MASTER

Inventory replenishment and optimization of the pick locations at SPAR's distribution centers

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Inventory replenishment and optimization of the pick locations at SPAR's distribution centers

by

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Abstract

This report is about a graduation research conducted at supermarket chain SPAR in the Netherlands and this research has two main objectives. The first one is the development of an inventory replenishment system that takes costs of handling operations in SPAR's DCs and costs of outdated products into account. The second objective is to develop a method which can be used to divide the total available pick location storage space among the SKUs in the most cost efficient way. As part of this research, an inventory replenishment system, based on the theory of van Donselaar and Broekmeulen (2014), has been used to show that including costs of handling operations and outdating of perishable products results in lower costs than using the current inventory replenishment system that is used by SPAR. Furthermore, four algorithms have been developed to optimize the allocation of the total pick location storage space among the SKUs that are stored in SPAR's distribution centers. The results of using these algorithms have shown to have a potential cost reduction of up to 43% compared to the currently used allocation.

Preface

This report is the result of my graduation project for the master study Operations Management & Logistics at the Technical University of Eindhoven. I have conducted my graduation project at SPAR Holding B.V., specifically at the Supply Chain department of SPAR.

In the process of making this graduation project to a success, my first supervisor, Rob Broekmeulen has been of great help. He gave me lots of help with the outline of my project and always gave me a heads up in the right direction whenever I thought I was lost in the field. Therefore, I would like to thank Rob. Furthermore, I would like to thank my second supervisor, Karel van Donselaar, for his feedback on my research in making sure that my project would not only be relevant in practice but it would also be a valid graduation project.

I would especially like to thank Edwin Brekelmans for making this whole project available by hiring me as a graduate intern and supporting me throughout the project. Our meetings have always been very valuable to me and to the project. Furthermore, I would like to thank Leo Steur and Boudewijn van Putten for helping me finding the right data and the right products to use in my pilot test group and I would like to thank my colleagues Gert, Jan, Hans, Liesbeth and Wim for having a great time.

Last but not least, I would like to thank my friends and family and especially my girlfriend Sandra for supporting me not only throughout this project, but during my entire study period.

Many thanks,

Loek Nolten

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Management Summary

SPAR is a globally operating supermarket chain in which each country has its own organization. In The Netherlands, SPAR focusses on neighborhood stores and most stores can be found in small towns and districts with 2,000 up to 4,000 inhabitants. This means that SPAR, compared to other supermarket chains, faces low volumes of demand and therefore low volumes of ordered quantities. On the other hand, SPAR does have a wide variety of products. This research focusses on the SKUs that are being stored in either one of the two DCs of SPAR. SPAR stores all of its SKUs in the North DC, covering the northern part of the Netherlands, and in the South DC, covering all southern stores. From these two DCs, SPAR ships all SKUs to the stores around the country and it has agreed an overall 98% service level with the stores, which is the most important KPI of the Supply Chain department of SPAR.

Problem context

SPAR's Inventory Management department is currently using the inventory replenishment system Slim4, which is designed to keep the inventory on hand as low as possible by only ordering sufficient goods to cover the review period and the lead time, taking into account the desired service level. The downside of using this method is that the DCs receive many shipments of small quantities of products. This results in pallets that contain several different kinds of products, which all have to be stacked on separate pallets before they can be stored. This also results in pallets that only contain a small amount of case packs, which is not efficient for transportation. A third result of using this method is that, for some products, the DCs receive one pallet layer each week, which they have to receive, transport and store in the shelves of the DC. All of these results of minimizing the total inventory on hand, end up in a lot of handling for the employees in the DCs and therefore, in relatively high handling costs. Therefore, this research focusses on taking into account these handling operations as well as the outdating of perishable goods in order to minimize the total inventory related costs at SPAR's DCs.

This brings us to a first objective of the research, which is:

Develop an inventory replenishment system that determines the optimal order quantities for the SKUs of SPAR in its DCs, which minimizes the total inventory costs, taking into account the service level restrictions, ordering in batches, and the perishability of SKUs.

Besides the topic of the inventory replenishment system, SPAR is also experiencing issues with the capacity of its DCs. This is a clear issue in the North DC, since the North DC is a lot smaller than the South DC. All dry groceries slow moving SKUs in both DCs as well as many dry groceries fast moving SKUs in the North DC have pick location spaces which are smaller than a full pallet load. This means that whenever a full pallet of one of these SKUs arrives at the DC, the amount that fits in the pick location will be stored in this location and the rest will be stored at the bulk storage space. As Eroglu et al. (2012) depict, the backroom effect may substantially change the optimization problem faced by retailers. In this case, the situation at the SPAR DCs is very comparable to the problem of a retailer which can store part of the incoming SKUs at the store shelves and part of the goods in the back room. Therefore, in optimizing the inventory replenishment system of SPAR's DCs, the incoming amount of goods and the shelf space of the pick locations should be aligned in order to reduce the replenishment costs of replenishing the pick locations.

This raises the following problem:

Given the total storage capacity of the pick locations in SPAR's DCs, how to determine the capacity of the pick location of each SKU in such a way that the total inventory related costs are minimized?

Inventory replenishment

The main objective of an inventory replenishment system is to minimize the total costs. Therefore, in order to come up with a suitable inventory replenishment system, the costs that will be taken into account have to be defined first. Broekmeulen and van Donselaar (2009) have developed the EWA-policy that makes use of holding costs, outdating costs, and lost sales costs. Furthermore, van Woensel et al. (Working paper) have shown that handling costs need to be taken into account as well when one is dealing with perishable products in a lost sales system. For the inventory replenishment policy of the distribution centers of SPAR, the following costs are determined for all SKUs:

- Ordering costs;
- Holding costs;
- Outdating costs;
- Replenishment costs.

Minimizing the sum of these inventory related costs is the first objective of this research. SPAR has agreed to order in specified batch at specified moments, with specified lead times and review periods sizes with almost all of its suppliers. Therefore, an (R,s,nQ) system should give the best results. Van Donselaar and Broekmeulen (2014) have recently developed an Excel based tool to calculate several KPIs for both (R,s,nQ) and R,s,S). This tool is called the DoBr tool and can be used to calculate several KPIs or cost drivers, which are needed in order to calculate the four types of inventory costs of the cost function of this project. Using this tool, approximations for the expected inventory on hand, the expected number of order lines, the expected outdating, and the expected number of replenishments of the pick location can be determined. By multiplying these numbers with the respective costs, the total inventory related costs can be determined for all amounts of order quantities. By doing so, the order quantity that results in the lowest cost per week can be determined. The inventory related costs of this model are compared to the costs of the order quantities that Slim4 calculates in order to determine the potential cost reduction by including the costs of handling operations and costs of outdating in the inventory replenishment system. This is done for a pilot group of 35 SKUs in this research. As a result, it shows that the potential cost reduction is €6.44 per year per SKU, based on the outcome of the pilot group. In total, there are over 5,000 SKUs that meet the restrictions of the model and therefore, the potential for cost saving is estimated to be higher than €30,000 a year.

Pick location capacity

The problem of which amount of storage space of the pick locations to allocate to which SKU can be modeled quite similar to a Knapsack problem. The total available storage capacity can be seen as the capacity of the Knapsack, SPAR's SKUs can be seen as the different items that can go into the Knapsack and the amount of pallet layers of an SKU can be seen as the number of copies of an item that can go into the Knapsack. However, SPAR's problem does substantially differ from a standard Knapsack problem in two ways. First, all of SPAR's SKUs need to have an appointed pick location.

Otherwise, the products cannot be picked and shipped to the supermarkets. Second, for each SKU, the cost reductions of extending the capacity of the pick location are not linear. Therefore, SPAR's "Knapsack" problem can be modeled as a large tower with the length and width of the size of a pallet and a total height capacity *V*, which is equal to the total height of the pallet locations minus the height of the needed planks and the needed head space. This tower should be filled with *n* item types (SKUs), where item type *i* has a height w_i and inventory related costs c_{ij} for each *j* pallet layers in the SKUs pick location capacity. Each SKU has an upper bound m_i, which either states the amount of pallet layers at which adding an extra pallet layer does not result in lower costs, or states the number of pallet layers that fit into one pallet location.
The problem can be defined as follows:

$x_{ij} \in \{0,1\}: SKU\ i\ gets\ j\ layers\ allocated\ as\ its\ pick\ location\ capacity$
$j \in \{1, \dots, m_i\}$

$$Minimize \left\{ \sum_{i=1}^{n} \sum_{j=1}^{m_i} c_{ij} x_{ij} \right\}$$

$$s.t. \qquad \forall i: \sum_{j=1}^{m_i} x_{ij} = 1$$

$$\sum_{i=1}^{n} \sum_{j=1}^{m_i} w_i x_{ij} \leq V, \qquad V = total\ height - height\ of\ planks - head\ space$$

Calculating the potential cost reductions of ordering an extra pallet layer of each SKU is done by using the DoBr tool. Ranking the potential cost reductions based on their cost reduction and the extra height that is needed to achieve that reduction is done in three ways in this project, namely:

1. The cumulative cost reduction of extending the SKU's pick location capacity to j pallet layers, compared to the cost of having a pick location capacity to the minimal amount of 1 pallet layer, is divided by the extra height necessary of making this extension possible, which is equal to the height of the SKU multiplied by (j-1), since all SKUs need a pick location that is equal to at least one pallet layer. In this case, the cost reduction s_{ij} can be determined as
$$s_{ij} = \frac{(c_{i,j-1} - c_{ij})}{w_i}$$
2. The incremental cost reduction of extending the SKU's pick location by one extra pallet layer is divided by the extra height necessary of making this extension possible, which is equal to the height of the SKU. In this case, the cost reduction s_{ij}' can be determined as
$$s_{ij}' = \frac{(c_{i1} - c_{ij})}{w_i(j-1)}$$
3. The incremental cost reduction of extending the SKU's pick location to j pallet layers compared to (j-1) extra pallet layers is divided by the cumulative extra height necessary of making this extension possible, which is equal to the height of the SKU multiplied by (j-1). In this case, the cost reduction s_{ij}'' can be determined as
$$s_{ij}'' = \frac{(c_{i,j-1} - c_{ij})}{w_i(j-1)}$$

Based on these three options to calculate the cost reductions for adding extra pallet layers to the pick location capacity and based on the auctioning algorithm of Bartholdi and Hackman (2011) and the iterative heuristic of Kök and Fisher (2007), four algorithms are tested in order to come up with the best solution that minimizes the total costs per week. This has been tested for a group of 20 SKUs from the canned fruits and vegetables product group and the results show that all four algorithms come up with a much less expensive distribution of the pick location capacity than the current distribution in terms of the four inventory related costs that are specified in this research. The potential cost reduction even goes up to 43% compared to the current distribution of the pick location capacity of these 20 SKUs.

Implications

The results of this research clearly indicate that taking costs of handling operations in the DC into account when developing the inventory replenishment policy is very beneficial in terms of total inventory related costs. However, Slimstock, the developing company of Slim4, states that its specialty does not lie in the determination of the ordering quantity but in the forecasting of the future demand of an SKU. This has also been the main reason why SPAR chose to introduce Slim4 as their inventory management system in 2012. Combining the benefits of having a good working forecasting tool and a good working inventory replenishment system would be the desired outcome. Unfortunately, we cannot simply combine the theory behind the DoBr tool and the Slim4 inventory management system as the underlying assumptions regarding the used demand distributions differ fundamentally. Slim4 assumes that most SKUs have a normally distributed demand distribution, while the expected outdating used in the DoBr tool is based on a discrete demand distribution. Since Slim4 does not even take outdating into account when determining the reorder level, suitable estimations cannot be made for perishable products. Therefore, we suggest Slimstock to investigate into the possibility of including outdating in their inventory system, especially since it has been shown that outdating costs can play such an important role in the determination of the total inventory related costs.

Further cost savings have been shown in this research by aligning the order quantity and the capacity of an SKUs pick location. Besides, the data on the current distribution shows that the data management of the WMS needs an update. The best performing algorithm is the one that calculates the cost reduction of adding an extra pallet layer by taking the incremental cost reduction dividing this by the cumulative height of all the pallet layers that need to be added.

All in all, the following recommendations for SPAR can be made based on this research:

- Continue the current process of reorganizing the DC by regrouping SKUs of the same product family together;
- Update the data of the WMS after regrouping the SKUs and keep updating this regularly;
- Calculate the optimal distribution of the pick location capacities of SKUs for all product groups that meet the restrictions. These calculations should be updated at least four times a year since a substantial part of SPAR's SKUs face seasonal effects in their demand. Updating four times a year might not even be enough, since SPAR's SKU portfolio keeps changing. Therefore, the updating schedule should be investigated properly;

- Calculate the optimal order quantities based on the calculated pick location capacities for all SKUs that meet the restrictions. Because of the seasonality, these calculations need to be updated as well;
- Use the calculations of the optimal order quantity to renegotiate the MOQ and IOQ restrictions with suppliers in order to save additional costs.

Content

1. Introduction

Optimizing processes and reducing costs are a very important part of supply chain management, especially in a highly competitive environment, such as the retail market. This study focuses on reducing the inventory related costs of the distribution centers of supermarket chain SPAR Holding B.V., which will be referred to as SPAR in the remainder of this report.

1.1 Report structure

This report is the outcome of a graduation project that has been carried out at SPAR on the topic of optimizing the processes related to incoming goods at SPAR's distribution centers. In chapter 1, an introduction to the company and its supply chain is given. In the second chapter, the outline of the project is discussed. The third chapter gives an overview of methodology that is used in this project. Chapter 4 elaborates on the model that is used to improve the current processes. In chapter 5, the results of this model will be compared to the current situation. Based on these results, chapter 6 focusses on what SPAR can actually accomplish by using the model of this project and how can this be implemented. Finally, in chapter 7, conclusions are drawn and opportunities for future research are given.

1.2 Introduction to the company

As discussed above, this project is conducted at SPAR. This chapter gives a brief introduction to the company as well as the characteristics of the company and its environment. Since SPAR stores take position as neighborhood stores, clear consequences for the size of the stores and the amount of customer's demand follow. Small volumes and a heavy dependence on seasonality are main characteristics that define SPAR compared to other supermarket chains in the Netherlands.

1.2.1 Company structure

In 1932, wholesaler Adriaan van Well came up with the philosophy that independent wholesalers and retailers could achieve more by cooperating, rather than working by themselves. He starts working together with sixteen of his customers and thereby he benefits from centralized purchasing, joint advertisement, and frequent meetings between wholesalers and retailers. Within five years, SPAR consists of fourteen wholesalers and over 2,200 retailers. Nowadays, SPAR worldwide is the largest food store chain in the world with over 12,000 stores in 35 different countries. Worldwide, SPAR is organized by SPAR International. Although each national SPAR holding is responsible for its own operations, SPAR International is responsible for the overall co-ordination and development of the worldwide SPAR organization. The main activities of SPAR International can be summarized as:

- Protection of SPAR's corporate identity
- Organizing the international PR activity
- Acting as the overarching secretary of the worldwide SPAR chain
- Arranging international commercial activities such as the import of products
- Developing the international formats of SPAR
- Exchanging knowledge and experiences between the national SPAR holdings

SPAR stores around the world can be categorized in one of the four international retail formats. These are the SPAR neighborhood store, the larger supermarket SUPERSPAR, the INTERSPAR hypermarket, and convenience retailer SPAR Express. In the Netherlands, SPAR is known for its neighborhood stores. Most SPAR stores are located in small towns and districts with 2,000 up to 4,000 inhabitants. Besides that, SPAR is expanding its format with the introduction of university and city stores. SPAR Netherlands consists of over 260 SPAR stores, 105 Attent stores, and about 100 neutral grocery stores, such as bungalow park stores. All of these stores are supplied by one of the two distribution centers, which are located in Alkmaar and Waalwijk. SPAR Holding BV is the overarching Dutch organization, which arranges the assortment and format development as well as the promotional activities. The headquarters of SPAR Holding BV are located in Waalwijk next to the distribution center. SPAR Holding BV is owned by Sligro for 45%, by Sperwer for 45% and by a cooperation of retailers for the remaining 10%.

Furthermore, SPAR is a member of the Superunie purchasing organization. Superunie is a purchasing organization that represents thirteen independent retail organizations with a combined market share of 30%. For most products, Superunie negotiates purchasing agreements such as the purchasing price and the minimal order quantity with many suppliers, since Superunie has a better position for negotiation than a small retail organization has by itself. This means that SPAR is quite dependent on the agreements of Superunie when ordering products at the suppliers. (SPAR, 2013)

1.2.2 Characteristics

As described above, SPAR is known for its neighborhood stores in the Netherlands, which are predominantly located in small towns and districts with 2,000 up to 4,000 inhabitants. The stores have an average floor space of 150 up to 600 square meters, which is very small for a supermarket.

1.2.2.1 Small volumes

SPAR does want to fulfill a large part of the grocery demand of customers and therefore, SPAR offers a large assortment of both premium brands and private label brands. Because SPAR stores have a wide assortment of products in relatively small stores with relatively small customer pools, SPAR sales volumes are quite low compared to other supermarket chains. Small sales volumes per product in the stores result in the fact that the distribution centers have to transport small quantities of products to the particular stores. Subsequently, the small quantities in store demand result in small order quantities by SPAR at its suppliers. Small order quantities are very characteristic for SPAR, especially since many of SPAR's products can only be held on stock for a short time due to the perishability. These low volumes cause a lack of economies of scale in terms of transportation and handling activities in the distribution centers.

The effect of having small order quantities is only enlarged by the continuous development of SPAR's format in the Netherlands. An example of these developments is the opening of the first city store in The Hague in 2013. This is a store that focuses on business people that buy meals for just one person. The same holds for the university stores that SPAR is opening nowadays. The one person portions of different products contribute to extra products with low sales volumes and, subsequently, low order quantities. Furthermore, SPAR wants to distinguish its concept compared to other supermarket chains, by offering services and products that contribute to the involvement with the local community. This also leads to a broader assortment of products and, therefore, even lower volumes per product.

1.2.2.2 Seasonal effect

Another typical aspect of SPAR is that SPAR's customer demand is very dependent on seasonal effects. One reason for this aspect is that SPAR supplies a lot of stores that are only open during the summer season, such as stores, which are located at bungalow parks. These stores mostly offer particular products such as beverages, snacks, ice cream, and barbecue products. This means that during the summer season, the demand for these groups of products is a lot higher than during the regular season. A second reason for the fluctuation in customer demand at SPAR stores is that most customers do their weekly grocery shopping at a larger supermarket, while using the SPAR store for satisfying their extra daily demand. This daily demand is very dependent on seasonal effects such as the weather conditions. For instance, when the weather is warm and sunny, a lot more people want to have barbecue products than when it is raining. On the other hand, the demand for soups and smoked sausage is a lot higher during the winter season. These fluctuations in customer demand have to be taken into account at all times when inventory replenishment actions are decided.

1.2.2.3 Customer image

GfK, an organization that conducts market research, studies the experiences and appreciations of customers of 23 supermarket chains in the Netherlands. The most recent study shows that SPAR stores are considered the second worst of the 23 supermarket chains. This can mainly be contributed to the price levels at SPAR that are perceived very high by customers and promotions that are not valued well enough by the same customers. This is a quite logical result of the fact that SPAR's sales volumes are relatively small, which results in the fact that SPAR cannot offer the same prices as large retailers due to a lack of economies of scale. In terms of customer friendliness, SPAR scores really well and during the last few years, SPAR has improved its service level and the quality of the fresh supplies substantially. Figure 1 shows the overall valuation of all supermarket chains in terms of service level and pricing. (GfK, 2013)

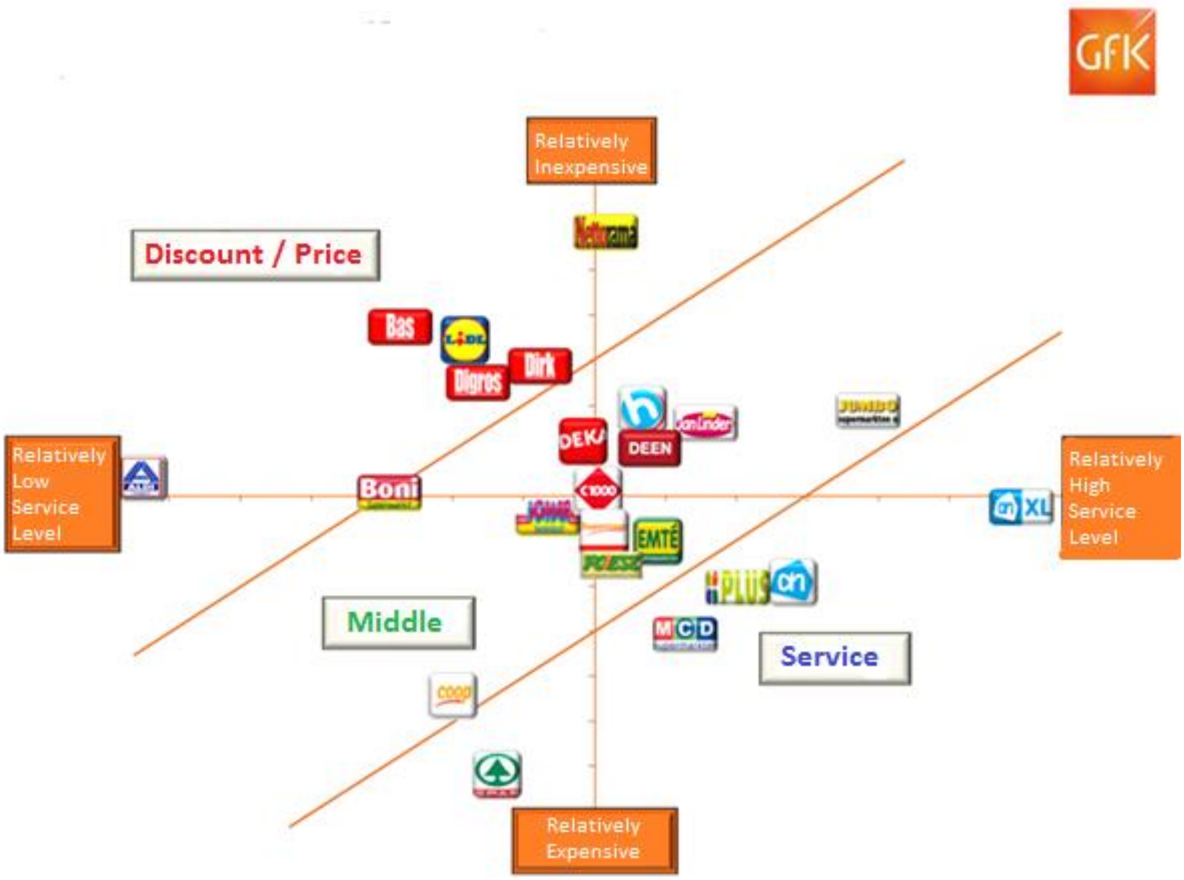

Figure 1: Consumer valuation of supermarket chains. (GfK, 2013)

1.3 SPAR's Supply Chain

SPAR operates two distribution centers (DCs) in the Netherlands to supply the Dutch stores with the demanded groceries, one in Waalwijk and one in Alkmaar. The DC in Alkmaar is also known as the North DC and all stores in the northern half of the Netherlands are supplied by this DC. All southern stores are supplied by the South DC, which is located in Waalwijk. Both DCs store and distribute all dry groceries, perishables, and frozen products, except for the slow moving cooled perishable products, which are only stored in the South DC and some highly perishable products that are shipped to the store directly by the supplier or through crossdocking. Figure 2 shows the total supply chain of SPAR.

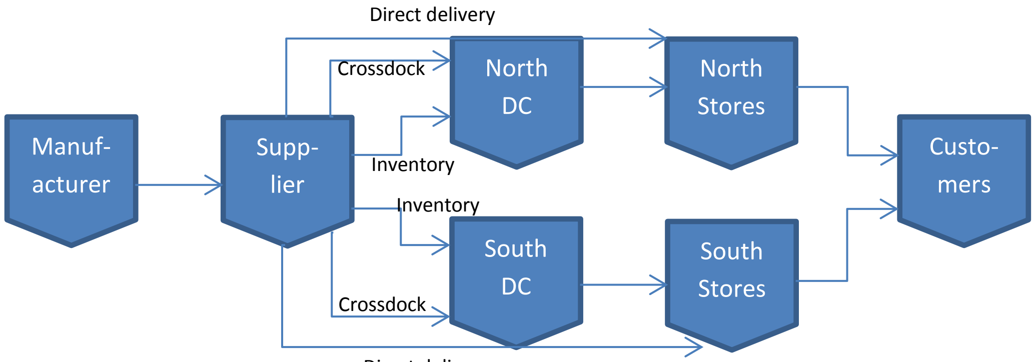

Figure 2: SPAR's Supply Chain

The employees at SPAR's department 'Inventory Management', which is located at the headquarters in Waalwijk, is responsible for the inventory levels of all products in both DCs. They order all products for both DCs at the suppliers according to the agreements between the suppliers and employees at the department 'Category Management' or according to the agreements Superunie has made with the suppliers. These agreements include, among others, purchasing prices, minimal order quantities, batch sizes, lead times, fixed replenishment moments, and shelf life restrictions. Whenever products are ordered, the supplier is responsible for the on-time delivery at the desired DC, where the products are accepted as SPAR's responsibility. In total, SPAR handles around 12,000 SKUs divided over two DCs. This means that each DC handles about 6,000 SKUs. So, when a product is shipped to the North DC, it is considered as a different SKU than the same product that is shipped to the South DC.

1.3.1 Distribution Center

Once the supplier unloads the products at the DC, employees of SPAR check the received quantity, the shelf life, and the temperature for cooled perishable products. If these features satisfy the restrictions, the goods are accepted and the employees scan each pallet or pallet layer dependent on the received quantity. Some products have to be unpacked and restacked into crates since the amount of consumer units in the case pack is not equal to the amount in which the product is sold to the stores. As soon as the products are scanned, the inventory level of that particular product is increased by the received quantity and a reach truck driver receives a task to transport the articles from the entry floor to the shelves in the DC. This can be done in three different ways, according to the space on the shelves. These shelves consist of storage space for pallets of bulk inventory and storage space at a pick location at which the outgoing orders to the stores can be picked from. If the received batch is small enough to fit in the pick location entirely and the remaining shelf life is the same as the remaining shelf life of the products that are already in the pick location, the received batch will go straight to the pick location. If the remaining shelf life is the same, but the received batch is larger than the capacity that is left in the pick location, the pick location will be filled and the remainder will go to the bulk storage space as close as possible to the pick location. Otherwise, if the remaining shelf life is larger than the remaining shelf life of the current products in the pick location, the entire received quantity is stored at the free bulk storage space closest to the pick location. At all times, when the number of products in the pick location becomes too low, this will be replenished by a designated reach truck driver.

If a store manager orders a number of products, these orders will be picked by an order picker. Order pickers either walk through the DC while they are pushing a rolling container or they drive on an electric pallet truck (EPT), which has room for four rolling containers at the same time. A warehousing system tells the order pickers exactly which product and which quantity they have to pick and place in their container. When all products of a particular order have been picked, the container will be transported to one of the shipping docks. At the docks, all store orders are collected and combined for transportation to the different stores. Besides that, SPAR's management has determined that at least five percent of the outgoing containers has to be checked for errors.

Both DCs contain three different departments, namely a department in which dry groceries are stored, a department in which cooled perishable products are stored, and a department for deep frozen products. These three departments are subsequently divided into smaller sections, mainly dependent on the throughput rate of the products.

The dry grocery department in the South DC contains five different sections; one for promotional products, one for fast moving products, one for slow moving products, one for premium products that are extremely slow moving or that need careful handling, and finally one for explosive and flammable products. In the latter two the shelve aisles are a lot smaller than in the other sections and products are picked by an order picker using a rolling container instead of an EPT, which is being used in the other sections. In the North DC, the dry groceries department is divided into four sections. Compared to the South DC, the North DC does not contain a premium section, but all of the premium articles are stored either in the slow moving section or in the flammable section. Also, the section that contains flammable and explosive is located on the second floor of the DC due to capacity issues on the main floor. This results in extra replenishment time for reach truck drivers that transport products from the entry floor to this section. Furthermore, the North DC receives export orders from time to time, which get shipped in large maritime containers. This is a further utilization of the already scarce storage capacity in the North DC.

The department in which cooled perishable products are stored in the South DC is divided into three sections, one for promotional products, one for fast moving products, and one for slow moving products. In the North DC, this department uses about one fifth of the space that is used in the South DC, because the slow moving cooled perishable products are stored in the South DC and shipped to the North DC when a store manager orders these products. Whenever this happens, the cooled perishable products in the order are picked in the South DC and transported to the North DC to be combined with the rest of the order. This is done due to capacity problems in the North DC and to increase the throughput time of these slow moving products in the South DC. Therefore, the department in the North DC only contains one section. In both DCs, the deep frozen only contains one section in which all deep frozen products, which usually have a long remaining shelf life, are stored.

1.3.2 Store replenishment

On fixed moments during the week, a store manager checks the store's inventory and orders new products at the headquarters. The ordered products are picked at the DC and shipped to the stores. Most stores receive three shipments of cooled perishables combined with deep frozen products and two shipments of dry groceries each week. The planning of transportation to the stores is centralized at the headquarters, which makes it possible to combine shipments for stores that are located close to each other in order to use trucks efficiently.

An agreement between the headquarters and the store managers, and also the main Supply Chain Key Performance Indicator (KPI), is that, on average, 98 percent of the order lines ordered by store managers have to be satisfied. This is the agreed service level that SPAR takes into account and it does include all external factors such as suppliers that are out of stock, which leads to the DC being out of stock as well. However, the calculation of the service level only looks upon the order lines that are satisfied instead of the number of products that are satisfied. So, if a wrong product or a wrong quantity is picked and distributed, this actually is considered as satisfied demand, since the order line could directly be satisfied by the inventory in the DC. To make up for this, store managers receive a yearly pre-determined compensation fee. Looking from a supply chain perception, it would have been even better to take the actual end customer demand as a basis for the service level, because that reflects the actual service as experienced by the end customers of the supply chain rather than the customers of the distribution center. (Teunter, Zied Babai, & Syntetos, 2010)

1.4 Slim4

Slim 4 is a forecasting and inventory management system developed by Slimstock B.V. It is used to calculate inventory replenishment levels for all products based on statistics and a predetermined service level. Based on the calculated replenishment level and the actual inventory position, a replenishment advice is generated which minimizes the total inventory on hand. Slim4 is a dynamical system since all its parameters are calculated again at the start of each month. The Inventory Management department of SPAR uses Slim4 to order products at SPAR's suppliers. Slim4 was introduced at SPAR in 2012.

For each product, Slim4 analyses the historical demand patterns of the last two years in order to determine whether seasonal effects are effective. The demand pattern of two years ago is compared to the demand pattern of last year. Using an F-test, these two demand patterns are compared. If the F-test score is higher than 2.82, which corresponds to a 95% certainty, a seasonal effect is assumed and this effect is used for forecasting the demand pattern of the next twelve months. If the F-test score is below 2.82, no seasonal effect is assumed except for when this seasonal effect is included manually. These seasonal effects can be recalculated at each desired moment.

Based on the demand pattern of the last twelve months and the seasonal effect, a monthly demand forecast is calculated for the next twelve months. In order to correct for recent developments in customer's demand, exponential smoothing is used. The regular monthly forecast for the next month is taken into account for 80% and the actual demand of last month is taken into account for the other 20%. The monthly forecasted demand is divided in a daily demand forecast based on an average weekly demand pattern. There is no weekly demand forecast, which is not very convenient since supermarket chains arrange most of their processes, such as promotions and delivery schedules, on a weekly basis. Fortunately, Slimstock is working on a new update of Slim4, which forecasts customer's demand on a daily basis instead of a monthly basis.

As discussed in chapter 2, a supermarket chain such as SPAR agrees on fixed order and delivery moments with their suppliers. This means that the review period and the lead time are constant and known. Slimstock refers to the period between a particular review moment and the moment at which the next order is delivered as cover period. In other words, the cover period is equal to the review period added by the lead time. The forecasted demand during this cover period is used as a basis for the calculation of the desired inventory position.

In order to calculate the desired safety stock of a particular product, the demand distribution of the product has to be determined. Slim4 uses demand classes to categorize products based on their demand distribution. Some of the commonly used classes are Normal, Lumpy, Slow, and User specified. Most products are categorized in class Normal. For products in demand class Normal, Slimstock states that these products' demand follows a normal distribution, but it is unclear how this is determined. For most products with a fairly steady and high average monthly demand, this should not be a problem. However, there are products in this class that only have an average monthly demand less than five case packs with clear outliers in their demand pattern. This seems to justify the concern of what method is used to determine the demand distribution. Lumpy products are products that do not have a demand pattern that is steady enough to assume a normal distribution according to Slimstock, such as seasonal or temporary products that only have a positive demand in six months a year. For these products, Slimstock uses high safety stocks to cope with high demand in particular months. Products in demand class Slow are characterized by customer's demand of relatively small amounts in low frequencies. These products' demand is assumed to follow a Poisson distribution. For products for which Slim4 cannot determine a suitable demand distribution, users can set a manual forecast of the demand. These products are categorized in class User specified.

The safety stock of each product is calculated to be able to cover peaks in a product's demand. In Slim4, this is based on a P2-service level and the standard deviation of the forecast error of the product's forecasted demand during the cover period. The service level can be determined for each product separately, for a group of products at once or for a large group of products based on an ABC-classification. At SPAR, most service levels are determined for groups of products with similar characteristics. This method differs from the measurement of SPAR's Service Level KPI. SPAR measures its service level by determining which percentage of the overall customer's demand can be satisfied by direct delivery from one of the distribution centers. This is equal to an overall P2-service level. Slim4 uses set fill rates for each of the SKUs individually. The SKU-specific service levels in Slim4 have to be adjusted and validated such that the overall P2-service criteria of SPAR can be satisfied. (Silver, Pyke, & Peterson, 1998)

At each review moment, Slim4 compares the current inventory position of a product with the dynamic desired inventory position, which is determined by adding up the forecasted demand during the cover period and the safety stock. Whenever the current inventory position is lower than the desired inventory position, a replenishment advice is given. Otherwise, no products need to be ordered. The replenishment advice takes into account a specified minimal order quantity (MOQ) and an incremental order quantity (IOQ). In many cases, suppliers require orders consisting of at least a certain amount of case packs. For instance, whenever you order a certain product, you need to order at least a pallet of this product. Furthermore, the IOQ does not need to be equal to the MOQ. For instance, once you have ordered the minimum of one pallet, you can order extra products in amounts of pallet layers. However, for almost all SKUs of SPAR, these two quantities are equal. Slim4 gives a replenishment advice equal to the MOQ and an integer number of the IOQ such that the current inventory position added by the replenishment advice is equal to the lowest possible amount above the desired inventory position. This is done to minimize the total inventory on hand.

All in all, Slim4 has been designed as an inventory replenishment system that is similar to an (R,s,S) system, but due to many restrictions of suppliers regarding batch ordering, it is used as an inventory replenishment system that is similar to an (R,s,nQ) system. The system is used to keep the total inventory on hand minimal. It does not take handling costs or ordering costs into account. By changing the parameters on which Slim4 calculates its replenishment advice, the inventory level, the order quantity, and the number of orders can be adjusted as desired. (Slimstock, 2011)

2. Research project

This research focusses on optimizing the inventory replenishment process and the storage process of incoming goods in the DCs in order to reduce the total inventory related costs without reducing the service level that SPAR provides to its supermarkets. This chapter gives an overview of the current literature on these topics, it defines the problem SPAR is facing and it discusses the outline of this graduation project.

2.1 Literature review

Dealing with inventory in an efficient manner is very important for a supermarket chain, since profit margins in the retail industry are extremely low and competition is rather high, and thus, cost saving is very important. Therefore, the retail industry is constantly developing new methods to optimize their supply chain. Supermarket chains typically have to deal with a large variety of products, a high variability in customer's demand, perishability of the products, lost sales when customer's demand cannot be satisfied directly, and order quantity restrictions from their suppliers. All of these factors complicate the inventory management system throughout the supply chain, making an adequate inventory replenishment system essential for a supermarket supply chain.

Over the years, extensive research has been done on the topic of inventory replenishment systems. In a variety of contexts, continuous (s,S) and periodical (R,s,S) policies have been shown to be optimal. However, under the assumptions that are applicable in a supermarket chain environment, these policies do not work properly. For a lost sales system with periodic review and a service level restriction, an (R,s,nQ) policy has been shown to perform close to optimal. (Bijvank, 2009) Based on this policy, Broekmeulen and van Donselaar (2009) have developed the EWA-policy, which subsequently outperforms the (R,s,nQ) policy when the perishability of products is taken into account. The EWA-policy does not include predetermined service level restrictions but it takes outdating and lost sales costs into account. However, by changing the lost sales costs, the service level can be modified such that the desired service level can be achieved. Van Woensel et al. (2013) have shown that, for such a system, not only costs of outdating, lost sales, and holding inventory are important factors, but handling costs should also be taken into account.

While batch ordering is a commonly used restriction from suppliers in order to achieve economies of scale, many suppliers also demand MOQ restriction that serve the same purpose. The optimal policy for this situation is too complicated for implementation in practice. Therefore, Kiesmüller et al. (2011) have come up with an approximation policy that performs close to optimal. Unfortunately, this approximation policy assumes a backordering system instead of lost sales.

In 2011, van Donselaar and Broekmeulen have found fill rate approximations for their EWA policy and in 2012, they derived approximations for the relative outdating, using the EWA policy. The relative outdating is the percentage of demand which is outdated because the expiration date of the product is exceeded before the product is sold. Based on these approximations, van Donselaar and Broekmeulen (2014) built an Excel based tool, called the DoBr tool, which can be used to calculate several KPIs for periodic inventory policies, taking outdating and shelf replenishment into account.

Eroglu et al. (2012) depict that the backroom effect may substantially change the optimization problem faced by retailers. Since the DoBr tool makes it possible to take shelf replenishment into account when determining a suitable inventory replenishment policy, this offers the opportunity to actually quantify the backroom effect, which gives room for optimization by aligning the incoming quantities of a product and the shelf space allocation. Kök and Fisher (2007) describe an iterative heuristic that searches for the best shelf space allocation, taking the overall storage capacity as a restriction. The heuristic is based on the premise that customers would be willing to substitute for similar products within a certain subcategory of products. Bartholdi and Hackman (2011) propose an auctioning algorithm in which each item makes a business case with which the item wants to compete for an allocation of the shelf space, based on the greedy algorithm. The idea of aligning the incoming quantities of products with their available shelf space in order to reduce the backroom effect and therefore, reduce costs provides a very promising research topic.

2.2 Problem definition

The inventory related problems that SPAR is facing can be divided in two research topics. The first topic is the problem SPAR has determined, namely the optimization of their inventory replenishment system using optimal order quantities. The second topic has come up while working on the first one and can best be described as optimizing the allocation of the DC's pick location capacity among all SKUs.

2.2.1 Inventory replenishment

As described in section 1.4, SPAR is using inventory replenishment system Slim4 by Slimstock to determine which products and which amounts of these products have to be ordered on a daily basis. Slim4 is designed to keep the total inventory on hand as minimal as possible. This is very beneficial for the available space in the DCs, for the average throughput time of the SKUs, and for the total inventory holding costs. The downside of using this method is that the DCs receive many shipments of small quantities of products. This results in pallets that contain several different kinds of products, which all have to be stacked on separate pallets before they can be stored. This also results in pallets that only contain a small amount of case packs, which is not efficient for transportation. A third result of using this method is that, for some products, the DCs receive one pallet layer each week, which they have to receive, transport and store in the shelves of the DC. All of these results of minimizing the total inventory on hand, end up in a lot of handling for the employees in the DCs and therefore, in relatively high handling costs. This could be avoided by ordering larger quantities of products at the same time and thus, lowering the number of shipments over a particular period of time.

Although ordering larger quantities at once will decrease the total handling costs, it will increase the average inventory on hand and thus, the total inventory holding costs. Furthermore, since most SKUs of SPAR have a limited shelf life, ordering too many products at once, combined with the limited demand SPAR faces compared to its competitors, could result in a problematic situation regarding the obsolescence of products. Another factor is that many suppliers change the unit size or the casing of their products, which results in the fact that the old version of the products can no longer be sold. By ordering larger quantities at once, the problem of having too many obsoletes for this reason is likely to increase. A third reason for the increase of obsoletes, and thus obsolescence costs, by ordering larger quantities, is that SPAR changes its assortment twice a year and this is only communicated to the Inventory Management department about four weeks before the change.

Furthermore, ordering larger quantities at once will most likely influence the average remaining shelf life of products on stock. When a large order is arriving at the DC, this order will consist of products having the same expiration date. When the same amount of ordered goods is ordered and arriving at different moments in time, the products that arrive at a second or third shipment may have expiration dates which lie further ahead than the products in the first shipment. This will result in lower average remaining shelf lives of products that are held on stock in the DC. This will also lower the average remaining shelf lives of products in the supermarkets, since the supermarkets are being replenished by the inventory of the DCs. In turn, this could result in more obsolescence in the supermarkets. On the other hand, supermarket managers will always receive products with a remaining shelf life that is at least equal to 2/3 of the total shelf life that has been agreed between SPAR and its suppliers. This is the shelf life that supermarket managers should take into account when making ordering decisions. Therefore, the effect of ordering larger quantities at once on the average remaining shelf lives of products at supermarkets will be considered out of scope in this project. Besides, it is not possible to calculate an accurate estimate of the real remaining shelf lives of all SKUs at the moment they arrive at SPAR's DCs and at the moment they are shipped to the supermarkets, since the data on this topic is very limited.

The supply chain department of SPAR uses three methods to define their performance. These three KPIs are, in consecutive order of importance:

- The average fill rate of the demand by store managers has to be at least 98%;
- The total obsolescence costs have to be less than 0.17% of the total purchasing costs;
- The average throughput time of SKUs in the dry grocery department has to be less than 15 days, the average throughput time of SKUs in the cooled perishable department has to be less than 5.6 days, and the average throughput time of SKUs in the deep frozen department has to be less than 20 days.

Currently, SPAR is operating at a fill rate that is slightly better than the agreed 98%, but the obsolescence costs are also higher than the agreed 0.17%. The current average throughput time is about equal to the agreed value. Taking these KPIs into account, a better solution to the current problem of having too much handling costs can still be developed. This can be achieved by determining all the possible cost factors and minimizing the total costs within the framework that has been determined by the KPIs. Using Slim4, this can be achieved by implementing a cost function, which results in the optimal order quantity for a certain SKU. Of course, this order quantity has to comply with the MOQ and IOQ restrictions, which are input parameters in Slim4.

This brings us to a first objective of the project, which is:

Develop an inventory replenishment system that determines the optimal order quantities for the SKUs of SPAR in its DCs, which minimizes the total inventory costs, taking into account the service level restrictions, ordering in batches, and the perishability of SKUs.

This objective can be achieved by answering the following research questions:

- Which inventory related costs are relevant when determining the optimal order quantities and how can these costs be determined?
- How can the total of these costs be minimized?
- For which product groups can this inventory replenishment system be applied?
- Can this inventory replenishment system be implemented in Slim4?

2.2.2 Pick location capacity

Besides the topic of the inventory replenishment system, SPAR is also experiencing issues with the capacity of its DCs. This is a clear issue in the North DC, since the North DC is a lot smaller than the South DC. All dry groceries slow moving SKUs in both DCs as well as many dry groceries fast moving SKUs in the North DC have pick location spaces which are smaller than a full pallet load. This means that whenever a full pallet of one of these SKUs arrives at the DC, the amount that fits in the pick location will be stored in this location and the rest will be stored at the bulk storage space. As Eroglu et al. (2012) depict, the backroom effect may substantially change the optimization problem faced by retailers. In this case, the situation at the SPAR DCs is very comparable to the problem of a retailer which can store part of the incoming SKUs at the store shelves and part of the goods in the back room. Therefore, in optimizing the inventory replenishment system of SPAR's DCs, the incoming amount of goods and the shelf space of the pick locations should be aligned. One of the inventory related costs, which have been taken into account in this project, are the costs related to the replenishment of the pick locations. This means that whenever the amount of replenishments of a certain SKU can be reduced, this reduces the overall costs, assuming that the other costs remain the same. This could be accomplished by adjusting the capacity of the pick location to the ordering quantity in which the goods arrive. In the ideal case, the pick locations of all SKUs are large enough to store the total incoming quantity, which makes replenishments unnecessary and reduces the replenishment costs to zero. Unfortunately, this would take a huge amount of storage space, which is not available in SPAR's DCs. In other words, the total storage capacity of the pick locations is limited.

This raises the following problem:

Given the total storage capacity of the pick locations in SPAR's DCs, how to determine the capacity of the pick location of each SKU in such a way that the total inventory related costs are minimized?

2.3 Scope

This project includes all products that are being stored in the DCs of SPAR. Products that are being delivered directly from the suppliers to the stores or through crossdocking are not be part of this project, since these products will never be stored at a DC and have not been taken into account in the ordering process of the Inventory Management department. Promotional products are also excluded from this project, since the demand of promotional products can vary substantially from regular customer's demand. This is also the reason these products have been excluded from the regular ordering process using the Slim4 program. A third group of products that have not been taken into account is the group of products that is used for export, since the demand of this group is even more unreliable than promotional products and this group is also excluded from the regular ordering process.

The cost functions of this project consist only of ordering costs, holding costs, outdating costs, and replenishment costs such as they are specified in the next chapter. All other types of costs will not be taken into account in this project. In the minimization of these costs, the calculation of the most cost effective order quantities will be the objective. Other parameters, such as the forecasting of customer's demand, review periods, and lead times will be considered given parameters and will not be adjusted.

The method for the allocation of the storage space is especially designed for the slow moving dry groceries SKUs in both DCs and the fast moving dry groceries SKUs in the North DC that currently have a pick location with a storage capacity that is smaller than a full pallet layer and which have to be ordered in batches equal to multiples of a pallet layer. SKUs that have to be ordered in multiples of full pallets, usually have a pick location with a capacity equal to a full pallet and this will not be changed as part of this method.

3. Research methodology

The first part of this chapter describes the cost structure and the inventory related costs that have been taken into account in this project. Also, the determination of the actual costs is described in this chapter. Furthermore, the division into different product groups, based on the location at which the products are stored, and the usage of a pilot group, which is used to test the method , are described in this chapter.

3.1 Cost structure

The main objective of an inventory replenishment system is to minimize the total costs. Therefore, in order to come up with a suitable inventory replenishment system, the costs that will be taken into account have to be defined first. The standard EOQ formula takes both ordering costs and inventory holding costs into account. By minimizing the sum of these two costs, the optimal ordering quantity for an item can be calculated. (Silver, Pyke, & Peterson, 1998) Because of the specific assumptions of this policy, the EOQ policy cannot be used for inventory replenishment decisions at the distribution centers of SPAR. For instance, the demand is not at all constant, products cannot be ordered in an unlimited quantity because of the perishability, and orders that cannot be satisfied directly from the shelf are lost. Other inventory replenishment systems, such as the EWA-policy that has been developed by Broekmeulen and van Donselaar (2009), make use of holding costs, outdating costs, and lost sales costs. In the EWA-policy system, all of these costs are normalized on the purchasing costs of one unit. Van Woensel et al. (2013) show that handling costs need to be taken into account as well when one is dealing with perishable products in a lost sales system. Zhou et al. (2007) and Kiesmüller et al. (2011) make use of penalty costs for each demanded item that cannot be satisfied directly.

For the inventory replenishment policy of the distribution centers of SPAR, the following costs have been determined:

- Ordering costs;
- Holding costs;
- Outdating costs;
- Replenishment costs.

Penalty costs for customer's demand that cannot be met are not specified in this project, but the outcome of the inventory replenishment system will have to satisfy a specified service level constraint. The constraints that apply for this project have been discussed in chapter 2.

3.1.1 Ordering costs

Silver et al. (1998) define fixed ordering costs as costs that "include the costs of order forms, postage, telephone calls, authorization, typing of orders, receiving, inspection, following up on unexpected situations, and handling of vendor invoices." (Silver, Pyke, & Peterson, 1998) At SPAR, as discussed in chapter 1, the department of Inventory Management is dealing with the inventory in both DCs. The department consists of five employees, which together order all SKUs at the suppliers. The composition of this department will not change immediately as a result of a change in the number of order lines, and therefore will be considered fixed. Since the model of this project will focus on minimizing the total costs based on the number of order lines, the fixed costs of the Inventory Management department are not be included in the model. The costs of receiving, inspecting, and handling the incoming goods do vary with the number of order lines and are, therefore, included in the model.

Curşeu et al. (2009) estimates the handling time per SKU required to stack the items on the shelves in a supermarket and, based on this, van Woensel et al. (2013) show that the costs of these handling operations need to be taken into account. The handling operations in both DCs of SPAR can be divided into handling operations depending on the number of orders and order lines ordered by the Inventory Management department at the suppliers of SPAR (incoming orders) and handling operations depending on the number of orders and order lines ordered by the supermarket managers (outgoing orders). After consultation with SPAR's management, we have decided to use the first group of handling operations in order to calculate the handling costs. The number of these handling operations per SKU can be influenced by the amount of orders directly and the number of outgoing orders is usually based on the demand of the end customers, which cannot directly be influenced by SPAR.

The handling operations of the incoming orders consist of two processes. The first one is the receiving process. This operation consists of accepting a delivery, scanning the incoming pallets, checking the amount and the best before date, and, for some products, restacking the units from a pallet into crates. The second process consists of the transportation of the products to the shelves in the DC. As described in chapter 1, this can be done in three ways, namely directly to the pick location, directly to the bulk storage space, or to a combination of both locations. Costs for these handling operations have to be determined in order to determine the handling costs per SKU. This will be discussed in the remainder of this chapter.

3.1.2 Holding costs

"The cost of carrying items in inventory includes the opportunity cost of the money invested, the expenses incurred in running a warehouse, handling and counting costs, the costs of special storage requirements, deterioration of stock, damage, theft, obsolescence, insurance, and taxes" according to Silver et al. (1998). Normally, holding costs are expressed as a percentage of the purchasing price of an item. This percentage can vary for different product groups. For instance, running a deep frozen warehouse is a lot more expensive than running a warehouse at regular temperatures. After consultation with both the management and the finance department of SPAR, only the capital investment of holding products on stock will be included as holding costs, since the available warehousing space and the expenses incurred in running a warehouse will not vary as a result of the number of orders or order lines. Therefore, the holding costs are equal to the yearly interest expenses paid by SPAR's finance department, which are equal to 2% of the purchasing price of the stored products.

3.1.3 Outdating costs

Many of the products that are sold in supermarkets have limited shelf lives. SPAR has agreed with its supermarket managers that at the moment a product arrives at the store, the remaining shelf life has to be equal to at least two third of the remaining shelf life at the moment the product has arrived at the DC. This means that whenever a supplier ships a product with a shelf life of 180 days, this product has to arrive at the store at most 60 days after the product has arrived at the DC. The amount of days a product is allowed to be stored at the DC is called the DC shelf life. Whenever a product exceeds its permissible DC shelf life, it is sold to an independent buyer. For products stored at the dry groceries department, the buyer has to pay 50% of SPAR's purchasing price and for products stored at the cooled perishable and deep frozen departments, the buyer has to pay 25% of SPAR's purchasing price. This means that whenever a products exceeds its DC shelf life, the outdating costs of this product are equal to 50% or even 75% of the purchasing price of the product.

3.1.4 Replenishment costs

As discussed in chapter 1, there are three ways in which the received goods at the entry floor of the DC can be transported to the shelves in the DC, either straight to the pick location, partly to the pick location and partly to the bulk storage space, or entirely to the bulk storage space. Whenever the pick location runs out of goods and these goods are stored in the bulk storage space, this pick location has to be replenished with products from the bulk inventory. Reach truck drivers automatically receive a replenishment task as soon as the amount of products in a pick location becomes less than a predetermined amount. Replenishing the pick locations results in additional handling operations for the reach truck drivers and, therefore, in additional costs. These costs can be determined by projecting the amount of pick location replenishments during an inventory replenishment cycle and multiplying this amount by the costs of each pick location replenishment.

3.2 Product groups

To determine the duration of handling operations, SPAR's SKUs have to be categorized in a group of products based on the location at which they are located, since we expect that handling operations may vary because of different ways of working between different locations. Therefore, we would like to differentiate for different product groups on four levels. Figure 3 shows a clear overview of the differentiation of product groups.

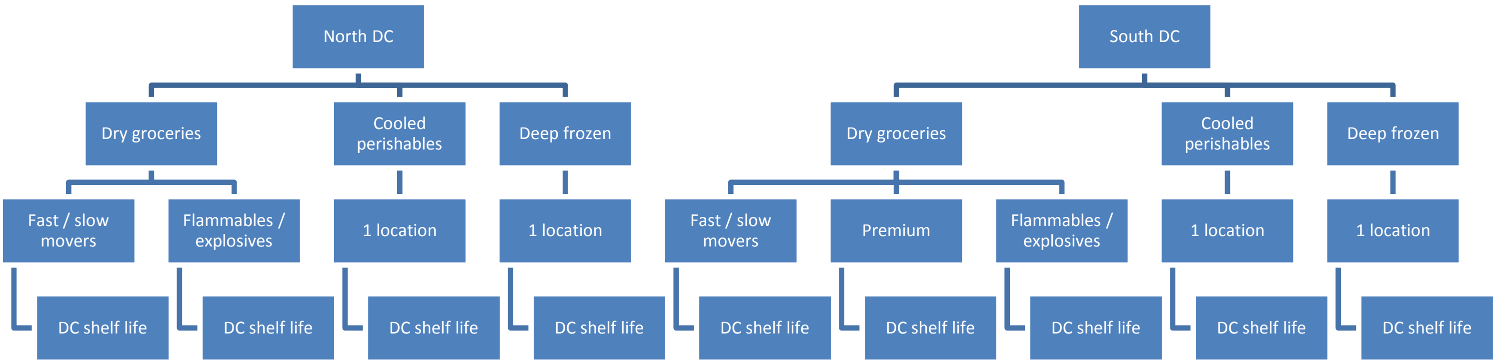

Figure 3: Distinction based on storage location

First, a distinction has been made between SKUs that are stored in the North DC and SKUs that are stored in the South DC. The South DC is a lot larger than the North DC and therefore, we expect that transporting goods from the entry floor to the shelves will take longer.

Secondly, we have differentiated on the warehouse department in which the product is being stored. Because the dry grocery department is usually a lot larger than the other types, transporting the incoming products from the entry floor to the shelves will take longer. Furthermore, products in the deep frozen department are usually stored at full pallets in the pick locations instead of pick locations that consist of shelves or rolling racks. Therefore, we expect a clear distinction is the duration of handling operations between different warehouse departments.

The third differentiation is based on the section within the departments. The sections in which fast moving products are being stored, usually have full pallets instead of case packs in their pick locations. Furthermore, in the sections for flammable and explosive products, products that are distributed in small case packs and these sections are located at outlying locations of the warehouse. Therefore, a distinction between sections within a warehouse department might result in better approximations for the duration of handling operations of different product groups.

Finally, a distinction between different groups of shelf lives has made, since perishability is a very important factor for the inventory management of products at SPAR. In order to make this distinction, all products that are being stored in one of the three warehouse departments have been split up into equally large groups based on their DC shelf life. An overview of the distinction based on shelf lives is given in table 1.

Dry Groceries	Cooled perishable	Deep frozen
Unlimited	15 days and more	100 days and more
90 – 350 days	9 – 14 days	60 – 99 days
40 – 89 days	5 – 8 days	21 – 59 days
4 – 39 days	2 – 4 days	

Table 1: Distinction in product groups based on DC shelf life

3.3 Cost measurement

The four types of inventory costs that are used in this project have been explained in section 3.1. Since both holding and outdating costs have been expressed as a percentage of the purchasing price, these costs can easily be determined. The ordering costs and replenishment costs are based on the number of order lines and number of replenishments of the pick locations respectively. These costs have to be calculated by determining the duration of a handling activity and multiplying this by the average wage of an employee that executes this activity, since there usually are several employees executing the same activity.

The duration of all handling operations within the receiving, transportation and replenishment processes have been measured over a period of three weeks to gather sufficient data on the duration of these handling operations. This has been done for all sections in both DCs, as they have been described in chapter 1, to be able to distinguish the durations of handling operations for different product groups, based on the location at which the products are being stored. The measurements of each operation at each section has been divided over multiple days and multiple parts of a day such that the results of the measurements are representative for all SKUs and all incoming shipments. During this period of measurements, we have encountered around 1200 pallets. The durations and costs of different handling activities can be found in Appendix A. Since the durations of all handling operations have been measured during the end of November and beginning of December, which is fairly quiet period of the year, the durations might not be representative for all periods of the year. Although SPAR does use less employees during a quiet period, and therefore tries to keep the total work load per employee steady over the course of a year, it might be the case that employees work harder during an intense period such as the summer period.

The measurements have been done by simply measuring the duration of handling operations by using a stopwatch. Since we want to know the duration of the direct operations themselves and we are not interested in the amount of time employees are idle, we cannot simply use the times that are logged in the WMS system. Another possible method for determining the duration of operations is to use cameras. Using a single camera or a small number of cameras will not lead to better results than using a stopwatch, since a reach truck driver cannot be followed closely enough while he is driving through the DC. Installing multiple cameras throughout the DC such that all areas can be covered may lead to better results than using a simple stopwatch, but this will drastically exceed our budget. Therefore, the duration of the handling operations have been measured using a stopwatch.

3.3.1 Measuring the receiving process

The duration of the receiving process per order line has been measured in the following way. Whenever a supplier's truck driver has unloaded the pallets with products from the truck to the entry floor of the DC, the receiver starts scanning and controlling the products. The time it takes for the receiver to scan and control the entire load has been measured and the amount of pallets in each load has been measured as well. The time it takes a receiver to scan and control a pallet of incoming goods does not vary much with the amount of case packs on that particular pallet, since the receiver only has to scan one case pack and check the expiration date on that case pack. All other items on that same pallet are assumed to have the same expiration date, unless this has been specified by the supplier. SPAR has agreed with most of its suppliers that each SKU has to be stacked on a new pallet, therefore we assume that each pallet corresponds with one order line. In the end, the total amount of time has been divided by the total amount of received pallets to come up with the number of pallets that can be received in an hour. The average wage of a receiver that is working at that particular warehouse department has been divided with the number of pallets that can be received in one hour to come up with the costs of receiving one order line.

There are two exceptions to the assumption that one pallet equals one order line. Some cosmetic goods are ordered in such small sizes that SPAR allows its suppliers to stack multiple SKUs on one pallet. The receiver, however, still needs to scan and control each of these SKUs separately, so we have also considered these SKUs as separate order lines when measuring the duration of the receiving process and the number of order lines. The second exception to the assumption is whenever an order line consists of more case packs than the amount of case packs that fit on one single pallet. When, for instance, two full pallets of one product are received by a supplier, the receiver has to scan and control these two pallets separately. Therefore, we have also considered these two pallets as two separate order lines. In reality, however, this would be just one order line. In the receiving process, and in the transportation process as well, receiving two pallets of one SKU will take twice as long as receiving one pallet of this SKU. Thus, when measuring the costs of the handling activities, this justifies to consider each pallet as one order line. The downside of this assumption is that it will not be possible to check whether it is beneficial to order multiple pallets at once instead of one at a time. This assumption limits the project to order lines consisting of maximally the amount of case packs that fit on one pallet.

3.3.2 Measuring the transportation process

At the moment a pallet is received by the receiver at the entry floor, the warehouse management system (WMS) sets up a task for the reach truck drivers to pick up this pallet at the entry floor and transport it to the shelves. This process is executed with one pallet at the time. The duration of the transportation process is measured for each warehouse section separately. The duration of one task is measured from the moment a reach truck driver accepts a task until the moment the reach truck driver finalizes the task by scanning the location at which the goods are stored after this location has been filled, such that the driver is ready to accept a new task. By taking the average of the durations of the total tasks in a warehouse section and multiplying this by the average hourly wage of a reach truck driver in that particular warehouse section, the costs of transporting one pallet from the entry floor to the storage locations have been calculated for each warehouse section. The costs of the receiving process added by the costs of the transporting process give the total ordering costs of one order line. As discussed, this varies for the different DCs, warehouse departments, and warehouse sections.

3.3.3 Measuring the replenishment process

Measuring the duration of the replenishment process is done in a quite similar way to measuring the transportation process. The replenishment of a pick location is done by a reach truck driver, as discussed in chapter 1. Whenever the amount of goods in a pick location becomes lower than a predetermined limit, the WMS sets up a task for a reach truck driver to fill up the pick location with goods stored at the bulk location. The duration of this process is again measured from the moment a reach truck driver accepts a task until the moment the reach truck driver finalizes the task by scanning the location at which the goods are stored after this location has been filled, such that the driver is ready to accept a new task. By taking the average of the durations of the total tasks in a warehouse section and multiplying this by the average hourly wage of a reach truck driver in that particular warehouse section, the costs of replenishing a pick location have been calculated for each warehouse section. Since these costs cannot be expressed in terms of costs per order line, the expected number of replenishments per order line, based on the order quantity, has to be determined to come up with the replenishment costs of an order line. This will be part of the model and will be discussed in the next chapter.

3.4 Pilot group

Since it is impossible to validate a model for over 6000 SKUs, a group of 46 pilot products has been selected for this purpose. Each product group is represented in this pilot group in order to check whether the model will be beneficial for all product groups and all shelf lives compared to the current inventory replenishment system SPAR is using. The products in the product group have been selected based on the following criteria:

- All product groups have to be represented;
- Customer’s demand of the last 24 months has to be available;
- Customer’s demand of this product has to be close to the average customer’s demand of the entire product group;
- The minimal order quantity of the product has to be less than the amount of case packs that fit on one pallet;
- The DC shelf life multiplied by the average daily customer’s demand has to be larger than the minimal order quantity;

4. Model

For the same reason as the one that applied to section 2.2, the problem definition, this chapter is divided into two sections as well. The first section discusses the model for the inventory replenishment system and the second section discusses the model for the allocation of storage space among the pick locations of SKUs.

4.1 Inventory replenishment

As discussed in chapter 2, one of the objectives of this project is to develop an inventory replenishment system that minimizes the defined inventory costs by determining the optimal order quantities. SPAR has agreed to order in specified batch at specified moments, with specified lead times and review periods sizes with almost all of its suppliers. Therefore, an (R,s,nQ) system should give the best results. Van Donselaar and Broekmeulen (2014) have recently developed an Excel based tool to calculate several KPIs for both (R,s,nQ) and R,s,S). This tool is called the DoBr tool and can be used to calculate several KPIs or cost drivers, which are needed in order to calculate the four types of inventory costs of the cost function of this project.

Using the notation of van Donselaar and Broekmeulen (2014), the following input parameter need to be known for all SKUs:

- Stochastic customer's demand with mean μ and standard deviation σ. All customer's demand is specified in terms of case packs, since this is also the unit in which DCs are supplied. The unit of time is weeks, since a supermarket chain as SPAR arranges all its delivery schedules based on weeks;
- Specified non-negative lead time L and review period R measured in weeks;
- Batch size Q in terms of case packs;
- Capacity V of the pick location in the DC shelf of an SKU;
- Amount of case packs that fit on one pallet;
- Fill rate of the product. SPAR has agreed an average fill rate of 98%, but this may vary between different SKUs;
- Purchasing price p;
- DC shelf life in weeks;
- Ordering costs per order line;
- Outdating costs per case pack;
- Replenishment costs per replenishment task;

Based on these input variables and by using the DoBr tool, the reorder level s, which is needed to achieve the specified fill rate, can be calculated. This reorder level is, in combination with the stochastic customer's demand during the lead time and review period and in combination with the batch size Q, needed to calculate the average inventory on hand $E[IOH]$. Based on the average inventory on hand, the weekly holding costs of this SKU can be calculated. This can be calculated for all values of integer multiples of Q to specify the holding costs for different order sizes in order to ultimately find the optimal order quantity for the SKU.

The order quantity also has a direct influence on the weekly ordering costs. When, for instance, the order quantity doubles, the number of orders in a week will halve. Because the ordering costs have been specified in euros per order line, the weekly ordering costs will also halve in this case. By estimating the amount of weekly order lines, by using the stochastic customer's demand and the order quantity, the weekly ordering costs can be calculated for different order quantities, which again have to multiples of batch size Q.

The outdating costs depend on the order quantity is such a way that whenever the order quantity is larger than the customer's demand during the DC shelf life, products will outdate. Thus, the expected outdating has to be calculated using the stochastic customer's demand, the DC shelf life, the order quantity, and the reorder level. SPAR always demands FIFO delivery from its suppliers and also ships products to its customers based on the FIFO principle. By using the DoBr tool, the relative outdating can be calculated. "The relative outdating is defined as the percentage of demand which is outdated since the expiration date is exceeded before its sold." (van Donselaar & Broekmeulen, 2014) Approximations for the relative outdating have been derived by van Donselaar and Broekmeulen (2012) based on the EWA inventory policy, which they have developed in 2009. The EWA policy is an inventory replenishment policy similar to an (R,s,nQ) policy, but especially designed to take the perishability of products into account. The EWA policy is only applicable if the shelf lives of the SKUs are known upfront. This is the case at SPAR's DCs, since SPAR and its suppliers have agreed upon minimal shelf lives. The relative outdating can easily be multiplied by the weekly customer's demand in order to get the expected weekly outdating. By multiplying the outdating costs per unit by the expected outdating for different order quantities, the outdating costs for different order quantities can be calculated.

The replenishment costs depend on the number of expected replenishments of the pick location from inventory stored in the bulk storage location. Whenever the order quantity can fit in the pick location entirely, there is no need for extra replenishments, which saves lots of replenishment costs. However, in many cases, the ordered quantity does not immediately fit in the pick location. In order to calculate the expected number of replenishments in an inventory replenishment cycle, the expected amount of goods in the pick location at the beginning has to be calculated. Together with the expected beginning inventory in the pick location and the order quantity, the number of expected replenishments during an inventory replenishment cycle can be determined, since this has been implemented the DoBr tool. Multiplying this number with the expected yearly amount of order lines gives the expected number of yearly replenishment tasks. Multiplying this number with the costs of one replenishment task, results in the yearly replenishment costs. This can, as for all the other inventory costs, be calculated for different order quantities.

By taking the sum of these four inventory costs for different order quantities (multiples of Q), the optimal order quantity for an SKU can be calculated. This can easily be compared by the inventory costs using the order quantity that is currently used by the Inventory Management department using Slim4. Namely, the currently used order quantity is equal to the lowest multiple of Q that is needed to have an inventory large enough to meet all customer's demand during $R + L$ with a 98% probability based on a normal distribution. In Slim4, most SKUs are treated as if their demand follows a normal distribution, but calculating the relative outdating, using the DoBr tool, can only be done for products that follow a discrete demand distribution. This does make a lot more sense, since SPAR does not sell parts of a product, but only entire products, which are usually packed together in a case pack. By comparing the inventory costs for the currently used order quantity and the inventory costs for the optimal order quantity as a result of the new replenishment system, the benefits of using this system can be expressed. The results will be discussed in the next chapter.

4.2 Pick location capacity

The problem of which amount of storage space of the pick locations to allocate to which SKU can be modeled quite similar to a Knapsack problem. Since most products at SPAR have to be ordered in batches equal to multiples of pallet layers, the capacity of the pick location of an SKU can be described by multiples of pallet layers as well. In terms of the Knapsack problem, the total available storage capacity can be seen as the capacity of the Knapsack, SPAR's SKUs can be seen as the different items that can go into the Knapsack and the amount of pallet layers of an SKU can be seen as the number of copies of an item that can go into the Knapsack. However, SPAR's problem does substantially differ from a standard Knapsack problem in two ways. First, all of SPAR's SKUs need to have an appointed pick location. Otherwise, the products cannot be picked and shipped to the supermarkets. Second, for each SKU, the cost reductions of extending the capacity of the pick location are not linear, as can be seen in Figure 4. This means that if you extend an SKU's pick location by two layers, this does not give a reduction of costs equal to two times the reduction that extending the pick location by one layer would give. Figure 4 shows that large cost reductions can be achieved by increasing the pick location capacity, since the replenishment costs reduce very quickly. As the pick location capacity is increased further, the total inventory related costs keep declining, but at a decreasing rate until there is a point at which the pick location is large enough to store the entire incoming order quantity as well as the expected inventory on hand at the moment the new order is being delivered.

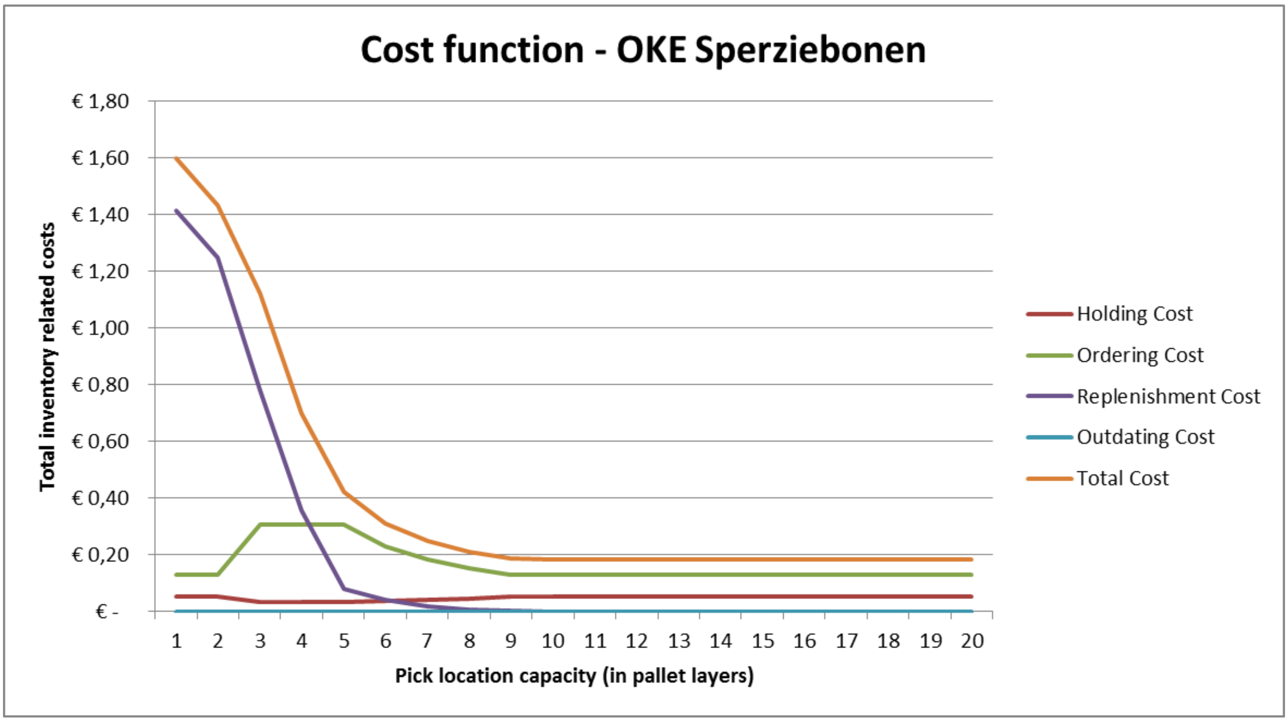

Figure 4: Graph of the cost function when adding extra layers to the pick location capacity of an SKU.

The change in ordering costs in this figure can be explained by a shift in the optimal order quantity. As soon as the pick location capacity is increasing, the expected number of replenishments reduces for all possible order quantities. However, this number reduces at a higher rate for small order quantities than for large order quantities until it approaches 0. At that point, the expected number of replenishments keeps getting lower for large quantities but does not change for the small order quantities. Therefore, the optimal order quantity shifts as the pick location capacity increases. This effect can be seen in Figure 5.

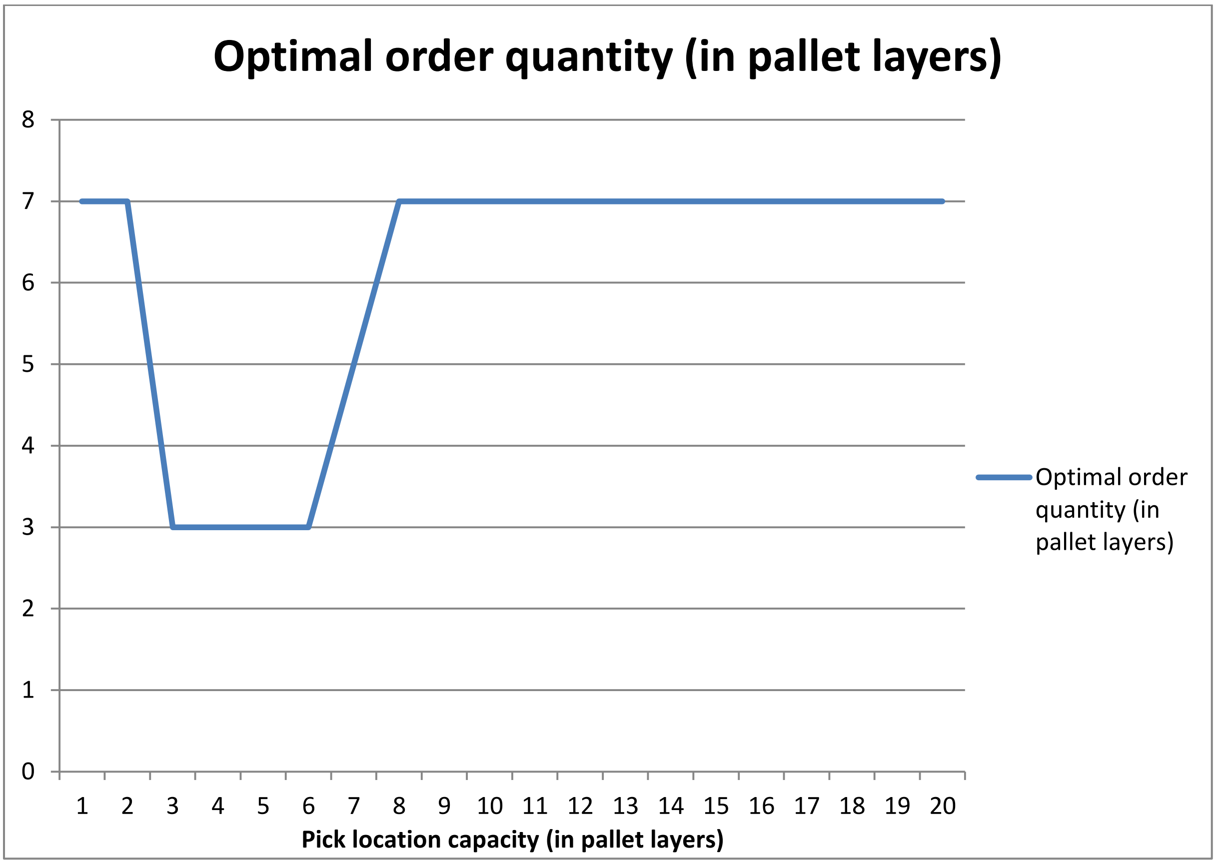

Figure 5: The shift in the optimal order quantity as the pick location capacity increases.

Kellerer, Pferschy and Pisinger (2004) describe the "Multiple Choice Knapsack Problem with a knapsack of *capacity c* that should be filled with *m* mutually disjoint classes $N_1,\ldots,N_m$ of items. Each item $j\epsilon N_i$ has a profit p_{ij} and a weight w_{ij}. The problem is to choose exactly one item from each class such that the profit sum is maximized without exceeding the capacity *c* in the corresponding weight sum. After introducing the binary variables x_{ij} which take on value 1 if and only if item *j* is chose in class N_i, the problem is formulated as" (Kellerer, Pferschy, & Pisinger, 2004):

$$maximize \sum_{i=1}^{m} \sum_{j \in N_i} p_{ij}\, x_{ij}$$

$$\begin{aligned} subject\ to \sum_{i=1}^{m} \sum_{j \in N_i} w_{ij}\, x_{ij} &\le c, \\ \sum_{j \in N_i} x_{ij} &= 1, \quad \mathrm{i} = 1, \ldots, \mathrm{m}, \\ x_{ij} &\in \{0, 1\}, \qquad i = 1, \ldots, m, \ \ j \in N_i. \end{aligned}$$

SPAR's DCs consist of aisles with pick locations on each side of the aisle. The pick locations of all slow and fast moving dry groceries SKUs are distributed within pallet locations that have the width and length of the size of a pallet and a height of 2.10 meters. A pallet location usually holds pick locations of more than one different SKUs on top of one another, which are divided by a wooden shelf with a height of 2 centimeters. Furthermore, in order to be able to pick the products from the pick locations, a head space of 5 centimeters is needed for each SKU. For modelling purposes, the pallet locations are assumed to be stacked on top of one another in one large tower with the total capacity of the DC's pick location capacity. Therefore, SPAR's "Knapsack" problem can be modeled as a large tower with the length and width of the size of a pallet and a total height capacity *V*, which is equal to the total height of the pallet locations minus the height of the needed planks and the needed head space. This tower should be filled with *n* item types (SKUs), where item type *i* has a height w_i and inventory related costs c_{ij} for each *j* pallet layers in the SKUs pick location capacity. Each SKU has an upper bound m_i, which either states the amount of pallet layers at which adding an extra pallet layer does not result in lower costs, or states the number of pallet layers that fit into one pallet location. The problem can be defined as follows:

$x_{ij} \in \{0,1\}: SKU\ i\ gets\ j\ layers\ allocated\ as\ its\ pick\ location\ capacity$
$j \in \{1, \dots, m_i\}$

$$Minimize \left\{ \sum_{i=1}^{n} \sum_{j=1}^{m_i} c_{ij} x_{ij} \right\}$$

$$s.t. \qquad \forall i: \sum_{j=1}^{m_i} x_{ij} = 1$$

$$\sum_{i=1}^{n} \sum_{j=1}^{m_i} w_i x_{ij} \leq V, \qquad V = total\ height - height\ of\ planks - head\ space$$

The original Knapsack Problem is a known NP-hard problem, meaning that it cannot be solved computationally with realistic dimensions. Therefore, algorithms such as the greedy algorithm are used to come up with an approximate solution to the problem. The greedy algorithm iteratively searches for the best possible solution at the moment and solves the subproblem that arises next later. It keeps searching for the locally optimal solution. In case of the Knapsack Problem, the greedy algorithm would choose the item with the highest value per unit of weight first, then the item with the second highest value per unit of weight and so on. (Selman, Levesque, & Mitchell, 1992)

SPAR's problem is an extension to the original Knapsack Problem, and therefore, can also be considered to be an NP-hard problem. This means that we need an algorithm to come up with the best solution to the problem. Based on the greedy algorithm, Bartholdi and Hackman (2011) propose an auctioning algorithm in which each item makes a business case with which the item wants to compete for an allocation of space in the pick location. The business case would simply be the net-benefit per pallet location. As part of their space allocation theory, Bartholdi and Hackman (2011) propose the "Law of None, Min, or All", which states that an SKU should either be allocated no pick location, the minimal practical amount of locations, or all of its incoming pallets should be stored in the pick locations. They state that giving an SKU additional pick locations, beyond the minimum required, does not reduce the number of replenishments. In our case, increasing the capacity of an SKU's pick location does reduce the number of replenishment significantly and, in many cases, even leads to a shift in the optimal order quantity. This can be seen in Appendix B. Furthermore, each SKU should be allocated a pick location and since the pick locations of SPAR's SKUs are stacked on top of each other, the minimal capacity of an SKU's pick location should be equal to the size of one pallet layer. For these reasons, the "Law of None, Min, or All" does not apply in our situation, but the auctioning algorithm in which each SKU makes a business case for the allocation of space could be a viable algorithm in order to solve our problem.

Kök and Fisher (2007) describe an iterative heuristic that searches for the best shelf space allocation, taking the overall storage capacity as a restriction. The heuristic is based on the premise that customers would be willing to substitute for similar products within a certain subcategory of products. At SPAR's DCs, it is almost impossible to determine the willingness of supermarket managers to substitute among all available SKUs, let alone the willingness of end-customers. Therefore, the heuristic of Kök and Fisher (2007) cannot be applied in this situation, but the idea of maximizing the total profit by allocating the right amount of shelf space to the right SKUs within the available storage capacity is similar to the problem of SPAR. The SKUs that are currently having storage spaces smaller than a full pallet load can be reallocated according to the potential cost reduction. This means that an iterative heuristic can be developed by dividing the total storage capacity of the pick locations among the specified SKUs in order to achieve the highest possible cost reduction. As part of this heuristic, each SKU would have a pick location appointed which is equal to the amount of one pallet layer. The remainder of the storage capacity will then be divided according to the highest potential cost reduction. This will be divided in steps of one pallet layer at the time, since the vast majority of these SKUs have to be ordered in multiples of a pallet layer.

Calculating the potential cost reductions of extending the pick location capacity with an extra pallet layer of each SKU can be done by using the DoBr tool. Algorithms based on the auctioning algorithm and the iterative heuristic which are described above, can be used to find suitable solutions to our problem. These will be described later in this chapter. We focus on the slow moving dry groceries SKUs in both DCs and the fast moving dry groceries SKUs in the North DC that currently have a pick location with a storage capacity that is smaller than a full pallet layer and which have to be ordered in batches equal to multiples of a pallet layer. SKUs that have to be ordered in multiples of full pallets, usually have a pick location with a capacity equal to a full pallet and this will not be changed. Furthermore, we believe that this method is more applicable to SKUs with a long shelf life, which are usually the dry groceries, compared to fresh SKUs with a short shelf life. It is very important to ship products with a short shelf life through the supply chain to the end-customer as fast as possible to prevent outdating. Therefore, we believe that fresh products should get a higher capacity of pick locations per SKU than dry groceries in order to make sure that these products can always be picked as soon as they are needed.

The problem is an NP-hard problem and therefore, an absolute best solution cannot be found. As described above, this means that an algorithm has to be used to find a suitable solution. Since algorithms only come up with an approximation of the absolute best result because they only solve subproblems of the total problem subsequently, it seems irrelevant to take the whole dry groceries section into account at once when trying to find a solution to the problem. Taking a large amount of SKUs into account increases the possibility that the solution of the algorithm is further away from the optimal result, because it increases the possibility that the order in which subproblems are solved is not the best feasible order when it comes to the total problem. This is a known problem for greedy algorithms. Kellerer et al. (2004) describe that the error of a greedy algorithm due to the order in which subproblems are solved can be approximated by taking half of the highest profit that can be achieved by taking one item in the knapsack. In order to minimize this error, we propose to divide SPAR's problem by taking product groups or product families into account separately. Since most of SPAR's SKUs are already stored in product groups and SPAR is currently further optimizing its product family grouping, it seems only fair to look at the problem of how to allocate the right pick location space to the right SKU on a product family level.

For this reason, we have taken a sample of 20 products from the canned fruits and vegetables product group which are currently divided over 8 pallet locations in the South DC's slow moving section. This sample does not include the same products that are used in the pilot group that is used to compare the results of the DoBr tool and Slim4. These two groups of SKUs are completely different. Taking the head space and the wooden shelves that separate the different SKUs from one another into account, these 20 products have a total of 15.48 meters in height to divide among their own pick location capacities. In order to be able to divide the total space among all SKUs, the potential cost reductions of allocating an extra pallet layer to the pick location capacity of an SKU has to be known. The potential cost reduction of extending an SKU's pick location capacity by one pallet is equal to the difference between the minimal weekly inventory related cost of having a pick location capacity with the size of this extra pallet included and the minimal weekly inventory related cost when this pallet is not included. Therefore, using the DoBr tool, the minimal weekly costs of each SKU has been determined for a pick location capacity equal to 1, 2, 3, …, 20 pallet layers. The overview of these weekly costs can be found in Table 2 and clearly shows a wide variety among SKUs. Some SKUs tend to have a high potential cost reduction when the pick location capacity is extended with one or two pallet layers, while other SKUs only show potential cost reductions after extending the capacity by seven or eight layers. Figure 6 shows the cost graph of 6 of the 20 SKUs when the pick location capacity of each of these 6 SKUs is equal to j pallet layers, with j being equal to 1,…,20. This figure shows a clear difference between SKUs in terms of the slope of the cost curves. The biggest difference that can be seen is the difference between relatively slow moving and fast moving SKUs. In this group of 20 SKUs, the 'appelmoes cupjes' SKU or the blue graph is an SKU with a relatively high weekly demand and the 'haricots verts' SKU or the orange graph is an example of an SKU with a relatively low weekly demand. The graph of the SKU with a low demand shows a steep and short curve, which indicates that the replenishment costs of this SKU decrease quickly as the pick location capacity increases, but also that this effect diminishes quickly. For the faster moving SKU, the blue graph, the slope is more flat, but in the end the weekly costs are lower than the weekly costs of the slower moving SKU. This indicates that for faster moving SKUs, the replenishment costs decrease more slowly and therefore, a larger pick location capacity is needed to eliminate the replenishment costs. However, this does not say anything about the total potential cost reduction of an SKU as the figure shows that the blue graph clearly has a higher potential cost reduction, compared to a situation in which all SKUs have a pick location capacity equal to 1 pallet layer, when 8 or more pallet layers are allocated to the pick location of these two SKUs. The reason for the difference between slower and faster moving SKUs is that less pallet layers of SKUs with a relatively low demand are sold, and therefore shipped to the supermarkets, since the amount of case packs in one pallet layer is about the same for all SKUs. Since the allocation of the pick location capacity is measured in pallet layers, this makes the cost curve of a slower moving SKU short and steep compared to a faster moving SKU.

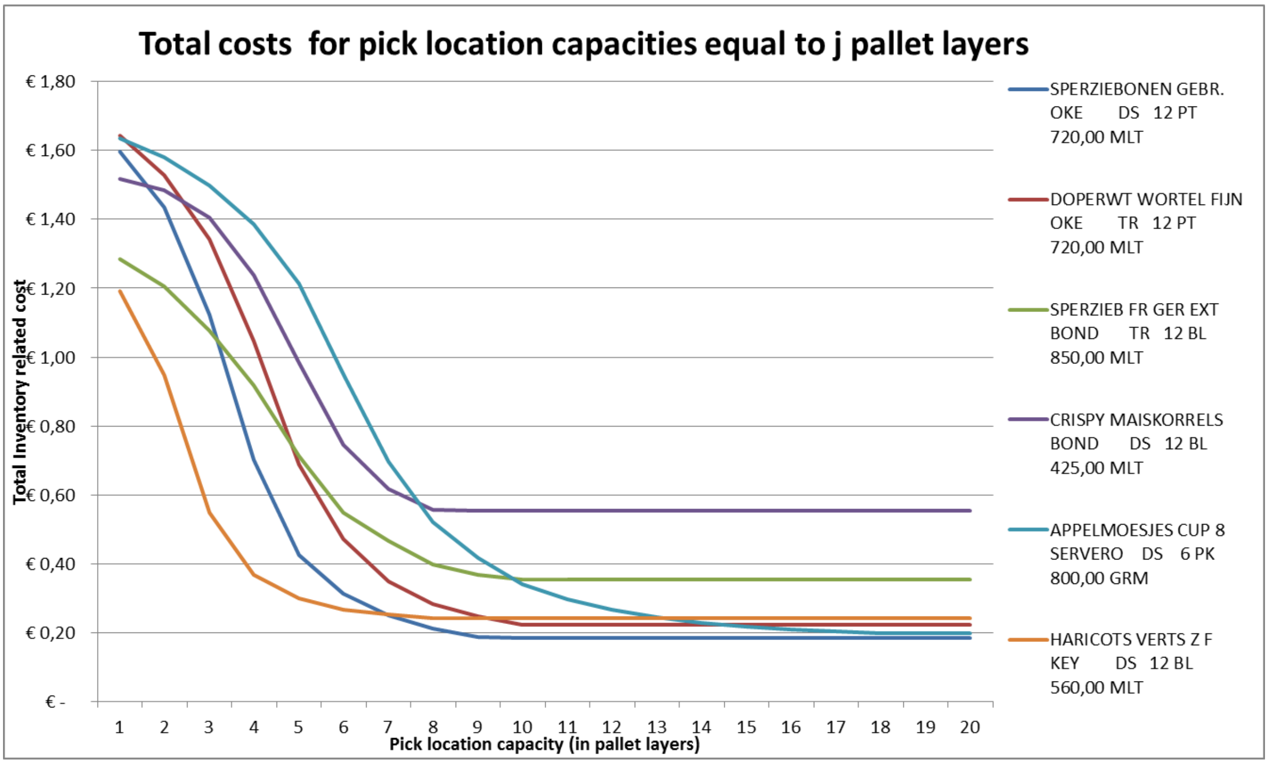

Figure 6: Total costs for pick location capacities equal to j pallet layers.

This effect is even clearer in figure 7, which shows the incremental cost reduction of adding one extra pallet to an SKU's pick location capacity step by step. For instance, the highest potential cost reduction of the 'doperwt wortel' SKU, or the red graph, can be achieved when the pick location capacity is increased from 4 to 5 pallet layers.

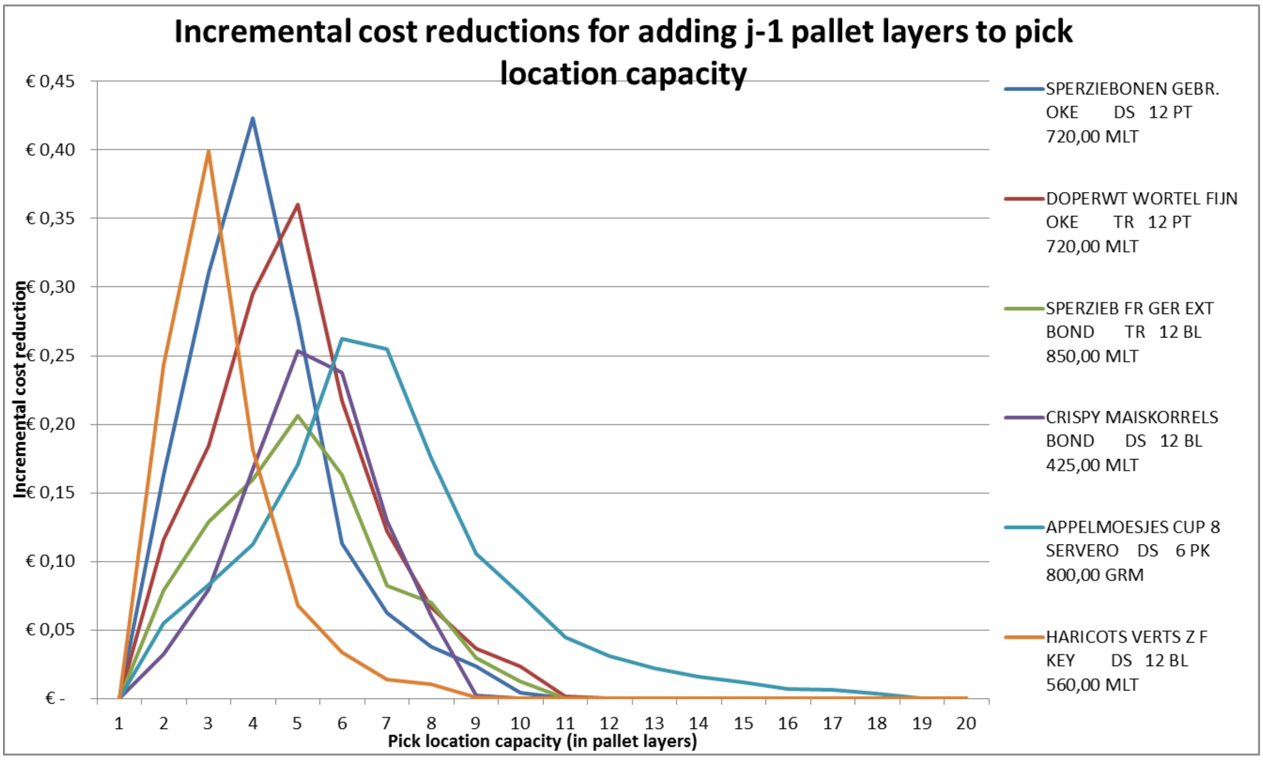

Figure 7: The incremental cost reduction of adding one extra pallet to an SKU's pick location capacity step by step.

Art nr	Product description	Minimal weekly cost corresponding with pick location capacity equal to X amount of pallet layers									
		1	2	3	4	5	6	7	8	9	10
193935	SPERZIEBONEN GEBR. OKE DS 12 PT 720,00 MLT	€ 1,60	€ 1,43	€ 1,12	€ 0,70	€ 0,42	€ 0,31	€ 0,25	€ 0,21	€ 0,19	€ 0,18
191976	DOPERWT WORTEL FIJN OKE TR 12 PT 720,00 MLT	€ 1,64	€ 1,53	€ 1,34	€ 1,05	€ 0,69	€ 0,47	€ 0,35	€ 0,28	€ 0,25	€ 0,22
102780	SPERZIEB FR GER EXT BOND TR 12 BL 850,00 MLT	€ 1,29	€ 1,21	€ 1,08	€ 0,92	€ 0,71	€ 0,55	€ 0,47	€ 0,40	€ 0,37	€ 0,36
48280	CRISPY MAISKORRELS BOND DS 12 BL 425,00 MLT	€ 1,52	€ 1,48	€ 1,40	€ 1,24	€ 0,98	€ 0,75	€ 0,62	€ 0,56	€ 0,55	€ 0,55
531469	APPELMOESJES CUP 8 SERVERO DS 6 PK 800,00 GRM	€ 1,63	€ 1,58	€ 1,50	€ 1,38	€ 1,21	€ 0,95	€ 0,70	€ 0,52	€ 0,42	€ 0,34
561910	HARICOTS VERTS Z F KEY DS 12 BL 560,00 MLT	€ 1,19	€ 0,95	€ 0,55	€ 0,37	€ 0,30	€ 0,27	€ 0,25	€ 0,24	€ 0,24	€ 0,24
525886	HALVE PERZIKEN SPAR DS 12 BL 850,00 MLT	€ 1,71	€ 1,70	€ 1,69	€ 1,66	€ 1,62	€ 1,54	€ 1,44	€ 1,32	€ 1,21	€ 1,08
192702	APPELMOES OKE TR 12 PT 360,00 GRM	€ 1,93	€ 1,93	€ 1,93	€ 1,92	€ 1,92	€ 1,90	€ 1,86	€ 1,80	€ 1,70	€ 1,55
185809	MAISKORRELS ZOET OKE TR 12 BL 300,00 GRM	€ 1,68	€ 1,67	€ 1,64	€ 1,60	€ 1,52	€ 1,38	€ 1,16	€ 0,93	€ 0,78	€ 0,73
520838	MANDARIJNEN LICHTE SPAR DS 24 BL 312,00 GRM	€ 1,54	€ 1,50	€ 1,38	€ 1,23	€ 1,00	€ 0,73	€ 0,59	€ 0,52	€ 0,48	€ 0,46
520524	ZON&FRUIT PERZIK HAK TR 6 BK 400,00 MLT	€ 1,14	€ 0,91	€ 0,47	€ 0,30	€ 0,22	€ 0,19	€ 0,17	€ 0,16	€ 0,16	€ 0,16
520522	ZON&FRUIT TROP.FRUI HAK TR 6 BK 400,00 MLT	€ 1,20	€ 1,11	€ 0,95	€ 0,69	€ 0,44	€ 0,32	€ 0,26	€ 0,23	€ 0,21	€ 0,20
132756	HALVE PEREN OP SIR SPAR DS 12 BL 425,00 GRM	€ 0,95	€ 0,43	€ 0,25	€ 0,19	€ 0,18	€ 0,17	€ 0,17	€ 0,17	€ 0,17	€ 0,17
232684	APPELMOES SPAR UW S TR 12 PT 720,00 GRM	€ 0,96	€ 0,39	€ 0,23	€ 0,19	€ 0,18	€ 0,18	€ 0,18	€ 0,18	€ 0,18	€ 0,18
114850	ANANASCHIJVEN OP SI DELMON TR 6 BL 820,00 GRM	€ 1,62	€ 0,72	€ 0,36	€ 0,30	€ 0,30	€ 0,30	€ 0,30	€ 0,30	€ 0,30	€ 0,30
193388	KAPUCIJNERS OKE DS 12 BL 840,00 MLT	€ 1,57	€ 1,40	€ 1,15	€ 0,84	€ 0,57	€ 0,39	€ 0,30	€ 0,26	€ 0,25	€ 0,25
193263	HALVE PERZIKEN SPAR DS 12 BL 425,00 GRM	€ 1,27	€ 1,09	€ 0,75	€ 0,49	€ 0,38	€ 0,33	€ 0,31	€ 0,30	€ 0,29	€ 0,29
522746	FRUIT COCKT LICHTE SPAR DS 6 BL 825,00 GRM	€ 1,79	€ 1,79	€ 1,78	€ 1,77	€ 1,75	€ 1,72	€ 1,68	€ 1,60	€ 1,49	€ 1,38
187348	HALVE PERZIKEN SIRO OKE DS 12 BL 850,00 MLT	€ 1,70	€ 1,69	€ 1,69	€ 1,68	€ 1,66	€ 1,63	€ 1,59	€ 1,52	€ 1,42	€ 1,31
521821	ANANASSCHIJF OPL.SI SPAR DS 6 BL 820,00 GRM	€ 1,37	€ 1,26	€ 1,08	€ 0,78	€ 0,52	€ 0,40	€ 0,35	€ 0,32	€ 0,30	€ 0,30

Art nr	Product description	Minimal weekly cost corresponding with pick location capacity equal to X amount of pallet layers									
		11	12	13	14	15	16	17	18	19	20
193935	SPERZIEBONEN GEBR. OKE DS 12 PT 720,00 MLT	€ 0,18	€ 0,18	€ 0,18	€ 0,18	€ 0,18	€ 0,18	€ 0,18	€ 0,18	€ 0,18	€ 0,18
191976	DOPERWT WORTEL FIJN OKE TR 12 PT 720,00 MLT	€ 0,22	€ 0,22	€ 0,22	€ 0,22	€ 0,22	€ 0,22	€ 0,22	€ 0,22	€ 0,22	€ 0,22
102780	SPERZIEB FR GER EXT BOND TR 12 BL 850,00 MLT	€ 0,36	€ 0,36	€ 0,36	€ 0,36	€ 0,36	€ 0,36	€ 0,36	€ 0,36	€ 0,36	€ 0,36
48280	CRISPY MAISKORRELS BOND DS 12 BL 425,00 MLT	€ 0,55	€ 0,55	€ 0,55	€ 0,55	€ 0,55	€ 0,55	€ 0,55	€ 0,55	€ 0,55	€ 0,55
531469	APPELMOESJES CUP 8 SERVERO DS 6 PK 800,00 GRM	€ 0,30	€ 0,27	€ 0,24	€ 0,23	€ 0,22	€ 0,21	€ 0,20	€ 0,20	€ 0,20	€ 0,20
561910	HARICOTS VERTS Z F KEY DS 12 BL 560,00 MLT	€ 0,24	€ 0,24	€ 0,24	€ 0,24	€ 0,24	€ 0,24	€ 0,24	€ 0,24	€ 0,24	€ 0,24
525886	HALVE PERZIKEN SPAR DS 12 BL 850,00 MLT	€ 0,94	€ 0,83	€ 0,75	€ 0,68	€ 0,64	€ 0,61	€ 0,60	€ 0,60	€ 0,60	€ 0,60
192702	APPELMOES OKE TR 12 PT 360,00 GRM	€ 1,30	€ 1,11	€ 1,00	€ 0,97	€ 0,95	€ 0,94	€ 0,93	€ 0,93	€ 0,93	€ 0,93
185809	MAISKORRELS ZOET OKE TR 12 BL 300,00 GRM	€ 0,73	€ 0,73	€ 0,73	€ 0,73	€ 0,73	€ 0,73	€ 0,73	€ 0,73	€ 0,73	€ 0,73
520838	MANDARIJNEN LICHTE SPAR DS 24 BL 312,00 GRM	€ 0,46	€ 0,46	€ 0,46	€ 0,46	€ 0,46	€ 0,46	€ 0,46	€ 0,46	€ 0,46	€ 0,46
520524	ZON&FRUIT PERZIK HAK TR 6 BK 400,00 MLT	€ 0,16	€ 0,16	€ 0,16	€ 0,16	€ 0,16	€ 0,16	€ 0,16	€ 0,16	€ 0,16	€ 0,16
520522	ZON&FRUIT TROP.FRUI HAK TR 6 BK 400,00 MLT	€ 0,20	€ 0,20	€ 0,20	€ 0,20	€ 0,20	€ 0,20	€ 0,20	€ 0,20	€ 0,20	€ 0,20
132756	HALVE PEREN OP SIR SPAR DS 12 BL 425,00 GRM	€ 0,17	€ 0,17	€ 0,17	€ 0,17	€ 0,17	€ 0,17	€ 0,17	€ 0,17	€ 0,17	€ 0,17
232684	APPELMOES SPAR UW S TR 12 PT 720,00 GRM	€ 0,18	€ 0,18	€ 0,18	€ 0,18	€ 0,18	€ 0,18	€ 0,18	€ 0,18	€ 0,18	€ 0,18
114850	ANANASCHIJVEN OP SI DELMON TR 6 BL 820,00 GRM	€ 0,30	€ 0,30	€ 0,30	€ 0,30	€ 0,30	€ 0,30	€ 0,30	€ 0,30	€ 0,30	€ 0,30
193388	KAPUCIJNERS OKE DS 12 BL 840,00 MLT	€ 0,25	€ 0,25	€ 0,25	€ 0,25	€ 0,25	€ 0,25	€ 0,25	€ 0,25	€ 0,25	€ 0,25
193263	HALVE PERZIKEN SPAR DS 12 BL 425,00 GRM	€ 0,29	€ 0,29	€ 0,29	€ 0,29	€ 0,29	€ 0,29	€ 0,29	€ 0,29	€ 0,29	€ 0,29
522746	FRUIT COCKT LICHTE SPAR DS 6 BL 825,00 GRM	€ 1,28	€ 1,15	€ 1,00	€ 0,89	€ 0,81	€ 0,76	€ 0,72	€ 0,69	€ 0,69	€ 0,69
187348	HALVE PERZIKEN SIRO OKE DS 12 BL 850,00 MLT	€ 1,21	€ 1,09	€ 0,96	€ 0,84	€ 0,75	€ 0,70	€ 0,64	€ 0,61	€ 0,61	€ 0,61
521821	ANANASSCHIJF OPL.SI SPAR DS 6 BL 820,00 GRM	€ 0,29	€ 0,29	€ 0,29	€ 0,29	€ 0,29	€ 0,29	€ 0,29	€ 0,29	€ 0,29	€ 0,29

Table 2: Minimal weekly inventory related costs when the SKU's pick location capacity is equal to j amount of pallet layers.

In order to rank the potential cost reductions, they have to be divided by the height of the SKU. For instance, when product A would show a potential cost reduction of €1.50 a week and product B has a potential cost reduction of €1 a week, but the height of product A is twice the height of product B, it would be better to extend the capacity of product B by an extra layer. Ranking the SKUs based on their potential cost reductions can be done in several ways. When taking the auctioning algorithm into account, an SKU would have to make a business case to increase its capacity by one, two, three, or even more pallet layers and the outcome of each of these business cases should be a clear value. There are multiple options to determine this value. Three of these options are taken into account in this project:

1. The cumulative cost reduction of extending the SKU's pick location capacity to j pallet layers, compared to the cost of having a pick location capacity to the minimal amount of 1 pallet layer, is divided by the extra height necessary of making this extension possible, which is equal to the height of the SKU multiplied by (j-1), since all SKUs need a pick location that is equal to at least one pallet layer. In this case, the cost reduction s_{ij} can be determined as
$$s_{ij} = \frac{(c_{i,j-1} - c_{ij})}{w_i}$$
2. The incremental cost reduction of extending the SKU's pick location by one extra pallet layer is divided by the extra height necessary of making this extension possible, which is equal to the height of the SKU. In this case, the cost reduction s_{ij}' can be determined as
$$s_{ij}' = \frac{(c_{i1} - c_{ij})}{w_i(j-1)}$$
3. The incremental cost reduction of extending the SKU's pick location to j pallet layers compared to (j-1) extra pallet layers is divided by the cumulative extra height necessary of making this extension possible, which is equal to the height of the SKU multiplied by (j-1). In this case, the cost reduction s_{ij}'' can be determined as
$$s_{ij}'' = \frac{(c_{i,j-1} - c_{ij})}{w_i(j-1)}$$

Whenever an SKU shows a high potential cost reduction by adding, for example, six pallet layers, in order to achieve this cost reduction, the first five pallet layers have to be added to the pick location capacity of this SKU as well. Therefore, the first option seems feasible. The downside of this option is that when an SKU has a very high potential cost reduction by adding only one or two layers, these reductions will still be calculated as part of the potential cost reduction of adding more layers. This could lead to increasing the pick location capacity of this SKU by more pallet layers than optimal. The latter does not occur when only the incremental cost reduction from adding one extra pallet layer is used to rank the potential cost reductions, such as in the second option. However, the downside of this option is that it does not take into account the height of adding layers before the actual high cost reduction can be achieved. For instance, when a certain SKU shows a very high potential cost reduction after adding six layers, but only small reductions after adding the first five layers, adding six layers would seem to be the best option. But there may be other SKUs with cost reductions spread more evenly, resulting in a larger cumulative cost reduction after adding six layers. Therefore, in the total objective of minimizing the total costs, allocating six layers to the SKU with the evenly spread but higher cumulative cost reduction would be a better solution. However, by only looking at the incremental cost reductions of adding one pallet layer, this solution would not be chosen. This problem is less likely to occur when the third option is chosen, since that option does take the height of all layers that have to be added into account. However, if an SKU has cost reductions spread quite evenly, this SKU will still not be on top of the ranking. Using algorithms, the best of the three options can be determined by looking at the minimal total costs per week of all SKUs combined. Based on these three options to calculate the cost reductions for adding extra pallet layers to the pick location capacity and based on the auctioning algorithm and the iterative heuristic, four algorithms are tested in order to come up with the best solution that minimizes the total costs per week. These algorithms consist of the following steps:

Algorithm 1 (based on the auctioning algorithm)

Step 1: Start by allocating one pallet layer as pick location capacity of each SKU;
Step 2: Rank the potential cost reductions by using Option 1;
Step 3: Delete all potential cost reductions for which the total amount of pallet layers exceeds the height of one pallet location, including the height of the wooden shelf and the head space;
Step 4: Calculate the total height of the pick locations of all SKUs;
Step 5: Take the highest potential cost reduction. Check if allocating these pallet layers to the pick location capacity fits in the total height of all pallet locations. If so, allocate these pallet layers to the pick location capacity of this SKU. If not, delete this potential cost reduction and perform Steps 4 and 5 again;
Step 6: Delete all potential cost reductions of this SKU;
Step 7: Perform Steps 4-6 again;
Step 8: Stop when there is no feasible potential cost reduction left.

Algorithm 2 (based on the auctioning algorithm)

Step 1: Start by allocating one pallet layer as pick location capacity of each SKU;
Step 2: Rank the potential cost reductions by using Option 1;
Step 3: Delete all potential cost reductions for which the total amount of pallet layers exceeds the height of one pallet location, including the height of the wooden shelf and the head space;
Step 4: Calculate the total height of the pick locations of all SKUs;
Step 5: Take the lowest potential cost reduction of the SKU with the highest potential cost reduction that still is higher than the highest potential cost reduction of any other SKU. Check if allocating these pallet layers to the pick location capacity fits in the total height of all pallet locations. If so, allocate these pallet layers to the pick location capacity of this SKU. If not, delete this potential cost reduction and perform Steps 4 and 5 again;
Step 6: Delete all potential cost reductions of this SKU;
Step 7: Perform Steps 4-6 again;
Step 8: Stop when there is no feasible potential cost reduction left.

Algorithm 3 (based on the iterative heuristic)

Step 1: Start by allocating one pallet layer as pick location capacity of each SKU;
Step 2: Rank the potential cost reductions of adding one extra layer to the pick location of all SKUs by using Option 2;
Step 3: Delete all potential cost reductions for which the total amount of pallet layers exceeds the height of one pallet location, including the height of the wooden shelf and the head space;
Step 4: Calculate the total height of the pick locations of all SKUs;

Step 5: Take the highest potential cost reduction. Check if adding this pallet layer fits in the total height of all pallet locations. If so, add this pallet layer to the pick location capacity of this SKU. If not, delete this potential cost reduction and perform Steps 4 and 5 again;
Step 6: Perform Steps 2-5 again;
Step 7: Stop when there is no feasible potential cost reduction left.

Algorithm 4 (based on the auctioning algorithm)

Step 1: Start by allocating one pallet layer as pick location capacity of each SKU;
Step 2: Rank the potential cost reductions by using Option 3;
Step 3: Delete all potential cost reductions for which the total amount of pallet layers exceeds the height of one pallet location, including the height of the wooden shelf;
Step 4: Calculate the total height of the pick locations of all SKUs;
Step 5: Take the highest potential cost reduction. Check if allocating these pallet layers to the pick location capacity fits in the total height of all pallet locations. If so, allocate these pallet layers to the pick location capacity of this SKU. If not, delete this potential cost reduction and perform Steps 4 and 5 again;
Step 6: Delete all potential cost reductions of this SKU up to the chosen amount of pallet layers including the chosen amount itself;
Step 7: Perform Steps 4-6 again;
Step 8: Stop when there is no feasible potential cost reduction left.

The first two algorithms use the cumulative cost reduction and height in order to rank the potential cost reductions and to decide which SKU gets which amount of pallet layers allocated. The first algorithm is the most straightforward one. Each SKU gets the amount of pallet layers allocated that gives that SKU the highest cost reduction per unit of height. The outcome of this algorithm may be improved by using algorithm 2, since there may be allocations for which the second or third highest cost reduction per unit of height still is a better option than taking the highest cost reduction of other SKUs, resulting in a better overall outcome. Algorithm 3 ranks the potential cost reductions based on their incremental cost reductions. When using this option to rank the potential cost reductions, SKUs with a high potential cost reduction when increasing the capacity from 8 to 9 layers will likely get ranked on top, even if adding the first 8 layers hardly reduces the weekly costs. This would never lead to an optimal solution. Therefore, algorithm 3 is based on the idea of an iterative heuristic, so it only considers adding one extra layer step by step to the SKU with the highest potential cost reduction from adding that particular layer. Finally, algorithm 4 does take the height of preceding layers into account, but it still focuses on incremental cost reductions. The reason for using this algorithm is the fact that, as can be seen in figures 6 and 7, some SKUs (mainly faster moving SKUs) tend to achieve their highest potential cost reduction after allocating multiple pallet layers to their pick location capacity. In some cases, when the initial cost reduction for increasing the pick location capacity from 1 to 2 pallet layers is very small, the highest potential cost reductions of this SKU will not be reached when using algorithm 3, which is based on the iterative heuristic. Therefore, algorithm 4 might result in higher overall cost reductions. On the other hand, if the potential cost reductions of a certain SKU are spread very evenly, this SKU is not likely to get a high rank, and therefore, not likely to get its desired amount of pallet layers allocated as its pick location capacity, even if the cumulative cost reduction could be rather high. All of these four algorithms are tested using the group of 20 canned fruits and vegetables and the results will be discussed the next chapter.

5. Results

Using the DoBr tool, the total inventory related costs, as they are described in chapter 3, can be calculated for all pilot SKUs for all possible order quantities. Since the majority of SPAR's SKUs has to be ordered in multiples of pallet layers, we have decided to calculate the weekly costs for all quantities equal to a multiple of a pallet layer as well. Using the input variables shown in Table 3, this gives the outcome as shown in Table 4.

Product Name	BOND - R KOOL/APPEL	
DC North / South	1	
Average demand	14,57	[CP/week]
Standard deviation	5,89	[CP]
Pick location capacity	168	[CP]
Case packs (CP) per Pallet layer	15	
Layers per pallet	18	
MOQ	45	[CP]
IOQ	45	[CP]
DC shelf life	8	[weeks]
Review period	1,13	[weeks]
Lead time	0,69	[weeks]
Price	6,96	[€/CP]
Service Level	0,95	[P2]
Holding costs	0,00	[€/week]
Ordering costs	1,00	[€/OL]
Replenishment costs	1,91	[€/task]
Outdating	3,48	[€/CP]

Table 3: Input variables used for calculating the optimal order quantity of an SKU

Table 4 clearly shows the outcome in terms of cost per week for order quantities equal to any multiple of the SKUs pallet layer and an overview of the four types of costs that are taken into account is shown in figure 8. This SKU has a DC shelf life of 8 weeks and a weekly average demand of about one pallet layer (15 case packs). Therefore, when more than 5 case packs are ordered, the graph shows that the outdating costs are starting to play a role in the determination of the total inventory related costs. Since the pick location capacity of this SKU is quite large, about equal to 11 pallet layers, the replenishment costs do not play an important role in the determination of the total costs. The holding costs do not play a very important role either, since only the interest rate is taken into account as holding costs. Figure 8 shows that for this SKU, the inventory related costs almost only consist of the ordering costs when the order quantity is low. As soon as the order quantity increases, the order costs decrease as orders are not placed as often anymore. Therefore, the total cost graph follows the order cost graph until the outdating costs start to become effective. As soon as the outdating starts to play a role, this diminishes the effect of all other costs intensely and the outdating costs seem about the only type of cost that has an effect on the total costs.

Figure 9 shows the same graph for an SKU that has a larger DC shelf life and therefore, the outdating costs do not play a role. Here, the effect of the other cost types can be seen more clearly. Again, the order costs decrease quickly as the order quantity increases. Because the pick location capacity of

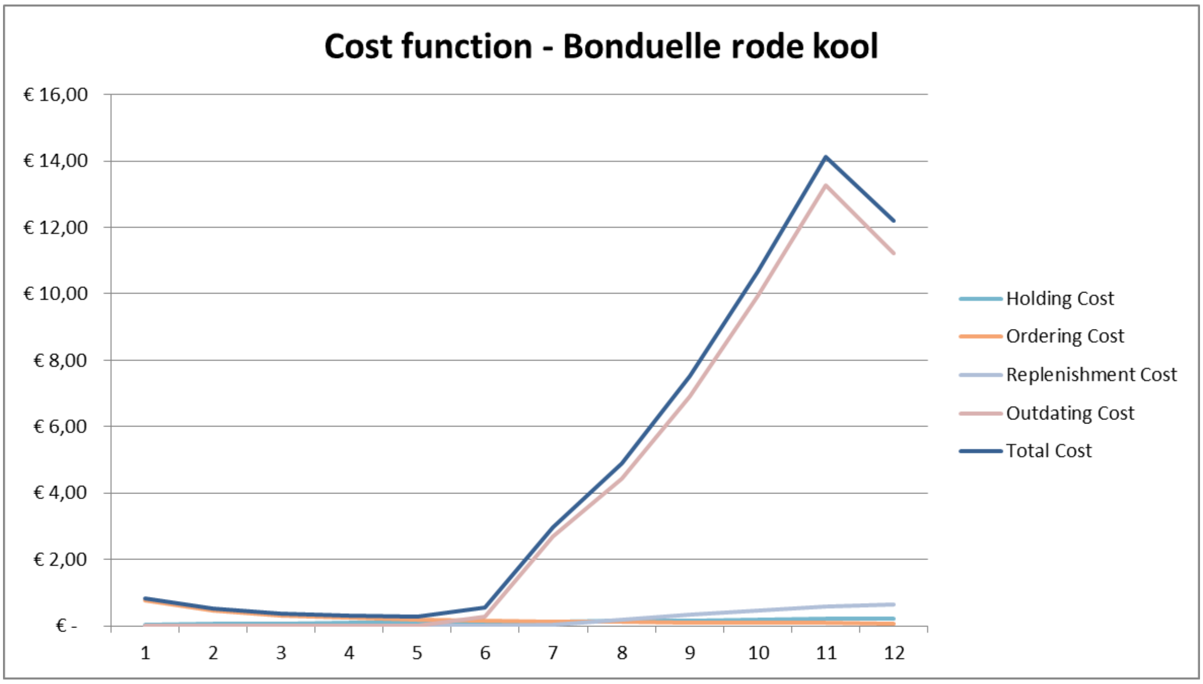

Figure 8: Cost overview of a perishable product.

this SKU is not as high as for the SKU in figure 8, the replenishment costs do play a role and as the order quantity increases, the replenishment costs determine the largest part of the total inventory related costs. Again, the holding costs do not play an important role. These figures provides another good example of the fact that reallocating the total pick location capacity at SPAR's DCs could lead to serious cost reductions, as the replenishment costs can be reduced for SKUs for which these costs are important using the overcapacity of SKUs for which the replenishment costs only play a very small role in the determination of the total costs. This topic will be discussed later in this chapter.

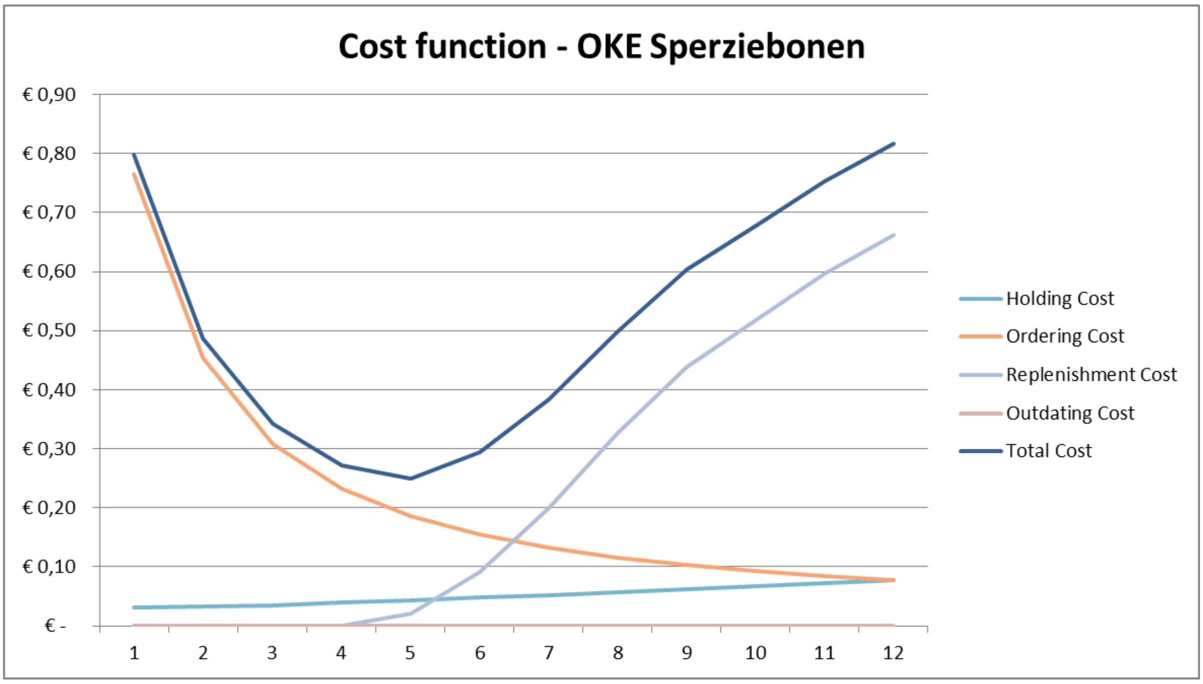

Figure 9: Cost overview of a product with a larger DC shelf life.

Table 4 also shows the order quantity that Slim4 calculates as the blue line at the bottom. This will be discussed later in this chapter. The order quantity which results in the lowest possible costs per week can be determined as the optimal order quantity for this SKU. However, due to agreements with SPAR's suppliers, it might occur that an SKU has to be ordered in multiples of larger quantities than pallet layers. This is the case when the MOQ and IOQ, as described in Chapter 1, are larger than the amount of case packs that fit in one pallet layer. In this case, the optimal order quantity has to be rounded to the multiple of the MOQ/IOQ that results in the lowest cost per week. This is done for all the SKUs in the pilot group in order to determine for which products the order quantity determined by the DoBr tool would result in lower inventory related costs than the current order quantity that Slim4 calculates.

Batch size in pallet layers	Batch size in CP	Reorder level	Fill rate	Expected order lines	Expected Replenishments	Expected outdating	Cost / week
1	15	29	0,954	0,767	0	0	€ 0,82
2	30	25	0,952	0,460	0	0	€ 0,52
3	45	23	0,955	0,309	0	0	€ 0,38
4	60	21	0,955	0,232	0	0	€ 0,32
5	75	19	0,952	0,185	0	0	€ 0,29
6	90	18	0,954	0,154	0	0	€ 0,55
7	105	16	0,950	0,132	0	0,770	€ 2,95
8	120	15	0,951	0,115	0	1,273	€ 4,70
9	135	14	0,951	0,103	0	1,986	€ 7,18
10	150	13	0,951	0,092	0	2,853	€ 10,21
11	165	12	0,951	0,084	0,005	3,810	€ 13,55
12	180	11	0,951	0,077	0,059	3,228	€ 11,65
13	195	10	0,950	0,071	0,118	3,905	€ 14,13
14	210	10	0,954	0,066	0,173	4,667	€ 16,90
15	225	9	0,953	0,062	0,217	5,404	€ 19,56
16	240	8	0,952	0,058	0,255	6,161	€ 22,28
17	255	7	0,951	0,054	0,289	6,935	€ 25,05
18	270	6	0,951	0,051	0,319	7,723	€ 27,87
3	45	23	0,955	0,309	0	0	€ 0,38

Table 4: Weekly costs for ordering quantities equal to multiples of pallet layers

When comparing the optimal order quantity as an outcome of the DoBr tool and the order quantity Slim4 calculates, a problem arises for SKUs with a short shelf life. Since Slim4 does not take outdating into account, and therefore, does not take the expected outdating into account when calculating the reorder level, while the DoBr tool does, the outcome of the two is not comparable. For the service levels Slim4 uses, the DoBr tool results in tremendously higher reorder levels than Slim4, because it takes outdating into account. These reorder levels result in such a high relative outdating that the DoBr tool cannot provide a feasible solution. In order to solve this problem, the service level used in the DoBr tool should be lowered substantially. This does not mean that the calculation of the service level of the DoBr tool is wrong. In fact, the calculation of the service level that Slim4 uses is wrong.

When a product expires, a new product has to be ordered to be able to provide SPAR's customers with the same service level. Slim4 does not take this into account, while the DoBr tool does. Unfortunately, in the case of lowering the target service level, the outcome of the two models are no longer comparable. Figure 10 shows that, in order to reduce the outdating of a cooled perishable product, the service level of the DoBr tool substantially differs from the 0.95 fill rate that Slim4 uses for this product. Therefore, we have decided to focus the comparison of the two models on SKUs with a larger shelf life than the SKUs stored in the cooled perishable department of SPAR's DC. This leaves the pilot group with 35 suitable SKUs and in total, about 5,000 SKUs of SPAR comply with this restriction as well as the other restrictions of the pilot group. For these SKUs, the optimal order quantities and corresponding costs have been compared to the order quantities Slim4 suggests. The result, in terms of cost per year, can be found in Table 5. Originally, we had planned to compare the yearly costs as a result of the model to the actual costs that have been made in 2013, since that is the first full year in which SPAR has used Slim4. Unfortunately, this proved to be unachievable, since there was no data available on the number of replenishments of the pick locations in 2013 and the data on the number of obsolete products because of outdating proved to be inaccurate. This can be seen in Appendix C, which shows the average inventory on hand of some SKUs over the course of 2013, based on the available data of demand, purchase orders and outdating. These figures clearly show that the inventory on hand of the SKUs is rising over the course of 2013, which did not actually occur during 2013. Therefore, we have compared the outcome of the model to the order quantities Slim4 calculates.

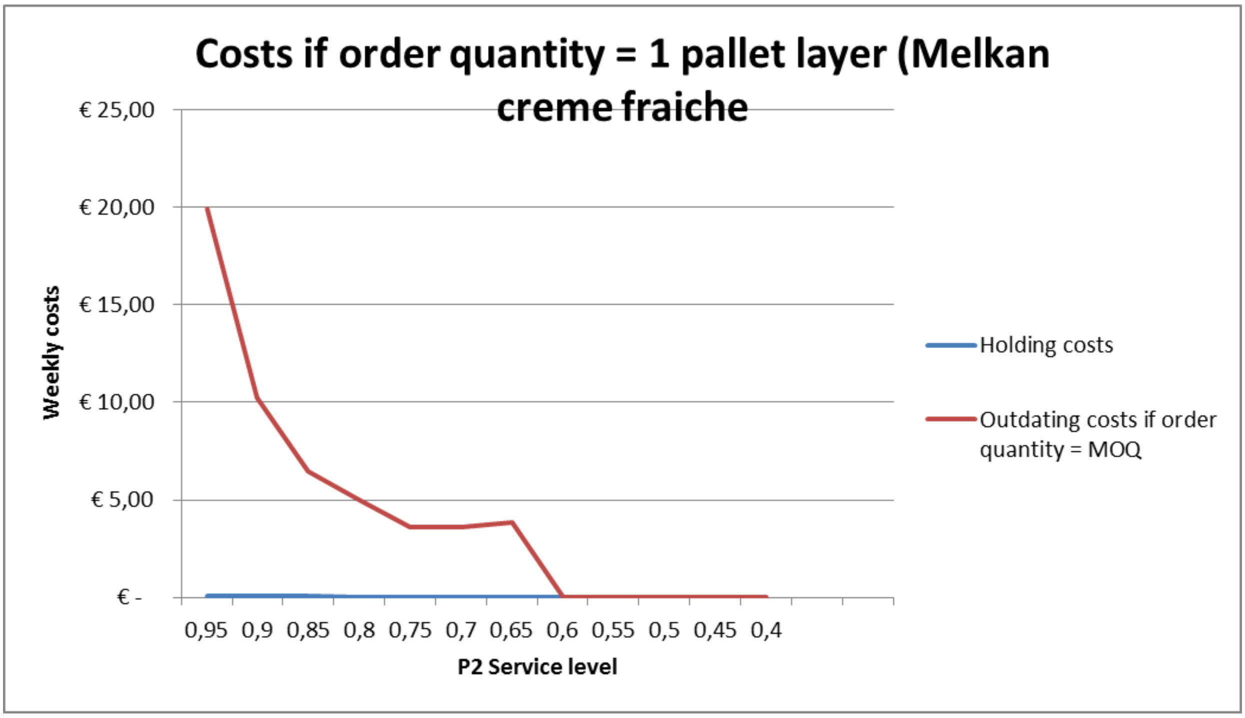

Figure 10: Costs of a perishable product calculated by the DoBr tool for different service levels.

Table 5 clearly shows that there is a potential for cost reduction by using the DoBr tool instead of the ordering advice of Slim4. The table shows a potential reduction of about 9% over these 35 SKUs. Since, due to our shelf life restriction, to which only 5,000 of SPAR's total of 12,000 SKUs comply, this would mean an average increase of the total inventory on hand of SPAR by 4%. Unfortunately, as noted above, an overview of SPAR's total yearly inventory related costs cannot be established.

Therefore, in order to quantify the total potential cost reduction, the average potential cost reduction in euros can be used. Based on the average of the pilot group, the usage of the DoBr tool yearly saves €6.44 per SKU per DC compared to the usage of Slim4. Based on the restrictions of SKUs in the pilot group and on the newly added shelf life restriction, SPAR still has slightly over 2,500 SKUs in their two DCs for which the DoBr tool could be very beneficial in terms of cost savings. If the tool is used for all these 5,000 SKUs, this would mean a potential cost reduction of over €30,000 a year, based on the average cost reduction of the pilot group. The potential cost saving could even be higher if the restrictions on MOQ and IOQ could be renegotiated with the suppliers. Since SPAR is currently looking into their MOQ and IOQ restrictions, the DoBr tool could be used to quantify the extra potential cost reduction by changing the restrictions on the order quantities.

So, the usage of the tool does save costs, which is the prime objective, however, it does also seem to increase the total inventory on hand, due to larger order quantities. Since the average throughput time is one of the KPIs with which SPAR measures the performance of their supply chain, we should take this into consideration. Based on the pilot group, the weighted average inventory on hand of the products, for which the DoBr tool is used, increases by 22%. A weighted average is used since the products in this pilot are just a sample of all of SPAR's SKUs in order to make the contribution of all of the pilot SKUs to the average increase of inventory equal. Since, due to our shelf life restriction, to which only 5,000 of SPAR's total of 12,000 SKUs comply, this 22% increase would mean an average increase of the total inventory on hand of SPAR by 9%. The increase of inventory is likely going to increase the average throughput time of SPAR's SKUs. On the other hand, since the order quantities by using the DoBr tool are higher than the order quantities by using Slim4, this means that the pallet locations in the bulk storage space will likely be used more efficiently by using the DoBr tool. Since each incoming pallet that does not fit in the pick location entirely gets its own pallet location in the bulk storage space assigned, ordering larger quantities could reduce the number of pallet locations used by a single SKU. Further research is needed to quantify this effect.

Art nr	Product description	Yearly Costs DoBr	Yearly Costs Slim4	Potential cost reduction	Average Inventory on hand DoBr	Average Inventory on hand Slim4	Increase in %
1000770	BOND - R KOOL/APPEL	€ 21,91	€ 21,91	€ -	27,081	27,081	0
1120504	KNORR - SOEPPAKKET	€ 30,23	€ 36,07	€ 5,84	19,912	15,890	25
1350232	DEHEER - CHOC.PINDAROTSJES MELK	€ 42,87	€ 49,06	€ 6,19	43,539	50,549	-14
1512497	ALPRO SOYA - SOYA DRINK LIGHT NAT	€ 29,29	€ 45,38	€ 16,09	25,403	16,402	55
1540224	SPAR - SPOELGLANSMIDDEL	€ 37,59	€ 37,59	€ -	28,000	28,000	0
1350589	DEVOS -LEMMENS - MAYONAISSE CITROEN	€ 17,14	€ 17,14	€ -	9,977	9,977	0
1351216	VITALU - ONTBIJTCR.VOLKOREN	€ 243,49	€ 273,87	€ 30,39	40,036	21,059	90
1347260	BOND - WORTELEN EF	€ 15,27	€ 29,43	€ 14,16	38,073	20,609	85
1351567	ZONNATUR - BIO VENKELTHEE	€ 17,28	€ 29,56	€ 12,28	25,246	15,733	60
1280139	PRODEN - TP COOLMINT	€ 50,52	€ 53,44	€ 2,91	71,499	55,493	29
1531489	MENTOS - BOTTLE MIGHTY MINT	€ 34,77	€ 51,47	€ 16,70	7,786	4,283	82
1350592	CONIMEX - KRUIDENMIX VOOR NASI	€ 29,93	€ 29,93	€ -	21,889	21,889	0
1879330	IGLO - VISSCHNITZELS 4ST	€ 28,25	€ 38,70	€ 10,45	66,973	43,024	56
2533602	BECKER - MAGN.LOEMPIA KIP 2ST	€ 24,84	€ 37,74	€ 12,90	35,326	16,311	117
2315638	AVIKO - ZWITSER SCHOTEL ZONNEBL.	€ 35,54	€ 41,16	€ 5,63	75,319	61,311	23
2520448	IGLO - GROENTENSOEP	€ 23,52	€ 37,72	€ 14,20	26,515	10,428	154
2517116	WESTER - RIETSUIKER	€ 54,95	€ 60,09	€ 5,15	34,568	61,044	-43
2256170	BONZO - MINIKLUIF	€ 42,72	€ 44,69	€ 1,97	43,263	49,305	-12
2398920	SPAR - KLETSKOPPEN	€ 61,56	€ 61,91	€ 0,34	79,713	85,717	-7
2361500	CELEBRATION - DOOS GROOT	€ 245,85	€ 254,54	€ 8,70	41,415	35,413	17
2529082	BIO - MUESLI	€ 139,78	€ 139,78	€ -	35,583	35,583	0
2000770	BOND - R KOOL/APPEL	€ 25,67	€ 26,06	€ 0,39	18,720	24,218	-23
2239620	CONIMEX - SEROENDENG	€ 15,12	€ 15,12	€ -	24,421	24,421	0
2518145	NESCAFE - GUSTO LATTE MACCHIATO	€ 55,45	€ 55,82	€ 0,37	23,569	29,608	-20
2026140	CONIMEX - SAMBAL OELEK	€ 42,26	€ 42,26	€ -	33,334	33,334	0
2509926	LAVAZZ - BLACK PACK ESPRESSO	€ 39,78	€ 40,40	€ 0,61	18,409	13,390	37
2531489	MENTOS - BOTTLE MIGHTY MINT	€ 52,24	€ 52,24	€ -	10,856	10,856	0
2540318	GALLO - CABERNET SAUVIGNON	€ 55,13	€ 55,13	€ -	17,811	17,811	0
2526074	FLIX - LUCIFERS MEDIUM	€ 15,41	€ 15,41	€ -	19,404	19,404	0
2357760	BRISE - AEROS LAV& VIOL	€ 90,16	€ 104,89	€ 14,73	53,919	67,923	-21
2522453	WELLA - HAIRSPRAY ULTRA STRONG	€ 22,39	€ 23,66	€ 1,27	38,891	22,387	74
1168637	SPAR - COCKTAILNOTEN MILD	€ 274,43	€ 299,59	€ 25,16	81,627	67,617	21
2168637	SPAR - COCKTAILNOTEN MILD	€ 111,65	€ 130,52	€ 18,87	95,055	101,043	-6
1275700	SPAR - PASTA FUSILLI TRIC.	€ 160,57	€ 160,57	€ -	254,609	254,609	0
2275700	SPAR - PASTA FUSILLI TRIC.	€ 163,01	€ 163,01	€ -	490,304	490,304	0
	SUM	**€ 2.350,57**	**€ 2.575,88**	**€ 225,31**	**1978,045**	**1862,026**	
			Average	**€ 6,44**		**Average**	**22**

Table 5: Comparing DoBr and Slim4.

Since an alignment between the optimal ordering quantity and the size of the pick location of an SKU is likely going to increase the potential cost reduction for SPAR even further, due to the impact of the number of replenishments on the total inventory related costs, we compare the current situation of the pick location distribution with the outcome of the four algorithms that have been described in chapter 4. In order to compare the results of the four algorithms, first the current situation of the allocation of the pick location capacities of each SKU in the group of 20 canned fruits and vegetables has to be known. These 20 SKUs are divided over 8 pallet locations in the slow moving dry groceries section of the South DC of SPAR. The current pick capacity is known for each SKU, but the data on the pick location capacities of each SKU has not been updated recently. Table 6 shows all 20 SKUs, their current pick location capacity, and their current optimal order quantity. Furthermore, this table shows the starting situation of all four algorithms, namely the situation in which each SKU has a pick location equal to one pallet layer. This table shows again that changing the pick location capacity does have quite an impact on the optimal order size and the table shows indeed that the data of the current pick location capacities have not been updated, since the total amount of products would not fit in 8 pallet locations. Most importantly, the table shows that the current allocation of pick location capacities among these 20 SKUs costs €20.47 a week.

Table 7 shows the results of each of the four algorithms. Because all the algorithms are based on the greedy procedure and the maximal error of a greedy algorithm has been defined in chapter 4 as half of the maximal profit, which is the maximal cost reduction in this case, the result of all algorithms is shown in intervals. The maximal potential cost reduction is calculated using the overview of all potential cost reductions in table 2 and is equal to €1.44.

Table 7 clearly shows that each algorithm provides a better solution than the current situation, ranging between about €11 and €14 a week, and it shows that algorithm 4 results in the lowest total cost per week, which ranges from €10.96 to €12.39 a week. Compared to the current situation, this is a difference of €8.79 a week on average, which is equal to a cost reduction of 43%. Unfortunately, as stated above, an overview of SPAR's total inventory related costs is unavailable, but this cost reduction of 43% clearly indicates that there is room for improvement when it comes to the distribution of pick location space among SKUs in SPAR's DCs. The cost reduction is likely to be even higher, considering the fact that the data on the current distribution of the pick location storage space is incorrect. However, it should be noted that in order to reveal the true potential cost savings of the model, we did not take MOQ and IOQ restrictions into account. These restrictions might decrease the potential cost reductions, but will not abolish them. Furthermore, the cost reduction is likely to be reduced because of the fact that in the actual DC, the pick location cannot be regarded as one large tower but it has to be regarded as several pallet locations next to each other.

		Current situation					Pick location capacity = 1 layer		
Art nr	Product description	Pick location capacity	# of layers	Optimal order quantity	Cost / week	Height	Optimal order quantity	Cost / week	Height
193935	SPERZIEBONEN GEBR. OKE DS 12 PT 720,00 MLT	77	11	55	€ 0,25	1,98	77	€ 1,60	0,18
191976	DOPERWT WORTEL FIJN OKE TR 12 PT 720,00 MLT	77	11	44	€ 0,35	1,87	77	€ 1,64	0,17
102780	SPERZIEB FR GER EXT BOND TR 12 BL 850,00 MLT	24	2	36	€ 0,92	0,24	42	€ 1,29	0,12
48280	CRISPY MAISKORRELS BOND DS 12 BL 425,00 MLT	20	1,25	36	€ 1,47	0,11	36	€ 1,52	0,09
531469	APPELMOESJES CUP 8 SERVERO DS 6 PK 800,00 GRM	20	1,43	140	€ 1,58	0,16	140	€ 1,63	0,11
561910	HARICOTS VERTS Z F KEY DS 12 BL 560,00 MLT	20	2	33	€ 1,02	0,26	77	€ 1,19	0,13
525886	HALVE PERZIKEN SPAR DS 12 BL 850,00 MLT	64	6,4	80	€ 1,32	0,83	80	€ 1,71	0,13
192702	APPELMOES OKE TR 12 PT 360,00 GRM	70	14	70	€ 1,92	1,68	70	€ 1,93	0,12
185809	MAISKORRELS ZOET OKE TR 12 BL 300,00 GRM	30	1,88	33	€ 1,65	0,17	33	€ 1,68	0,09
520838	MANDARIJNEN LICHTE SPAR DS 24 BL 312,00 GRM	22	3,14	84	€ 1,51	0,53	84	€ 1,54	0,17
520524	ZON&FRUIT PERZIK HAK TR 6 BK 400,00 MLT	40	4	32	€ 0,67	0,48	112	€ 1,14	0,12
520522	ZON&FRUIT TROP.FRUI HAK TR 6 BK 400,00 MLT	40	4	112	€ 1,04	0,44	128	€ 1,20	0,11
132756	HALVE PEREN OP SIR SPAR DS 12 BL 425,00 GRM	140	14	84	€ 0,17	1,54	42	€ 0,95	0,11
232684	APPELMOES SPAR UW S TR 12 PT 720,00 GRM	90	10	40	€ 0,18	1,2	10	€ 0,96	0,12
114850	ANANASCHIJVEN OP SI DELMON TR 6 BL 820,00 GRM	30	3	40	€ 1,29	0,36	60	€ 1,62	0,12
193388	KAPUCIJNERS OKE DS 12 BL 840,00 MLT	40	8	32	€ 0,57	1,04	40	€ 1,57	0,13
193263	HALVE PERZIKEN SPAR DS 12 BL 425,00 GRM	140	14	112	€ 0,29	1,54	112	€ 1,27	0,11
522746	FRUIT COCKT LICHTE SPAR DS 6 BL 825,00 GRM	160	16	160	€ 1,38	2,08	160	€ 1,79	0,13
187348	HALVE PERZIKEN SIRO OKE DS 12 BL 850,00 MLT	80	8	80	€ 1,31	0,96	80	€ 1,70	0,12
521821	ANANASSCHIJF OPL.SI SPAR DS 6 BL 820,00 GRM	48	4,8	80	€ 1,08	0,62	160	€ 1,37	0,13
	Total capacity =	**15,48**			**€ 20,47**	**18,10**		**€ 29,77**	**2,99**

Table 6: Current and starting situation for allocation of pick location capacities

	Algorithm 1			Algorithm 2			Algorithm 3			Algorithm 4		
Art nr	# Layers	Cost / week	Height	# Layers	Cost / week	Height	# Layers	Cost / week	Height	# Layers	Cost / week	Height
193935	4	€ 0,70	0,72	5	€ 0,42	0,9	8	€ 0,21	1,44	6	€ 0,31	1,08
191976	5	€ 0,69	0,85	7	€ 0,35	1,19	9	€ 0,25	1,53	7	€ 0,35	1,19
102780	6	€ 0,55	0,72	8	€ 0,40	0,96	9	€ 0,37	1,08	7	€ 0,47	0,84
48280	6	€ 0,75	0,54	7	€ 0,62	0,63	8	€ 0,56	0,72	7	€ 0,62	0,63
531469	8	€ 0,52	0,88	8	€ 0,52	0,88	14	€ 0,23	1,54	9	€ 0,42	0,99
561910	3	€ 0,55	0,39	3	€ 0,55	0,39	6	€ 0,27	0,78	5	€ 0,30	0,65
525886	13	€ 0,75	1,69	16	€ 0,61	2,08	1	€ 1,71	0,13	11	€ 0,94	1,43
192702	13	€ 1,00	1,56	13	€ 1,00	1,56	1	€ 1,93	0,12	12	€ 1,11	1,44
185809	9	€ 0,78	0,81	9	€ 0,78	0,81	3	€ 1,64	0,27	9	€ 0,78	0,81
520838	6	€ 0,73	1,02	10	€ 0,46	1,7	9	€ 0,48	1,53	7	€ 0,59	1,19
520524	3	€ 0,30	0,36	3	€ 0,47	0,36	6	€ 0,19	0,72	5	€ 0,22	0,6
520522	5	€ 0,44	0,55	5	€ 0,44	0,55	9	€ 0,21	0,99	6	€ 0,32	0,66
132756	2	€ 0,43	0,22	3	€ 0,25	0,33	5	€ 0,18	0,55	4	€ 0,19	0,44
232684	2	€ 0,39	0,24	2	€ 0,39	0,24	4	€ 0,19	0,48	4	€ 0,19	0,48
114850	2	€ 0,72	0,24	3	€ 0,36	0,36	4	€ 0,30	0,48	4	€ 0,30	0,48
193388	5	€ 0,57	0,65	6	€ 0,39	0,78	8	€ 0,26	1,04	7	€ 0,30	0,91
193263	4	€ 0,49	0,44	5	€ 0,38	0,55	7	€ 0,31	0,77	5	€ 0,38	0,55
522746	8	€ 1,60	1,04	1	€ 1,79	0,13	1	€ 1,79	0,13	1	€ 1,79	0,13
187348	15	€ 0,75	1,8	2	€ 1,69	0,24	1	€ 1,70	0,12	1	€ 1,70	0,12
521821	5	€ 0,52	0,65	6	€ 0,40	0,78	8	€ 0,32	1,04	6	€ 0,40	0,78
Total capacity = 15,48		**€ 13,22**	**15,37**		**€ 12,27**	**15,42**		**€ 13,08**	**15,46**		**€ 11,68**	**15,4**
Highest reduction = €1,44												
Cost interval		**€ 12,50**	**€ 13,93**		**€ 11,55**	**€ 12,99**		**€ 12,36**	**€ 13,80**		**€ 10,96**	**€ 12,39**

Table 7: Outcome of algorithms used to allocate pick location capacities

6. Managerial implications

The results of this research clearly indicate that taking costs of handling operations in the DC into account when developing the inventory replenishment policy is very beneficial in terms of total inventory related costs. Slim4, the current inventory replenishment system that the Inventory Management department of SPAR uses, calculates the order quantity based on the minimal amount of an SKU that is needed to achieve a predetermined service level over the cover period, which consists of the review period and the lead time of that particular SKU. Using the DoBr tool, we have calculated that taking holding, ordering, outdating, and replenishment costs into account can lead to serious cost reductions compared to the Slim4 inventory replenishment sytem.

However, Slimstock, the developing company of Slim4, states that its specialty does not lie in the determination of the ordering quantity but in the forecasting of the future demand of an SKU. This has also been the main reason why SPAR chose to introduce Slim4 as their inventory management system in 2012. Combining the benefits of having a good working forecasting tool and a good working inventory replenishment system would be the desired outcome. Unfortunately, we cannot simply combine the theory behind the DoBr tool and the Slim4 inventory management system as the underlying assumptions regarding the used demand distributions differ fundamentally. Slim4 assumes that most SKUs have a normally distributed demand distribution, while the expected outdating used in the DoBr tool is based on a discrete demand distribution. Since Slim4 does not even take outdating into account when determining the reorder level, suitable estimations cannot be made for perishable products. Therefore, we suggest Slimstock to investigate into the possibility of including outdating in their inventory system, especially since it has been shown that outdating costs can play such an important role in the determination of the total inventory related costs.

Further cost savings have been shown in this research by aligning the order quantity and the capacity of an SKUs pick location. This has been done by using the same DoBr tool to calculate the potential cost reduction of allocating an extra amount, equal to a pallet layer, to the pick location capacity of an SKU. Subsequently, the total pick location capacity of the product group to which an SKU belongs, has been divided over all the SKUs in that product group using several algorithms. All algorithms used result in much lower costs than the current distribution of the pick location capacity does. Besides, the data on the current distribution shows that the data management of the WMS needs an update. The best performing algorithm is the one that calculates the cost reduction of adding an extra pallet layer by taking the incremental cost reduction dividing this by the cumulative height of all the pallet layers that need to be added.

All in all, the following recommendations for SPAR can be made based on this research:

- Continue the current process of reorganizing the DC by regrouping SKUs of the same product family together;
- Update the data of the WMS after regrouping the SKUs and keep updating this regularly;
- Calculate the optimal distribution of the pick location capacities of SKUs for all product groups that meet the restrictions. These calculations should be updated at least four times a year since a substantial part of SPAR's SKUs face seasonal effects in their demand. Updating four times a year might not even be enough, since SPAR's SKU portfolio keeps changing. Therefore, the updating schedule should be investigated properly;

- Calculate the optimal order quantities based on the calculated pick location capacities for all SKUs that meet the restrictions. Because of the seasonality, these calculations need to be updated as well;
- Use the calculations of the optimal order quantity to renegotiate the MOQ and IOQ restrictions with suppliers in order to save additional costs.

7. Conclusions

In this final chapter of the report, the conclusions of the research are drawn, the limitations of the research are discussed and opportunities for future research are given.

7.1 General conclusions

As described in Chapter 2, this research has two main objectives. The first one is the development of an inventory replenishment system that takes costs of handling operations in SPAR's DCs and costs of outdated products into account. The second objective is to develop a method which can be used to divide the total available pick location storage space among the SKUs in the most cost efficient way.

Van Donselaar and Broekmeulen (2014) recently developed an Excel based tool which can be used to calculate several KPIs for inventory policies. Based on these KPIs, optimal order quantities for SPAR's SKUs have been calculated as part of this research. Using the KPIs, costs of handling, ordering, outdating, and replenishments can be determined. These costs are used to calculate the optimal order quantities of SPAR's SKUs. The results of this model show that, based on the pilot group of SKUs for which we have tested the model, the model results in lower costs than the current inventory replenishment system, Slim4, that is being used by SPAR. The Slim4 system does not take handling or outdating costs into account. Therefore, the findings of this research are compliant with the hypothesis that taking these costs into account would result in a more cost efficient inventory replenishment system. Because of the fundamental differences in terms of used demand distributions between the theory of van Donselaar and Broekmeulen (2014) and Slim4, the results of the model and the Slim4 system have only been compared for SKUs with a fairly long DC shelf life. This still results in a potential reduction of yearly costs of €6.44 per SKU based on the SKUs used in the pilot group. Because SPAR distributes over 5,000 SKUs that satisfy the restrictions, this shows that taking the cost of handling operations, outdating and replenishment into account could lead to decent cost reductions.

This research furthermore shows that there is another potential for reducing the inventory related costs, namely by reducing the expected amount of replenishments by reallocating the total pick location storage space among SPAR's SKUs. Again, this has only been tested for a part of SPAR's SKUs, but it shows fairly large cost savings of up to 43%. Although the used algorithms have only been tested for one product group, the potential cost savings are so high, SPAR should definitely look into the possibility to use this method to distribute their pick location capacity among their SKUs. However, since an algorithm does not likely result in the optimal solution, first the SKUs of SPAR should be grouped together in product families before the method of this research can be used.

7.2 Limitations

The results of this research are quite promising, but there are some limitations of this research. However, some limitations of this study show opportunities for future research. More on this topic will be discussed in the next section. The limitations to this study are described below:

- The duration of the handling operations in the DCs have been measured in November / December 2013. This is typically a period in which the demand is quite low and therefore, the amount of incoming goods is also quite low. Although SPAR does take this into account by using less employees, the timing of the measurements could result in durations of handling operations that are not representative for the handling operations that have to be done during the entire year.

- When determining the costs, we have restricted the model to SKUs that are ordered in quantities smaller than one pallet size. This has been done since the incoming goods are scanned, controlled and transported to the storage locations pallet by pallet and because most SKUs are actually ordered in quantities smaller than a pallet size. However, this does limit this research.
- The shelf life of SKUs in the DCs is measured by taking the shelf life SPAR has agreed with its suppliers instead of the actual remaining shelf life the products usually have when they are shipped to SPAR's DCs. This has been done since there is not enough data available to calculate an estimate of the DC shelf life, but it does limit the usability of this study.
- The expected number of replenishments that are calculated using the DoBr tool are specified as idle replenishments. At SPAR, however, pick locations can be replenished before the inventory in that pick location runs empty, since the replenishment tasks are triggered whenever the inventory in a pick location is lower than a specified amount of goods.
- In order to compare the outcome of the model to the currently used inventory replenishment system, Slim4, the order quantities have been compared and costs have been attributed using the model. The actual costs that have been made by using Slim4 over the course of a year could not be determined.
- The current data on the distribution of the pick location capacity is incorrect. Therefore, the result of the algorithm compared to the current situation might not be completely accurate.
- For the calculation of the potential cost reduction for optimizing the distribution of the pick location capacity among SKUs, the pick location is regarded as one large tower. Therefore, the cost reduction is likely to be reduced because of the fact that in the actual DC, the pick location cannot be regarded as one large tower but it has to be regarded as several pallet locations next to each other.

7.3 Future research

This last section of the report provides some opportunities for future research, which have come up during this research but could not be included as part of this research. These opportunities are:

- Look into the possibility to calculate the expected replenishments based on replenishments that take place when the pick location is almost empty;
- Look into the effect of having optimal batch sizes on the used number of pallet locations in the bulk storage space;
- Look into opportunities to find approximations for the outdating of products and number of replenishments when the demand follows other than discrete distributions;
- Look into whether the DoBr tool provides optimal solutions for SKUs with a short shelf life, since this could not be determined by comparing the results of the model with the current used inventory replenishment system.

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List of abbreviations

DC	Distribution center
DC shelf life	Amount of time the product can be stored at the distribution center
DoBr tool	Model designed by van Donselaar and Broekmeulen (Working paper)
FIFO	First in first out
IOQ	Incremental order quantity
KPI	Key performance indicator
MOQ	Minimal order quantity
Q	Order quantity
SKU	Stock keeping unit
WMS	Warehouse management system

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Appendix A

Costs of each handling activity

Receiving	Pallets / hour	Costs / pallet
South Dry Groceries	110,46	€ 0,21
North Dry Groceries	117,98	€ 0,25
South Cooled Perishables / Deep Frozen	87,21	€ 0,26
North Cooled Perishables / Deep Frozen	109,55	€ 0,26
Transportation	Pallets / hour	Costs / pallet
South Dry Groceries	33,01	€ 0,70
North Dry Groceries	32,50	€ 0,75
South Cooled Perishables	41,24	€ 0,57
North Cooled Perishables	31,38	€ 0,73
South Deep Frozen	31,92	€ 0,73
North Deep Frozen	28,72	€ 0,79
North Dry Groceries Flammable	111,16	€ 0,21
Ordering		Costs / pallet
South Dry Groceries		€ 0,91
North Dry Groceries		€ 1,00
South Cooled Perishables		€ 0,83
North Cooled Perishables		€ 0,99
South Deep Frozen		€ 1,00
North Deep Frozen		€ 1,06
North Dry Groceries Flammable		€ 1,42
Replenishment	Tasks / hour	Costs / task
South Dry Groceries fast / slow	20,71	€ 1,12
South Dry Groceries premium / flammable	21,06	€ 1,10
North Dry Groceries	12,84	€ 1,91
South Cooled Perishables	25,67	€ 0,91
North Cooled Perishables	24,24	€ 0,94
Unpack Dry groceries	case packs / hour	costs / case pack
South DC incl. RT	283,91	€ 0,08
North DC	213,42	€ 0,11
Unpack Cooled perishables	case packs / hour	costs / case pack
South DC	244,72	€ 0,09

Appendix B

Shift in optimal ordering quantity because of the changing capacity of an SKU's pick location capacity.

Input variables:

Product Name	ALPRO SOYA - SOYA DRINK LIGHT NAT	
DC North / South	1	
Average demand	11,58	[CP/week]
Standard deviation	4,28	[CP]
Pick location capacity	***X***	***[CP]***
Case packs (CP) per Pallet layer	24	
Layers per pallet	6	
MOQ	24	[CP]
IOQ	24	[CP]
DC shelf life	20	[weeks]
Review period	0,71	[weeks]
Lead time	1,31	[weeks]
Price	8,26	[€/CP]
Service Level	0,95	[P2]
Holding costs	0,00	[€/week]
Ordering costs	1,00	[€/OL]
Replenishment costs	1,91	[€/task]
Outdating	4,13	[€/CP]

Weekly costs for batch sizes equal to multiples of pallet layers with X = 24 (1 pallet layer):

Batch size in pallet layers	Batch size in CP	Reorder level	Fill rate	Expected order lines	Expected Replenishments	Expected outdating	Cost
1	24	24	0,954	0,460	0,468	0	€ 1,38
2	48	21	0,956	0,230	0,846	0	€ 1,88
3	72	19	0,957	0,154	0,995	0	€ 2,10
4	96	17	0,955	0,115	1,070	0	€ 2,22
5	120	15	0,952	0,092	1,114	0	€ 2,30
6	144	14	0,954	0,077	1,154	0	€ 2,37

Weekly costs for batch sizes equal to multiples of pallet layers with X = 48 (2 pallet layers):

Batch size in pallet layers	Batch size in CP	Reorder level	Fill rate	Expected order lines	Expected Replenishments	Expected outdating	Cost
1	24	24	0,954	0,460	0,000	0	€ 0,48
2	48	21	0,956	0,230	0,156	0	€ 0,56
3	72	19	0,957	0,154	0,525	0	€ 1,20
4	96	17	0,955	0,115	0,717	0	€ 1,55
5	120	15	0,952	0,092	0,832	0	€ 1,76
6	144	14	0,954	0,077	0,919	0	€ 1,92

Weekly costs for batch sizes equal to multiples of pallet layers with X = 72 (3 pallet layers):

Batch size in pallet layers	Batch size in CP	Reorder level	Fill rate	Expected order lines	Expected Replenishments	Expected outdating	Cost
1	24	24	0,954	0,460	0,000	0	€ 0,48
2	48	21	0,956	0,230	0,000	0	€ 0,27
3	72	19	0,957	0,154	0,073	0	€ 0,34
4	96	17	0,955	0,115	0,364	0	€ 0,87
5	120	15	0,952	0,092	0,550	0	€ 1,22
6	144	14	0,954	0,077	0,684	0	€ 1,47

Weekly costs for batch sizes equal to multiples of pallet layers with X = 96 (4 pallet layers):

Batch size in pallet layers	Batch size in CP	Reorder level	Fill rate	Expected order lines	Expected Replenishments	Expected outdating	Cost
1	24	24	0,954	0,460	0,000	0	€ 0,48
2	48	21	0,956	0,230	0,000	0	€ 0,27
3	72	19	0,957	0,154	0,000	0	€ 0,20
4	96	17	0,955	0,115	0,035	0	€ 0,24
5	120	15	0,952	0,092	0,268	0	€ 0,68
6	144	14	0,954	0,077	0,449	0	€ 1,02

Weekly costs for batch sizes equal to multiples of pallet layers with X = 120 (5 pallet layers):

Batch size in pallet layers	Batch size in CP	Reorder level	Fill rate	Expected order lines	Expected Replenishments	Expected outdating	Cost
1	24	24	0,954	0,460	0,000	0	€ 0,48
2	48	21	0,956	0,230	0,000	0	€ 0,27
3	72	19	0,957	0,154	0,000	0	€ 0,20
4	96	17	0,955	0,115	0,000	0	€ 0,18
5	120	15	0,952	0,092	0,016	0	€ 0,20
6	144	14	0,954	0,077	0,213	0	€ 0,58

Weekly costs for batch sizes equal to multiples of pallet layers with X = 144 (6 pallet layers):

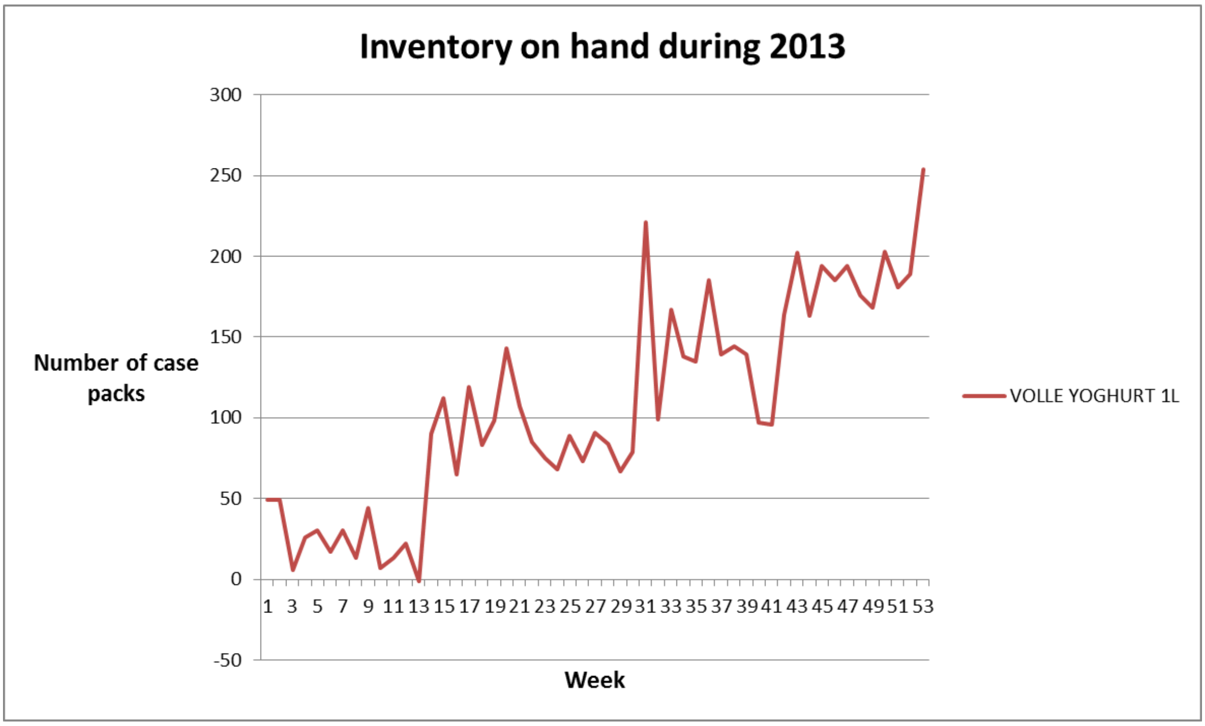
Batch size in pallet layers	Batch size in CP	Reorder level	Fill rate	Expected order lines	Expected Replenishments	Expected outdating	Cost
1	24	24	0,954	0,460	0,000	0	€ 0,48
2	48	21	0,956	0,230	0,000	0	€ 0,27
3	72	19	0,957	0,154	0,000	0	€ 0,20
4	96	17	0,955	0,115	0,000	0	€ 0,18
5	120	15	0,952	0,092	0,000	0	€ 0,17
6	144	14	0,954	0,077	0,010	0	€ 0,19

Weekly costs for batch sizes equal to multiples of pallet layers with X = 168 (7 pallet layers):

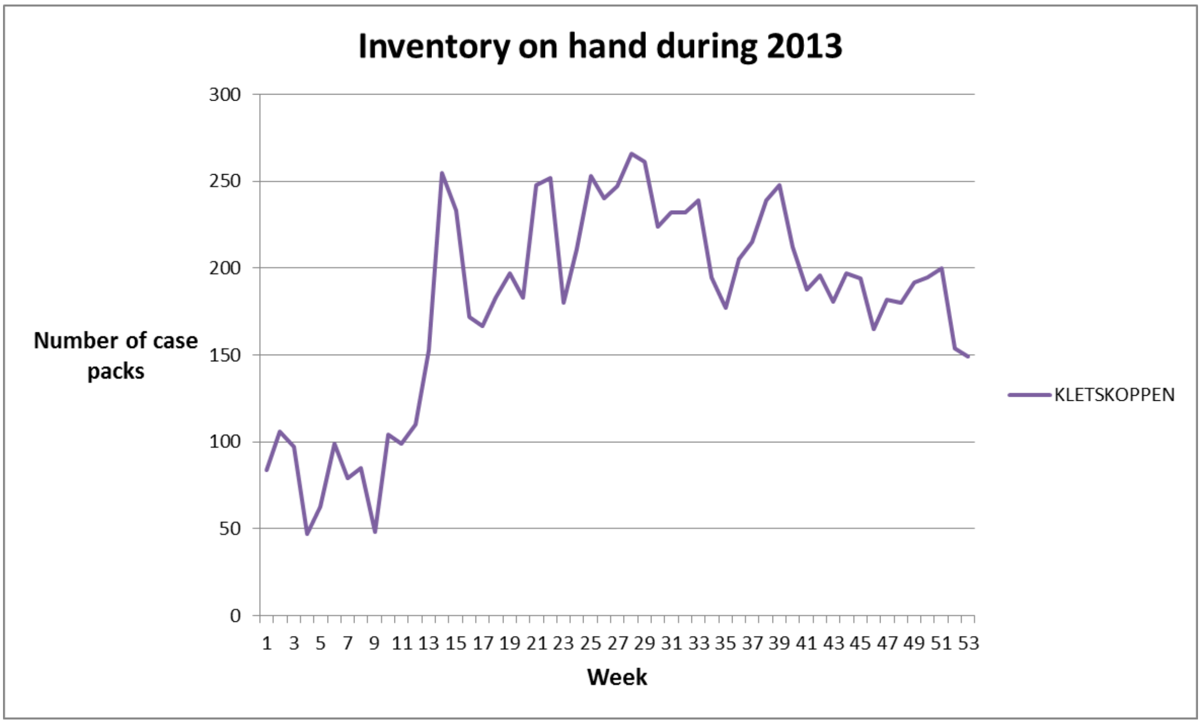
Batch size in pallet layers	Batch size in CP	Reorder level	Fill rate	Expected order lines	Expected Replenishments	Expected outdating	Cost
1	24	24	0,954	0,460	0,000	0	€ 0,48
2	48	21	0,956	0,230	0,000	0	€ 0,27
3	72	19	0,957	0,154	0,000	0	€ 0,20
4	96	17	0,955	0,115	0,000	0	€ 0,18
5	120	15	0,952	0,092	0,000	0	€ 0,17
6	144	14	0,954	0,077	0,000	0	€ 0,17

Appendix C

The figures in this appendix show the inventory on hand of four of SPAR's SKUs over the course of 2013, based on the available data on demand, on the purchase orders and on the number of obsoletes as a result of outdating. The figures clearly show that, based on the available data, the inventory on hand increased over the course of 2013. The Inventory Management department indicates that this has not been the case. Therefore, we assume the data is incorrect.




Inventory on hand during 2013
Number of case packs
300
250
200
150
100
50
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51 53
Week
MUESLI


Inventory on hand during 2013
Number of case packs
300
250
200
150
100
50
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51 53
Week
KLETSKOPPEN