Order policies for perishable products in retail

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Abstract
Slimstock, an inventory optimisation company, offers companies a structural solution to optimise inventory. Inventory management for perishable products is a challenging process for retailers. Food waste and product availability have increased in importance nowadays. Retailers need to make a trade-off between waste reduction and availability of products. Moreover, also costs are important to consider. In this research, there is sought for suitable approaches in scientific literature to determine order policies for perishable products. The suitability of the approaches is evaluated based on three KPIs, namely: amount of waste, service level and total costs that result. The models of Lowalekar, et al. (2016) and Pauls-Worm & Hendrix (2016) are selected for evaluation. The selected approaches are modelled and evaluated by simulation with historical sales data. The results of both models are compared and evaluated. From this comparison, a recommendation is made for Slimstock, which model fits which type of products best.

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Preface

I am glad to present you my Master thesis as a completion of the Master Management, Economics, and Consumer Studies at Wageningen University. This thesis is done in cooperation with the inventory optimisation company Slimstock from Deventer. The last six months I have learnt a lot about inventory management for perishable products in retail. It was very interesting to see how inventory management is done by retailers and what challenges they face, while ordering perishable products.

First of all, I would like to thank God Almighty for His blessings. For providing me with the capability to write this thesis and giving health, strength and inspiration.

Second, I would like to thank my supervisor Karin Pauls-Worm for her time and input throughout the entire period. Moreover, I would like to thank her for the support by giving useful tips and feedback to improve my research. Also thanks to my second supervisor, Eligius Hendrix. With his eye for details and language competence he had a substantial contribution to this research.

I am grateful for the trust I have gotten from Slimstock. From the start, I was warmly welcomed by Bart van Gessel and Anne van der Weerd. They had an important contribution to this research. First, by informing me of the company and the sector. Their enthusiasm and knowledge inspired me and was, especially in the beginning, very useful to make a good start. Second, their useful feedback and arranging the visit of supermarket chain Marqt were very helpful. I would like to thank both for their time, effort and nice communication.
Thanks to Peter de Lepper, Supply Chain Specialist of supermarket chain Marqt, as well, for the interesting and informative day. Thanks to the interview and tour he guided, I got a better understanding of inventory management in practice and its challenges.

Moreover, I would like to thank Aigul Nazmutdinova for the nice cooperation, easy communication and great support this period. Your ideas and comments inspired me and gave me new thoughts for my research. Last but not least, I would thank my parents, family and friends, who supported me and provide me with useful feedback and inspiration.

Roel Poot

Wageningen, March 2017

Management summary

Inventory management for perishable products is a challenging process for retailers. Food waste and product availability have increased in importance nowadays. Retailers need to make a trade-off between waste reduction and availability of products. The aim of this research is to find suitable approaches to determine order policies for perishable products in retail. This is done to decrease waste and to improve the availability of products. The main question answered in this research is: '*What is the most suitable approach to determine an order policy for certain types of perishable products, in terms of achieving the best trade-off between service-level and waste, in retail?*'.

The main question is investigated with help of the following specific research questions:

1. What are the characteristics of ordering perishable items in retail practice?
2. What inventory models for ordering perishable items with a fixed shelf life, that are applicable to retail, are available in scientific literature?
3. How can perishable products be classified in order to design a decision tree to select a suitable approach to determine an order policy?
4. What approach, to determine an order policy, is applicable for which type of perishable product?
5. How do the results of the chosen approaches relate to historical demand and waste data?

A literature study is conducted to find suitable approaches in scientific literature. The models developed by Lowalekar, et al. (2016) and Pauls-Worm & Hendrix (2016) are selected and programmed in a Python software program. The order policies that resulted from both models are simulated with the use of Microsoft Excel to see how each of them performs. The order policies are determined for sixteen stores and two products (shelf life of six and seventeen days).

The model of Lowalekar, et al. (2016) is not a good method to determine order policies for perishable products in retail. In almost all cases the model gave infeasible solutions for products with a lead time of two days. Although waste was decreased for both products (66.55% (shelf life = 6) and 100% (shelf life = 17), the target service level was met in almost no case.
The model of Pauls-Worm & Hendrix (2016) performs better. The waste is lowered by 95.77% and 100% for respectively the product lifetime 6 and 17. Though, the basic model meets the target service level for product lifetime 6 at only five of the sixteen stores. Whereas for product lifetime 17, the model overestimates the needed products and has a fill rate of 100% at fifteen of the sixteen stores. This high fill rate is accompanied with high costs. For both products, a correction of the model is needed to be suitable in practice. When a fraction is included in the model it meets almost always the target service level. This fraction should be calculated for each store and product. If further research show that these calculations are suitable in practice, this would be a suitable method to determine order policies for perishables in retail.

Comparison of both models with the model of Broekmeulen & Van Donselaar (2009) studied by Nazmutdinova (2017) gives Table M1, Figure M1 and Figure M2. Although the model of Lowalekar, et al. (2016) has the lowest costs, it gives infeasible solutions. Therefore, this is not a suitable model in practice. For product lifetime 6, the model of Broekmeulen & Van Donselaar (2009) gives feasible solutions for all stores and does not have much more costs in comparison to Pauls-Worm & Hendrix (2016). Therefore, this model is recommended for products with lifetime 6. If waste and fill rate are the only KPIs, Pauls-Worm and Hendrix (2016) would be recommended for products with lifetime 17. However, when costs are also considered, Broekmeulen & Van Donselaar (2009) performs better for this product as well (see Figure M3).

Table M1. Total costs of all stores per product, resulted from the order policies of the models.

	Product lifetime 6	Product lifetime 17
Lowalekar, et al. (2016)	€ 12,177.90	€ 20,595.46
Pauls-Worm & Hendrix (2016)	€ 12,348.62	€ 23,229.69
Broekmeulen & Van Donselaar (2009)	€ 12,420.22	€ 21,347.44

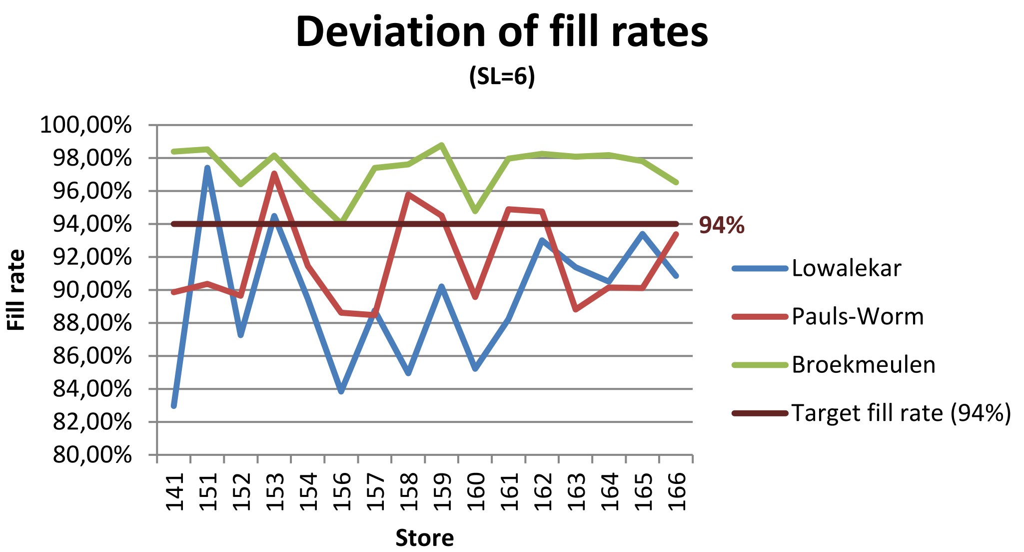

Figure M1. Deviation of fill rates from the target service level for product lifetime 6, for the models of Lowalekar, et al. (2016), Pauls-Worm & Hendrix (2016, basic model) and Broekmeulen & Van Donselaar (2009).

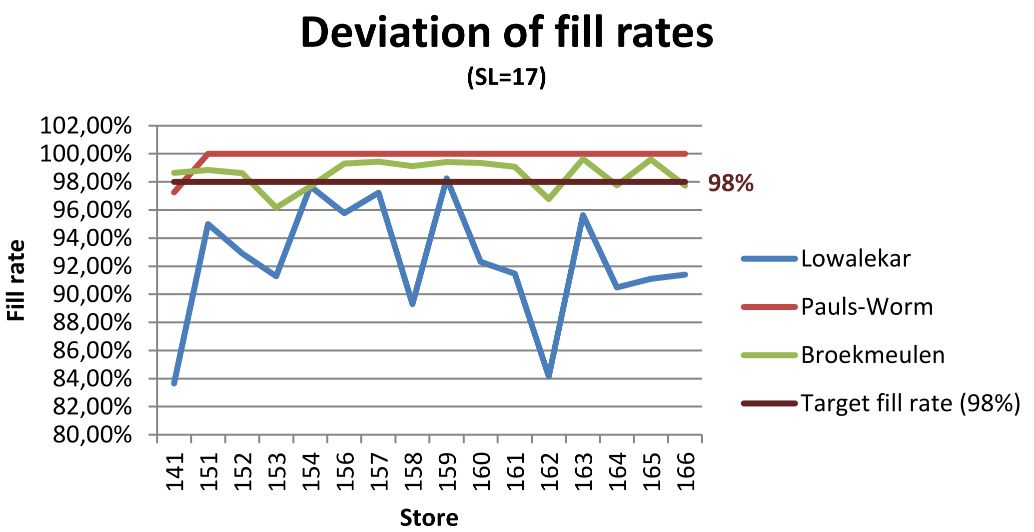

Figure M2. Deviation of fill rates from the target service level for product lifetime 17, for the models of Lowalekar, et al. (2016), Pauls-Worm & Hendrix (2016, basic model) and Broekmeulen & Van Donselaar (2009).

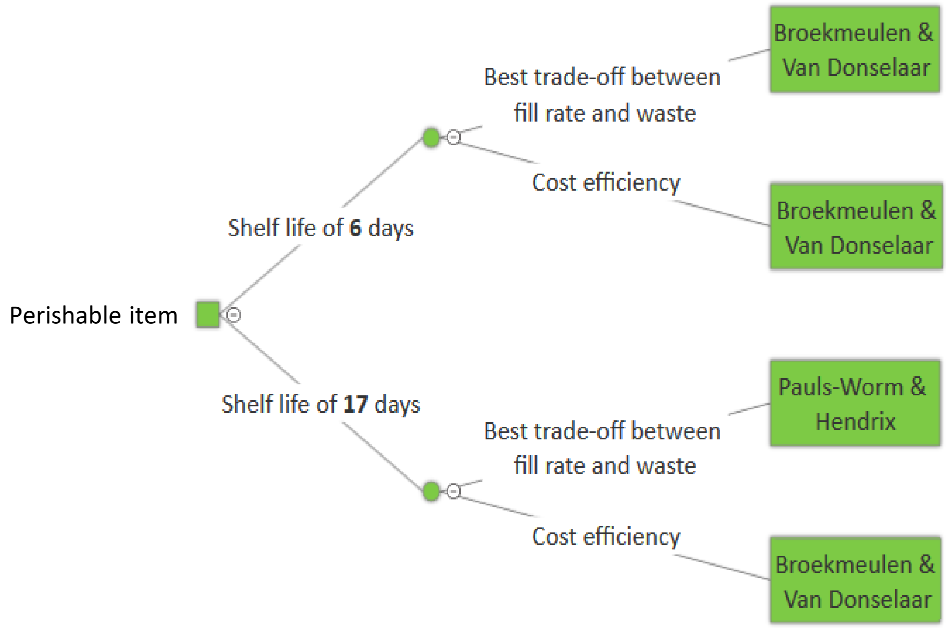

Figure M3. Decision tree for selecting the most suitable model for a perishable item.

Contents

1. Introduction

Within this chapter an introduction of the topic is made. In Section 1.1 the background of the topic is given, followed by the problem statement in Section 1.2. The aim of this study is discussed in Section 1.3 and the research framework and materials are treated in Sections 1.4 and 1.5 respectively.

1.1 Background

Food waste has increased in importance nowadays. Customers, retailers and even whole supply chains are being more and more confronted with reducing food waste. The focus is not anymore on making as much money as possible only, but the social responsibility of companies is raised in importance as well. Although food shortage is still a big problem all around the world, nearly one third of all food that is produced is thrown away (Gustavsson et al. 2011). These authors found that 40% of this amount is lost at the end of the food supply chain, at the retail- and consumer-level. From the study of (Buzby, 2009) it is found that 11.4% of the total amount of fresh fruit, 9.7% of fresh vegetables and 4.5% of fresh meat, poultry and seafood is wasted at supermarkets annually. Not only hunger, poverty and a reduction of income are results of food waste, it is a loss of production resources like land, energy, water and other inputs as well. Moreover, food waste affects the sustainability of food production systems as well (Rijpkema et al., 2014). These results show that it is important for retailers to make a good estimation of the demanded products to have an inventory level that satisfies demand, but does not create (a lot of) waste.

Most (food) products have a limited life time; they deteriorate within a certain amount of time (Pahl and Voß, 2014). Deterioration is the process which causes that items no longer can be used for their original purpose due to damage, decay or spoilage. Within this process the item will change during the time that it is stored and thereby losing its utility continuously (Dave, 1986). In this research, the focus is on inventory models which take perishability of products into account. As Van Donselaar et al. (2006) found, there are clear differences between perishable and non-perishable products. The differences can be found at for instance the number of sales, average time between two replenishment orders, shelf life and minimum inventory norm. Within the report of Van Donselaar et al. (2006) perishable products are stated as products with a maximum shelf life of less than 30 days. After this fixed time period the product is not acceptable for consumption anymore or obsolete. This research focusses not on all perishable products but only on perishable products with a fixed shelf life (of less than 30 days), that is, products with a ‘best before’, ‘use by’ or ‘sell by’ date.

One important cost of a retailer is the cost of food that has to be thrown away and/or discounted. Perished items do not yield money for a company, but will only increase the costs of the organisation. Excessive inventories will result in waste. Items could be marked down just before the sell-by-date, or if the sell-by-date has reached the items are thrown away. Both cases result in financial consequences for the retailer (Van Donselaar et al., 2006). These authors suggest three options to reduce the amount of waste for items with a short shelf life, namely: reduction of the lead time and/or review period, demand substitution, and limiting the assortment.

First of all, a reduction of the lead time will result in a longer remaining shelf life in the store. The less time is spent on the delivery of a product (towards a retailer), the longer the remaining shelf life will be. Therefore, a longer time period is available to sell the product to the end-consumer. Demand substitution is another option to decrease the waste. If a product could be substituted by another product, it is not necessary to have a large inventory for every individual product to fulfil the demand of the customer. Instead of large inventories and therefore a lot of waste, less inventory is needed for individual products and therefore less waste will result.

Last but not least, limit the assortment; when the assortment is kept relatively small, the average demand of a product will be relatively large on a daily basis. For this reason, it is relatively certain what the demand will be, resulting in a reduction of the total amount of waste (Van Donselaar et al., 2006). However, customers nowadays demand for a larger variety of products in product categories. This leads to a less certain demand for these products. Besides, the demand for the perishable products has a low to medium demand rate, with an average of less than five products sold per day. This makes it hard for retailers to determine the right reorder quantities, resulting in the problem of having too much waste or running out of stock. (Broekmeulen & Van Donselaar, 2009).

Not only uncertain demand has an influence on the amount of waste that results, but the withdrawal policy has a large impact on it as well. The focus is here on the age of the products that are available on the shelves. Do all items have the same remaining shelf life or do they have different shelf lives? As Rijpkema et al. (2014) mention, the use of real time, product quality information is a key element in the supply chain of perishable products. It is necessary to have information of the expiration dates of the available products to order the right number of products.
One problem is the difference in policies preferred by retailers and by customers. Mostly a first in, first out (FIFO) issuing policy is wished for by retailers to be able to sell products for an as long as possible time period. However, customers typically prefer products with an as long as possible remaining shelf life. Therefore, their choice leads to a last in, first out (LIFO) withdrawal policy (Broekmeulen & Van Donselaar, 2009). By selecting the newest products (last in), consumers have more time to consume the products before expiration. If customers are allowed to select the item (and thereby the remaining shelf life) it is complex to have an optimal reorder, because it is difficult to know the age distribution of the inventory of all different items. An approach which incorporates both policies could be necessary to find the best possible order policy. Moreover, because the focus is on the retail store replenishment, the model should be a single echelon model.

Being able to deliver demanded products to customers, is growing in importance due to lower switching barriers. Nowadays customers have a lot of alternatives available within their environment and thereby could easily change supplier/retailer/etc. Therefore, not only costs but also service level is of great importance for companies at the moment. High costs could be fatal for a company, and so does a low service level. However, also here a difficult decision has to be made, as a high service level results in more waste. To increase the availability of a product, the number of items in inventory is increased, resulting in more perished items. Therefore, a trade-off has to be made between the desired service level and the amount of outdating that is allowed.
This trade-off is extensively discussed, by comparing different approaches to calculate the amount of waste resulting from a certain service level. If the amount of waste that results from a certain service level is known, then a company's management is able to make better decisions in inventory management. Currently, a company's management determines a certain target maximum waste percentage, for instance 3% of the inventory will be thrown away. If the real results are lower than this percentage, inventory is based on a higher service level in the next period. Since more inventory is hold, a higher amount of waste will result and the percentage of waste will raise towards the target percentage. If the real results are higher, inventory is based on a lower service level in the next period. (B. van Gessel & A. van der Weerd, personal communication, September 13, 2016)

The waste percentage is arbitrarily chosen and depends on the company's strategy. For instance, Albert Heijn and Spar focus on a high service level, resulting in a higher inventory level, and therefore more waste. According to reasoning of these companies: a good store has waste. Whereas Aldi for instance focusses on low costs/prices, resulting in less variation in products, lower inventories and therefore less waste. For this reason, the estimated percentage of waste differs between companies and depends among others on the strategy of the company (B. van Gessel & A. van der Weerd, personal communication, September 13, 2016).

The process of reordering is not a yearly process. The process of determining the optimal reorder quantity takes place several times a week, and it might even take place every day. Taking into account that supermarkets often carry more than 30.000 stock keeping units (SKUs) (Agrawal & Smith, 2015), and roughly 15% of these are perishable items (Van Donselaar et al., 2006), a reorder quantity for more than 4500 products has to be determined. For this reason, the order decision method should be as quick as possible for every product. Therefore, having a fast method to calculate the optimal quantity is a necessity.

A lot of retailers use an automated store ordering (ASO) system for the reordering of products (Broekmeulen & Van Donselaar, 2009). However, these systems do not take the age of inventory into account. For this reason, stock outs could appear when products with a remaining shelf life of, for instance, only one day are not taken into account. The next day the remaining products are obsolete and thrown away. As a result, these obsolete products might result in an inventory level which does not fulfil customer demand. To overcome this problem, the remaining shelf life should be included in the reorder decision making. However, this is a complication in the decision making.

Software may help a retailer to order the right quantity at the right time. Slimstock is a company which supplies software to organisations to optimise their inventory. With more than 600 customers, Slimstock has become market leader in Europe based on inventory optimisation. The company was founded in 1993 by Rolf Pflitsch and Eric van Dijk. For inventory optimisation, Slimstock developed the software package Slim4, which helps their clients to get the right inventory to the right place at the right moment. By using this software package, the inventory is reduced and the service level increased. This will increase the turnover while costs are lowered. Slimstock does not only supply software solutions, but they also offer project based support and professional services like coaching, analysis and interim professional support (Slimstock, 2016). Since Slimstock is not only delivering a product (the Slim4 software package), it is a combination of a manufacturing and service company.

1.2 Problem statement

Still a large part of the total food produced is wasted (at the retail-level); ordering the optimal number of perishable products is hard for retailers. For this reason, a suitable order policy is needed to meet the target service level and decrease the amount of waste. Moreover, the low to medium demand rate (on average ≤5 products per SKU per day) for their products, makes it hard for retailers to order the right number of products.

Retail supplies a variety of perishable products with a fixed shelf life (1-30 days), characterised by e.g. differences in the remaining shelf life, demand pattern, costs and price of the product. Consequently, different types of products have different order policies. Therefore, an inventory manager should have a tool to decide what order policy is most appropriate for a specific perishable product.

Besides the different variety of perishable products, there are a several approaches for determining order policies for perishable products in literature. The suitability of the approaches depends on the calculation time and accuracy of the approaches. Due to the large number of SKUs, a fast approach is desired. Meeting service level requirements and limited amounts of waste (according to the specific company) define the accuracy of the approach. The most suitable approach for determining order policies has to be found to reduce waste and increase the service level.

To select the most suitable approach for the different types of perishable products, key performance indicators (KPIs) have to be assigned. The trade-off between waste and service-level is most important within this research. For this reason, the amount of waste resulting from a certain order policy is the first KPI that is used. Also service-level is used as a KPI to determine the best approach available. Based on these two KPIs the different approaches are evaluated. The choice for the best approach is based on the one that gives the highest target service-level in combination with the lowest amount of waste (best trade-off). Moreover, also costs are calculated in order to see how cost efficient the order policies are.

1.3 Aim

The aim of this research is to find a suitable approach to determine an order policy for different types of perishable products with a fixed lifetime, by evaluating several approaches. Within this research, two approaches are evaluated. The evaluation consists of a comparison of the reached value of the KPIs following these policies with the historically reached value for the KPIs. Moreover, research outcomes are compared with the results of two approaches evaluated by Nazmutdinova (2017).
Therefore, the main research question is the following: What is the most suitable approach to determine an order policy for certain types of perishable products, in terms of achieving the best trade-off between service-level and waste, in retail?

To find the best possible order policy, the following specific research questions are investigated within this study:

1. What are the characteristics of ordering perishable items in retail practice?
2. What inventory models for ordering perishable items with a fixed shelf life, that are applicable to retail, are available in scientific literature?
3. How can perishable products be classified in order to design a decision tree to select a suitable approach to determine an order policy?
4. What approach, to determine an order policy, is applicable for which type of perishable product?
5. How do the results of the chosen approaches relate to historical demand and waste data?

1.4 Research Framework

Different methods are used in this research to investigate the main and specific research questions. In the process of finding the most suitable approach, for the different types of perishable products, a desk research is conducted. By conducting a literature research, several inventory models for perishable products are explored. The approaches should be suitable in retail and meet all requirements. When different approaches are found, a selection is made of the approaches that is used within this research for evaluation and comparison. This selection is made in consultation with Slimstock, based on their knowledge and expertise.

In addition to the literature research, a data analysis is part of the research. To classify the perishable products into groups of products, the demand and waste data, provided by Slimstock, is analysed in order to create different groups of products. According to characteristics, products are assigned to specific product groups. This division of types is based on the classification of perishable products used in literature. This literature research gives a first insight in the types that could be distinguished.

To assign the right order policy to each type of perishable product, the selected approaches are evaluated by running them with data from retailers. The evaluation is done by using a Python software program. Each approach is inserted into the program and run for a variety of products. Within the evaluation phase, a sensitivity analysis is conducted to evaluate the influence of different scenarios on the results.

Last, an interview at supermarket chain Marqt is held to get a better insight in the world of store replenishment and perishable food items with a fixed shelf life. This interview is done with the Supply Chain Specialist whom is able to show the main challenges retailers face in practice.

1.5 Research materials

The research material consists of two parts; the approaches which are evaluated and data that is needed to evaluate the approaches. First of all, suitable inventory models are needed for the evaluation and comparison. As explained, this is done by conducting a literature study. A literature research has been performed for approaches that meet all requirements or that could be adopted in such a way that all requirements are met. This step is followed by the selection process of the approaches.

For evaluating the inventory models, data is required. This data is collected by Slimstock and consists of sales data, inventory data, data of lead times, etc. It is demand and waste data collected from retailers and is anonymised for privacy reasons. The specific data that are required depend on the approaches that are selected. Besides, the information from the interview with the Supply Chain Specialist of Marqt is used for determining the important model characteristics.

2. Literature review and model characteristics

Within this chapter, a literature review is presented in order to find suitable approaches to determine an order policy for certain types of perishable products. Also an interview with the Supply Chain Specialist of supermarket chain Marqt (Peter de Lepper) has been held to get a better understanding of practice. At first, several characteristics are described that are required for the approaches in order to be applicable to the practical situation. When the characteristics are described, approaches are mentioned with their pros and cons. The chapter is finalised with the selection process of the approaches; i.e. which models are further investigated in the remaining of this research.

2.1 Characteristics

Retailers face an important decision every day: how much to order? On the one hand, retailers can order a high number of products to fulfil all customer demand, and as not to run out-of-stock. On the other hand, when too many products are ordered, the retailer will face waste which costs (a lot of) money. Therefore, a retailer should find a balance between availability (service level) and waste. Retailers are not only faced by costs, but they are faced with the social stigma of waste as well (Broekmeulen & Van Donselaar, 2016). Companies should be as 'green' as possible. For this reason, it is important that retailers have an accurate tool to estimate the optimal amount to order.

Several authors have written articles about inventory management of perishable products. A couple of authors have made an overview of available order policies for perishable products with a fixed lifetime. Such overviews are made by Nahmias (1982), Goyal & Giri (2001), Karaesmen et al. (2011), and Bakker et al. (2012). Each of them discusses important inventory model characteristics like: periodic review, issuing policy and lead time. Based on the characteristics used in these articles and mentioned as important by the Supply Chain Specialist of Marqt, a list of characteristics results, as is discussed in the sequel.

2.1.1 Outdating

Broekmeulen & Van Donselaar (2016) state the optionality of waste: '*Waste is not a given, but a choice*'. The amount of waste depends heavily on decisions made, for instance on the replenishment policy. Waste can be reduced a lot by making appropriate decisions. This may even have a huge impact on the profitability of the retailer. The authors argue that net income can be increased by 17% when waste is reduced with only 0.5% point. These numbers show that there are huge potential benefits when waste could be reduced.

Each approach, found in literature, should meet several requirements, in order to be suitable for a retailer in the ordering process of perishable items. The current methods Slimstock is using for determining the right order policy for perishable products are not sufficient, according to themselves. Products that outdate require other order policies than products without expiration date. The possibility of outdating has such an impact on the results (both the amount of waste and the service level) that a different approach is necessary in order to reach a solution which is as near to optimality as possible. For this reason, the first, and maybe most important characteristic, is an approach which includes the outdating of products.

2.1.2 Periodic review

Retailers most often order products a couple of times per week, if not every day. A periodic reviewing system is the most common way in which orders are placed at the retail stage. Periodic review is checking the status of inventory and placing orders at regular periodic intervals (Chopra & Meindl, 2016).

A continuous review system is not suitable for perishable products in the current retail environment. For a continuous review system, it is necessary to have a precise overview of the products in stock and, in case of perishable products, their expiration dates. When a product is sold, it is necessary to know whether a product with five days of shelf life is sold or a product which would expire the next day. A possible solution to overcome this problem is to use radio-frequency identification (RFID) tags on every product which could store the expiration date and other characteristics of the product. However, due to the costs of these tags it is rarely used by retailers. Since the age distribution of the inventory is unknown a continuous review system is not suitable for retailers.

Marqt

At the supermarkets of Marqt, inventory is checked every day by hand. Both the number of available products and the number of outdated products are counted. Subsequently, the Slim4 system of Slimstock calculates overnight the order quantities and these replenishment orders are placed the morning after (P. de Lepper, personal communication, November 16, 2016). These facts indicate a periodic review system as well. Therefore, periodic review is included in the list of characteristics.

2.1.3 Lead time

In the replenishment process, retailers are confronted with spatial and time dimensions. First of all, the spatial dimension, since retailers offer more than 30.000 different SKUs (Agrawal & Smith, 2015) it has a lot of suppliers from everywhere in the world/region. Due to the spatial distance between suppliers and/or distribution centres (DC) and the retail shop, retailers face lead times which complicates the ordering decisions. Instead of immediate replenishment, it may take one day or even more.

Lead time in practice

Considering the practical situation, the minimum lead time Marqt has, is one day for instance. For perishable products with a shelf life of maximum 30 days, this could even be seven days (P. de Lepper, personal communication, November 16, 2016). Therefore, it is important to look several days in advance in order to prevent stock outs due to perished products. So, lead times of one day and more should be taken into account when replenishment orders are made. By not taking lead time into account, a bigger amount of products will be perished than is assumed.

2.1.4 FIFO/LIFO

According to Lütke Entrup (2005), one of the most important criteria of consumers for buying a product is product freshness. He even argues that the price of a product is replaced for freshness as the primary concern for food of consumers. Estimating the freshness of a product is currently quite easily done by checking the expiration dates on the package of a product. As mentioned in Chapter 1, customers prefer a last in, first out (LIFO) withdrawal policy. Whereas a first in, first out (FIFO) withdrawal policy is preferred by retailers. When a shelf contains items with two different shelf lives: e.g. two days and five days, a retailer is faced with the problem of FIFO and LIFO. If the oldest (FIFO) item is bought, he still got five days to sell the other item. However, when the newest (LIFO) item is bought, he just has two remaining days to sell the item. As a result, the expected amount of waste will increase.
To stimulate customers to buy the oldest item on the shelf, retailers put the oldest items on the front of the shelf and the newest ones at the back. This strategy only works partially, because it is a common strategy, known by a lot of customers. They would still seek for the freshest item on the shelf.

For these reasons, the different withdrawal policies are another characteristic that should be taken into account. Because not all people pick the newest items from the back of the shelf, complete LIFO is not applicable to retail. However, complete FIFO is not the case either, due to selecting the newest items by customers. Therefore, a combination might be most useful and suitable for the retail environment.

2.1.5 Lost sales

Retailers try to prevent stock outs at any times. As said in the Chapter 1, daily sales are not equal to existing demand. When products are out-of-stock, there still could be any unfulfilled demand. However, the size of this unfulfilled demand is unknown for retailers. Customers have several possibilities to cope with their unfulfilled demand, namely: do not purchase the item at all, buy item at another store, buy a substitute of the product or delay their purchase till the product is available again. Corsten and Gruen (2003) found that, in case of a stock out, 9% of the customers would not purchase the item at all. 15% would wait for the item, 45% would substitute the product and 31% of the customers would buy it at another store. As a result of this, 40% of unfulfilled demand will harm the store, either by not selling the product (thereby losing profit) or even by switching to a competitor. Moreover, these numbers show that 85% of the original demand could be seen as lost, for the specific product (only 15% would wait for the specific item) (Bijvank & Vis, 2011). Lost sales therefore assumes that customers are unwilling to wait for their ideal product(s) (Ehrenthal et al., 2014).

Practical situation

Different authors assume unfulfilled demand to be backordered, this is, unmet demand is not lost but delivered after the inventory replenishment arrives. This assumption does not match with practice however. According to Peter de Lepper (personal communication, November 16, 2016) all unmet demand is lost. The only exceptions for backlogging products that are out-of-stock, are promotion products. These products are the only ones that are backlogged, however this amount is negligible. In order to have an approach as close to practice as possible, the lost sales assumption is included in the list of characteristics.

2.1.6 Service level

Having no shortages as a retailer is accompanied by high inventory costs and a lot of waste, due to high inventory levels. Moreover, fresh food products have a big influence on cross selling within a retail store. Unavailability of fresh food products influences the sales of other product categories. If fresh products are out of stock, sales are lost for other products as well and the goodwill of the retail store is harmed (Minner & Transchel, 2010). For these reasons, a trade-off has to be made in which the service-level is as high as possible, whereas the amount of waste is limited. But what is exactly meant by 'service-level'? There are different definitions of service-level, the two most used ones are:

- α service-level, this is the probability that the stock does not fall below a critical level ('ready rate').
- β service-level, this is the expected fraction of demand that is directly met from inventory on hand ('fill rate') (Chen & Krass, 2001).

As explained in Chapter 1, retailers determine a certain amount of waste that is allowed ('a good store has waste'). Also a decision is made on the service-level that should be met. Because these two KPIs play an important role in retail, these should be included in the software which Slimstock provides. Questions like 'what amount of waste will I have, regarding this service-level?' and 'what happens with both KPIs when the number of order days change?' need to be answered. Therefore, approaches which includes service-level constraints or take service-level in another way into account do have an advantage.

2.1.7 Stochastic demand

As said, demand is uncertain for retailers. As a consequence, the main challenge for retailers is to match replenishment and demand, so providing enough items to fulfil upcoming customer demand (Ehrenthal et al., 2014). They do not know how many customers will visit their store at day X, and they do not know what and how many products these customers want to buy. Demand varies per day of the week and differs on the time of year. Holidays like Christmas, Easter and New Year effects the demand.

Not only holidays have an influence on the demand, also weather conditions have an influence on the demand. For instance, more ice cream is bought on sunny days and pea soup is higher demanded in winter months. Demand may also not be evenly distributed within a single day. Dependence on working hours result in customers visiting the retail store after regular working hours on weekdays. So, demand also depends on specific customer buying habits (Ehrenthal et al., 2014). Last but not least, promotions have their influence on customer demand as well. Promotions will increase the demand variation and thereby increase the difficulty to estimate demand. Since demand is unknown, stochastic demand is a prerequisite for the approaches.

2.1.8 Conclusion

Several articles have been written about inventory management of perishable products. A couple of authors have made an overview of the available models on this topic, based on specific model characteristics. From these literature overviews and retail practice several important characteristics of inventory models for perishable products were found. The most important characteristic is outdating; a model should take outdating of products into account. Also periodic review is an important characteristic, based on current retail practices. The third characteristic is lead time, to cope with demand while having outstanding orders. Fourth, withdrawal policies of products are uncertain, by including FIFO, LIFO or a combination of both, a model could better cope with this uncertainty. If demand cannot be met, it is assumed to be lost. Therefore, lost sales is included as model characteristic as well. In line with unmet demand, service level is included. Service level is a useful tool to see how a model performs regarding shortages. The last characteristic is stochastic demand, due to the fact that demand is uncertain for retailers.

2.2 Approaches

In order to find suitable approaches, a literature study was conducted. As mentioned in Section 2.1, among others, Karaesmen et al. (2011) provided an overview of reviewing models for perishables with a fixed lifetime. Besides, from other articles diverse approaches were found which might be suitable for this research as well. In this section nine papers with inventory models are discussed. This selection has been made based on the characteristics described in Section 2.1. All articles that included at least outdating, periodic review and stochastic demand were selected.

The following articles with their approaches to determine an order policy for perishable products, were selected for further investigation:

1. Chiu – 1995
2. Williams & Patuwo – 1999
3. Ferguson & Ketzenberg – 2006
4. Broekmeulen & Van Donselaar – 2009/2012
5. Minner & Transchel – 2010
6. Haijema & Minner – 2015
7. Lowalekar, Nilakantan & Ravichandran – 2016
8. Muriana – 2016
9. Pauls-Worm & Hendrix – 2016

2.2.1 Chiu

The first approach that is selected is the one of Chiu from 1995. Chiu has created a perishable inventory model in which fixed positive order lead times are included. A heuristic model is provided to solve the inventory problem; this is a positive aspect of this approach. Heuristics reduces the calculation time and thereby make it more suitable within a retail environment.

Periodic review is used to check the inventory level at a certain interval. The nonnegative, random demand is assumed as independent and identically distributed (tested for Poisson and normally distributed demand). FIFO is used as issuing policy; LIFO is unfortunately not included in this approach. Another assumption that is not (completely) fulfilled is the lost sales assumption. In the approach of Chiu unsatisfied is completely backlogged instead of lost. Besides, service level is not included in the approach. In Table 1 an overview of the assumptions is given.

Table 1. Assumptions Chiu – 1995

Outdating	Periodic review	Lead time	FIFO or LIFO	Lost sales	Service level	Stochastic demand
Yes	~	Yes	-	No (BO)	No	Yes

2.2.2 Williams & Patuwo

Williams and Patuwo (1999) developed a periodic review, perishable inventory model with a positive lead time. The model is developed for products with a lifetime of two periods. It is not tested for products with a longer shelf life than two periods, the effect on products with a longer shelf life should be investigated, whether this model is suitable for those products as well. The stationary demand is assumed to be independent in successive periods and is a random variable. The results are tested for uniform, triangular and exponential distributed demand. Demand that is not satisfied within that period is assumed to be lost. The authors included different positive lead times, namely of one to four days. Products are sold according to a FIFO issuing policy. LIFO is not included in this approach, and therefore giving a less accurate reflection of practice. Another disadvantage of this approach is the absence of service level. In order to reach a service level as high as possible and lowering the amount of waste, the model calculates costs for shortage and waste. By including these costs, the authors try to improve the KPIs of waste and service level. However, the exact service level is not given by this approach. The assumptions described above could be found in Table 2.

Table 2. Assumptions Williams & Patuwo - 1999

Outdating	Periodic review	Lead time	FIFO or LIFO	Lost sales	Service level	Stochastic demand
Yes	Yes	Yes	FIFO	Yes	No	Yes

2.2.3 Ferguson & Ketzenberg

Ferguson and Ketzenberg (2006) designed a periodic review model for products with a fixed lifetime. The main goal of the authors is showing the value of information (VOI) within the supply chain. They want to show the (potential) benefits of good communication between suppliers and their customers (retailer). Information sharing in this case means that retailers would share information about inventory levels and order policies with their supplier. The other way around, the supplier would inform the retailer about the age of the products to be supplied. Although this article is mainly on showing the benefits of sharing information, it still might be useful for Slimstock to use for inventory replenishment. Lead time is assumed to be one period, so products ordered in period *t* are delivered in period *t+1*. Three different issuing policies are investigated within the article. FIFO, LIFO and SIRO issuing policies are tested to see the differences in benefits each policy has.

If the inventory does not fulfil the demand for an item, this unsatisfied demand is lost. The cost of this lost sale is established as the lost margin (selling price minus costs). Besides, service level (fill rate) is mentioned in the article as well, results are shown however the calculations are missing in the text. Last but not least, demand is assumed to be discrete, stochastic, and stationary.
Not only a model is provided, also heuristics are provided to implement it more easily, to compute the results extremely fast and give near optimal results. Table 3 shows the assumptions made by Ferguson and Ketzenberg.

Table 3. Assumptions Ferguson & Ketzenberg - 2006

Outdating	Periodic review	Lead time	FIFO or LIFO	Lost sales	Service level	Stochastic demand
Yes	Yes	Yes	FIFO, LIFO & SIRO	Yes	Yes	Yes

2.2.4 Broekmeulen & Van Donselaar

The next possible suitable approach is the one developed by Broekmeulen & Van Donselaar (2009) in combination with Van Donselaar and Broekmeulen (2012). An approximation model has been created for calculating the expected amount of outdating, this for products with a shelf life of 2-30 days. The quality of the results is, after the approximation is done, improved by using regression. It is a periodic reviewing system with a positive lead time of one or two periods. According to the most common way for retailers to offer their products, the authors assume a FIFO withdrawal policy. A LIFO withdrawal policy is not taken into account at all, neither complete LIFO nor partial LIFO. Demand for products is assumed as stochastic, stationary discrete demand. When demand is larger than the number of available products, this unfulfilled demand is lost. The focus of the authors is on two KPIs: relative outdating and customer service level (fill rate). As a result, they included service level in the model and focussed on the trade-off between outdating and service level. This would be an approach that would be in line with the assumptions that are stated in the first paragraphs of this chapter. The only characteristic that is not fulfilled is the issuing policy, instead of a combination between FIFO and LIFO, this approach is focussing only on complete FIFO issuing. The assumptions, made by Broekmeulen and Van Donselaar, are shown in Table 4.

Table 4. Assumptions Broekmeulen & Van Donselaar– 2009/2012

Outdating	Periodic review	Lead time	FIFO or LIFO	Lost sales	Service level	Stochastic demand
Yes	Yes	Yes	FIFO	Yes	Yes	Yes

2.2.5 Minner & Transchel

Approach number four is the one of Minner and Transchel (2010). They have created an approach to determine, for perishable products with a fixed shelf life, dynamic order quantities. A periodic review system is used for the inventory replenishment with a deterministic lead time and orders can be placed every day. This lead time differs from one, two, three to five periods. Besides, both FIFO and LIFO are included in the model. Unfortunately, a combination of both is not included. The unfulfilled non-stationary random demand is assumed to be lost, like the case was at the preceding approaches. The authors took two different service level measures into account. They use both an α and β service level constraint within their model. As a result, they measure the non-stock out probability and the fill rate.

Instead of minimizing costs, the focus is on satisfying a certain service level. This is beneficial for this research because real costs are hard to get. See Table 5 for the complete overview of the assumptions made by Minner and Transchel.

Within the article a comparison with the BSP and COP heuristic policies is made. The approach of Minner and Transchel shows their superiority over the BSP and COP policies. However, they do not include any approximations or heuristics themselves. Although it fulfils all different requirements, it might not be the most suitable approach to use within this research. Because it is a stochastic dynamic programming (SDP) model it takes quite some time to calculate the results, especially when parameters change.

Table 5. Assumptions Minner & Transchel - 2010

Outdating	Periodic review	Lead time	FIFO or LIFO	Lost sales	Service level	Stochastic demand
Yes	Yes	Yes	FIFO & LIFO	Yes	Yes	Yes

2.2.6 Haijema & Minner

In the article of Haijema and Minner (2015), several policies are investigated in order to improve existing replenishment policies. The policies are options in-between base-stock policies (BSP) and constant order policies (COP). A base-stock policy is an order policy which uses an order-up-to level for the replenishment. This means that inventory is supplemented up to this level. Constant order policies however mean ordering a constant quantity every period. Instead of looking at the current inventory level and adapting the replenishment amount to this level, a fixed quantity is ordered every period (Huh et al., 2009). However, the authors do not present any heuristics, results are calculated by stochastic dynamic programming. This fact makes this approach more difficult to use in retail practice, due to the need for a fast approach. Not only different order policies are investigated, also different issuing policies are tested. FIFO and LIFO are included in the research and even a combination of the two is possible. This is an important aspect, because this is a better reflection of practice instead of complete FIFO or LIFO withdrawal. Lead time is included in the model as well, and is assumed to be deterministic. Demand is assumed to be stochastic and unsatisfied demand is lost, a penalty cost is calculated for every unit of lost demand. The focus is on shortage and waste costs; this is a positive aspect in order to decrease waste and increase the product availability. A disadvantage of the given model is the absence of service level. The trade-off between waste and service level is central to this research. However, the effect of waste on the service level could not be seen, based on the model in current form. Table 6 provides an overview of the assumptions described above.

Table 6. Assumptions Haijema & Minner - 2015

Outdating	Periodic review	Lead time	FIFO or LIFO	Lost sales	Service level	Stochastic demand
Yes	Yes	Yes	FIFO & LIFO	Yes	No	Yes

2.2.7 Lowalekar, Nilakantan & Ravichandran

Lowalekar, Nilakantan and Ravichandran (2016) have created an approach for perishables as well. They present both an approximation model and gradient search-based heuristic in their article, as well as a mathematical model. Products, with a fixed lifetime, are ordered by using a periodic reviewing system.

A disadvantage of this approach is the assumption of zero lead time. Orders are received instantaneously when an order is placed, whereas in practice it takes at least one day, in almost all cases.
In this study, they used 'service-in-random-order' (SIRO), so products are issued randomly instead of complete FIFO or LIFO. Because in practice, products are issued in between a complete FIFO and LIFO issuing policy, this could be a way to better reflect the practical situation. Although products are rarely picked randomly by consumers, consumers either follow the issuing policy of the retailer (FIFO) or otherwise, pick products from the back of the shelf using a LIFO policy, this might be a useful way to organize the replenishment. Demand that could not be fulfilled immediately is lost and is Poisson distributed. Service level is included in the article as fill rate. This fill rate is compared with the amount of waste that results, so the relationship between fill rate and average waste is shown, thereby it uses the same KPIs as this research does. In Table 7 an overview of the assumptions is shown.
Due to the combination of the approximation and heuristic model that are presented and the different assumptions that are met in the article of Lowalekar et al., this approach would be a suitable one to further investigate within this research.

Table 7. Assumptions Lowalekar, Nilakantan & Ravichandran - 2016

Outdating	Periodic review	Lead time	FIFO or LIFO	Lost sales	Service level	Stochastic demand
Yes	Yes	Zero	SIRO	Yes	Yes	Yes

2.2.8 Muriana

The eighth possible approach is the one of Muriana (2016). Muriana provided an alternative EOQ model for perishable products which have a fixed shelf life. A periodic reviewing system is used and the approach includes a constant, deterministic lead time. This approach is made for a very short period; it could be used like a repeated newsboy problem. Only one batch (so only one shelf life) of products is on hand, when these products are sold out, a new batch is ordered. If there is excess demand during a period, this demand is lost, so no backordering takes place. According to a fixed service level the safety stock is calculated. When a retailer has a target service level it could be implemented in the safety stock calculations to reach this target level. Also the last assumption is met, a stochastic, normally distributed demand is used in the approach. See Table 8 for an overview of the assumptions made in the article of Muriana.

Table 8. Assumptions Muriana - 2016

Outdating	Periodic review	Lead time	FIFO or LIFO	Lost sales	Service level	Stochastic demand
Yes	Yes	Yes	Not applicable	Yes	Yes	Yes

2.2.9 Pauls-Worm & Hendrix

Last but not least, the approach developed by Pauls-Worm and Hendrix (2016) is discussed. A stochastic programming model (SP model) and a mixed integer linear programming approximation model (MILP model) are described within this article. This last model (MILP) is most suitable for this research, because it is a fast approach to find a solution. Outdating of products is taken into account by testing products with a fixed lifetime of three days.

A lead time of one day is used (following the assumption of today ordered, tomorrow delivered) but this could be extended. Products are issued according to either a complete FIFO issuing policy, or by a combination of FIFO and LIFO. The possible combinations of FIFO and LIFO are (FIFO/LIFO): 100% / 0%, 60% / 40% and 40% / 60%. By using these combinations, this approach will give a better reflection of the practical situation. Demand is stationary over the weeks, while being non-stationary within the week. This demand is independently Poisson distributed and the demand that occurs during periods of stock outs is assumed to be lost. An α service level is used in this approach. Therefore, the probability of not having a stock out at the end of the day is searched for. This approach is a good approach to include in the remaining of the research. It fulfils all assumptions that are described in the beginning of this chapter. Especially the combination of FIFO and LIFO makes it more suitable by give a better reflection of the practical situation. Moreover, by using an approximation model it is a fast approach. In Table 9 all assumptions of Pauls-Worm and Hendrix could be found.

Table 9. Assumptions Pauls-Worm & Hendrix - 2016

Outdating	Periodic review	Lead time	FIFO or LIFO	Lost sales	Service level	Stochastic demand
Yes	Yes	Yes	FIFO & LIFO	Yes	Yes	Yes

2.2.10 Conclusion

Different approaches are found in literature which correspond with the assumptions made in Section 2.1 (see Table 10 for a complete overview of all assumptions made). First of all, the approach developed by Pauls-Worm and Hendrix (2016). This approach fulfils all requirements and has an approximation method in order to ensure a short calculation time. This would be a good approach to further investigate in the remaining of this research. Also the approach of Broekmeulen & Van Donselaar (2009/2012) fulfils most of the requirements, only the issuing policy assumption is partly deviated by assuming only FIFO withdrawal. However, it investigates the same KPIs as this research and presents approximations for easier calculations. This makes the approach a suitable one to investigate further.

The third possible approach is the one of Lowalekar, Nilakantan and Ravichandran (2016). Although they assume zero lead time and a SIRO issuing policy it might be a good approach to determine an order policy. Especially the approximation and heuristic model they present is useful in practice. The articles of Minner and Transchel and the one of Haijema and Minner do not present any heuristics. Therefore, these article are less useful for Slimstock. Muriana fulfils six of the seven characteristics, only the issuing policy is not applicable to this model. Based on this fact this might be a useful method to test. The approaches of Chiu and Williams and Patuwo are not further investigated as well, this as a result of a deviation of assumptions like the service level in both approaches. Last but not least, Ferguson and Ketzenberg; although their approach meets all the assumptions, it is not further investigated here due to the absence of some important constraints, like the one for service level.

So, there are four possibly suitable approaches found in literature, namely: Pauls-Worm & Hendrix (2016), Lowalekar et al. (2016), Muriana (2016) and Broekmeulen and Van Donselaar (2009/2012). In consultation with Slimstock it has been determined that the approaches of Pauls-Worm and Hendrix, and the one of Lowalekar, Nilakantan and Ravichandran are further investigated within this research.

Table 10. Assumptions overview of the nine approaches.

	Outdating	Periodic review	Positive lead time	FIFO or LIFO	Lost sales	Service level	Stochastic demand
Chiu - 1995	Yes	Yes	Yes	FIFO	No	No	Yes
Williams & Patuwo – 1999	Yes	Yes	Yes	FIFO	Yes	No	Yes
Ferguson & Ketzenberg - 2006	Yes	Yes	Yes	FIFO & LIFO, SIRO	Yes	Yes	Yes
Broekmeulen & Van Donselaar – 2009/2012	Yes	Yes	Yes	FIFO	Yes	Yes	Yes
Minner & Transchel – 2010	Yes	Yes	Yes	FIFO & LIFO	Yes	Yes	Yes
Haijema & Minner - 2015	Yes	Yes	Yes	FIFO &LIFO	Yes	No	Yes
Lowalekar, Nilakantan & Ravichandran - 2016	Yes	Yes	0 lead time	SIRO	Yes	Yes	Yes
Muriana - 2016	Yes	Yes	Yes	Not applicable	Yes	Yes	Yes
Pauls-Worm & Hendrix - 2016	Yes	Yes	Yes	FIFO & LIFO	Yes	Yes	Yes

3. Data analysis

Within this chapter a data analysis is made and products are divided in specific product groups. At first the dataset, which is provided by Slimstock, is described and analysed. In the remaining of the chapter characteristics of the products are discussed and assumptions for subsequent steps are made.

3.1 Data from Slimstock

Slimstock has provided a dataset with a set of products with fixed shelf lives. This dataset consists of demand data of approximately nine weeks, namely from 30 September till 5 December. For the ease of the simulation and trustworthiness of this research, only entire weeks are included in this research. Therefore, only data from the 3rd of October till 4 December is used.

The dataset relates to sixteen stores with for each store sales and outdating numbers per product. In total there are 107 products in the dataset, which together have eleven shelf lives, ranging from 6-30 days. The shelf life of the products, mentioned in the dataset, is the remaining shelf life on shelf replenishment. Each individual item has several characteristics that are mentioned in the dataset, namely:

1) Number of items sold per day
2) Number of items that are outdated per day
3) Shelf life in number of days
4) Lead time in number of days
5) Delta buying price, this is sales price minus buying price
6) Target service level

There are several aspects on which products can be distinguished. First of all, the variety in demand for products. There are high demanded products and products that are sold less regularly. This is partly due to the store which sells the product. One store has a larger reach and/or another target audience that visits the store resulting in a different demand pattern. Therefore, the size of demand for a product is the first aspect which is taken into account. Secondly, the length of the shelf life is important, the longer the shelf life. The longer the retailer is able to sell the product, and making it more easy to prevent waste. When the shelf life is short, inventory management is more difficult due to waste. For this reason, also the shelf life of the products is taken into account.

Within this research, all sixteen stores are compared to see the effect of high and low demanded products on the KPIs. For instance, store 141 has an average of 76.30 items sold a day for product lifetime 6, whereas store 156 only sells an average of 2.65 items a day. Not only the amounts that are sold differ widely, also the numbers of days on which products are sold / thrown away differ. Store 141 for instance has sales and outdating data of nearly all days while store 157 has sales and outdating data on approximately half of the days. This is due to the fact that some products do not have demand and/or waste every day and some stores do not sell particular products. For this reason, the number of days of demand for each product is calculated per store.
It is assumed that there are crucial differences between stores, like the target audience and the demand pattern. Therefore, it is important to select only products that are sold in every store to have a good and complete overview when the appropriateness of the models is assessed.

The shelf life of the products in the dataset differs widely. The shortest shelf life is six days (product 93437). Due to the fact that the second shortest shelf life product (ten days) is not sold in every store, product lifetime 6 is selected to evaluate how the models perform with the shortest available shelf life. The product has a lead time of two days and a target service level of 94%. €0.54 is the delta buying price for this product.
The second product that is investigated is product 66081, as given in the provided dataset by Slimstock. This product has a shelf life of seventeen days, a lead time of two days and a target service level of 98%. The delta buying price is €1.02 per product. This product is selected due to the fact that this product has a very long shelf life and almost on all days (within the nine-week time period) sales and/or outdating for all sixteen stores. Seventeen days is already a long time for perishables. Therefore, evaluating this product will give good insights for longer shelf lives as well.
Due to time limitations and the need of thorough research, only these two products are selected for research. However, these are investigated for all sixteen stores, covering products with a high and low demand. See Table 11 for an overview of the product characteristics of both products.

Table 11. Characteristics overview of the products that are further investigated.

	Product 93437	Product 66081
Shelf life	6 days	17 days
Lead time	2 days	2 days
Target service level	94%	98%
Delta buying price	€0.54	€1.02

3.2 Research assumptions

To be able to do consistent research for both models, some assumptions should be made to have equal circumstances that occur. First of all, the daily pattern is discussed, 'What does a particular day look like?', 'What time a day are orders placed and when are products sold?', are questions to be asked. Moreover, the demand pattern and costs involved are considered as well.

3.2.1 Sequence of events

Within this research, a particular sequence of events occurs every day. A certain pattern is followed for ordering, selling and receiving products. The sequence of events that is assumed within this research is as follows:

1) Store opening
2) A new order is placed if inventory is lower than order-up-to-level
3) Delivery of the order (Q_{t-L})
4) Demand during the day, Poisson distributed
5) Ages of products are updated and waste is thrown away

A new day is announced by 'store opening', which only means that a new day has started. The first thing that happens when a new day is started is the ordering of products. Overnight, the order quantities are calculated, based on the inventory that is available in period t. The morning after, the orders are confirmed and send to the suppliers. When the orders are placed, the order of Q_{t-L} is delivered at the store. Afterwards, products are demanded by customers. The demand is considered Poisson distributed. At the end of the day, after closing the store (so no demand is fulfilled anymore), ages of products are updated and items that are outdated are thrown away. After the inventory is updated, the whole cycle starts all over again.

3.2.2 Demand

Although daily sales are not always equal to demand, sales as given in the dataset, are assumed as the total demand. The average demand (sales) per day of the week is used. For this reason, the average of all demand on Mondays is taken, the average of all demand on Tuesdays, etc. This subdivision in average per day is used, because a certain weekly pattern could be distinguished from the data. Figure 1 shows for example the demand pattern of store 165 for all nine weeks. The large peak on Saturday and the low demand on for instance Thursday show the non-stationarity of the demand.

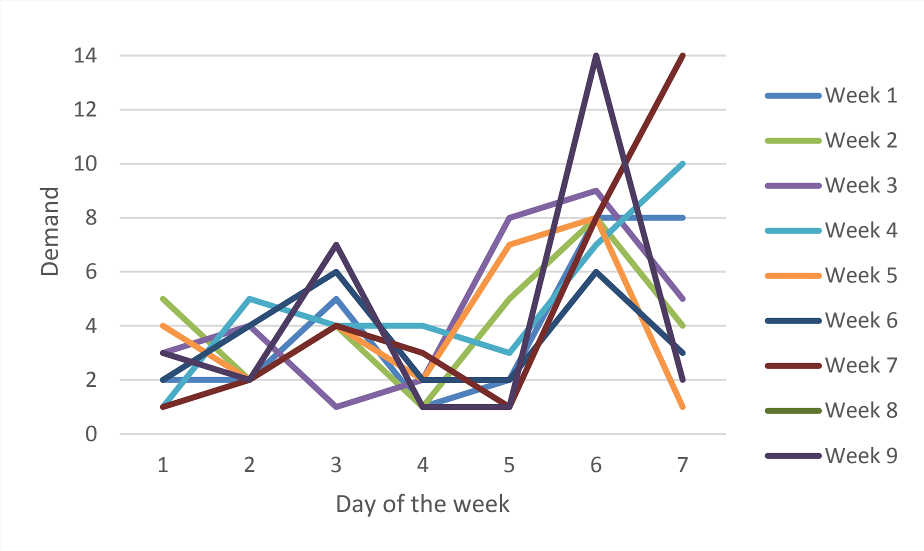

Figure 1. Demand pattern of product SL=6 at store 165 (Monday = 1, etc.).

This clear non-stationary pattern can also be observed taking the average of each day, as shown in Figure 2. Also here the large peak on Saturday is obvious and the figure shows the big variation of demand over days of the week which have averages of approximately 50% of the demand on Saturdays.

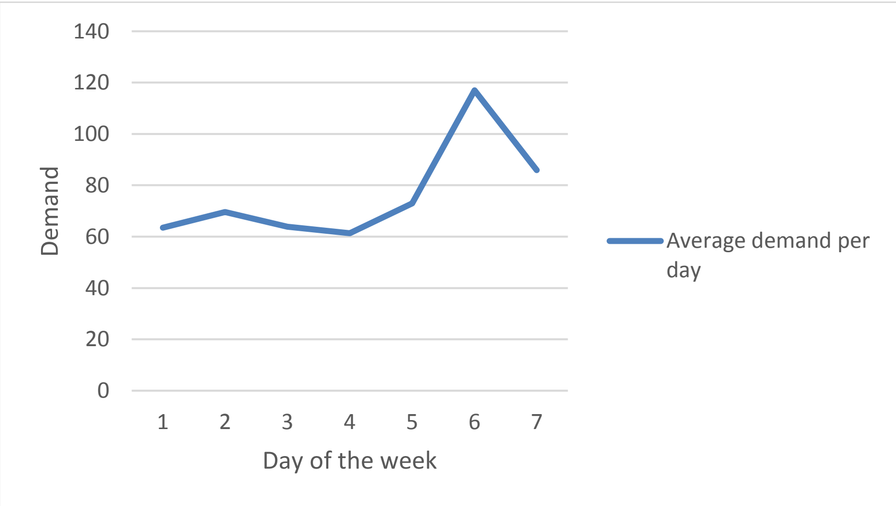

Figure 2. Average demand per day of product SL=17 at store 141 (Monday = 1, etc.).

Demand distribution
To determine the probability distribution of demand, Adan et al. (1995) developed a procedure based on the mean and standard deviation.

The formula: $a = \frac{\frac{\sigma^2}{\mu} - 1}{\mu}$ is used to determine the probability distribution of each product. The authors provided four different possibilities for the distribution, namely:

- if $-1 < a < 0$, then it is a binomial distribution;
- if $a = 0$, it is a Poisson distribution;
- if $0 < a < 1$, the demand is negative binomial distributed;
- if $a \geq 1$, the demand is geometric distributed.

The results of this procedure show (close to) Poisson distributed demand for a couple of stores. Although several stores do not have Poisson distributed demand for either one or both products, Poisson distributed demand is assumed. This is especially based on the selected models, which derived expressions for the special case of Poisson distributed demand.

3.2.3 Costs
Both the models of Lowalekar et al. (2016), and Pauls-Worm & Hendrix (2016) use costs in their model. Several costs are taken into account for the calculations of the order policies. First of all, variable costs per unit. These are the cost of acquiring the product as a retailer. It is assumed that the delta buying price, as given in the provided dataset, is 40% of the cost price. When this assumption is made, the variable cost per unit is then: $\frac{delta\ buying\ price}{0.4}$.

The second type of cost is the shortage cost which occur when demand cannot be fulfilled by the inventory on hand. The costs that are involved with having shortage are quite complicated. When a product is not in stock, customers have different opportunities, among others: either not buying anything at all at the store, buying a substitute or wait for the product to arrive. When a customer decides to buy the product and all other demanded items at another store, the shortage cost will be increased with the missed profit of the other items as well. Therefore, it is hard to estimate the real shortage cost. Marqt assumed shortage cost to be equal to the profit that is missed for only the unavailable product (P. de Lepper, personal communication, November 16, 2016). Although shortage costs are very hard to estimate, these costs are assumed in this research to be only the profit that is missed on the item that could not be delivered (i.e. the delta buying price).

Waste costs money as well. Therefore, waste costs are the third type of cost. These are the cost resulting from having waste. According to Marqt, items that exceed their expiring date are donated to the Voedselbank. Because Marqt does not have to pay money for disposal of these items, the only cost that is involved with waste is the loss of the buying price. This type of cost is equal to the buying price of the product, so it is equal to the variable cost price. Also inventory on hand costs money, this is called holding costs and has a value of €0.01 per item per night that an item is kept in stock.

Both the fixed setup cost and the cost of one review are assumed to be zero. From the interview at Marqt it becomes clear that a retailer pays a certain price for a product which is included all different kind of costs, like product cost and transportation cost. For this reason, the fixed setup cost is set to zero, because this would be part of the buying price already (P. de Lepper, personal communication, November 16, 2016). Review costs are seldom used in inventory models; however, these are included in the model of Lowalekar, et al. (2016). The cost of a review is set to zero as well, because all products are already checked every day, so reviewing the inventory every day would not increase any current costs.

3.2.4 Simulation

Two products are selected for further investigation. For these two products, a simulation study is conducted in order to see whether the results from the model are a good predictor for demand and thereby optimising availability and waste. For both products, four different issuing policies are evaluated; first complete FIFO issuing is evaluated. As a result of this policy, the oldest items on the shelf are selected first. Also complete LIFO, and two combinations of FIFO/LIFO are simulated; 80% / 20% and 60% / 40%. Due to the uncertainty of the ratio of FIFO and LIFO issuing, this sensitivity analysis is done to see what the effect is on the results. When the simulation includes LIFO withdrawal, first the LIFO demand is met, followed by the FIFO demand. Although complete LIFO withdrawal is not the case in real life (due to FIFO stimulating strategies of retailers), it shows a worst-case scenario.

4. Lowalekar, Nilakantan & Ravichandran

The first model that is evaluated is the one studied by Lowalekar, Nilakantan & Ravichandran (2016). In the remaining of this research this article, is denoted by 'LNR'. The perishable inventory model of these authors firstly is described with help of the made assumptions and notations. Afterwards, the model is evaluated with the provided dataset and at the end of this chapter, a conclusion is drawn whether this would be a suitable model for Slimstock to use in their Slim4 software.

4.1 Model

In this section, the main assumptions of the model of LNR are described and the main notations are mentioned. This part is followed by an overview of the constraints used, in Section 4.1.2.

4.1.1 Assumptions

The authors of the article made a couple of assumptions. At first, a periodic review is studied with regular intervals. The period between two reviews is called T and each review has a cost of A. The authors assumed a fixed lifetime of m (integer number) periods for each product, which arrive fresh with age 0. When an item reaches the end of the mth period, the item is discarded and a cost of C_W is charged per item. Every review period is started with ordering a number of items, calculated by subtracting the on-hand inventory (x) from the order-up-to-level (R). Each order is received instantaneously and x reaches the level of R immediately after a review is done. For every item that is ordered, a fixed cost of C_V is charged. Demand that is not met, is assumed to be lost. All items which cannot be delivered from on-hand stock, are charged for a cost of C_S per item. Items that stay overnight at the store have a cost of C_H per item per period. Items that are issued from inventory are selected randomly. The likelihood of selecting an item with a specific age is equal for all ages at any point in time. Last but not least, the stationary demand is discrete and distributed following a Poisson distribution with rate λ. (Lowalekar et al., 2016)

4.1.1.1 Notations

L	Life of the perishable item
T	Time period between two consecutive reviews
$m=L/T$	Life of the perishable item in periods (rounded down values)
x	On-hand stock
λ	Demand rate (for Poisson demand distribution)
$\bar{d}$	Average demand per period (for general demand distribution)
A	Cost of one review
C_V	Variable cost per unit
C_S	Shortage cost per unit
C_W	Wastage cost per unit
C_H	Holding cost per unit per period
$p_d(.)$	Probability mass function of demand during one period
$F_d(.)$	Cumulative distribution function of demand during one period
R	Order-up-to-level
EHC	Expected holding cost per period
ES	Expected shortage per period
ESC	Expected cost of shortage per period
W_{avg}	Average wastage per period
Q_{AVG}	Average order quantity per period
$\tilde{p}_{nu}$	Probability of not using an item in a particular period for a given R
$\tilde{p}_w$	Probability of wasting an item for a given R
$C(R, T)$	Total cost per period (average) for a given R and T
$C'(R, T)$	Total cost per unit time (average) for a given R and T

4.1.2 Poisson model

The authors present an exact model first, followed by an approximation model to decrease the computational burden of the problem. This approximation is a good substitute for the exact model. As it is shown in this article, there is hardly any difference between both outcomes when the order-up-to-level is small (below 40). Due to the low demand per day, this approximation model will be suitable to use instead of the more complicated/time consuming exact model. Only store 141 might encounter less accurate results due to the fact that this store has a higher demand for both products (averages above 69).

The authors gave special attention to Poisson distributed demand by deriving expressions for this demand distribution. This Poisson model consists of a number of constraints to determine the order policy. First the total cost function, which consists of the cost of one review, cost for acquiring the products, costs of waste, shortage and holding items.

$$C(R,T) = A + C_V Q_{AVG} + C_W W_{AVG} + C_S ES + C_H(R - \frac{\bar{d} + ES}{2})$$

To calculate the total costs, some values have to be obtained, like the order quantity (Q_{AVG}), amount of waste (W_{AVG}) and the expected shortage (*ES*). The order quantity depends on the average demand, the expected shortage and the probability of having waste. This is shown in the next formula:

$$Q_{AVG} = \frac{\lambda T - ES}{1 - \tilde{p}_w}$$

$\tilde{p}_w$ is the probability of wasting an item and is calculated in the following way:

$$\tilde{p}_w = [\tilde{p}_{nu}]^m = \left[F_d(R-1) - \frac{\lambda T}{R} F_d(R-2)\right]^m$$

As shown above, the order quantity depends on the expected shortage that occurs. Therefore, the expected shortage should be calculated, this is done by:

$$ES = \left[\lambda T\big(1 - F_d(R-2)\big) - R\big(1 - F_d(R-1)\big)\right]$$

The average waste is obtained by taking the average demand per review period minus the expected shortage and divide this amount by the probability of not wasting an item. When this total amount is multiplied by the probability of waste, the average waste per period results:

$$W_{AVG} = (\frac{\lambda T - ES}{1 - \tilde{p}_w})\tilde{p}_w$$

The last formula that is used in this approximation model is for calculating the fill rate. This is done by subtracting the expected shortage divided by the average demand from one:

$$Fill\ Rate\ (FR) = 1 - \frac{ES}{\bar{d}}$$

In order to find an optimal combination of *R* and *T*, the gradient search heuristic can be used:

1. Having input for the models' parameters (L, A, C_S, C_V, C_W and C_H)
2. Set *m* = 1
3. While $m \leq L$ do steps 4-8
4. Determine *Precision* and *StepSize* (integer). Guess an initial value for *R* (recommended: $R = \bar{d}$). Set $R_{old} = 0, R_{new} = \bar{d}$ (where $\bar{d}$ is the average demand for a period length of *T*). For Poisson demand: $\bar{d} = \lambda T = \frac{\lambda L}{m}$
5. While $|R_{new} - R_{old}| > Precision$: $R_{old} = R_{new}$ and $R_{new} = R_{old} - StepSize * \frac{dC(R,\frac{L}{m})}{dR}$
   For Poisson demand: $R_{new} = R_{old} - StepSize * (C\left(R, \frac{L}{m}\right) - C\left(R-1, \frac{L}{m}\right))$

6. $R_T^* = R_{new}$
7. Compute $C(R_T^*, T)$, which is the minimum cost at $T = \frac{L}{m}$
8. $m = m + 1$
9. Find the combination of R_T^* and T among m pairs for which $C(R_T^*, T)$ is minimum. This combination is the optimum pair (R^*, T^*).

This gradient search heuristic searches for the optimal combination of *R* and *T*. Because it is assumed that there is a review every day, this heuristic is of less importance for this research, but could be useful when the review period is not fixed at one day. For this reason, a brief investigation of this method is made as shown in the remaining of this chapter.

The model of LNR is investigated with the help of two software programs, namely Python and Microsoft Excel. For calculating suitable order policies, Python is used in order to determine the order-up-to-levels. The entire approximation model is programmed in Python and afterwards run for each individual store. Microsoft Excel is used for the simulation part, by simulating the obtained order-up-to-levels with the demand data from the dataset, the effect of the order policies is evaluated. This to see what amount of waste, what shortage and what fill rate will occur as a result of a certain policy.

4.2 Results

The different order policies for the different stores and products are calculated in this section. This is followed by the simulation to evaluate whether the order policies meet the requirements. At first, the gradient search heuristic is evaluated to see whether this is already a good predictor or not.

An optimum combination of order-up-to-level (*R*) and time between two review periods (*T*) is sought for by using the gradient search heuristic. The search steps, as shown in Table 12, results from the heuristic. This search gives several combinations of *R* and *T*. However, calculating the optimum combination of *R* and *T*, given a certain fill rate is not possible. As could be seen, the target service level of 94% is not given. Store 141 is the only one which has a fill rate higher than the target (for *T*=1). Therefore, this seems not to be a useful method to determine the order policies.

Table 12. Search steps of the gradient search heuristic for product with lifetime 6 at store 151. Q, ES and W are given in items per period.

Store: 151		Product SL = 6					
Minimal costs (C):	Order-up-to-level (R):	Review period (T):	Order Quantity (Q):	Expected Shortage (ES):	Fill Rate (FR):	Average Waste (W):	Periods (m):
31.767	23.434	6	23.444	0.000	1.000	0.00000	1
15.848	11.838	3	11.671	0.054	0.995	0.00238	2
9.909	7.287	2	6.986	0.830	0.894	0.00050	3
6.870	5.369	1.5	4.546	1.318	0.775	0.00254	4
5.388	4.244	1.2	3.509	1.181	0.748	0.00055	5
4.806	3.907	1	3.308	0.599	0.847	0.00004	6

In order to get this target service level, a solution could be found by fixing the review period (*T*). Instead of searching for the optimal combination of *R* and *T*, combinations of *R* and a fixed *T* could be calculated. Afterwards the combination that gives a fill rate of at least 94% (or in case of product with lifetime 17, 98%) could be selected. For the value of *R* is chosen to calculate all numbers from one up to $\lambda * shelf\ life$ (*L*). These combinations could be found in Table A25 in the Appendix.

As could be seen in the table, for a given target service level of (at least) 94%, order-up-to-levels of seven, ten and eleven are necessary for respectively a review period of one, two and three periods. The results differ a little from each other; since the fill rates differ (none of them is exactly 94%), the expected shortage, waste and costs differ. For instance, $T = 1$ has a fill rate of 97.18% and a shortage of 0.12 item per period (7.61 items for the entire nine-week period). Contrary, $T = 2$ has a fill rate of 96.72% and a shortage of 0.14 item per period (8.85 items in total).

One of the disadvantages of this model is the absence of lead time. The authors assume orders to be delivered instantaneously instead of having a lead time of two to seven days, as is applicable to products in retail. Although they see this as a major limitation, they do not provide a solution to take lead time into account. Within this chapter, two different scenarios are evaluated for both products, first the model without lead time, secondly the model which takes lead time into account. In order to cope with the problem of lead time, the order-up-to-levels given for $T = 3$ are used to prevent stock outs during lead time. When $T = 3$ is used, safety stock for the period of lead time is included as well, this will result in less stock outs and thereby a higher fill rate. The order-up-to-levels for both a lead time of zero and two are given in Table 13. These numbers are used in the simulation with the demand data provided by Slimstock.

Table 13. Order-up-to-levels per item for lead time (LT) zero and two.

Store:	SL = 6, FR = 94%		SL = 17, FR = 98%	
	LT = 0	LT = 2	LT = 0	LT = 2
141	75	90	75	88
151	7	11	8	10
152	6	10	12	16
153	7	11	8	11
154	5	9	6	9
156	5	8	5	8
157	8	11	6	9
158	11	15	11	15
159	7	10	6	9
160	11	15	9	12
161	8	12	11	14
162	7	11	10	13
163	7	12	8	11
164	7	11	10	13
165	7	11	7	10
166	7	12	7	9

As shown in Chapter 3, demand follows a certain pattern during the week and thereby is non-stationary. This model assumed stationary demand, but due to the non-stationarity of demand both non-stationary and stationary demand were evaluated. From these evaluations, it could be concluded that the model works better when stationary demand is assumed. If non-stationary demand is assumed, the model increases the number of shortages that occur, while most of the times the waste is equal or sometimes even higher in comparison to stationary demand. The order-up-to-levels are nearly always lower than the order-up-to-level at stationary demand. This causes less inventory, resulting in more shortages. The amount of waste will not increase since the additional inventory items fulfil unsatisfied demand. These extra items will be sold instead of being wasted at the end of their shelf life. Due to these results, the remaining results are based on stationary demand, so the total average demand per period is used.

For the simulation part, the following assumptions are made:

- depending on the issuing policy is fraction *l* of the demand fulfilled with the oldest items (FIFO), whereas the fraction (1-*l*) is fulfilled with the newest items (LIFO);
- orders are placed every day if the inventory level is lower than the order-up-to-level;
- orders arrive either immediately (without lead time) or after two days (with lead time);
- starting inventory of the simulation without lead time is equal to the order-up-to-level;
- starting inventory of the simulation with lead time is equal to the order-up-to-level at the first day (Monday), Tuesday and Wednesday it is the order-up-to-level minus the remaining inventory. This last assumption is made to ensure enough inventory for the first days when no orders arrive, due to the lead time of two days.

A couple of KPIs are tracked to see how the model performs under different conditions (different stores and different issuing policies). First, the number of shortages that occur are tracked. Each demand that is not fulfilled is counted as shortage, the total of shortage therefore is the number of items that were demanded but not delivered. Secondly, the amount of waste that occurs is tracked by counting the number of items that outdate. Also this KPI is counted in total number of items for the nine weeks of simulation. Thirdly, the total costs are counted based on the number of items that are ordered, hold, wasted and fall short. These costs are for the entire period of nine weeks and based on the prices assumed in Chapter 3. Last but not least, the fill rate is calculated based on the amount of shortage and the number of items demand.

4.2.1 Product lifetime 6

When the results of the model are simulated, outcomes as shown in Table 14 and Table 15 result. These tables show the results of simulating the order policies of product lifetime 6 for the different issuing policies and all sixteen stores. The first table shows the results of having no lead time, whereas Table 15 shows the results of product lifetime 6 including a lead time of two days.

Table 14 compares the results obtained by the simulation with the results of current practice. Also the fill rates are compared with the target fill rate that is applicable to product lifetime 6, that is 94%. The colour of the cells shows the performance of the model, when a cell has a green colour the performance of the order policy for that specific case is better than current practice (in case of waste). For the cells with fill rates, a green coloured cell means that it meets the target service level. When the cell has not colour, it means that the order policy does not outperform the current order policy.

It is apparent from Table 14 that in 95.3% (61 of 64) of the cases the waste is improved by the model of LNR. In most of these cases the stores would not have any waste at all. If you would look only at the waste, you could say that this is a very good model which improves the current situation a lot. However, waste is not the only KPI that is important; the fill rate should meet the target service level as well to be an appropriate model to use in the Slim4 software. On this point, the model scores much less in comparison to the waste. Only six of the sixteen stores would have a fill rate that is equal to or higher than the target service level. For these stores the prediction is quite well when the focus is on the height of the fill rate. These six stores, for the different issuing policies, have a fill rate close to the target of 94%. None of them has a fill rate of around or equal to 100%, thereby having no more inventory (and thus costs) than necessary. For these stores the model is a good predictor, they will have less waste and fulfil the target service level.

As can been seen from this table as well is the effect of the issuing policy. When a complete FIFO issuing policy is applicable, there is hardly any waste. If we now turn to the amount of waste when LIFO withdrawal is involved, this has an increasing effect. The higher the LIFO percentage, the more waste will result, followed by an increase in shortage and a decrease of the fill rate. For the evaluated issuing policies, only complete LIFO resulted in a higher amount of waste than currently (see Table A26 and Table A27 in the Appendix).

Since retailers organize their stores such that FIFO is stimulated, complete LIFO will seldom, if not never, be the case. These amounts could therefore be seen as a maximum amount of waste that will occur. This increase in waste and shortage could be seen in the total costs as well. The items that are wasted and the cost of shortage increase the total costs. It is obvious that a FIFO issuing policy has the lowest costs, the lowest number of items needed to fulfil demand and the lowest amount of waste will occur. The more LIFO demand, the higher the costs are, accompanied by an increase in waste and shortage.

Table 14. Simulation results of product lifetime 6 without lead time. Shortage and waste are in number of items for nine weeks. Green cells in 'waste'-column indicate improvements in comparison to current situation, green cells in 'Fill rate'-column indicate the compliance with the target service level.

SL=6, LT=0		Complete FIFO				80% FIFO - 20% LIFO				60% FIFO - 40% LIFO			
Store	Current waste	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate
141	142	558.0	0.0	€ 6,042.23	88.39%	558	0.0	€ 6,042.23	88.39%	558	0.0	€ 6,042.23	88.39%
151	2	11.0	0.0	€ 357.41	95.93%	11	0.0	€ 357.41	95.93%	11	0.0	€ 357.41	95.93%
152	19	18.0	0.0	€ 325.72	92.83%	18	0.0	€ 325.72	92.83%	18	0.0	€ 325.72	92.83%
153	14	16.0	0.0	€ 356.09	94.12%	16	0.0	€ 356.09	94.12%	16	0.8	€ 358.24	94.12%
154	4	20.0	0.0	€ 253.81	89.95%	20	0.0	€ 253.81	89.95%	20	0.0	€ 253.81	89.95%
156	9	18.0	1.0	€ 215.22	89.22%	18	1.4	€ 215.98	88.98%	18.8	1.8	€ 216.73	88.74%
157	5	27.0	0.0	€ 448.42	92.22%	27	0.0	€ 448.42	92.22%	27	0.0	€ 448.42	92.22%
158	18	29.0	0.0	€ 714.03	94.68%	29	0.0	€ 714.03	94.68%	29	0.0	€ 714.03	94.68%
159	7	0.0	0.0	€ 428.99	94.80%	17	0.0	€ 428.99	94.80%	17	0.0	€ 428.99	94.80%
160	6	55.0	0.0	€ 733.43	90.43%	55	0.0	€ 733.43	90.43%	55	0.0	€ 733.43	90.43%
161	7	26.0	0.0	€ 508.18	93.35%	26	0.0	€ 508.18	93.35%	26	0.0	€ 508.18	93.35%
162	5	12.0	0.0	€ 378.05	95.80%	12	0.0	€ 378.05	95.80%	12	0.0	€ 378.05	95.80%
163	5	23.0	0.0	€ 405.43	92.65%	23	0.0	€ 405.43	92.65%	23	0.0	€ 405.43	92.65%
164	1	32.0	0.0	€ 345.97	88.32%	32	0.0	€ 345.97	88.32%	32	0.0	€ 345.97	88.32%
165	24	29.0	0.0	€ 347.03	89.38%	29	0.0	€ 347.03	89.38%	29	0.0	€ 347.03	89.38%
166	16	16.0	0.0	€ 416.39	94.95%	16	0.0	€ 416.39	94.95%	16	0.0	€ 416.39	94.95%

Turning now to the results of the model when lead time is taken into account; these can be found in Table 15. It is apparent from this table that the model performs worse. Instead of six stores that would improve their amount of waste and comply the target fill rate, now only one store (153) would both decrease its waste and meet the target service level. This would only be achieved when complete FIFO issuing or a combination 80% FIFO / 20% LIFO is applicable.
Moreover, the fill rates do not meet the target level for almost all cases. The differences with the target level are quite big and thereby a large correction is needed to fulfil the required KPI levels. The table shows that the outcome of the model for a review period of three days is not good enough to comply the requirements. It underestimates the number of items that is necessary to fulfil demand, resulting in shortages and waste. This underestimation could be seen from the differences in total costs as well. The fill rates and total costs, for the simulation without lead time, are (much) higher, resulting from higher inventory levels / order quantities. Due to these higher inventory levels and order quantities, the costs increase as well, more items are ordered and kept in stock.

The model seems to work good for a lead time of zero, so an immediately delivery of orders, but it shows its difficulty to predicts for a longer term by taking lead time into account. A possibility to overcome this problem could be to include a certain safety factor per store. When a specific number of items is added to the order-up-to-level the shortage will decrease (fill rate increase) and the results might comply with the requirements. This amount or fraction should then be calculated for each individual store.

Table 15. Simulation results of product lifetime 6 including two days of lead time. Shortage and waste are in number of items for nine weeks. Green cells in 'waste'-column indicate improvements in comparison to current situation, green cells in 'Fill rate'-column indicate the compliance with the target service level.

SL=6, LT=2		Complete FIFO				80% FIFO - 20% LIFO				60% FIFO - 40% LIFO			
Store	Current waste	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate
141	142	819.0	0.0	€ 5,777.22	82.96%	819	0.0	€ 5,777.22	82.96%	819	0.0	€ 5,777.22	82.96%
151	2	7.0	3.0	€ 385.55	97.41%	13	8.6	€ 394.36	95.33%	18.4	13.4	€ 400.63	93.19%
152	19	32.0	7.0	€ 330.95	87.25%	35	9.6	€ 335.90	86.22%	40	16.8	€ 350.94	84.06%
153	14	15.0	4.0	€ 363.39	94.49%	16	9.0	€ 373.58	94.04%	17	15.4	€ 384.07	93.75%
154	4	21.0	15.0	€ 297.23	89.45%	26	21.4	€ 310.31	86.73%	30.4	26.4	€ 320.68	84.72%
156	9	27.0	27.0	€ 285.92	83.83%	36	35.6	€ 300.76	78.44%	34.4	38.2	€ 306.16	79.40%
157	5	39.0	0.0	€ 440.37	88.76%	39	0.0	€ 440.37	88.76%	39	0.0	€ 440.37	88.76%
158	18	82.0	0.0	€ 672.42	84.95%	82	0.0	€ 672.42	84.95%	82	0.0	€ 672.42	84.95%
159	7	32.0	0.0	€ 426.37	90.21%	32	0.0	€ 426.37	90.21%	35.6	3.6	€ 433.17	89.11%
160	6	85.0	0.0	€ 683.40	85.22%	85	0.0	€ 683.40	85.22%	85	0.0	€ 683.40	85.22%
161	7	46.0	0.0	€ 483.61	88.24%	46	0.0	€ 483.61	88.24%	46	0.0	€ 483.61	88.24%
162	5	20.0	0.0	€ 386.27	93.01%	26	5.8	€ 397.23	90.98%	26	6.4	€ 393.39	90.91%
163	5	27.0	5.0	€ 444.31	91.37%	35	12.8	€ 459.21	88.95%	37.8	16.8	€ 444.52	87.92%
164	1	26.0	15.0	€ 393.95	90.51%	29	19.2	€ 411.17	89.56%	25.6	21.8	€ 416.62	90.66%
165	24	18.0	5.0	€ 373.58	93.41%	27	11.8	€ 384.51	90.04%	38	22	€ 403.39	86.08%
166	16	29.0	14.0	€ 433.36	90.85%	33	16.0	€ 439.64	89.53%	33.8	18.0	€ 445.69	89.34%

4.2.2 Product lifetime 17

Table 16 provides the results of the simulation for product lifetime 17 without taking lead time into account. These results show similarities with the results of product lifetime 6 without lead time. In all cases waste is reduced for all sixteen stores when a complete FIFO issuing policy is applicable or a combination of FIFO and LIFO. Only for LIFO withdrawal there are increases of waste (see Table A28 and Table A29 in the Appendix), as was the case for the other product as well. The stores that have a sufficient fill rate (above 98%), just have a small deviation from the target service level. The results are quite close to the target; this ensures no more inventory than necessary, and thereby lowering the costs as much as possible. Although only six stores have a fill rate that meets the target service level, four other stores are very close to this target as well. Four stores have a very low fill rate, the model with the assumptions made, shows to be a bad predictor for these stores. However, by correcting the order-up-to-level this problem might be solved. These four all have zero waste, so the order amount could be increased without harming the waste for these stores. If these order-up-to-levels are increased a little bit, the fill rates will increase towards the target level and possibly do not have any increase in waste since the extra items are used to cover unfulfilled demand. Altogether this seems a suitable model for products with a long shelf life as well. It does not predict the order-up-to-level well for products with a shelf life of just a couple of days only, but for products with a shelf life of 2.5-3 weeks as well (when no lead time is included).

Table 16. Simulation results of product lifetime 17 without lead time. Shortage and waste are in number of items for nine weeks. Green cells in 'waste'-column indicate improvements in comparison to current situation, green cells in 'Fill rate'-column indicate the compliance with the target service level.

SL=17, LT=0		Complete FIFO				80% FIFO - 20% LIFO				60% FIFO - 40% LIFO			
Store	Current waste	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate
141	15	329	0.0	€ 10,652.05	92.47%	329	0.0	€ 10,652.0!	92.47%	329	0.0	€ 10,652.05	92.47%
151	1	5	0.0	€ 657.84	98.08%	5	0.0	€ 657.84	98.08%	5	0.0	€ 657.84	98.08%
152	0	47	0.0	€ 1,223.90	90.73%	47	0.0	€ 1,223.90	90.73%	47	0.0	€ 1,223.90	90.73%
153	0	7	0.0	€ 723.38	97.56%	7	0.0	€ 723.38	97.56%	7	0.0	€ 723.38	97.56%
154	0	3	0.0	€ 436.10	98.26%	3	0.0	€ 436.10	98.26%	3	0.0	€ 436.10	98.26%
156	5	5	0.0	€ 356.23	96.48%	5	0.0	€ 356.23	96.48%	5	0.0	€ 356.23	96.48%
157	0	6	0.0	€ 454.40	96.69%	6	0.0	€ 454.40	96.69%	6	0.0	€ 454.40	96.69%
158	0	5	0.0	€ 1,162.65	98.91%	5	0.0	€ 1,162.65	98.91%	5	0.0	€ 1,162.65	98.91%
159	1	4	0.0	€ 432.04	97.66%	4	0.0	€ 432.04	97.66%	4	0.0	€ 432.04	97.66%
160	0	7	0.0	€ 787.51	97.76%	7	0.0	€ 787.51	97.76%	7	0.0	€ 787.51	97.76%
161	0	8	0.0	€ 1,094.59	98.15%	8	0.0	€ 1,094.59	98.15%	8	0.0	€ 1,094.59	98.15%
162	0	31	0.0	€ 904.06	91.67%	31	0.0	€ 904.06	91.67%	31	0.0	€ 904.06	91.67%
163	0	2	0.0	€ 700.50	99.27%	2	0.0	€ 700.50	99.27%	2	0.0	€ 700.50	99.27%
164	0	9	0.0	€ 899.40	97.48%	9	0.0	€ 899.40	97.48%	9	0.0	€ 899.40	97.48%
165	8	18	0.0	€ 604.43	92.71%	18	0.0	€ 604.43	92.71%	18	0.0	€ 604.43	92.71%
166	0	1	0.0	€ 564.23	99.55%	1	0.0	€ 564.23	99.55%	1	0.0	€ 564.23	99.55%

As said, the model does not include lead time. When the model is evaluated by taking lead time into account, the results show that it underestimates the number of items that is needed to fulfil demand. Like product lifetime 6, also product lifetime 17 has zero waste in case of FIFO and the combinations of FIFO/LIFO issuing. However, the shortages are high, resulting in low fill rates. These results are in line with the reasoning above, when too few items are ordered, all items will be sold before they expire. Moreover, since there are too few items to fulfil demand, there are shortages. Store 159 is the only one which comply the target service level of 98%. Store 154 and 157 are the only stores that are close to the target level; all others perform far below the target. Also here the impact of ordering less, resulting in higher shortages, could be seen in the total costs of each store. These costs are a little bit lower than the total costs when lead time is excluded. An adaption of the model is required in order to be able to use it in the Slim4 software. At this moment, the model does not give suitable order-up-to-levels to meet all KPI targets when a lead time is involved.

Another issue of this model is the size of the demand. The fill rates of store 141, with an average demand of approximately 70 (lifetime 6) and 76 (lifetime 17) products per day, are quite far below the target level for both products. As already announced in the beginning of this chapter, the error due to approximation is growing when the order-up-to-level is increased. This makes the model less suitable (at least the approximation method) for products with a high average demand. However, since only one store has such a high demand, further investigation is needed to draw trustworthy conclusions.

Table 17. Simulation results of product lifetime 17 including lead time. Shortage and waste are in number of items for nine weeks. Green cells in 'waste'-column indicate improvements in comparison to current situation, green cells in 'Fill rate'-column indicate the compliance with the target service level.

SL=17, LT=2		Complete FIFO				80% FIFO - 20% LIFO				60% FIFO - 40% LIFO			
Store	Current waste	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate
141	15	715	0.0	€ 9,870.82	83.65%	715	0.0	€ 9,870.82	83.65%	715	0.0	€ 9,870.82	83.65%
151	1	13	0.0	€ 635.62	95.00%	13	0.0	€ 635.62	95.00%	13	0.0	€ 635.62	95.00%
152	0	36	0.0	€ 1,259.54	92.90%	36	0.0	€ 1,259.54	92.90%	36	0.0	€ 1,259.54	92.90%
153	0	25	0.0	€ 694.01	91.29%	25	0.0	€ 694.01	91.29%	25	0.0	€ 694.01	91.29%
154	0	4	0.0	€ 432.71	97.67%	4	0.0	€ 432.71	97.67%	4	0.0	€ 432.71	97.67%
156	5	6	0.0	€ 345.64	95.77%	6	0.0	€ 345.64	95.77%	6	0.0	€ 345.64	95.77%
157	0	5	0.0	€ 456.66	97.24%	5	0.0	€ 456.66	97.24%	5	0.0	€ 456.66	97.24%
158	0	49	0.0	€ 1,089.40	89.30%	49	0.0	€ 1,089.40	89.30%	49	0.0	€ 1,089.40	89.30%
159	1	3	0.0	€ 428.99	98.25%	3	0.0	€ 428.99	98.25%	3	0.0	€ 428.99	98.25%
160	0	24	0.0	€ 729.27	92.31%	24	0.0	€ 729.27	92.31%	24	0.0	€ 729.27	92.31%
161	0	37	0.0	€ 1,035.37	91.45%	37	0.0	€ 1,035.37	91.45%	37	0.0	€ 1,035.37	91.45%
162	0	59	0.0	€ 883.47	84.14%	59	0.0	€ 883.47	84.14%	59	0.0	€ 883.47	84.14%
163	0	12	0.0	€ 693.14	95.64%	12	0.0	€ 693.14	95.64%	12	0.0	€ 693.14	95.64%
164	0	34	0.0	€ 867.19	90.48%	34	0.0	€ 867.19	90.48%	34	0.0	€ 867.19	90.48%
165	8	22	0.0	€ 634.55	91.09%	22	0.0	€ 634.55	91.09%	22	0.0	€ 634.55	91.09%
166	0	19	0.0	€ 539.08	91.40%	19	0.0	€ 539.08	91.40%	19	0.0	€ 539.08	91.40%

4.2.3 Deviations of results

A possible cause of the deviations could be the probability distribution of demand of both products. In this research, the demand is assumed to be Poisson distributed. However, this is not the case for all combinations of products and stores. The procedure of Adan et al (1995), as explained in Chapter 3, is used to calculate the demand distribution for each store and product.

When the fill rates are compared with the demand distributions of both products, an interesting reasoning for these deviations is found. As could be seen in Figure 3 and Figure 4, a downward sloping line describes the relation between the fill rate, that results from the model, and the probability distribution of demand. When a is closer to zero (the absolute value of a is used in these figures), the fill rate is higher and more close to the target service level. For this reason, the demand pattern of every store should be analysed and afterwards the best suitable probability distribution should be selected.

As could be seen in Table A26 - Table A29 in the Appendix, the model works good (compliance with the target service level and a low amount of waste) for Poisson distributed demand. Stores that have a (close to, $a \leq 0.05$) Poisson distributed demand are shown by a blue coloured cell. When the demand has another distribution, the model does not work that good anymore, and therefore should be adapted to the particular demand distribution, for instance binominal distribution.

The effect of the probability distribution function for both products when lead time is included is less than if no lead time is included. Since there is hardly any correlation between the probability distribution and the height of the fill rate for product lifetime 6 when lead time is included, this seems not to be the cause of the deviations. The trend line is nearly flat and fill rates are not particularly higher when a is small. These deviations are supposed to be the result of the capability of the model itself. Due to time limitations, the evaluation of other distributions is not possible within this research, this would be a recommendation for further investigations.

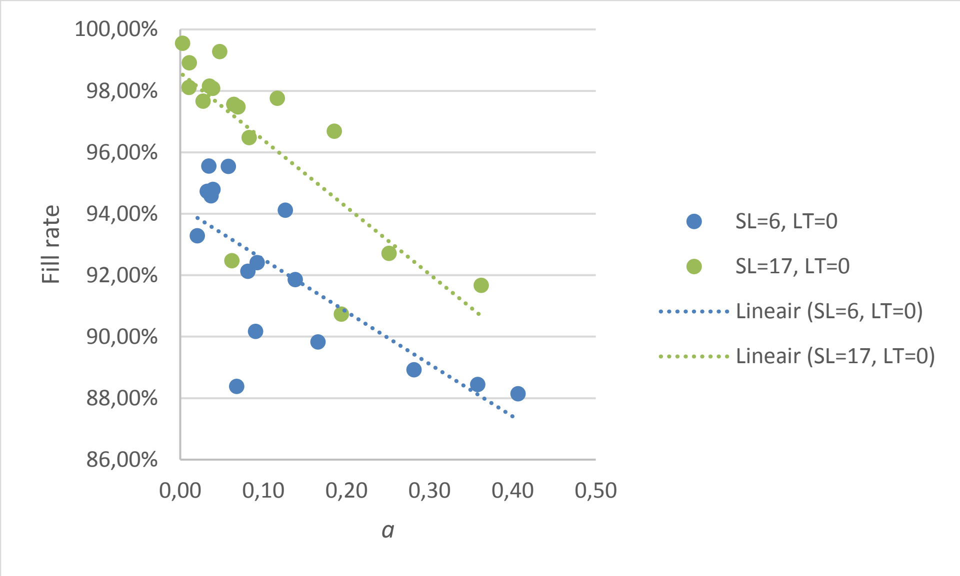

Figure 3. Relation of fill rate with probability distribution (items with lead time). When a = 0, the demand of an item has a Poisson distributed probability. When *α* is closer to zero, the better the demand distribution fits the used probability distribution in the model.

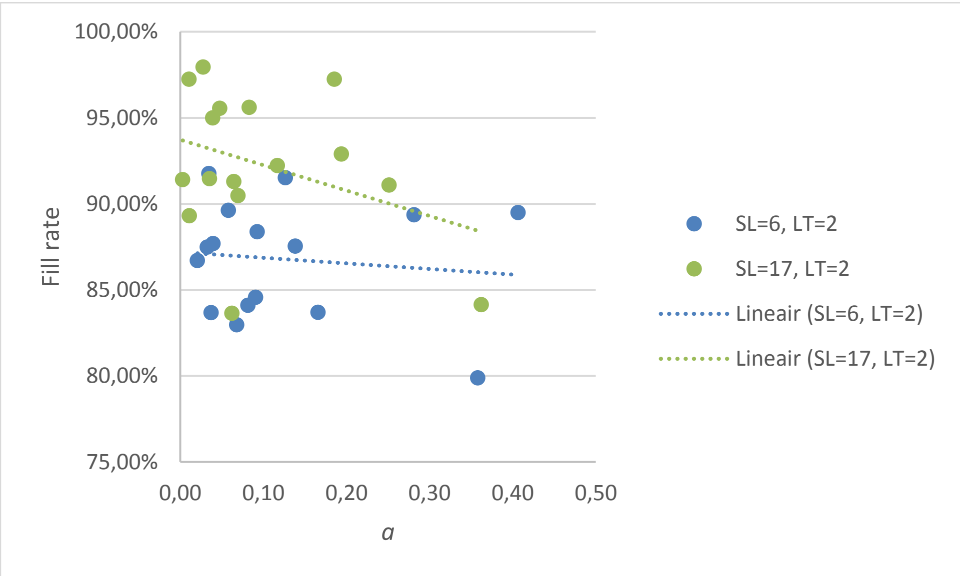

Figure 4. Relation of fill rate with probability distribution (items without lead time). When *α* = 0, the demand of an item has a Poisson distributed probability. When *α* is closer to zero, the better the demand distribution fits the used probability distribution in the model.

The results of the simulation show that for both products and in case of excluded and included lead time, almost all stores improve their amount of waste. Only a couple of stores have more waste resulting from the order policies in comparison to the current situation, mostly resulting from LIFO withdrawal. Although the model could be very useful to reduce waste, it does not give a result that fulfils the target service level in most of the situations.

In Table 18, the average fill rate per issuing policy and product is taken of the ones that does not fulfil the target service level (so all fill rates which are below respectively 94% and 98%). As could been seen from these numbers, there is quite a large deviation from the target if the target is not met, even till twelve percent point (pp). Therefore, the conclusion could be drawn that the model either gives a satisfying result (with regard to the fill rate) or gives a quite dramatic result.

Table 18. Average fill rates and deviation (percent point, pp) from the target service level per issuing policy, when the target fill rate is not met (<94% - item lifetime 6 and <98% - item lifetime 17).

Issuing policy	SL = 6				SL = 17			
	LT = 0	Average deviation	LT = 2	Average deviation	LT = 0	Average deviation	LT = 2	Average deviation
FIFO	90.67%	3.33 pp	88.57%	5.43 pp	95.12%	2.88 pp	91.96%	6.04 pp
LIFO	89.48%	4.52 pp	82.02%	11.98 pp	95.35%	2.65 pp	92.08%	5.92 pp
80/20	90.65%	3.35 pp	87.20%	6.80 pp	95.12%	2.88 pp	91.96%	6.04 pp
60/40	90.63%	3.37 pp	87.45%	6.55 pp	95.12%	2.88 pp	91.96%	6.04 pp

Table A30 - Table A33 in the Appendix show the differences between the outcomes of the model and the obtained values from the simulation. The values of the model are compared with the values of the FIFO issuing policy for each product (both with and without lead time). It is chosen to compare the values with the FIFO issuing policy, because complete FIFO issuing is most beneficial for the retailer, so the lowest amount of waste and a high fill rate will be obtained. Therefore, model outcomes are compared with the results in the best possible scenario. The improvements are again highlighted with a green background colour. It is apparent from this table that only in five cases (of the 64, so 7.8%) a better or equal outcome results from the simulating with demand data. Waste is in quite some cases (57.8%) equal or improved in comparison to the model outcomes. These results show that the model outcomes should be a little bit higher than targeted in order to meet the requirements.

As expected, the results are in almost all cases worse than the model outcomes. This is an expected result since the model runs an 'ideal world' with a stable demand without outliers, etc. For this reason, the simulated values are in most cases worse. Table 19 provides the average deviations from the fill rates in percent points for both products with and without lead time (LT). The average of all sixteen stores is taken and it shows that the model outcomes for both products when lead time is not included is much better than when lead time is included. Besides a couple of stores that would perform better or just a little bit worse, most stores perform some percent points below the model outcomes.

Table 19. Average deviations from models' fill rates in percent points (pp).

SL = 6, LT = 0	SL = 6, LT = 2	SL = 17, LT = 0	SL = 17, LT = 2
3.34 pp	6.78 pp	2.18 pp	6.53 pp

Although these deviations are not a positive aspect of this model, these could be explained (partly) by the probability distribution as well. Figure 5 shows the effect of the probability distribution on the size of the deviation. As it could be seen from this figure, the closer the a is to zero, the lower the deviation is. When the demand is (or close to) Poisson distributed, the simulated fill rates come close or are even better than the outcomes of the model. If the demand is not close to a Poisson distribution, the fill rates deviate a lot.
These deviations could possibly be filtered out by using another probability distribution in the model. So, no conclusions could be drawn from this relationship for both products when lead time is included (see Figure 6).

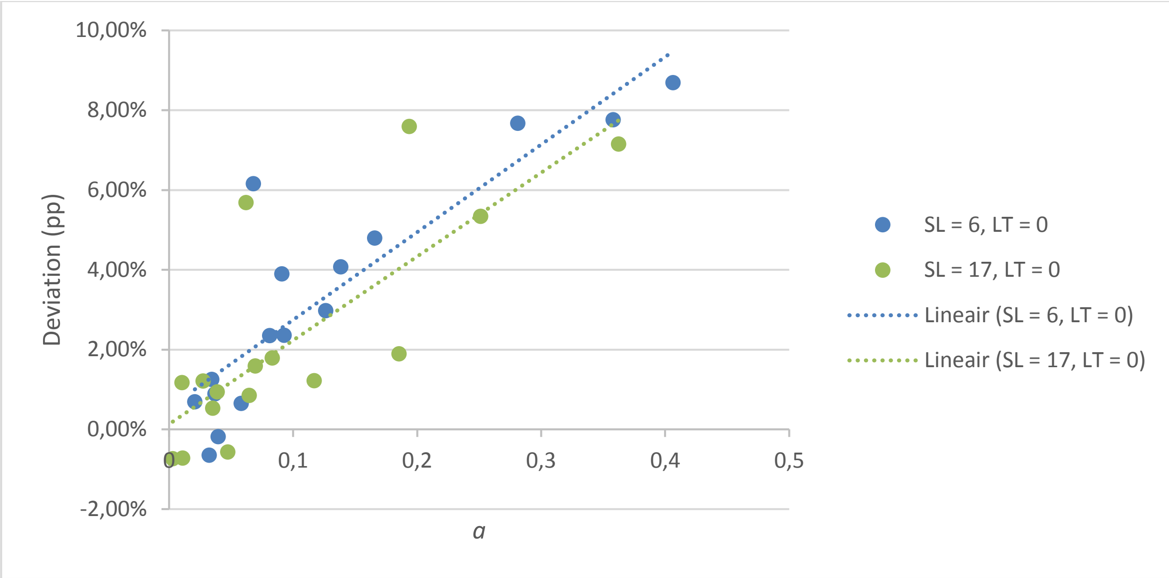

Figure 5. Relation of deviation with probability distribution (items without lead time). When a = 0, the demand of an item has a Poisson distributed probability. When a is closer to zero, the better the demand distribution fits the used probability distribution in the model.

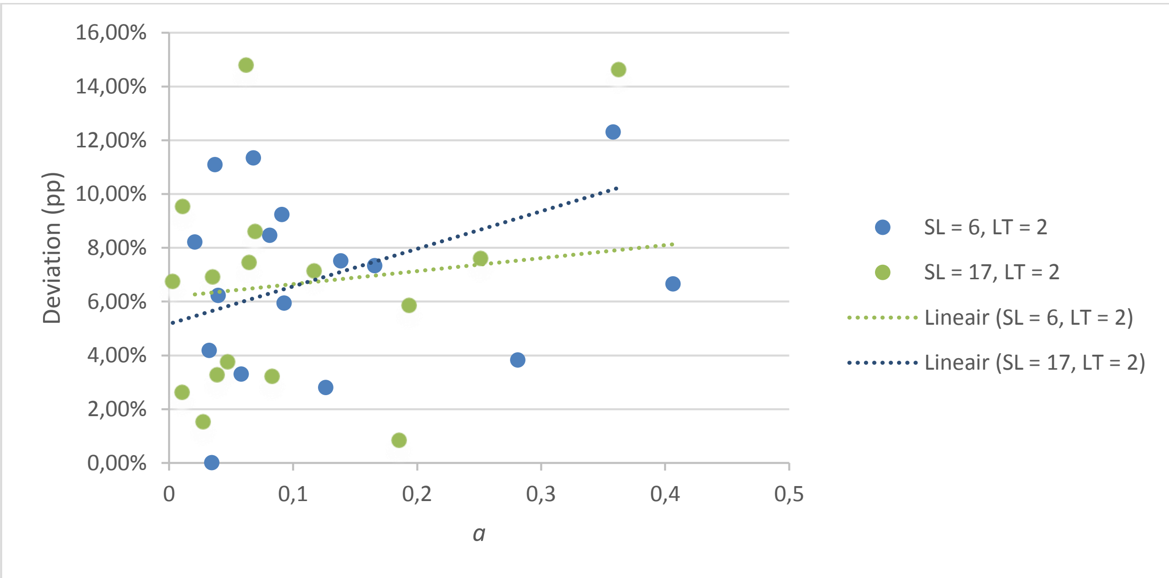

Figure 6. Relation of deviation with probability distribution (items with lead time). When a = 0, the demand of an item has a Poisson distributed probability. When a is closer to zero, the better the demand distribution fits the used probability distribution in the model.

4.3 Conclusion

It shows to be a good model to use in the Slim4 software if no lead time is applicable. The model gives good results for the stores that has a probability demand distribution function which is close to Poisson. Waste would be reduced from 284 items to only one item for a nine-week period. The target fill rate is met by four of the five stores that have a (close to) Poisson distributed demand. However, the model shows not to be suitable, in current form, for products that have a lead time of two periods. Although waste is reduced from 284 till 95 items, the target service level is only met by two stores. All other stores show large deviations from the target level.

Based on the analysed product types (shelf life lengths), it seems not to matter what product is investigated by the model. In case of a lead time of zero, the waste is reduced from 30 to zero for the product lifetime 17. Also for a lead time of two the waste is reduced to zero. However, instead of having six meeting fill rates when LT = 0 (of the seven stores with Poisson distributed demand), only one store will meet the target level if lead time is included.
If demand is not Poisson distributed, it should be evaluated (in further research) whether the model is still useable for that specific distribution. Besides, the model underestimates the number of items that should be ordered to fulfil demand. Using order-up-to-levels which are based on a T equal to 3, appears not to be a useful method to incorporate lead time for this model. Due to too few ordered items, shortages occur and thereby the target service levels are not met.
In total, the suitability of the model is largely dependent on using the right probability distribution and whether lead time is involved or not. If lead time is involved, corrections are necessary to meet the requirements, otherwise the model gives infeasible solutions for almost all stores.

5. Pauls-Worm & Hendrix

In this chapter, the model of Pauls-Worm & Hendrix (2016) is investigated and evaluated. In the remaining of this research, this article is denoted as 'PH'. First the main assumptions made are discussed, followed by an overview of the main notations and formulas. This part is followed by a simulation of the found order policies and conclusions are based on this.

5.1 Model

5.1.1 Assumptions

A perishable inventory model with the focus on retail is studied in this article. The model includes a positive lead time of *L* days. Days follow a standardized pattern, namely:

1) Store opening;
2) Delivery Q_{t-L};
3) Order Q_t;
4) Demand during the day;
5) Ages of items are updated and waste is disposed.

As it could be seen from these events, it is slightly different from the sequence of events made in Chapter 3. Instead of ordering first and afterwards receiving the order Q_{t-L}, it is the other way around, by ordering after the delivery of Q_{t-L}. However, in the end the results will be the same, since the order quantity (Q_t) is determined by taking the order that arrives in period *t* and the inventory on-hand into account ($Q_t = S_t - I_t - Q_{t-L}$). Items that are delivered in period *t* have age *b*=1 at the end of period *t*. Inventory is checked at the end of every day, items that reach the shelf life of *b* = *M* are disposed (at a cost of *w*). Items that are in the store overnight have a holding cost of *h*. The time horizon (*T*) of 7 days, starts at Monday with *t* = 1. Expected inventory levels at the end of the week, are equal to the expected inventory levels at the beginning of the week after. And at least every *M* days an order should be placed to prevent stock-outs as a result of wasted items.
Demand during the day is independently Poisson distributed, which has an expectation of $\mu_t \epsilon \mathbb{R}$ for period *t*. As service-level, the alpha service-level is selected, to bring the safety stock at the end of every replenishment cycle to a minimal level. As stated in the book of Axsäter et al. (2006), the alpha- (ready rate) and beta-service level (fill rate) are equivalent for a Poisson demand distribution. This fact makes a good comparison with the model of LNR possible.

5.1.1.1 Notations

The following notations are used in the model of PH:
t = period
j = number of periods
b = age of the item
T = time horizon
L = lead time
h = holding cost
w = cost of waste
k = fixed setup cost
M = age on which products outdate
l = is fraction of demand for freshest items (LIFO) ($0 \leq l \leq 1$)
$\mathcal{M}$ = sufficiently large number
Q_t = order quantity in period *t*
S_t = order-up-to-level in period *t*
I_{bt} = inventory level in period *t* of age *b*
Y_t = binary variable to determine whether an order is placed in period *t* (1) or not (0)
Z_{jt} = binary variable that indicates the most recent order prior to period *t* to meet demand for *j* periods

$G_t(d_t)$ = cumulative distribution function of demand
EI_{bt} = expected inventory in period *t* of age *b*
EQ_t = expected order quantity in period *t*
EI_{Mt} = expected inventory in period *t* which is outdated
EIl_{bt} = expected inventory of age *b* after LIFO demand in period *t*
EXl_{bt} = residual LIFO demand for items of age *b* in period *t*
EX_{bt} = residual FIFO demand for items of age *b* in period *t*
BXl_{bt} = binary variable that indicates

5.1.2 MILP approximation model

Within this research the Mixed Integer Linear Programming (MILP) approximation model is evaluated which is described in the article of PH. The objective of this approximation model is to minimise total costs. This is done by using the following objective function:

$$Min\ E(TC) = \sum_{t=1}^{T} \left\{ kY_t + h \sum_{b=1}^{M-1} EI_{bt} + cEQ_t + wEI_{Mt} \right\}$$

While: $EQ_t \ \leq \ \mathcal{M}_t Y_t$

In order to meet the target service level, safety stock is determined by subtracting demand during lead time and the replenishment cycle from the basic order-up-to-level. To fulfil this safety stock requirement, the expected inventory is set by the constraint:

$$\sum_{b=1}^{M} EI_{bt} \ \geq \ \sum_{j=1}^{M} \left(G_{t-L-j,t}^{-1}(\alpha) - \sum_{n=t-L-j+1}^{t} \mu_n \right) * Z_{jt}$$

To prevent that multiple orders are placed for the same period, the next constraint is set:
$\sum_{j=1}^{M} Z_{jt} = 1$ and for this reason, $Z_{jt} \geq \ Y_{t-L-j+1} - \sum_{n=t-L-j+1}^{t-L} Y_n$ holds ($Z_{1t} = \ Y_{t-L}$ in case of *j*=1).

The order quantity is equal to the order-up-to-level minus the outstanding order that arrives in period *t* minus the inventory on hand. The order quantity can be set as follows:

$$EQ_t = \ S_t - \ EQ_{t-L} - \sum_{b=1}^{M-1} EI_{b,t-1}$$

PH have implemented the issuing policy in their model as well. For this reason, there are a couple of constraints that deal with the way at which products are withdrawn:

$$EQ_{t-L} - l * \mu_t = \ EIl_{0t} - \ EXl_{0t}$$
$$EI_{b,t-1} - \ EXl_{b-1,t} = \ EIl_{bt} - \ EXl_{bt}$$

For FIFO demand:

$$EIl_{M-1,t} - (1 - l) * \mu_t - \ EXl_{2t} = \ EI_{Mt} - \ EX_{M-1,t}$$
$$EIl_{bt} - \ EX_{b+1,t} = \ EI_{b+1,t} - \ EX_{bt}$$

By using the fraction '*l*' different issuing policies could be used in the model. When *l* is set to zero, a complete FIFO issuing policy is used, while *l* is one means a complete LIFO policy. Besides, all numbers in between zero and one are possible to correct for all different combinations of FIFO and LIFO. As done at the model of LNR, the combinations 80% FIFO and 20% LIFO, and 60% FIFO and 40% LIFO are evaluated (i.e. *l* = 0.2 and *l* = 0.4).

The following constraints are needed to ensure that only one variable on the right side (of the constraints above) has a positive value:

$$\mathcal{M} * BXl_{bt} \geq EXl_{bt}$$
$$\mathcal{M} * (1 - BXl_{bt}) \geq EIl_{bt}$$
$$\mathcal{M} * BX_{bt} \geq EX_{bt}$$
$$\mathcal{M} * (1 - BX_{bt}) \geq EI_{b+1,t}$$

The starting inventory level of a certain period is equal to the end inventory level of the period before. This situation is covered in the model by setting $EI_{b0} = EI_{bT}$. And orders that are delivered in period one (EQ_{1-L}) are equal to EQ_{T+1-L}.

The model calculates the order-up-to-level ($\hat{S}_{L+r,t}$), which could be increased with the expected waste that would occur during the replenishment cycle. To meet the target service level, the value of S_t has to be found that has a non-stock out probability equal to α (Poisson distributed). This is done by including the next formula: $P(d \leq S) = e^{-\mu} \sum_{i=0}^{S} \frac{\mu^i}{i!} \geq \alpha$.

The software programs MPL and Microsoft Excel are used for evaluating and simulating the model of PH. MPL is used for calculating the order policies. The MILP model is programmed in MPL and order policies are calculated for the different stores. Like the model of LNR, Microsoft Excel is used for the simulation part; the order policies are evaluated by using the demand data of nine weeks here as well. The resulted amount of waste, shortage and fill rate levels are investigated for possible improvements in comparison to current practices.

5.2 Results

Also this model is evaluated for the four different scenarios: complete FIFO, complete LIFO, 80%/20% and 60%/40% (FIFO/LIFO). PH implemented the option to calculate order-up-to-levels based on the issuing policy. For this reason, the order-up-to-levels, in case of complete FIFO issuing, differ from the levels when customers issue the items according to a LIFO policy. Moreover, due to the non-stationarity of demand, every day of the week has its own order-up-to-level. So, for every day there are four order-up-to-levels, for each issuing policy one.

The results from the model are simulated by using demand data. For both products, the starting inventory is equal to the basic order-up-to-level (Poisson distributed) for the first three days (to cover the demand on the first day plus the demand during the lead time).
Almost every day an order is placed. However, when the inventory level is above the order-up-to-level no order is placed. In this research, no minimum order quantity is assumed. Even if one single item is necessary (according to the order-up-to-level) this is ordered. In practice, there may be a minimum number of items that should be ordered. When this is the case, results will change, either shortages occur when no order is placed or waste might occur when the minimum order quantity is ordered especially when only one item is needed.

5.2.1 Product lifetime 6

After conducting the simulation, conclusions could be drawn with regard to the performance of the model. The results of the simulation are shown in Table 20 (Table A37 in the Appendix shows the complete LIFO withdrawal as well). The main focus of the model shows to be the amount of waste that occurs in the retail store. In 85.4% of the cases (68.75% when complete LIFO is included), the amount of waste is improved in comparison to the current situation. Only store 164 would not improve its amount of waste, all other stores would improve their amount of waste, at least in case of complete FIFO demand. When waste would have been the only KPI, it would be a good model.

Table 20. Simulation results of order-up-to-levels for product lifetime 6. Order quantity is corrected for all orders outstanding ($Q_t = R - I_t - Q_{t-1} - Q_{t-L}$). Green cells in 'waste'-column indicate improvements in comparison to current situation, green cells in 'Fill rate'-column indicate the compliance with the target service level.

		Complete FIFO				80% FIFO - 20% LIFO				60% FIFO - 40% LIFO			
Store:	Current waste	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate
141	142	487	0	€ 6,065.12	89.87%	487	0	€ 6,065.12	89.87%	487	0	€ 6,065.12	89.87%
151	2	26	0	€ 354.71	90.37%	26	1	€ 356.32	90.37%	26	1.2	€ 357.94	90.37%
152	19	26	0	€ 317.83	89.64%	26	0	€ 317.83	89.64%	27.8	2.8	€ 323.92	88.92%
153	14	8	0	€ 357.75	97.06%	8	3	€ 364.12	97.06%	8	3.8	€ 367.61	97.06%
154	4	17	0	€ 262.24	91.46%	17	0	€ 262.24	91.46%	18.8	2.2	€ 266.75	90.55%
156	9	19	8	€ 230.85	88.62%	20	10	€ 236.33	87.90%	22.2	13.6	€ 243.32	86.71%
157	5	40	0	€ 451.50	88.47%	46	0	€ 449.59	86.74%	51.2	5.2	€ 459.42	85.24%
158	18	23	0	€ 702.69	95.78%	23	0	€ 702.69	95.78%	23	0	€ 702.69	95.78%
159	7	18	0	€ 425.53	94.50%	18	0	€ 425.53	94.50%	18	0	€ 425.53	94.50%
160	6	60	0	€ 729.54	89.57%	65	5	€ 738.99	88.70%	72.4	10	€ 746.65	87.41%
161	7	20	0	€ 516.50	94.88%	20	0	€ 516.50	94.88%	20	0	€ 516.50	94.88%
162	5	15	0	€ 376.20	94.76%	16	1	€ 377.71	94.48%	17.2	2.2	€ 381.97	93.99%
163	5	35	0	€ 402.20	88.82%	40	5	€ 411.65	87.22%	39.4	5	€ 412.12	87.41%
164	1	27	2	€ 372.43	90.15%	27	2	€ 372.43	90.15%	28.4	3.4	€ 375.06	89.64%
165	24	27	2	€ 373.64	90.11%	27	3	€ 375.77	90.11%	27	4	€ 379.21	90.11%
166	16	21	0	€ 409.89	93.38%	21	1	€ 413.24	93.44%	20.6	1.4	€ 413.92	93.50%

Five stores have a fill rate that meet the target service level of 94% for a complete FIFO demand and for both combinations of FIFO and LIFO (store 162 when the fill rate is rounded). These fill rates are quite close to the 94%, resulting in having no more inventory than necessary. If a store has a much higher fill rate, it has more inventory and thereby higher costs than the strategy of the company prescribes.

If the target level is not met, the deviation from the target level is on average between the four and five percent point. In Table 21 the average fill rates of the stores that does not meet the target service level are shown. These results show that if the model does not have an outcome that meet the target level, it has on average a deviation of 4.47 percent point in case of FIFO issuing.

Table 21. Average fill rates and deviation (percent point, pp) from the target service level per issuing policy, when the target fill rate is not met (<94%).

SL = 6	Average fill rate	Average deviation
FIFO	89.53%	4.47 pp
LIFO	89.60%	4.40 pp
80/20	89.48%	4.52 pp
60/40	89.48%	4.52 pp

As Table 21 shows, there is still quite some deviation from the target service level. This is the result of ordering too few items, and thereby running out-of-stock during the day. Therefore, the order-up-to-levels should be increased a bit to fulfil a larger part of the total demand. This could be done by taking the inventory and outstanding orders into account differently.

The results are based on the MILP model described in the article of PH. In the article the authors gave three alternative policies for calculating order policies. From their simulation, the policy $YS_{\gamma \sum I}$ gave the best results. This policy uses the following formula for calculating the order quantity in period t: $Q_t = S_t - Q_{t-L} - \gamma \sum_{b=1}^{M-1} I_{b,t-1}$. The difference of this formula and the formula used in the simulation of this research is the fraction γ. This is the fraction γ of the inventory that is available at period t.

When a fraction of the inventory is taken, the number of items ordered is higher, resulting in a higher fill rate.
This option is evaluated for the stores that do not meet the target service level. A trial on error method is used to find suitable fractions of γ. As expected, the fill rates will meet the target service level and even lowers the amount of waste in some cases (see Table 22). Due to this fraction, the target service level is nearly always met. By changing the fraction γ it is possible to meet the target service level quite precise and thereby having no more inventory than necessary. The costs will increase a bit by having more inventory and more ordered items (these costs are higher than the current shortage costs). However, this will be outcompeted in the end by the extra profit that is made. Therefore, this shows to be a useful method to meet the requirements and keep the waste low.

As shown in the last column of Table 22, the fractions are still quite high (above 0.7), only for store 164 and 165 it is hard to find a fraction that will give a suitable solution. For instance, store 165 has a fill rate of 95.03% when a fraction of 0.7 is included in the model. This fraction gives a better result in comparison with a fill rate of 94%. If the fraction is set to 0.056, a fill rate of exactly 94% results, but it increases the waste a lot (sixteen items). Store 164 needs a very low fraction as well, when the fraction is 0.119 it has a waste of ten items when the fill rate is just above 94%. When this is compared to a fill rate of just below 94%, as shown in the table, this small increase results in five more wasted items. This result shows that using this fraction is not that simple. As it is shown, high fill rates could be accompanied by a few wasted items and fill rates that are close to the target level could be accompanied by a lot of wasted items. This characteristic of using this fraction makes it more difficult to calculate the optimal fraction. If this could be done efficiently, much higher fill rates could be achieved without having waste.
Another disadvantage of this method is that for every store and issuing policy this correction factor should be calculated which may take a lot of time. Nonetheless, this would not be an everyday task but is needed the first time the order policies are determined and at moments that it does not fulfil anymore.

Table 22. Results of using a fraction γ in the order quantity calculations for complete FIFO demand (product lifetime 6).

	Complete FIFO					Fraction					
Store	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Order quantity	Sim. Shortage	Sim. Waste	Total Costs	Fill rate	Order quantity	γ
141	487	0	€ 6,065.12	89.87%	4279	281	0	€ 6,255.59	94.14%	4500	0.70
151	26	0	€ 354.71	90.37%	249	15	0	€ 361.51	94.28%	258	0.91
152	26	0	€ 317.83	89.64%	222	15	0	€ 327.02	94.08%	233	0.87
153	8	0	€ 357.75	97.06%	259						
154	17	0	€ 262.24	91.46%	185	12	0	€ 265.28	94.01%	189	0.83
156	19	8	€ 230.85	88.62%	153	10	5	€ 231.97	94.11%	161	0.84
157	40	0	€ 451.50	88.47%	314	21	0	€ 462.79	94.08%	331	0.78
158	23	0	€ 702.69	95.78%	507						
159	18	0	€ 425.53	94.50%	305						
160	60	0	€ 729.54	89.57%	511	34	0	€ 749.05	94.15%	536	0.87
161	20	0	€ 516.50	94.88%	371						
162	15	0	€ 376.20	94.76%	270						
163	35	0	€ 402.20	88.82%	280	19	0	€ 412.92	94.03%	294	0.86
164	27	2	€ 372.43	90.15%	259	17	5	€ 397.61	93.65%	276	0.24
165	27	2	€ 373.64	90.11%	260	14	0	€ 374.25	95.03%	268	0.70
166	21	0	€ 409.89	93.38%	292	19	0	€ 411.40	94.04%	294	0.96

A Poisson distributed demand is assumed in this research. However, the demand is not Poisson distributed at each store. As discussed in the previous chapter for the model of LNR, Adan et al. (1995) developed a method to determine the probability distribution of demand. When the simulation results are compared with the probability distributions of the different stores, Figure 7 results. As it could be seen from this figure, the distribution of demand has some influence on the results of the model. The trend line shows a negative correlation between the a and fill rate of the stores. For this reason, different distributions implemented in the model might give suitable order policies for the stores with non-Poisson distributed demand. Due to time limitations, this would be a recommendation for further research.

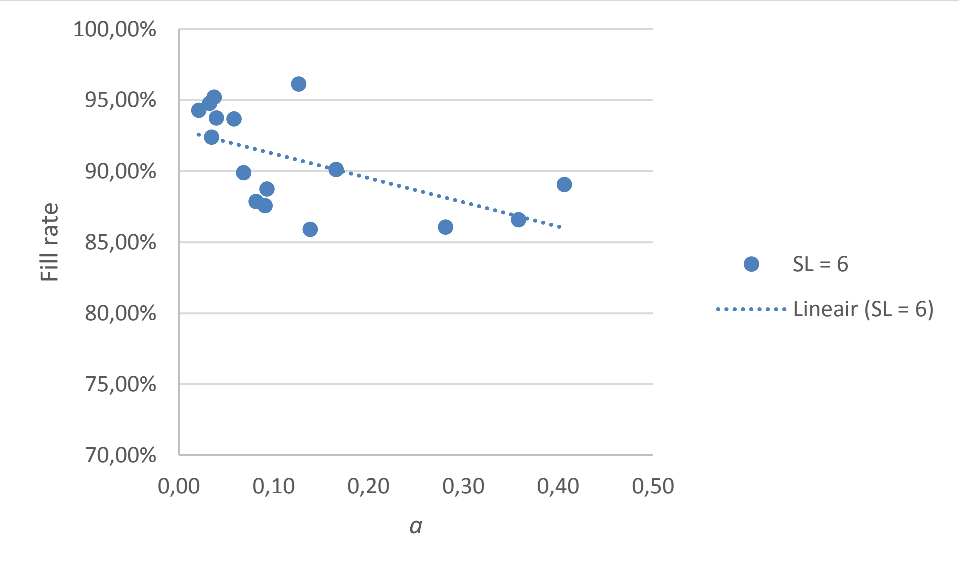

Figure 7. Relation of fill rate with probability distribution (items with lead time). When a = 0, the demand of an item has a Poisson distributed probability. When a is closer to zero, the better the demand distribution fits the used probability distribution in the model

For the reasons described in the previous paragraphs, this model is a suitable predictor for products with a shelf life of six days when the demand is Poisson distributed. Without any corrections of the order quantities, the model is not suitable for other demand distributions, adaptions of the model to handle other demand distributions are needed to have suitable results for these stores as well. Or, if corrections are made for each individual store (by using the fraction γ), these would give suitable results as well. However, this may cost a lot of time to determine a correction factor for each individual store. One of these two solutions is necessary to make this model suitable for practice.

5.2.2 Product lifetime 17

A product with seventeen days of shelf life has such a long shelf life that it nearly is a non-perishable item, especially when a review period of one day is used. When a review period of one day is used, products which have a shelf life of fourteen days or more can be treated like a non-perishable product in inventory management (K.G.J. Pauls-Worm, personal communication, February 16, 2017). For this reason, in accordance with Pauls-Worm, the model is investigated by leaving the perishability out of sight in the calculations of the order-up-to-levels. In comparison to the product with a shelf life of six days, it has only one set of order-up-to-levels (Monday till Sunday), instead of four (for each issuing policy). Although perishability is not taken into account in the calculations for the order policies, the four withdrawal policies were still evaluated at the simulation.

The model better performs for the product with a shelf life of seventeen days (Table 23). Waste is in case of a complete FIFO issuing policy and the combination 80%/20% for all stores zero. Except one, all stores for the combination 60%/20% have a waste equal to zero as well. When complete LIFO demand is applicable, the model does not perform well in case of waste (see Table A38 in the Appendix). Only store 141 has an improvement of waste, all other stores have a very high amount of waste. But again, the probability of having complete LIFO demand is almost zero.

In 93,75% (60 out of 64) of the cases the target service level is met. Store 141 is the only store for which the fill rate does not meet the target level. All other stores meet the target service level for every issuing policy. Except for four stores, while having LIFO demand, all stores have a fill rate of 100% for every issuing policy. Although this sounds great, not having any waste and not having any shortages, it has a disadvantage. When the strategy of the organisation is to have a fill rate of 98%, the two extra percent points are unwanted costs. Too much inventory is hold during the nine-week period time and thereby too much items are ordered. The costs could be lowered by lowering the order quantities, the fill rate will remain still above the target and the waste, if already there, will be lowered any further.
Also for these products a correction might be necessary to decrease costs. Instead of increasing the order quantities, the correction now should lower the amount ordered by using a fraction which is greater than one.

In comparison to product lifetime 6, checking the effect of the demand distribution is not a possibility here. Except for one, all stores have a fill rate of 100% and as a result of this, also stores that do not have Poisson distributed demand have high fill rates. Therefore, it is not possible to check whether the results will be better when the demand is Poisson distributed. It is the expectation that the demand distribution has an influence on the results for the product with a shelf life of seventeen days as well.

In contrast to the other stores, store 141 does not meet the target service level of 98% for product lifetime 17. This store is the only one which does not have a fill rate of 100%. The fill rate is not that far below the target, only 0.74 percent point, and thereby maybe the most accurate order policy of all. This result may be the effect of the demand size of this store. Store 141 is the only store that has an average demand higher than ten (average of ±70 items a day). For this reason, it shows that the size of the demand matters for this model. However, to be sure, further research is needed to determine the impact of the demand size on the outcome of the model.

Almost all order policies are an improvement of the current situation and thereby making this model a suitable one for, at least, products with a shelf life of seventeen days. Only the costs might be a problem, this would be solved by including a fraction γ, which decrease the number of items ordered. Again, this will take quite some time to calculate the right factor for each individual store.

Table 23. Simulation results of order-up-to-levels for product lifetime 17. Order quantity is corrected for all orders outstanding ($Q_t = R - I_t - Q_{t-1} - Q_{t-L}$). Green cells in 'waste'-column indicate improvements in comparison to current situation, green cells in 'Fill rate'-column indicate the compliance with the target service level.

		Complete FIFO				80% FIFO - 20% LIFO				60% FIFO - 40% LIFO			
Store:	Current waste	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate
141	15	120	0	€ 11,167.76	97.26%	120	0	€ 11,167.76	97.26%	120	0	€ 11,167.76	97.26%
151	1	0	0	€ 716.71	100%	0	0	€ 716.71	100%	0	0	€ 716.71	100%
152	0	0	0	€ 1,382.80	100%	0	0	€ 1,382.80	100%	0	0	€ 1,382.80	100%
153	0	0	0	€ 775.92	100%	0	0	€ 775.92	100%	0	0	€ 775.92	100%
154	0	0	0	€ 479.55	100%	0	0	€ 479.55	100%	0	0	€ 479.55	100%
156	5	0	0	€ 418.49	100%	0	0	€ 418.49	100%	0	2.4	€ 424.66	100%
157	0	0	0	€ 518.81	100%	0	0	€ 518.81	100%	0	0	€ 518.81	100%
158	0	0	0	€ 1,245.77	100%	0	0	€ 1,245.77	100%	0	0	€ 1,245.77	100%
159	1	0	0	€ 477.23	100%	0	0	€ 477.23	100%	0	0	€ 477.23	100%
160	0	0	0	€ 845.69	100%	0	0	€ 845.69	100%	0	0	€ 845.69	100%
161	0	0	0	€ 1,184.20	100%	0	0	€ 1,184.20	100%	0	0	€ 1,184.20	100%
162	0	0	0	€ 1,023.85	100%	0	0	€ 1,023.85	100%	0	0	€ 1,023.85	100%
163	0	0	0	€ 752.04	100%	0	0	€ 752.04	100%	0	0	€ 752.04	100%
164	0	0	0	€ 963.58	100%	0	0	€ 963.58	100%	0	0	€ 963.58	100%
165	8	0	0	€ 694.17	100%	0	0	€ 694.17	100%	0	0	€ 694.17	100%
166	0	0	0	€ 583.12	100%	0	0	€ 583.12	100%	0	0	€ 583.12	100%

When the results of the simulation are compared with the outcomes of the model there is a surprising result. As shown in Table A34 - Table A36 in the Appendix, in almost all cases the simulated values are an improvement of the model outcomes for product lifetime 6. First, fill rates are much higher, the expectation was that these should be at or around 98%. However, these are almost all 100%. Secondly, as shown in these two tables, costs are only in 9.4% (six of the 64 cases) higher than the model outcomes. This lower amount of costs is partly due to the fact that all order quantities are lower in comparison to the model outcomes, so a higher fill rate is achieved with less items ordered. Only waste has worse scores by having in approximately 40% of the cases more waste. For product lifetime 17 all KPIs have better or equal results. Just as the outcome of the model, all waste is zero, but the quantities ordered are much lower (a total of 7491 items are ordered less). As is apparent from these results, the model overestimates the number of items that are needed to fulfil customer demand. The impact of this is having higher inventory levels and thereby higher costs than necessary as a retailer.

5.3 Conclusion

Taken all together, this model performs well on waste. For the product lifetime 6, waste is reduced from 284 items to twelve items for a nine-week period. The fill rates however do not meet the target service level for eleven of the sixteen stores, thereby giving infeasible solutions for most of the stores (68.75%). When a fraction of inventory is included in the model it performs better by meeting the target service level for all stores. The disadvantage of this fraction is that it should be calculated for each individual store and product, and thereby might be too time consuming in practice.

Based on the KPIs waste and service level, the model performs better for the product lifetime 17. Waste is reduced from 30 to zero and fill rates are, except for one, 100% for all stores. Since the fill rates are almost all 100%, too much inventory is on hand, resulting in high costs. For this reason, also here a fraction is needed to decrease the fill rates to the target level and thereby reducing costs.

This PH model will give suitable solutions if there is a correction included for inventory on hand. If this fraction is not included in the model it gives either infeasible solutions (SL = 6) or too high costs due to too high inventory levels (SL = 17). To be suitable in practice these fractions are needed, but it should be investigated whether calculating these fractions for each store and product individually is suitable in practice as well.

6. Conclusion

This conclusion is divided in two parts. In Section 6.1, the different research questions are discussed. While in Section 6.2 the models of LNR and PH are compared with the models investigated by Nazmutdinova (2017).

6.1 Research questions

This study has shown that there are in literature a couple of models that can be used in practice to determine an order policy for certain types of perishable products. Within this research, two models have been evaluated on how they perform based on KPIs as waste, service level and costs. At the beginning of this study, several research questions were drafted to investigate the main research question: *What is the most suitable approach to determine an order policy for certain types of perishable products, in terms of achieving the best trade-off between service-level and waste, in retail?*

6.1.1 Challenges

At first, the main challenges in retail practice were investigated. The corresponding research question was partly investigated by conducting a literature study, besides the interview with the Supply Chain Specialist of Marqt (P. de Lepper) helped to get a better insight in practice. First, outdating of products should be taken into account when perishable items are ordered. A second important characteristic of a model should be the use of periodic reviewing. Also lead time is an important component of a model. Complete FIFO, complete LIFO, 80% FIFO / 20% LIFO and 60% FIFO / 20% LIFO demand were investigated in this research due to the uncertainty of withdrawal policies.

When demand cannot be fulfilled, this demand is assumed to be lost. Following from these lost sales, unfulfilled demand (shortage) is measured by using the service level, which should meet a target level. The last characteristic of the model is including stochastic demand.

6.1.2 Scientific models

A literature study was conducted for the second specific research question as well. A lot has been written about inventory management for perishable products. Nine possibly suitable models were found in scientific literature, of which four were selected for further investigation. The models of Lowalekar et al. (2016) and Pauls-Worm & Hendrix (2016) were investigated in this research. The models of Muriana (2016) and Broekmeulen & Van Donselaar (2009) were investigated by Nazmutdinova (2017).

6.1.3 Types of products

The products of the dataset were classified into several groups. First of all, the shelf life of the product is a way to distinguish different types of products. This was investigated by using a product with a shelf life of six days and one of more than two weeks (seventeen days). Also, the size of demand for a certain product is a distinctive aspect of products. The dataset included only one store with a high average demand (>50 products a day). Therefore, further research is needed to draw conclusions on this type of products.

6.1.4 Suitability of models per product type

The fourth specific research question is treated in Chapter 4 and 5. As discussed here, both models (LNR and PH) have limitations to be used in practice. The model of LNR has suitable results when lead time is equal to zero. When lead time is included, the model gave infeasible solutions for almost all stores. Although waste was reduced, in comparison to the current situation, and costs were low, the fill rate was far below the target. Therefore, the model of LNR will not be applicable for either a product with lifetime 6 as lifetime 17. When costs would be the only KPI, it would be applicable for both products. However, this is not the case in practice.

The PH model performs better by having more stores that meet the target service level and there is a larger waste reduction. The costs are just a little bit higher than for LNR. This is mainly the result of the low inventory LNR had. The authors recommend to use a fraction of inventory into account and meeting the target service level in almost all cases. When this fraction is calculated for each individual store and product, this would be a useful model to implement in the Slim4 software. Waste would be reduced and the target service level is met. If this is the case, this model will be applicable for both the products with lifetime 6 as lifetime 17. So, without any corrections, both models would not be suitable for any of the product types. However, if a fraction is included in the model of PH, it is for both lifetime 6 as 17 suitable.

6.1.5 Current results

When the results of the models are compared with the current results, both models show an improvement of current waste. Waste is reduced for both products and perform better than the current used method. However, the target service levels are rarely met by both models. So, regarding this KPI both performing worse. But, if a fraction is included for the model of PH, it would outperform the current results and thereby be an improvement of current situation.

6.2 Comparison of models

Not only the models of LNR and PH are investigated. Also two other models are investigated by Nazmutdinova (2017). Both the two models discussed in this research as two models investigated by Nazmutdinova (2017) are elaborated on in this section. She found that the model of Muriana (2016), is not a useful model to use for inventory management of perishable products with a shelf life of six or seventeen days. Since this is not a useful model, this one is excluded for the remaining of this section. For this reason, the models of Lowalekar et al. (2016), Pauls-Worm & Hendrix (2016) and Broekmeulen & Van Donselaar (2009) (in the remaining of this chapter referred to as BD) are discussed.
As is shown in Table A39 and Table A40 in the Appendix, there are quite some differences in terms of KPI performance between the models of LNR, PH and BD. In these tables the differences are marked by different cell colours, namely: a green cell indicates the best result of the three models, a red cell the worst result.

For the product with a shelf life of six days, LNR has for most of the stores the highest costs. However, in total, the costs are the lowest of the three (see Table 24). This is specifically the case for the low costs at store 141, which has a high demand resulting in a large difference in costs. However, the fill rate for this store is so low, that this result is infeasible in practice. The model of BD shows the best results (see Figure 8). Except for four stores it has the lowest costs in comparison to the model of PH. Moreover, it has for all stores a higher fill rate and lower amount of waste. This makes the model of BD a suitable model to use in practice for a product with a shelf life of six days.

Table 24. Total costs of all stores per product, resulted from the order policies of the models.

	Product lifetime 6	Product lifetime 17
Lowalekar, et al. (2016)	€ 12,177.90	€ 20,595.46
Pauls-Worm & Hendrix (2016)	€ 12,348.62	€ 23,229.69
Broekmeulen & Van Donselaar (2009)	€ 12,420.22	€ 21,347.44

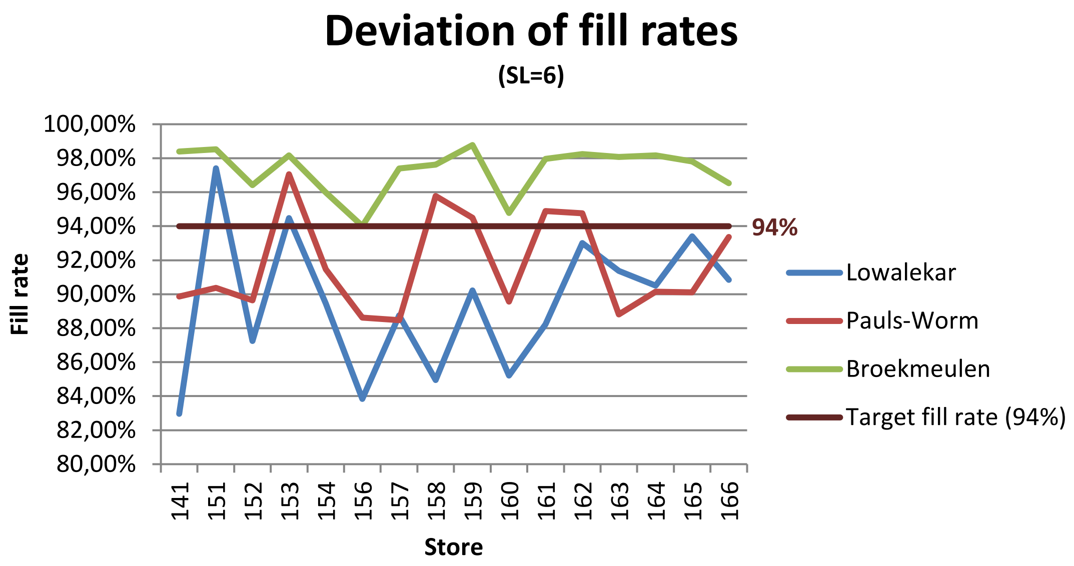

Figure 8. Comparison of fill rates of the models of LNR, PH (basic model) and BD for a product with shelf life 6. The target service level is 94%.

For product lifetime 17, LNR has the lowest costs again. Especially the result of having a very low fill rate at store 141 again. LNR does not give acceptable results (except for waste) for this type of products as well. Therefore, in current form without any corrections, it would not be a useful model to implement in the Slim4 software. Considering the difference between PH and BD, the waste is for both models zero for all stores, but PH has the highest fill rates for fifteen of the sixteen stores (see Figure 9. As mentioned in Chapter 5, this is mainly the result of high inventory levels and this results in much higher costs. In total, the costs of PH are approximately €2,000 higher in comparison to BD. Taking a fraction of inventory into account is needed here as well for PH to perform better on all three KPIs, than BD. At this moment, the high, unnecessary costs might be a reason to not use this model in practice. The combination of zero waste, low costs and meeting fill rates for almost all stores would be the reason to select the model of BD as the most suitable one for products with a shelf life of seventeen days. The decision tree shown in Figure 10 could be made based on the founded results.

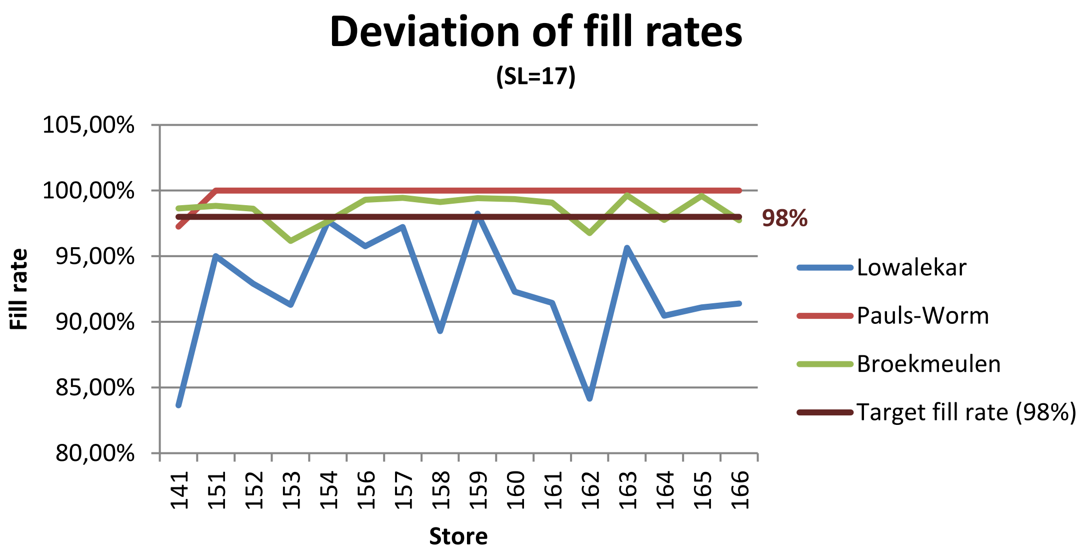

Figure 9. Comparison of fill rates of the models of LNR, PH (basic model) and BD for a product with shelf life 17. The target service level is 98%.

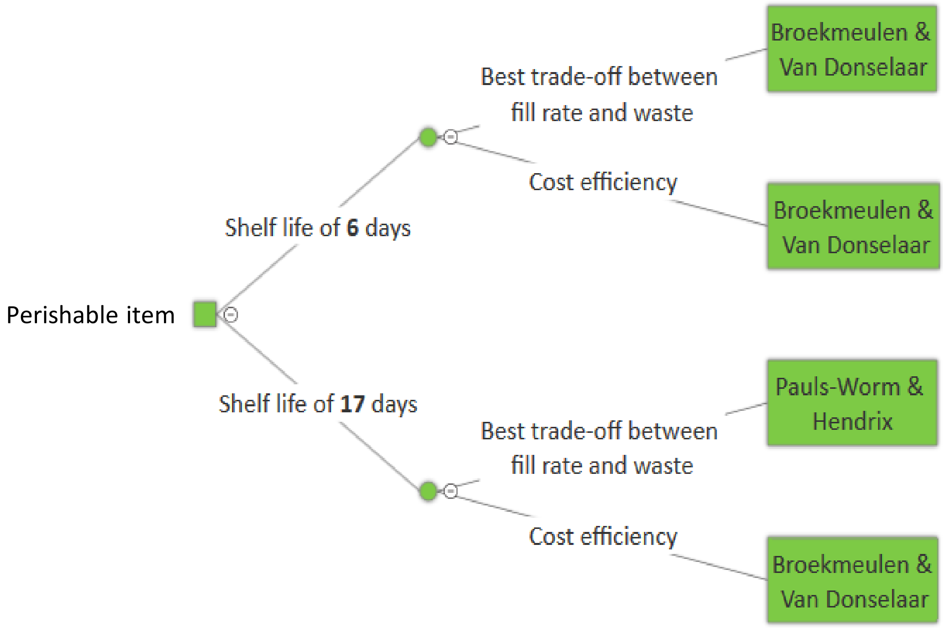

Figure 10. Decision tree for selecting the most suitable model for a perishable item.

7. Discussion

The aim of this research was to find suitable approaches to determine order policies for perishable products in retail. Results show that both evaluated models do not meet all requirements, in their current form. As shown, corrections are needed to be suitable in practice. This study can be used as a basis for further investigation of these two models in order to see whether these would be suitable in practice for a diverse set of products and stores.

There are some limitations of this research. The major limitation is the demand data that is used. Instead of having a separate dataset for simulation, the same dataset is used as input for both the model and the simulation part. Moreover, the data was only for a timespan of nine weeks, which is too short to draw reliable conclusions.
Although the inventory models for perishable products are mostly developed for products with a very short shelf life of only a couple of days, the dataset provided only one product with a shelf life shorter than one week. For this reason, it is important to do further investigations on the performance of the model for different ages.
Moreover, the current study only examined two different products (lifetimes) and only includes one store with a high average demand. For this reason, further research is required to assess the performance of the models when other ages and higher demand are applicable.

This study was limited by only taking a Poisson distribution into account. Further research regarding other demand distributions is strongly recommended to see what the effect will be on the models results. As the results show, the distribution of demand has an influence on the results, and therefore other distributions should be investigated to see whether these will improve the results or not.

This research was unable to analyse the effect of having minimal order quantities due to the absence of this data. It is assumed that even one single product could be ordered, whereas in practice an entire box or at least multiple items have to be ordered. This will have an influence on the results, either by having waste in case of ordering the minimal quantity, especially when only one product is needed. Or shortages will occur when the retailer waits till the moment that the minimal quantity should be ordered (or something in between).

Another important limitation, especially in case of the LNR model, is the uncertainty of costs. In Chapter 3, costs are determined for the remaining of the study. However, in the model of LNR the order policies are determined based on minimising costs. As could be seen in the results, the shortages are too high to meet the target service level. To meet the target service level, the costs of shortage should be increased to prevent shortage, resulting in a higher fill rate. For this reason, determination of costs is for this model a very important aspect. If the right price for shortage could be determined, it might be a suitable model for practice. However, as explained in Chapter 3 as well, shortage costs are hard to determine. Possibly the model of LNR is still a useful one. However, this depends on the estimation of costs. This would be a recommendation for further research as well, to see whether this would improve the results of the model.

The different withdrawal policies are a point of notice as well. The withdrawal policy that is applicable to practice is uncertain. Since no data is available of the remaining shelf lives in stock, the withdrawal policy of customers is not known by retailers. In this research, four different scenarios are discussed (FIFO, LIFO and two combinations of both). As already noticed, complete LIFO withdrawal is not applicable and complete FIFO issuing is not the case either. These two issuing policies could be seen as boundaries for which holds that the value in practice will be somewhere in between.

The demand used in this research for the evaluation of the models are the sold products (sales). However, daily sales are not always equal to demand. So, there can be more shortage when there is still some unfulfilled demand left. Though, this number is uncertain, but should be kept in mind.

Analysis of the used method showed a difference in costs of waste used. The costs of waste were assumed as the costs for acquiring the product. However, these costs are already paid when the products are ordered. Instead of taking costs of zero into account, the costs of waste were set to the cost price in the calculations (so counted double). Because of this, the costs given in this research are higher than would be the case in practice. The effect on the outcome of this research is expected to be limited. This, due to the low amounts of waste (even no waste at product lifetime 17) and the fact that this method is used for all four models.

Last, the model of PH is designed for the situation where not every day products are ordered. But on fixed days of the week an order is placed. This situation is not investigated in this research. This because the other approaches are not developed to handle this situation. For this reason, the model is not used in the setting for which it is developed. This model is expected to perform better when fixed order days are included. This situation should be further investigated.

In total, the models should be tested for more different products (shelf lives and demand sizes) and demand distributions to draw better conclusions. Also, some assumptions made are not in line with the practical situation, the effect of these assumptions on the results should be evaluated as well to draw reliable conclusions on the performance of the models. Last but not least, the impact of the provided dataset should be investigated, whether the nine-week period gives suitable solutions or is not representative at all. Based on these results, it would be recommended to Slimstock to further investigate these models to see whether adaptions of both models would give suitable results in practice.

References

Adan, I., Eenige, M., & van Resing, J. (1995). Fitting discrete distributions on the first two moments. *Probability in the Engineering and Informational Sciences, 9*, 623-632.

Agrawal, N., & Smith, S. A. (2015). *Retail Supply Chain Management: Quantitative Models and Empirical Studies*: Springer US.

Axsäter, S. (2006). *Inventory control*. New York: Springer.

Bakker, M., Riezebos, J., Teunter, R.H. (2012). *Review of inventory systems with deterioration since 2001.* European Journal of Operational Research, 221, 275-284.

Bijvank, M., & Vis, I.F.A. (2011). *Lost-sales inventory theory: A review.* European Journal of Operational Research, 215, 1-13.

Broekmeulen, R. A. C. M., & Van Donselaar, K. H. (2009). *A heuristic to manage perishable inventory with batch ordering, positive lead-times, and time-varying demand*. Computers & Operations Research, 36(11), 3013-3018. doi:http://dx.doi.org/10.1016/j.cor.2009.01.017

Broekmeulen, R., & Van Donselaar (2016). *Sell more, waste less. Increasing sales and reducing waste in the fresh supply chain.* Brussels, Belgium: ECR Community.

Buzby, J. C., Wells, H. F., Axtman, B., & Mickey, J. (2009). *Supermarket Loss Estimates for Fresh Fruit, Vegetables, Meat, Poultry, and Seafood and Their Use in the ERS Loss-Adjusted Food Availability Data*. United States Department of Agriculture Retrieved from http://purl.umn.edu/58313

Chen, F.Y., & Krass, D. (2001). *Inventory models with minimal service level constraints.* European Journal of Operational Research, 134, 120-140.

Chiu, H.N. (1995). *A heuristic (R, T) periodic review perishable inventory model with lead times.* International Journal of Production Economics, 42, 1-15.

Chopra, S, & Meindl, P. (2016). *Supply Chain Management: Strategy, Planning, and Operation (6th ed.)*. Harlow, England: Pearson Education.

Corsten, D., & Gruen, T. (2003). *Desperately seeking shelf availability: an examination of the extent, the causes, and the efforts to address retail out-of-stocks.* International Journal of Retail & Distribution Management, 31(12), 605-617.

Dave, U. (1986). *A probabilistic scheduling period inventory model for deteriorating items with lead time*. Zeitschrift für Operations Research, 30(5), A229-A237. doi:10.1007/BF01919292

Ehrenthal, J.C.F., Honhon, D., & Van Woensel, T. (2014). *Demand seasonality in retail inventory management*. European Journal of Operational Research, 238, 527-539.

Ferguson, M., & Ketzenberg, M.E. (2006). *Information Sharing to Improve Retail Product Freshness of Perishables.* Production and Operations Management, 15(1), 57-73.

Goyal, S.K., Giri, B.C. (2001). *Recent trends in modelling of deteriorating inventory.* European journal of Operational Research, 134, 1-16.

Gustavsson, J., Cederberg, C., Sonesson, U., van Otterdijk, R., Meybeck, A. (2011). *Global Food Losses and Food Waste: Extent, Causes, and Prevention.* Food and Agricultural Organization: Rome, Italy, 2011.

Haijema, R. (2014). *Optimal ordering, issuance and disposal policies for inventory management of perishable products.* International Journal of Production Economics, 157, 158-169, http://dx.doi.org/10.1016/j.ijpe.2014.06.014.

Haijema, R., & Minner, S. (2015). *Stock-level dependent ordering of perishables: A comparison of hybrid base-stock and constant order policies*. International Journal of Production Economics, 181(Part A), 215-225, http://dx.doi.org/10.1016/j.ijpe.2015.10.013

Huh, W.T., Janakiraman, G., Muckstadt, J.A., & Rusmevichientong, P. (2009). *Asymptotic optimality of order-up-to policies in lost sales inventory systems.* Management science, 55(3), 404-420.

Karaesman, I.Z., Scheller-Wolf, A., & Deniz, B. (2011). *Managing Perishable and Aging Inventories: Review and Future Research Directions,* in: Kempf, K.G., Keskinocak, P., & Uzsoy, R. (Eds.), *Planning Production and Inventories in the Extended Enterprise.* Springer, 393-436.

Lowalekar, H., Nilakantan, R., & Ravichandran, N. (2016). *Analysis of an order-up-to-level policy for perishables with random issuing.* Journal of the Operational Research Society, 67, 483-505.

Lütke Entrup, M. (2005). *Advanced planning in fresh food industries: integrating shelf life into production planning*. Heidelberg: Physica-Verslag/Springer.

Minner, S., & Transchel, S. (2010). *Periodic review inventory-control for perishable products under service-level constraints.* OR Spectrum, 32, 979-996.

Muriana, C. (2016). *An EOQ model for perishable products with fixed shelf life under stochastic demand conditions.* European Journal of Operational Research, 255, 388-396.

Nahmias, S. (1982). *Perishable inventory-theory – a review.* Operations Research, 30, 680-708.

Nazmutdinova, A. (2017). *Replenishment policies for perishable goods in retail* (Unpublished master thesis). Wageningen University, Wageningen, the Netherlands.

Pahl, J., & Voß, S. (2014). *Integrating deterioration and lifetime constraints in production and supply chain planning: A survey*. European Journal of Operational Research, 238(3), 654-674. doi:http://dx.doi.org/10.1016/j.ejor.2014.01.060

Pauls-Worm, K.G.J., & Hendrix, E.M.T. (2016). *YS policy in retail*, in: Pauls-Worm, K.G.J., *Inventory control for a perishable product with non-stationary demand*. Wageningen University, Netherlands. DOI: 10.18174/385217

Rijpkema, W. A., Rossi, R., & Van der Vorst, J. G. A. J. (2014). *Effective sourcing strategies for perishable product supply chains*. International Journal of Physical Distribution & Logistics Management, 44(6), 494-510. doi:10.1108/IJPDLM-01-2013-0013

Slimstock. (2016). About us. Retrieved from http://www.slimstock.com/en/about-us/?jjj=1473065004440

Van Donselaar, K.H., & Broekmeulen, R.A.C.M. (2012). *Approximations for the relative outdating of perishable products by combining stochastic modeling, simulation and regression modeling.* International Journal of Production Economics, 140, 660-669.

Van Donselaar, K., Van Woensel, T., Broekmeulen, R., & Fransoo, J. (2006). *Inventory control of perishables in supermarkets*. International Journal of Production Economics, 104(2), 462-472. doi:http://dx.doi.org/10.1016/j.ijpe.2004.10.019

Williams, C.L., & Patuwo, B.E. (1999). *A perishable inventory model with positive order lead times.* European Journal of Operational Research, 116, 352-373.

Appendix

Table A25. Results for finding most suitable combination of order-up-to-level (R) and interval time (T). Q, ES and W are given in items per period (LNR model). The first result that meets the target service level for each review period is coloured green.

Store: 151		Product: SL = 6					
Order-up-to-level (R):	Review period (T):	Costs:	Order Quantity (Q):	Expected Shortage (ES):	Fill Rate (FR):	Average Waste (W):	Costs per period:
1	1	€ 3.09	1.0	3.2995	23.01%	0.00	€ 3.09
2	1	€ 3.85	1.9	2.3722	44.65%	0.00	€ 3.85
3	1	€ 4.51	2.7	1.5714	63.33%	0.00	€ 4.51
4	1	€ 5.03	3.3	0.9511	77.81%	0.00	€ 5.03
5	1	€ 5.39	3.8	0.5243	87.77%	0.00	€ 5.39
6	1	€ 5.61	4.0	0.2633	93.86%	0.00	€ 5.61
7	1	€ 5.76	4.2	0.1208	97.18%	0.01	€ 5.76
8	1	€ 5.86	4.3	0.0508	98.81%	0.02	€ 5.86
9	1	€ 5.97	4.3	0.0197	99.54%	0.05	€ 5.97
10	1	€ 6.10	4.4	0.0071	99.84%	0.09	€ 6.10
11	1	€ 6.25	4.4	0.0024	99.95%	0.14	€ 6.25
12	1	€ 6.43	4.5	0.0007	99.98%	0.20	€ 6.43
13	1	€ 6.64	4.6	0.0002	100%	0.28	€ 6.64
14	1	€ 6.88	4.6	0.0001	100%	0.36	€ 6.88
15	1	€ 7.13	4.7	0.0000	100%	0.45	€ 7.13
16	1	€ 7.39	4.8	0.0000	100%	0.54	€ 7.39
17	1	€ 7.68	4.9	0.0000	100%	0.65	€ 7.68
18	1	€ 7.97	5.0	0.0000	100%	0.75	€ 7.97
19	1	€ 8.28	5.1	0.0000	100%	0.86	€ 8.28
20	1	€ 8.59	5.3	0.0000	100%	0.97	€ 8.59
21	1	€ 8.91	5.4	0.0000	100%	1.09	€ 8.91
22	1	€ 9.24	5.5	0.0000	100%	1.20	€ 9.24
23	1	€ 9.57	5.6	0.0000	100%	1.32	€ 9.57
24	1	€ 9.91	5.7	0.0000	100%	1.45	€ 9.91
25	1	€ 10.25	5.9	0.0000	100%	1.57	€ 10.25
1	2	€ 5.38	1.0	7.5852	0%	0.00	€ 2.69
2	2	€ 6.19	2.0	6.5990	0%	0.00	€ 3.10
3	2	€ 7.06	3.0	5.5453	0%	0.00	€ 3.53
4	2	€ 8.02	4.2	4.3833	0%	0.00	€ 4.01
5	2	€ 9.01	5.4	3.1826	25.74%	0.00	€ 4.50
6	2	€ 9.90	6.5	2.0925	51.18%	0.00	€ 4.95
7	2	€ 10.61	7.3	1.2393	71.08%	0.00	€ 5.31
8	2	€ 11.09	7.9	0.6616	84.56%	0.00	€ 5.55
9	2	€ 11.38	8.3	0.3197	92.54%	0.00	€ 5.69
10	2	€ 11.54	8.4	0.1405	96.72%	0.00	€ 5.77
11	2	€ 11.61	8.5	0.0565	98.68%	0.00	€ 5.81
12	2	€ 11.66	8.6	0.0209	99.51%	0.00	€ 5.83
13	2	€ 11.69	8.6	0.0072	99.83%	0.00	€ 5.84
14	2	€ 11.72	8.6	0.0023	99.95%	0.01	€ 5.86

15	2	€ 11.76	8.6	0.0007	99.98%	0.02	€ 5.88
16	2	€ 11.82	8.6	0.0002	100%	0.04	€ 5.91
17	2	€ 11.89	8.6	0.0000	100%	0.06	€ 5.95
18	2	€ 11.98	8.7	0.0000	100%	0.09	€ 5.99
19	2	€ 12.09	8.7	0.0000	100%	0.13	€ 6.05
20	2	€ 12.22	8.7	0.0000	100%	0.17	€ 6.11
21	2	€ 12.36	8.8	0.0000	100%	0.22	€ 6.18
22	2	€ 12.52	8.9	0.0000	100%	0.28	€ 6.26
23	2	€ 12.70	8.9	0.0000	100%	0.34	€ 6.35
24	2	€ 12.89	9.0	0.0000	100%	0.41	€ 6.44
25	2	€ 13.09	9.1	0.0000	100%	0.48	€ 6.55
1	3	€ 7.67	1.0	11.8709	0%	0.00	€ 2.56
2	3	€ 8.53	2.0	10.8257	0%	0.00	€ 2.84
3	3	€ 9.61	3.3	9.5192	0%	0.00	€ 3.20
4	3	€ 11.01	5.0	7.8155	0%	0.00	€ 3.67
5	3	€ 12.63	7.0	5.8409	0%	0.00	€ 4.21
6	3	€ 14.20	8.9	3.9216	8.50%	0.00	€ 4.73
7	3	€ 15.48	10.5	2.3577	44.99%	0.00	€ 5.16
8	3	€ 16.38	11.6	1.2724	70.31%	0.00	€ 5.46
9	3	€ 16.92	12.2	0.6196	85.54%	0.00	€ 5.64
10	3	€ 17.21	12.6	0.2740	93.61%	0.00	€ 5.74
11	3	€ 17.36	12.7	0.1107	97.42%	0.00	€ 5.79
12	3	€ 17.42	12.8	0.0411	99.04%	0.00	€ 5.81
13	3	€ 17.45	12.8	0.0141	99.67%	0.00	€ 5.82
14	3	€ 17.47	12.9	0.0045	99.90%	0.00	€ 5.82
15	3	€ 17.48	12.9	0.0013	99.97%	0.00	€ 5.83
16	3	€ 17.50	12.9	0.0004	99.99%	0.00	€ 5.83
17	3	€ 17.51	12.9	0.0001	100%	0.00	€ 5.84
18	3	€ 17.52	12.9	0.0000	100%	0.00	€ 5.84
19	3	€ 17.54	12.9	0.0000	100%	0.00	€ 5.85
20	3	€ 17.56	12.9	0.0000	100%	0.01	€ 5.85
21	3	€ 17.59	12.9	0.0000	100%	0.02	€ 5.86
22	3	€ 17.63	12.9	0.0000	100%	0.03	€ 5.88
23	3	€ 17.68	12.9	0.0000	100%	0.04	€ 5.89
24	3	€ 17.74	12.9	0.0000	100%	0.06	€ 5.91
25	3	€ 17.81	12.9	0.0000	100%	0.08	€ 5.94

Table A26. Simulation results of product lifetime 6 without lead time of the LNR model. Shortage and waste are in number of items for nine weeks. Green cells in 'waste'-column indicate improvements in comparison to current situation, green cells in 'Fill rate'-column indicate the compliance with the target service level. Blue coloured cells represent stores with (close to, *α≤0.05*) Poisson distributed demand.

SL=6, LT=0		Complete FIFO				Complete LIFO				80% FIFO - 20% LIFO				60% FIFO - 40% LIFO			
Store	Current waste	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate
141	142	558.0	0.0	€ 6,042.23	88.39%	559	1.0	€ 6,044.12	88.37%	558	0.0	€ 6,042.23	88.39%	558	0.0	€ 6,042.23	88.39%
151	2	11.0	0.0	€ 357.41	95.93%	15	10.0	€ 381.11	94.44%	11	0.0	€ 357.41	95.93%	11	0.0	€ 357.41	95.93%
152	19	18.0	0.0	€ 325.72	92.83%	25	9.0	€ 344.33	90.04%	18	0.0	€ 325.72	92.83%	18	0.0	€ 325.72	92.83%
153	14	16.0	0.0	€ 356.09	94.12%	16	8.0	€ 377.61	94.12%	16	0.0	€ 356.09	94.12%	16	0.8	€ 358.24	94.12%
154	4	20.0	0.0	€ 253.81	89.95%	21	4.0	€ 263.77	89.45%	20	0.0	€ 253.81	89.95%	20	0.0	€ 253.81	89.95%
156	9	18.0	1.0	€ 215.22	89.22%	22	9.0	€ 233.54	86.83%	18	1.4	€ 215.98	88.98%	18.8	1.8	€ 216.73	88.74%
157	5	27.0	0.0	€ 448.42	92.22%	32	5.0	€ 457.87	90.78%	27	0.0	€ 448.42	92.22%	27	0.0	€ 448.42	92.22%
158	18	29.0	0.0	€ 714.03	94.68%	31	2.0	€ 717.81	94.31%	29	0.0	€ 714.03	94.68%	29	0.0	€ 714.03	94.68%
159	7	0.0	0.0	€ 428.99	94.80%	18	5.0	€ 441.64	94.50%	17	0.0	€ 428.99	94.80%	17	0.0	€ 428.99	94.80%
160	6	55.0	0.0	€ 733.43	90.43%	61	6.0	€ 744.77	89.39%	55	0.0	€ 733.43	90.43%	55	0.0	€ 733.43	90.43%
161	7	26.0	0.0	€ 508.18	93.35%	27	2.0	€ 512.76	93.09%	26	0.0	€ 508.18	93.35%	26	0.0	€ 508.18	93.35%
162	5	12.0	0.0	€ 378.05	95.80%	15	9.0	€ 399.86	94.76%	12	0.0	€ 378.05	95.80%	12	0.0	€ 378.05	95.80%
163	5	23.0	0.0	€ 405.43	92.65%	26	5.0	€ 416.48	91.69%	23	0.0	€ 405.43	92.65%	23	0.0	€ 405.43	92.65%
164	1	32.0	0.0	€ 345.97	88.32%	34	3.0	€ 352.44	87.59%	32	0.0	€ 345.97	88.32%	32	0.0	€ 345.97	88.32%
165	24	29.0	0.0	€ 347.03	89.38%	34	6.0	€ 359.17	87.55%	29	0.0	€ 347.03	89.38%	29	0.0	€ 347.03	89.38%
166	16	16.0	0.0	€ 416.39	94.95%	18	3.0	€ 422.86	94.32%	16	0.0	€ 416.39	94.95%	16	0.0	€ 416.39	94.95%

Table A27. Simulation results of product lifetime 6 including two days of lead time of the LNR model. Shortage and waste are in number of items for nine weeks. Green cells in 'waste'-column indicate improvements in comparison to current situation, green cells in 'Fill rate'-column indicate the compliance with the target service level. Blue coloured cells represent stores with (close to, *α≤0.05*) Poisson distributed demand.

SL=6, LT=2		Complete FIFO				Complete LIFO				80% FIFO - 20% LIFO				60% FIFO - 40% LIFO			
Store	Current waste	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate
141	142	819.0	0.0	€ 5,777.22	82.96%	819	0.0	€ 5,777.22	82.96%	819	0.0	€ 5,777.22	82.96%	819	0.0	€ 5,777.22	82.96%
151	2	7.0	3.0	€ 385.55	97.41%	51	51.0	€ 478.32	81.11%	13	8.6	€ 394.36	95.33%	18.4	13.4	€ 400.63	93.19%
152	19	32.0	7.0	€ 330.95	87.25%	53	52.0	€ 426.00	78.88%	35	9.6	€ 335.90	86.22%	40	16.8	€ 350.94	84.06%
153	14	15.0	4.0	€ 363.39	94.49%	44	51.0	€ 470.74	83.82%	16	9.0	€ 373.58	94.04%	17	15.4	€ 384.07	93.75%
154	4	21.0	15.0	€ 297.23	89.45%	52	58.0	€ 388.65	73.87%	26	21.4	€ 310.31	86.73%	30.4	26.4	€ 320.68	84.72%
156	9	27.0	27.0	€ 285.92	83.83%	37	53.0	€ 343.45	77.84%	36	35.6	€ 300.76	78.44%	34.4	38.2	€ 306.16	79.40%
157	5	39.0	0.0	€ 440.37	88.76%	56	22.0	€ 485.99	83.86%	39	0.0	€ 440.37	88.76%	39	0.0	€ 440.37	88.76%
158	18	82.0	0.0	€ 672.42	84.95%	110	28.0	€ 725.34	79.82%	82	0.0	€ 672.42	84.95%	82	0.0	€ 672.42	84.95%
159	7	32.0	0.0	€ 426.37	90.21%	64	32.0	€ 494.89	80.43%	32	0.0	€ 426.37	90.21%	35.6	3.6	€ 433.17	89.11%
160	6	85.0	0.0	€ 683.40	85.22%	100	20.0	€ 725.24	82.61%	85	0.0	€ 683.40	85.22%	85	0.0	€ 683.40	85.22%
161	7	46.0	0.0	€ 483.61	88.24%	70	27.0	€ 543.79	82.10%	46	0.0	€ 483.61	88.24%	46	0.0	€ 483.61	88.24%
162	5	20.0	0.0	€ 386.27	93.01%	47	50.0	€ 476.03	83.57%	26	5.8	€ 397.23	90.98%	26	6.4	€ 393.39	90.91%
163	5	27.0	5.0	€ 444.31	91.37%	46	40.0	€ 518.91	85.30%	35	12.8	€ 459.21	88.95%	37.8	16.8	€ 444.52	87.92%
164	1	26.0	15.0	€ 393.95	90.51%	35	43.0	€ 444.56	87.23%	29	19.2	€ 411.17	89.56%	25.6	21.8	€ 416.62	90.66%
165	24	18.0	5.0	€ 373.58	93.41%	33	39.0	€ 453.71	87.91%	27	11.8	€ 384.51	90.04%	38	22	€ 403.39	86.08%
166	16	29.0	14.0	€ 433.36	90.85%	60	51.0	€ 540.70	81.07%	33	16.0	€ 439.64	89.53%	33.8	18.0	€ 445.69	89.34%

Table A28. Simulation results of product lifetime 17 without lead time of the LNR model. Shortage and waste are in number of items for nine weeks. Green cells in 'waste'-column indicate improvements in comparison to current situation, green cells in 'Fill rate'-column indicate the compliance with the target service level. Blue coloured cells represent stores with (close to, *α≤0.05*) Poisson distributed demand.

SL=17, LT=0		Complete FIFO				Complete LIFO				80% FIFO - 20% LIFO				60% FIFO - 40% LIFO			
Store	Current waste	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate
141	15	329	0.0	€ 10,652.05	92.47%	329	0.0	€ 10,652.05	92.47%	329	0.0	€ 10,652.05	92.47%	329	0.0	€ 10,652.05	92.47%
151	1	5	0.0	€ 657.84	98.08%	5	2.0	€ 668.02	98.08%	5	0.0	€ 657.84	98.08%	5	0.0	€ 657.84	98.08%
152	0	47	0.0	€ 1,223.90	90.73%	47	0.0	€ 1,223.90	90.73%	47	0.0	€ 1,223.90	90.73%	47	0.0	€ 1,223.90	90.73%
153	0	7	0.0	€ 723.38	97.56%	7	0.0	€ 723.38	97.56%	7	0.0	€ 723.38	97.56%	7	0.0	€ 723.38	97.56%
154	0	3	0.0	€ 436.10	98.26%	4	5.0	€ 460.03	97.67%	3	0.0	€ 436.10	98.26%	3	0.0	€ 436.10	98.26%
156	5	5	0.0	€ 356.23	96.48%	5	2.0	€ 366.41	96.48%	5	0.0	€ 356.23	96.48%	5	0.0	€ 356.23	96.48%
157	0	6	0.0	€ 454.40	96.69%	6	0.0	€ 454.40	96.69%	6	0.0	€ 454.40	96.69%	6	0.0	€ 454.40	96.69%
158	0	5	0.0	€ 1,162.65	98.91%	5	2.0	€ 1,172.83	98.91%	5	0.0	€ 1,162.65	98.91%	5	0.0	€ 1,162.65	98.91%
159	1	4	0.0	€ 432.04	97.66%	4	2.0	€ 442.22	97.66%	4	0.0	€ 432.04	97.66%	4	0.0	€ 432.04	97.66%
160	0	7	0.0	€ 787.51	97.76%	7	2.0	€ 797.69	97.76%	7	0.0	€ 787.51	97.76%	7	0.0	€ 787.51	97.76%
161	0	8	0.0	€ 1,094.59	98.15%	8	0.0	€ 1,094.59	98.15%	8	0.0	€ 1,094.59	98.15%	8	0.0	€ 1,094.59	98.15%
162	0	31	0.0	€ 904.06	91.67%	31	0.0	€ 904.06	91.67%	31	0.0	€ 904.06	91.67%	31	0.0	€ 904.06	91.67%
163	0	2	0.0	€ 700.50	99.27%	2	3.0	€ 715.77	99.27%	2	0.0	€ 700.50	99.27%	2	0.0	€ 700.50	99.27%
164	0	9	0.0	€ 899.40	97.48%	9	0.0	€ 899.40	97.48%	9	0.0	€ 899.40	97.48%	9	0.0	€ 899.40	97.48%
165	8	18	0.0	€ 604.43	92.71%	18	0.0	€ 604.43	92.71%	18	0.0	€ 604.43	92.71%	18	0.0	€ 604.43	92.71%
166	0	1	0.0	€ 564.23	99.55%	1	2.0	€ 574.41	99.55%	1	0.0	€ 564.23	99.55%	1	0.0	€ 564.23	99.55%

Table A29. Simulation results of product lifetime 17 including lead time of the LNR model. Shortage and waste are in number of items for nine weeks. Green cells in 'waste'-column indicate improvements in comparison to current situation, green cells in 'Fill rate'-column indicate the compliance with the target service level. Blue coloured cells represent stores with (close to, *α≤0.05*) Poisson distributed demand.

SL=17, LT=2		Complete FIFO				Complete LIFO				80% FIFO - 20% LIFO				60% FIFO - 40% LIFO			
Store	Current waste	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate
141	15	715	0.0	€ 9,870.82	83.65%	715	0.0	€ 9,870.82	83.65%	715	0.0	€ 9,870.82	83.65%	715	0.0	€ 9,870.82	83.65%
151	1	13	0.0	€ 635.62	95.00%	13	0.0	€ 635.62	95.00%	13	0.0	€ 635.62	95.00%	13	0.0	€ 635.62	95.00%
152	0	36	0.0	€ 1,259.54	92.90%	36	0.0	€ 1,259.54	92.90%	36	0.0	€ 1,259.54	92.90%	36	0.0	€ 1,259.54	92.90%
153	0	25	0.0	€ 694.01	91.29%	25	2.0	€ 699.11	91.29%	25	0.0	€ 694.01	91.29%	25	0.0	€ 694.01	91.29%
154	0	4	0.0	€ 432.71	97.67%	7	3.0	€ 445.97	95.93%	4	0.0	€ 432.71	97.67%	4	0.0	€ 432.71	97.67%
156	5	6	0.0	€ 345.64	95.77%	7	1.0	€ 349.18	95.07%	6	0.0	€ 345.64	95.77%	6	0.0	€ 345.64	95.77%
157	0	5	0.0	€ 456.66	97.24%	5	1.0	€ 456.74	97.24%	5	0.0	€ 456.66	97.24%	5	0.0	€ 456.66	97.24%
158	0	49	0.0	€ 1,089.40	89.30%	49	0.0	€ 1,089.40	89.30%	49	0.0	€ 1,089.40	89.30%	49	0.0	€ 1,089.40	89.30%
159	1	3	0.0	€ 428.99	98.25%	5	5.0	€ 479.22	97.08%	3	0.0	€ 428.99	98.25%	3	0.0	€ 428.99	98.25%
160	0	24	0.0	€ 729.27	92.31%	25	1.0	€ 732.82	91.99%	24	0.0	€ 729.27	92.31%	24	0.0	€ 729.27	92.31%
161	0	37	0.0	€ 1,035.37	91.45%	37	1.0	€ 1,040.44	91.45%	37	0.0	€ 1,035.37	91.45%	37	0.0	€ 1,035.37	91.45%
162	0	59	0.0	€ 883.47	84.14%	59	0.0	€ 883.47	84.14%	59	0.0	€ 883.47	84.14%	59	0.0	€ 883.47	84.14%
163	0	12	0.0	€ 693.14	95.64%	13	1.0	€ 696.71	95.27%	12	0.0	€ 693.14	95.64%	12	0.0	€ 693.14	95.64%
164	0	34	0.0	€ 867.19	90.48%	34	0.0	€ 867.19	90.48%	34	0.0	€ 867.19	90.48%	34	0.0	€ 867.19	90.48%
165	8	22	0.0	€ 634.55	91.09%	22	0.0	€ 634.55	91.09%	22	0.0	€ 634.55	91.09%	22	0.0	€ 634.55	91.09%
166	0	19	0.0	€ 539.08	91.40%	19	1.0	€ 541.63	91.40%	19	0.0	€ 539.08	91.40%	19	0.0	€ 539.08	91.40%

Table A30. Comparison model outcomes and simulated values of the LNR model (SL = 6, LT = 0). Green cells show improvements or equal results in comparison to the outcomes of the model.

SL = 6, LT = 0		Model outcome			Simulated values			
	Order-up-to-level (R):	Expected Shortage (ES):	Fill Rate (FR):	Expected Waste (W):	Shortage (ES):	Fill Rate (FR):	Waste (W):	Deviation in pp
141	75	262	94.55%	0.00	558	88.39%	0	6.16%
151	7	8	97.18%	0.47	11	95.93%	0	1.25%
152	6	12	95.18%	0.22	18	92.83%	0	2.35%
153	7	8	97.10%	0.44	16	94.12%	0	2.98%
154	5	10	94.74%	0.32	20	89.95%	0	4.79%
156	5	5	96.98%	1.04	18	89.22%	1	7.76%
157	8	13	96.29%	0.17	27	92.22%	0	4.07%
158	11	24	95.57%	0.03	29	94.68%	0	0.89%
159	7	19	94.15%	0.07	0	94.80%	0	-0.65%
160	11	33	94.33%	0.01	55	90.43%	0	3.90%
161	8	23	94.04%	0.04	26	93.35%	0	0.69%
162	7	10	96.45%	0.29	12	95.80%	0	0.65%
163	7	16	95.01%	0.12	23	92.65%	0	2.36%
164	7	8	97.01%	0.42	32	88.32%	0	8.69%
165	7	8	97.05%	0.43	29	89.38%	0	7.67%
166	7	17	94.77%	0.10	16	94.95%	0	-0.18%

Table A31. Comparison model outcomes and simulated values of the LNR model (SL = 6, LT = 2). Green cells show improvements or equal results in comparison to the outcomes of the model.

SL = 6, LT = 2		Model outcome			Simulated values			
	Order-up-to-level (R):	Expected Shortage (ES):	Fill Rate (FR):	Expected Waste (W):	Shortage (ES):	Fill Rate (FR):	Waste (W):	Deviation in pp
141	90	274	94.31%	0.00	819	82.96%	0	11.35%
151	11	7	97.42%	0.00	7	97.41%	3	0.01%
152	10	11	95.72%	0.00	32	87.25%	7	8.47%
153	11	7	97.29%	0.00	15	94.49%	4	2.81%
154	9	6	96.79%	0.00	21	89.45%	15	7.34%
156	8	6	96.15%	0.00	27	83.83%	27	12.31%
157	11	39	96.28%	0.00	39	88.76%	0	7.52%
158	15	65	96.04%	0.00	82	84.95%	0	11.09%
159	10	55	94.40%	0.00	32	90.21%	0	4.18%
160	15	96	94.46%	0.00	85	85.22%	0	9.24%
161	12	42	96.45%	0.00	46	88.24%	0	8.21%
162	11	11	96.31%	0.00	20	93.01%	0	3.30%
163	12	8	97.32%	0.00	27	91.37%	5	5.94%
164	11	8	97.17%	0.00	26	90.51%	15	6.66%
165	11	8	97.23%	0.00	18	93.41%	5	3.82%
166	12	9	97.08%	0.00	29	90.85%	14	6.23%

Table A32. Comparison model outcomes and simulated values of the LNR model (SL = 17, LT = 0). Green cells show improvements or equal results in comparison to the outcomes of the model.

SL = 17, LT = 0		Model outcome			Simulated values			
	Order-up-to-level (R):	Expected Shortage (ES):	Fill Rate (FR):	Expected Waste (W):	Shortage (ES):	Fill Rate (FR):	Waste (W):	Deviation in pp
141	75	81	98.16%	0.00	329	92.47%	0	5.68%
151	8	3	99.02%	0.00	5	98.08%	2	0.94%
152	12	9	98.32%	0.00	47	90.73%	0	7.59%
153	8	5	98.41%	0.00	7	97.56%	0	0.85%
154	6	2	98.85%	0.00	4	97.67%	5	1.17%
156	5	2	98.27%	0.00	5	96.48%	2	1.79%
157	6	3	98.58%	0.00	6	96.69%	0	1.89%
158	11	8	98.18%	0.00	5	98.91%	2	-0.72%
159	6	2	98.87%	0.00	4	97.66%	2	1.21%
160	9	3	98.97%	0.00	7	97.76%	2	1.22%
161	11	6	98.68%	0.00	8	98.15%	0	0.53%
162	10	4	98.82%	0.00	31	91.67%	0	7.15%
163	8	4	98.70%	0.00	2	99.27%	3	-0.57%
164	10	3	99.07%	0.00	9	97.48%	0	1.59%
165	7	5	98.05%	0.00	18	92.71%	0	5.34%
166	7	3	98.81%	0.00	1	99.55%	2	-0.74%

Table A33. Comparison model outcomes and simulated values of the LNR model (SL = 17, LT = 2). Green cells show improvements or equal results in comparison to the outcomes of the model.

SL = 17, LT = 2		Model outcome			Simulated values			
	Order-up-to-level (R):	Expected Shortage (ES):	Fill Rate (FR):	Expected Waste (W):	Shortage (ES):	Fill Rate (FR):	Waste (W):	Deviation in pp
141	88	204	98.44%	0.00	715	83.65%	0	14.80%
151	10	14	98.26%	0.00	13	95.00%	0	3.26%
152	16	19	98.77%	0.00	36	92.90%	0	5.87%
153	11	11	98.74%	0.00	25	91.29%	2	7.45%
154	9	2	98.56%	0.00	7	95.93%	3	2.63%
156	8	2	98.28%	0.00	7	95.07%	1	3.21%
157	9	3	98.09%	0.00	5	97.24%	1	0.85%
158	15	16	98.83%	0.00	49	89.30%	0	9.53%
159	9	2	98.61%	0.00	5	97.08%	5	1.53%
160	12	8	99.12%	0.00	25	91.99%	1	7.14%
161	14	21	98.37%	0.00	37	91.45%	1	6.92%
162	13	14	98.77%	0.00	59	84.14%	0	14.63%
163	11	8	99.03%	0.00	13	95.27%	1	3.76%
164	13	10	99.08%	0.00	34	90.48%	0	8.60%
165	10	10	98.70%	0.00	22	91.09%	0	7.60%
166	9	12	98.15%	0.00	19	91.40%	1	6.75%

Table A34. Comparison model outcomes and simulated values of the PH model for item with SL = 6 for complete FIFO and complete LIFO demand. Red cells show worse results; no cell colour means equal or better than the outcomes of the model.

SL = 6	Model outcome - FIFO			Simulated values			Model outcome - LIFO			Simulated values		
Store	Costs	Waste	Order quantity	Costs	Waste	Order quantity	Costs	Waste	Order quantity	Costs	Waste	Order quantity
141	€ 6,501.76	0	4807	€ 6,065.12	0	4279	€ 7,053.66	205.2	5012	€ 6,097.19	7	4297
151	€ 367.47	0	270	€ 354.71	0	249	€ 497.49	33	333	€ 466.56	33	307
152	€ 341.75	0	251	€ 317.83	0	222	€ 471.41	48.2	299	€ 377.12	23	237
153	€ 370.22	0	272	€ 357.75	0	259	€ 505.62	50.3	322	€ 401.33	20	267
154	€ 271.15	0	199	€ 262.24	0	185	€ 383.05	41.6	241	€ 317.95	22	201
156	€ 227.78	0	167	€ 230.85	8	153	€ 331.61	38.6	206	€ 268.02	23	163
157	€ 471.86	0	347	€ 451.50	0	314	€ 613.65	42	410	€ 542.96	30	348
158	€ 752.79	0	555	€ 702.69	0	507	€ 941.53	70.2	625	€ 758.48	18	525
159	€ 444.72	0	327	€ 425.53	0	305	€ 591.33	54.5	382	€ 485.64	19	332
160	€ 970.10	0	575	€ 729.54	0	511	€ 970.10	55	660	€ 870.28	47	560
161	€ 531.46	0	391	€ 516.50	0	371	€ 691.32	48	461	€ 605.93	36	396
162	€ 389.11	0	286	€ 376.20	0	270	€ 523.61	50	336	€ 419.67	15	284
163	€ 425.74	0	313	€ 402.20	0	280	€ 568.66	37	381	€ 532.36	39	342
164	€ 372.88	0	274	€ 372.43	2	259	€ 485.48	32	325	€ 437.62	27	278
165	€ 371.55	0	273	€ 373.64	2	260	€ 495.81	36	329	€ 429.37	22	283
166	€ 431.16	0	317	€ 409.89	0	292	€ 574.62	53.3	370	€ 470.82	22	317

Table A35. Comparison model outcomes and simulated values of the PH model for item with SL = 6 for both combinations of FIFO and LIFO demand. Red cells show worse results; no cell colour means equal or better than the outcomes of the model.

	Model outcome – 80%/20%			Simulated values				Model outcome – 60%/40%			Simulated values		
Store	Costs	Waste	Order quantity	Costs	Waste	Order quantity	Store	Costs	Waste	Order quantity	Costs	Waste	Order quantity
141	€ 6,501.76	0	4807	€ 6,065.12	0	4279	141	€ 6,501.76	0	4807	€ 6,065.12	0	4279
151	€ 367.47	0	270	€ 356.32	1	250	151	€ 367.47	0	270	€ 357.94	1.2	250
152	€ 341.75	0	251	€ 317.83	0	222	152	€ 341.75	0	251	€ 323.92	2.8	223
153	€ 370.22	0	272	€ 364.12	3	261	153	€ 370.22	0	272	€ 367.61	3.8	263
154	€ 271.15	0	199	€ 262.24	0	185	154	€ 271.15	0	199	€ 266.75	2.2	185
156	€ 227.78	0	167	€ 236.33	10	154	156	€ 227.78	0	167	€ 243.32	13.6	155
157	€ 471.86	0	347	€ 449.59	0	310	157	€ 471.86	0	347	€ 459.42	5.2	310
158	€ 752.79	0	555	€ 702.69	0	507	158	€ 752.79	0	555	€ 702.69	0	507
159	€ 444.72	0	327	€ 425.53	0	305	159	€ 444.72	0	327	€ 425.53	0	305
160	€ 780.50	0	575	€ 738.99	5	511	160	€ 780.50	0	575	€ 746.65	10	509
161	€ 531.46	0	391	€ 516.50	0	371	161	€ 531.46	0	391	€ 516.50	0	371
162	€ 389.11	0	286	€ 377.71	1	270	162	€ 389.11	0	286	€ 381.97	2.2	271
163	€ 425.74	0	313	€ 411.65	5	280	163	€ 425.74	0	313	€ 412.12	5	281
164	€ 372.88	0	274	€ 372.43	2	259	164	€ 372.88	0	274	€ 375.06	3.4	259
165	€ 371.55	0	273	€ 375.77	3	261	165	€ 371.55	0	273	€ 379.21	4	262
166	€ 431.15	0	317	€ 413.24	1	293	166	€ 431.15	0	317	€ 413.92	1.4	294

Table A36. Comparison model outcomes and simulated values of the PH model for item with SL = 17.
Red cells show worse results; no cell colour means equal or better than the outcomes of the model.

SL = 17	Model outcome - FIFO			Simulated values		
Store	Costs	Waste	Order quantity	Costs	Waste	Order quantity
141	€ 15,121.72	0	5924	€ 11,167.76	0	4311
151	€ 1,681.88	0	658	€ 716.71	0	276
152	€ 2,682.93	0	1050	€ 1,382.80	0	535
153	€ 1,819.85	0	712	€ 775.92	0	299
154	€ 1,285.96	0	503	€ 479.55	0	184
156	€ 1,155.70	0	452	€ 418.49	0	160
157	€ 1,308.91	0	512	€ 518.81	0	199
158	€ 2,540.00	0	994	€ 1,245.77	0	482
159	€ 1,288.53	0	504	€ 477.23	0	183
160	€ 1,916.88	0	750	€ 845.69	0	326
161	€ 2,389.27	0	935	€ 1,184.20	0	458
162	€ 1,854.84	0	726	€ 1,023.85	0	397
163	€ 1,735.49	0	679	€ 752.04	0	290
164	€ 2,077.71	0	813	€ 963.58	0	372
165	€ 1,623.13	0	635	€ 694.17	0	267
166	€ 1,551.71	0	607	€ 583.12	0	224

Table A37. Simulation results of order-up-to-levels for product lifetime 6 of the PH basic model. Order quantity is corrected for all orders outstanding ($Q_t = R - I_t - Q_{t-1} - Q_{t-L}$). Green cells in 'waste'-column indicate improvements in comparison to current situation. Blue coloured cells represent stores with (close to, *α≤0.05*) Poisson distributed demand.

		Complete FIFO				Complete LIFO				80% FIFO - 20% LIFO				60% FIFO - 40% LIFO			
Store:	Current waste	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate
141	142	487	0	€ 6,065.12	89.87%	481	7	€ 6,097.19	89.99%	487	0	€ 6,065.12	89.87%	487	0	€ 6,065.12	89.87%
151	2	26	0	€ 354.71	90.37%	4	33	€ 466.56	98.52%	26	1	€ 356.32	90.37%	26	1.2	€ 357.94	90.37%
152	19	26	0	€ 317.83	89.64%	40	23	€ 377.12	84.06%	26	0	€ 317.83	89.64%	27.8	2.8	€ 323.92	88.92%
153	14	8	0	€ 357.75	97.06%	18	20	€ 401.33	93.38%	8	3	€ 364.12	97.06%	8	3.8	€ 367.61	97.06%
154	4	17	0	€ 262.24	91.46%	24	22	€ 317.95	87.94%	17	0	€ 262.24	91.46%	18.8	2.2	€ 266.75	90.55%
156	9	19	8	€ 230.85	88.62%	25	23	€ 268.02	85.03%	20	10	€ 236.33	87.90%	22.2	13.6	€ 243.32	86.71%
157	5	40	0	€ 451.50	88.47%	47	30	€ 542.96	86.46%	46	0	€ 449.59	86.74%	51.2	5.2	€ 459.42	85.24%
158	18	23	0	€ 702.69	95.78%	35	18	€ 758.48	93.58%	23	0	€ 702.69	95.78%	23	0	€ 702.69	95.78%
159	7	18	0	€ 425.53	94.50%	14	19	€ 485.64	95.72%	18	0	€ 425.53	94.50%	18	0	€ 425.53	94.50%
160	6	60	0	€ 729.54	89.57%	76	47	€ 870.28	86.78%	65	5	€ 738.99	88.70%	72.4	10	€ 746.65	87.41%
161	7	20	0	€ 516.50	94.88%	29	36	€ 605.93	92.58%	20	0	€ 516.50	94.88%	20	0	€ 516.50	94.88%
162	5	15	0	€ 376.20	94.76%	22	15	€ 419.67	92.31%	16	1	€ 377.71	94.48%	17.2	2.2	€ 381.97	93.99%
163	5	35	0	€ 402.20	88.82%	22	39	€ 532.36	92.97%	40	5	€ 411.65	87.22%	39.4	5	€ 412.12	87.41%
164	1	27	2	€ 372.43	90.15%	36	27	€ 437.62	86.86%	27	2	€ 372.43	90.15%	28.4	3.4	€ 375.06	89.64%
165	24	27	2	€ 373.64	90.11%	22	22	€ 429.37	91.94%	27	3	€ 375.77	90.11%	27	4	€ 379.21	90.11%
166	16	21	0	€ 409.89	93.38%	17	22	€ 470.82	94.64%	21	1	€ 413.24	93.44%	20.6	1.4	€ 413.92	93.50%

Table A38. Simulation results of order-up-to-levels for product lifetime 17 of the PH basic model. Order quantity is corrected for all orders outstanding ($Q_t = R - I_t - Q_{t-1} - Q_{t-L}$). Green cells in 'waste'-column indicate improvements in comparison to current situation, green cells in 'Fill rate'-column indicate the compliance with the target service level. Blue coloured cells represent stores with (close to, *α≤0.05*) Poisson distributed demand.

		Complete FIFO				Complete LIFO				80% FIFO - 20% LIFO				60% FIFO - 40% LIFO			
Store:	Current waste	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate	Sim. Shortage	Sim. Waste	Total costs	Fill Rate
141	15	120	0	€ 11,167.76	97.26%	120	0	€ 11,167.76	97.26%	120	0	€ 11,167.76	97.26%	120	0	€ 11,167.76	97.26%
151	1	0	0	€ 716.71	100%	0	41	€ 960.76	100%	0	0	€ 716.71	100%	0	0	€ 716.71	100%
152	0	0	0	€ 1,382.80	100%	0	34	€ 1,555.52	100%	0	0	€ 1,382.80	100%	0	0	€ 1,382.80	100%
153	0	0	0	€ 775.92	100%	0	31	€ 939.03	100%	0	0	€ 775.92	100%	0	0	€ 775.92	100%
154	0	0	0	€ 479.55	100%	0	29	€ 622.34	100%	0	0	€ 479.55	100%	0	0	€ 479.55	100%
156	5	0	0	€ 418.49	100%	0	25	€ 520.76	100%	0	0	€ 418.49	100%	0	2.4	€ 424.66	100%
157	0	0	0	€ 518.81	100%	0	35	€ 704.43	100%	0	0	€ 518.81	100%	0	0	€ 518.81	100%
158	0	0	0	€ 1,245.77	100%	0	43	€ 1,459.95	100%	0	0	€ 1,245.77	100%	0	0	€ 1,245.77	100%
159	1	0	0	€ 477.23	100%	0	36	€ 675.63	100%	0	0	€ 477.23	100%	0	0	€ 477.23	100%
160	0	0	0	€ 845.69	100%	0	42	€ 1,041.00	100%	0	0	€ 845.69	100%	0	0	€ 845.69	100%
161	0	0	0	€ 1,184.20	100%	2	41	€ 1,389.76	99.54%	0	0	€ 1,184.20	100%	0	0	€ 1,184.20	100%
162	0	0	0	€ 1,023.85	100%	0	25	€ 1,156.04	100%	0	0	€ 1,023.85	100%	0	0	€ 1,023.85	100%
163	0	0	0	€ 752.04	100%	4	40	€ 937.18	98.55%	0	0	€ 752.04	100%	0	0	€ 752.04	100%
164	0	0	0	€ 963.58	100%	3	38	€ 1,150.29	99.16%	0	0	€ 963.58	100%	0	0	€ 963.58	100%
165	8	0	0	€ 694.17	100%	0	31	€ 857.20	100%	0	0	€ 694.17	100%	0	0	€ 694.17	100%
166	0	0	0	€ 583.12	100%	4	32	€ 740.16	98.19%	0	0	€ 583.12	100%	0	0	€ 583.12	100%

Table A39. Comparison of the three models (Lowalekar et al., Pauls-Worm & Hendrix (basic model) and Broekmeulen & Van Donselaar) for a product with shelf life of six days. Green cells show the best result(s), red cells show the worst result(s), no coloured cells are the 2nd best result. Blue coloured cells represent stores with (close to, *α≤0.05*) Poisson distributed demand.

	Fill rate			*Total costs*			*Simulated waste*			*Reported waste*	*Simulated shortage*		
Store	*LNR*	*PH*	*BD*	*LNR*	*PH*	*BD*	*LNR*	*PH*	*BD*	*Slimstock*	*LNR*	*PH*	*BD*
141	82.96%	89.87%	98.40%	€ 5,777.22	€ 6,065.12	€ 6,203.90	0	0	0	142	819	487	77
151	97.41%	90.37%	98.52%	€ 385.55	€ 354.71	€ 354.98	3	0	0	18	7	26	4
152	87.25%	89.64%	96.41%	€ 330.95	€ 317.83	€ 322.01	7	0	0	19	32	26	9
153	94.49%	97.06%	98.16%	€ 363.39	€ 357.75	€ 366.18	4	0	4	14	15	8	5
154	89.45%	91.46%	95.98%	€ 297.23	€ 262.24	€ 255.23	15	0	0	4	21	17	8
156	83.83%	88.62%	94.01%	€ 285.92	€ 230.85	€ 212.59	27	8	1	9	27	19	10
157	88.76%	88.47%	97.41%	€ 440.37	€ 451.50	€ 450.25	0	0	0	5	39	40	9
158	84.95%	95.78%	97.61%	€ 672.42	€ 702.69	€ 698.95	0	0	0	2	82	23	13
159	90.21%	94.50%	98.78%	€ 426.37	€ 425.53	€ 423.70	0	0	0	7	32	18	4
160	85.22%	89.57%	94.78%	€ 683.40	€ 729.54	€ 721.55	0	0	0	6	85	60	30
161	88.24%	94.88%	97.95%	€ 483.61	€ 516.50	€ 504.21	0	0	0	7	46	20	8
162	93.01%	94.76%	98.25%	€ 386.27	€ 376.20	€ 373.61	0	0	0	5	20	15	5
163	91.37%	88.82%	98.08%	€ 444.31	€ 402.20	€ 404.59	5	0	0	5	27	35	6
164	90.51%	90.15%	98.18%	€ 393.95	€ 372.43	€ 362.37	15	2	0	1	26	27	5
165	93.41%	90.11%	97.80%	€ 373.58	€ 373.64	€ 361.27	5	2	1	24	18	27	6
166	90.85%	93.38%	96.53%	€ 433.36	€ 409.89	€ 404.83	14	0	0	16	29	21	11
Total	**89.49%**	**91.71%**	**97.30%**	**€ 12,177.90**	**€ 12,348.62**	**€ 12,420.22**	**95**	**12**	**6**	**284**	**1325**	**869**	**210**

Table A40. Comparison of the three models (Lowalekar et al., Pauls-Worm & Hendrix (basic model) and Broekmeulen & Van Donselaar) for a product with shelf life of seventeen days. Green cells show the best result(s), red cells show the worst result(s), no coloured cells are the 2nd best result. Blue coloured cells represent stores with (close to, *a≤0.05*) Poisson distributed demand.

	Fill rate			*Total costs*			*Simulated waste*			*Reported waste*	*Simulated shortage*		
Store	*LNR*	*PH*	*BD*	*LNR*	*PH*	*BD*	*LNR*	*PH*	*BD*	*Slimstock*	*LNR*	*PH*	*BD*
141	83.65%	97.26%	98.65%	€ 9,870.82	€ 11,167.76	€ 10,622.22	0	0	0	15	715	120	59
151	95.00%	100.00%	98.85%	€ 635.62	€ 716.71	€ 636.59	0	0	0	1	13	0	3
152	92.90%	100.00%	98.62%	€ 1,259.54	€ 1,382.80	€ 1,243.34	0	0	0	0	36	0	7
153	91.29%	100.00%	96.17%	€ 694.01	€ 775.92	€ 687.60	0	0	0	0	25	0	11
154	97.67%	100.00%	97.67%	€ 432.71	€ 479.55	€ 412.64	0	0	0	0	4	0	4
156	95.77%	100.00%	99.30%	€ 345.64	€ 418.49	€ 348.33	0	0	0	5	6	0	1
157	97.24%	100.00%	99.45%	€ 456.66	€ 518.81	€ 445.09	0	0	0	0	5	0	1
158	89.30%	100.00%	99.13%	€ 1,089.40	€ 1,245.77	€ 1,110.17	0	0	0	0	49	0	4
159	98.25%	100.00%	99.42%	€ 428.99	€ 477.23	€ 419.56	0	0	0	1	3	0	1
160	92.31%	100.00%	99.36%	€ 729.27	€ 845.69	€ 760.62	0	0	0	0	24	0	2
161	91.45%	100.00%	99.08%	€ 1,035.37	€ 1,184.20	€ 1,053.89	0	0	0	0	37	0	4
162	84.14%	100.00%	96.77%	€ 883.47	€ 1,023.85	€ 893.46	0	0	0	0	59	0	12
163	95.64%	100.00%	99.64%	€ 693.14	€ 752.04	€ 672.75	0	0	0	0	12	0	1
164	90.48%	100.00%	97.76%	€ 867.19	€ 963.58	€ 873.85	0	0	0	0	34	0	8
165	91.09%	100.00%	99.60%	€ 634.55	€ 694.17	€ 618.57	0	0	0	8	22	0	1
166	91.40%	100.00%	97.74%	€ 539.08	€ 583.12	€ 548.76	0	0	0	0	19	0	5
Total	**92.35%**	**99.83%**	**98.57%**	**€ 20,595.46**	**€ 23,229.69**	**€ 21,347.44**	**0**	**0**	**0**	**30**	**1063**	**120**	**124**