Using pre-packs to preload stores at the beginning of the high demand season

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Using pre-packs to preload stores at the beginning of the high demand season

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Abstract

This Master Thesis investigates preloading of stores at the start of the high season with pre-packs in a situation with seasonal demand. Because the order-up-to policy has a large impact on the composition and benefits of pre-packs, methods for calculating the order-up-to levels are also discussed. We use a case study to test whether the policies would work in practice and could lead to a benefit. We show that the lingerie retailer in our case study can achieve a cost benefit when it would implement the use of pre-packs for their slow-moving items.

Preface

This Master thesis is the culmination of my study “Operations Management and Logistics” at the Eindhoven University of Technology. It is the result of six months of extensive research at Hunkemöller, a large lingerie retailer. This research required me to put the theory I have learned during my study into practice, without losing myself in the many practical problems I encountered. As a result, I gained a lot of experience while conducting this research.

First, I would like to thank Rob Broekmeulen for guiding me through the field of Retail Logistics. Thanks for the useful meetings at the university, which provided me with feedback and directions required to finalize my research. My thanks also go to Zümbül Atan for her assistance and feedback during the final stages of my research. In addition, I would like to thank Alaa Elwany, for his help during the preparation phase.

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Finally, I would like to thank my family and friends for their support during my study. A special thanks goes out to my friends from the university for their daily electronic motivating messages. Finally yet importantly, a special word of thanks goes to Femke Fokkert for her support during the difficult times and her permanent confidence in me.

Machiel Bakema

Hilversum, December 2010

Management summary

This research focuses on items that are sold during the whole year but experience seasonality. To cope with the seasonality a policy with two different order-up-to levels is used. To increase the order-up-to levels at the beginning of the high season pre-packs are used. Pre-packs are units that contain several different SKUs. Sending pre-packs at the start of the high season can decrease costs in situations where the costs of picking and packaging are lower at the manufacturer than at the distribution center. In this research, we focus on four different cost factors:

- The inventory costs.
- The handling costs.
- The system control costs.
- The implementation costs.

The seasonal pre-packs only work in situations with a substantial difference between the seasons. Next to a substantial difference between the seasons, there are some other criteria for selecting SKUs that are good candidates to include in the pre-pack:

- The SKU should be in a stable phase of the product lifecycle and demand should be predictable.
- The high season should start at approximately the same moment for all different SKUs included in the pre-pack.
- The SKUs that are included in the pre-pack are part of the assortment of all stores that receive a pre-pack. If pre-packs are created at the supplier, only items that are purchased at that supplier can be included.
- Management might set some constraints on which SKUs can be put together into one pre-pack.

Whether pre-packs can decrease costs is dependent on several factors, for example; the number of stores, handling costs, holding costs, demand and differences in order-up-to levels. Based on the four cost factors we developed a simple rule to select appropriate candidates to put into the pre-pack, and to test whether using pre-packs can lead to a benefit in a specific situation.

After candidate products are selected the pre-pack problem (PPP) remains. In order to solve the PPP a cost function is developed. Given an instance in which the picking costs, holding costs, difference in order-up-to levels and demand is known; the aim is to find a set of stores and items that maximizes the objective function. In some situations, there can be a limitation on the size, weight or another dimension of the pre-pack. In these cases, a capacity constraint should be included in the model. In the objective function, only holding and handling costs are considered. The objective function does not include other costs like; the costs of cross-docking pre-packs, the supplier charge for delivering in pre-packs and the costs of calculating and ordering pre-packs are excluded. Therefore, these costs need to be estimated and subtracted from the pre-pack benefit calculated with the objective function. Only if there remains a substantial cost benefit one should implement pre-packs.

Because the multiplicative relation of the two decision variables the pre-pack problem is non-linear and combinatorial. Furthermore, the number of different combinations of the two decision variables is infinite. Therefore, it is extremely difficult to find the optimal solution; for that reason, a greedy heuristic solution is presented. For the stores a drop-type of greedy heuristic is used. This drop-type of greedy heuristic starts with including all stores and then the stores that do not lead to a benefit are dropped. On the other hand, an add-type of greedy heuristic is used for the items to be included in the pre-pack. This add-type of greedy heuristic starts with excluding all SKUs and then the items of all SKUs that lead to a benefit are included.

- The first step of the heuristic is to exclude the clear underperforming stores from the set of stores. This is only required when the optimal quantity of products included in the pre-pack would be zero if all stores receive a pre-pack. In this case, the heuristic is "locked" into a solution that does not lead to a benefit. Excluding the underperforming stores prevents the heuristic from being locked in this situation.
- During the second step, the optimal set of items for the selected set of stores is identified. By checking whether adding items can lead to a benefit and then only including the items that do so, the optimal set of items for the selected set of stores can be identified.
- In the third step, the optimal set of stores for the selected set of items is identified. This is done by excluding all stores for which the extra inventory costs do not outweigh the handling benefits of pre-packs.
- To find a good solution several iterations are needed, in these iterations we repeat step two and three until we converge to a solution. By iterating step two and three a better solution can be found, since the optimal set of stores affect the optimal set of items and vice versa.

To test whether pre-packs can be used in a real life situation; the model is applied to Hunkemöller, a large international lingerie retailer. To test the method we focus on bras that were sold during the whole year. We selected a few product groups (type of bra) and stores to select an appropriate method to set order-up-to levels, and to test whether two order-up-to levels are needed. For these slow moving items, which are controlled by a (R, S) policy a method to calculate correct order-up-to levels under a service criterion, is applied. In contrary to the currently used method to calculate order-up-to levels, we assume that demand is stochastic. To calculate the order-up-to level calculation we tested the following two methods for demand fitting:

- The method of Adan et al. (1995) which fits an analytic demand distribution on the data.
- Assuming that the demand is Poisson distributed.

With a simulation method, we compared the current order-up-to levels with the proposed methods. All methods reach the proposed service criterion, the Poisson method reaches the service criterion with the lowest amount of inventory (-19% compared to the current method). Furthermore, it is the easiest method to implement and use. Next to finding the correct method for finding the order-up-to levels we also show that using two order-up-to levels does decrease inventory costs (for the different product groups it ranged from 4,2 to11,7%). Compared to the current method, the difference in order-up-to levels calculated under the Poisson assumption is much smaller, this reduces the need for and benefit of using pre-packs.

After calculating the order-up-to levels, we applied the PPP on this situation to test whether the proposed seasonal pre-pack could lead to a benefit. Management decided that pre-packs could only include SKUs from one product group. Therefore, four different pre-packs were calculated. The results are displayed in the following table:

Table I comparison and benefits of pre-packs

Product group	Number of items in the pre-pack	Number of stores	Expected gross benefit (euro)	Other costs (threshold level)	Expected net benefit (euro)
A	18	181	210,93	71,72	139,21
B	17	318	434,35	88,16	346,19
C	9	121	73,24	64,52	8,72
D	8	139	59,43	66,68	-7,25

For two product groups with a large seasonal effect (A and B) pre-packs could lead to a significant net benefit. For the other two product groups that experience less seasonality (C and D), using pre-packs could not lead to a significant benefit. For these product groups the number of items included in the pre-pack and the number of stores that receive a pre-pack is smaller.

Next to the cost benefit, the pre-packs also decreased the workload at the DC. For product group A the picking workload decrease with 3077 items, this is equal to the average workload of product group A during 1.4 weeks. For product group B the picking workload decrease with 5406 items, this is equal to the average workload of product group B during 1.9 weeks.

The heuristic assumes that the optimal set of stores does not include all stores. We tested the effect of the number of stores included in the pre-pack and displayed the results in the following graph. This graph shows the expected benefits of using pre-packs, for different numbers of stores included, next to the benefits of using pre-packs it also shows the effect of the number of stores on the pre-pack composition.

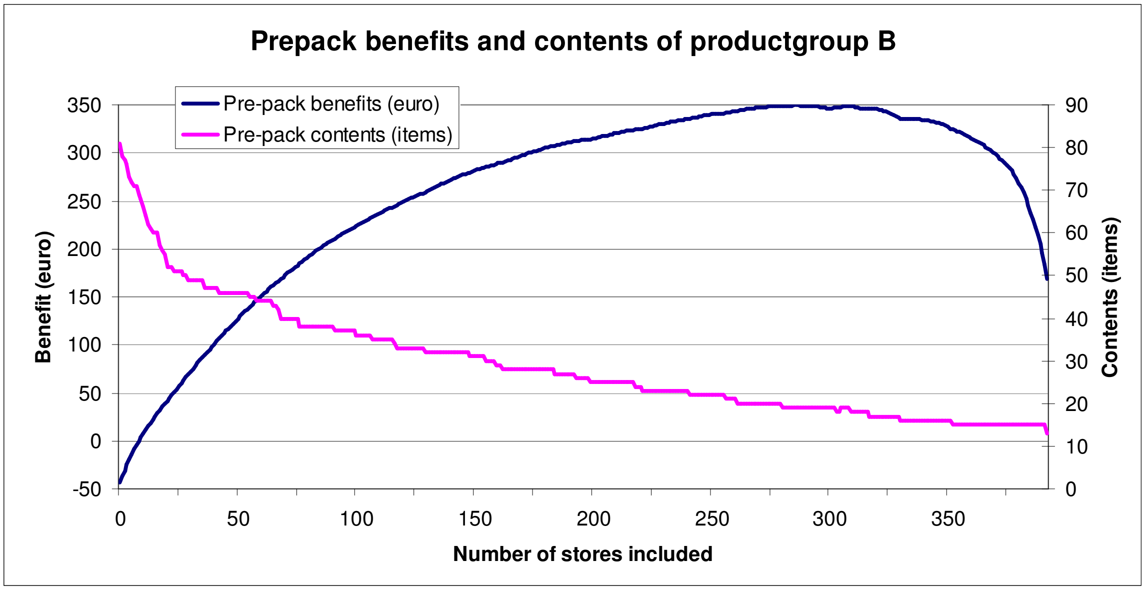

Figure I: Pre-pack benefits for product group B with different number of stores

The graph clearly shows that there is an optimal amount of stores to be included. Furthermore, the optimal set of stores is robust, around the optimum number of stores, small deviations only have a very limited effect on the overall benefits.

We also tested the product selection rule, the results show that the selection rule is effective in selecting SKUs and product groups that are appropriate to put in pre-packs in this case study. None of the SKUs for which the rule did not hold lead to a significant benefit and all SKUs for which the rule holds were included in the pre-pack. Furthermore, only for the product groups which had a large number of SKUs for which the product selection rule holds, a pre-pack could be composed which lead to a significant benefit.

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List of abbreviations

A_i	Size, weight or other dimension of the item
C_i^P	Decrease in picking costs if one item of SKU i is included in one pre-pack (euro/week)
C_i^H	Holding costs for SKU i (euro/week)
$C_{decrease}$	Relevant costs decrease by using two order-up-to levels instead of one (%)
C_1	Relevant costs per year with one order-up-to level
C_2	Relevant costs per year with two order-up-to levels
CODP	Customer Order Decoupling Point
Cx	Coefficient of variation
d	Value in the range of the demand distribution
D_{L+R}	Demand during lead-time+ review period (random variable)
D_L	Demand during lead-time (random variable)
DC	Distribution Center
DRP	Distribution Resource Planning
E(x)	Expected demand during lead-time and review period
$E[\mu_{nopp}]$	Expected average weekly demand in the stores who do not receive pre-packs
I_{avr}	Average inventory (units)
LAP	Load Assembling Point
MRP	Material Requirement Planning
NOS	Never-out-of-stock
OOS	Out-of-stock
PPP	Pre-pack problem
s	Order-up-to level (units)
s_h	Order-up-to level during the high season (units)
SKU	Stock Keeping Unit
μ_{avri}	Average store demand for SKU i. (items/week)
μ_r	Average demand during the review period (units)
μ_{avr}	Average yearly demand (units/week)
μ_{ij}	Demand for SKU i in store j during the high season (items/week)
σ_{L+R}	Standard deviation of the demand during lead-time + review period.
W	Capacity of the pre-pack in the same dimension of A
x_i	The number of items of SKU i in the pre-pack.
y_j	Decision variable, if store j participates in pre-packs then 1, otherwise 0.
Δ_{ij}	Increase in order-up-to level of SKU i in store j at the start of the high season (items)
$\Delta_{\%i}$	Percentage of stores which do not have an increase in order-up-to level for SKU i.

1. Research introduction

The effects of postponement are often studied in the field of Operations Management. With postponement, final customization processes are delayed. By delaying the final customization processes, companies can facilitate rapid customer response in highly customized manufacturing environments. The most familiar examples happen in high-tech industries, for example at HP (Feitzinger and Lee, 1997). By using postponement, the uncertainty in demand for different products can be pooled. By pooling uncertainty the total amount of safety stock can be reduced, which reduces the total inventory holding costs while attaining the same customer service level. On the other hand delaying customization steps can increase the process costs. However, the decrease in inventory holding costs can outweigh the costs of delaying customization steps. Such strategies that increase the responsiveness of the supply chain can be effective for products with short lifecycles and highly uncertain demand (Fisher, 1997). However, for supply chains with products that experience longer lifecycles and where demand is predictable, responsiveness is less important. These supply chains benefit more from increasing their efficiency (Fisher, 1997).

This research discusses preponement, which is the opposite of postponement. With preponement certain processes, like manufacturing or packaging, are scheduled to an earlier time. Preponement often leads to a (small) increase in inventory costs; however, preponing certain steps can decrease process costs. For products with longer lifecycles and predictable demand, this decrease in process costs can outweigh the increase in inventory costs. Under these circumstances, preponement can be an effective way of decreasing overall costs.

This study focuses on preponing the packaging and picking processes. Preponing can decrease the costs of these processes when the costs of picking and packaging are lower at the manufacturer than at the distribution center. This is often the case when the manufacturer is located in a low-wage country, like China, while the distribution center is situated in a country with higher wages, like the Netherlands.

Preponing the packaging and picking processes can be done by the use of pre-packs. In pre-packs, several different SKUs are bundled together. This pre-pack is than cross-docked at the distribution center.

1.1. Problem description

This study focuses on SKUs that are sold during the whole year. However, the demand for these SKUs is low and highly seasonal. Ordinary reorder policies cannot effectively cope with this seasonality because they are designed for approximately stable demand. One simple method to cope with this seasonality is dividing the year into two seasons and use different order-up-to-levels for each of those seasons. When the order-up-to-levels are set correctly, such a policy should work properly during the seasons. However, the transition from one season to the other creates challenges, especially when the difference in order-up-to levels is large.

At the start of the high demand season, order-up-to levels at the stores are increased to cope with the increased demand. Changing the order-up-to levels creates a peak in the workload at the DC since a relatively large amount of order-lines need to be picked and transported to the stores in a short time period. By using pre-packs, this problem can be decreased, because picking one pre-pack takes considerably less time than picking all items in the pre-pack separately.

At the end of the season, the order-up-to levels are decreased again. However, only changing the order-up-to level does not directly change the inventory position, because the inventory position only decreases when demand occurs. Therefore excess inventory remains in the stores. Because we focus on slow moving SKUs, it can take a lot of time before the excess inventory is sold. The start of the low season is predictable, therefore order-up-to levels might be reduced just before the high season ends, in order to reduce the inventory at the start of the low season, creating a policy to do so is not part of this research.

1.2. Research description

The aim of this master thesis is to investigate whether and how pre-packs can be used to decrease costs in a situation with slow moving items that experience high seasonality. In addition to investigating pre-packs, we also investigate appropriate policies to set order-up-to levels for slow moving items. A good policy for calculating order-up-to levels can decrease costs. Furthermore, this policy can have a large effect on the difference in order-up-to levels and therefore the composition and benefits of pre-packs.

In order to do so, we propose a method to test whether there is a significant difference in demands between the two seasons. Then we use two fitting procedures to fit a discrete distribution on the data. Then, the store order-up-to levels are calculated for a (R,S)-system. In this first phase, we assume a complete pull system, so orders are triggered only when the inventory level reaches the order-up-to level minus one. Next, the differences in order-up-to levels between the seasons are analyzed. Finally, we develop a generic model to calculate the pre-pack contents. While we use a (R,S)-system with slow-moving items for the calculation of the order-up-to levels, the pre-pack policy is generic, therefore it can also be applied to other inventory systems as long as demand is seasonal and two or more different order-up-to levels are used to cope with this demand.

We assume that the SKUs are kept on stock in the DC during the whole year. Therefore, policies that try to cover the demand for the whole season by one push order, without the option of additional replenishments are left out of scope.

1.3. Relevant cost factors

For the calculation of the order-up-to levels, we use the fill rate, which can be defined as the fraction of demand delivered directly from stock. However, the pre-pack model can also be used in situations with different service level criteria. We try to minimize relevant costs while attaining this service level. Because we use a service criterion, the costs of lost sales or backorders are not taken into account. Therefore, the relevant costs are composed of four parts: inventory costs, handling costs, system control costs and implementation costs.

The inventory costs are the costs of carrying inventory, these include the costs of capital invested in inventory and furthermore the costs of storage space occupied by the inventory.

The handling costs are the costs of the handling activities executed at the DC. By the use of pre-packs, the number of picking hours and therefore the costs can be decreased. Handling costs in the stores are not taken into account since we assume that these costs are unaffected by the change in policy.

The system control costs are the costs that are associated with using a certain policy. This contains the costs of computations, system maintenance and data acquisition. Since we focus on the relevant costs, only the difference in operating costs is taken into account. It is difficult to calculate these costs; therefore, we make an assumption about these costs.

The implementation of a new control system requires changes in the way of working. Therefore, the IT-systems might need modifications; we should ensure that the costs of these modifications can be recovered in a short time period.

1.4. Research question

The main research question for the master thesis is:

How can a retailer use pre-packs to decrease the overall costs and the peak load of the DC?

This project delivers a contribution to the scientific literature since, to our knowledge; the preloading of stores during seasonal changes with pre-packs is never discussed in the scientific literature. The scarce scientific literature that does investigate the use of pre-packs to supply stores shows that pre-packs can decrease costs (Freimer et al., 2006; Teulings & Van der Vlist, 2007). However, in these cases, the pre-packs are used to supply the stores all year round with SKUs that do not experience seasonality. Therefore this master thesis project is the first to discuss preloading seasons with pre-packs.

1.5. Research design

Studies in the field of Operations Management are often research-oriented or design-oriented. Research-oriented studies are often called rigorous and try to develop scientific knowledge, however this knowledge is difficult to implement in specific situations. In design-oriented studies, the aim is to analyze and solve real-life problems. These studies are relevant, but it is often difficult to generalize the result (Bertrand & Fransoo, 2002). The aim should always be to combine rigour and relevance into one study. Since this research aims at creating a model that fits reality, developing policies, strategies and actions to improve the situation, it can be defined as an empirical normative research project. Mitroff et al. (1974) developed a methodology for doing empirical normative research. Four phases are included in their model, see figure 1. The researcher must conduct all these four phases to complete the research project. Furthermore, sometimes multiple iterations are needed to complete the project. The methodology of Mitroff et al. (1974) is used as a basis for this research.

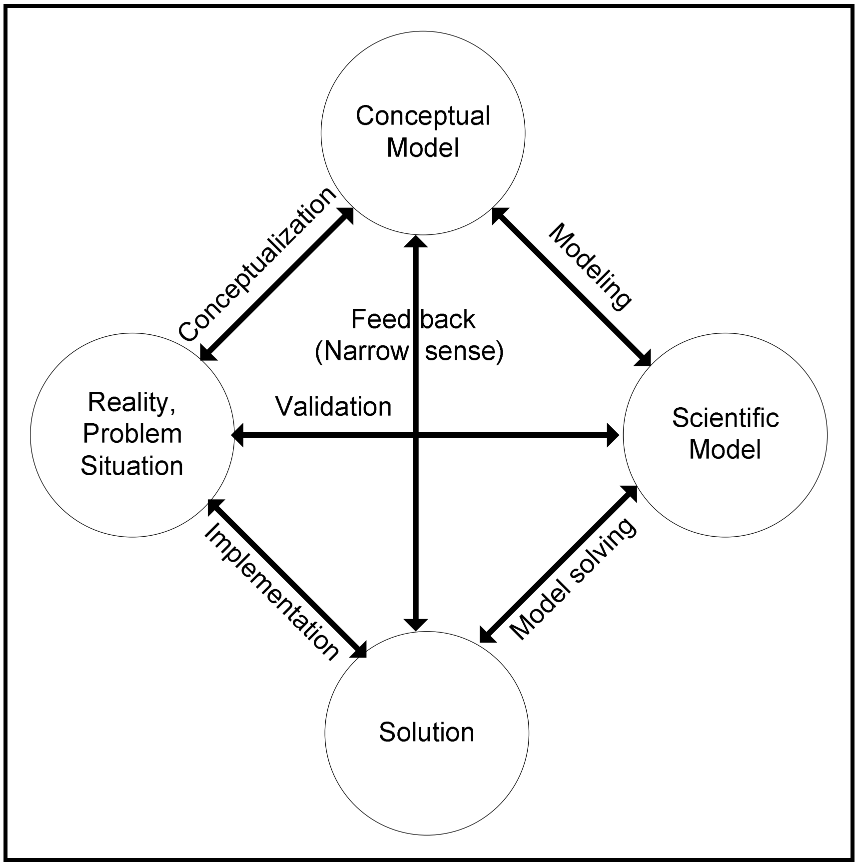

Figure 1: The conceptual model of Mitroff et al. (1974)

Conceptualization phase

In the conceptualization phase or master thesis preparation phase, a conceptual model of the problem is created. In addition, related factors are identified and analyzed and the scope is defined.

Modeling phase

In the second phase the causal relations between the variables are defined, furthermore these relations are used to create a quantitative model. This model includes all steps to calculate pre-packs.

Model solving phase

In this phase, the model is tested and evaluated, in order to do so we perform a case study at a large lingerie retailer. After this evaluation, a conclusion is made. Furthermore, the limitations of the research and possibilities for future research are discussed.

Implementation phase

In this phase, the solution is implemented. The implementation is not part of this research however; the aim is to create solutions that are ready to be implemented at the case study company.

Scope of the project

This project is focused on SKUs with seasonal demand where the seasonality is large enough to justify the use of two order-up-to levels. For these SKUs, we show whether pre-packs can lead to a benefit. Because calculation of order-up-to levels is required before the pre-pack can be calculated, we do this in our case study. However, we are mainly focused on the use of seasonal pre-packs. Furthermore, actual implementation is not taken into account.

Based on the methodology of Mitroff (1974) the following thesis outline is developed, see figure 2:

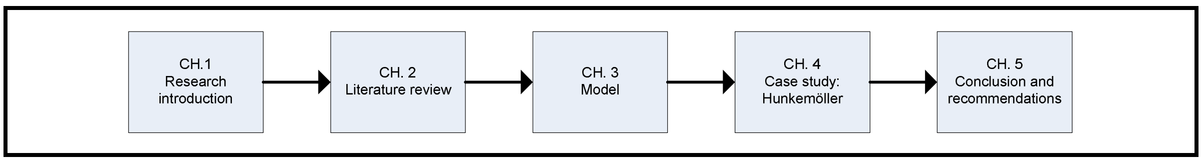

Figure 2: Thesis outline

In the second chapter, the existing literature is discussed. In chapter three, the pre-pack problem is defined and a heuristic solution is given. In chapter four, the model is applied to a case study. Finally, in chapter five we give our conclusions and recommendations.

2. Literature review

To understand why some supply chains benefit from postponing steps while others benefit from preponing we have to understand the nature of demand. Fisher (1997) distinguishes two product categories: functional and innovative. Functional products satisfy basic needs, these needs are relatively stable over time and therefore the demand is relatively stable and predictable. On the other hand, innovative products include fashion and/or technology that give additional value. Due to changes in fashion and/or the evolution of technology this additional value decreases in time and new products are launched which give more additional value. Therefore, these products have short lifecycles in which the demand is unpredictable. Note that the nature of demand is crucial for the distinction between innovative and functional products and not the product itself, since the actual differences between innovative and functional products can be infinitesimal. Therefore, a company can change the nature of demand for their products without notice. Because of the differences between functional and innovative products, they both require fundamentally different supply chains.

To explain this, Fisher (1997) distinguishes two types of functions within a supply chain: a physical function and a market mediation function. The physical function contains all actions to transform and transport raw materials to finished goods in the stores. The costs of the physical function are production, transportation and inventory holding. The market mediation function tries to balance supply and demand. The costs of the market mediation function include; lost sales, obsolescence and markdowns. Since functional items have a predictable demand, the market mediation costs are small compared to the physical costs. Therefore, one should focus on decreasing the physical costs. This can be achieved by minimizing inventory and maximizing production efficiency throughout the supply chain. On the other hand, innovative items have large market mediation costs, compared to the physical costs; therefore decreasing the market mediation costs has top priority. This can be realized by reading market signals in early stages of the product lifecycle and by creating a fast and flexible supply chain (Fisher 1997). Figure 3 shows a matrix that can be used to match products and supply chain.

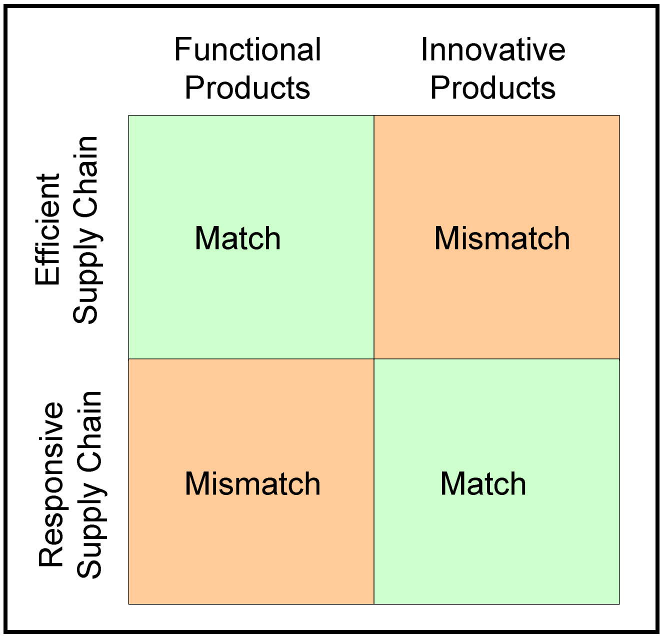

Figure 3: Matching Supply Chain with products

2.1. Order-up-to level calculation for slow moving items

For normal and fast moving items, the normal distribution provides a good empirical fit to observed data (Silver et al, 1998). In general, the normal distribution is appropriate to use practice since the impact of using another distribution is often small. However, in the case of slow moving items, the use of the normal distribution is less appropriate. First, the actual demand is discrete (only whole items can be sold) while the normal distribution is continuous. Furthermore, especially when the variation is high compared to the average sales, which is often the case with slow moving items, the normal distribution can take on negative values, which is inappropriate (Silver et al, 1998). To cope with this problem, Adan et al. (1995) developed a method to fit discrete analytical distributions on the historic data. Based on these distributions, the correct order-up-to levels can be calculated. Van Donselaar and Broekmeulen (2009) developed a method to determine the service level based on these distributions in a lost-sales environment for different order-up-to levels.

2.2. Pre-packs

The bundling of items into larger units can be used throughout the supply chain, increasing the number of items in the unit decreases the handling costs (Broekmeulen et al. 2006; Van der Vlist, 2007; Zelst et al. 2009). Often case-packs are used for bundling; case-packs contain a fixed amount of items of the same SKU.

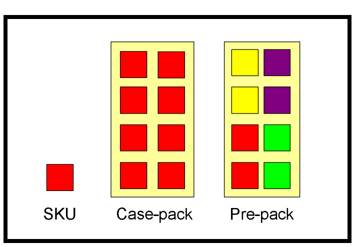

Figure 4: Separate SKU, case-packs and pre-packs

Another option is to bundle different SKUs into one pre-pack, see figure 4. This bundling further decreases the handling costs because the number of items in one unit gets larger. Furthermore, the pre-packs can help to decrease the load on the distribution centre during peak hours; Chao et al. (2005) describe one example of such a system. Chao et al. (2005) use pre-packs to decrease the workload of an order assembly line during peak hours. In their situation, pre-packs are created on the same order assembly line during calm periods. The result was a decrease in overtime, and an increase in maximum capacity.

However, the development of the pre-pack configuration is a major challenge. Literature about pre-packs is limited. In the literature, pre-packs are used to replenish all demands and the models are only studied in stable situations. In scientific research, pre-packs are often referred as standard mixed loads. When only one fixed standard mixed load can be ordered, there is no way of controlling inventory because of stochastic demand and variations in demand between stores. Van der Vlist (2007) proposes two options to cope with these variations in demand:

- An average fixed load in the pre-packs and the option to order separate items.
- A complementary set of standard mixes, which includes different quantities of items.

2.2.1. Complementary standard mixed loads

In the complementary standard mixed load concept, no separate items can be ordered. All demand variation must be controlled by the different quantities included in the standard mix. In order to create these standard mixes, candidate products for the standard mix must be found. These products must be in a stable phase of the product lifecycle and have enough volume. A group of products in a standard mix should only include a low number of different items (two, three or four) which have the same seasonal pattern otherwise the control of inventory positions becomes difficult. When only one type of standard mix is defined per product group, the ability to control the separate inventory levels of the different items is lost. Therefore, different types of standard mixes must be defined which have an overdose of one of the items in the group, compared with the long-term demand ratio. In addition, the number of standard mixes per product group is equal to the number of items in a group. Demand patterns of the items are subject to changes hence, changes to the standard mixes should be made in order to prevent unstable situations where fluctuations in the mix rate cannot be compensated with the different types of standard mixes (Teulings & Van der Vlist, 2000).

2.2.2. Average standard mixed loads

When using average standard mixed loads, retail stores need a method to control inventory. One option is to allow retailers to order separate items. Another option is to use price promotions to sell-off excess inventory or the ability to send goods back to the DC. Ordering separate items can be an effective strategy in cases of functional items, while price promotions (clearance) are more common for fashion items (Van der Vlist, 2007). If there are large differences between the store demand rates, smaller stores can receive one pre-pack while the larger stores receive multiple pre-packs (Van der Vlist, 2007). Another option is to use different sizes of pre-packs depending on the store sales. Freimer et al. (2006) studied the use of average standard mixed loads in a retail environment. They tried to develop an ordering policy for stores, while assuming that the size and design of the pre-pack is given. They calculated an optimal ordering strategy for retail stores. Freimer et al. (2006) assumed that it would be difficult to concisely describe the form of the optimal policy; therefore, they assume that implementation would also be difficult. Thus, they investigated the performance of a strict order-up-to policy and a pre-pack only policy. They conclude that a strict order-up-to policy is near optimal when there is only a small cost penalty for ordering separate items. In case of a large cost penalty, the pre-pack only policy performs better. For extreme values of the pre-pack size and the cost penalty one of these policies is near optimal, however with moderate values they perform significantly worse than the optimal policy. Furthermore, their results suggest that it is preferable to bundle SKUs with positively correlated items into one pre-pack. For example, when combining SKUs that can be distinguished on size, color and style; style and color might be negatively correlated because of fashion. On the other hand the sizes sold of a color-style combination may be positively correlated (fashion does not change the size bought). In this case, it would be best to bundle different sizes of the same style-color combination into one pre-pack (Freimer et al., 2006).

2.2.3. Using a separate LAP

Typically, customer orders are assembled and allocated at the customer order decoupling point (CODP). In the standard mixed loads concept, the assembly process is separated from the allocation process. A separate load assembling point (LAP) is created upstream of the CODP. At the LAP, a mix of goods is assembled onto a loading device (package, pallet or truckload). These loads are assigned to the customer at the CODP, which is at a downstream echelon. By doing so, the downstream echelons only handle the larger mixed-goods loads, which reduce handling costs (Teulings & Van der Vlist, 2000). Teulings and van der Vlist (2000) describe two types of applications; shifting the LAP upstream or shifting the CODP downstream in the chain.

2.2.4. Shifting the LAP upstream

Originally, separate goods are shipped from the supplier to the DC, where they are stocked. When the retail outlets place orders, goods are picked and shipped to the store. With this application of the standard mix concept, the LAP is placed at the supplier; the DC only receives assembled loads that have to be allocated to the different stores (figure 5). Because of the larger mixed-goods loads, handling is reduced. Another option is to reduce the batch size of the individual products; this reduces cycle stock in the retail stores. Furthermore, standard mixed loads reduce the effect of order pick errors on individual products (Teulings & Van der Vlist, 2000). There are several points where the LAP can be placed; directly after production, just before shipping from the supplier, or at the goods reception at the central depot. From a handling point of view, placing the LAP directly after production is optimal. However, because products are dedicated to one type of standard mix in an early stage, the flexibility of the supply chain decreases. When the standard mixes are assembled to order at the supplier, the chain becomes more flexible to react to changes in the demand, hence less safety stock is needed at the supplier. The LAP can also be placed at the goods reception of the distribution center; this has the advantage that products from different suppliers can be combined into one standard mix. Compared to the original situation, the lead-time to the retailers can be reduced, and since the mixes are standardized instead of order specific, the assembly process can be automated (Teulings & Van der Vlist, 2000).

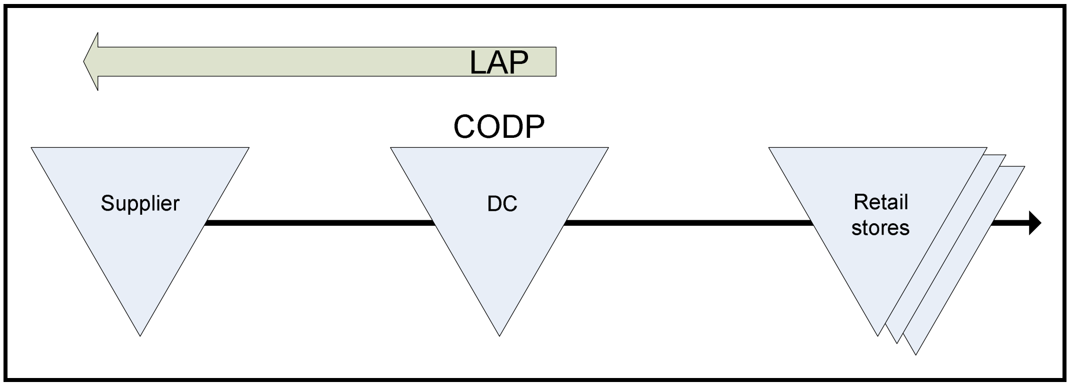

Figure 5: Shifting the LAP upstream

2.2.5. Shifting the CODP downstream

This application can be used for larger stores, which originally ordered full truckloads directly from the supplier. This leads to inventory levels that are equal to the safety stock plus half the truckload. When the standard mix concept is applied, the CODP is shifted downstream to a new DC, see figure 6 (Teulings & Van der Vlist, 2000).

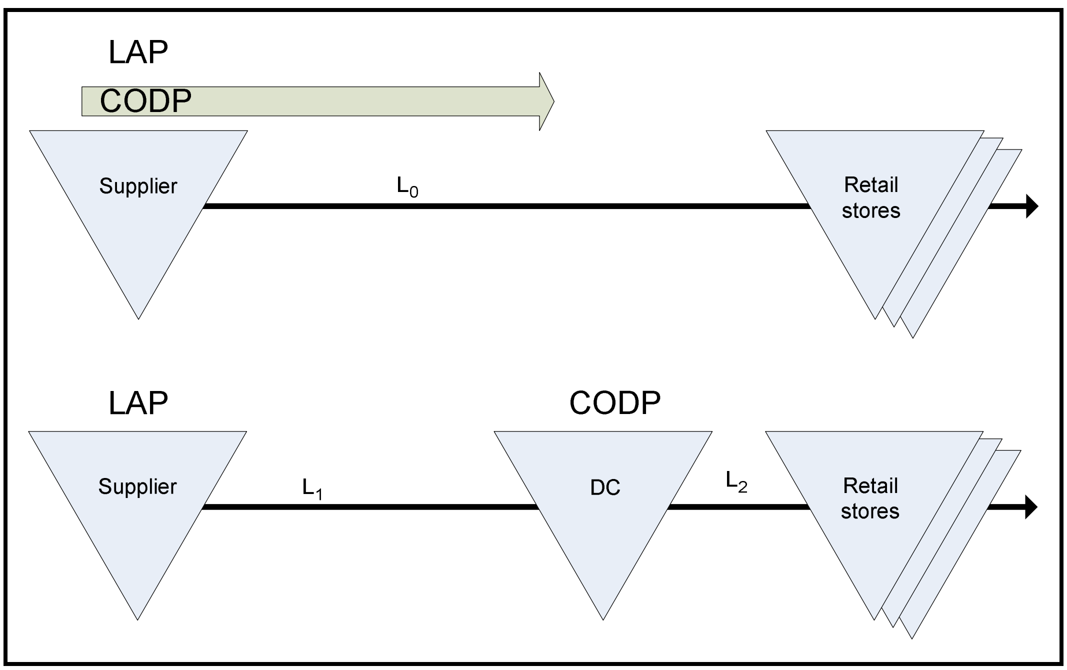

Figure 6: Shifting the CODP downstream

In this new situation, retail outlets order at the new DC, from which a standard mixed load is sent to the retail store. Safety stocks in the outlets may drop since lead-time L_2 is shorter than L_0. Furthermore, cycle stock decreases since the order quantities are lower. However, in the DC, safety stock should be kept in order to buffer against demand variation during L_1 (Teulings & Van der Vlist, 2000).

2.3. *Cost factors*

Within a supply chain, there are many different costs. When discussing the use of pre-packs, the most important cost factors are:

- Inventory costs.
- Handling costs.
- Cost of lost sales.
- System control and implementation costs.

We now discuss these points briefly.

2.3.1. Inventory costs

In most supply chains, the holding of inventory imposes significant costs.
According to Silver et al. (1998), there are six categories of inventory: safety stock, cycle stock, congestion stock, anticipation stock, pipeline inventories and decoupling stock. This research only focuses on safety stock. Safety stock is used as a buffer for variability in demand and supply in the short run. By changing safety stock levels, companies can adjust their customer service levels.

A general formula to calculate the inventory costs is:

Inventory carrying costs per year = average inventory expressed in euros × carrying charge.

The carrying charge consists of several factors like; the opportunity costs of capital invested, expenses of running a warehouse, damage, theft, obsolescence insurance and taxes.

The opportunity costs of the capital are often the largest cost factor. Silver et al. (1998) theoretically define this as "*the return of investment that could be earned on the next most attractive opportunity that cannot be taken advantage of because of a decision to invest the available funds in inventory*". In practice, this level is often set by management, which expects all investments to yield a specified percentage of profit.
Furthermore, there are also costs incurred for the actual storing of inventory. Lastly, there are some risks involved when holding inventory, for example; items can become obsolete, damaged or stolen.

Often different parties of a supply chain use EOQ equations. These equations consider the local inventory costs as an important factor. However, when taking an integral supply chain approach, one should realize that the inventory carrying costs are born at the moment that the goods are produced. When the storage costs between the different locations of the supply chain is roughly equal, the reallocation of inventory between different parties hardly affects the overall inventory costs (Van der Vlist, 2007), however the party that is responsible may change dependent of the location of the inventory.
When considering this knowledge, reorder decisions should be based on the difference between the carrying costs instead of the actual carrying costs (Van der Vlist, 2007).

2.3.2. Handling costs

Manufactures often produce in large batches, like full truckloads to decrease setup costs. However, when products move downstream in a supply chain the order sizes decrease repeatedly, the full truckloads are broken into smaller units like full pallets, case packs and finally separate items.

These smaller units are picked in combination with other products to fulfill orders from a downstream party (Van der Vlist, 2007).The break bulk and handling operations of these smaller units is labor intensive. According to van Donselaar et al. (2006), labor is an important cost factor in retail chain, since handling costs at the warehouse and particularly at the store level usually far outweigh the relevant inventory holding costs for regular items. Broekmeulen et al. (2006) investigated the operational logistic costs for a partial supply chain of dry groceries where obsolescence costs are negligible, including the warehouse and retail store, see figure 7. Their results show that handling is responsible for 66% of the total costs, while the inventory costs only represent 12% of the total costs. Therefore, investigation of the handling costs is worthwhile; however, most of the recent scientific literature does not take these costs into account (Van Zelst et al, 2009). According to Van der Vlist (2007) there are several options to decrease handling costs. For example, moving larger units to downstream parties, elimination or simplification of one or more stages of the process, and breaking time constraints by preparing work outside of the order cycle.

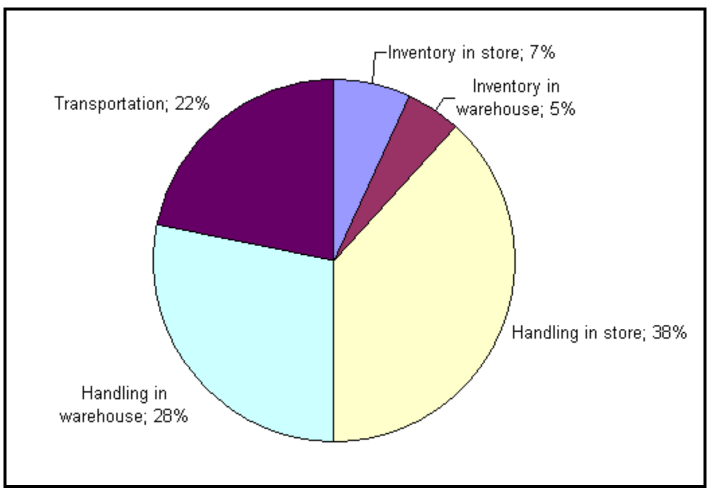

Figure 7: Distribution of logistic costs at a grocery retailer (Broekmeulen et al, 2006)

Tompkins et al. (2003) investigated the order pick cycle at the warehouse. This cycle always consists of a fixed setup time at the beginning and end of the order pick cycle, which includes activities such as getting instructions and organize a loading device. Furthermore, there are variable costs depending on the number of order lines. Activities such as traveling and searching are included in these variable costs. The actual time for picking one order line depends on the location, size and number of requested units. A typical distribution of time for picking single orders is given by figure 8 (Tompkins et al, 2003). Next to effects on handling costs in the warehouse also handling in the store is affected by ordering pre-packs. According to van Zelst et al. (2009), increasing the number of units in a case pack and ordering more case pack simultaneously can decrease in-store handling by respectively 24-49% and 8-31%.

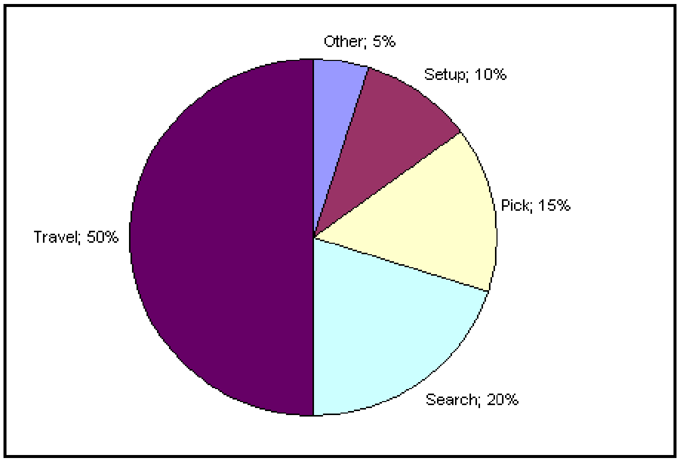

Figure 8: Distribution of warehouse handling cost (Tompkins et al, 2003)

2.3.3. Lost sales

In 2003, a study showed that European stores usually have an out of stock (OOS) rate of 7 until 10% (Corsten & Gruen, 2003). Furthermore, for items on promotion the OOS rates are twice as high as items with regular items. Decreasing of OOS levels can increase profits by up to 5%.

When customers are faced with OOS, they respond in different ways.
Corsten and Gruen (2003) studied these responds worldwide in eight different categories. They found the following responses:

- Buy items at another store (31%).
- Substitute with a different brand (26%).
- Substitute with the same brand (19%).
- Delay purchase (15%).
- Do not purchase item (9%).

Note that there are differences between products, countries and categories.
For example, their results suggest that when the opportunity costs of directly consuming an item is low; costumers more often delay or cancel their purchase. Often studies only focus on the direct sales loss, when determining the costs of OOS. According to Corsten and Gruen (2003), OOSs create costs in four different areas, namely:

- Retailer shopper loss: Customers decide to shop elsewhere because of frequent OOS.
- Retailer sales loss: The direct lost sales for the retailer due to OOS, customers cancel the purchase, buy elsewhere or substitute to lower priced products.
- Manufactures shopper loss: The customer decides to start using another product.
- Manufactures sales loss: The direct lost sales for the manufacturer due to OOS.

Furthermore, because of OOS the actual sales data is lower than the actual demand. Often the actual sales data are used to forecast demand. If the OOS are not taken into account, the ordered quantity is too low. Hence, the margin of error in the forecast increases.

Corsten and Gruen (2003) also investigated why OOS occur and they found the following causes:

- Store ordering (34%).
- Store shelving (25%).
- Retail headquarter or manufacturer (14%).
- Store forecasting (13%).
- Distribution center (10%).
- Other cause (4%).

The stores cause approximately 70% of the lost sales. Thus for decreasing OOS the focus should be on the store processes.

2.3.4. System control and implementation costs

While system control costs are difficult to quantify and are often neglected, it is important to consider these costs. A more complicated and accurate policy might decrease the sum of inventory, ordering and handling costs, but the system control costs might overrule the additional benefits. Because the system control costs should be in line with the benefits that can be attained, Silver et al. (1998) propose to classify SKU depending on their sales value. Depending on this classification, the management time and financial resources should be distributed where products with a high sales value get more attention.

Implementation costs include all costs that are associated with the start-up of a new policy. In our case, most important are the changes to the IT-system and training of employees who have to maintain the new policy.

3. The pre-pack problem

In this chapter, the pre-pack problem is presented. However, before calculating the pre-pack composition, several other steps need to be undertaken. First, appropriate products need to be selected which are good candidates to include in a pre-pack. Second, a method is proposed to test whether there is a substantial difference in demand between the different seasons, to justify the use of two different order-up-to levels. Then, the pre-pack model is defined. Then, a heuristic solution is explained to find a good solution in a capacitated and uncapacitated situation.

3.1. Product selection

It is important to consider which products are good candidates to include in a pre-pack. For the selection of appropriate items, the following criteria need to be considered:

- The SKU should be in a stable phase of the product lifecycle and demand should be predictable.
- The SKU is sold during the whole year; however, it does experience seasonality.
- The difference in demand between the seasons is enough to justify the use of two different order-up-to levels.
- The high season should start at approximately the same moment for all different SKUs included in the pre-pack.
- The SKUs that are included in the pre-pack are part of the assortment of all stores that receive a pre-pack. Otherwise, pre-packs need to be opened at the DC to remove these SKUs, or stores need to find another way of clearing them.
- If pre-packs are created at the supplier, only items that are purchased at that supplier can be included.
- Management might set some constraints on which SKUs can be put together into one pre-pack.
- The costs of creating pre-packs by the supplier are substantially lower than picking items at the DC.

Note that the group of selected stores also affects these criteria. For example, instead of excluding SKUs from the pre-packs because they are not sold in every store, we can exclude the stores that do not have these products in their assortment.

The proposed pre-pack model can only be used in situations with seasonality. Whether a pre-pack can decrease costs is dependent on the combination of several factors, like; the number of stores, picking costs, holding costs, demand and differences in order-up-to level. In chapter 3.6, we derive a product selection rule from the pre-pack problem objective function of chapter 3.3 to select the appropriate products.

3.2. Two order-up-to levels

Using a policy with two order-up-to levels is only justified when this leads to a substantial decrease in the costs compared to using only one order-up-to level. With the following formula, we can calculate the difference:

$$C_{decrease} = 100 * \left(\frac{C_1 - C_2}{C_1} \right)$$

Where;

$C_{decrease}$	Relevant cost decrease by using two order-up-to levels instead of one (%)
C_1	Relevant costs per year with one order-up-to level
C_2	Relevant costs per year with two order-up-to levels

We assume handling costs are unaffected by the use of one or two order-up-to levels. In situations with a service measure criterion, only inventory holding costs are relevant. Lost sales do not have to be taken into account since they are incorporated in the service measure criterion. We recommend that in these situations, there should be an inventory holding cost decrease of at least α percentage to justify the use of two order-up-to levels. A part of this α percentage needs to cover the increase in system control costs. The actual value of α can differ depending on the situation. Some factors which affect α are; the total amount of inventory costs, whether the policy is automated and management decisions.

3.3. The pre-pack problem definition

In the following section, we define the pre-pack problem (PPP). The aim is to find the optimal combination of stores and items to optimize the pre-pack benefit. The objective function consists of two parts; the decrease in handling costs because pre-packs are used, and the increase in inventory holding costs because some stores experience inventory overshoot.

Before defining the PPP objective function, we explain all definitions:

$y_j \in N$	Decision variable, the number of pre-packs that store j receives.
$x_i \in N$	Decision variable, the number of items of SKU i in the pre-pack.
A_i	Size, weight or other dimension of the item.
W	Capacity of the pre-pack in the same dimension of *A*.
C_i^P	Decrease in picking costs if one item of SKU i is included in one pre-pack (euro/week).
C_i^H	Holding costs for SKU i (euro/week).
E[μ_{ij}]	Demand rate for SKU i in store j during the high season (items/week).
Δ_{ij}	Increase in order-up-to level of SKU i in store j at the start of the high season (items).

Furthermore, we make the following assumptions:

- The demand during the season is known, constant and discrete.
- The inventory is at the low order-up-to level when the pre-pack arrives.
- The complete inventory overshoot is sold during the high season.
- The quantity of items for SKU i included in the pre-pack is positive and integer.

Handling

The first part of the BPPP equation evaluates the effects of the pre-packs on handling. We assume that for each item that is distributed to the store with the use of pre-packs, there is a decrease in picking costs, which is equal to the costs of picking one item. This also holds when the number of items is larger than the difference in the order-up-to level, because these extra items decrease the picking costs in the near future. Therefore, we can calculate the savings on the picking costs by multiplying the total amount of items that are send to the stores in pre-packs by the costs of picking one item.

Extra inventory

The second part of the BPPP equation evaluates the effects of the pre-packs on inventory. When store j receives more items of SKU i, than the difference in the order-up-to level for SKU i in store j, there is an inventory overshoot. This excess inventory increases the inventory holding costs at store j. Figure 9 graphically displays the increase in inventory:

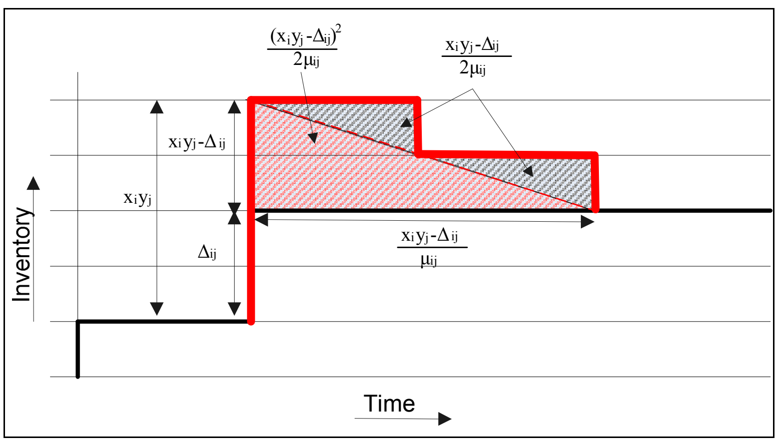

Figure 9: graphical explanation of inventory overshoot.

During the period with excessive inventory, the fraction of demand delivered directly from stock increases. Since the actual stock level is temporarily higher than the order-up-to level. However, we assume that this effect is small, because the store has a high service level and therefore we do not consider these benefits.

Definition of the pre-pack problem

Given an instance in which the picking costs (C_i^P) , holding costs (C_i^H),difference in order-up-to levels (Δ_{ij}) and expected demand rate $E[\mu_{ij}]$ is known, the aim is to find a set of stores (y_j) and items (x_i) that maximizes the objective function:

$$B_{PPP} : \left\{ \sum_i \sum_j C_i^p x_i y_j - \sum_i \sum_j C_i^H * \left(\frac{\left(\left[x_i y_j - \Delta_{ij}\right]^+\right)^2 + \left(\left[x_i y_j - \Delta_{ij}\right]^+\right)}{2E\left[\mu_{ij}\right]} \right) \right\}$$

In some situations, there can be a limitation in the size, weight or another dimension of the pre-pack. If there is a possibility that the derived quantity exceeds this limitation, we should include a capacity constraint into the model. Note that including such a constraint makes it more difficult to solve. In our case study, we not use this constraint since products are small. If there are any capacity constraints on the pre-pack, the following constraint needs to be satisfied:

$$\sum_i A_i x_i \leq W$$

Cost threshold

The PPP objective function does not include all costs of using pre-packs. The costs of cross-docking pre-packs, the supplier charge for delivering in pre-packs and the costs of calculating and ordering pre-packs are excluded. Therefore, these costs need to be estimated and subtracted from the pre-packs benefit calculated with the equation. Only if there remains a substantial cost benefit, one should consider implementing pre-packs. Because the costs of implementation, which include educating the planners and possible changes required to the IT system, have to be earned back.

3.4. Decomposition of the PPP

The objective function is non-linear. Furthermore, the objective function is combinatorial because the number of different combinations of the two decision variables is exponential. Therefore, it is extremely different to find the optimal solution; therefore, we propose a heuristic solution. First, we assume that stores can only receive one or no pre-packs.

If every store experiences the same demand rate and difference in order-up-to level for each product, it would be best to include all stores. Since the number of pre-packs increases while there is no effect on the optimal composition of the pre-pack. Therefore, the benefits would increase linearly with the amount of stores that are included. However in reality, stores experience different demand rates, and they often have different order-up-to levels. In this case, the set of participating stores affects the optimal pre-pack composition and this makes the problem difficult to solve.

The heuristic starts with decomposing the PPP in two parts: First, select the set of participating stores, and then try to find the optimal pre-pack composition for that specific set of stores. Afterwards we can use iterations to increase the benefits. This heuristic is able to find the optimal quantity included in the pre-pack for a specific set of stores, in an uncapacitated situation and capacitated situations in which the items have the same size. We should realize that the heuristic is not able to find the optimal situation of items and stores; however, it is able to find a reasonable solution in most situations.

3.4.1. Selection of the initial set of participating stores

We select a group of stores, based on the average demand of all SKUs included in the pre-pack. If there are only small differences in demand between the stores, the effects of the set of stores on the pre-pack is probably small. In these situations, we should try to include all stores, since the total benefit increases when the number of stores increases.

When the differences in demand between the stores are large, we should consider excluding the stores with low demand, since these stores experience high holding costs when they receive too many items. Therefore, they generate negative benefits and this also result in fewer items included in the optimal pre-pack. This leads to a decrease in total benefits. When there are clear underperforming stores, we should exclude them before continuing with the following step. This is only required if the optimal quantity of products included in the pre-pack would be zero if all stores receive a pre-pack. In this case, the heuristic is "locked" into a solution that does not lead to a benefit. Excluding the underperforming stores prevents the heuristic from being locked in this situation.

3.4.2. Selection of the items to be included in the pre-pack

For the selection of the items included in the pre-pack we propose an add type of greedy heuristic. If there are no capacity constraints on the pre-pack, the amount included from SKU i is independent from the rest of the SKUs. For that reason, we can optimize the SKUs one by one, with a basic search procedure. We start with including one item of SKU i in the pre-pack, then checking whether this increases the benefits. If not, we should not include this item in the pre-pack. When it increases the benefit we try to include more items of SKU i into the pre-pack. The number of items of SKU i that generates the highest increase in benefits should be included in the pre-pack. After SKU i we repeat the same procedure for the other SKUs.

If there are capacity constraints on the pre-pack, solving the problem becomes more difficult. However, a greedy heuristic can be used to solve the problem. In this case, we start with no items at all in the pre-pack. Then we calculate the benefit from including one extra item of all SKUs separately. We then include one item of the SKU that leads to the highest increase in benefits per unit. Again, we select one item of the SKU that leads to the highest increase in benefits per unit, we continue this procedure until the maximum capacity is reached or when there are no items left that give a positive benefit.

3.4.3. Selection of the set of stores

After finding the optimal composition of the pre-pack, we can use a drop type of greedy heuristic to define the optimal set of stores, by checking the benefits for each store separately. If there are stores that experience a negative benefit, we should exclude them to increase the total benefit. After the selection of a new set of stores, we often can increase the total benefits by doing several iterations. During each iteration, the optimal set of items included in the pre-pack for the set of stores is calculated, and then the optimal set of stores is calculated for the new set of items. After several iterations, the heuristic converges to a solution.

3.5. Product selection rule

Because solving the Bppp objective function takes a lot of time, especially when there are many SKUs, we derived a selection rule from the Bppp. This can be used to test whether SKUs can lead to a substantial benefit without solving the Bppp, This rule can also be used to test whether using pre-packs can lead to a benefit in specific situations, an for selecting good SKUs. We start with explaining the definitions:

C^P	Decrease in picking costs if one item is included in one pre-pack (euro/week).
C^H	Holding costs (euro/week).
N	Total number of stores.
N_0	Number of stores that do not have an increase in order-up-to level.
$E[\mu_{nopp}]$	Expected average weekly demand in the stores who do not receive pre-packs.
$\Delta I = 1$	If there is no increase in order-up-to level, $\Delta I = 0$ otherwise.

For the product selection rule, we make extra assumptions compared to the PPP objective function. We assume that a pre-pack can only contain one item of a specific SKU, note that in the Bppp objection function pre-packs can contain more items of the same SKU. However, we want to know whether a SKU should be included. If one item of a specific SKU does not lead to a benefit, the second item will definitely not lead to a benefit. Since we are only interested in whether the first item can lead to a benefit, we are only interested whether stores have an increase in order-up-to level or not. Furthermore, to estimate the holding costs we use the expected average weekly demand over all stores that do not have an increase in order-up-to level. Note that using the expected average weekly demand over all stores, to calculate the holding costs is not exact, but only an approximation. Especially when there are large differences in demand between the stores, this approximation underestimates the holding cost. In particular, the holding costs in the stores with the lowest demand rates are underestimated, and are much higher in reality. However, we assume that these stores are not included in the set of stores that receives a pre-pack if the heuristic is used to solve the Bppp objective function.

Under these assumptions, we can write the approximated Bppp objective function in the following form:

$$Bppp' = N * C^P - N_0 * C^H * \frac{\Delta I}{E[\mu_{nopp}]}$$

From this objective function, we can derive a product selection rule that should hold in order for included in a pre-pack to generate a substantial gross benefit:

$$\frac{E[\mu_{nopp}] * C^H}{C^P} > \frac{N_0}{N}$$

Note that if only a subset of the stores receive a pre-pack, the ration of N_0 over N changes. Items that are not beneficial if they are sent to all stores can be beneficial if only a subset of the stores receive a pre-pack. Therefore, this rule is not a strict lower bound. However, if an item is not beneficial if it is send to all stores it probably does not generate a large benefit if only a subset of the stores receives a pre-pack. For pre-packs to beneficial there need to be several SKUs for which the product selection rule holds. The exact number of SKUs required is dependent on the situation.

We can define two specific cases in this product selection rule:

$N_0 = 0$

In this case all stores have a decrease in order-up-to level, therefore using pre-packs always generate a gross benefit, since there is only a decrease in picking costs while there is no increase in holding costs.

$N_0 = N$

In this case there is no difference in order-up-to level between the seasons for al stores, Note that this situation not occurs in practice, because there is no significant difference in demand. However, in case the α-value is set very low it can occur that it there are almost no stores with an increase in order-up-to level.
Nonetheless, it can be that the product selection rule states that the use of pre-packs is beneficial even if there are no stores which have an increase in demand if:

$$C^P > \frac{C^H}{E[\mu_{nopp}]}$$

In this case, using pre-packs is beneficial, independent of whether there is a seasonal change or not. In this case, one should consider using the standard mixed loads concept as proposed by Teulings & Van der Vlist (2000).

At the end of the case study, we test this rule by comparing the SKUs for which the rule holds with the SKUs that are selected by the heuristic in chapter 3.4.

3.6. Application of the PPP

To test if pre-packs can be used in a real life situation, we now apply the model on a case study. In this case, study demand is slow moving and there is a considerable amount of seasonality in the demand. With this case study, we show that using pre-packs can lead to a benefit.

4. Case study: Hunkemöller

In this chapter, the PPP is applied to a real life scenario. For this purpose, the situation of Hunkemöller is used. First, in chapter 4.1 a short company introduction is given. Then, in chapter 4.2, the demand data is analyzed and appropriate distributions are fitted on the data. In chapter 4.3, a method is explained to use the fitted demand distributions to calculate the order-up-to levels. Then we test whether the use of two order-up-to levels is appropriate. Finally, to ensure that the methods and models are correct, we test them using simulation. In chapter 4.4, the PPP applied on this situation. We use the heuristic to find a good set of items and stores and test whether pre-packs can lead to a benefit. Finally, we test whether the product selection rule proposed in chapter 3.6 is a good indication whether pre-packs can be used or not.

4.1. *Hunkemöller*

Hunkemöller is founded in 1886. The company focuses on retailing its in-house designed lingerie products. Hunkemöller owns 384 stores in seven European countries (France, Spain, Denmark, The Netherlands, Belgium, Germany and Luxembourg).
Furthermore, circa 86 franchise stores are located in The Netherlands, Dutch Antilles, Russia, Egypt, Poland, Aruba, Saudi Arabia and Israel. Hunkemöller is currently market leader in terms of market share in the Netherlands, Belgium and Luxembourg.

Table 1: Number of stores

Hunkemöller			**Franchise**	
The Netherlands	141		The Netherlands	62
Germany	114		Saudi Arabia	10
Belgium	74		Egypt	5
Denmark	23		Russian Fed.	5
France	16		Dutch Antilles	2
Spain	9		Poland	2
Luxembourg	7			

4.1.1. Products

Hunkemöller sells a wide range of bras, underwear, nightwear, swimwear and accessories. Hunkemöller targets on women in the age of 18 to 49. Their products range from the middle to top segment. The products are differentiating by great fit, attractive design and seductive appeal. Three different product categories exist, based on sales performance and seasonality. These categories are; fashion (these items are sold only one period), repeat (these items are sold during one period every year) and never-out-of-stock (NOS, these items are sold during the whole year). Note that the products are sold in a range of sizes; hence, one product has multiple underlying SKUs. Only the products in the never-out-of-stock category are sold during the whole year, this category represents 28% of the total sales value. Therefore, we can only apply the pre-pack problem on the NOS category.

For NOS items there are several types of promotions; I, II and III. Most of these promotions are currently four weeks long. Furthermore, Hunkemöller uses flyers and newspapers to advertise their products. While these promotions are an essential part of the marketing mix, they increase the variation in sales, making the supply of goods more difficult and expensive.

4.1.2. Supply chain

Figure 10 gives an overall view of the supply chain. Hunkemöller controls the DC and most of the stores. Therefore, the network of Hunkemöller can be defined as a divergent 2-echelon distribution network:

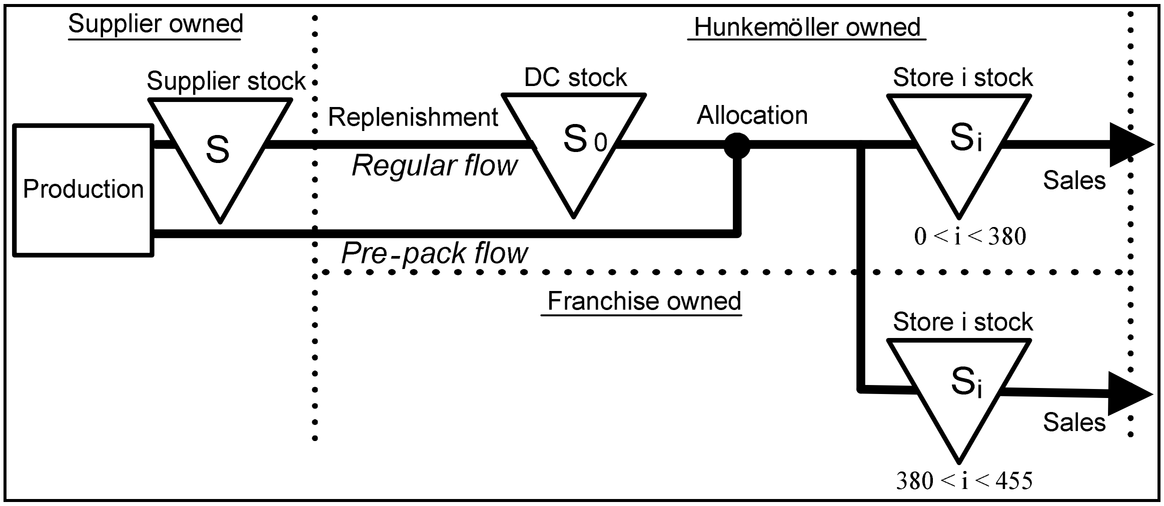

Figure 10: NOS supply chain of Hunkemöller.

The NOS items in the stores are replenished by a pull system. The stores use an (R,S) inventory policy to control the stock levels. The store inventory levels are reviewed twice a week in the Netherlands. In most other countries, the inventory levels are only reviewed once a week. Currently the order-up-to levels are based on a common time supply of seven weeks.

Most goods follow the regular flow, in which items are made-to-stock at one of the seven suppliers in Asia. Depending on the orders placed by the purchase managers of Hunkemöller, the goods are shipped to the DC in Hilversum where they are stored until they are allocated to the stores. The purchase managers can also place pre-packed orders at the supplier; these are made-to-order and cross-docked at the DC in Hilversum. This flow is used to decrease workload peaks and costs at the DC. Now this flow is only used for promotions and fashion products.

4.1.3. Store selection

To test whether the use of two different order-up-to levels can decrease costs, we only focus on a few stores located in the Netherlands. In total, there are 203 stores in the Netherlands; but we only use six stores as a sample. To get an unbiased sample, every store is randomly selected out of one of the six store groups. These groups are based on the number of BH-pins and sales of the stores.

4.1.4. Product selection

Because we focus on NOS bras, we are left with a group of 26 different types of bras that are sold in different sizes leading to approximately 700 SKU's. Management set constraint on the SKUs that could be included into a pre-pack: only different sizes of the same type of bra were allowed to be put together into one pre-pack. To decrease our workload we selected four different types of bras to test whether using pre-packs could lead to a decrease in costs. These are listed in table 2:

Table 2: Selected products

Product group	Product name	Number of SKUs
A	Bra A	22
B	Bra B	18
C	Bra C	23
D	Bra D	14

The reason for selecting these four product groups is that they represent two typical different demand patterns at Hunkemöller. The first two product groups, A and B, have a large increase in sales during the high season. The other two product groups, C and D, do not have a large difference in sales between the high and low period. However, these products show an increase in sales at the beginning and end of the high season. These peaks are caused by promotions. The graphs of appendix B shows this seasonally of these four products. This report uses sales data from 2006 until 2009, however some products are introduced after the beginning of 2006, therefore we have less sales data available. These items are D (introduced in week 17 of 2007) and B (introduced in week 1 of 2008).

4.1.5. Promotions

During the year, Hunkemöller uses several promotions. Some promotions cause large increases in sales while others do not. For the calculation of the order-up-to levels, we have to investigate which promotions need additional actions to cope with the increase in demand and which promotions do not. Only the promotions that have a significant effect on the demand, are excluded from the data, the others are kept in, so that the order-up-to level is high enough to cope with these promotions. Hunkemöller uses three promotions; I, II and III. Since the III was not executed on a regular basis, demand during this promotion was excluded. Now, the effect of the other two promotions is tested.

4.1.6. Promotion significance

Before undertaking any actions in order to cope with the effect of the I and II promotions, we test whether the demand is substantially higher during the promotional periods. First, the I promotions are analyzed:

Table 3: Effects of I promotion

Product	**Relative increase in demand during the promotion.**
A	-40%
B	-52%
C	-20%
D	0%

For the analyzed products, the sales during the I promotion are lower than during the summer season (table 3). Therefore the order-up-to levels calculated for the summer period are sufficient to use during the I promotion.

Second the test of the II promotion:

Table 4: Effects of the II promotion

Product group	Relative increase in demand during the promotion.
A	36%
B	10%
C	120%
D	83%

According to table 4, product group A and B experience a small increase in sales during the promotion; therefore, the store order-up-to levels calculated for the summer are sufficient to reach the service constraints. We include these promotional periods in the simulation in order to ensure that this assumption is correct. For product groups C and D which have an increase in sales of respectively 120 and 83 percent it is most likely that some additional actions have to be undertaken to ensure that the service constraints is reached. However creating methods to do so is not part of this thesis.

4.1.7. Lead-times

All Hunkemöller stores that are located in the Netherlands are replenished two times a week. For half of these stores, orders are automatically generated at the end of each Sunday and Tuesday. For the other half, orders are generated at the end of Monday and Wednesday. After the orders are generated the orders are picked, this process takes one day. The next day the goods are transported to the stores. At the same day, the goods arrive in the store where they are unpacked and placed in the store and backroom. It can happen that there is no time to unpack the goods the same day, in that case goods are unpacked the next morning. Nonetheless, we still assume that the total replenishment lead-time (L) is approximately 2 days. The length of the review period (R) is depended on whether it is the first or second replenishment during the week, and is respectively 5 or 2 days. This leads to a total lead-time and replenishment period (R+L) of 7 days or 4 days. However, for the ease of calculation we use a (R+L) of 7 days. Outside of the Netherlands, the lead-times and review periods are longer; the differences in lead-time should be taken into account when calculating the order-up-to levels for these stores.

4.2. Demand analysis

In order to get insight into the sales data, we analyzed the average weekly sales at store/SKU level of the six stores and the four product groups that contain 77 SKUs in total. This created a sample size of 462 store/SKU combinations. In the histogram (figure 11), store/SKU combinations are grouped depending on the average weekly sales. The histogram shows the percentage of store/SKU combinations which fall into a specific group. Note that we excluded weeks that had a negative sales value (more returns than sales) and used year-round data since 2006 until the end of 2009.

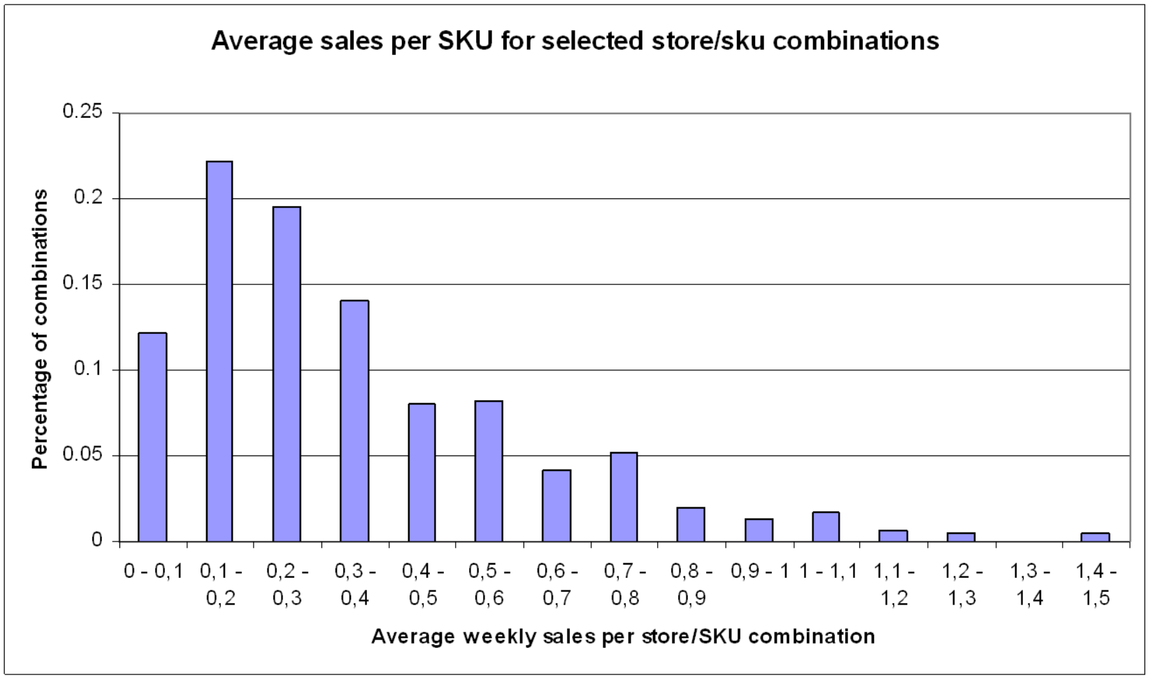

Figure 11: Average sales in the selected stores.

Figure 11 shows that all items are slow moving, around 75% of the store/SKU combinations have average sales that are less than 0.5 items per week. Furthermore, only 3% of the store/SKU combinations have an average weekly sale above one.

4.2.1. Significance of the difference between seasons

Because Hunkemöller assumes the demand of many products depend significantly on the season, Hunkemöller currently uses two different order-up-to levels for each product depending on the season. Before assuming that two order-up-to levels are required, we first have to determine whether the difference in demand between the two seasons is large enough to require two different order-up-to levels. Table 5 shows the average increase in demand during the high season

Table 5: Difference in demand between the seasons

Product group	Relative increase in demand during the high seasons
A	110%
B	326%
C	77%
D	37%

All product groups show a clear increase in sales during the high season, ranging from 37% until 326%. Based on these differences we assume that, for at least some of the underlying SKUs, two different order-up-to levels are required. In the remainder of this report, we show the difference in inventory holding costs between one or two order-up-to levels and make a decision whether two order-up-to levels are required.

4.2.2. Fitting a distribution on the data

Fitting the normal distribution on our data is inappropriate, because demand experiences a high coefficient of variation during the lead-time, and because the actual distribution is discrete instead of continuous. Therefore, we use the method described by Adan et al. (1995) to fit an approximately equal analytical discrete distribution on the first two moments of the actual distribution. Adan et al. created a method to fit a discrete analytical distribution based on the first two moments. These first two moments (mean and standard deviation) can be derived from the historic sales data. Depending on the combination of the mean and the coefficient of variation, this can be derived from the mean and standard deviation. One of four distribution classes can be applied: Mixtures of Binomial, Poisson, Mixtures of Negative-binomial or Mixtures of Geometric. The calculations for fitting the analytical distribution on the first two moments of the historic sales data is discussed in the appendix A.

Figure 12 shows the demand distribution for the six stores and four product groups graphically. Four different areas and their according analytical distributions are also depicted. Note that only the demand during the summer period is analyzed; items that had no sales during the summer were excluded. Furthermore, the graph is cutoff at Cx^2 25 for readability reasons; therefore, 7 points fall outside the range of the graph:

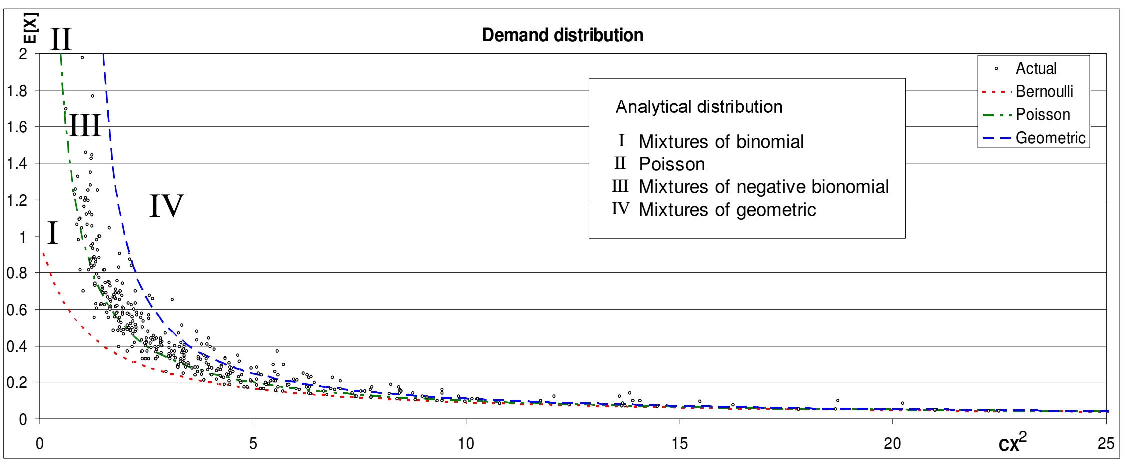

Figure 12: The four classes of distributions used to match the first two moments of the demand data.

4.2.3. Assumption of Poisson distributed data

While the method of Adan et al. (1995) is accurate, using it in the situation of Hunkemöller creates practical problems. Cleaning the data, finding the mean and standard deviation for each store/SKU combination, fitting the correct distribution and then using these distributions to calculate the order-up-to levels is a lot of work to do for all SKUs when Hunkemöller would use this method. Obviously, this can be automated, however this is costly and it is difficult to convince the planners that the calculated order-up-to levels are correct. Therefore, we should consider the assumption that the demand is Poisson distributed. The advantage of this assumption is that only the average demand is required to characterize the distribution. This makes it easier for use in practice. According to Silver et al. (1998) such an assumption is appropriate when the variation during lead-time (σ_{L+R}) is within 10 percent of the square root of the demand during the lead-time ($\sqrt{E(X_{L+R})}$). For our sample, the σ_L is on average 6.42% higher than $\sqrt{E(X_{L+R})}$.

Looking at the 462 separate store/SKU combinations, 67% falls in the -10% until 10% region (figure 10). Therefore, we assume that the Poisson distribution is accurate enough to use when calculating the order-up-to levels. However, to test the assumption we compare the order-up-to levels calculate under the assumption of Poisson distributed demand with order-up-to levels that are based on the method of Adan et al.

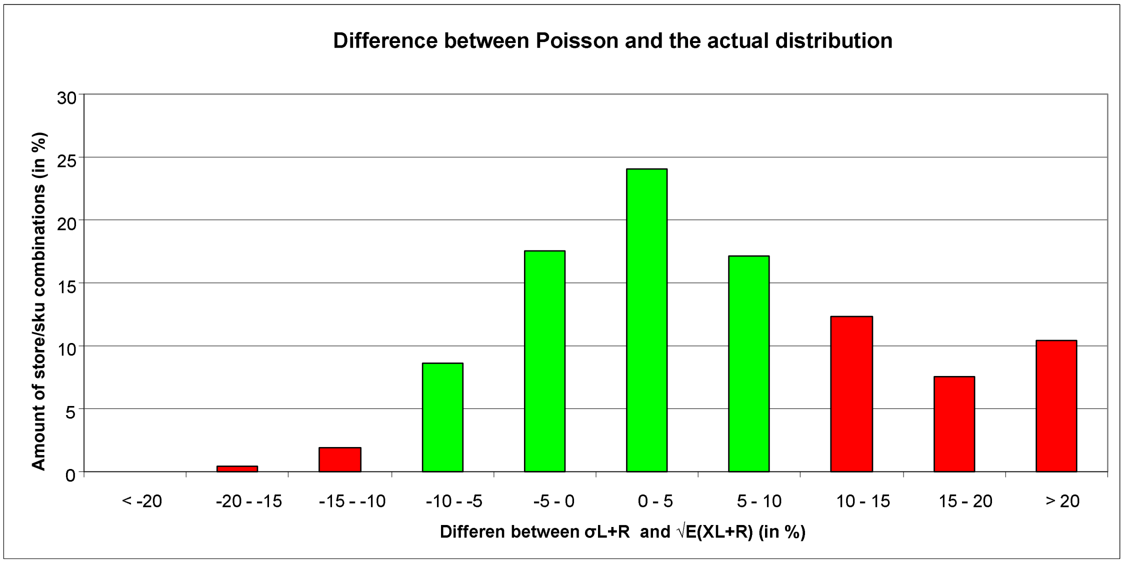

Figure 13: Difference between actual and Poisson distribution.

4.3. Order-up-to levels

We now calculate the order-up-to levels, starting with explaining the method, and then we calculate the order-up-to levels for the selected stores and SKUs. Then we simulate the inventory system to ensure the methods and models are appropriate. After this step, we test whether the use of two order-up-to levels is appropriate by calculating the difference in average inventory between a policy with one and two order-up-to levels.

4.3.1. Calculation method

Hunkemöller aims at having a positive inventory at the stores during 97% of the time, while minimizing the inventory levels. This service measure is also known as the ready rate (Silver et al., 1998). Because the calculation of the ready rate requires a huge amount of effort we use the fill rate instead, this service measure is identical to the ready rate if the demand is Poisson distributed (Silver et al., 1998). The demand at the Hunkemöller stores differs to some extend from the Poisson distribution, so probably it is a small difference between the ready-rate and the fill-rate, with a simulation model we can determine the ready rate so we can compare the different methods on the service measure. In order to calculate the order-up-to levels of the stores we make several assumptions:

- The DC has a service level of 100%. In reality, it is 97-98%, but in situations with such high service levels, the DC has limited effect on the service of the store.
- The lead times from the DC to the store are fixed.

- The historic sales data is a good approximation of the actual demand.

- Shortages are backordered because lost sales systems are difficult to calculate. In reality, most shortages result in lost sales, however the difference in performance of a lost sales and backorder system is small at high service levels.

- The demand is discrete, stochastic and the average changes little during the season.

- Periodic review inventory control.

As discussed earlier the method of Adan et al. (1995) fits one of four types of analytical discrete distributions on the demand data. There are no simple methods to calculate the fill rate based on these distributions. Therefore, the demand distributions are used to calculate the fractions of occurrences of weekly sales quantities. With these probabilities, the fill rate can be calculated for backorder systems with the following formula. This formula is to a large extend similar to the one of Donselaar and Broekmeulen (2009); however, they also include the effects of case-packs.

$$Fillrate(s) = \frac{1}{\mu_R}\left(\sum_{d=1}^{d=\infty}\max(d-s,0)*pr(D_{L+R}=d) - \sum_{d=1}^{d=\infty}\max(d-s,0)*pr(D_L=d)\right)$$

Where,

d	Value in the range of the demand distribution.
s	Order-up-to level.
D_{L+R}	Demand distribution during lead-time + review period.
D_L	Demand distribution during lead-time.
μ_R	Demand rate during the review period.

Under the assumption that the demand is Poisson distributed, the fill rate is only depended on the order-up-to level, the length of the lead-time and review period and the average demand. It is independent from the standard deviation of the historic data since the Poisson distribution assumes that the standard deviation is equal to the square root of the mean. Therefore, we can display the fill rate graphically for all stores in the Netherlands (because they all have a review period and lead-time of ½ a week). We used the same formula to calculate the fill rate under the Poisson assumption as we used for calculating the fill rate with the method of Adan et al. (1995).

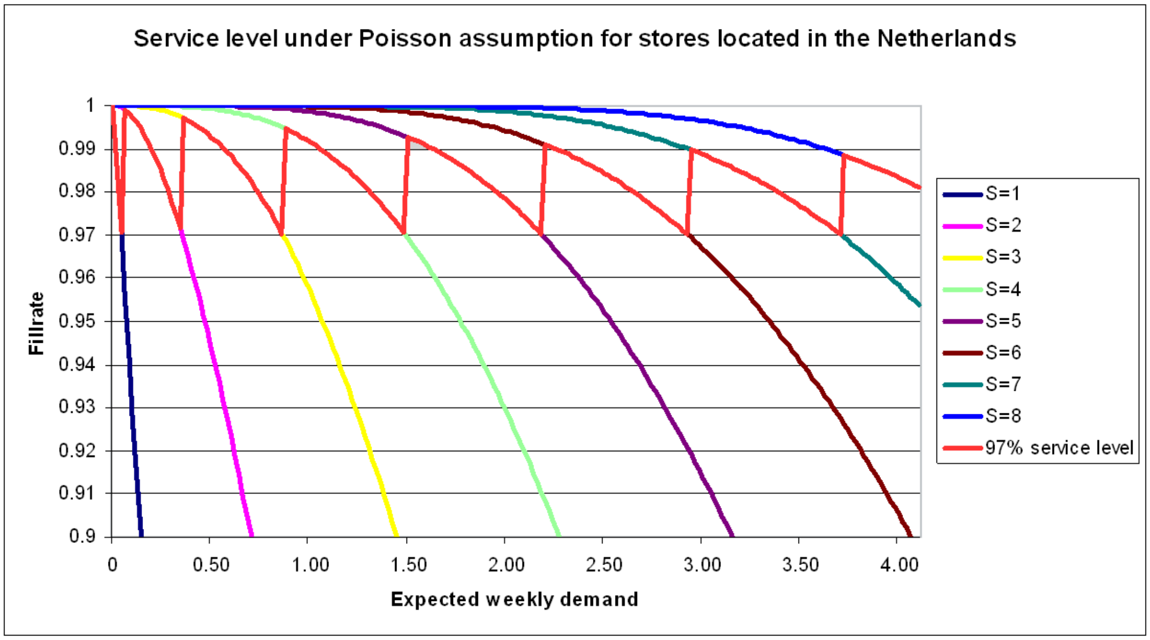

Figure 14: Service level under the Poisson assumption.

In table 6 below we show the average order-up-to level calculated for the high and low season four the different products groups, this is based on the actual data. Furthermore, the table also shows the percentage difference between these two order-up-to levels:

Table 6: Average order-up-to level for different order-up-to policies and product group

Product group	Current			Adan et al.			Possion		
	High	*Low*	*Percentage difference*	*High*	*Low*	*Percentage difference*	*High*	*Low*	*Percentage difference*
A	3,89	1,86	52	3,45	2,3	33	2,83	2,18	23
B	3,82	1,56	59	3,06	1,83	40	2,74	1,94	29
C	2,77	1,54	44	3,04	1,89	38	2,52	1,96	22
D	2,57	2,02	21	2,64	2,07	22	2,43	2,26	7
Average	3,26	1,75	46	3,05	2,02	34	2,63	2,09	21

During the low demand periods, the average order-up-to level for the Adan et al. and Poisson method is approximately equal and slightly higher than the current method. However, during high demand period the current method proposes to places more inventory in the stores than the Adan et al. and especially the Poisson method. The difference in average order-up-to level between the Adan et al. and Poisson method is due to a group of very-slow moving items that experienced a lot of variation in the data set; this variation is cause by the relative small sample size. Since the Adan et al. method incorporates the variation it proposed higher order-up-to levels than the Poisson method. To properly apply the method of Adan et al. at the extremely slow moving items, a more accurate reading of the variation is needed, therefore more data is required. However, demand changes over time therefore using data from earlier years is inappropriate, furthermore it is not available for most products.

The difference in order-up-to levels is the highest for the current method. The Adan et al. method and especially the Poisson method show smaller differences in order-up-to levels between the seasons.

Note that because these methods show smaller differences between the seasons the need for pre-packs decreases, since the peak at the DC decreases. Furthermore, the optimal quantity included in the pre-packs becomes smaller when the difference in order-up-to level becomes smaller, which decreases the possible benefits that can be gained from the use of pre-packs.

4.3.2. Simulation results

The order-up-to level calculation methods assume that the demand remains equal over the horizon. To test how the policies would behave in a real life situation, we developed a simulation model, see appendix C. The simulation model is the most accurate since the two different review periods are included; in addition, it is a lost sales system like the real situation and not a backorder system as assumed by the model. Furthermore, Hunkemöller tries to measure the ready rate by dividing the total amount of SKUs that have a net stock of zero at the end of the day by the total amount of SKUs. In the simulation model, we use the same method to calculate the ready rate. While the simulation is more accurate than the proposed calculation method, the service level of the DC is still not taken into account. However, we assume that because the service level at the DC is high (above 97%); therefore, it only has a minor impact on the store service levels. Since the simulation takes a lot of time (5 minutes per store/SKU/set of order-up-to levels), we randomly selected 20 store/SKU combinations from each product to simulate. From the simulation we derived three performance indicators; the ready rate, the fill rate and the average sales. For product group C and D we argued that the promotions required additional actions to achieve the required service level, therefore we excluded the promotions for the simulations for these two products. For the other two methods, we kept the promotions in when the demand was simulated. The average simulation results of the 20 simulations for each product group are depicted in table 7:

Table 7: Simulation results for the order-up-to level policy.

Product group	**Current**			**Adan et al.**			**Poisson**		
	Ready rate	*Fill rate*	*Average stock*	*Ready rate*	*Fill rate*	*Average stock*	*Ready rate*	*Fill rate*	*Average stock*
A	97.7	97.8	2.79	99.0	98.3	2.84	98.9	97.0	2.33
B	98.9	99.2	3.91	98.7	97.4	2.66	98.9	97.3	2.35
C	97.1	97.5	2.38	99.2	99.0	2.68	99.3	98.1	2.26
D	99.5	97.5	2.34	99.3	99.0	2.60	99.3	98.1	2.20
Total	**98.3**	**98.1**	**2.86**	**99.0**	**98.3**	**2.70**	**99.1**	**97.6**	**2.29**

On average, all methods realize the required ready rate of 97% and a fill rate of 97% for each product. Note that for the Adan et al. and Poisson method we expect the simulation to be substantially higher than 97%, which is the case. This is because we set order-up-to levels that would lead to at least 97% fill rate for each SKU. Furthermore, the first part of the low season the service is higher than calculated since the inventory only slowly decreases to the lower order-up-to level. Both the Adan et al. and Poisson method realize a +97% ready rate with less average stock than the current method, -0,16 for Adan et al. and -0,57 for Poisson. Note however that the Adan et al. method reaches a higher fill than the Poisson method and even larger than the current method. Our aim was to realize a ready rate of at least 97% with the least amount of stock. The Poisson method achieves this with the lowest amount of inventory. Furthermore, the system control costs for this method are lower than for the Adan et al. method. For the calculation of pre-packs, we use the Poisson method to set order-up-to levels.

4.3.3. Requirement of two order-up-to levels

As discussed in chapter 3, the reason for using two order-up-to levels is the decrease of inventory holding cost during the low season. We now test whether using two order-up-to levels can lead to a substantial decrease in costs. We assume that if we only use one order-up-to level, we use the one calculated for the high season, since only this order-up-to level ensures a 97% service level during the whole season. Since we have a service measure criterion and we assume that the handling costs are unaffected by the order-up-to policy, the relevant costs are only dependent on the average inventory level. Table 8 shows the difference in demand and the decrease in order-up-to level for the selected stores and SKUs. We compared the simulation average inventory levels of the 80 SKUs stores with two-order-up-to levels, with a policy using only one order-up-to level. The average inventory for the one order-up-to level policy is calculated with the following formula:

$$I_{avr} = S_H - \frac{\mu_{avr} * (L+R)}{2}$$

Where,

I_{avr} Average inventory.

s_H Order-up-to level during the high season.

L+R Average lead-time + review period.

μ_{avr} Average demand.

We compared the results of this formula with the simulation model that was also used to test the effects of the two order-up-to level policy. The absolute error was only 1,35% therefore; we assume this formula to calculate the average inventory is accurate.

Table 8: Effects of using two order-up-to levels on average inventory

Product	Relative difference in demand between the high and low seasons	Decrease in order-up-to level during the low season	Decrease in average inventory
A	110%	22,7%	10,7%
B	326%	29,1%	11,9%
C	77%	22,4%	5,6%
D	37%	6,9%	4,2%

Note that the average decrease in inventory created by the use of two order-up-to levels is only approximately one-tenth of the relative difference in sales between the seasons. This is because the required order-up-to levels are not linearly related to the demand. Furthermore, decreasing the order-up-to levels does not directly decrease the inventory level: this decreases only when demand occurs. Nonetheless, the use of two order-up-to levels can decrease average inventory significantly for all products. Note however that a small part of this benefit is used for extra system control costs, because of the extra time it takes to set the inventory levels twice a year.

4.4. Pre-packs

We now focus on the use of pre-packs for the four different products. Therefore, we first calculate the average sales during the high and low season for each store/SKU combination. Note that we excluded all stores that did not sell one item of the whole product group during a period that is longer than 10 weeks. Based on this we calculated the order-up-to level for each size/store combinations during both seasons, since the Poisson method worked best in the test we used this to set order-up-to levels. In total, we did this for around 400 stores. However, we noticed that there was a group of stores that showed poor sales performance. If we included all the stores for product group C and D the optimal quantity of items included in the pre-pack is zero, therefore we removed stores with the lowest sales value until a pre-pack could lead to a benefit. Now we applied the pre-pack model of chapter 3.3 to estimate the cost effects of using the pre-pack. We assumed carrying charge of 20% and the product price ranged from €17,99 until €22,99. Furthermore, picking costs were estimated on €0,12 per item. Since the products that are included in the pre-pack are small and lightweight we have no capacity constraint, therefore we could use the simple search procedure. We used the add type of greedy heuristic for the items and drop type of greedy heuristic for the stores of chapter 3.4 to find a solution. After several iterations, we converged to a solution.

Next to the holding costs included in the pre-pack model, there are also system control, cross-docking and supplier costs. These have to be subtracted from the benefits after the optimal composition is found. In the case of Hunkemöller, the suppliers were willing to deliver in pre-packs without charging extra costs. The costs of cross docking the pre-pack are the number of stores who receive a pre-pack multiplied by €0,12. An estimation of the system control costs is difficult. We assume that without any steps automated, it would take between 1 and 2 hours extra per product group for the planner to order pre-packs instead of single items. This would result in approximately €50.-. Table 9 shows the results:

Table 9: Composition and benefits of pre-packs

Product group	Number of items in the pre-pack	Number of stores	Expected gross benefit (euro)	Other costs (threshold level)	Expected net benefit (euro)
A	18	181	210,93	71,72	139,21
B	17	318	434,35	88,16	346,19
C	9	121	73,24	64,52	8,72
D	8	139	59,43	66,68	-7,25

For two product groups with a large seasonal effect (A and B) pre-packs could lead to a significant net benefit. For the other two product groups that experienced less seasonality

(C and D) using pre-packs could not lead to a significant benefit. For these product groups the number of units included in the pre-pack and number of stores that receive a pre-pack was smaller.

Next to the cost benefit, the pre-packs also decreased the workload at the DC. For product group A the picking workload decrease with 3077 items, this is equal to the average workload of product group A during 1,4 weeks. For product group B the picking workload decrease with 5406 items, this is equal to the average workload of product group B during 1,9 weeks.

While the use of seasonal pre-packs can lead to a benefit, the implementation of seasonal pre-packs is not free of costs. However, Hunkemöller already uses pre-packs for promotions and fashion products, therefore, their supply chain is already able to cope with pre-packs. Consequently, only the new calculation method leads to implementation costs. The models we created in Excel during this research are almost ready to implement at Hunkemöller after instructing the planners. Therefore, we assume that the total implementation costs are low and can be retrieved within one year.

4.4.1. Effect of the number of stores

After decomposing the pre-pack model in chapter 3.4, we argued that there would be an optimal number of stores to include in the pre-pack and including more (slow-selling) stores would decrease the maximum benefit. For the product group B we tested this by calculating the optimal pre-pack for all possible numbers of stores. To do this we used the same add type of greedy heuristic for the SKU and a drop type of greedy heuristic for the stores. However, instead of removing all stores that created a negative benefit, we removed the stores one by one, starting with the stores that generated smallest benefit. After removing each store, we tested whether including extra items in the pre-pack could increase the benefit. Figure 15 shows the results.

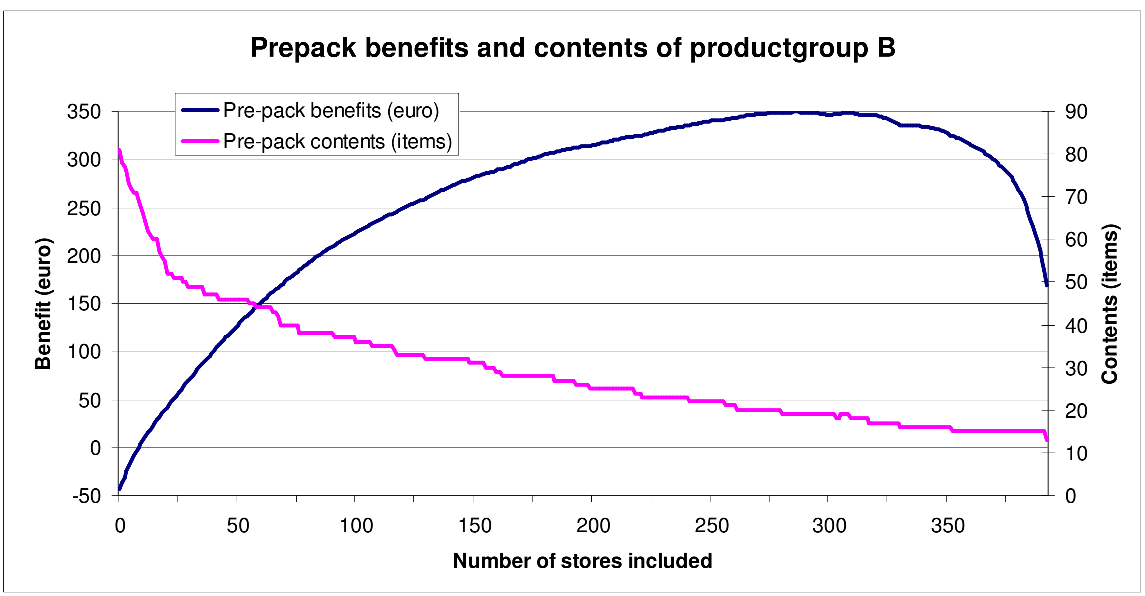

Figure 15: Pre-pack benefits for product group B with different number of stores

The graph clearly shows that there is an optimal amount of stores to be included, which is 288 in this case, which lead to a net benefit of € 349,36. Including more stores decreases the benefits. Note that this optimal amount of stores and the benefit slightly deviates from the optimal amount found by the heuristic (318 stores and €346,19). However, this difference in benefit is small. Therefore, the solution seems to work well. Furthermore, the model seems robust, small deviations from the optimal number of stores have almost no effect on the gross benefit. Furthermore, the graph also shows that if much more stores are included (or excluded) the optimal content of the pre-pack becomes less. In an extreme case, (which we encountered with product group C and D) when all stores are included the optimal quantity included in the pre-pack and the gross benefits are zero. Therefore step one of the heuristic, which is removing the under-performing stores from the set was required; otherwise the heuristic becomes "trapped" in a situation with all stores included and no items in the pre-pack.

4.4.2. Test of the product selection rule

In Chapter 3.5, we proposed a rule to select the SKUs to put in a pre-pack. So far, we have not used this rule in the case study. Now we compare the SKUs for which the rule holds with the items included in the pre-packs. We tested the rule on all the SKUs. Each SKU for which the rule hold was also selected by the heuristic, however, there were also some SKUs for which the rule did not hold which were selected for the pre-pack, see table 11.

Table 10: Product selection rule test results

Product group	SKUs include in the pre-pack, for which the rule holds	SKUs include in the pre-pack, for which the rule did not hold	Percentage of gross pre-pack benefit gained if the rule is used
A	9	4	88%
B	11	0	100%
C	2	7	52%
D	3	9	64%

Both product groups A and B lead to significant pre-pack benefits, these product groups contained many SKUs for which the rule holds (9 and 11). Furthermore, the pre-pack for product group B did not include any SKUs for which the rule did not hold, the pre-pack for product group A did contain four SKUs for which the constraint did not hold. We also calculated the gross benefits with only the SKUs selected by the rule in the pre-pack, for product group A this would decrease the gross benefits by 12%, and for product group B there is no difference.

Product group C and D did not lead to a significant pre-pack benefit. These product groups contained only a few SKUs for which the rule holds (2 and 3). In this case, many SKUs for which the rule did not hold were included, because the heuristic converged to a solution where only a small subset of the stores was included. For product group C and D we also calculated the gross benefit of pre-pack if only SKUs selected by the rule were included. Note that, according to the rule, using pre-pack is not be beneficial because there are only 2 or 3 SKUs for which the rule holds. According to the product selection rule, pre-packs are only beneficial if there is a substantial amount of SKUs for which the rule holds. Nonetheless, we use the selected SKU to create a pre-pack, in these two cases the gross benefit would decrease by 48 and 36%.

Based on these results we can say that the selection rule is effective in selecting SKUs and product groups that are appropriate to put in pre-packs in this case study. None of the SKUs for which the rule did not hold, lead to a significant benefit and all SKUs for which the rule holds were included in the pre-pack. Furthermore, only for the product groups which had a large number of SKUs for which the constraint hold (A and B), a pre-pack could be composed which lead to a significant benefit. Further research has to confirm that this selection rule would also work in other situations.

5. Conclusion

In this chapter, the conclusions are presented first, and then the recommendations for the company are given. Finally, the limitations and directions for future research are highlighted.

5.1. Conclusions

Based on the research a number of conclusions were derived:

- Using two order-up-to levels can decrease the average relevant costs substantially, however only in situations where the demand during the seasons substantially differs.
- The method to calculate the order-up-to levels can have a large impact on the difference in order-up-to level between the seasons, and therefore they have a large effect on the benefits of pre-packs.
- The case study shows that the proposed pre-pack model can lead to savings and a significant decrease in workload at the DC
- The case study shows that there is an optimal amount of stores that receive pre packs. Therefore, a set of stores that receives a pre pack should be determined instead of selecting all stores.
- The case study also gives evidence that the product selection rule works, since it was able to select only the SKUs that created larger benefits.

5.2. Recommendations

For Hunkemöller the following is recommended:

- A good method to calculate the order-up-to levels can decrease average inventory levels. The proposed method, under the assumption of Adan et al. or Poisson, outperforms the current "equal time supply" method. Because the Poisson assumption is easier to use and implement, it is better to use in this situation.
- During this research, the aim was to reach a 97% service level (ready rate) in the stores. With the new method, we achieve this service level for all items. However, we argue whether having one service level for all items is appropriate. A better rule would be to set different service levels for slow moving and faster moving items.
- Currently, the stores are grouped and for that group of stores the order-up-to levels are calculated. When order-up-to levels are calculated for each store separately, the same service levels can be attained with less inventory.
- With the use of order-up-to levels calculated under the Poisson assumption the same service levels can be attained with even less inventory, furthermore the season changeover effects are decreased with approximately two-third.
- With the use of seasonal pre-packs a benefit can be gained, furthermore the peak load at the DC is decreased significantly, which would enable the DC to handle a larger group of stores in the future.

5.3. Research limitations and areas for future research

This research is the first that investigates the use of pre-packs for seasonal products to preload the high season. In this research, a model is developed for calculating the benefits of using a composition of pre-packs and this is applied to a case study. This research provides confirms that the use of pre-packs to preload stores at the start of the high season can decrease costs. While this research covers a large part of the use of pre-packs, it also has its limitations. These limitations need to be addressed in future research in order to really grasp and use pre-packs to the fullest potential.

- In this research, the model is applied to only one situation, applying it to other situations gives a better understanding about the situation in which pre-packs can be beneficial. Furthermore, applying it to other situations can provide more proof that our product selection rule, proposed in chapter 3.1 works good in general.
- Although the optimal composition is calculated, it is not actually implemented during this research. All decisions that need to be taken during implementation, like the moment of ordering, cross docking, and the cost of implementation need further research.
- The proposed model to calculate the order-up-to levels assumes that the demand is equally spread over all days of the week, in reality this is not the case. This effect of this should be tested.
- The pre-pack model uses the expected demand and a fixed picking cost per item, especially this last assumption needs more consideration.
- We did not discuss the builddown of inventory at the end of the high season in detail; further research is needed to find a good method to do so.
- In our heuristic, a store can only receive no pre-packs or one pre-pack. In some situations with large differences between the stores, it might be beneficial to expand the model to allow stores to receive more than one pre-pack. However, this makes solving the model more difficult.

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Appendix A: Adan et al. approximation method

Calculation in order to fit an analytical discrete distribution on the first to moments of demand.

$$C^2x = \left(\frac{\sigma}{EX}\right)^2$$

The distribution is a mixture of Binomial if:

$$\frac{1}{C^2x+1} \le EX < \frac{1}{C^2x}$$

The distribution is Poisson if:

$$EX = \frac{1}{C^2x}$$

The distribution is a mixture of Negative-binomial if:

$$\frac{1}{C^2x} \le EX < \frac{1}{C^2x-1}$$

The distribution is a mixture of geometric distributions with balanced means if:

$$EX > \frac{1}{C^2x-1}$$

$$\alpha = C^2x - 1/EX$$

If $1/(k+1) \le a \le 1/k$ for certain k = 1,2,3,….., demand is Negative-binomial

Where,

then

$$Y = \begin{cases} NB(k,p) & with\ \ probability\ q. \\ NB(k+1,P) & with\ \ probability\ (1-q). \end{cases}$$

Where,

$$q = \frac{(1+k)a - \sqrt{(1+k)(1-ak)}}{1+a}$$

And,

$$P = \frac{EX}{k+1-q+EX}$$

The negative-binomial distribution is described by:

$$pr(D=x)=\binom{x+k-1}{k-1}(1-p)^x P^r$$

If $a \geq 1, then$ demand is geometric.
Where,

$$Y=\begin{cases} GEO(p1) & with\ \ probability\ \ q1 \\ GEO(P2) & with\ \ probability\ \ q2 \end{cases}$$

Where

$$q1=\frac{1}{1+a+\sqrt{A^2-1}}$$
$$q2=\frac{1}{1+a-\sqrt{A^2-1}}$$

And,
$$p1=\frac{EX\left[1+a+\sqrt{a^2-1}\right]}{2+EX\left[1+a+\sqrt{a^2-1}\right]}$$
$$p2=\frac{EX\left[1+a-\sqrt{a^2-1}\right]}{2+EX\left[1+a-\sqrt{a^2-1}\right]}$$

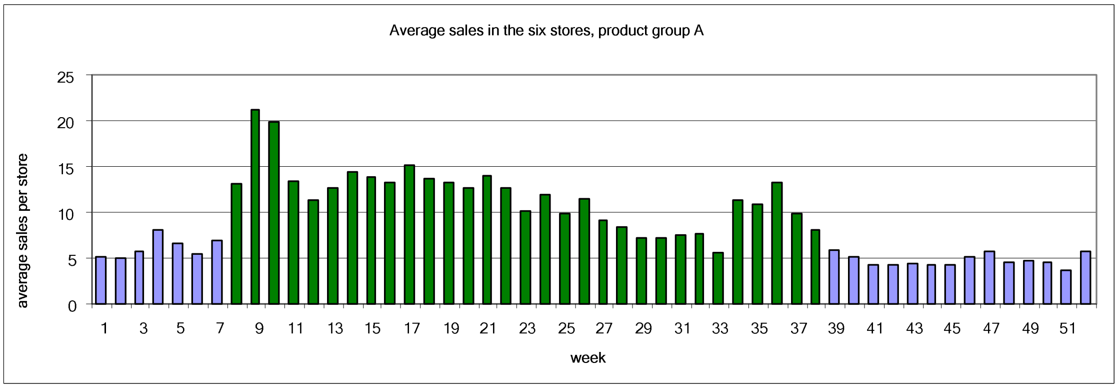
The geometric distribution can be described by:

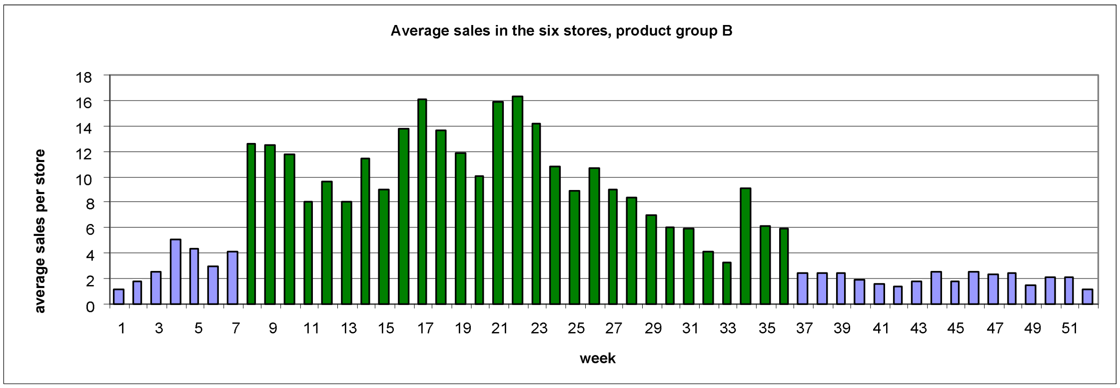
$$pr(D=x)=(1-p)p^x$$

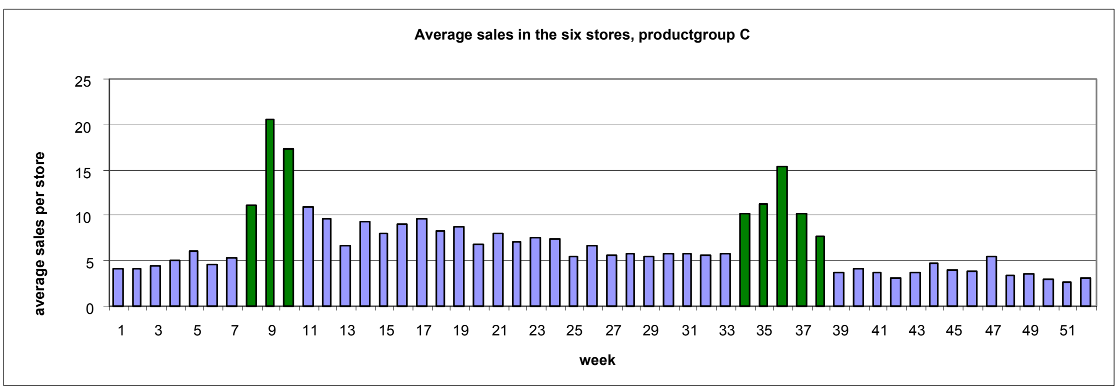
If $-1/k \leq a \leq -1/(k+1)$ for certain k=1,2,3…., then
$$y=\begin{cases} BIN(k,p) & w.p.\ q \\ BIN(k+1,p) & w.p.\ 1-q \end{cases}$$

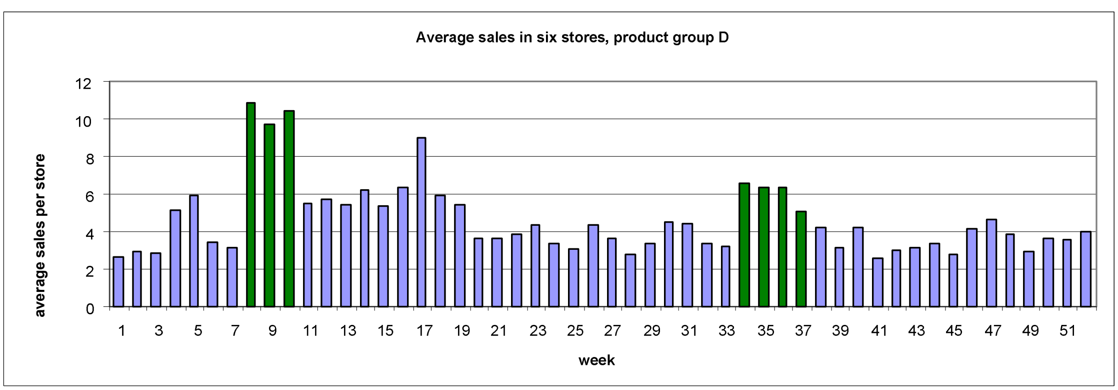
Where,
$$q=\frac{1+a(1+k)+\sqrt{-ak(1+k)-k}}{1+a}$$
And:
$$p=\frac{EX}{k+1-q}$$
The binomial distribution can be described by:
$$pr(D=x)=\left(\frac{n}{x}\right)p^x(1-p)^{n-x}$$

Appendix B: Seasonality of the six selected products









Appendix C: Simulation model

To test the performance of the two order-up-to policy, a simulation model is developed in Excel with the use of the @risk 5.5.

This model simulates the daily demand, for this purpose we divided the year into three periods, 2+1 promotion, summer and winter. For each of these periods derived an analytic discrete demand distribution with the use of historic data and the method of Adan et al. (1995). This demand distribution was used to simulate the daily demand.

The inventory was modeled in the following way; each day started with an initial inventory level that was equal to the inventory level that is equal to end inventory level of the previous day. Then the demand simulated for that day was subtracted. Because it is a lost-sales system, the inventory level was set to zero and the lost sales were recorded separately if demand was higher than the inventory level. After the demand is subtracted, new items are ordered. The order quantity is equal to the difference between the order-up-to level and the inventory level. Depending on the period, there are two different order-up-to levels, one week before the season change the new order-up-to levels from the coming season were used. Two days after ordering the goods are received at the end of the day. Therefore, the inventory level was increased with the order quantity.

Three performance indicators were recorded; ready rate, which was measured as percentage of days at which the inventory was positive at the beginning of the day, the average inventory at the beginning of the day, and the fill rate. The fill rate was calculated as 1- (number of lost sales divided by the average demand). For calculating the average fill rate for the product groups, we used the following formula:

$$averagefillrate = \frac{\sum_j fillrate_j * yearlydemand_j}{\sum_j yearlydemand_j}$$

For product groups C and D we assumed that there was a large increase in demand during the promotions that needed extra action. We excluded these from the simulation. For the other product groups A and B, we did include the promotions, during the promotions the order-up-to levels were at the high level.

To ensure the simulation model was correct we visually tracked the simulation during a few simulations to ensure it works properly. Furthermore, we did several test runs with no difference in demand between the seasons; the simulated results were approximately equal to the fill rate calculated with the method of chapter 3.4.1.

The run-in period of the simulation is 1 year, 2 years are simulated and recorded, 1.000 iterations were executed to ensure the results were stable. To test ensure 1.000 iterations are enough we used the results of the first simulation to calculate a confidence interval.
To calculate the confidence interval we used the method discussed by Law and Kelton (1991), the results are depicted in table 11.

Table 11: Confidence intervals of the simulation test run

Average ready rate	Confidence interval on the ready rate	Average fill rate	Confidence interval on the fill rate	Average inventory	Confidence interval on the inventory
99,153%	±0,040%	99,213%	±0,058%	3,285%	±0,016%

These confidence intervals are small enough for our use.