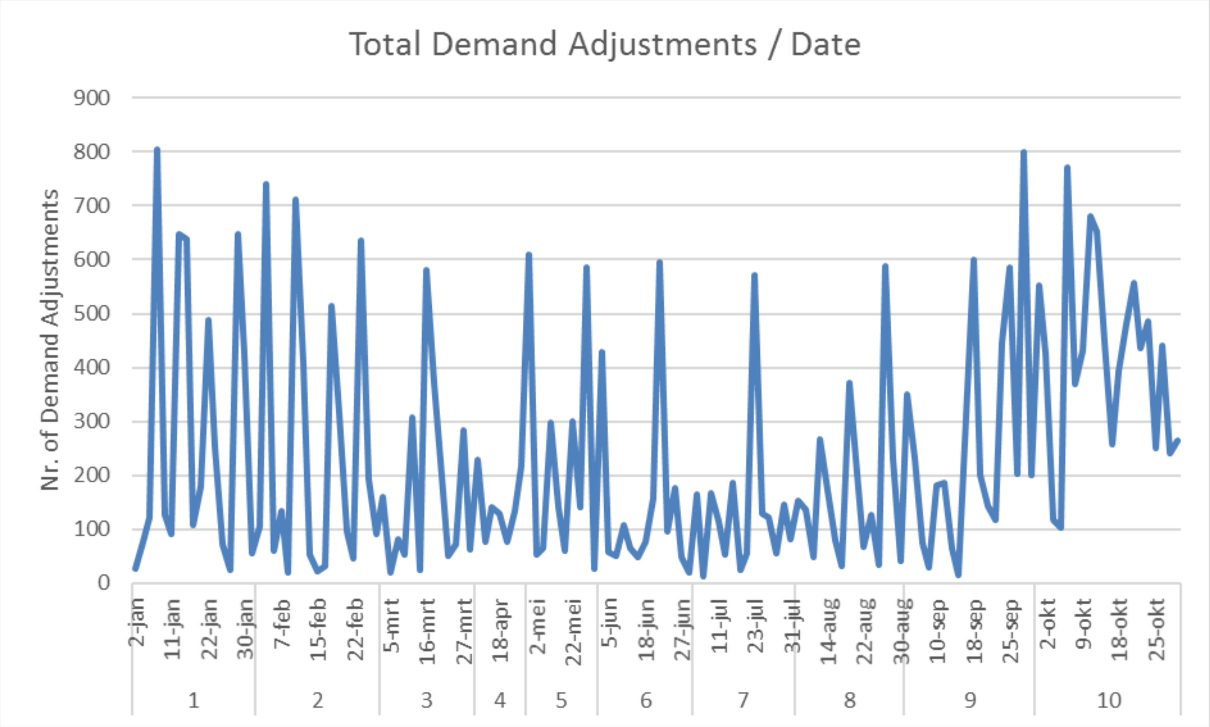

Figure 13: Number of demand adjustments per workday (cleansed above 1000)

Appendix 10: Hideout Quantities and Demand Pattern

In this appendix, three different figures are shown. Figure 14 shows the total units hidden from the system per workday. Figure 15 shows the percentage of the total assortment in GOH that has a hideout quantity per workday. Figure 16 shows the total weekly sales of 2018. All figures have time on the horizontal axis, from the 1st of January 2018 till the 31st of October 2018.

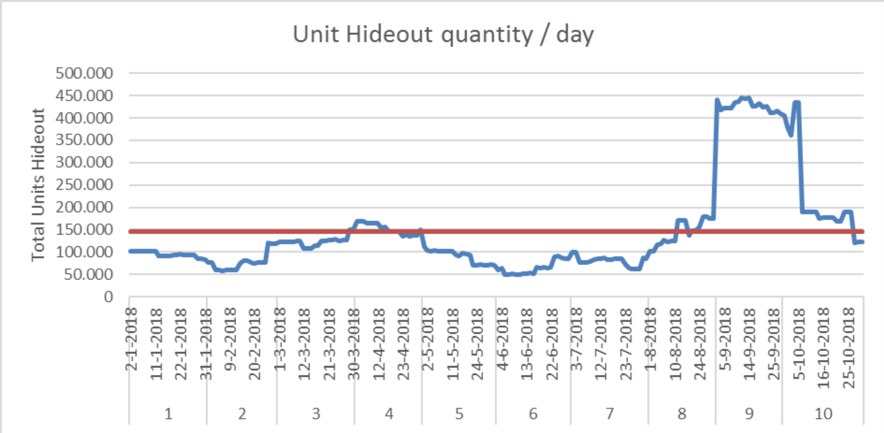

Figure 14: Total units hidden from inventory control model per workday

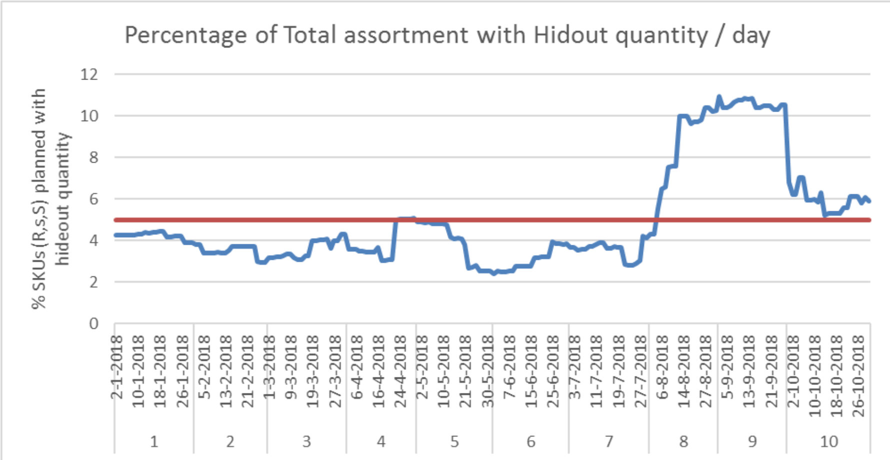

Figure 15: Percentage of total assortment with hideout quantity per workday

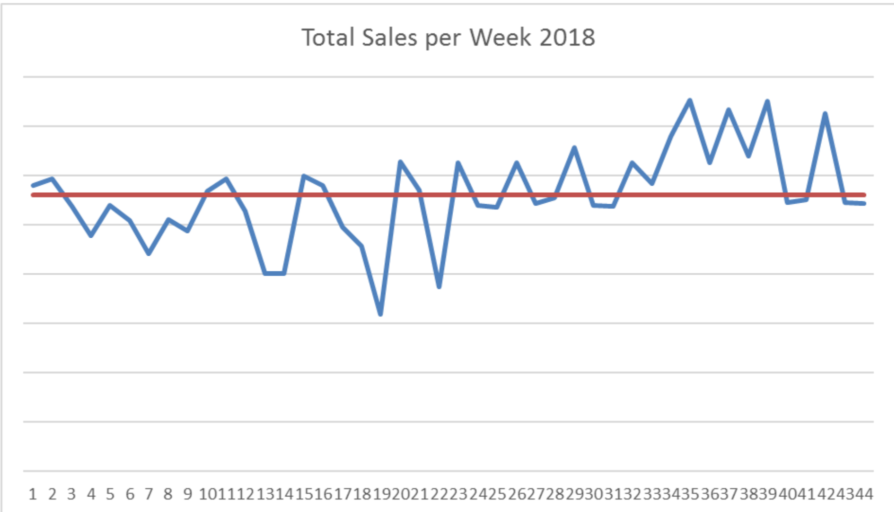

Figure 16: Total sales per week 2018

Appendix 11: AOQ and SOQ Comparison Logic

The following logic is used: When an actual OL is placed, the SOQ at that moment is checked and compared to the AOQ. The historical order day is not saved. Ordering on another day can be seen as a form of human intervention, but because this information is missing, the choice is made to look at the SOQ when an order was placed. This provides the following results:

Definition	Percentage
Percentage of OQ adjustments	48,4
Percentage of adjustments up (AOQ>SOQ)	91,9
Percentage of adjustments down (SOQ>AOQ)	8,1

Table 31: SOQ vs. AOQ total January till October

Table 33 states that at 48,4% of the OLs placed, the quantity is adjusted by human intervention. When the OQ is adjusted by a planner, in 91,9% of the cases more of a SKU is ordered, compared with the SOQ by the (R,s,S) model. In only 8,1% of all adjusted OLs, the AOQ is less than the SOQ. When looking at the data, the observation can be made that a lot of OLs are triggered when the system tells not to order. In this case, the SOQ is zero, and with the logic above, this is seen as an up adjustment. Because capturing the historical data used to calculate the SOQ happens at the end of the workday, and the refresh button has to be used at the start of the next workday, the difference can be explained.

This is why workdays with POs raised and SOQs in place are used to calculate the adjustments in OQ, because when looking at the POs raised and SOQ not in place, it might be the case that a demand adjustment was placed.

This is why in Table 34, only orders are compared when there was a SOQ given by the system. When an order was placed, but there was no order suggested by the system, this data is not used.

Definition	Percentage
Total percentage OL in consideration after cleansing	57,5
Percentage of OQ adjustments	17,0
Percentage of adjustments up (AOQ>SOQ)	62,7
Percentage of adjustments down (SOQ>AOQ)	37,3

Table 32: SOQ vs. AOQ total January till October, when SOQ in place

Appendix 12: Performance per Review Period

Review Period (Workdays)	% of SKUs	% Average Weekly Sales	% Inventory value
0	0,1	0,0	0,2
1	0,1	0,0	0,1
2	2,1	7,3	2,5
3	12,1	28,5	22,0
4	0,5	0,2	0,8
5	78,0	61,9	66,9
6	0,2	0,0	0,3
7	0,2	0,0	0,1
8	0,5	0,1	0,4
9	1,0	0,1	0,8
10	1,2	0,1	0,5
20	4,0	1,7	5,5
30	0,0	0,0	0,0
Total	100,0	100,0	100,0

Table 33: Number of SKUs, IOH value and importance per review period

Appendix 13: Performance per Targeted Fill Rate

TFR	% of SKUs	% Average Weekly Sales	% Inventory value
No Target	1,1	0,3	1,4
96,0	6,6	2,0	8,2
97,0	0,2	0,2	0,3
97,1	0,0	0,0	0,0
97,5	0,9	0,1	0,8
98,0	11,6	7,7	11,5
98,5	2,2	0,4	1,6
98,9	0,4	0,0	0,3
99,0	60,1	21,2	30,4
99,1	6,3	13,5	12,0
99,2	5,1	39,0	23,3
99,3	0,0	0,6	0,3
99,4	4,4	14,4	7,4
99,5	1,0	0,7	2,6
99,9	0,0	0,0	0,0
Total	100,0	100,0	100,0

Table 34: Number of SKUs, IOH value and importance per TFR

Appendix 14: Performance per Item Classification

Item Classification	% of SKUs	% Average Weekly Sales	% Inventory value
AX1	5,2	38,6	25,5
AX2	1,5	12,4	5,0
AX3	0,1	1,6	0,6
AY1	2,8	10,9	11,3
AY2	1,4	5,4	4,5
AY3	1,0	5,4	3,9
AZ1	0,2	1,0	2,3
AZ2	0,2	0,6	1,9
AZ3	0,4	4,3	2,8
BX1	5,5	3,6	4,4
BX2	0,4	0,2	0,9
BX3	0,1	0,0	0,2
BY1	12,2	6,8	7,8
BY2	2,2	1,5	1,4
BY3	0,2	0,2	0,2
BZ1	2,5	1,2	3,4
BZ2	1,3	0,6	1,7
BZ3	1,3	0,7	1,8
CX1	11,2	0,7	3,5
CX2	1,8	0,1	0,7
CX3	0,2	0,0	0,2
CY1	14,0	1,9	4,0
CY2	0,2	0,0	0,1
CZ1	27,1	1,5	7,9
CZ2	5,5	0,5	2,9
CZ3	1,5	0,2	1,2
Total	100,0	100,0	100,0

Table 35: Nr of SKUs, IOH value and importance per item classification

Appendix 15: Assumptions for Simulations

For the simulation of the IP, IOH, BOs and SOQs, the following assumptions were made:

1. There were no promotions in 2018.
2. When there is demand on weekend days, this demand is added the Monday after.
3. A subvendors performance is about the same through a year.
4. OLs are always fully delivered.
5. First week of January uses the input parameters calculated at the 5th of January.
6. Week 51 and 52 of 2017 and week 1 of 2018 are not used in calculating the forecasted demand. Three earlier weeks are used instead.
7. The TFR, review period, CLPs, fixed order days, item purchase price in euros, by-vendor required MOQs, and by-vendor required IOQs used in the (R,s,S) model are correct and stayed the same through the whole year.
8. The forecasted demand and its standard deviation are calculated based on the weekly demand data for the DC in GOH for weeks 1 till 31, and week 45 till the last week of 2018. For week 32 till week 44, the forecasted demand and its standard deviation are calculated based on the weekly demand for the DC in GOH and in Zwolle.
9. Hidden quantity on workdays without this data have the same value as the workday before.
10. Counting workdays to see whether or not reviewing is needed starts on the 1st of January 2018.
11. The IOH at the 1st of January 2018 is equal to the IP at that date.

Appendix 16: Cycle Updates

Figure 17 provides an overview of all cycle updates for GOH in the year 2018. Cycle updates happen every Friday, from the Monday after the cycle update, the new forecasted values are used. The reorder levels and order-up-to levels are adjusted after every cycle update, based on the new forecasts.

Date	January	February	March	April	May	June	July	August	September	October	November	December
1												
2		Cycle update DE	Cycle update DE									
3												
4												
5	Cycle update DE											
6												
7												Cycle update DE
8												
9											Cycle update DE	
10												
11												
12										Cycle update DE		
13												
14									Cycle update DE			
15												
16												
17								Cycle update DE				
18												
19												
20							Cycle update DE					
21												
22						Cycle update DE						
23												
24												
25					Cycle update DE							
26												
27				Cycle update DE								
28												
29												
30			Cycle update DE									
31												

Figure 17: Cycle updates 2018

Appendix 17: Performance of Combined Importance- and Forecastability Class

	Hideout Quantities		Demand Adjustments		Both	
Class	Average amount of human interventions per SKU	Average less BOs per human intervention	Average amount of human interventions per SKU	Average less BOs per human intervention	Average amount of human interventions per SKU	Average Less BOs per human intervention
AX	1,25	0,00746%	3,52	0,00686%	4,77	0,00527%
AY	0,93	0,00437%	4,08	0,00453%	5,01	0,00383%
AZ	0,55	0,00112%	1,61	0,00234%	2,16	0,00185%
BX	0,84	0,00118%	2,32	0,00069%	3,16	0,00076%
BY	0,57	0,00059%	3,17	0,00068%	3,74	0,00061%
BZ	0,28	0,00280%	1,60	0,00089%	1,89	0,00103%
CX	0,37	0,00042%	1,56	0,00042%	1,93	0,00038%
CY	0,30	0,00040%	2,24	0,00036%	2,53	0,00035%
CZ	0,13	0,00040%	0,32	0,00058%	0,46	0,00050%

Table 36: Percentage less backorders caused by human intervention (classes combined)

Appendix 18: Including Human Intervention in Annual Costs

Costs of human intervention are based on the average time spent to fill the demand adjustment file. This is tested on two different moments for three different planners.

It is measured how many seconds to do the daily demand adjustments. By dividing the time needed for the daily demand adjustments by the amount of demand adjustments placed, the amount of time per placed demand adjustment is determined. The least time needed per adjustment was 75 seconds, while the most time needed per adjustment was 104 seconds.

The time needed per adjustment is multiplied the amount of human interventions placed and the average costs of a planner. The same costs per planner for the company is used as the Supply Chain Optimization team used in other analyses.

Appendix 19: Top Ten Performing Product Groups

Product Group	Average less BOs per human intervention	Average amount of human interventions per SKU
Office Paper - Business Segment	0,01120%	5,29
Standard Lever Arch Files	0,01081%	8,07
Special Pens	0,00796%	0,80
Office Paper - Green Segment	0,00630%	3,09
Winter Supplies	0,00585%	1,25
Correction Products	0,00505%	2,67
Scissors	0,00479%	2,88
Coloring	0,00377%	1,63
Fine Liners	0,00366%	1,33
Rollerball Pens	0,00329%	1,08

Table 37: Percentage less backorders caused by human intervention per product group