A simulation based approach to reduce fresh food waste at Marko cash & carry

van Andel, S.

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A simulation based approach to reduce fresh food waste at Makro cash & carry

by
S. van Andel

BSc Industrial Engineering & Management Science – TU/e 2015
Student identity number 0777357

in partial fulfilment of the requirements for the degree of

Master of Science
in Operations Management and Logistics

University supervisors:
dr. K.H. (Karel) van Donselaar, Eindhoven University of Technology, OPAC
dr. M. (Maximiliano) Udenio, Eindhoven University of Technology, OPAC

Company supervisors:
H. (Harald) Lek, Head of Category Management Fresh, Makro cash & carry Netherlands
P. (Philip) van Binsbergen, Senior Category Manager, Makro cash & carry Netherlands
Abstract

This study describes a step by step procedure to reduce costs of waste and overall costs for perishables. Improvements are sought in operations and logistics. With a close to real-world simulation model, performances of different configurations are assessed. Costs that are taken into account are costs of waste, inbound logistics and handling in the DC.

As a first step, it is investigated how some key parameters of the ordering system could be defined best. It is found that by decreasing the Minimal Shelf Stock (MSS) settings and simultaneously increasing and differentiating the service levels, overall costs and costs of waste could be significantly reduced. Secondly, to further reduce overall costs, it is examined how customer behavior relates to waste and how this behavior can be positively influenced. Finally, the distribution flow type selection is described, which describes the design of the physical distribution structure from supplier to store. In particular, it is assessed what the potential benefits are of holding inventory in the DC and what the possibilities are of unpacking case packs in the DC. We find that for some suppliers reductions in waste are critical when they choose to hold inventory in the DC and potentially unpack case packs. For others, inbound logistics savings determine the potential. The used methodology and the created simulation model can be used for various fresh product categories. Thereby it facilitates strategical decision making to reduce overall costs in the whole fresh food department.
Executive Summary

Reducing food waste is a practice that is placed high on the agenda of many retailers that sell perishables. Hence, wasting less directly improves profitability by reducing costs. Moreover, it enhances store image, as being sustainable is a hot topic that modern customers find important. Makro cash & carry realizes this importance as well and continuously tries to improve its supply chain and operations to reduce costs of waste and overall costs. This Master Thesis contributes to this desire by regarding the waste problem from a broad perspective, involving evaluation of the ordering system, the store procedures and the flow type selection problem. The latter concerns the design of the physical distribution structure from supplier to store. It analyzes decisions about whether products should be kept on stock in the DC and how products are transported and handled in the chain. The wide scope of this study touches three critical and interconnected areas that offer significant opportunities in reduction of waste and overall costs. The defined research question is as follows:

| Which ordering system parameters, store procedures and flow types minimize overall costs and costs of waste for Makro’s fresh product categories? |

This study is performed on two fresh product categories: Milk Products and Sandwiches & Spreads. However, the used methodology can also be used on other fresh product categories. As a constraint on availability we aim for a fill rate of 97%.

Analysis current situation

In Figure 1 the distribution of operational costs in Makro’s fresh supply chain is depicted. Waste represents the largest cost component of the pie. This shows that measures to reduce waste could significantly impact overall costs. The following cost components are regarded as relevant for the analyzed measures in this study: (1) waste costs, (2) inbound transportation costs and (3) handling costs in the DC. From statistical analyses, experiments and interviews five interconnected drivers of waste were identified at Makro: (1) long lead times and review periods, (2) non-optimal parameter settings of the ordering system, (3) high degree of human interference in order proposals, (4) limitation of the Minimal Order Quantity (MOQ) on ordering and (5) LIFO customer picking behavior in stores. The first four drivers lead to waste as they influence unhealthy stock levels.

To assess whether customers pick the oldest date at the front of the shelf (FIFO) or reach for a fresher date in the back of the shelf (LIFO), a customer picking behavior experiment has been conducted at two of Makro’s stores. It was found that when customers have a choice in date, 46% of them pick LIFO. Furthermore, some significant relationships were identified: (1) more dates per SKU in the shelf leads to more LIFO picking, hence to higher waste; (2) more facings per

![Figure 1. Distribution of operational costs in Makro’s fresh supply chain](image-url)
SKU leads to more LIFO picking, hence to higher waste; (3) the shorter the shortest shelf life is in the shelf, the higher the chance of LIFO picking and; (4) picking behavior in the classic store is higher than in the junior store, since the classic store has more facings per SKU, more expiration dates in the shelf and more space between products.

Simulation model and results
In the conceptual model a stepwise procedure is defined which sequentially describes 4 improvement steps. Three of these steps are assessed in this study using a simulation model that uses real historical sales data to investigate the impact of certain operational and logistical adjustments. The results per step are described below.

1. Optimizing the parameter settings of the ordering system
Two parameter groups of the ordering system have been denoted as especially influential for the current levels of waste: service level settings and the Minimal Shelf Stock (MSS). The current defined service levels and MSS settings result in a situation with excessively large simulated costs of waste when no human interference takes place in the order proposals (see the fictitious waste and cost performances per configuration in Table 1, where relative performance differences represent reality). The current settings of the MSS are too high. Since the MSS is an extra stock assurance on top of the calculated forecast and safety stock (which assures a certain customer availability), it is often extra stock that is not sold and subsequently gets wasted. Reducing the MSS to one or to zero while increasing the service levels (which are input for safety stock calculations) leads to significant reductions in overall simulated costs (respectively 25% and 32% reduction) while having only a minor reduction in availability. Furthermore, differentiating service levels for slow movers and fast movers can reduce overall costs, while meeting the same customer availability. As in practice also beneficial human interference can take place together with more advanced forecasting methods (including calendar effects, seasonality, outlier detection etc.), the actual potential can be even larger.

Table 1. Simulation performance of different parameter configurations. Cost figures are scaled with an undisclosed key.

<table>
<thead>
<tr>
<th>Current actual performance</th>
<th>Simulation results</th>
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<tr>
<td></td>
<td>Differentiated service levels</td>
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<tr>
<td></td>
<td>MSS=1</td>
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<tr>
<td>Waste per year in €</td>
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<td>Picking costs per year in €</td>
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<td>Overall costs per year in €</td>
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<td>Customer availability</td>
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<td>Service level ultra slow movers 1</td>
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<tr>
<td>Service level ultra slow movers 2</td>
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</tr>
<tr>
<td>Service level slow movers 1</td>
<td>0.90</td>
</tr>
<tr>
<td>Service level slow movers 2</td>
<td>0.90</td>
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<tr>
<td>Service level fast movers 2</td>
<td>0.93</td>
</tr>
</tbody>
</table>

2. Promoting FIFO behavior
In Figure 2 it can be observed that the relationship between the proportion of LIFO picking and percentage of waste is exponential. Overall costs for pure LIFO are almost 2.5 times as large as pure FIFO. This emphasizes the importance of controlling and influencing picking behavior. Makro can reduce costs significantly if they manage to promote customer picking behavior more towards FIFO. A policy
showed to be effective, is to limit the amount of dates in the shelf to two by keeping surplus stock in the backroom. For the currently used BBXD flow type, an MSS of 1, and optimized service levels, this policy resulted in a cost reduction of 13.5% in yearly waste costs. Other opportunities to promote FIFO can be sought in space management, for example reducing the amount of facings and align it with demand, or reducing shelf space to hinder checking of dates. Offering a discount of products close to their expiration date is another policy that can reduce waste and promote FIFO.

3. Flow type selection

The flow type selection is analyzed per supplier. The fill rate in the store is aimed to be approximately 0.97 for the aggregate and is set at 0.80 for the DC to guarantee product freshness. Based on literature, four potential flow types for the studied categories are compared: Break-Bulk-Cross-Docking (BBXD), Traditional Warehousing in full Case Packs (TWCP), Traditional Warehousing in Consumer Units (TWCU) and Traditional Warehousing Mixed (TWMIXED). The different flow types are explained in Section 1.3 and visualized in Appendix D (here transito is another name for BBXD). BBXD is the currently used flow type. A substantial reduction in waste when the transition towards Traditional Warehousing is made, especially takes place for suppliers that initially don’t have more than 2 delivery moments a week and have long lead times (higher than 2). For these suppliers the decision to hold inventory on the DC decreases costs of waste because stores are much more flexible in ordering (daily ordering and delivery moments). However, for a large part of these suppliers the reduction in waste gets outweighed by increased costs of handling in the DC and demand planning in the HQ. For some suppliers however, the reduction in waste is substantial enough to make TWCP the preferred flow type.

For suppliers with initially more than two delivery moments and/or short lead times, the waste reduction of TWCP compared to BBXD is mostly low or even slightly negative (the number of delivery moments are reduced to two and as a result the average shelf life at arrival in the store gets lower). The potential for these suppliers can especially be found in the reduction of inbound logistics. It has been shown that these savings are crucial in the flow type selection and can make TWCP or TWCU very preferable over BBXD, depending on the actual savings per supplier.

Unpacking case packs in the DC is regarded in TWCU and TWMIXED. In the latter, per SKU the best performing flow type of TWCU and TWCP is chosen. Unpacking takes away the limitation of the case pack and can reduce waste costs significantly, but on the other hand increases handling costs in the DC. If extra costs for unpacking are relatively balanced, it has been shown that a mix of TWMIXED can lead to large overall cost reductions for some suppliers. Unpacking is especially interested for high valued SKU’s, since for these products costs of waste are large relative to the extra picking costs.
Recommendations

Finally, based on these findings, we describe a list of recommendations:

- Reduce the Minimal Shelf Stock (MSS) to one for all products in the studied categories. Simultaneously increase the system’s service level parameters to the levels defined in Section 7.1. If implementation is successful, consider setting MSS to zero to further reduce overall costs. This measure should be combined with briefing/training of department managers on how the ordering system (SAF) works and why the new settings require limited human interference. Trust in the system should be regained.

- Align facings and shelf space with the demand characteristics of the SKU/store combinations. Currently this often means reducing the amount of facings and shelf space. Hence, less facings and shelf space leads to a lower proportion of LIFO picking behavior, which in turn leads to lower numbers of waste.

- Emphasize compliance in the stores towards the ‘limit the amount of dates in the shelf to 2’ policy. As this policy reduces the number of dates in the shelves, it promotes FIFO picking and therefore reduces costs of waste (13.5% per year).

- Analyze per supplier the potential inbound logistics savings and negotiate with the logistic service provider the costs of unpacking products in the DC. Based on this costs, determine the optimal flow type per supplier by altering these costs in the created Excel file per supplier. Flow type selection should be conducted after previous steps are effectively implemented. It is recommended to do a pilot for a supplier with high potential for TWCP or TWMIXED to assess the practical performance. After that, potentially for other suppliers the shift could be made towards another flow type.

- Consider re-implementing the markdown stickers for products that approach their expiration date. Markdown stickers can reduce costs of waste significantly and may increase store visits. However, this procedure should only be considered after previous steps in this study are effectively implemented. Hence, using markdown stickers when operations and logistics are not optimized, would result in a situation (as formerly) that requires the use of the stickers too often, which negatively influences store image and profitability. Another requirement, is that sales in the system should get adjusted for the amount of products that are sold with sticker, so that the data doesn’t get polluted.

- Investigate how the Traditional Warehousing flow types can be implemented. Flow racks are a good storage alternative for efficient order picking of the perishables. Besides that, processes have to be defined at the DC, but also for the demand planning department at the HQ. It is important that stock is accurately and smartly managed, as freshness needs to be guaranteed and no waste is desired in the DC. When the unpacking decision is made, crates in combination with trolleys should be used to transport the single CU’s, since pallets aren’t suitable anymore.

- Negotiate to reduce lead times and increase ordering moments per supplier (if interesting considering costs). Furthermore, investigate opportunities for synchronization of deliveries with production schedules to increase shelf life.

- Conduct the defined steps of the conceptual model for other fresh categories as well, since they offer similar opportunities.
This thesis is the apotheosis of my Master’s program in Operations Management and Logistics at Eindhoven University of Technology (TU/e). It is the result of my six-month graduation project at Makro, a large Dutch self-service wholesaler. My student career towards this point has been inspiring, educational and most important, enjoyable. For this I am very grateful to my fellow students. Great dedication and countless (frequently late night) hours were put into delivering the very best we could during the many group projects we had. Not only was this helpful for developing myself professionally, but it also contributed to some very valuable personal connections. Besides that, I feel rewarded to have received guidance and knowledge from incredibly proficient professors. I would like to express my gratitude in particular to some persons who have played an important role in the process leading up to this document:

Karel van Donselaar
Thank you very much for your guidance and support throughout this last six months. With your enormous expertise on retail and food waste you were always able to give me focus when I needed it. Your sincere interest in the progress and findings during the project made every contact moment a thought-provoking brainstorm session of at least one hour where we could ‘philosophize’ about how certain issues could be tackled best. You were able to guide me in the right direction without telling me the direction. Sentences like “mmm, that’s interesting, research x and research y shows that this is troublesome under this condition” made me reevaluate my vision several times. I think you have positioned yourself well between being helpful, and demanding autonomy and vision. Also on a personal level you were interested and understanding for some situations I have had. Hopefully we can connect and/or collaborate sometime in the future again.

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Thank you for being my second supervisor. You were always approachable to give me advice. Your down-to-earth attitude and academic insight has been valuable for me to formulate the thesis so that it is a comprehensive and consistent story which shows general academic quality and logic.

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Thank you for your support and the opportunity to conduct this graduation project at Makro. Every meeting I found it very gratifying to present new insights in the project and receive feedback. You have shown great interest in the topic and have always helped me to bridge between the academic and practical relevance of my research. You trusted me on choosing the right direction and gave me the freedom and support to gather every piece of needed information. Moreover, it was enriching to work in the middle of a dynamic and developing category management team at the HQ of Makro. Many lessons about the industry and the company have been learned and I am glad to have been able to assist the team with some practical issues too. I am indebted to my colleagues at Makro for the past six months, who have helped me greatly, but also made the office more than just a place to work.

Mom, dad, Bobbie & my close friends
Finally, I would like to thank the ones who are the closest to me. You have always supported me and given me trust when I needed it. Writing a Master thesis comes at a price, so I promise you all that from now on more of my time will be reserved to spend with you.

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## Abbreviations and terminology

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<td>OOS</td>
<td>Out-Of-Stock</td>
</tr>
<tr>
<td>Waste, shrinkage</td>
<td>Product loss due to deterioration</td>
</tr>
<tr>
<td>Case pack size/MOQ</td>
<td>Standardized amount of SKU’s in one packaging unit which represents the granularity of possible order sizes. Also referred to as Minimal Order Quantity</td>
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<td>FTL</td>
<td>Full Truckload</td>
</tr>
<tr>
<td>LTL</td>
<td>Less than Truckload</td>
</tr>
<tr>
<td>DC</td>
<td>Distribution Center</td>
</tr>
<tr>
<td>LSP</td>
<td>Logistics Service Provider</td>
</tr>
<tr>
<td>PAXD</td>
<td>Pre-allocated Cross-docking</td>
</tr>
<tr>
<td>BBXD</td>
<td>Break-Bulk Cross-docking</td>
</tr>
<tr>
<td>TW</td>
<td>Traditional Warehousing</td>
</tr>
<tr>
<td>F&amp;V</td>
<td>Fruit &amp; Vegetables</td>
</tr>
<tr>
<td>BLS</td>
<td>Breakfast, Lunch &amp; Snack</td>
</tr>
<tr>
<td>SKU</td>
<td>Stock Keeping Unit</td>
</tr>
<tr>
<td>FIFO</td>
<td>First In, First Out</td>
</tr>
<tr>
<td>LIFO</td>
<td>Later In, First Out</td>
</tr>
<tr>
<td>MSS</td>
<td>Minimal Shelf Stock</td>
</tr>
<tr>
<td>CU</td>
<td>Consumer Unit</td>
</tr>
</tbody>
</table>
1. Introduction

“The total global costs associated with food loss or waste is estimated to be equal to 856 billion euro’s each year.” [1]

“We keep on wasting lots of food in the Netherlands: 135 kilograms per capita.” [2]

“Food waste is a global scandal of mind-boggling proportion: while millions still suffer from hunger and malnutrition, one third of the food produced worldwide is never eaten, representing a colossal waste of natural resources.” [3]

Food waste is an increasingly discussed topic in literature, media and public. Although only a small amount of food waste can be attributed to retailers (according to HLPE (2014) [4] about 12%), the costs involved are substantial. Food loss reduction is of great interest for a retailer’s profitability; since margins in grocery retail are low, any improvement in waste reduction can have a significant effect. Moreover, given the societal trend of doing business greener and more environmental friendly, actions towards waste reduction also have an image improving effect. Gusstavsson et al. (2011) [5] emphasize that improvements in waste at the retail level implies a multiple-win effect: if for example a retailer manages to increase the remaining shelf life available for the customer, their actions not only reduce their own operational costs and waste, but also help to reduce waste at the consumer level, and at the same time increase the product freshness experienced by the consumers.

This Master Thesis project is carried out at Makro cash & carry Netherlands. Makro realizes that both financially and environmentally there is a lot of potential in reducing food waste in their stores. Currently the amount of food that gets wasted is high compared to the industry and is a major cost item. This Master Thesis will therefore research how Makro can better control waste in their stores. Since Makro searches for a reliable solution to reduce waste in their stores, we aim to approach the real world as much as possible in this research. As a result we conduct this research with as few assumptions as possible. Since fewer assumptions result in higher complexity, a simulation based optimization approach is used in this thesis to model different supply chain and operational configurations.

This chapter starts off with a company description, followed by a problem introduction, a synoptic literature review, the scope of the project and finally the thesis outline and adopted methodology.

1.1. Company Description
Makro cash & carry is an international operating self-service wholesaler. Established in 1968 in Amsterdam by SVH Holdings, Makro soon expanded its operations in the Netherlands and several other European countries. In the 1970s and 1980s Makro also extended its business to South Africa, America and Asia. In 1989 Kmart bought the US locations and in 1998 SVH Holdings sold the European Makro stores to Metro Group. The focus in this graduation project will be on Makro’s operations in the Netherlands, which are part of Metro Group. Makro cash & carry Netherlands comprises 17 stores throughout the country. These stores are for the largest part of the food assortment supplied from two DC’s. In Figure 3 the geographical locations of all stores and the headquarters are depicted. One of the DC’s, DCFRESH, focusses on the fresh and temperature sensitive food products, whilst the other DC (DCDRY) focusses on the rest of the food assortment.
The different stores depicted in Figure 3 can be categorized into two different store types:

- **Classic stores** - these are the oldest Makro stores and are characterized by a larger assortment (more SKU’s), an older store formula and typically higher amounts of sales compared to the junior stores. The 9 Makro classic stores are: Amsterdam, Best, Breda, Delft, Duiven, Groningen, Hengelo, Nuth and Vianen.

- **Junior stores** - these are the newest Makro stores (acquired in 1990 from Lukas Klamer) and are characterized by a smaller assortment (less SKU’s), a new and modern store formula, and typically lower amounts of sales compared to the classic stores. The 8 Makro junior stores are: Barendrecht, Beverwijk, Dordrecht, ’s Hertogenbosch, Leeuwarden, Nieuwegein, Nijmegen and Wateringen.

1.2. Problem Introduction

Food waste is a significant problem for Makro. During the last couple of years Makro has encountered decreasing sales, which combined with an increased focus on availability has had a detrimental influence on waste of perishable products [6] (see Appendix C for general relationship between waste and availability). Makro has realized that costs can be substantially reduced when they manage to better control waste in their operations. Therefore, this Master Thesis project is about how Makro can reduce...
food waste in their stores by improving logistics and store operations. Only fresh products that are provided via DCFRESH will be part of this study. DCFRESH is employed for all fresh and frozen products (except bread and a fraction of fish, which are delivered directly). Given the fact that the most potential for waste reduction can be found in article groups with lower expiration dates (also referred as perishables), frozen is not regarded in this thesis. Table 2 (fictitious percentages) shows that waste in frozen is relatively low compared to the fresh categories. Fresh at Makro is subdivided in four groups, called solutions. The solution names are also depicted in Table 2. In the last columns, waste figures are depicted for only the stores, whilst the other waste figures also include waste at the DC and Food Service Delivery (FSD) hub.

Table 2. Waste in frozen and the fresh categories at Makro (30 weeks from 3-10-2016 until 30-4-2017). Waste figures are scaled with an undisclosed key.

<table>
<thead>
<tr>
<th>Solution name</th>
<th>Waste in % of sales</th>
<th>Waste in % of sales (only stores)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S001 Dinner - Meat</td>
<td>1.69%</td>
<td>1.59%</td>
</tr>
<tr>
<td>S002 Dinner - Fish</td>
<td>1.72%</td>
<td>1.67%</td>
</tr>
<tr>
<td>S003 Dinner – F&amp;V</td>
<td>2.13%</td>
<td>1.96%</td>
</tr>
<tr>
<td>S004 Breakfast, Lunch &amp; Snack</td>
<td>2.06%</td>
<td>1.95%</td>
</tr>
<tr>
<td>S008 Dry Food Market - Frozen</td>
<td>0.46%</td>
<td>0.46%</td>
</tr>
</tbody>
</table>

One of the biggest focuses of Makro currently is increasing the customer availability. Especially because sales and the amount of store visits are declining, availability is believed to be a core aspect to keep and attract customers. For this reason, it is important to monitor the availability when assessing different measures, so that deliberate decision making is facilitated and a certain standard is assured. However, from the figure in Appendix C it can be observed that waste and availability are exponentially related to each other. One should thoroughly define what the optimal position is on this exponential line. Aligned with a company’s vision, a ‘sweet spot’ range could be identified where availability and waste are balanced.

This Master Thesis specifically focuses on waste reduction for a set of article groups/categories. These article groups are ‘Milk products’ and ‘Sandwiches & Spreads’. These article groups have a high percentage of waste, whilst the shelf lives are relatively high for perishables (on average 21 days for Milk products and 27.5 days for Sandwiches & Spreads). This characteristic makes these two groups especially interesting, since significant improvements are highly likely to be possible. Waste information for these two article groups can be found in Table 3 (fictitious percentages). In both Table 2 and Table 3, the waste figures include more than only waste due to deterioration. In the measurements for waste, also factors like theft, stock differences, demo and breakage are included. This aggregate is referred to as shrinkage at Makro. In this Master Thesis the focus is only on waste due to deterioration, since this accounts for the largest part of the waste (around 80%) and is most treatable from an operations and logistics point of view.

Table 3. Sales and waste from article groups Milk product and Sandwiches & Spreads (30 weeks from 3-10-16 until 30-4-17). Cost figures are scaled with an undisclosed key.

<table>
<thead>
<tr>
<th>Solution name</th>
<th>Waste in %</th>
<th>Waste in % (only stores)</th>
</tr>
</thead>
<tbody>
<tr>
<td>215 Milk product</td>
<td>4.32%</td>
<td>4.00%</td>
</tr>
<tr>
<td>244 Sandwiches &amp; Spreads</td>
<td>3.27%</td>
<td>3.12%</td>
</tr>
</tbody>
</table>
1.3. Literature review

In this section the literature on food waste is reviewed, especially from an operational and logistics point of view. In accordance with the analysis in Chapter 2, in particular the following subjects are pinpointed: flow type selection, case pack size related improvements, customer behavior, waste versus availability, store operations and the Sell More, Waste Less tool [6]. In preparation of this study, an extensive literature review was conducted to study the field on waste [7]. For a more comprehensive review on this and other topics, this particular document should be regarded.

1.3.1. Flow type selection

The distribution flow type refers to the design of the physical distribution network from the supplier to the customer. Decisions about stock point locations, means of transportation and order fulfillment (where/how are manufacturer orders broken up or where/how are store orders put together) are key in making such a design. The chosen flow type has an impact on supply chain costs, but also on freshness and replenishment, and as a result on waste. Various flow types can be distinguished:

1. Traditional Warehousing (TW)
2. PAXD
3. BBXD
4. Direct Store Delivery

In Appendix D all of these flow types are visualized (here transito/pick-to-zero represents the BBXD flow type).

In TW products move in (mixed) pallets to the retail distribution center. Retail stores in turn re-order frequently at the DC’s, where on pallets or rolling cages products from different suppliers are combined per family to accelerate the shelf stacking process. Van der Vlist (2007) [8] emphasizes that inventory should be held at the retailer, which is close to the client. In this design, products are moved to the retailer at the lowest logistic costs. Transport should happen prior to replenishment needs, as soon as goods become available from production. Important is that distribution is synchronized with the production schedule (as also emphasized by Wijshoff (2016) [9]). Advantages of traditional warehousing are high responsiveness, low inventories in the stores because of the possibility of frequent ordering, and low transportation costs. However, disadvantages are substantial handlings costs at the warehouse and longer transportation times, having influence on freshness. Another option in traditional warehousing is to pick at the DC in consumer units (TWCU) instead of in full case packs (TWCP). This means breaking up/unpacking case packs. Muskens (2016) [10] concludes this is very effective for products whose demand during shelf life is smaller than the case pack size, because savings in waste outweigh increased costs in handling.

In Pre-Allocated Cross-Docking (PAXD) orders of different stores are picked at the supplier onto separate trolleys/pallets and shipped to the cross-docking point. From the literature it is found that especially products with high demand, low coefficient of variation and a large physical volume are good candidates for cross-docking. Cross-docking is especially efficient for products that are produced daily [10]. Shipping more often than production does not bring any advantages considering freshness, but does increase inbound transportation costs a lot. Furthermore, cross-docking is optimal for products with a very short shelf life. Only for these products the extra transportation costs are outweighed by a decrease in waste.

Van den Heijkant (2006) [11] also defines a flow type called Break-Bulk Cross-Docking (also referred to as pick-to-zero, put-to-zero or transito). In Break-Bulk Cross-Docking (BBXD) different store orders are
combined into one order. This one order is delivered by the supplier to the cross-docking point, where it is broken up and shipped directly to the stores. Since products are ordered at the supplier and have to be picked, and have to be sorted at the DC, the lead time to the store is at least two days. Muskens (2016) [10] and Zwaan (2015) [12] conclude that this is not an efficient flow type because of low responsivity and long lead times, which makes it insufficient for facilitating fresh products.

Direct store delivery is desirable for products with a very short life time as it guarantees a maximum shelf life by minimizing transportation and storage time [13]. However, transportation costs are high as a result of more LTL shipments. Van den Heijkant (2006) [11] shows that direct store delivery becomes more beneficial when (i) the volume of the shipment increases, i.e. more approaching a FTL (ii) labour costs at supplier are low compared to labour costs at the warehouse and (iii) the number of stores decreases.

Data sharing and collaboration in the supply chain is also often mentioned in literature as an improvement opportunity for retailers and their supply chain partners [9, 4, 14, 15, 16, 17]. Data sharing for management of slow-moving perishables can lead to a supply chain profit of ~4.2% and an increased shelf life of ~18.3% [14]. Furthermore information exchange in general in the food chain was reported to decrease inventory levels by 55% and increase product freshness by 3.8 days.

Flow type selection is an interesting area for improving the supply chain, not only in terms of waste, but also in terms of overall costs. Still, every distribution network has its own characteristics and hence its own optimal flow type environment. It is important to take an integrated approach in determining the flow type for perishables, including the most important supply chain costs: handling, transport and waste.

1.3.2. Case pack size
A case pack is a collection of multiple items, typically of a single SKU, used in retail distribution for lowering distribution and handling costs. The case pack size refers to the amount of SKU’s bundled together and is equal to the base quantity (MOQ) in which an item has to be ordered by a store [6]. The case pack size forms limitations in ordering flexibility at the store [18] (stores have to order in multiples of the case pack size, which can cause a non-optimal inventory position). The case pack can lead to overstocking, which makes the case pack size one of the key drivers of waste [6, 19]. Broekmeulen and van Donselaar (2016) [6] describe that unpacking items in the DC and shipping to stores in smaller quantities is an improvement option that delivers a large reduction in waste (32.5% by unpacking all items). Although this seems a motivator to unpack all the items in the DC, as described earlier also other costs (e.g. extra costs of handling in the DC) should be taken into account. Broekmeulen and van Donselaar (2016) [6] also found another indicator for waste incorporating the case pack size: the Fresh Case Cover (FCC). This indicator is described in Section 2.4.

1.3.3. Customer behavior
Important in retail is understanding and influencing customer behavior. A critical subject here is customer withdrawal behavior: which expiration date do customers choose when they pick a product from the shelf. In literature it is often assumed that customers withdrawal according to the ideal world, where customers buy the oldest item from the shelf, i.e. First In First Out (FIFO). However, according to Broekmeulen and Bakx (2010) [20] consumers of perishable products in retail prefer to buy the newest/freshest product (LIFO) instead of the older/less fresher products that are presented on shelves. The more that customers buy the freshest item on the shelf (LIFO), the more the older items are left on
the shelf and eventually get wasted. As a consequence, costs will be significantly higher. Typically a mix of FIFO and LIFO consumers exist [21]. If a relatively large part of the customers buy the oldest item, the effect on the percentage of waste is expected to be limited [6].

1.3.4. Waste versus availability
Waste has a direct and strong relationship with out-of-stocks/on-shelf availability (the percentage of customer demand delivered from the shelf). Clearly the amount of waste is minimized when only very few inventory is held. Contrary, the amount of out-of-stocks is minimized when holding very large amounts of inventory. For this reason, waste and on-shelf availability (OSA) is a trade-off which has to be made. Since supermarket managers typically aim for a high service level (so high OSA) from a commercial point of view, reorder levels are set rather high to meet this service level. In Appendix C it can be observed that the amount of waste exponentially increases as the OSA approaches 100%. From this observation it can be concluded that from a cost point of view 100% OSA is not desirable, but we instead search for the right balance between %OSA and %Waste. One of the improvement possibilities for waste reduction described by Broekmeulen and van Donselaar (2016) [6], is differentiating service levels. They show that when lowering the OSA with 3% for slow movers (80% of assortment) and increasing OSA with 3% for fast movers, waste can be reduced with 12%, while the overall % OSA even increases with 0.2%.

1.3.5. Store operations
Store operations refer to the common operational practices carried out in a store, which doesn’t include the physical handling of products: e.g. organization of the backroom, registration of almost expiring products, behavior in ordering, and design of planograms/display. Store operations also have an important influence on waste. First of all, ordering behavior is a very important driver of overstocking, and consequently waste. It is especially a problem in an environment without an automated store ordering system, in an environment with only an ordering support system, or in stores where managers structurally deviate from such systems. However, Van Donselaar et al. (2010) [22] and Trapero et al. (2013) [23] describe that store managers can also improve upon an automated replenishment system. Secondly, aligning the planogram with demand is important for a good operational balance [6]. Multiple facings can better be used for fast-moving items, since too many facings or shelf space allocated to products motivates higher stock and subsequently waste [15, 6].

1.3.6. Sell More, Waste Less tool
Broekmeulen & Van Donselaar (2016) [6] created a tool that helps managers in making better inventory control decisions: the ‘Sell More, Waste Less’ tool. The assumptions on which the tool is based are: withdrawal behavior is FIFO or LIFO and there is no week pattern. The tool is an excel file with macros to calculate several Key Performance Indicators (KPI’s) specifically for perishable inventory systems at retail stores [6]. The tool can be especially used to review performances of stores in terms of waste and on-shelf availability when e.g. lead times are decreased or shelf life is improved by one day. Based on the input parameters the tool can also calculate (i) freshness to the customer (average number of remaining shelf life in days the customer gets when he buys the item) (ii) number of order lines per day and (iii) probability of non-empty shelves (probability the shelf is not empty just before a new delivery takes place for that item or another item in its category). The tool moreover helps in getting insight into the relationship between %Waste and %OSA and can guide supermarket managers in finding the reorder level that fulfills a certain %OSA (service level).
1.4. **Scope**

In order to obtain a manageable but still comprehensive research, the scope needs to be framed and the key aspects of the problem should be defined. In this chapter the scope and level of detail is described. Per aspect it is described why it is put in or out of scope.

1.4.1. **Focus area**

To define the focus area, the retail demand and supply chain planning framework by Hübner *et al.* (2010) [24] is used (see Figure 4). This framework describes and structures the coherent demand and supply chain problems in (grocery) retail. It shows the hierarchical (vertical axis) and sequential (horizontal axis) aspects for decision making. The areas marked by a blue rectangle are into scope of this thesis. First of all we focus on the ‘Physical distribution structure’. This includes the design of the physical distribution structures between warehouses and outlets. One hierarchical layer down, ‘Planning product-delivery modes’ is located. This phase comprises decisions about product-supplier allocation to the modes defined in the ‘Physical distribution structure’. Together these two describe the flow type selection problem: how should the products flow from producer to store outlet. ‘Supplier order management’ is also into scope, since this regards how often and at which moments suppliers have transport to the DC. In ‘Building product segment with related order patterns’ products are segmented based on equal order characteristics (e.g. shelf life, temperature and other logistical factors). ‘Selection of dispatch units’ is also into scope, which represents the choices made in standardized order units (MOQ’s). Finally, we focus on ‘Outlet order management’, as we also focus on the ordering system and ordering behavior in this study. It has to be emphasized that all modules are interrelated, so adjustments in one of the modules into scope can require adoptions of modules out of scope.

![Figure 4. Retail demand and supply chain planning framework](image)

1.4.2. **Assortment**

This Master Thesis project focusses on perishable products. This means that non-perishables are out of scope. As indicated by Van Donselaar *et al.* (2005) [13], the main difference between perishables and non-perishables is the shelf life, which in this report is defined as the number of days until the day a

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1 From “Demand and Supply Chain Planning in Grocery Retail: An Operations Planning Framework” by Hübner *et al.* (2010) [28], Ingolstadt, Germany, p. 21
product becomes unacceptable for sale. Perishables are defined as products with a short shelf life and non-perishables are defined as products with a longer shelf life. Based on empirical data, Van Donselaar et al. (2005) [13] define the threshold value for perishables vs. non-perishables at 30 days.

As mentioned before, we focus on the article groups ‘Milk products’ and ‘Sandwiches & Spreads’ in the modeling/simulation section of this research. However, the developed method can also be used to evaluate other perishable article groups. In particular, this would only require the extra effort of carrying out the data collection steps for the concerning article group(s). Only minor adjustments in the data reading functions of the simulation have to be made. A requirement for the simulation, is that a SKU has a defined shelf life. Products that often don’t have a fixed shelf life can mostly be found in the F&V and Fish solutions. Here quality is often assessed by a specialist in the store and products are disposed based on his/her expertise. Moreover, a lot of articles in these groups are sold by weight, which is also a characteristic which puts SKU’s out of scope for the simulation model. Fresh bread and pastry are out of scope for the flow type selection, since products in these groups are characterized by very short shelf lives (mostly 1 or a couple of days). Because of this characteristic, these products need to be delivered directly and other flow type configurations don’t need to be investigated.

1.4.3. **Shrinkage codes**

As indicated before, shrinkage at Makro is defined as all product losses, which includes amongst others theft, in-store demo and waste due to expired products in the store. Only this last part is of interest in this thesis, since it is the only part of the shrinkage which can be directly influenced by the measures that are investigated in the research. Hereafter we refer to this part as we talk about ‘waste’.

1.4.4. **Sales**

In scope of the project will only be periods of regular sales. Since regular sales for the researched article groups account for the highest amount of the total sales, the regular sales should be leading in the concerning decisions. Promotional demand (mostly multiple factors higher than regular) is very different from regular demand, and should for this reason be excluded to avoid polluting the data and influencing decision making. Promotional logistics are expected to be adaptable to regular logistics. Currently promotional logistics are already managed quite separate from regular sales, so the impact of changing the regular environment won’t negatively impact promotion periods. Performance during promotions could even highly benefit from better regular sales configurations.

1.5. **Methodology and thesis outline**

This research is structured using the life cycle of a simulation study (see Figure 5) of Balci (1994) [25]. This model is developed to facilitate insight in the different processes of a simulation study and how these processes are interconnected. Balci (1994) [25] describes that validation, verification and testing (VV&T) is extremely important for the success of a simulation study. The dashed arrows in the life cycle describe the processes which relate the phases to each other. The solid arrows refer to credibility assessment stages. The life cycle is not a strictly sequential one. Iterations and reverse transitions can take place and when an error is identified, it might be necessary to return to an earlier process and start from scratch again.
Based on the life cycle, the outline of the thesis is defined next. Chapter 2 describes the current situation and researches the communicated problem by data analysis and interviews. In Chapter 3, the problem is formulated into a research assignment. Chapter 4 describes the second part of the analysis of the current situation: a customer picking behavior experiment at two Makro stores. This experiment is amongst others conducted to define an important input parameter for the simulation study. In Chapter 5, the conceptual model is created which describes the sequential simulation procedure for waste and overall cost reduction. Chapter 6 describes the creation of the simulation model and Chapter 7 the simulation results. Finally, the conclusions, recommendations, contribution to the literature, limitations and the directions for future research are discussed in Chapter 8.

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2 From “Validation, verification, and testing techniques throughout the life cycle of a simulation study” by Osman Balci (1994) [28], Virginia, Germany, p. 216
2. Analysis current situation – Part I: interviews and data analysis

In this chapter the current situation is analyzed based on interviews and data from Makro’s information systems. Each section of this chapter focusses on a separate topic considering Makro’s operations and logistics. Communicated problems during interviews are researched and complemented with data analyses. Problem identification interviews and conversations were performed with Makro employees in the stores (fresh department managers, fresh department assistants, store managers and other store employees) and employees at HQ (category management, supply chain management, controlling, demand planning, platform coordinators, customer analysts).

2.1. Distribution of operational costs

In order to get insight in the magnitude of the different operational costs in the supply chain, in Figure 6 a rough cost calculation is made for all fresh products (solutions Meat, Fish, F&V and BLS) that are delivered through DCFRESH. The graph is created from 6 months of data, collected from different information systems and sources at Makro. The included costs are handling, transportation, inventory and waste costs. Handling occurs both in the DC as in the store. Moreover transportation costs occur from inbound logistics (supplier to DC) and outbound logistics (DC to stores). Because for inbound transportation costs no explicit data is available, it is assumed this cost component is equal to outbound transportation costs. Inbound transportation costs are often included in the buying price. Per supplier the cost structure is defined differently, which makes it impossible to define this costs accurately.

![Figure 6. Distribution of operational costs in the supply chain for all fresh products supplied via DCFRESH (30 weeks from 3-10-16 until 30-4-17)](image)

From Figure 6 it can be observed that waste represents the largest cost component of all the operational costs. This corresponds to findings by Muskens (2016) [10] at Jan Linders. Store handling costs are however significantly higher at Makro, which might be explained by expenses for specialists (e.g. fish, F&V, cheese, meat) in Makro stores. These specialists are not only more expensive because they are more skillful, but also because they are typically older than the average supermarket clerk.

Because waste accounts for the largest part of the costs, successful measures for waste reduction could significantly impact the overall operational costs. If a certain alteration in operations or logistics reduces
waste costs with 50%, but increases handling at the warehouse with 100%, it can be concluded that this would result in a net profit below the line.

As can be observed in Figure 6, inventory costs are very small relative to the other costs. Hence, perishability demands high inventory rotation. This results in relatively low inventories and makes the impact of inventory costs negligible.

Costs mainly affected by the researched improvement possibilities in our simulation study, are costs of waste, inbound logistics and DC handling. For this reason, changes only in these cost components are used for evaluation in this study. First of all, outbound transportation costs are excluded, because they are expected to stay constant and independent of the measures described in this thesis. This is because every day (except Sunday) a truck drives from DCFRESH to the store independent of how big certain order quantities are. Volume differences because of less waste are ignored. Furthermore handling activities at the store are assumed to stay approximately constant and are not taken into consideration. Van de Ven (2014) [26] defines five sub activities for store handling:

1. Stacking the shelf
2. FIFO - checking expiration dates of old inventory and putting this old inventory aside, and replacing it back in the shelf after sub activity 1
3. Search and walk to location
4. Mark down
5. Remove waste

Makro doesn’t mark down, so this activity is not relevant. Removing waste and stacking the shelf can be affected by measures described in this study; as waste gets reduced also the removal of waste gets reduced and the amount of products that need to be stacked. Moreover, as the change is made towards a TW flow type, more often products will be ordered, resulting in more order lines. This could result in an increase in search and walk and FIFO activities. But as currently some stores already have daily walks between the backroom and the shelves (to assess if backroom inventory can be put in the shelves), this effect might be limited. Moreover, as products can be ordered daily, more often does the ordering decision has to be made, which demands more time from department managers. On the other hand, this could actually save time as the system doesn’t require human interference anymore. All this effects are probably different for stores as the store lay-out and procedures differ. As a result, effects on store handling could be positive for one store and negative for the other. The high complexity and uncertainty of the aggregated contra effects of measures on store handling costs led us to the assumption that the overall handling costs are not affected.

2.2. Lead times and review periods are long

From various interviews and conversations an often mentioned problem, is the current inflexibility at the stores in ordering and delivery from the DC. Currently the largest part of the fresh food products are supplied using BBXD. In the BBXD flow type (see Figure 7), at each ordering moment the demand of all stores are aggregated at the supplier and delivered to the DC. Once arrived in the DC, an employee picks the specific store orders from the pallet with aggregated products and allocates them to store specific pallets or trolleys. The next day the store is supplied. The amount of ordering moments in a week differ strongly for different suppliers (between 1 and 6 times a week). As depicted in Figure 8, for the largest part of the Breakfast Lunch & Snack (BLS) assortment (containing e.g. dairy, bread, cheese, spreads, cold cuts, fresh juices), the ordering and delivery moments in a week are relatively limited.
(around 66% of the SKU’s only have 1 to 3 delivery moments a week). This number is low compared with the retail industry, where most retailers have ordering possibilities every day for (almost) every product. Few ordering possibilities result in being less flexible considering demand fluctuations. One has to order for a longer period of time, which results in more difficulties and uncertainties in forecasting. To offer a guaranteed service level to the customer, consequently high inventories must be kept, resulting in a higher risk of waste. If the possibility exists to order every day and to be delivered every day, demand only has to be forecasted for 2 days and one can rapidly react to customer demand that takes place during the week. Higher rotating inventory can lower waste. Especially because Makro is characterized by stronger fluctuations in demand (a wholesaler encounters bigger customer orders that cause higher fluctuations), the current ordering process and delivery schedule result in more out-of-stocks, but especially in more waste. However, the reason for the limited number of ordering moments, is that currently the total quantities ordered from a supplier are not large enough for daily ordering and delivery from the supplier. Given the volumes, handling and transport costs would be too high when more delivery moments are demanded from the supplier. This is caused by more inefficient LTL drops.

Figure 7. Break-Bulk Crossdocking (BBXD) at Makro Netherlands

![Figure 7. Break-Bulk Crossdocking (BBXD) at Makro Netherlands](image)

Figure 8. Percentage of SKU’s with a certain amount of ordering moments per week in BLS

Besides the often limited ordering moments, also lead times observed at the two article groups (Milk products and Sandwiches & Spreads) are often high (see Figure 35 in Appendix E). Makro’s stores are supplied from the DC from Monday to Saturday. The lead time from the DC to the store is mostly 1 day.

However, the lead times from the supplier to the DC differs strongly. Lead times can be as high as 6 days in total. From the in total 414 SKU’s in these two groups, 91% have a lead time higher than or equal to 2.67 days. 41% even have a lead time higher or equal than 4 days. This long lead times and review periods together result in a highly inflexible replenishment system, having a strong contribution to high waste costs [10].

From our findings in the literature, a potential solution might be to research traditional warehousing as flow type. In TW, inventory is held at the DC, so that stores could be delivered every day (except Sunday), resulting in a lead time and review period of both 1.17 on average. However, average shelf lives at arrival in the stores reduce because products spend more time in the chain. Furthermore, handling/inventory costs at the DC increase because of more touch points. On the other hand, inbound logistics costs could be reduced when lowering the amount of ordering/delivery moments from supplier to store. Potentially, the aggregation of all effects is positive, so that TW is a cost efficient flow type.

2.3. Stock levels are too high
Because the current situation is characterized by long lead times and long review periods, high inventories need to be held to cover the gap between an ordering moment and the next delivery moment. Hence, one needs to order enough so that no (or a very limited amount of) OOS’s take place. It is observed that a gap can for instance be as large as 8 days. This means that for 8 days of inventory needs to be ordered. On top of that, safety stock is added to this amount to guarantee a certain availability (e.g. 97%). However, adding safety stock to guarantee this availability for 8 days requires a substantial amount of extra products which increases the chance of overstocking and subsequently waste. When it is decided to hold inventory in the DC and facilitate daily ordering and delivery for the stores, the period until the next delivery possibility gets significantly lower, only 2 days. The required order quantity significantly drops. This means faster product rotation, lower inventory levels, lower risk of overstocking (leading to waste), lower risk of understocking (out-of-stocks) and easier forecasting. The whole system gets more reactive and flexible. However, as we have discussed in previous section, this demands holding inventory on the DC, which also has disadvantages: higher handling costs and lower shelf lives at arrival in the store (products spend more time in the chain).

In Figure 9 and Figure 10 two graphs are depicted that show the average amount of weeks of inventory and the amount of SKU/store combinations belonging to each range for ‘Milk products’ and ‘Sandwiches & Spreads’ combined. Figure 9 shows the absolute amount of SKU/store combinations belonging to a range, and Figure 10 shows the cumulative percentage. It can be observed that a large amount of SKU/store combinations have more than 2 weeks of demand on stock (from Figure 10 ≈54%). When customers don’t pick FIFO, but a combination of FIFO and LIFO (which is most common), 2 weeks of inventory is getting troublesome considering the shelf life (which is mostly between 2 and 4 weeks). Also a substantial amount of the SKU/store combinations have more than 3 weeks of inventory on stock (from Figure 10 36%). For a lot of products this is bigger than their shelf life, indicating that products will be wasted even when customers pick 100% FIFO.

In interviews it was often mentioned that the current ordering system doesn’t perform well. A considerable amount of department managers responsible for ordering, strongly deviate from the order proposals. Some even ignore the order proposals totally. This is bothersome given our findings in the literature review that waste in retail is especially a problem in an environment without an automated store ordering system, in an environment with only an ordering support system, or in stores where
managers structurally deviate from such systems. To get an impression about how much stores deviate from the ordering system (SAF), data is gathered considering order adjustments. This data is plotted against waste percentages of the stores for the 30 weeks of data. Results are depicted in Figure 11. The x-axis represents the percentage of proposals that are adjusted by each store. We distinguish classic and junior stores, since we have shown that these two are typically different from each other. In Figure 11 for both classics and juniors some linearity can be observed, indicating that more interference leads to less waste. This linearity is observable, even given the fact that lots of other drivers influence waste (e.g. sales). The biggest store in terms of sales (so also highest rotation) interferes one of the least from all stores, but has a relative high amount of waste. The second largest store in terms of sales interferes the most of all stores and has the lowest waste percentage. Because theoretically stores with more sales are able to achieve a lower percentage of waste [27, 6], this observation is especially interesting. This gives the impression that the SAF order proposals are not optimal (too high) and that human interference (if done smartly) can outperform the ordering system to a significant degree.

\[ R^2 = 0.6469 \]

\[ R^2 = 0.5877 \]

5.0% 10.0% 15.0% 20.0% 25.0% 30.0%

% Waste

Total SAF interference %

Figure 9. Average amount of demand weeks on stock for Milk products and Sandwiches & Spreads (from stock data from 3-10-2016 until 30-4-2017)

Figure 10. Cum demand weeks on stock for Milk products and Sandwiches & Spreads (from stock data from 3-10-2016 until 30-4-2017)

Figure 11. SAF total interference % per store (last 14 days from 30-4-2017) for the 4 fresh solutions versus %waste (from 3-10-2016 until 30-4-2017)
The replenishment system that Makro currently uses (SAF) is an automated store replenishment system, but is currently often used as a support system and sometimes even completely disregarded. Since SAF appears to be an intelligent piece of software (advanced functionalities like taking into account calendar effects, promotions, seasonality, outlier detection, zero stock correction, general exponential smoothing forecasting etc.) it is especially interesting what causes this structural deviations by department managers from the order proposals. It was found that SAF works with a large amount of parameters that can be adjusted and defined by the administrator and department managers. Two bundles of parameters seemed especially influential as they directly influence the reorder level and the availability: target service levels and the Minimal Shelf Stock (MSS). The group service levels serve as a measure to offer the customer a certain percentage of availability. Hence, a calculated forecast is an average, which is in 50% of the situations not sufficient to meet demand because demand is stochastic. For this fluctuations in demand, a safety stock is calculated based on the settings for the service levels in the ordering system. The higher the desired availability for the customer, the higher the service level parameters must be set and the higher the safety stock will be. However, higher stocks lead to more waste and moreover to lower product freshness. The definition of the service level in SAF, is what in literature is described as the cycle service, or Type 1 service. This represents the chance of having inventory left on the shelf just before the next delivery. This shouldn’t be confused with the Type 2 service level, which is the fraction of demand that is fulfilled directly from stock. Since this last indicator is an important indicator for real customer availability, this parameter will be monitored closely throughout this report and constraints will be set on this indicator.

Currently the service levels of Makro are defined in different groups. Products are allocated to a group based on average sales per week. The boundaries of these groups can be manually set. However, optimization of this will not be into scope of this project, but is an interesting area for future research. In each group, a different service level can be determined. The six different service level groups are classified as follows:

- Fast Seller 2 (FS2): > 20 sales per week
- Fast Seller 1 (FS1): >8 & <=20 sales per week
- Slow Seller 2 (SS2): >5 & <=8 sales per week
- Slow Seller 1 (SS1) >0.7 & <=5 sales per week
- Ultra Slow Seller 2 (USS2) >0.3 & <=0.7 sales per week
- Ultra Slow Seller 1 (USS1) >0 & <=0.3 sales per week

The parameter settings haven’t been assessed since 2011. However, Makro has been subject to a substantial amount of changes: declining sales, new store formulas, organizational changes, new vision etc. For this reason it can be concluded that a new examination of the SAF parameters might be very beneficial. A sub-optimal definition of these parameters might be a driver for high waste.

Secondly, the MSS is a parameter that serves as a last guarantee besides the forecast and the safety stock for having remaining stock on the shelves. MSS is added to the forecast and safety stock in the order calculation of SAF and can be set for each SKU/store combination separately. However, in the service level definition it is already determined what service to the customer is desired. Extra stock in the shape of MSS (which has no correlation with the demand characteristics) increases this service level and stock level, which in its turn lead to higher waste. Currently store managers have the possibility to
set the MSS at whatever level they desire for their store. However, it is believed that managers are often not well educated and informed that a guarantee to the customer is already included in the calculation of the safety stock. Currently the MSS is set very differently amongst SKU/store combinations: mostly 2, but for a substantial fraction even higher as can be observed in Figure 12. Given that the median sales of all the SKU/store combinations under investigation are 0.53, already 4 days of inventory are held only in MSS when it is set to 2. This is substantial, but as MSS settings are getting higher than 2, the influence is getting even more substantial. The MSS reaches a maximum value of 80 for some SKU/store combinations. The MSS might be an important driver of waste for Makro and might also explain the distrust amongst managers in SAF. In Table 31 in Appendix L it can moreover be observed that the average set value for the MSS parameter differs substantially among different stores.

![Figure 12. current MSS quantity distribution for Milk products and Sandwiches & Spreads](image)

### 2.4. Minimal order quantity

From interviews an often indicated bottleneck for waste is the Minimal Order Quantity (MOQ). Especially for the Makro stores with lower sales and rotation, the MOQ can form a problem for some articles. Sometimes stores are not able to sell a case pack (which typically defines the MOQ) in the shelf life of that product, leading to guaranteed waste. Broekmeulen & Van Donselaar (2009) [6] define an important driver of waste including the case pack size: the Fresh Case Cover (FCC). The formula of this indicator is described in Equation 1. Here $Q$ is the case pack size, $m$ the shelf life in units of time and $\mu$ the average sales in units of time

\[
\text{Fresh Case Cover} = \frac{Q}{m \mu}
\]

For the studied categories, this indicator is plotted against the current waste percentages per SKU/store combination. In Figure 13 this relationship is depicted. It can be observed that the $R^2$ (explained variance) of the linear regression model is 0.76, which is relatively high considering the fact that we are dealing with real world figures. The corresponding formula is described in Equation 2. Waste is measured as a negative value here.
This relationship shows that one can reduce waste directly by reducing the case pack size, increasing the shelf life or increasing demand. This can serve as a useful formula for category management to see the impact of changes on these indicators or to forecast the waste of new product introductions. In negotiations with suppliers this can bring significant advantages for substantiating the best settings for these variables. Another potential for reducing the MOQ and subsequently waste is to unpack products in the DC when it is decided to hold stock there.

To improve the regression model, also other variables have been assessed as independent variables to predict waste. First of all, we include the store influence in the model. Hence, some stores might perform better in terms of ordering and/or store operations, which might contribute to good or bad waste performance. Secondly we include per SKU/store combination the MSS divided by the average weekly sales (MSS_div_u). This might be a significant predictor of waste, since it shows how big this extra held stock is in terms of weeks of stock for that SKU/store combination. We also include the cross product of FCC and MSS_div_u (FCC_MSS). The results of the stepwise regression analysis can be found in Table 32, Table 33 and Table 34 of Appendix M. Some of the stores’ influence on waste are significant. Moreover, both MSS_div_u and FCC_MSS are found to be significant predictors. Although the model is more complex, the explained variance is higher ($R^2=0.82$) and consequently yields more accurate results. From the model it can also be concluded that high MSS values relative to the amount of sales are significantly detrimental for waste in the stores. The corresponding formula can be found in Equation 3. Multicollinearity is not regarded as problematic in the model, since the highest variance inflation factor (VIF) is 2.86, which is lower than the rule of thumb value of 4.

$$\% \text{waste in colli} = -0.61FCC$$  \[2\]

$$\% \text{waste in colli} = 0.162 - 0.687FCC - 0.049\text{MSS}_\text{div}_u + 0.004FCC\_\text{MSS} + 0.164\text{Leeuwarden} - 0.148\text{Amsterdam} - 0.140\text{Delft} + 0.094\text{Wateringen} - 0.077\text{Duiven}$$  \[3\]

Figure 13. Fresh Case Cover (FCC) plotted against % waste in units (30 weeks from 3-10-16 until 30-04-17)
3. Research project

After the introduction of the problem and the in-depth analysis of the current situation, the research project can be defined next. The research question is formulated and sub research questions are defined to help answering the main research question.

It is shown that there are potential operational and logistic adjustments which can reduce the current amount of waste at Makro. We have shown that this potential improvements can especially be found in three topics: flow type selection, store procedures and optimization of ordering system parameters. This brings us at the following research question.

| Which ordering system parameters, store procedures and flow types minimize overall costs and costs of waste for Makro’s fresh product categories? |

To answer this research question, a set of sub questions are formulated:

1. What is the customer picking behavior at Makro currently? In other words, what is the balance between FIFO picking and LIFO picking?
2. Which flow types should be taken into consideration?
3. What are the relevant costs and performance measures where the flow type selection and parameter optimization should be based on?
4. How should the simulation be designed and which costs and functionalities should be taken into consideration?
5. What do the results imply for the management and what actions should be taken.

This study focusses on two product categories: Milk Products and Sandwiches & Spreads. However, the used methodology can also be used for other fresh categories, which is strongly advised. Moreover, some of the recommendations count for the fresh department as a whole.
4. Analysis current situation – Part II: Customer picking behavior experiment

Whether customers choose the shortest or a longer expiration date when they pick a product from the shelf has a substantial influence on food waste in the store. Obviously when a large proportion of the customers pick a longer expiration date, waste is higher [21]. However, if a substantial part of the customers buy the oldest CU on the shelf, the effect on waste is limited [6]. When customers pick the shortest expiration date of a product, we refer to it as First-In-First-Out (FIFO) behavior. This means that from all the different expiration dates of an SKU in the shelf, the product that has arrived first, gets picked/sold first. FIFO picking behavior can be described as choosing the least fresh product in the shelf. Ideally a retailer aims to sell its inventory according to the FIFO principal, since this results in the lowest amount of waste in the stores. For this reason, FIFO picking behavior is almost always promoted, amongst others by placing the shortest expiration dates in front of the shelf and the longer expiration dates successively further in the back (FIFO replenishment). In this way it is more difficult and time consuming to grab items with a longer expiration date (they often have to reach further in the shelf, have to take out items at the front of the shelf and have to check and compare the different expiration dates). As a result customers are often encouraged to pick FIFO. Contrary to FIFO behavior, customers may choose to buy the freshest product with the longest expiration date on the shelf, also referred to as Last-In-First-Out (LIFO) behavior. If a high share of the customers pick the longest expiration date, the items with shorter expiration dates will remain unsold, and consequently get wasted with a higher possibility. Because at Makro it can occur that more than two expiration dates of an SKU are present on the shelf, customers might pick an expiration date that is between the shortest and longest date. In this report ‘LIFO’ is defined as Later-In-First-Out; representing every customer pick of an item from an SKU with a longer expiration date than the shortest expiration date on the shelf. Because customer picking behavior has a big influence on waste, it is important to analyze this behavior at Makro. Quantifying this behavior and investigating potential influencers of this behavior might enable the identification of process improvements for waste. Moreover, this customer behavior is influential in the effectiveness of most of the improvement projects for waste reduction described in this study. In this chapter, an experiment at two Makro stores considering customer picking behavior is described. The found proportion FIFO versus LIFO customers is amongst others an important input parameter for the simulation model described later in this report. Furthermore, we conduct some statistical analyses to assess relationships of the picking behavior with certain variables.

4.1. Methodology and hypotheses

From the research of Van Burgh (2007) [1] it followed that customer picking behavior in the store is likely to be influenced by the space between shelves. A lot of space between shelves makes it easier for customers to check expiration dates, which promotes LIFO picking. In the research, the larger supermarkets had higher LIFO picking (49.7%). Because Makro stores are characterized to be large, it is expected that a substantial amount of LIFO picking takes place. The same research also concludes that if the inventory is low (or looks low), the amount of LIFO picking is higher. Hence, smaller stores with smaller shelf spaces have advantages considering this matter, since a shelf looks fuller at lower inventories. In the study it was also found that when a product at the front of the shelf reaches its expiration date, LIFO picking is more likely to occur. For the retailer described in Van Burgh (2007) [1], only for 35% of the observations the customer had a choice in expiration date. For the other 65% there was only one choice in expiration date on the shelf. The research also indicates that there can be
significant differences in FIFO/LIFO picking between article groups. Reasons for this deviations can be differences in shelf lives, in kind of customers that buy products in the article group, in product sizes, in shelf design and in product placement.

Similar to Van Burgh (2007) [1], the amount of FIFO/LIFO picking will be investigated at Makro. Measurements considering customer picking behavior will be conducted at two stores for the studied product categories: one classic store and one junior store. Both a classic and junior store are investigated in order to find potential differences. The classic store that is investigated is Makro Amsterdam, which is the store with the highest sales from all Makro stores. From all the classics, this store is chosen because it is likely to have a high amount of traffic in the investigated article groups, and for this reason will result in more observations and a higher sample size. This subsequently leads to more reliable conclusions. As junior store Barendrecht is selected, which is the junior with the highest amount of sales. Because classic stores are typically larger, have more shelf space (so dates could be checked more easily) and probably have more dates in the shelves (because of higher inventories), it is expected that the proportion of LIFO customers is higher. The smaller shelves at the junior stores are expected to make it more difficult to check dates, but also limit the ability to store a lot of inventory (and consequently a lot of different dates). This is expected to result in less LIFO picking. An opposite reasoning might be that the classic store has higher product rotation, so better dates in the shelf and therefore less LIFO picking. However, we follow Van Burgh (2007) [1] and his results for our hypotheses.

From interviews with various employees and managers at Makro, together with the literature findings above, it is expected that the largest part of the customers pick LIFO at Makro. For this reason, the following hypothesis is formulated:

\[
H1: \text{More than 70\% of the customers pick LIFO if there are more expiration dates in the shelf}
\]

Furthermore because of the different characteristics of juniors and classics, a second hypothesis is formulated:

\[
H2: \text{LIFO customer picking behavior is higher in the Amsterdam than in Barendrecht}
\]

In the research of Van Burgh (2007) [1] a supermarket is investigated. Since Makro is a wholesaler and in general characterised by larger stores, larger shelves, more facings per SKU and higher inventories, it is expected that on average more different dates are on the shelves compared with the supermarket investigated by Van Burgh (2007) [1]. For this reason, the third hypothesis can be formulated:

\[
H3: \text{The proportion of sales where customers don’t have a choice in expiration date is expected to be less than 65\%}
\]

During the experiment, at each store 3 days of measurements will take place. Hence, a total of 6 days of measurements. For both stores measurements will be conducted on a Tuesday, Wednesday and Saturday. Each day there will be measurement moments as described in Table 4. Only on Saturday the amount of measurement moments will be limited to the first 5. This is because the opening times of the stores are shorter on this day. At each measurement moment, per SKU the inventory per batch will be registered. A batch is defined as group of consumer units of a product that have the same expiration date. During the experiment, the notation is as described in Table 5 will be used.
Table 4. Measurement moments specified throughout a measurement day

<table>
<thead>
<tr>
<th>Measurement moment</th>
<th>Classic store</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>9:00</td>
</tr>
<tr>
<td>2</td>
<td>11:00</td>
</tr>
<tr>
<td>3</td>
<td>13:00</td>
</tr>
<tr>
<td>4</td>
<td>15:00</td>
</tr>
<tr>
<td>5</td>
<td>17:00</td>
</tr>
<tr>
<td>6</td>
<td>19:00</td>
</tr>
</tbody>
</table>

Table 5. Notation used for the customer picking behavior experiment

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I_{i,ag,s,m,d,\beta}$</td>
<td>Inventory of batch $\beta$ of SKU $i$ of article group $ag$ at store $s$ at day $d$ at measurement moment $m$</td>
</tr>
<tr>
<td>$EXP_{i,ag,s,m,d,\beta}$</td>
<td>Expiration date of batch $\beta$ of SKU $i$ of article group $ag$ at store $s$ at day $d$ at measurement moment $m$</td>
</tr>
<tr>
<td>$i$</td>
<td>Article group: (1) Milk Products, (2) Sandwiches &amp; Spreads</td>
</tr>
<tr>
<td>$ag$</td>
<td>Store: (1) classic, (2) junior</td>
</tr>
<tr>
<td>$s$</td>
<td>Measurement moment: 1, 2, 3, 4, 5 or 6</td>
</tr>
<tr>
<td>$m$</td>
<td>Day number: (2) Tuesday, (3) Wednesday and (6) Saturday</td>
</tr>
<tr>
<td>$d$</td>
<td>The number of the expiration date batch: (1) the batch with the most recent expiration date/shortest shelf life on the front of the shelf, (2) the batch with the second most recent expiration date after batch 1, (3) the batch with the third most recent expiration date after batch 2 etc.</td>
</tr>
</tbody>
</table>

To find changes in inventory of a certain batch (sales), the notation below is used:

$R_{i,ag,s,m,d,\beta}$: Amount of products which are picked from batch $\beta$ of SKU $i$ of article group $ag$ at store $s$ at day $d$ at observation moment $o$.

$\forall o: o = m; R_{i,ag,s,m,d,\beta} = I_{i,ag,s,m+1,d,\beta} - I_{i,ag,s,m,d,\beta}$ \[4\]

From all the SKU’s in the article groups that are researched in this report, randomly 35 SKU’s were selected for the experiment. Given the fact that two stores will be measured, this will give a total of 70 SKU/store combinations. During the experiment randomly extra SKU’s were added to the set to gather a larger sample size. Eventually for 111 SKU’s data was gathered. When comparing the two stores, we assume that picking behavior doesn’t differ among products inside the category in the store. Hence, the partly different sets of examined SKU’s can be compared between the stores. Sales during observation moments were allocated to different groups, defining how a product has been picked during the observation moment. Each sold consumer unit is allocated to one of the picking groups. The three main picking groups are described in Table 6.

Besides these groups, exception picking groups are defined. Exceptions can occur when for an item pick it can’t be concluded with 100% to which picking group it belongs. Exceptions occur when either: (1) one of the batches is sold out during an observation period or; (2) inventory has been replenished during an observation period.

The three exception picking groups to which a pick can belong during an observation moment are described in Table 7.
Table 6. Three main picking groups describing how a consumer unit is picked

<table>
<thead>
<tr>
<th>Picking group</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. FIFO when choice</td>
<td>A CU is picked from the SKU batch with the shortest expiration date (least fresh product at the front of the shelf). A pick only belongs to this group if the customer also had the possibility to pick a CU from the same SKU with a longer expiration date (batch with longer expiration date).</td>
</tr>
<tr>
<td>2. LIFO</td>
<td>A CU is picked from the batch which does not have the shortest expiration date (a fresher products behind or next to the batch with the shortest expiration date).</td>
</tr>
<tr>
<td>3. FIFO no choice</td>
<td>There is only one SKU expiration date batch in the shelves. Therefore customers have no choice in expiration date for an SKU and accordingly is forced to pick FIFO.</td>
</tr>
</tbody>
</table>

Table 7. Exception picking groups defined for unknown item picks

<table>
<thead>
<tr>
<th>Exception picking group</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>4. FIFO when choice or FIFO no choice</td>
<td>This exception can occur when before an observation moment there is only one batch in the shelf and during the observation period inventory is replenished with a new batch and a longer expiration date than the first one. When a pick from the batch with the shortest expiration date has taken place in the observation period, it is not known if at the time of picking one or two batches were available for the customer to choose from. Therefore the pick was either FIFO when choice or FIFO no choice. This exception can also occur when there are two batches in the shelf and during an observation period the 2nd batch gets sold out. Picks of the first batch could either have been FIFO when choice or FIFO no choice.</td>
</tr>
<tr>
<td>5. FIFO when choice or LIFO</td>
<td>This exception occurs when there are three batches of a SKU at the beginning of an observation moment. When during an observation moment the batch with the shortest expiration date (batch 1) is sold out and at the end of the observation moment CU’s have been picked from the second batch (which has a longer expiration date than batch 1 but shorter than batch 3), it is unknown whether they have taken place when batch 1 still was available or when batch 1 was already sold out. For this reason, the pick was either LIFO or FIFO when choice.</td>
</tr>
<tr>
<td>6. LIFO or FIFO no choice</td>
<td>This exception is similar to exception 5, but here there are only two batches of the SKU available at the beginning of an observation moment. For this reason when batch 1 is sold out during an observation moment and CU’s are picked from batch 2, it is unknown whether this picks were LIFO or FIFO no choice.</td>
</tr>
</tbody>
</table>

As the methodology is described, in the next section the results of the experiment will be discussed.

4.2. Results

4.2.1. Aggregated results

In this section the aggregated outcomes (both stores and product groups combined) of the experiment will be discussed. When all the data from the in total 6 measurement days is aggregated, the results described in Table 8 are obtained. It can be observed that from the 671 total observed sales, 68 (10.13%) belonged to an exception group. Consequently for 89.87% (603) of the sales it is exactly known how they have been picked. To gain insight in the customer behavior when customers have a choice in date, only the first two rows of Table 8 should be regarded. From these two rows, Figure 14 is created. In this figure it can be observed that if customers have a choice between more expiration dates, the fraction of the customers that pick FIFO is 54% and the fraction that pick LIFO is 46%. It turns out that the amount of LIFO customers is lower than the expected 70%. Hypothesis 1 can be rejected on basis of a χ² (chi-squared) test (see test nr. 3 in Table 19 of Appendix B). This test checks whether there is a significant difference between two groups (e.g. one group with observed values and another group with expected values). Since the p-value is significantly lower than 0.05, it can be concluded that the observed values are significantly different from the hypothesized values. The test shows that the difference is not a result of randomness. For this reason, H1 is rejected.

Table 9 shows average shelf life and expiration date information obtained during all the measurement days. The figures have been derived from the stock information which was registered at each
measurement moment. Here the average shelf life is defined as the mean of the available dates in the shelf. The weighted shelf life also weighs the quantity per date in its calculation. In this study the ‘avg. weighted shelf life per SKU/avg. shelf life at arrival’ is used as indicator for freshness.

Table 8. Aggregated customer picking behavior results

<table>
<thead>
<tr>
<th>Picking group/exception group</th>
<th>Number of observations</th>
<th>Percentage 100% sure picking group</th>
<th>Percentage all picking group</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. FIFO when choice</td>
<td>191</td>
<td>32%</td>
<td>28%</td>
</tr>
<tr>
<td>2. LIFO</td>
<td>160</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. FIFO no choice</td>
<td>252</td>
<td>42%</td>
<td>38%</td>
</tr>
<tr>
<td>4. FIFO or FIFO no choice</td>
<td>24</td>
<td></td>
<td>4%</td>
</tr>
<tr>
<td>5. LIFO or FIFO</td>
<td>18</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. LIFO or FIFO no choice</td>
<td>26</td>
<td></td>
<td>4%</td>
</tr>
<tr>
<td>Total main allocation groups (1+2+3)</td>
<td>603</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td>100% sure FIFO or LIFO (1+2+3+4)</td>
<td>627</td>
<td></td>
<td></td>
</tr>
<tr>
<td>All total (1+2+...+6)</td>
<td>671</td>
<td>100%</td>
<td></td>
</tr>
</tbody>
</table>

Table 9. Shelf life and expiration date information: aggregated results

<table>
<thead>
<tr>
<th></th>
<th></th>
<th>1.75</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. # dates per SKU</td>
<td>Avg. shelf life at arrival per SKU</td>
<td>20.81</td>
</tr>
<tr>
<td>Avg. shelf life per SKU</td>
<td>Avg. shortest shelf life per SKU</td>
<td>13.76</td>
</tr>
<tr>
<td>Avg. weighted shelf life per SKU</td>
<td>Avg. (shortest shelf life per SKU/avg. shelf life at arrival)</td>
<td>0.56</td>
</tr>
<tr>
<td>Avg. (shelf life/avg. shelf life at arrival)</td>
<td>Avg. (weighted shelf life/avg. shelf life at arrival)</td>
<td>0.69</td>
</tr>
<tr>
<td>Avg. (weighted shelf life/avg. shelf life at arrival)</td>
<td>0.72</td>
<td></td>
</tr>
</tbody>
</table>

In general, it can be concluded that the LIFO customer behavior is less than expected. The fraction of ‘FIFO when choice’ picks is even slightly larger than the fraction of LIFO picks. However, it can’t be significantly concluded that ‘FIFO when choice’ picking occurs more than LIFO picking (see test nr. 2 in

Figure 14. Percentage LIFO vs. FIFO customers when customers have a choice (picking group 1 versus 2)

Figure 15. Percentage LIFO vs. FIFO customers including ‘FIFO no choice’ picks (picking group 1+3 versus 2)
Table 19 of Appendix B). Potential explanations for the higher than expected amount of ‘FIFO when choice’ picking might be: (1) customers are more satisfied than not with the expiration date at front of the shelf; (2) customers trust Makro or the particular store for offering a good expiration date and don’t check it; (3) It is too time consuming to grab a product in the back of the shelf; (4) the expiration dates of the investigated article groups are on average highly sufficient, so that the customer knows that he will consume the product (far) before the expiration date; (5) the customer knows that he will consume the product soon and accepts the shorter expiration date intentionally and (6) the customer just chooses at random and doesn’t consider consequences of his choice.

In Figure 15 also the ‘FIFO no choice’ picks and the picks from the exception group ‘FIFO or FIFO no choice’ are included. The outcome is what percentage of the total amount of customers pick FIFO (forced or intentional) versus the ones that pick LIFO. The result is biased towards FIFO as it includes picks where customers didn’t have a choice in date, so where forced to pick FIFO. In Table 8 it can be seen that the ‘FIFO no choice’ group is the biggest group with the highest number of observations: 252 of the 603 sales (42%). This is a positive result because this compulsory FIFO picking has a positive effect on waste. If this wouldn’t be the case, customers would have a choice and as a result part of them would pick LIFO. LIFO picking consequently results in a higher percentage of waste. The fraction of ‘FIFO no choice’ picks is significantly less than found by Van Burgh (2007) [1] (see test nr. 10 in Table 19 of Appendix B). For this reason hypothesis H3 is not rejected and it can be concluded that indeed the proportion of ‘FIFO no choice’ picking at Makro is less than the proportion for the described supermarket in the study of Van Burgh (2007) [1]. In total, in Figure 15 it can be observed that 74% of the customers pick FIFO (forced or intentional) and 26% pick LIFO. Given this results it can be concluded that the LIFO behavior is currently quite under control and less than expected. Still the behavior can be improved, for example by aiming for a lower number of expiration dates in the shelf, less space between shelves (making it harder to check dates) and good shelf replenishment. As a result more people are forced to pick FIFO. This however demands a higher degree of inventory monitoring and/or improved ordering/operations. Cost/benefits of such practices have to be examined.

It is expected that leaving out the exception picking groups in the results doesn’t result in a bias towards a certain picking group, which would be the case if the actual picking in the exception groups would be dominated by a certain picking group. Based on observations in the stores, and from Figure 14 and Figure 15 it is assumed that in the exception groups 5 and 6 the proportion FIFO versus LIFO customers is 1:1, so exclusion won’t result in biased conclusions. Moreover the fraction of observations belonging to an exception group is limited (only 10.13%).

In the next sections the picking behavior is analyzed on store and category level.

### 4.2.2. Store and category analysis

The results per store and category are depicted in Table 10. It can be observed that the total observed sales in Barendrecht are higher than in the Amsterdam, 398 versus 273. However, this does not mean that the average sales in Barendrecht are higher than in Amsterdam. The reason that the amount of observed sales in Barendrecht are higher, is because the sample size in Barendrecht was larger than in Amsterdam. Because of both the increased competence in doing the measurements and the more compact shelf design in Barendrecht, it was possible to include more products in the measurement list in Barendrecht. The difference in behavior is depicted in Figure 16 and Figure 17. Table 11 shows the observed shelf life and expiration date information per store and article group. When customers have a choice (Figure 16), it can be observed that in Barendrecht they pick FIFO in 59% of the cases and LIFO
in 41% of the cases. In Amsterdam this proportion is 47% FIFO and 53% LIFO. The amount of LIFO picking is higher in Amsterdam. This difference in picking behavior is significant (see test nr. 12 in Table 19 of Appendix B). This difference in behavior can’t be attributed to the policy for removing products from the shelves approaching their expiration date, since this policy is identical for both: 3 days before the expiration date, products get wasted. For this reason, H2 is not rejected.

Table 10. Results per store and category

<table>
<thead>
<tr>
<th>Picking group/exception groups</th>
<th>#Amsterdam</th>
<th>#Barendrecht</th>
<th>#Milk Prod.</th>
<th>#Sand. &amp; Spr.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. FIFO</td>
<td>63</td>
<td>128</td>
<td>130</td>
<td>61</td>
</tr>
<tr>
<td>2. LIFO</td>
<td>70</td>
<td>90</td>
<td>123</td>
<td>37</td>
</tr>
<tr>
<td>3. FIFO no choice</td>
<td>121</td>
<td>131</td>
<td>167</td>
<td>85</td>
</tr>
<tr>
<td>4. FIFO or FIFO no choice</td>
<td>3</td>
<td>21</td>
<td>10</td>
<td>1</td>
</tr>
<tr>
<td>5. LIFO or FIFO</td>
<td>10</td>
<td>8</td>
<td>16</td>
<td>14</td>
</tr>
<tr>
<td>6. LIFO or FIFO no choice</td>
<td>6</td>
<td>20</td>
<td>17</td>
<td>10</td>
</tr>
<tr>
<td>100% sure which picking group (1+2+3)</td>
<td>254</td>
<td>349</td>
<td>420</td>
<td>183</td>
</tr>
<tr>
<td>100% sure FIFO or LIFO (1+2+3</td>
<td>257</td>
<td>370</td>
<td>437</td>
<td>190</td>
</tr>
<tr>
<td>All total (1+2+...+6)</td>
<td>273</td>
<td>398</td>
<td>463</td>
<td>208</td>
</tr>
</tbody>
</table>

Table 11. Shelf life and expiration date information: Amsterdam vs. Barendrecht & Milk Products vs. Sandwiches & Spreads

<table>
<thead>
<tr>
<th></th>
<th>Amsterdam</th>
<th>Barendrecht</th>
<th>Milk Prod.</th>
<th>Sand. &amp; Spr.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. # dates per SKU</td>
<td>1.91</td>
<td>1.63</td>
<td>1.77</td>
<td>1.69</td>
</tr>
<tr>
<td>Avg. shelf life at arrival per SKU</td>
<td>20.85</td>
<td>20.80</td>
<td>18.80</td>
<td>24.31</td>
</tr>
<tr>
<td>Avg. shortest shelf life per SKU</td>
<td>10.12</td>
<td>11.87</td>
<td>10.38</td>
<td>12.69</td>
</tr>
<tr>
<td>Avg. shelf life per SKU</td>
<td>13.34</td>
<td>14.02</td>
<td>12.87</td>
<td>15.38</td>
</tr>
<tr>
<td>Avg. weighted shelf life per SKU</td>
<td>14.38</td>
<td>14.47</td>
<td>13.44</td>
<td>16.25</td>
</tr>
<tr>
<td>Avg. (shortest shelf life per SKU/avg. shelf life at arrival)</td>
<td>0.50</td>
<td>0.59</td>
<td>0.56</td>
<td>0.54</td>
</tr>
<tr>
<td>Avg. (shelf life/avg. shelf life at arrival)</td>
<td>0.66</td>
<td>0.70</td>
<td>0.69</td>
<td>0.67</td>
</tr>
<tr>
<td>Avg. (weighted shelf life/avg. shelf life at arrival)</td>
<td>0.71</td>
<td>0.73</td>
<td>0.72</td>
<td>0.71</td>
</tr>
</tbody>
</table>

Figure 16. Picking behavior in Barendrecht and Amsterdam if customers have a choice

Figure 17. Picking behavior Barendrecht vs. Amsterdam including FIFO no choice
The higher proportion of LIFO picking in Amsterdam is expected to be driven by:

- **More facings** - For some of the investigated products it was observed that Amsterdam had more facings and consequently more shelf space. In Figure 31 and Figure 32 in Appendix A it can be seen that ‘Vifit’ drinks have more facings and shelf space in Amsterdam. Because there are more CU’s of the same SKU at front of the shelves, the chance that a product with a longer expiration date than the shortest expiration date is on front of the shelf is higher. Because expiration dates at front of the shelves can be easily checked by the customer, LIFO picking is more likely to occur.

- **More expiration dates in the shelves** - In Amsterdam there are on average more different dates on the shelves, on average 1.91 dates per SKU in Amsterdam vs. 1.63 per SKU in Barendrecht (see Table 11). More dates on the shelves give the customers more choice and therefore may promote LIFO picking behavior.

- **Shorter shelf lives** - In Table 11 it can be observed that both the shortest average shelf life, the average shelf life, the average weighted shelf life and the proportion of those three as part of the average shelf life at arrival are lower in Amsterdam. From the results it can be concluded that customers in Amsterdam encounter in general a worse quality of products, which might affect the picking behavior of the customer. Increased LIFO picking might be caused directly by customers who encounter a too short expiration date at front of the shelf and therefore grab a product further in the back of the shelf, or indirectly by customers who might have less confidence in Amsterdam for offering a satisfying expiration date, so in general check the dates more often.

Next, the results between the different categories are compared. In Table 10, Table 11, Figure 18 and Figure 19 these are depicted.

In Table 11 it can be seen that Milk Products are typically characterized by shorter shelf lives. From Figure 18 and Figure 19 it can be observed that for Milk Products, ‘FIFO when choice’ vs. LIFO picking is approximately 50/50. However, the fraction of ‘FIFO when choice’ picking in the Sandwiches & Spreads category is substantially higher (62%). The difference is nevertheless not large enough given the sample size to be significant (see test nr. 14 in Table 19 of Appendix B). However, a possible explanation for the
difference might be that the SKU’s in the Sandwiches & Spreads category are typically larger in size, so products fill up the shelves more and consequently checking the dates is made harder for the customer. Moreover the amount of different dates in the shelves are less (see Table 11), possibly because less products fit in the shelf. Furthermore, the general shelf life is larger for Sandwiches & Spreads, which may give customers less motive to check dates (because they are mostly fulfilling). These characteristics might reduce the chance of LIFO picking. In Figure 19 it can be observed that when all FIFO picking groups are combined, the proportion FIFO vs. LIFO for Milk products is respectively 72% vs. 28% whereas for Sandwiches & Spreads this is 81% vs. 19%. From test nr. 13 in Table 19 of Appendix B it follows that this difference is not significant.

In this chapter some expected influencers of customer picking behavior have been mentioned. In the next chapter some of these potential relationships are statistically evaluated.

4.3. Statistical correlations
Given the results obtained in the customer behavior experiment, a number of statistical tests are conducted in order to check the following hypotheses:

H4: The number of dates in the shelf of an SKU has a positive correlation with the amount of LIFO picks.
H5: The shortest shelf life of an SKU has a negative correlation with the amount of LIFO picks.
H6: The amount of facings of an SKU has a positive correlation with the amount of LIFO picks.
H7: The difference between the shelf life of the first and the second batch has a positive correlation with the amount of LIFO picks.

These hypotheses are assessed based on only the LIFO versus ‘FIFO with choice’ groups. In order to test the relationships, for each hypothesis two statistics are computed: Pearson’s and the Spearman’s correlation coefficient. The Pearson’s correlation coefficient tests the statistical relationship between two variables. The test measures linear correlation, which consequently makes the test not suitable for identifying nonlinear relationships. For this reason, per potential correlation also the Spearman’s correlation is calculated. This statistic is less restrictive than the Pearson’s correlation coefficient in that it measures a monotonic association between two variables. In Figure 20, the middle image shows a relationship that is monotonic but not linear. The Spearman’s statistic is especially suitable for testing relationships between an ordinal variable and a binary variable, which is the case in all the tested potential correlations. By calculating both the Pearson’s and Spearman’s statistic more can be concluded about the potential correlation (linear or non-linear) and moreover results can be verified (if the Pearson’s statistic is significant, also the Spearman’s statistic should be significant).

4.3.1. Dates vs. customer behavior
A potential influencer of customer behavior is the amount of dates of an SKU that a customer faces on the shelf when he/she wants to pick a CU. More dates on the shelf might be associated with a higher degree of LIFO picking behavior. The Pearson’s and Spearman’s correlation statistics are calculated to test the relationship. The result of the Pearson’s test is depicted in Table 12. The Spearman’s correlation statistic (see Table 20 in Appendix G) shows identical results. Both tests show a high significance, which means that there is a correlation between the number of dates in the shelf and the customer behavior. H4 is confirmed. Since the coefficient is negative, it can be concluded that more dates in the shelves leads to a higher degree of LIFO picking (FIFO represents 1 and LIFO represents 0 in the tests). In Table
30 in Appendix K a crosstab of the values is depicted. When the actual count is compared with the expected count, it can be observed that the proportion \( \frac{\text{Count}}{\text{Expected Count}} \) gets higher for the LIFO column (indicated by the .00 column) as the amount of dates increase.

Figure 20. What is a monotonic relationship?^{4}

Table 12. Pearson’s statistic for testing the relationship between customer picking behavior and the amount of dates in the shelf.

<table>
<thead>
<tr>
<th>FIFO vs #dates</th>
<th>Pearson Correlation</th>
<th>Sig. (2-tailed)</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>FIFO_1.0</td>
<td>-.291**</td>
<td>.000</td>
<td>351</td>
</tr>
</tbody>
</table>

**. Correlation is significant at the 0.01 level (2-tailed).

4.3.2. Shortest shelf life vs. customer behavior

When customers face a shorter expiration date at the front of the shelf, he/she might be triggered to check dates and pick LIFO. The Pearson’s and the Spearman’s tests for this correlation however show insignificant results (see Table 23 and Table 24 Appendix G). An additional analysis is performed where three groups are created: (1) shortest shelf life is not larger than 1 week; (2) shortest shelf life is between one and two weeks and (3) shortest shelf is larger than 2 weeks. For this experiment design, the Pearson’s test is just insignificant (Table 25 of Appendix G) and the Spearman’s test is significant (Table 26 of Appendix G) at a p-value of 0.027 and coefficient of 0.137. For this reason it can be concluded that there is a correlation between the shortest shelf life and amount of LIFO behavior, but not linear. The coefficient shows that the larger the shortest shelf life is in the shelf, the higher the proportion of FIFO picking is. \( H5 \) is confirmed.

4.3.3. #Facings vs. customer behavior

When a customer encounters more facings of an SKU, more CU’s of that SKU are at front of the shelf. Consequently it is more likely that a CU of a fresher batch than the first batch is at the front of the shelf, making it easier for the customer to spot. As a result it is expected that customers have a better overview of the different dates in the shelf and therefore pick more often longer expiration dates, which influences waste. Both the Pearson’s (\(-.268\)^*) and the Spearman’s (\(-.213\)^*) test show a significant negative correlation between the number of facings and the amount of FIFO picking (see Table 21 and Table 22. As a result it can be stated that more facings result in more LIFO picking behavior. \( H6 \) is confirmed.

---

4.3.4. Difference between shelf life of first and second batch versus customer behavior

When a customer observes a larger gap between the first two expiration dates in the shelf, they might be triggered to pick LIFO sooner (they observe a quality difference which is worth the extra effort to pick LIFO). It is expected that the bigger this difference is, the more likely a customer is to pick the longer expiration date.

Table 27 and Table 28 in Appendix G show that both the Pearson’s and Spearman’s tests are not significant, from which we can conclude that no monotonic correlation is present between both variables. $H7$ is rejected. A possible explanation might be that a large difference between two batches influence more the long term behavior of customers instead of the direct behavior; therefore, it might influence customer behavior, but is in fact untraceable on a direct level.

4.4. Additional observed contributors to waste

During the experiment additional contributors to waste have been observed. These findings are based on one week of observations per store. Hence, they are only indicators of problem areas and not reliable enough to be interpreted as absolute truth and representative for Makro in general. More research is required to support this statements. The observed contributors are regarded more in-depth in Appendix H. The observed contributors are:

- **Too high inventory levels** - it is observed that for a substantial part of the studied SKU’s in the experiment, the inventory levels are large. Regularly the observed stock of an SKU comprises multiple weeks of stock, leading to lower freshness, which leads to higher LIFO picking and in turn to higher waste. If the weeks of stock is higher than the weeks of shelf life, the stock can’t be sold before the expiration date, and waste takes place guaranteed, even under FIFO picking. As at Makro a proportion of the customers pick LIFO, the amount of weeks of stock already get problematic if it only approaches the weeks of shelf life. It is found that for some products the case pack size (MOQ) drives this relative high stock levels. For others, the case pack size isn’t a limitation and inventory can be easily reduced. This indicates that ordering behavior is bad, either caused by the ordering system, manual adjustments or a combination of both.

- **Too many facings per product** - it was found that a considerable amount of products have more than 1 facing, while also having a substantial amount of weeks of inventory. This is an indication that facings might not be aligned with demand. As we have shown, the amount of facings are positively correlated with LIFO behavior, which in turn leads to waste. Furthermore, for a good store image, department managers want to have full looking shelves. Consequently, they often fill the shelves, but overstock the shelves because they have to fill multiple facings.

- **Imperfections in store replenishment** - first of all, some situations were encountered where shelves were not replenished perfectly FIFO (so fresher products in front of older products). For 8% of the SKU’s in the experiment, a non-optimal shelf was encountered. If replenishment is not done FIFO, older dates are never picked (FIFO and LIFO customers all pick a fresher date now). For this reason, it is very important that this process is executed correctly. Moreover, situations were encountered where products were replenished at the wrong shelf, products were found expired and price tags were missing.
5. Conceptual model

In this chapter the conceptual model is presented. The conceptual model shows the different steps and the sequence in which these steps need to be performed in order to design Makro’s operations and logistics such that overall costs and costs of waste are reduced/minimized. The roadmap shows all the dependencies which need to be addressed to achieve the desired goal. The model is structured such that the most basic/low investment measures to reduce waste/overall costs are analyzed first. Subsequently after each step it is regarded what the potential is of more mature/high investment measures. The defined steps are based on our literature study and the in-depth analysis conducted in the previous chapter. The waste/overall cost reduction roadmap for Makro is depicted in Figure 21.

It has to be addressed that this improvement roadmap focusses on operational and logistical improvements and not on commercial improvements for waste like assortment selection, increasing sales, product presentation etc. One of the core reasons for this decision is that during interviews with category management it was brought up that the assortment had already been reduced recently and that concerning Makro’s competence and positioning in the market, it is not desired to reduce this even more. Furthermore, operations and logistics are given our previous analysis regarded as the areas with most potential for the least investment. Finally, impacts of measures in this area are better quantifiable, which is a plus for operational research. The results of the performed steps in the roadmap can however serve as input for decision making in category management. For example, when the outcome of the roadmap is that overall costs are too high for a particular SKU, even when operations and logistics is reduced/minimized, this might be a trigger for category management to make a decision on whether it is desired to have this product in the assortment.

The model starts with a category or a set of categories for which overall costs and costs of waste are aimed to be reduced or minimized. In the first step of the model, the parameter settings of the ordering system are optimized/improved. In particular, settings for the service levels and MSS are analyzed in this study. However, there are more influential parameters which can be improved or optimized, but these are not into scope of the study. Optimizing parameters of the ordering system can be highly beneficial for maintaining better stock in the stores. However an important dependency of the success of this optimization is that stores get more trust in the ordering system and interfere significantly less in the order proposals than currently. For this reason, in the left upper corner ‘Ordering behavior’ is depicted as important dependency. Although the parameter settings have to be analyzed and redefined, the only thing that has to be altered, is changing some values in the system. For this reason, this step is regarded as the lowest investment improvement opportunity.

In the second step, logistical and operational terms are negotiated with suppliers. Part of this step is determining the MOQ, the delivery schedule (and how this can be synchronized with production) and the delivered shelf life. Decisions in this step are closely related with DC and store characteristics. For example, a smaller MOQ can be beneficial to reduce waste in the store, but raises expenses for order picking in the DC. The characteristics and cost structures in the DC and store determine whether certain measures are beneficial. Ordering and delivery moment decisions are amongst others dependent on the delivery days to the store and the store workforce availability to process deliveries. Because most of these terms have to be negotiated on a supplier level (who also have limitations and desires), this step of the conceptual model is not investigated closely in this report. However, some opportunities for lead time reduction have been negotiated with a selection of suppliers. After significant changes in this
In the third step, the aim is on promoting FIFO behavior in the stores. As has been discussed, customer picking behavior has a large influence on waste in the stores. All measures in the store to promote FIFO behavior, directly benefit waste and profitability. Picking behavior is strongly interconnected with space management and store replenishment. We have found that more facings and dates result in more LIFO behavior. For this reason it is important that the shelf size and amount of facings are matched with the demand characteristics of a product. Moreover, FIFO replenishment is important to minimize waste. Also store policies for limiting the amount of dates in the shelf can benefit the amount of waste. Because parameter optimization is dependent on the FIFO/LIFO balance, the settings have to be re-evaluated if there are significant changes in customer picking behavior. More FIFO picking generally results in less waste and higher availability, so parameters have to be reduced if the aim is to have equal availability.
as formerly. In this higher investment step, store layout has to be altered and policies have to be implemented and communicated to the stores.

Finally, when the first three steps are conducted, the last step is the flow type selection. This is regarded as the highest investment step, since it requires the most operational and logistical adjustments for Makro. In this step, four different flow types are regarded: Break-Bulk-Crossdocking (BBXD), Traditional Warehousing in Case Packs (TWCP), Traditional Warehousing in Consumer Units (TWCU) and Traditional Warehousing Mixed (TWMixed). In TWCU products are unpacked and in TWMixed per product it is determined whether it is unpacked or not. Normal crossdocking (XD) is not taken into consideration since the investigated product characteristics (too low demand) don’t allow every day delivery. Inbound logistics would be too high. Especially when TW is regarded as flow type, processes at the DC have to be re-designed, the system has to be adjusted, agreements have to be made with suppliers and the inventory held on the DC has to be managed by a demand planner. Also when it is decided to unpack, processes have to be changed, since trolleys are needed instead of pallets. A different flow type might be beneficial for some suppliers, but considering the high investment, it is the last step in the diagram and improvements should first be sought in previous steps.
6. Simulation model

Based on the conceptual model described in the previous chapter, the quantitative model will be defined next. First of all, the required input data and the data collection process will be explained in 6.1. Subsequently, the used notation will be discussed in 6.2, after which the assumptions of the model are described in 6.3. In 6.4 the objective function (the measure which assesses performance) will be presented. Subsequently, the most important elements of the one echelon and the two echelon system are described in 6.5 and 6.6. Finally, conform Balcı(1994) [25] this chapter concludes with a description of the validation and verification of the model in 6.7.

6.1. Data collection

In this section, per input variable the data collection process and the variable’s function in the simulation will be described.

6.1.1. Shelf life

The shelf life of a product is an important indicator to be taken into consideration in the simulation. This variable is defined as follows:

\[ \text{Shelf life} = \text{remaining time of a product in days until it is thrown away in the store} \]

As inventory deteriorates, the shelf life of a product gets shorter every day. Currently every store has a different policy considering the removal of products from the shelves. Some stores throw away products 3 days before the expiration date and some do this 1 day before the expiration date. On the basis of policies from four different stores, an average of two days is found. Consequently the shelf life in this study represents the amount of days until 48 hours before the expiration date. Because there is not a strict policy on what moment of the day the products are thrown away, this assumption is made.

Shelf lives are collected per SKU. Because Makro only stores a minimum shelf life in their systems (a lower limit which suppliers need to meet for the DC to accept the products), average shelf lives are not known. Consequently these had to be collected from both the supplier’s information systems and store employees who noted down expiration dates at arrival of the products. In the simulation, every end of day, the inventory ages with 1 day until the shelf life is zero and products get wasted. In reality, shelf life can fluctuate at different delivery moments. For simplicity it is assumed that the shelf life is fixed at the average value found from the collected dataset.

6.1.2. Delivery schedule

The delivery schedule per product is important for simulating the ordering and delivery moments per supplier. The delivery schedule is obtained from Makro’s information system. In the one echelon system (BBXD) there is one delivery schedule that describes the ordering moments of the store and the lead time until delivery. In the two echelon system (all TW flow types) there are two delivery schedules. The delivery schedule from the one echelon system represents the delivery schedule with \( L-1 \) (L from store to the DC is one in the one echelon system) from the supplier to the DC in the two echelon system. However, the amount of ordering/delivery moments are limited to two (only if there initially are more than two) to save in inbound logistics. Besides that, the second delivery schedule in the two echelon system is from the DC to the store, which is daily ordering from Monday to Saturday and delivery from Monday to Saturday (L of one and only on Saturday an L of two).
6.1.3. Daily regular sales

For the 30 week period analyzed in this study, the daily regular sales for Milk Products and Sandwiches & Spreads per SKU/store combination have been extracted from Makro’s information system. As mentioned before, this study only focusses on regular sales. For this reason, promotional periods are excluded from the dataset. Additionally, a period after the promotion is filtered out, since it often occurs that sales are still influenced by discounts that are given because of surplus inventory that is left from the promotional period. The period that is filtered out, is the promotional period plus the shelf life of the product. This ensures that the superfluous stock from the promotional period is not present in the store anymore and doesn’t influence the data.

Subsequently, the periods of zero stock were filtered out. Since no sales occur when there is no stock, this would give a misleading impression of the demand during that day or period. After this, missing data points were imputed based on local mean: average of four weeks around the week of the missing observation. When more than two days of data was missing in a week, the whole week was excluded from the database. Also outliers were identified and corrected based on the local mean value.

Finally, per SKU/store combination the excluded weeks in the dataset were deleted and the data was shifted to the left so there were no ‘empty week’ gaps between data points. Furthermore, SKU/store combinations with less than 11 weeks of data were excluded because a certain initialization period is required and a certain sample size is demanded in order to guarantee valid conclusions. Finally, the dataset with the sample size characteristics as described in Table 13 is obtained.

<table>
<thead>
<tr>
<th>Table 13. Simulation sample size characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
</tr>
<tr>
<td>----------------</td>
</tr>
<tr>
<td>Number of SKU’s</td>
</tr>
<tr>
<td>Number of SKU/store combinations</td>
</tr>
<tr>
<td>Number of demand days</td>
</tr>
<tr>
<td>Number of suppliers</td>
</tr>
</tbody>
</table>

In the simulation, the system iterates through 210 days (30 weeks) and all the SKU/store combinations. Every day inventory gets picked and reduced from inventory conform the sales that occur for that SKU/store combination that day.

6.1.4. Current waste

To calculate the potential improvements, the current situation should be assessed. Waste data per SKU/store combination for the 30 week period has been extracted from the database. The overall current performance has been described in Table 3. To show the potential of certain measures on a yearly basis, the values are translated to yearly figures in the simulation.

6.1.5. MOQ

Per SKU a minimal order quantity (MOQ) is extracted from the information system. This MOQ (mostly determined by the case pack size) serves as a minimum order quantity for the store. This means that every order gets rounded up until an integer number of case packs. During the simulation it is investigated what the potential is of lowering the MOQ by unpacking items in the DC.

6.1.6. Week pattern

From the daily sales data, per SKU/store combination the week pattern is determined. This week pattern is determined from the 30 weeks of input data (so determined afterwards). This is done under the
assumption that the week pattern stays constant during the sales period and also in the near future. Every week day represents a certain fraction of the demand of the total week. For the determination of the forecast at an ordering moment, the day fractions from the current day until \( R+L-1 \) are summed up and multiplied with the week forecast. The observed aggregated week pattern is described in Table 14. It can be observed that the week pattern is more present at the Sandwiches & Spreads category than at the Milk products category. An explanation for this might be that the SKU’s in Sandwiches & Spreads are more bought in the weekend when customers put more effort and time in preparing special meals (e.g. barbeque or celebrations). For both groups we see peaks on Thursday, Friday and Saturday. A significant through can be observed on Sunday (partly because of the limited opening hours). Further on in this report it will be investigated whether accounting for the week pattern brings significant advantages over not accounting for the week pattern.

<table>
<thead>
<tr>
<th>Table 14. Aggregated week pattern for all SKU’s</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>All</td>
</tr>
<tr>
<td>Milk products</td>
</tr>
<tr>
<td>Sandwiches &amp; Spreads</td>
</tr>
</tbody>
</table>

6.1.7. Financial information

For every SKU, both the sales and the buying price were collected. This is necessary to be able to calculate the percentage waste in money as percentage of sales. It has to be emphasized that \( \text{€waste \%} \) is a different measure as waste \% in CU. This difference is a result of the gap between sales and buying price. In Table 15 the difference is demonstrated with a simple example. As can be observed, \( \text{€waste \%} \) is typically smaller because of a products’ margin. Waste \% in CU serves as a good measure for waste from operational point of view: it is independent of the gap between sales and buying price and allows for a fair comparison amongst products. On the other side \( \text{€waste \%} \) is a good measure to show financial impact of certain measures, which is interesting when talking about cost reductions.

<table>
<thead>
<tr>
<th>Table 15. Example comparison of %waste in CU and %waste in €</th>
</tr>
</thead>
<tbody>
<tr>
<td>SKU x</td>
</tr>
<tr>
<td>-------</td>
</tr>
<tr>
<td>100</td>
</tr>
</tbody>
</table>

6.1.8. Minimal shelf stock

The minimal shelf stock (MSS) is extracted from the ordering system of Makro and specified per SKU/store combination. The MSS is an addition to the reorder level (which consists of the forecast and the safety stock) of an SKU/store combination at an ordering moment.

6.1.9. Start inventory

In order to start the simulation, a certain start stock has to be identified. The start stock is extracted from historical stock data from the beginning of the observation period (3-10-2016) per SKU/store combination. This serves as start stock for all simulation experiments. It is assumed that the inventory has changed to a representative level for each configuration run after the eight-week initialization period. The age of the start stock (1\(^{st}\) batch) at day 1 is defined by multiplying the average shelf life at arrival in the store multiplied with the weighted average shelf life obtained from the customer picking behavior experiment. In Table 29 in Appendix I the used notation is explained.

\[
\text{BatchAge}_{1,j,r,1} = (\text{SL}_{\text{arrival,DC}})_{j} + 1) \times \text{WASL}
\]
### 6.1.10. FIFO/LIFO behavior in store

The defined simulation system needs to model from which expiration date batch a product gets picked. As indicated in previous chapter, often a combination of FIFO and LIFO picking behavior exists in a supermarket/wholesaler. Results of the customer behavior experiment will serve as input for the system to model a certain chance of picking a certain batch during the simulation. Sensitivity of the picking behavior on the performance indicators will be assessed in the next chapter.

### 6.2. Notation

In Table 29 in Appendix I, the used notation in the simulation model is described. The defined sets, indices, parameters and variables are used to define all the formulas of the simulation model. In the next sections of this chapter, the most important formulas are described. Finally, these lead to the definition of the objective function.

### 6.3. Assumptions

In this section the assumptions of the simulation model are listed:

- Food Service Delivery (FSD) is included in the sales number of the stores. However, waste that occurs at the FSD warehouse is measured independently. The result is higher sales at the stores, but a lower relative actual waste percentage. It is assumed that this influence is limited. Moreover there is no possibility to differentiate the sales from FSD from the sales from the store, which makes this assumption necessary.
- Reliability of supplier deliveries are 100%.
- Orders at the DC (when using a TW flow type) get picked FIFO in order to minimize waste in the DC.
- The historical 30 weeks of data that is used as input, is representative for current and near future demand.
- Volume effects on outbound logistics and replenishment due to different waste percentages are ignored and assumed to be limited.
- The observed week pattern per SKU/store combination is constant.
- Effects of different flow types on store handling is ignored and assumed to be limited.
- Effects on inventory costs are ignored and assumed to be limited.
- Products that arrive in the morning at the store are stacked on the shelf before the store opens.
- Outbound transportation reliability is 100%.
- On every day (except Sunday) there is transport from the DC to each store.
- Inventory in the store and DC is replenished FIFO.
- No backorders take place and every Out-Of-Stock (OOS) is considered as lost sale.
- Shelves always have enough capacity to store stock of an SKU.
- Case pack sizes are assumed to be constant and equal to the current settings.
- In the currently used BBXD flow type, the delivery schedule is assumed to be constant and equal to the current situation.
- Orders always arrive before the store is opened.
• Products get wasted 48 hours before they reach their expiration date.
• Service levels in the ordering system can be defined for each flow type at category level.
• The shelf life delivered by the supplier is constant per SKU and equal to the found average.

6.4. Objective function
With the conceptual model and the research project in mind, the objective functions of the simulation model are defined in this section. First of all, the constraint considering availability is discussed. Subsequently we elaborate on the different cost components that together result in the objective function, where we distinguish between the one echelon and the two echelon objective function. The mathematical formulations of the objective functions are described in Appendix J.

6.4.1. Constraint on availability stores
As indicated before, Makro aims for an overall availability of 98% in their stores. This is however an overall target in which the non-food categories are also included. This offers room for differentiation among different categories or solutions in the stores. Hence, a lower availability for perishables can be balanced by a higher availability for non-perishables and non-food. Currently Makro measures availability as stock availability, which is defined as the probability that there is positive inventory on hand at the end of the day. There is no exact definition in literature that corresponds to this availability measure. Silver et al. (1998) [28] describe the so called ready rate (Type 3 service level) as the fraction of time that inventory on hand is positive. The stock availability defined by Makro can be regarded as most similar to this definition. However, the Type 3 service level is measured continuously in time and the stock availability at discrete moments (once a day) in time. The current stock availability for the two studied categories is measured at 95.5%. This measure of availability is different from the fill rate (which represents the availability constraint in the model). The fill rate is regarded as a better indicator as it represents the amount of demand that could be fulfilled instead of the fraction of days that stock is present. The fill rate is typically higher than the stock availability (see results in Chapter 7). Since we are dealing with perishables, but perishables with a relatively long shelf life), we aim to differentiate from the 98% target, but not too much. Since we know the current fill rate is probably higher than 95.5%, we set the target fill rate in between these two percentages at 97%. In chapter 7.4 a sensitivity analysis will be conducted on the influence of different fill rates. As mentioned before, the first 8 weeks (56 days) are used to initialize the system. For this reason, the availability gets measured from day 57 onwards. The total time span comprises 210 days (30 weeks), so for 154 days (22 weeks) the performance gets measured. The availability in the simulation is calculated by dividing the total sales of the studied product set by the total demand. The used formula is described in Equation 20 in Appendix J.

6.4.2. Constraint on availability DC
In the two echelon system (TWCP, TWCU and TWMIXED) also inventory is held at the DC and it has to be simulated that stores order products at the DC and the DC subsequently maintains its inventory by ordering products at the supplier. In the two echelon system the DC has to order at the supplier with a certain availability target. According to Muskens (2016) [10], in the DC it should be aimed to maintain a fill rate of 80% to keep the remaining shelf life as long as possible. For this reason, this percentage is also taken as fill rate for the DC in this study. Since the ordering system bases its orders on a cycle service level (which is typically lower), we have to search for a service level that results in a fill rate of approximately 80%. When we set the amount of inbound delivery moments to the DC to two per week
(unless it is already 1 currently), this corresponds to approximately a DC service level of 62%. The availability formula is described in Equation 21 in Appendix J.

Both the availability criteria for the store and the availability criteria for the DC counts on a total group level (both categories of this study combined), and not on a supplier or SKU level.

### 6.4.3. Handling costs DC

An important cost component is the handling that occurs in the DC. In the current situation, where BBXD is the used flow type, costs per handled case pack \((c_{h,\text{BBXD}})\) are €0.27. When the change is made to TWCP, the costs per case pack \((c_{h,\text{TW}})\) will be €0.42. The increase in costs is a result of increased handling per case pack. In TWCP two picking actions (putting products delivered from supplier into stock and picking store orders from stock) have to be performed instead of one picking action during BBXD (allocating delivered goods from supplier to the right pallet/trolley). The affected fraction of the TWCP handling costs for unpacking is \(c_{f,\text{TWCU}}\). Initially, this affected fraction is 100%, which means that the cost of handling an unpacked CU is equal to handling a whole case pack. Since part of the tariff is unaffected by unpacking (e.g. fixed warehouse costs, system costs, inventory costs), the affected percentage might be less. In the sensitivity analysis in Section 7.4, lower affected fractions than 100% are assessed. For example, if the \(c_{f,\text{TWCU}}\) is 40%, the costs of handling a case pack with six products is \(0.40 \times 6 \times c_{h,\text{TW}} + 0.60 \times c_{h,\text{TW}}\). The formulas for total picking costs for the one echelon system (BBXD) and two echelon system (TWCP and TWCU) are respectively presented in Equation 22, 23 and 24 in Appendix J. Picking costs for TWMIXED are determined per SKU. These picking costs are defined by the formula corresponding to the flow type that leads to the lowest overall costs for that SKU.

To determine the yearly picking costs, first all ordered products in the simulation are divided by the MOQ of that product, which yields the total handled case packs. Subsequently, this number is divided by the simulation sales in CU. This proportion is multiplied with the current actual demand of the investigated set of SKU’s per year and the concerning cost tariff of handling in the DC and the availability from the simulation. When unpacking takes place, picking costs are calculated using the formula that is explained in previous paragraph.

### 6.4.5. Costs of waste

The yearly costs of waste are a result of the yearly amount of products that are thrown away in the stores and in the DC multiplied by their buying price. Because the simulation model only simulates a fraction of a year, the costs of waste have to be scaled to yearly costs. First of all, the total simulation waste is calculated by multiplying all wasted products (both in stores and DC) with their buying price. This number is subsequently divided by the total sales in money to get the waste percentage as a fraction of sales. This fraction is then multiplied with the current actual demand per year and the simulation availability for the studied product set, to obtain the yearly waste costs. The current actual yearly demand is calculated by dividing the current actual sales by the assumed current fill rate, which is 0.97. In case of BBXD, the costs of waste at the DC are always 0. The formula for the yearly costs of waste is described in Equation 25 in Appendix J.

### 6.4.6. Savings inbound logistics

When the decision is made to hold inventory in the DC, potential costs can be saved in reducing inbound logistics. Only when the initial amount of delivery moments for a supplier is higher than two, savings can be made. In that case the amount of delivery moments get restricted to 2. Delivery moments are not further decreased to ensure sufficient shelf life and rotation. Cost reductions in inbound logistics
are very complicated to quantify at Makro, because it is dependent on amongst others current price agreements, supplier routing, current used capacity of truck at deliveries (LTL or FTL), location relative to DC etc. For that reason, the following assumption is made: cost savings in inbound logistics will be based on the savings in distance from the supplier’s production site to the DC, measured as fastest route from Google Maps, where the tariff is €1.00 per km (this includes savings in handling from the supplier). This tariff is determined from interviews with supply chain management. The formula for the yearly savings in inbound logistics is depicted in Equation 26 in Appendix J.

### 6.4.7. Demand planning

When it is decided to hold inventory in the DC, this inventory has to be managed. Currently this inventory management (currently for frozen products) is largely done manually and performed by demand planners. When aiming for an integral decision, the extra costs of demand planning have to be taken into consideration for the TW flow types. From conversations with supply chain management, the following estimate of demand planning costs per SKU is made: €109 per SKU per year. This leads to Equation 27 in Appendix J if the decision for TW is made.

### 6.4.8. Objective function

All the described cost components together make up the objective function. This function is described below.

\[
\min (\text{Overall Relevant Yearly Costs}_{SKUSET})
\]

Where

if flowtype is BBXD

\[
\text{Overall Relevant Yearly Costs}_{SKUSET} = \text{Year Picking Costs}_{BBXD,SKUSET} + \text{Year Waste Costs}_{SKUSET}
\]

Subject to

\[
\text{Availability stores}_{SKUSET} \sim 0.97
\]

if flowtype is \{TWCP,TWCU,TWmixed\}

\[
\text{Overall Relevant Yearly Costs}_{SKUSET} = \text{Year Picking Costs}_{(flow \ text)}_{SKUSET} + \text{Year Waste Costs}_{SKUSET} - \text{Year Savings Inbound Logistics Logistics}_{SUPPESUPPLIER} + \text{Year Demand Planning Costs}_{SKUSET}
\]

Subject to

\[
\text{Availability stores}_{SKUSET} \sim 0.97
\]

\[
\text{Availability DC}_{SKUSET} \sim 0.80
\]

Only when TW is taking place, inbound logistic savings and yearly demand planning costs are different from zero.
6.5. One echelon system

In the one echelon system products get delivered using BBXD. The DC only serves as a cross-docking hub where products stay over a period of 1 day in most situations. The most important formulas involved in the simulation of the one echelon system will be discussed in this section.

6.5.1. Order calculation

The possibility of ordering is dependent on the delivery schedule of the respective supplier. Only on an ordering moment, the described formulas in this section get invoked. For determination of the order size, first of all the calculation of the safety stock is important in defining the reorder level \( ROL \). As we have mentioned before, the system currently calculates the safety stock based on the Type 1 service level. The formula for calculating the safety stock is defined in Equation 6. Here \( SS \) is the safety stock for the demand period (the days until the potential delivery moment of the next ordering moment) for a defined service level. The \( z \)-score represents the signed number of standard deviations from the mean to guarantee a certain availability. The higher the defined service level, the higher the \( z \)-score. As we have discussed, the service level is not equal to the customer availability. A normal distribution is assumed to calculate the \( z \)-score from the defined service level. The service level is dependent on the service level group to which an SKU/store combination \( j,s \) is allocated on the day of ordering \( i \). \( \sigma d_{i,j,s} \) represents the standard deviation for the demand period (period from current ordering moment until next delivery moment) and is calculated by taking the square root of the sum of the day fractions of the demand period multiplied by the forecasted week variance. The demand period comprises the days from current day \( i \) till \( i \) plus the review period \( R \) plus the lead time of next ordering moment \( L_{R+} \) minus one. The weekday \( d \) and week number \( w \) automatically advance relative to \( i \).

\[
SS_{i,j,s} = Z_{i,j,s} \cdot \sigma d_{i,j,s} \tag{6}
\]

\[
\sigma d_{i,j,s} = \sqrt{\sum_{i}^{i+R+L_{R+}-1}(day fraction_{j,s,d} \cdot VarianceUsed_{j,s,w})} \tag{7}
\]

Subsequently, the reorder level will be calculated by summing up the safety stock, the forecast for the demand period \( (\mu d) \) and the MSS (if there is any).

\[
ROL_{i,j,s} = MSS_{j,s} + SS_{i,j,s} + \mu d_{i,j,s} \tag{8}
\]

The forecast for the demand until the next delivery moment is calculated as follows:

\[
\mu d_{i,j,s} = \sum_{i}^{i+R+L_{R+}-1}(day fraction_{j,s,d} \cdot WeekDemand_{j,s,w}) \tag{9}
\]

Finally, the order quantity is determined based on the reorder level minus the inventory position (see Equation 10). If this value is negative, nothing is ordered. Because there is a certain case pack size, the order amount gets rounded up until an integer amount of case packs is ordered.

\[
Order_{i,j,s} = \left\lceil \frac{\max(0,ROL_{i,j,s}-IP_{i-1,j,s})}{MOQ_{j}} \right\rceil \cdot MOQ_{j} \tag{10}
\]

The order subsequently arrives after the lead time of that supplier.

6.5.2. Forecasting

Another critical component of the simulation, is the creation of the forecasts. Per SKU/store combination a weekly forecast will be made every end of the week (end of Sunday). For the first 5 weeks of the simulation, the week forecast per SKU/store combination will be based on simply the mean of...
the historical week sales so far. This is identical to how the current ordering system determines forecasts on products with limited amount of historical data. From week 6 on, single exponential smoothing will be used as forecasting method. This forecasting method weights past observations with exponentially decreasing weights to forecast future values. For every new forecast, last week’s forecast (smoothed observations) and last week’s real observation will be used. The formula for calculating the forecast can be observed below.

$$WeekForecast_{j,s,w+1} = (1 - \alpha) \times WeekForecast_{j,s,w} + \alpha \times WeekDemand_{j,s,w}$$ \[11\]

The value for alpha ($\alpha$) influences the speed of dampening (smoothing). When this value is set close to 1, dampening is quick. As a result, the most recent real observation accounts for the biggest share of the forecast. On the other hand, when $\alpha$ is close to 0, dampening is slow and older observations (which are included in the last forecast) have larger influence on the forecast. As a result, this forecasts are more steady throughout the observation period. The current setting of the ordering system for $\alpha$, is 0.20. This value is also used in the simulation and not optimized in this study. Though, this might be interesting for future research. The ordering system of Makro also uses a more advanced exponential smoothing method that can account for seasonality and calendar effects. First of all, considering the limited historical demand, we were not able to incorporate seasonality. However, from inspection seasonality does not seem to be a problem. Furthermore, if calendar effects caused strong uplifts, these periods were excluded from the data. For the weekly calculation of the variance to use for the safety stock calculation, also exponential smoothing is used (see Equation 12).

$$VarianceUsed_{j,s,w+1} = (1 - \alpha) \times VarianceUsed_{j,s,w} + \alpha \times WeekVariance_{j,s,w}$$ \[12\]

### 6.6. Two echelon system

In the two echelon system, inventory is held in the DC, also referred to as traditional warehousing (TW). It is simulated that stores order products at the DC and the DC subsequently maintains its inventory by ordering products at the supplier. In the two echelon system also the demand from the stores to the DC has to be forecasted and a certain availability has to be maintained.

#### 6.6.1. Order calculation

As mentioned before, in the two echelon system stores can order at the DC from Monday to Saturday and can be delivered from Monday to Saturday (a lead time of 1 except Saturday with a lead time of 2). The ordering formulas for the stores remain identical to the formulas for the one echelon system. The only thing that changes, is that there are more ordering moments (smaller $R$) and shorter lead times ($L$).

Orders to the supplier have to be made by the DC to fulfill the aggregated demand of all stores. The DC order calculation is identical to the one from the stores. However, observed demand at the DC represents the aggregated orders that are placed by the stores. The z-score for a SKU at the DC is similar for all SKU’s and based on a single defined service level of 62%.

$$SSDC_{i,j} = ZDC_{i,j} \times \sigma dDC_{i,j}$$ \[13\]

$$\sigma dDC_{i,j} = \sqrt{\sum_{d=1}^{i+R+L+1} dayfractionDC_{j,w,d} \times VarianceUsedDC_{j,w}}$$ \[14\]

Because no week pattern at the DC is known, the week pattern gets measured and updated every end of the week, based on the observed orders that arrive in the DC. The formula for calculating the week
pattern can be found underneath in Equation 15. When no demand of an SKU has taken place yet at the DC, so \( \sum_{x=1}^{D} DDC_{x,j} = 0 \), the day fractions of that particular SKU are set to 1/7th.

\[
\forall d \in \text{DAY}: \text{dayfraction}_{j,w+1,d} = \frac{\sum_{x=1}^{D} DDC_{x,j}(x-(\lceil\frac{|w-7|}{7}\rceil))=d)}{\sum_{x=1}^{D} DDC_{x,j}} \tag{15}
\]

6.6.2. Forecasting
Because the first 4 weeks of the simulation are part of the initialization to obtain a good forecast and variance for safety stock calculation, no orders are placed by the stores at the DC during that weeks. For this reason, during the first 4 weeks, the DC’s weekly demand (from stores) per SKU is based on the observed weekly demand of that SKU for all the stores that have the SKU in the assortment. From the fifth week on, the weekly demand at the DC for an SKU is based on all the orders that the DC has received from the stores that week.

\[
\text{if } (i - (w - 1) \times 7) > 7 \text{ then}
\]

\[
\text{WeekDemand}_{j,w} = \begin{cases} 
\sum_{s \in S_{j,w}} \text{WeekDemand}_{j,s,w} & w \in \{1,2,3,4\} \\
\sum_{s \in S_{j,\geq w-6}} \text{OnorderDC}_{x,j} & w \geq 5
\end{cases} \tag{16}
\]

Subsequently, the forecast is made identical to the forecast from the store, where the first 5 weeks the week forecast and variance is based on the mean of the historical weeks so far and afterwards exponential smoothing is used for the calculation. However, something which has to be taken into account in the forecasting for the DC, is that when for a certain SKU/store combination no sales data is available anymore, that the forecast of the DC has to be adjusted for the reduced demand. Also the variance has to be adjusted accordingly. When at end of week \( w \) it is observed that an SKU/store combination at \( w + 1 \) has no sales data anymore (in real life this can correspond to a product that is not in the assortment in a store anymore), the corrections in Equation 17 are carried out.

\[
\text{if } s \in S_{j,w} \land s \notin S_{j,w+1} \text{ then}
\]

\[
\text{WeekForecast}_{j,w} = \text{WeekForecast}_{j,w} - \text{WeekForecast}_{j,s,w}
\]

\[
\text{WeekDemand}_{j,w} = \text{WeekDemand}_{j,w} - \text{WeekDemand}_{j,s,w}
\]

\[
\text{VarianceUsed}_{j,w} = \text{VarianceUsed}_{j,w} - \text{VarianceUsed}_{j,s,w}
\]

\[
\text{WeekVariance}_{j,w} = \text{WeekVariance}_{j,w} - \text{WeekVariance}_{j,s,w} \tag{17}
\]

6.6.3. Store order fulfilment
Orders from the stores at the DC, are delivered next day or two days later if the order is placed on Saturday. The order is delivered completely if there is sufficient stock at DC. If the inventory of an SKU at the DC is not sufficient to fulfill all orders of the stores, the available stock on the DC gets allocated to the stores based on the following method. First of all, the fraction of the total amount of orders that can be fulfilled gets calculated per SKU. We call this the fulfillment fraction \( D_{i,j} \). It gets calculated by dividing the quantity that is on stock (so can be delivered) by the quantity that is demanded by the stores.

\[
\text{fulfillmentfraction}_{i,j} = \frac{\text{OrderedQuantity}_{i,j}}{\sum_{s \in S_{j,w}} \text{Order}_{i,s}} \tag{18}
\]
Subsequently products get allocated to stores based on their order quantity multiplied with the fulfilment fraction of the DC and rounded up. They get delivered after the corresponding lead time.

\[ \forall s \in S_j: \text{Delivered}_{i+1,j,s} = \lceil \text{fulfilment fraction}_{DC,j} \times \text{Order}_{i,j,s} \rceil \]  

Orders are allocated to stores until no inventory is left on the DC. No backorders are made for the part of the orders that could not be fulfilled.

6.7. Validation and verification

Balci (1994) [25] emphasizes that validation, verification and testing (VV&T) is extremely important for the success of a simulation study. Conform the simulation life cycle in Figure 5, VV&T has been anchored in the steps towards creating the final results. The iterative character of the life cycle together with VV&T ensured that in steps, the simulation modules where tested and redesigned (going a step back in the life cycle) if deficiencies where found. Validation, verification and testing techniques that were used are informal techniques (inspections, walkthroughs, face validation, audit, desk checking), static techniques (structural analysis, consistency checking, data flow analysis), dynamic techniques which requires execution of the model (e.g. visualization, black-box testing, debugging, execution monitoring, sensitivity analysis, graphical comparisons), symbolic techniques (path analysis, partition analysis) and constraint techniques (assertion checking, boundary analysis). This taxonomy has been the basis of guaranteeing the simulation quality.
7. Results

In this section, the results of the simulation will be discussed. The results will be generated according to the sequence as described in the conceptual model.

7.1. Optimizing SAF parameters

The first step is optimization of the parameters of the ordering system. This optimization is performed for the two studied categories combined. In particular, we aim to find the MSS and service levels that minimize the objective function. For different configurations of the MSS, the simulation performances are described in column 2 to 6 of Table 16. Per configuration, 162 service level group combinations are computed. Per configuration, the service level combination that minimizes the objective function, and meets the availability criteria is chosen and depicted. In column 1, the current actual performance in the categories is presented, where store managers structurally deviate from the order proposals. Column 2 represents the costs when the current parameter settings are used in the simulation and where no human interference takes place. Column 3 and 4 show the results when the MSS is set to respectively 1 and 0 for every SKU. Column 5 and 6 show the performance when the safety stock is a max function of the calculated safety stock and the MSS of respectively 2 and 1.

First of all, it can be observed that when the current parameter settings are used without interfering in the system, the costs of waste from the simulation are really high relative to the costs of waste of the other configurations. This is a sign that the current settings of the parameters are far from optimal. The high MSS (uncorrelated with demand characteristics) together with the relative low service level definitions (correlated with demand characteristics) results in a situation where the stock levels are often too high for the wrong products. This observation supports the feedback of the store managers that the ordering system’s performance is insufficient. From the difference between the simulated waste costs and the current actual waste costs, it can be concluded that currently store managers improve significantly on the order proposals. However, it has to be emphasized that the simulation is a simplified representation of the real ordering system. The used ordering system has more historical data, includes seasonality, calendar effects and more advanced tools for e.g. outlier detection. For this reason, it is expected this gap would be somewhat less in reality. Still, considering the magnitude of the gap, it is convincing that managers currently improve upon the order proposals. Donselaar et al. (2010) [22] and Trapero et al. (2013) [23] also describe that store managers can improve upon an automated replenishment system by incorporating factors like in-store handling costs, sales improvement potential through better in-stock, and judgmental adjustments. We regard this improvement potential at a wholesaler larger than at a supermarket, since managers can incorporate for example large customer orders when doing order adjustments.

When setting the MSS to 1 (column 3 of Table 16), a significant drop in waste costs (29%) takes place compared to the simulation results with the current parameter settings (column 2). When overall costs are regarded (including picking costs), the reduction is 25%. Compared to the current performance (column 1), the overall costs are reduced with 4.1%. However, in reality it is expected that the more advanced functionalities of the system will result in better order proposals. This together with occasional but useful interference of store managers (for e.g. customer orders, weather influence, local events), will probably result in a substantially higher potential than 4.1%.
<table>
<thead>
<tr>
<th>Current performance</th>
<th>Simulation results</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Differentiated service levels</strong></td>
<td><strong>Single service level performance with MSS=1</strong></td>
</tr>
<tr>
<td></td>
<td>Current parameters</td>
</tr>
<tr>
<td>Waste per year in €</td>
<td>117k</td>
</tr>
<tr>
<td>Picking costs per year in €</td>
<td>30k</td>
</tr>
<tr>
<td>Overall costs per year in €</td>
<td>147k</td>
</tr>
<tr>
<td>% waste € of sales</td>
<td>3.38</td>
</tr>
<tr>
<td>Stock availability</td>
<td>0.954</td>
</tr>
<tr>
<td>Customer availability</td>
<td>-</td>
</tr>
<tr>
<td>Freshness</td>
<td>0.62</td>
</tr>
<tr>
<td>Service level uss1</td>
<td>0.90</td>
</tr>
<tr>
<td>Service level uss2</td>
<td>0.90</td>
</tr>
<tr>
<td>Service level ss1</td>
<td>0.90</td>
</tr>
<tr>
<td>Service level ss2</td>
<td>0.90</td>
</tr>
<tr>
<td>Service level fs1</td>
<td>0.93</td>
</tr>
<tr>
<td>Service level fs2</td>
<td>0.93</td>
</tr>
</tbody>
</table>
When the MSS is set to 0 (column 4), the improvement is even larger. Compared to the simulation results with the current parameters, a reduction of 32% in overall costs takes place. Compared to the current performance, this improvement is 13.2%. Again it is expected that the real ordering system together with useful human interference will create a substantially higher potential.

The results of the max functions (column 5 and 6) only differ slightly from the MSS=0 configuration. This can be explained by the fact that it is very rare that the safety stock gets lower than 1 or 2, so mostly outcomes of ordering will be identical to the MSS=0 setting. From all the settings, MSS=0 results in the lowest costs. However, because Makro prefers some certainty considering stock availability (which is how they currently measure availability), the MSS=1 (stock availability of 0.955) setting will be used as default setting for further improvement steps in this report. Based on management preferences, the adjustment can be made to set the MSS to zero as an alternative choice.

It can be observed that reducing the MSS together with increasing and optimizing the service level parameters, can lead to significant reductions in overall costs while meeting the same customer availability. The shift is made from high MSS levels (uncorrelated with demand) to higher service levels (correlated with demand). This results in more compliant inventory management, which not only has a cost advantage, but also positively influences product freshness (see Table 16). As mentioned before, Makro currently measures availability in stock availability. From Table 16 it can be seen that the stock availability drops as MSS gets lower. This can be explained by the service level differentiation. Since slow movers have a relatively lower service level, this results in more frequent stock outs for this products. However, since the faster moving products create more demand, higher availability here has a higher impact on customer availability. This fact has to be taken into consideration when recommendations are implemented. Stock availability is likely to drop, but customer availability stays the same. A slight increase in stock outs for slower moving products is not expected to be harmful for sales and image, since these are often products where customers are willing to substitute, especially in the categories that are studied here.

### 7.1.1. Service level differentiation

To investigate whether service level differentiation has a benefit on the overall costs compared to setting a single service level for all products, an additional analysis is performed. This analysis also shows how waste and overall costs relate to customer availability. For 17 different single service levels, the simulation was performed with the MSS=1 setting. The results comprise a customer availability between 0.95 and 0.98. From column 7 to 23 in Table 16, the performance per single service level is depicted. The single service level performance is compared with the performance of the differentiated service levels of the MSS=1 configuration (column 3). From the results it can be observed that when we aim for a customer availability of 0.97, a single service level between 0.94 and 0.95 should be taken. When we compare this with the optimized and differentiated service levels in column 3, we observe that the single service level definition results in 2.8% higher overall costs. This cost difference is almost completely provoked by the increase in waste (3.6% increase in waste). It is questionable whether this percentage is worth the extra computational effort and managerial complexity. Still, a 2.8% cost reduction in a low-margin industry is substantial and a valuable step towards a more efficient supply chain.

To get an impression of the direct impact of reduced customer availability on lost sales costs, an example is given. As it is assumed that the customer availability in the actual current situation is equal to 97%, the hypothetical sales of €3.46 million would translate to a yearly demand of €3.57 million. Accordingly, a 1% drop in availability means approximately €36k of lost sales. Looking to the missed profit, this
amount is even substantially lower because of the products’ margin. When margin is around 20%, this means a profit loss of €7.2k. The reduction in overall costs when we lower the customer availability from 0.97 to 0.96, is approximately €24k. Hence, €7.2k in lost profit costs relates to €24k reduction in overall costs. Although other factors like the effect of reduced availability on customer visits (negative effect) and substitution (positive effect) have to be taken into consideration, this shows the importance of a good balance between waste and availability. When decreasing the customer availability from 0.97 to 0.95 (which is often used as fill rate for perishables by retailers), a drop of €39k in overall costs relates to €71k in lost sales and €14k in lost profit.

7.2. Promoting FIFO behavior
We have discussed the influence of FIFO and LIFO behavior on waste in previous chapters. However, we are particular interested in what the improvement potential is at Makro when they manage to better promote FIFO amongst customers. Since it is advised to change the MSS to 1 for all products in the previous section, this setting is used for making the comparison between pure FIFO, the current proportion FIFO/LIFO and pure LIFO. Again we aim for a fill rate of 0.97.

The results are depicted in Table 17. It can be observed that the relation between customer behavior and the overall costs doesn’t seem linear, but rather exponential. The influence of more LIFO behavior on overall costs gets larger as the proportion of LIFO picking increases. In Figure 22 a plot is shown of the overall costs versus the amount of LIFO behavior. The x-axis of this graph represents the proportion of LIFO picks, so 0.1 implies that 10% of the customers pick LIFO and the other 90% pick FIFO when they have a choice. The convex relationship between the picking behavior and the costs might be explained by the fact that in the current situation where the picking behavior is partly LIFO, still enough FIFO is picked to sell the batch before its shelf life is reached. At a certain point towards the pure LIFO side, the oldest batch doesn’t get sold completely anymore and gets partly wasted. This finding is in agreement with Broekmeulen & Van Donselaar (2016) [6]:

“If a relatively large part of the consumers still trust the supermarket and buy the oldest item on the shelf, the effect on the percentage of waste is limited (compared with the situation that all consumers buy the oldest item on the shelf)”
(Broekmeulen & Van Donselaar, 2016, p. 16)

Substantial advantages can be obtained when customer behavior can be better promoted towards FIFO. The results show a potential of 20.4% overall cost reduction compared to the current picking behavior scenario with optimized parameters. The reduction in waste compared to the waste of the current picking behavior is 24.9%.

It can be concluded that measures to influence customer picking behavior can be highly effective to reduce waste, but also to reduce picking costs in the DC. Furthermore, it likely leads to reduced handling costs in the stores, since less products have to be handled and thrown away. However, as indicated before, this potential is very uncertain and different amongst stores, so for this reason not included as a cost factor in this report. From Figure 22 it can be seen that from the middle point in the graph (current situation), the first reduction in proportion LIFO along the x-axis results in a larger reduction in overall costs than a reduction close to pure FIFO. If Makro manages to reduce LIFO picking behavior in this
article groups to 25%, it will employ approximately 75% of the potential cost reduction of pure FIFO. This is due to the convexity of the relationship. It can be stated that when there is a substantial amount of LIFO picking, a small reduction in this proportion can lead to relatively high reductions in overall costs.

Table 17. Simulation results for different proportions of FIFO/LIFO, and the impact on performance of including week pattern. For all tests MSS is set to 1 and the service levels are differentiated. Cost figures are scaled with an undisclosed key.

<table>
<thead>
<tr>
<th>Waste per year in €</th>
<th>FIFO</th>
<th>Limit the # dates in the shelf to 2</th>
<th>Current FIFO/LIFO proportion</th>
<th>LIFO</th>
<th>Performance when not including week pattern in order calculation</th>
</tr>
</thead>
<tbody>
<tr>
<td>€84k</td>
<td>€96k</td>
<td>€111k</td>
<td>€232k</td>
<td>€112k</td>
<td>Current FIFO/LIFO proportion</td>
</tr>
<tr>
<td>Picking costs per year in €</td>
<td>€29k</td>
<td>€29k</td>
<td>€30k</td>
<td>€34k</td>
<td></td>
</tr>
<tr>
<td>Overall costs per year in €</td>
<td>€112k</td>
<td>€128k</td>
<td>€141k</td>
<td>€266k</td>
<td></td>
</tr>
<tr>
<td>% waste € of sales</td>
<td>4.41</td>
<td>2.78</td>
<td>3.22</td>
<td>6.71</td>
<td></td>
</tr>
<tr>
<td>Stock availability</td>
<td>0.95c</td>
<td>0.955</td>
<td>0.955</td>
<td>0.947</td>
<td></td>
</tr>
<tr>
<td>Customer availability</td>
<td>0.971</td>
<td>0.971</td>
<td>0.970</td>
<td>0.969</td>
<td></td>
</tr>
<tr>
<td>Freshness</td>
<td>0.65</td>
<td>0.60</td>
<td>0.63</td>
<td>0.59</td>
<td></td>
</tr>
<tr>
<td>Service level uss1</td>
<td>0.93</td>
<td>0.93</td>
<td>0.93</td>
<td>0.95</td>
<td></td>
</tr>
<tr>
<td>Service level uss2</td>
<td>0.93</td>
<td>0.93</td>
<td>0.93</td>
<td>0.95</td>
<td></td>
</tr>
<tr>
<td>Service level ls2</td>
<td>0.93</td>
<td>0.93</td>
<td>0.93</td>
<td>0.97</td>
<td></td>
</tr>
<tr>
<td>Service level f31</td>
<td>0.95</td>
<td>0.95</td>
<td>0.95</td>
<td>0.98</td>
<td></td>
</tr>
<tr>
<td>Service level f32</td>
<td>0.95</td>
<td>0.95</td>
<td>0.95</td>
<td>0.98</td>
<td></td>
</tr>
</tbody>
</table>

Figure 22. Overall relevant costs as a function of the proportion of LIFO behavior. Cost figures are scaled with an undisclosed key.

An area that offers a lot of potential to promote FIFO at Makro is space management. It has been observed that currently there is often a high amount of shelf space and facings per SKU in the stores. Besides that, from the customer behavior experiment we have found a statistical significant positive correlation between the number of facings and the picking behavior. For this reason, it is recommended to reduce redundant shelf space for products and match the amount of facings and shelf space more with demand characteristics of the products. This will result in a lower proportion of LIFO picking behavior because of less facings. Moreover, as the shelves become fuller and products are placed closer to each other, it is also expected to make it more complicated for customers to check dates, which also has a positive influence on FIFO behavior [29]. Another advantage is that when shelf space is saved, the
possibility might arise to reduce the amount of used shelves in the stores, hence saving energy and offering more store space for other products in the store. How allocated shelf space could be a function of certain demand characteristics, will not be discussed in this report, but is an interesting area for further research.

Another interesting measure to promote FIFO behavior, is analyzing the store policy of reducing the amount of dates in the shelf to 2. By employing this policy, the amount of dates in the shelves are monitored and limited to two. When store employees observe that by replenishing the shelf the limit of the amount of dates gets exceeded, they store this batch in the backroom until it can be replenished without trespassing this limit. This policy is currently a recommendation from the headquarters, however a large part of the stores don’t (fully) adhere to this policy. The policy is expected to have benefits in that it reduces the LIFO behavior (in chapter 4 we concluded that more dates in the shelf lead to more LIFO picking). In the first and second column in Table 16, the current picking behavior with optimized service levels and MSS=1 is compared with the policy that limits the amount of dates in the shelf to two with optimized service levels and MSS=1. It can be observed that this policy has a lot of potential, as it reduces waste with 13.5%.

### 7.2.1. Week pattern
A limited studied area in inventory management is the influence of the week pattern for waste and out-of-stocks. We analyze if it is beneficial for the overall performance to include the week pattern in order calculation. Mattsson (2010) [30] describes that if the ratio between the busiest and quietest day is below 1.7, the week pattern doesn’t need to be taken into account. For the studied categories, the week pattern has been shown in Table 14. If the overall week pattern is regarded, it can be observed that the ratio between the busiest and the quietest day (Friday and Sunday) is 2.53. For this reason, according to Mattsson (2010) [30], the week pattern needs to be take into account. The ratio is especially high because of the low sales on Sunday. When the other days are regarded, there are no larger ratios than 1.7.

In the fifth column of Table 17 it can be observed that the overall costs in the simulation run where the week pattern is not taken into account are slightly higher with 0.53% compared to the situation when the week pattern is taken into account. It can be observed that the service levels need to be somewhat higher in the situation where the week pattern is not taken into account, in order to obtain the same customer availability. However, the eventual cost advantage is only marginal. For this reason, it can be concluded that the week pattern is not a critical factor for Makro which needs to be taken into account for dairy and salads. It is expected that the relatively high shelf life for perishables makes them not very sensitive to this pattern. The week pattern is more important to be taken into account for products with short shelf lives together with high week pattern. For this reason it is always advised to keep using this functionality in the ordering system. Moreover, because there is still a cost advantage, it is always beneficial to use the functionality for the studied categories too.

### 7.3. Flow type selection/unpacking
After improving the system’s parameter settings (and ordering behavior), the next step is to investigate different flow types. As indicated before, the flow type selection is analyzed down to a supplier level of detail. A first step in the flow type selection when the decision is made towards another flow type than BBXD, is to define a new optimized set of service levels that conform to the availability constraints. First of all, we regard the TWCP flow type. Because in TWCP the change is made to daily delivery from DC to
the store, the influence of the set service levels on the fill rate changes (the same service levels result in a lower fill rate because of lower lead times and uncertainty at the DC). As mentioned before, for the DC we aim for a fill rate of 0.80 to guarantee product freshness, which approximately corresponds to a service level of 0.62. Subsequently, the single service level that meets the 0.97 fill rate for the whole dataset, is determined when TWCP is the flow type. This corresponds to a service level of 0.98. Given this result, service levels are differentiated around this service level to investigate the advantage of differentiation for TWCP. The corresponding performances of the best differentiated service level configuration and the best single service level configuration are depicted in Table 18. All suppliers are investigated for flow type selection, except one. This particular supplier is excluded because given the short shelf life of the SKU’s (milk and yoghurt) that it delivers, the current flow type (cross-docking 6 times a week) is regarded as the most productive option. Moreover, during the steps that have been taken so far, waste for this supplier has dropped to a very low level compared to other suppliers, so offers low improvement potential for waste reduction.

From the results it is found that differentiation in the service levels results in a reduction of 4.1% in overall relevant costs for TWCP. When we compare the costs of TWCP and differentiated service levels (column 5) with BBXD costs and differentiated service levels (column 1), it can be seen that TWCP has lower costs of waste, with a cost reduction of 5.6%. However, the picking costs increase substantially as a result of the increased picking tariff in the DC (from €0.27 to €0.42). However, currently TWCP is only used for frozen products. For fresh produce Makro doesn’t hold inventory for any category. For that reason, it is a new process in the DC and might offer room for negotiating the tariff. For the current tariff, the increase in picking costs would be 50%, which outweighs the benefits in waste reduction of TWCP. Also costs for demand planning come into play when TWCP is the selected flow type. On the other hand, significant savings in inbound logistics can be observed which largely outweigh the demand planning and extra picking costs. As a result TWCP has lower overall costs than BBXD. Demand planning and inbound logistic costs are based on estimations from management. Since the exact costs and savings are not exactly known, a sensitivity analysis is performed on this parameters in Section 7.4. Especially the inbound logistics are uncertain, as it is highly dependent on agreements, the suppliers’ current distribution design and negotiations. If the potential savings are only one third of the currently used tariff (€0.33 per km), costs of TWCP would be approximately equal to BBXD. Hence, if the average tariff is larger than €0.33, TWCP would be the preferred flow type over BBXD.

Furthermore, it can be observed that when customer behavior is more promoted towards FIFO, the difference between TWCP and BBXD considering waste costs decrease. Costs of waste for BBXD are even lower than for TWCP when the number of dates in the shelves are limited to 2 or customer picking behavior is FIFO. This can be explained by the fact that the stock reducing influence of TWCP is less critical in waste reduction when a larger proportion of the customers pick FIFO. In Table 18 it can be observed that if the ‘limit the number of dates in the shelves to 2’ policy is used for BBXD, the number of dates in the shelves is strongly reduced, which offers a lower improvement for TWCP. When picking behavior is pure FIFO the number of dates in the shelf don’t matter at all, because all customers pick the oldest item. TWCP has the disadvantage of introducing an extra stock point which has a negative influence on the shelf life at arrival in the store. Moreover service levels for the stores at TWCP have to be higher to account for the uncertainty of the lower fill rate of the DC. The result is that BBXD is more cost efficient at higher FIFO proportions if the flow type selection is made for all suppliers combined.
Table 18. Performance per flow type for different service level definitions and customer behavior when all suppliers belong to the same flow type. Cost figures are scaled with an undisclosed key.

<table>
<thead>
<tr>
<th></th>
<th>BBXD</th>
<th>TWCP</th>
<th>TWCU</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>differentiated service levels and current behavior</td>
<td>differentiated service levels and current behavior</td>
<td>differentiated service levels and current behavior</td>
</tr>
<tr>
<td>Waste per year in €</td>
<td>111k 97k 84k</td>
<td>111k 105k 98k 86k</td>
<td>100k 88k 74k 61k</td>
</tr>
<tr>
<td>Picking costs per year in €</td>
<td>28k 28k 27k</td>
<td>42k 42k 42k 41k</td>
<td>200k 198k 194k 191k</td>
</tr>
<tr>
<td>Demand planning costs in €</td>
<td>- - -</td>
<td>10k 10k 10k 10k</td>
<td>10k 10k 10k 10k</td>
</tr>
<tr>
<td>Savings inbound logistics in €</td>
<td>- - -</td>
<td>54k 54k 54k 54k</td>
<td>54k 54k 54k 54k</td>
</tr>
<tr>
<td>Overall costs per year in €</td>
<td>139k 124k 111k</td>
<td>107k 103k 95k 83k</td>
<td>255k 242k 224k 208k</td>
</tr>
<tr>
<td>Stock availability</td>
<td>0.954 0.955 0.954</td>
<td>0.967 0.966 0.966 0.964</td>
<td>0.978 0.974 0.975 0.977</td>
</tr>
<tr>
<td>Customer availability</td>
<td>0.969 0.970 0.970</td>
<td>0.969 0.969 0.969 0.969</td>
<td>0.970 0.969 0.970 0.971</td>
</tr>
<tr>
<td>Freshness</td>
<td>0.63 0.60 0.64</td>
<td>0.59 0.59 0.57 0.60</td>
<td>0.61 0.62 0.57 0.63</td>
</tr>
<tr>
<td>Average freshness</td>
<td>0.47 0.48 0.51</td>
<td>0.45 0.45 0.46 0.49</td>
<td>0.44 0.45 0.46 0.49</td>
</tr>
<tr>
<td>Average number of dates</td>
<td>1.93 1.60 1.76</td>
<td>1.79 1.76 1.58 1.61</td>
<td>2.36 2.26 1.78 2.22</td>
</tr>
<tr>
<td>Service level uss1</td>
<td>0.93 0.93 0.93</td>
<td>0.98 0.96 0.96 0.96</td>
<td>0.995 0.98 0.98 0.98</td>
</tr>
<tr>
<td>Service level uss2</td>
<td>0.93 0.93 0.93</td>
<td>0.98 0.96 0.96 0.96</td>
<td>0.995 0.98 0.98 0.98</td>
</tr>
<tr>
<td>Service level ss1</td>
<td>0.93 0.93 0.93</td>
<td>0.98 0.97 0.97 0.97</td>
<td>0.995 0.98 0.98 0.98</td>
</tr>
<tr>
<td>Service level ss2</td>
<td>0.93 0.93 0.93</td>
<td>0.98 0.98 0.98 0.98</td>
<td>0.995 0.99 0.99 0.99</td>
</tr>
<tr>
<td>Service level fs1</td>
<td>0.95 0.95 0.95</td>
<td>0.98 0.98 0.98 0.98</td>
<td>0.995 0.997 0.997 0.997</td>
</tr>
<tr>
<td>Service level fs2</td>
<td>0.95 0.95 0.95</td>
<td>0.98 0.98 0.98 0.98</td>
<td>0.995 0.997 0.997 0.997</td>
</tr>
</tbody>
</table>
In the last three columns of Table 18 the performance of the Traditional Warehousing in Consumer Units flow type (TWCU) is described. In this flow type all products are unpacked in the DC, hence the MOQ for the stores is equal to 1. Because the case pack in which products are delivered to the DC doesn’t form a limitation anymore, this flow type results in the lowest costs of waste of all flow types. Stores now order an amount that exactly fits their needs in terms of demand, and as a result the FCC gets significantly lower. As we have found in Section 2.3, the FCC is a relatively good predictor of waste. However, if the MOQ gets reduced to one, stores order more often in smaller amounts. As a result the chance increases that more expiration dates of the same product will end up in the shelf, which as we have found in Section 4.3 results in more LIFO picking and hence in more waste. Compared with BBXD, the reduction in waste is 21% for current picking behavior. When the ‘limit the number of dates in the shelves to 2’ policy is used effectively, the reduction in waste is 23% when the flow type is TWCU instead of BBXD. When customer picking is pure FIFO, the reduction is 27%. This last configuration results in the lowest costs of waste so far. However, because the current costs of handling 1 CU in the DC is equal to the handling costs of a whole case pack, the picking costs are extremely high in TWCU (≈700% higher than BBXD), since now €0.42 are the handling costs for 1 CU. This results in TWCU being a tremendously inefficient flow type under this tariff. Because the unpacking costs are currently not balanced right and excessively high, negotiations have to take place in order to make unpacking interesting. In the sensitivity analysis it is analyzed under which picking tariff TWCU becomes interesting.

Given the differentiated service levels per flow type in Table 18, the next step is to analyze the flow type selection at a supplier level. Hence, for certain suppliers BBXD might be optimal, while for others e.g. TWCP is optimal. In Appendix F per supplier a cost overview is depicted, where the first column represents BBXD, the second column TWCP, the third column TWCU and the last column TWMixed. Currently unpacking is almost never beneficial because of the high picking costs. In Figure 23 for two of the suppliers the costs for the different flow types are shown. For Supplier G it can be observed that the inbound logistics savings are very influential in the flow type selection decision. Because the production site of Supplier G is geographically far from the DC, this savings potential is very large. The actual inbound logistics savings have to be determined in deliberation with the supplier in order to assess the actual potential. In Appendix F comparable situations can be found. For Supplier N in Figure 23 no savings in inbound logistics costs can be made (they already have two delivery moments per week). However, it can be observed that there is a considerable reduction opportunity in waste for TWCP. In overall costs, TWCP also performs better than BBXD. This difference can be even higher when one manages to reduce demand planning costs or the picking tariff in the DC. It can also be observed that for some SKU’s the current waste is so high, that under the current unpacking costs it is profitable to unpack them, hence TWMixed has lower overall costs than TWCP. With the current picking tariff for unpacking, that is a sign that an SKU is probably not profitable at all, and should be evaluated on whether it should be in the assortment in the first place.

7.4. Sensitivity analysis
In the previous section we have concluded that some parameters are especially influential in determining the most cost efficient flow type. In this section, different settings for these parameters will be evaluated to investigate the sensitivity of the objective function towards this parameters. Threshold values for the parameters will be sought for the two suppliers described in the previous section, so that the cost difference between two or more flow types can be assessed under different scenarios.
7.4.1. Picking costs

We have shown that the unpacking tariff of €0.42 results in excessive picking costs. These picking costs however also comprise things like depreciation of the warehouse, system costs and fixed costs. As order picking is only a certain fraction of the handling costs, part of this tariff doesn’t get influenced by unpacking. According to Van der Vlist (2007) [8] order picking costs accounts for approximately 20% of the logistics costs of the retailer. The service provider of Makro also charges transportation costs. According to Van der Vlist (2007) [8] these costs account for 32% of the logistics cost of the retailer. For the additional costs (which comprises 48% of the costs), it is not known how they are distributed over the two cost areas. When all these costs are incorporated in the picking tariff, the effected percentage would be 30%. When none of the costs are incorporated in the picking tariff, the effected percentage would be 100%, and results would be as described in previous section. When half of these costs are incorporated in the picking tariff, the effected percentage would be 45%.

For Supplier N, it is analyzed what the corresponding effect would be if respectively only 30% and 45% of the tariff would be influenced by unpacking. The results are depicted respectively in Figure 24 and Figure 27, where picking behavior is as current and MSS=1 with differentiated service levels. When the results are compared with the costs in Figure 23, a large overall cost difference can be observed for TWCU and TWMIXED. At an affected percentage of 30%, TWMIXED is the optimal flow type with a yearly cost benefit of 24.6% reduction compared to BBXD. Also when the percentage is 45%, TWMIXED is the optimal flow type. We can conclude that the flow type selection for Makro is highly dependent on the costs of unpacking case packs, where unpacking can offer significant cost reductions when unpacking costs are relatively balanced.

7.4.2. Customer picking behavior

The positive influence of effectively promoting FIFO picking on overall performance has been shown in previous chapter. This customer behavior also influences the flow type selection. For Supplier N, the overall costs per flow type, where effectively the ‘limit the number of dates in the shelf to 2’ policy is used, are depicted in Figure 26 and Figure 25. Results are again shown for the affected part of the tariff for unpacking of respectively 30% and 45%. It can be observed that as picking behavior is forced to move more towards FIFO, costs decrease for all flow types. However, for TWCU the improvement in waste is 2% instead of 1% for BBXD and TWCP. It can be concluded that the gap in waste between TWCU and
BBXD/TWCP becomes larger as picking is promoted more towards FIFO. As a result, the potential percentage reduction in overall costs becomes larger. In Figure 26 the overall cost improvement of TWMIXED versus BBXD is 26%. It can be concluded that as customer picking behavior is better controlled, unpacking becomes relatively more interesting.

**Figure 24. Overall costs per flow type when affected part of \( c^h_{TWCP} \) when unpacking is 30%**

**Figure 25. Overall costs for # dates to two policy when affected part of \( c^h_{TWCP} \) when unpacking is 30%**

**Figure 26. Overall costs per flow type when affected part of \( c^h_{TWCP} \) when unpacking is 45%**

**Figure 27. Overall costs per flow type when affected part of \( c^h_{TWCP} \) when unpacking is 45%**

**7.4.3. Inbound logistics cost**

Currently the savings in inbound logistics are calculated based on savings in transportation distance. The current used tariff is €1.00 per km. Consequently, suppliers that are located further away from the DC, have larger cost savings in inbound logistics per reduced ordering/delivery moment. The Supplier G’s production facility is located 285km from the DC. For the used tariff this would translate to a cost saving of 285*2=€570 per reduced ordering/delivery moment per week, which is €29,640 per year. The €1.00 saving per km might be overestimated. The supplier might do a certain routing in the area, which substantially reduces the transportation costs and as a result also the savings potential. For this reason, it is investigated how the graph looks if a fixed saving of respectively €50 or €150 per ordering/delivery moment can be made at the supplier. Results are depicted in Figure 28 and Figure 29. Here picking
behavior is as current, picking costs are as current and MSS=1. It can be observed that even if the savings are as low as €50 per delivery moment, the savings are substantial enough to be decisive in the flow type selection towards TWCP.

In this section, the simulation results are compared with results of the Sell More, Waste Less tool [6]. This comparison functions as part of the validation of the simulation model. Furthermore it can be investigated to what extent the Sell More, Waste Less tool might be appropriate to help managers at Makro in investigating the net benefits of certain operational and logistical adjustments. Because the Sell More, Waste Less tool bases its calculations for the reorder level on the target fill rate, the MSS is not included. Hence, MSS increases the reorder level and as a result influences the set fill rate. For this reason, the simulation and Sell More, Waste Less tool are compared for the current BBXD flow type with setting the MSS to 0. Because the Sell More, Waste Less tool only allows calculations with pure FIFO or LIFO behavior, the simulation model is run accordingly. For five fill rates (0.95 till 0.99), the results of both FIFO and LIFO are compared. The results are depicted in Figure 30 and Table 35 in Appendix N.

It can be observed that for fill rates in the upper middle of the researched range (0.98 and 0.97) the results are relatively similar. Especially the FIFO results at the 0.98 fill rate level are relatively close to each other. However, at lower fill rates the FIFO results start to differentiate more from each other. Also at higher levels the difference is significantly higher. For the LIFO results the movement is similar, the results deviate more for higher and lower fill rates. For the higher fill rates the difference can be caused by some outliers that are present in the simulation. As a result the service levels need to be set really high in order to have a high customer availability (see service levels in Table 35 in Appendix N for LIFO at a customer availability of 0.99). This however results in really high numbers of waste. It can be concluded that the range between FIFO and LIFO is larger in the simulation (see Figure 30). The response of % waste on fill rate adjustments, is higher in the simulation. At the current fill rate goal (0.97), the range of the Sell More, Waste Less tool is regarded similar enough to validate the model.

**7.5. Sell More, Waste Less tool**

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Some areas deserve extra attention when interpreting the differences. First of all, the Sell More, Waste Less tool does not take into account the week pattern, while the simulation model does. However, as we have concluded earlier in this report, including the week pattern (when it is limited) in order calculation only has a very small advantage. For that reason, it is not expected to be the major driver of the discrepancies between the two models. Secondly, when using the Sell More, Waste Less tool, some input values had to be scaled. The tool cannot work with values of L and R that are higher than 2.5, however many of the current lead times and review periods are larger than this value. This made scaling necessary. Nevertheless, this might have resulted in a lower accuracy, since the tool is based on real life data, which might not accurately allow scaling. Another factor influencing the difference can be the variance in lead times, which is not taken into account in the Sell More, Waste Less tool (fixed average lead times are used). Finally, a lot of other factors might be a driver of the differences, e.g. the forecasting method, the demand pattern, the characteristics of simulation in general or the use of an initialization period in the simulation (which was excluded from the results of the simulation).

Given computational differences, the similarity is satisfying at the targeted fill rate. For this reason, the Sell More Waste Less tool could be used with relative reliability to evaluate the impact of changing certain product, demand and logistical characteristics. However, since Makro currently has a mix of FIFO and LIFO, exact impacts can’t be investigated. What can be used to approximate impacts, is to use Figure 22 and estimate the position between FIFO and LIFO on the range that the tool gives. In this way, possible impacts of changing e.g. MOQ or the shelf life can be investigated. When analyzing the two echelon system, differentiating service levels or regarding the influence of MSS, the simulation model is the only method that is adequate for analysis.
8. Conclusions and Recommendations

This chapter will conclude the study by answering the research question and reflecting on the scientific contribution. Furthermore, the most important recommendations for Makro to reduce waste for their fresh products are presented. The recommendations are formulated from all insights that are gained throughout the study. These are based on the study of two fresh product groups: Milk products and Sandwiches & Spreads. However, a significant part of this findings are relevant for all Makro’s fresh products and especially the methodology and structure can be used to reduce costs in other fresh categories. This chapter ends with describing the limitations and directions for future research.

8.1. Conclusion

This study describes different improvement steps towards reduction of waste and overall costs for fresh products at Makro using a simulation model. Simulation allows close to real-world analysis of different configurations without the need to make many simplifying assumptions. The taken improvement steps facilitate overall cost reductions from an operational and logistics point of view. As a result, it considers the current assortment per store as fixed and investigates how under current demand characteristics overall costs can be minimized. For the studied categories, the group level fill rate at the store is aimed to be $\approx 0.97$, and if inventory is held at the DC, the DC fill rate is aimed to be $\approx 0.80$. We address our main research question and answer the three components which comprises it.

| Which ordering system parameters, store procedures and flow types minimize overall costs and costs of waste for Makro’s fresh product categories? |

8.1.1. Ordering system parameters

The first improvement opportunities analyzed in this study were focused on improving the current parameter settings of the ordering system. As this only requires altering system values, this is the lowest investment improvement potential and therefore the first unit of analysis. Two parameter groups in the ordering system have been denoted as especially influential for the current costs of waste: service level settings and the Minimal Shelf Stock (MSS). In agreement with previous research [6] it has been shown that the relationship between waste and availability is exponential of nature. Although retailers aim for a high customer satisfaction with high product availability, they should be aware that always aiming for the highest availability, isn’t the most profitable goal as it can have a very detrimental influence on waste costs. One should consciously choose at which point availability and waste should be balanced. It has been shown that the current defined service levels in combination with the MSS settings result in a situation with excessively large costs of waste when no human interference takes place in the order proposals. An important driver of these costs is the MSS, which is currently set too high for many SKU/store combinations. Since the MSS is an extra stock assurance on top of the calculated forecast and safety stock (which already assures a certain customer availability), it is often extra stock that is not sold and subsequently gets waste. MSS settings higher than one are especially problematic for slower moving products, since it shifts the balance between waste and availability towards unhealthy levels. It has been shown that reducing the MSS to one or to zero together with increasing (optimizing) the service levels (which are used for safety stock calculations), leads to significant reductions in overall costs while having only a minor reduction in availability. This can be explained by the shift from holding stock that is uncorrelated with demand characteristics (MSS) towards holding stock that is correlated with demand characteristics (safety stock). Furthermore, we show that differentiating service levels for slow movers and fast movers can reduce overall costs, while meeting the same customer availability. By
setting lower service levels for slower moving products, we reduce stock and consequently waste at products with the highest waste issues. By increasing service levels for faster moving products, we increase stock and sales at products that contribute most to the overall availability.

### 8.1.2. Store procedures

As a preliminary analysis for the simulation, an experiment considering customer picking behavior has been conducted at two of Makro’s stores. From the experiment it was concluded that the actual proportion of LIFO picking is less than expected, but still substantial at 46% when customers have a choice in dates. From statistical analysis a highly significant positive correlation was found between the amount of dates per SKU in the shelf and the proportion of LIFO picking. Moreover a highly significant positive correlation was found between the number of facings per SKU and the LIFO behavior. A third significant negative correlation was found between the shortest shelf life and the LIFO behavior. These findings support the proved hypothesis that LIFO picking behavior in Amsterdam is higher than in Barendrecht. Hence, Amsterdam is a larger store where each SKU has more facings and more expiration dates in the shelf. Moreover, shortest shelf lives were observed to be shorter than in Barendrecht.

The found proportion FIFO/LIFO from the experiment served as input for the simulation model. In the simulation we showed that the relationship between the proportion of LIFO picking and percentage of waste is exponential. Given the same customer availability, overall costs for pure LIFO can be 2.5 times as large as costs of pure FIFO. This emphasizes the importance of controlling and influencing this picking behavior. Makro can reduce costs significantly if they manage to promote customer picking behavior more towards FIFO. A policy showed to be effective, is to limit the amount of dates in the shelf to two by keeping surplus stock in the backroom. For the currently used BBXD flow type, MSS=1 and optimized service levels this policy resulted in a simulated cost reduction of 13.5% in yearly waste costs. Other opportunities to promote FIFO can be sought in space management, e.g. reducing the amount of facings and align it with demand or reducing shelf space to hinder checking of dates. Offering a discount of products close to their expiration date is another policy that can reduce waste and promote FIFO.

### 8.1.3. Flow type selection

As final focus area for improvement, it is analyzed how the distribution network could be designed best, which is also referred to as flow type selection [8, 12, 10]. The flow type selection is analyzed on a supplier level, where the fill rate of the store is aimed to be ≈0.97 and at the DC ≈0.80 to guarantee product freshness. Based on literature, four potential flow types for the studied categories are compared: BBXD (current flow type), TWCP, TWCU and TWMIXED. Based on Appendix F, some conclusions can be made. First of all, costs of waste are for the major part of the suppliers lower for TWCP than for BBXD. For some suppliers this difference is substantial, but for others the waste reduction is very low or even negative. Substantial reduction in waste when the transition towards TWCP is made, especially takes place for suppliers that initially don’t have more than 2 delivery moments a week and have long lead times (higher than 2). For these suppliers, the decision to hold inventory on the DC decreases costs of waste because stores are much more flexible in ordering (daily ordering and delivery moments). This effect is larger than the drawbacks of holding stock in the DC: average shelf life of products that enter the store is shorter and there is an extra stock point with extra uncertainty, which has to be taken into account in the definition of the service levels. However, for a large part of the suppliers the reduction in waste gets outweighed by increased costs in picking in the DC and demand planning in the HQ. For some suppliers however, the reduction in waste is substantial enough to make TWCP the preferred flow type.
Secondly, for suppliers with initially more than two delivery moments from the supplier and/or short lead times, the waste reduction of TWCP compared to BBXD is mostly low or negative. Short initial lead times offer less opportunities to further lower lead times in TW. Furthermore, for suppliers with initially more than two delivery moments, the absence of waste reduction can be explained by the reduced number of fresh produce that gets delivered. Together with lower reliability of the fulfillment of store orders and the general lower shelf life that enters the store, this drives that waste does not get significantly reduced. However, the potential for these suppliers can especially be found in the reduction of inbound logistics. It has been shown that these savings are crucial in flow type selection and can make TWCP very preferable over BBXD.

Finally, unpacking case packs in the DC is also regarded in the TWCU and TWMIXED flow types. Unpacking takes away the limitation of the case pack and can reduce waste costs significantly, but on the other hand increases handling costs in the DC. If extra costs for unpacking are relatively balanced, it has been shown that a mix of TWCP and TWCU (TWMIXED) can lead to substantial overall cost reductions. Unpacking is especially interesting for high valued items, since then costs of waste are large relative to extra picking costs.

8.2. Recommendations to Makro
In this section a list of recommendations for Makro is provided based on the study that has been conducted. The recommendations form the guidelines for Makro to reduce waste and overall costs of waste for their fresh products. First we identify the four most important recommendations of this study:

- Reduce the Minimal Shelf Stock (MSS) to one for all products in the studied categories and simultaneously increase the system’s service level parameters for the BBXD flow type as defined in section 7.1. When this implementation is successful, an opportunity to reduce costs of waste even more, is to completely eliminate MSS and set it to zero for all products. This measure should be combined with briefing/training of department managers on how SAF works and why the new settings require limited human interference. Trust in the system should be regained.

- Align the amount of assigned facings and shelf space per SKU with the demand characteristics of the product. In the current situation this often means reducing the amount of facings and shelf space. As the amount of facings and shelf space are related with higher proportions of LIFO picking, this leads to higher waste. A better alignment of facings on product characteristics reduces waste. Moreover from literature [6, 29] it is found that reducing shelf space lowers LIFO behavior and as a result waste.

- Emphasize compliance in the stores towards the ‘limit the number of dates in the shelf to 2’ policy. As this policy reduces the number of dates in the shelves, it promotes FiFO picking and therefore reduces costs of waste (13.5% per year). This policy however requires a higher degree of monitoring from the store employees and consequently takes more time. Nevertheless, this extra monitoring costs are expected to be small compared to reductions in waste.

- Analyze per supplier the potential for inbound logistics savings and negotiate and determine the extra costs of unpacking. Subsequently, based on this costs, determine the optimal flow type per supplier. This improvement step should be done after previous steps are effectively implemented. It is advised to do a pilot for a supplier with high potential for TWCP or TWMIXED for a certain period of time to observe the practical performance. After that, potentially for every supplier the flow type selection could take place.
Next, some additional recommendations are formulated:

- Start storing the actual send shelf lives of suppliers. In this way, the quality and freshness of send products can be assessed and compared with other retailers, so that possible discrepancies can be found and discussed with suppliers.

- Reconsider re-implementing the discount stickers for products that approach their expiration dates. Because of the wide assortment, high demand uncertainty and the substantial amount of highly priced products, the discount stickers can reduce cost of waste significantly and may also attract customers. However, this is only advised after the improvement steps in this study are effectively implemented. Hence, employing the discount stickers when operations and logistics are not optimized, would result in a situation (as formerly) that demands the need of the stickers too often, which negatively influences store image and profitability. Another requirement is that the sales in the system should get adjusted for the amount of products that are sold with sticker, so that the data doesn’t get polluted.

- Investigate how the Traditional Warehousing flow types can be implemented. Flow racks are considered as suitable for efficient order picking of fresh products, which rotate relatively fast. Furthermore, processes have to be defined at the DC, but also for demand planning in the HQ. It is important that the stock is accurately and smartly managed, as freshness needs to be guaranteed and no waste is desired in the DC. When the unpacking decision is made, crates in combination with trolleys should be used to transport the single CU’s, since as a result of breaking up the case packs, pallets can’t be used anymore.

- Communicate and negotiate lead times and the amount of ordering moments with suppliers. Some delivery schemes offer improvements and by reducing lead times or increasing the amount of ordering moments, waste can be reduced. Furthermore, synchronization of deliveries with production schedules can offer significant advantages considering shelf lives.

- It is recommended to conduct the steps defined in the conceptual model for other fresh categories as well, because they offer similar opportunities.

8.3. Scientific contribution

This study contributes to the scientific literature in a couple of ways. First of all, literature so far focusses mainly on the creation of theoretical models for e.g. prediction of key performance indicators (waste, amount of orderliness, availability) or for the flow type selection problem. Theoretical models have limitations in that a significant amount of assumptions have to be made (e.g. no week pattern, only FIFO or LIFO picking, identical demand characteristics for SKU’s in the store, normal distributed demand). This research contributes to the literature in that it models a close to real-world supply chain with few assumptions. First of all, Muskens (2016) [10] calls in his research for inclusion of the week pattern, which we have done in this study. We compared the performance with an ordering system that not includes the week pattern. The created simulation model furthermore facilitates analysis of the impact of a combination of FIFO and LIFO on performance, which is what typically is the scenario in practice. Moreover, we include the most relevant costs in the model: costs of waste, handling in DC and inbound logistics. All cost components are shown to be important to assess performance of fresh products considering overall costs. Store handling is not included for the analysis for Makro, but could be included if this impact is clear and processes in the stores are similar.
Furthermore, so far few studies focus on the impact of differentiation of service levels on performance. We have shown the potential and provided a method to set service levels such that overall fill rate stays the same, but overall costs are reduced by assigning higher service levels to fast movers and lower service levels to slow movers.

Finally, a simulation model has been created that can be adapted to other categories or even other retailers. It is unique in its form as it uses real historical data as input and acts as the ordering system that is used by retailers. This results in the opportunity to provide tailored and accurate recommendations.

8.4. Limitations

During the study, some assumptions have been made, and some steps have been taken that form limitations in the research. First of all, we don’t include store handling and inventory costs in the simulation model. We have shown that inventory costs are very small and therefore considered irrelevant. Store handling is likely to be effected by the measures that are taken in this study. However, as we have argued, the effect is probably different for stores as the store lay-out and procedures differ. As a result, effects on store handling could be positive for one store and negative for the other. The high complexity and uncertainty of the aggregated contra effects of measures on store handling costs, led us to the assumption that these overall costs are not affected. Based on observations in stores it is furthermore assumed that store employees at Makro have some flexibility in their capacity and are efficient in adapting to new procedures. Moreover, Muskens (2016) [10] showed that effects on store handling are very low relative to inbound logistics and costs of waste, especially when levels of waste are larger than 5%.

The unpacking tariff and inbound logistic savings couldn’t be validated because they depend on negotiations with the logistic service provider (who own the DC) and suppliers. In section 7.4 a sensitivity analysis is conducted for some suppliers. When exact costs are known, results can be easily adapted to assess the impact.

Furthermore, during the customer behavior experiment in the stores, extra SKU’s were included in the dataset to gather a larger sample size. However, for the comparison of the classic and the junior store this resulted in a comparison of picking behavior of two different sets of products. This could have influenced the reliability of the results. However, a trade-off had to be made between having a large sample size and having an identical set of SKU’s. Still, we expect that the effect of different sets is limited as we observed no significant difference in picking behavior between products in the studied categories.

Another limitation is that the simulation model could not be validated with current actual performance, because currently a lot of human interference takes place. However, validation has been assured in numerous other manners as described in section 6.7 and 7.5.

Finally, the simulation model doesn’t include some functionalities of the real ordering system, like including calendar effects, promotions, seasonality, outlier detection, zero stock correction and general exponential smoothing forecasting. As a result we expect that in practice the indicated performances are better and result in some higher potential. This together with the fact that in practice some beneficial human interference can take place, substantiates that the simulation performances can be interpreted as minimum performances. Modelling the basics of the system, facilitates a good comparison of main effects and supports solid recommendations for decision making.
8.5. Future research

Further research on mathematical tools for space management for perishables is suggested. A tool that takes into account demand characteristics per SKU/store combination together with the delivery schedule when making shelf designs, could be highly beneficial for reducing costs of waste in stores.

Furthermore future research could be conducted on the relationship between the cycle service level (which is defined as input for the ordering system at Makro) and the fill rate (which is the advised indicator to measure performance). It has been shown that a small cycle service level can translate to a much higher fill rate when R+L is high. In this study, service level definitions are found by enumeration, but it would be more efficient if one could compute which service levels translate to which fill rate, without the need to conduct multiple simulation runs. Even more relevant would be the design of an ordering system that uses fill rate definitions to calculate reorder levels.

Besides this, more research is recommended on simulation based models to assess the impact of different measures to reduce overall costs of fresh products in the chain. It has been shown that the ability to model complex real-world functionalities in simulation can lead to substantiated results, which are likely to obtain a high degree of trust by management. As the simulation is currently tailor made for Makro and involves a high degree of complexity to run correctly, it would be advantageous to compile a more user friendly tool which can be relatively readily used for other categories and retailers. With some small adjustments, other fresh categories at Makro can already be investigated with the simulation model.

Further research on the effects of using markdown stickers on products that approach their expiration date is recommended. As currently part of grocery retail uses the stickers and part doesn’t, it is interesting to identify the net benefits of the stickers and the operational requisites to use them successfully. Research on the optimal discount size and discount moment for different store and/or category characteristics can be valuable for many retailers, including Makro.

Finally, it is for Makro advised to investigate the handling tariff in the DC, and assess per supplier how inbound logistics costs are settled with the supplier. First of all, handling costs in the DC are currently calculated per handled unit. Hence, if a case pack from the supplier is halved (e.g. from 12 to 6), picking costs are doubled. Since the handling only represents a fraction of the picking tariff, costs are not balanced well in this way. As a result, smaller MOQ’s from suppliers, or unpacking is less interesting. Secondly, it is advised to clearly document and negotiate the contribution in costs of transport (inbound logistics) towards the supplier, in order to be have insight in agreements and structures and to be able to optimize the supply chain with the flow type selection.
Bibliography


[26] F. Van de Ven, „Reducing the amount of outdating for the stores of PLUS Retail by optimizing the case pack sizes for convenience products at Hollander Barendrecht BV, considering entailed additional supply chain operating costs,” TU/e, Eindhoven, 2014.


Appendix A - Drink yoghurt shelf pictures in Makro

Figure 31. Dairy drink yoghurt shelves in Barendrecht

Figure 32. Dairy drink yoghurt shelves in Amsterdam
Appendix B - Pearson's chi-squared tests FIFO/LIFO experiment

Table 19. Results of chi-squared tests between groups in the FIFO/LIFO experiment

<table>
<thead>
<tr>
<th>Test nr.</th>
<th>Value 1 description</th>
<th>Value 2 description</th>
<th>Obs. value 1a</th>
<th>Obs. value 2a</th>
<th>Obs. value 1b</th>
<th>Obs. value 2b</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>All FIFO</td>
<td>LIFO</td>
<td>280</td>
<td>90</td>
<td>190</td>
<td>70</td>
<td>0.461**</td>
</tr>
<tr>
<td>2</td>
<td>FIFO when choice</td>
<td>LIFO</td>
<td>128</td>
<td>90</td>
<td>63</td>
<td>70</td>
<td>0.0384*</td>
</tr>
<tr>
<td>3</td>
<td>FIFO when choice</td>
<td>LIFO</td>
<td>314</td>
<td>123</td>
<td>153</td>
<td>37</td>
<td>0.221*</td>
</tr>
<tr>
<td>4</td>
<td>FIFO when choice</td>
<td>LIFO</td>
<td>130</td>
<td>123</td>
<td>61</td>
<td>37</td>
<td>0.067**</td>
</tr>
</tbody>
</table>

Test description

1. Tests if all FIFO picking occurs significantly more often than LIFO picking.
2. Tests if ‘FIFO picking when choice’ occurs significantly more often than LIFO picking.
3. Tests if 'FIFO picking when choice' occurs significantly more often than hypothesized by H1: 30% or less FIFO picking when customers have a choice.
4. Tests if all FIFO picking in Barendrecht occurs significantly more often than LIFO picking.
5. Tests if 'FIFO picking when choice' in Barendrecht occurs significantly more often than LIFO picking.
6. Tests if 'FIFO picking when choice' in Barendrecht occurs significantly more than hypothesized by H1: 30% or less FIFO picking when customers have a choice.
7. Tests if all FIFO picking in Amsterdam occurs significantly more often than LIFO picking.
8. Tests if 'FIFO picking when choice' in Amsterdam occurs significantly more often than LIFO picking.
9. Tests if 'FIFO picking when choice' in Amsterdam occurs significantly more than hypothesized by H1: 30% or less FIFO picking when customers have a choice.
10. Tests if the amount of 'FIFO no choice' picking at Makro occurs significantly less than the 65% found by Van Burgh (2007) [1].
11. Tests if all FIFO picking occurs significantly more (or LIFO significantly less) in Barendrecht than in Amsterdam.
12. Tests if 'FIFO picking when choice' occurs significantly more (or LIFO significantly less) in Barendrecht than in Amsterdam.
13. Tests if all FIFO picking occurs significantly more (or LIFO significantly less) in the article group Sandwiches & Spreads than in Milk products.
14. Tests if 'FIFO picking when choice' occurs significantly more (or LIFO significantly less) in the article group Sandwiches & Spreads than in Milk products.
Appendix C - Relationship between availability and waste

Figure 33. The Efficient Frontier based on data for three retailers for the categories convenience, meat and fruit & vegetables\(^5\)

Appendix D - Distribution flow types

Figure 34. Different flow types as described by Muskens (2014) [10]

Appendix E - Lead times for Milk products and Sandwiches & Spreads

Figure 35. Number of SKU’s per average lead time to the store for the categories Milk products and Sandwiches & Spreads.
Appendix F - Flow type selection per supplier

Figure 36. Overall costs per supplier for the four analyzed flow types when picking behavior is as current and MSS=1

Supplier A

Overall costs per year in €

BBXD  TWCP  TWCU  TW MIXED

Waste 19%  Waste 19%  Waste 19%

Waste 20%  Waste 19%  Waste 19%

Supplier B

Overall costs per year in €

BBXD  TWCP  TWCU  TW MIXED

Waste 6%  Waste 9%  Waste 9%

Waste 11%  Waste 9%  Waste 9%

Supplier C

Overall costs per year in €

BBXD  TWCP  TWCU  TW MIXED

Waste 26%  Waste 33%  Waste 33%

Waste 35%  Waste 33%  Waste 33%

Supplier D

Overall costs per year in €

BBXD  TWCP  TWCU  TW MIXED

Waste 16%  Waste 15%  Waste 15%

Waste 11%  Waste 15%  Waste 15%

Supplier E

Overall costs per year in €

BBXD  TWCP  TWCU  TW MIXED

Waste 10%  Waste 10%  Waste 10%

Waste 11%  Waste 10%  Waste 10%

Supplier F

Overall costs per year in €

BBXD  TWCP  TWCU  TW MIXED

Waste 12%  Waste 15%  Waste 15%

Waste 15%  Waste 15%  Waste 15%

Legend:

- Waste
- Picking Costs
- Demand Planning Costs
- Inbound Logistics Cost Saving Potential
Overall costs per year in €

**Supplier G**
- BBXD: Waste 38%
- TWCP: Waste 33%
- TWCU: Waste 23%
- TWMixed: Waste 33%

**Supplier H**
- BBXD: Waste 17%
- TWCP: Waste 11%
- TWCU: Waste 11%
- TWMixed: Waste 8%

**Supplier I**
- BBXD: Waste 19%
- TWCP: Waste 16%
- TWCU: Waste 16%
- TWMixed: Waste 16%

**Supplier J**
- BBXD: Waste 17%
- TWCP: Waste 16%
- TWCU: Waste 11%
- TWMixed: Waste 16%

**Supplier K**
- BBXD: Waste 7%
- TWCP: Waste 6%
- TWCU: Waste 4%
- TWMixed: Waste 6%

**Supplier L**
- BBXD: Waste 34%
- TWCP: Waste 26%
- TWCU: Waste 21%
- TWMixed: Waste 26%

Legend:
- **Waste**
- **Picking Costs**
- **Demand Planning Costs**
- **Inbound Logistics Cost Saving Potential**
<table>
<thead>
<tr>
<th>Supplier</th>
<th>Waste</th>
<th>Picking Costs</th>
<th>Demand Planning Costs</th>
<th>Inbound Logistics Cost Saving Potential</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supplier S</td>
<td>Waste 7%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Supplier T</td>
<td>Waste 14%</td>
<td>Waste 13%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Supplier U</td>
<td>Waste 15%</td>
<td>Waste 23%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Appendix G – Customer behavior statistical tests

Table 20. Spearman’s statistic for testing the relationship between customer picking behavior and the amount of dates in the shelf.

<table>
<thead>
<tr>
<th>Spearman’s rho</th>
<th>Correlation Coefficient</th>
<th>Sig. (2-tailed)</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>FIFO_1_0</td>
<td>-0.291**</td>
<td>.000</td>
<td>351</td>
</tr>
</tbody>
</table>

**. Correlation is significant at the 0.01 level (2-tailed).

Table 21. Pearson’s statistic for testing the relationship between customer picking behavior and the amount of facings per SKU.

<table>
<thead>
<tr>
<th>FIFO_yes_no versus #facings</th>
<th>Pearson Correlation</th>
<th>Sig. (2-tailed)</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>FIFO_yes_no</td>
<td>-0.268**</td>
<td>.000</td>
<td>351</td>
</tr>
</tbody>
</table>

**. Correlation is significant at the 0.01 level (2-tailed).

Table 22. Spearman’s statistic for testing the relationship between customer picking behavior and the amount of facings per SKU.

<table>
<thead>
<tr>
<th>Spearman’s rho</th>
<th>Number_of_facings</th>
<th>Correlation Coefficient</th>
<th>Sig. (2-tailed)</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>FIFO_yes_no</td>
<td>-0.213**</td>
<td>.000</td>
<td>351</td>
<td></td>
</tr>
</tbody>
</table>

**. Correlation is significant at the 0.01 level (2-tailed).

Table 23. Pearson’s statistic for testing the relationship between customer picking behavior and the shortest shelf life of an SKU.

<table>
<thead>
<tr>
<th>Shortest_shelflife versus FIFO_yes_no</th>
<th>Pearson Correlation</th>
<th>Sig. (2-tailed)</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>FIFO_yes_no</td>
<td>0.041</td>
<td>.517</td>
<td>249</td>
</tr>
</tbody>
</table>

Table 24. Spearman’s statistic for testing the relationship between customer picking behavior and the shortest shelf life of an SKU.

<table>
<thead>
<tr>
<th>Spearman’s rho</th>
<th>Correlation Coefficient</th>
<th>Sig. (2-tailed)</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>FIFO_1_0</td>
<td>0.023</td>
<td>.721</td>
<td>249</td>
</tr>
</tbody>
</table>

Table 25. Pearson’s statistic for testing the relationship between customer picking behavior and the shortest shelf life of an SKU when grouping is used.

<table>
<thead>
<tr>
<th>Shortest_shelflife versus FIFO_yes_no</th>
<th>Pearson Correlation</th>
<th>Sig. (2-tailed)</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>FIFO_yes_no</td>
<td>0.116</td>
<td>.067</td>
<td>249</td>
</tr>
</tbody>
</table>
Table 26. Spearman’s statistic for testing the relationship between customer picking behavior and the shortest shelf life of an SKU when grouping is used.

<table>
<thead>
<tr>
<th>Spearman’s rho</th>
<th>FIFO_1.0</th>
<th>Correlation Coefficient</th>
<th>.139</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shortest_shelflife</td>
<td>Sig. (2-tailed)</td>
<td>.027</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td></td>
<td>249</td>
<td></td>
</tr>
</tbody>
</table>

Table 27. Pearson’s statistic for testing the relationship between customer picking behavior and the difference between the shelf lives of the first and second batch.

<table>
<thead>
<tr>
<th>FIFO_yes_no versus difference shelf life 1st and 2nd batch</th>
<th>Pearson Correlation</th>
<th>.018</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sig. (2-tailed)</td>
<td>.744</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>348</td>
<td></td>
</tr>
</tbody>
</table>

Table 28. Spearman’s statistic for testing the relationship between customer picking behavior and the difference between the shelf lives of the first and second batch.

<table>
<thead>
<tr>
<th>Spearman’s rho</th>
<th>FIFO_yes_no</th>
<th>Correlation Coefficient</th>
<th>.046</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sig. (2-tailed)</td>
<td>.395</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>348</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Appendix H – In-depth analysis of observed contributors to waste during customer picking experiment

High inventory levels

From both the observation series at Amsterdam and Barendrecht, the number of weeks of inventory per SKU have been calculated. This is done by dividing the observed inventory level per SKU by the total sales during the observation week for each SKU. Data is extracted from Makro’s POS database to ensure sales from the complete week are included (so also sales which have taken place outside the observation days and observation times during the week). In Figure 37 and Figure 38 the number of weeks of inventory are described respectively for Barendrecht and Amsterdam. Every bar describes the number of SKU’s that belong to a certain range of weeks of inventory, so in Figure 37, 29 SKU’s have an average inventory of 0 to 1 sales weeks. The last column in both figures shows the infinity sign. For this SKU’s no sales were observed during the week, so a division by 0 results in an infinite number. From both figures it can be observed that for a large amount of SKU’s more than 1 week of inventory is on stock (for Barendrecht 70% and for Amsterdam 67%). If we look to the proportion of SKU’s that have more than 2 and 3 weeks of inventory, this is respectively 44% and 36% for Barendrecht, and 56% and 34% for Amsterdam. From this it can be concluded that the inventory levels are really high compared to the observed sales. This could be an important indicator of the high amount of waste in this groups. Especially given the average shelf-life of 21 days, an inventory higher than 3 weeks always results in waste for most products, even if customers would only pick FIFO. Given the information that a proportion picks LIFO, the influence of the high inventories on waste is even higher.

What is interesting, is to know if this high inventory levels are caused by the too high MOQ’s or by too extensive ordering. To check this, the average inventory level is divided by the MOQ and plotted against

![Figure 37. Numbers of weeks of inventory at Barendrecht based on the observation week](image)

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the number of weeks of inventory per SKU. For Barendrecht and Amsterdam the results are depicted respectively in Figure 39 and Figure 40.

**Figure 38. Numbers of weeks of inventory at Amsterdam based on the observation week**

In both Figure 39 and Figure 40 the number of case packs on stock per SKU are plotted against the number of demand weeks on stock. Points more towards the right upper corner are especially interesting, since there is still room for lowering inventory despite the restriction of the MOQ/case pack.

**Figure 39. Number of case packs on stocks vs. number of demand weeks on stock Barendrecht**

*Reducing Waste at Makro: Appendix H - In-depth analysis of observed contributors to waste during customer picking experiment*
Together with the fact that for the largest part of the assortment products are delivered at least twice a week, this indicates that for some SKU’s just an excessive amount of inventory is held, provoked by either the replenishment system or the employees who do the ordering manually. Better inventory replenishment and rotation would improve the current amount of waste. It can be concluded that for a substantial portion of the SKU’s (in Amsterdam relatively more than in Barendrecht) the inventory position could be improved by ordering behavior and as a result waste could be reduced. Furthermore, especially the observations of SKU’s that are approaching and surpassing their shelf life in the amount of demand weeks are increasingly critical, since even under perfect operational characteristics (e.g. FIFO customer picking and perfect replenishment) waste occurs here. Amsterdam has 14 products (24% of all products) which have higher inventory than the store is able to sell in the shelf life of the product, but which is reducible given the fact that the amount of case packs is higher than 1.5. For Barendrecht this is the case for 17 products (18%). In both figures it can be seen that data points are bound to 13 on the y-axis. Because these points had 0 sales during the observation week, the y-value actually goes to infinity.

Products on the left side of the graph have on average a low amount of case packs on stock, but sometimes still a high amount of demand weeks. For this products, it can be concluded that the case pack size forms more of a limitation and is the major driver of waste. Measures to reduce the case pack size are especially useful here. If Figure 39 and Figure 40 are compared, one can see that for Barendrecht the case pack size forms more of a limitation than for Amsterdam. Contrary, in Amsterdam ordering seems to have a higher impact.

![Figure 40. Number of case packs on stocks vs. number of demand weeks on stock Amsterdam](image)

A reason that stores hold too much inventory, might be to create full looking shelves in the stores. Full shelves look good for customers and enhance the image of the store. Van Burgh (2007) [29] moreover finds that there is a relationship between the amount of inventory in the shelf and the picking behavior.
He finds that lower inventory levels result in higher LIFO picking behavior. Both reasons might substantiate that store managers want to keep the shelves filled. However, one of the key indicators of a lucrative supermarket/wholesaler is its ability to rotate its products (in particular perishables) correctly and making the right replenishment decisions [6]. Products on the shelves need to be sold, and as observed in Figure 37 and Figure 38, inventories are currently often too high and not accurately matched with demand, which contributes to higher waste. One of the reasons for this might be the current amount of facings assigned to each SKU, which as we have shown, influences customer picking behavior. Broekmeulen & Van Donselaar (2016) [6] also emphasize the importance of aligning the actual number of facings on the shelves with demand to control waste. At Makro the minimal shelf stock (MSS) for some products is dependent on the amount of facings. So if a product has more facings, higher inventory is held. The MSS is an extra addition to the forecast plus the safety stock, so if the amount of facings are not aligned with the demand (or this parameter is set too high), an excessive amount of inventory is held, which in the end leads to higher waste. For the investigated products at Makro it was observed that often more than 1 facings were assigned to an SKU. In Figure 41 it can be observed that for a substantial amount of SKU’s (in Amsterdam) with 2 and 3 facings, the number of weeks of inventory is substantial. This is an indication that the amount of facings assigned to this SKU’s might be too high. Redefinition and optimization of the amount of facings is therefore a potential improvement possibility.

![Figure 41. A plot of the number of facings vs. the average weeks of inventory (measured in the single observation week in Amsterdam) for each SKU that was included in the experiment.](image)

It has to be noted that the figures and demand averages in this chapter were only based on the week demand observed during that experiment week. Very likely the observed averages differ significantly from the real weekly average demand. For this reasons the results should be interpreted with cautiousness. Still, it are real observations, which very likely give an indication of what problems are present.
In both stores situations were encountered where shelves were not organized well or/and replenished FIFO. It was for example observed that longer dates were found at the front of the shelf, and the shorter dates were located behind them or even in the back of the shelf. Since in this situation all the customers (both FIFO and LIFO) grab the SKU with the longer expiration date, a significant higher amount of waste will take place compared with the situation where the shortest expiration date is accurately placed in the front of the shelf. In both stores for 8% of the observed SKU’s a non-optimal FIFO replenished shelf was found during the total observation period.

During the experiment in Amsterdam some already expired dates were found, which is very detrimental for the store image, customer experience and customer trust.

Furthermore it was observed that for 1 product no price tag could be found. When people can’t find the price and name of a product on a tag, they become more reluctant to buy such a product.

During the observation days, a couple of times products where located at the wrong shelf. Consumer units of the one SKU were found in the shelf of another (e.g. because the two products look similar). This leads to waste since customers only look for a product where the ESL tag indicates that a product should be, or where customers are used to finding the product. For this reason, the product probably just remains at the wrong shelf until it is wasted or observed by a store clerk. Moreover customers might be suspicious about the quality of the product when they do find it.
## Appendix I – Used notation in the simulation model

**Table 29. Used notation in the simulation model**

<table>
<thead>
<tr>
<th>Sets</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_{j,w}$</td>
<td>Set of stores where product j is in the stores at week w (⊆ S)</td>
</tr>
<tr>
<td>$S$</td>
<td>Set of all stores</td>
</tr>
<tr>
<td>SKUSET</td>
<td>Set of selected SKU’s</td>
</tr>
<tr>
<td>$I_{j,s}$</td>
<td>Set of available sales days for SKU j in store s</td>
</tr>
<tr>
<td>$I_j$</td>
<td>Set of available sales days for SKU j</td>
</tr>
<tr>
<td>$I$</td>
<td>Set of sales days in the observation period</td>
</tr>
<tr>
<td>$W_{j,s}$</td>
<td>Set of available sales weeks for SKU j in store s</td>
</tr>
<tr>
<td>$W_j$</td>
<td>Set of available sales weeks for SKU j</td>
</tr>
<tr>
<td>$W$</td>
<td>Set of sales weeks in the observation period</td>
</tr>
<tr>
<td>$\text{DAY}$</td>
<td>Set of week days {1,2,3,4,5,6,7}</td>
</tr>
<tr>
<td>SKUSET</td>
<td>Set of selected SKU’s</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Indices</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i$</td>
<td>Index for the current day since the start of the simulation (∈ I)</td>
</tr>
<tr>
<td>$w$</td>
<td>Index for the current week since the start of the simulation (∈ W)</td>
</tr>
<tr>
<td>$j$</td>
<td>Index for the SKU (∈ SKUSET)</td>
</tr>
<tr>
<td>$s$</td>
<td>Index for the store (∈ S)</td>
</tr>
<tr>
<td>$\text{supp}$</td>
<td>Index for the supplier (∈ SUPPLIER)</td>
</tr>
<tr>
<td>$dc$</td>
<td>Index representing the DC</td>
</tr>
<tr>
<td>$b$</td>
<td>Index representing the batch number</td>
</tr>
<tr>
<td>$d$</td>
<td>Index representing the week day (∈ DAY)</td>
</tr>
<tr>
<td>$R$</td>
<td>Review period</td>
</tr>
<tr>
<td>$L$</td>
<td>Lead time</td>
</tr>
<tr>
<td>$L_{R+}$</td>
<td>Lead time of the next ordering moment</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c_{dp}$</td>
<td>Costs of a demand planner per year to manage the inventory of 1 SKU</td>
</tr>
<tr>
<td>$c^b_{j}$</td>
<td>Buying price of SKU j</td>
</tr>
<tr>
<td>$c^s_{j}$</td>
<td>Sales price of SKU j</td>
</tr>
<tr>
<td>$c_{\text{BBXD}}$</td>
<td>Costs of handling one case pack in the DC when the flow type is BBXD.</td>
</tr>
<tr>
<td>$c_{\text{TWCP}}$</td>
<td>Costs of handling one case pack in the DC when the flow type is Traditional Warehousing in Case Packs (TWCP)</td>
</tr>
<tr>
<td>$cf_{\text{TWCP}}$</td>
<td>Fraction of the $c_{\text{TWCP}}$ tariff that is effected by unpacking a case pack</td>
</tr>
<tr>
<td>$c_{\text{km,it}}$</td>
<td>Costs per kilometer of inbound logistics</td>
</tr>
<tr>
<td>$\text{Shelf life at arrival in the DC of SKU j}$</td>
<td></td>
</tr>
<tr>
<td>$\text{Day fraction of week pattern of SKU j in store s on day d}$</td>
<td></td>
</tr>
<tr>
<td>$\text{MOQ}_{j}$</td>
<td>The Minimal Order Quantity at the supplier for SKU j</td>
</tr>
<tr>
<td>$\text{MOQDC}_{j}$</td>
<td>The Minimal Order Quantity at the DC for SKU j. This parameter is different when it is decided to unpack in the DC.</td>
</tr>
<tr>
<td>$D_{i,j,s}$</td>
<td>Demand on day i of SKU j in store s</td>
</tr>
<tr>
<td>$\text{DDC}_{i,j}$</td>
<td>Demand on day i of SKU j in the DC</td>
</tr>
<tr>
<td>$\text{Current sales in CU per year for SKU j in store s}$</td>
<td></td>
</tr>
<tr>
<td>$\text{Distance from supplier supp to the DC}$</td>
<td></td>
</tr>
<tr>
<td>$\text{Reduction in amount of delivery moments per week for supplier supp}$</td>
<td></td>
</tr>
<tr>
<td>Variables</td>
<td>Description</td>
</tr>
<tr>
<td>-----------</td>
<td>-------------</td>
</tr>
<tr>
<td>W ASL</td>
<td>Weighted average shelf life in store obtained from the customer picking behavior experiment</td>
</tr>
<tr>
<td><strong>Variables</strong></td>
<td><strong>Description</strong></td>
</tr>
<tr>
<td>BatchAge_{i,j,s,b}</td>
<td>Age of batch b from SKU j at day i in store s</td>
</tr>
<tr>
<td>BatchQuantity_{i,j,s,b}</td>
<td>The amount of products from batch b of SKU j on stock on day i in store s</td>
</tr>
<tr>
<td>SS_{i,j,s}</td>
<td>Calculated safety stock on day i for SKU j in store s</td>
</tr>
<tr>
<td>SSSDC_{i,j}</td>
<td>Calculated safety stock on day i for SKU j in the DC</td>
</tr>
<tr>
<td>Z_{i,j,s}</td>
<td>Z-score calculated on day i for SKU j in store s, based on the assigned service level to the SKU on that day</td>
</tr>
<tr>
<td>ZDC_{i,j}</td>
<td>Z-score calculated on day i for SKU j in the DC, based on service level for the DC</td>
</tr>
<tr>
<td>σ_{d,i,j,s}</td>
<td>Standard deviation of the demand period of SKU j at day i in store s</td>
</tr>
<tr>
<td>σ_{dDC,i,j,w}</td>
<td>Standard deviation of the demand period of SKU j in the DC</td>
</tr>
<tr>
<td>µ_{d,i,j,s}</td>
<td>Forecast for the demand period for SKU j at day i in store s</td>
</tr>
<tr>
<td>µDC_{i,j,w}</td>
<td>Forecast for the demand period for SKU j at day i in the DC</td>
</tr>
<tr>
<td>ROL_{i,j,s}</td>
<td>Reorder level at day i for SKU j in store s</td>
</tr>
<tr>
<td>ROLDC_{i,j}</td>
<td>Reorder level at day i for SKU j in the DC</td>
</tr>
<tr>
<td>Order_{i,j,s}</td>
<td>The order placed at day i for SKU j in store s</td>
</tr>
<tr>
<td>OrderDC_{i,j}</td>
<td>The order placed at day i for SKU j in the DC</td>
</tr>
<tr>
<td>WeekForecast_{j,s,w}</td>
<td>Week forecast made for SKU j in store s for week w</td>
</tr>
<tr>
<td>WeekDemand_{j,s,w}</td>
<td>Week demand for SKU j in store s at week w</td>
</tr>
<tr>
<td>WeekForecastDC_{j,w}</td>
<td>Week forecast made for SKU j for week w in the DC</td>
</tr>
<tr>
<td>WeekDemandDC_{j,w}</td>
<td>Week demand from all the stores at the DC for SKU j in week w</td>
</tr>
<tr>
<td>OrderDC_{i,j}</td>
<td>The aggregated store orders at the DC on day i for SKU j</td>
</tr>
<tr>
<td>VarianceUsed_{s,j,w}</td>
<td>The variance used for calculation of the safety stock for SKU j in store s week w</td>
</tr>
<tr>
<td>VarianceUsedDC_{j,w}</td>
<td>The variance used for calculation of the safety stock for SKU j in week w in the DC</td>
</tr>
<tr>
<td>WeekVariance_{s,j,w}</td>
<td>The forecasting error variance of SKU j in store s in week w</td>
</tr>
<tr>
<td>WeekVarianceDC_{j,w}</td>
<td>The forecasting error variance of SKU j in week w in the DC</td>
</tr>
<tr>
<td>dayfractionDC_{i,j}</td>
<td>The fraction of the week demand occurring on day i for SKU j in the DC</td>
</tr>
<tr>
<td>OI_{i,j,s}</td>
<td>On-hand inventory at the end of day i for SKU j in store s</td>
</tr>
<tr>
<td>OIDC_{i,j}</td>
<td>On-hand inventory at the end of day i for SKU j in the DC</td>
</tr>
<tr>
<td>IP_{i,j,s}</td>
<td>Inventory position at the end of day i for SKU j in store s</td>
</tr>
<tr>
<td>IPDC_{i,j}</td>
<td>Inventory position at the end of day i for SKU j in the DC</td>
</tr>
<tr>
<td>fulfillment fractionDC_{i,j}</td>
<td>The proportion of orders from the stores at DC which can be fulfilled on day i for SKU j</td>
</tr>
<tr>
<td>DeliveredQuantity_{i,j,s}</td>
<td>Delivered quantity at the beginning of day i of SKU j at store s</td>
</tr>
<tr>
<td>DeliveredQuantityDC_{i,j}</td>
<td>Delivered quantity at the beginning of day i of SKU j at the DC</td>
</tr>
<tr>
<td>DeliveredSL_{i,j,s}</td>
<td>Delivered shelf life at day i of SKU j at store s</td>
</tr>
<tr>
<td>DeliveredSLDC_{i,j}</td>
<td>Delivered shelf life at day i of SKU j at the DC</td>
</tr>
<tr>
<td>Wasted_{i,j,s}</td>
<td>The amount of wasted products at the end of day i of SKU j in store s</td>
</tr>
<tr>
<td>WastedDC_{i,j}</td>
<td>The amount of wasted products in the DC at the end of day i of SKU j</td>
</tr>
</tbody>
</table>
### Appendix J – Mathematical formulation of the objective functions and constraints

#### Constraint on availability stores

\[
\text{Availability stores}_{\text{SKUSET}} = 1 - \frac{\sum_{j \in \text{SKUSET}} \sum_{i \in \text{ISET}} (D_{i,j} - \text{Order}_{i,j} - \text{Wasted}_{i,j} - \text{Delivered}_{i,j})}{\sum_{j \in \text{SKUSET}} \sum_{i \in \text{ISET}} (D_{i,j})} \approx 0.97
\]  \[20\]

#### Constraint on availability DC

\[
\text{Availability DC}_{\text{SKUSET}} = 1 - \frac{\sum_{j \in \text{SKUSET}} \sum_{i \in \text{ISET}} (\text{Order}_{i,j} - \text{Delivered}_{i,j} - \text{DCU}_{i,j})}{\sum_{j \in \text{SKUSET}} \sum_{i \in \text{ISET}} (\text{Order}_{i,j})} \approx 0.80
\]  \[21\]

#### Picking costs

\[
\text{Year Picking Costs } \text{BBXD}_{\text{SKUSET}} = \left( \frac{\sum_{j \in \text{SKUSET}} \sum_{i \in \text{ISET}} \left( \frac{\text{Order}_{i,j}}{\text{MOQS}_{j}} \right) - \sum_{j \in \text{SKUSET}} \sum_{i \in \text{ISET}} (\text{CDY}_{i,j})}{\sum_{j \in \text{SKUSET}} \sum_{i \in \text{ISET}} (D_{i,j})} \right) \times c_{\text{BBXD}} \times \text{Availability stores}_{\text{SKUSET}} \]
\[22\]

\[
\text{Year Picking Costs } \text{TWCP}_{\text{SKUSET}} = \left( \frac{\sum_{j \in \text{SKUSET}} \sum_{i \in \text{ISET}} \left( \frac{\text{Delivered}_{i,j}}{\text{MOQS}_{j}} \right) - \sum_{j \in \text{SKUSET}} \sum_{i \in \text{ISET}} (\text{CDY}_{i,j})}{\sum_{j \in \text{SKUSET}} \sum_{i \in \text{ISET}} (D_{i,j})} \right) \times c_{\text{TW}} \times \text{Availability stores}_{\text{SKUSET}} \]
\[23\]

\[
\text{Year Picking Costs } \text{TWCU}_{\text{SKUSET}} = \left( \frac{\sum_{j \in \text{SKUSET}} \sum_{i \in \text{ISET}} \left( \frac{\text{Delivered}_{i,j}}{\text{MOQS}_{j}} \right) - \sum_{j \in \text{SKUSET}} \sum_{i \in \text{ISET}} (\text{CDY}_{i,j})}{\sum_{j \in \text{SKUSET}} \sum_{i \in \text{ISET}} (D_{i,j})} \right) \times c_{\text{TWC}} \times \text{Availability stores}_{\text{SKUSET}} + \left(1 - \frac{\sum_{j \in \text{SKUSET}} \sum_{i \in \text{ISET}} \left( \frac{\text{Delivered}_{i,j}}{\text{MOQS}_{j}} \right) - \sum_{j \in \text{SKUSET}} \sum_{i \in \text{ISET}} (\text{CDY}_{i,j})}{\sum_{j \in \text{SKUSET}} \sum_{i \in \text{ISET}} (D_{i,j})} \right) \times c_{\text{TW}} \times \text{Availability stores}_{\text{SKUSET}} \]
\[24\]

#### Costs of waste

\[
\text{Year Waste Costs}_{\text{SKUSET}} = \left( \frac{\sum_{j \in \text{SKUSET}} \sum_{i \in \text{ISET}} (\text{Wasted}_{i,j}) + \sum_{j \in \text{SKUSET}} \sum_{i \in \text{ISET}} (\text{Wasted}_{i,j})}{\sum_{j \in \text{SKUSET}} \sum_{i \in \text{ISET}} (\text{Sales}_{i,j})} \right) \times \sum_{j \in \text{SKUSET}} \sum_{i \in \text{ISET}} (\text{CDY}_{i,j} \times \text{Wasted}_{i,j}) \times \text{Availability stores}_{\text{SKUSET}} \]
\[25\]

#### Savings inbound logistics

\[
\text{Year Savings Inbound Logistics}_{\text{supp}} = c_{\text{km.H}} \times \text{distance}_{\text{supp}} \times \text{rdm}_{\text{supp}} \times 1 \times 52
\]  \[26\]

#### Demand planning costs

\[
\text{Year Demand Planning Costs}_{\text{SKUSET}} = \sum_{j \in \text{SKUSET}} \sum_{i \in \text{ISET}} \left( \frac{\text{Sales}_{i,j}}{\text{MOQS}_{j}} \right) \times \text{Availability stores}_{\text{SKUSET}} \]
\[27\]
# Appendix K – Pearson’s and Spearman’s correlation coefficient and values crosstab

Table 30. Pearson’s and Spearman’s correlation coefficient and values crosstab.

<table>
<thead>
<tr>
<th>Number_dates</th>
<th>FIFO_1.0</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>2,00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Count</td>
<td>70</td>
<td>136</td>
</tr>
<tr>
<td>Expected Count</td>
<td>93.9</td>
<td>112.1</td>
</tr>
<tr>
<td>3,00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Count</td>
<td>64</td>
<td>46</td>
</tr>
<tr>
<td>Expected Count</td>
<td>50.1</td>
<td>59.9</td>
</tr>
<tr>
<td>4,00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Count</td>
<td>25</td>
<td>9</td>
</tr>
<tr>
<td>Expected Count</td>
<td>15.5</td>
<td>18.5</td>
</tr>
<tr>
<td>5,00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Count</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Expected Count</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Count</td>
<td>160</td>
<td>191</td>
</tr>
<tr>
<td>Expected Count</td>
<td>160.0</td>
<td>191.0</td>
</tr>
</tbody>
</table>
# Appendix L – MSS information per store

Table 31. MSS information per store for Milk Products and Sandwiches & Spreads.

<table>
<thead>
<tr>
<th>Store</th>
<th>MAKRO AMSTERDAM</th>
<th>MAKRO DELFT</th>
<th>MAKRO BREDA</th>
<th>MAKRO NUTH</th>
<th>MAKRO BEST</th>
<th>MAKRO DUIVEN</th>
<th>MAKRO HENGELO</th>
<th>MAKRO VIANEN</th>
<th>MAKRO GRONINGEN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average MSS</td>
<td>2,9</td>
<td>4,1</td>
<td>3,5</td>
<td>2,9</td>
<td>3,0</td>
<td>3,2</td>
<td>2,9</td>
<td>2,4</td>
<td>3,3</td>
</tr>
<tr>
<td>Std. Deviation MSS</td>
<td>3,2</td>
<td>4,8</td>
<td>3,9</td>
<td>2,7</td>
<td>2,5</td>
<td>2,9</td>
<td>2,5</td>
<td>4,8</td>
<td>5,3</td>
</tr>
<tr>
<td>Store</td>
<td>MAKRO LEEUWARDEN</td>
<td>MAKRO NIEUWEGEN</td>
<td>MAKRO BEVERWIJK</td>
<td>MAKRO BARENDRECHT</td>
<td>MAKRO NIJMEGEN</td>
<td>MAKRO 'S-HERTOGENBOSCH</td>
<td>MAKRO WATERINGEN</td>
<td>MAKRO DORDRECHT</td>
<td></td>
</tr>
<tr>
<td>Average MSS</td>
<td>4,0</td>
<td>4,2</td>
<td>3,7</td>
<td>4,5</td>
<td>4,3</td>
<td>4,4</td>
<td>3,1</td>
<td>5,0</td>
<td></td>
</tr>
<tr>
<td>Std. Deviation MSS</td>
<td>6,9</td>
<td>6,7</td>
<td>5,4</td>
<td>7,0</td>
<td>7,2</td>
<td>7,3</td>
<td>3,2</td>
<td>8,6</td>
<td></td>
</tr>
</tbody>
</table>
Appendix M – Regression analysis actual current waste

Table 32. Included variables in the waste prediction regression model

<table>
<thead>
<tr>
<th>Model</th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
<th>t</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>Std. Error</td>
<td>Beta</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>(Constant)</td>
<td>.162</td>
<td>.009</td>
<td>17.995</td>
</tr>
<tr>
<td></td>
<td>FCC</td>
<td>-.687</td>
<td>.005</td>
<td>-.952</td>
</tr>
<tr>
<td></td>
<td>MSS_div_u</td>
<td>-.049</td>
<td>.002</td>
<td>-.273</td>
</tr>
<tr>
<td></td>
<td>FCC_MSS</td>
<td>.004</td>
<td>.000</td>
<td>.383</td>
</tr>
<tr>
<td></td>
<td>Leeuwarden</td>
<td>.164</td>
<td>.030</td>
<td>.037</td>
</tr>
<tr>
<td></td>
<td>Amsterdam</td>
<td>-.148</td>
<td>.026</td>
<td>-.038</td>
</tr>
<tr>
<td></td>
<td>Delft</td>
<td>-.140</td>
<td>.026</td>
<td>-.035</td>
</tr>
<tr>
<td></td>
<td>Wateringen</td>
<td>.094</td>
<td>.030</td>
<td>.020</td>
</tr>
<tr>
<td></td>
<td>Duiven</td>
<td>-.077</td>
<td>.026</td>
<td>-.020</td>
</tr>
</tbody>
</table>

a. Dependent Variable: perc_waste

FCC = Fresh Case Cover
MSS_div_u = minimal Shelf Stock (MSS) divided by average weekly sales
FCC_MSS = cross product of FCC and MSS_div_u
Leeuwarden, Amsterdam, Delft, Wateringen, Duiven = store influence

Table 33. Significance of waste prediction regression model

<table>
<thead>
<tr>
<th>Model</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Regression</td>
<td>3485,603</td>
<td>8</td>
<td>435,700</td>
<td>2382.840</td>
</tr>
<tr>
<td></td>
<td>Residual</td>
<td>793,383</td>
<td>4339</td>
<td>.183</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>4278,985</td>
<td>4347</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

a. Dependent Variable: perc_waste
b. Predictors: (Constant), Duiven, FCC_MSS, Leeuwarden, Delft, Wateringen, Amsterdam, FCC, MSS_div_u
Table 34. Waste regression model performance

<table>
<thead>
<tr>
<th>Model</th>
<th>R</th>
<th>R Square</th>
<th>Adjusted R Square</th>
<th>Std. Error of the Estimate</th>
<th>R Square Change</th>
<th>F Change</th>
<th>df1</th>
<th>df2</th>
<th>Sig. F Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.903</td>
<td>.815</td>
<td>.814</td>
<td>.42761</td>
<td>.815</td>
<td>2382.840</td>
<td>8</td>
<td>4339</td>
<td>.000</td>
</tr>
</tbody>
</table>

a. Predictors: (Constant), Duiven, FCC_MSS, Leeuwarden, Delft, Wateringen, Amsterdam, FCC, MSS_div_u
b. Dependent Variable: perc_waste
### Appendix N – ‘Sell More, Waste Less’ tool comparison with simulation

<table>
<thead>
<tr>
<th>Customer picking behavior</th>
<th>FIFO</th>
<th>LIFO</th>
<th>FIFO</th>
<th>LIFO</th>
<th>FIFO</th>
<th>LIFO</th>
<th>FIFO</th>
<th>LIFO</th>
<th>FIFO</th>
<th>LIFO</th>
<th>FIFO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Waste in €</td>
<td>136</td>
<td>300</td>
<td>110</td>
<td>254</td>
<td>95</td>
<td>226</td>
<td>84</td>
<td>205</td>
<td>77</td>
<td>188</td>
<td></td>
</tr>
<tr>
<td>% waste € of sales</td>
<td>3.94</td>
<td>8.66</td>
<td>3.17</td>
<td>7.34</td>
<td>2.74</td>
<td>6.54</td>
<td>2.43</td>
<td>5.91</td>
<td>2.21</td>
<td>5.41</td>
<td></td>
</tr>
<tr>
<td>Customer availability</td>
<td>0.99</td>
<td>0.99</td>
<td>0.98</td>
<td>0.98</td>
<td>0.97</td>
<td>0.97</td>
<td>0.96</td>
<td>0.96</td>
<td>0.95</td>
<td>0.95</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Customer picking behavior</th>
<th>FIFO</th>
<th>LIFO</th>
<th>FIFO</th>
<th>LIFO</th>
<th>FIFO</th>
<th>LIFO</th>
<th>FIFO</th>
<th>LIFO</th>
<th>FIFO</th>
<th>LIFO</th>
<th>FIFO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Waste in €</td>
<td>177</td>
<td>549</td>
<td>102</td>
<td>287</td>
<td>80</td>
<td>235</td>
<td>66</td>
<td>189</td>
<td>58</td>
<td>160</td>
<td></td>
</tr>
<tr>
<td>% waste € of sales</td>
<td>5.12</td>
<td>15.87</td>
<td>2.95</td>
<td>8.28</td>
<td>2.32</td>
<td>6.79</td>
<td>1.89</td>
<td>5.45</td>
<td>1.66</td>
<td>4.61</td>
<td></td>
</tr>
<tr>
<td>Customer availability</td>
<td>0.9999</td>
<td>0.99999999</td>
<td>0.98</td>
<td>0.998</td>
<td>0.965</td>
<td>0.99</td>
<td>0.92</td>
<td>0.965</td>
<td>0.88</td>
<td>0.93</td>
<td></td>
</tr>
</tbody>
</table>

Table 35. Sell More, Waste Less tool comparison with simulation at MSS=0 for FIFO and LIFO at different service levels. Cost figures are scaled with an undisclosed key.