MASTER

Promotion process in grocery supply chains at Sligro Food Groups N.V.

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Promotion process in Grocery Supply Chains at Sligro Food Group N.V.

by

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Abstract

In this master thesis it is described how the promotion process of EMTÉ can be improved. The current promotion process is inaccurate and results in unnecessary costs and lost sales. The promotion process in this research is split into two main research areas; forecasting of promotional sales and distribution of promotion products. To improve the current way of forecasting a mathematical forecasting model is developed based on multiple regression. Although a mathematical forecasting model can lead to a quite accurate demand forecast it remains difficult to forecast promotional sales. In order to react quickly on discrepancies between forecasts and actual sales during a promotion week a flexible distribution model is required. In this master thesis a flexible distribution model is developed to distribute promotion products based on early sales information. This model is able to distribute promotion products equally over all stores in the supply chain which can result in a substantial cost saving.

Management Summary

This research is directed at the promotion process of the food retail division of the Sligro Food Group: EMTÉ Supermarkets. In the last decades the promotion process has grown in importance due to fierce competition in the Dutch food retail market. At the moment promotional sales account for 17,5% of all sales of EMTÉ. It is expected that this promotional pressure will rise soon above 20%. The management team of EMTÉ noticed this trend, and realized that the current promotion process has to be reconsidered.

Problem definition

The performance of the current promotion process of EMTÉ is insufficient. The process is costly and EMTÉ is losing a serious amount of sales. Returned packages from the stores to the distribution centers (DC's) after a promotion week constitute a significant part of the unnecessary costs that are made. Based on a qualitative analysis two root causes are identified. The first root cause is the way in which the forecasting of promotional sales is organized. Too many stakeholders are involved in making forecasts which are to a large extent based on experience. The second root cause lies in the distribution mechanism that is used to distribute promotion products. Most promotion products are distributed in one delivery from the DC's to the stores which leads to inflexibility. Next to this, the order behavior of store managers disturbs the distribution of promotion products.

To assist EMTÉ in redesigning the promotion process the major attention of this research is put on the development of a new distribution mechanism. As a result the following research question has been investigated: *How can the current distribution and control mechanism of promotion products be improved considering both costs and lost sales?*

Distribution model and testing scenarios

In this research a flexible distribution model is developed in which promotion products are distributed in two deliveries from the DC's to the stores. To analyze how these deliveries should be determined, the setting of two decision variables is tested:

1. The setting of the aggregation level on which decisions are made

This research is conducted in a multi-product environment. The setting of the aggregation level is tested to investigate if it is possible to make different distribution decisions for different product groups. Two aggregation levels are tested: store level and store-product group level.

2. The setting of the coordination mechanism of the second delivery

It is unclear if the second delivery of promotion products should be coordinated at the stores (decentrally) or at the DC's (centrally). To test a decentral coordination store managers are actively involved in this research. The central coordination is based on an early sales forecast. In this forecast customer demand in the end of the promotion week is forecasted based on the first two sales days.

To test the different scenarios two input parameters are varied: the amount of promotion products that are sent to the stores in the first and in the second delivery. The effects of these parameters are evaluated against two performance measures: the costs of returned packages and the costs of lost sales. Basically, there exists always a trade-off between both performance measures.

Research results

In this thesis is demonstrated that product groups react differently to promotions. Moreover, product groups have different demand week patterns. For instance, the product group beer is typically sold in the weekend and the product group tea has more demand pressure in the beginning of a promotion week. This implies that there is potential to make different distribution decisions for different product groups. In an attempt to make different decisions for different product groups a slight model improvement has been achieved. Hence, including different demand characteristics of product groups can match supply and demand better. Nevertheless, the improvements are relatively small. Therefore more research is needed to reap the benefits of making decisions at a lower aggregation level in practice.

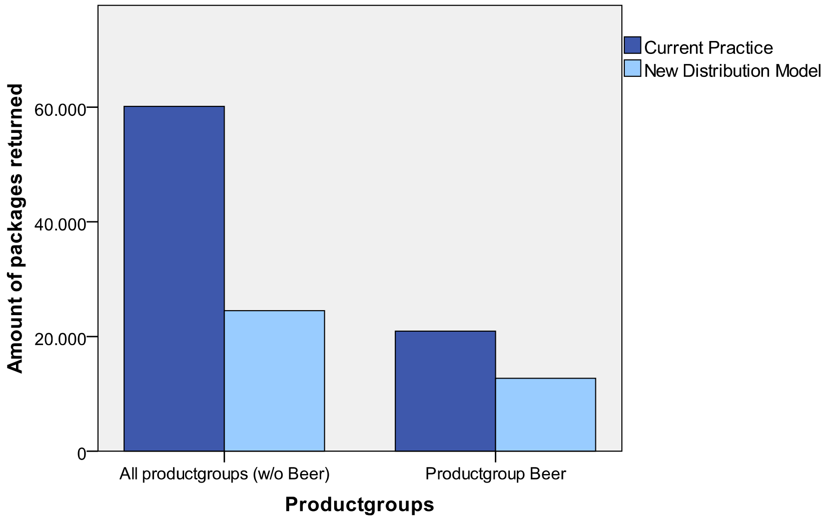
Based on a test in which 62 store managers could order extra promotion products during the promotion week it is shown that the order behavior of store managers is optimistic. This behavior can partly be explained by the major objective of a store manager: maximize turnover. Moreover, it appeared that store managers have difficulties to turn many environmental factors into an accurate order. Consequently, the amount of returned packages increases with 30% compared to a situation where orders are coordinated centrally. Although more products were ordered by store managers these extra products did not reduce the amount of lost sales. Therefore is concluded that it is better to coordinate the second delivery of promotion products centrally based on early sales forecasting.

When the developed distribution model is compared to the performance of the current distribution system a large reduction in returned packages is realized (see figure on the next page). Since returned packages are expensive (see figure on the next page), handling costs to process returned packages will be reduced with €312.000 annually. Other savings that will be realized with the centrally coordinated distribution model are:

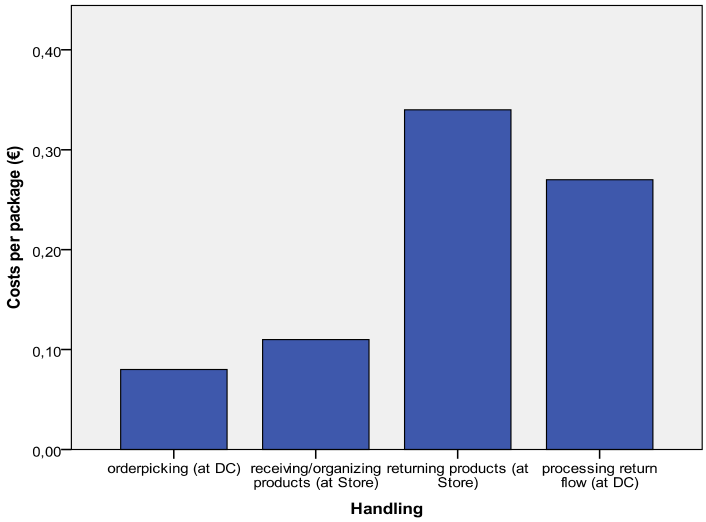
1. Reduction of transportation costs since less promotion products have to be transported
2. Improvement of store operations due to lower inventory levels of promotion products after a promotion week
3. Reduction of human resources needed to initiate orders for promotion products
4. Improvement of DC operations since the workload of promotion products is easier to manage since all orders are coordinated centrally
5. Marketing & Sales Department is better able to control profit margins of promotions since they can control the goods flow of all promotion products

The two main factors that are responsible for these improvements are:

1. More promotion products are withheld at the DC during the promotion week. About 70%-80% of the demand forecast is distributed to the stores in the first delivery.
2. The second delivery in the distribution model is coordinated centrally based on early sales forecasting. This excludes the optimistic and inaccurate orders made by store managers.



Comparison between the amount of returned packages based on 6 promotion weeks



Handling costs per package for several handling activities. Total costs per package are estimated to be € 0,80

Forecasting model

An additional part of this research is focused on the demand forecast which is the major input for the developed distribution model. This demand forecast predicts customer demand of a promotion on company level. In this research an existing demand forecasting model is tested. The following minor research question has been formulated: *Does the demand forecasting model of Van Loo (2006) lead to an accurate forecast of promotional sales in this research context?*

In the forecasting model the lift factor of a promotion is forecasted based on several independent variables. The lift factor is the promotional sales divided by the average sales in the recent non-promotion weeks. Based on a dataset of more than 4000 promotions it is concluded that the forecasting model of Van Loo (2006) leads to a quite accurate forecast in this research environment. Furthermore, it is demonstrated that making different forecasting decisions for different product groups can lead to a slight improvement in forecasting accuracy. However, also in this area more future research is needed.

The demand forecasting model is able to forecast promotional demand with a mean absolute percentage error of 36%. Compared to the current forecast that are made by the Purchasing Department and a specialized Demand forecaster this result is satisfactory and leads to an improvement. Nevertheless, the fact that each forecasts deviates 36% from the actual sales stresses the need for a flexible distribution system to cope with this forecasting bias.

Main recommendation

The final recommendation to EMTÉ is that they should redesign the current promotion process to reduce costs and lost sales. At first, it is important that responsibilities are clearly assigned to stakeholders of the promotion process. At second, it is recommended to implement the developed distribution and forecasting model. This will result in a flexible distribution of promotion products and a more accurate demand forecast. At third it is important to consider also the buy-side of the supply chain in the process redesign. The major focus of this study was on the sell-side of the supply chain of EMTÉ: how can we get the right product at the right place at the right time to service customers? Next to this, it is also important to consider profit opportunities like forward-buying on the buy-side of the supply chain. Forward-buying can lead in the promotion process to extra profit margins and overcome lost sales by creating extra inventory buffers. For this reason it is recommended to define the role of forward buying explicitly in the redesigned promotion process.

"So what's the problem? The unsatisfactory service is not for a dearth of inventory. The problem lies in lacking the right product, at the right place, at the right time to service customers."

Hau Lee, Vice President and Chief Scientist, Evant Inc (2003)

Preface

This master thesis is the final result of my master study Operations Management and Logistics at Eindhoven University of Technology. The six months during master thesis project is conducted at the supermarket division EMTÉ of the Sligro Food Group located in Veghel, Netherlands.

At the moment of writing this thesis I start to realize that a special chapter in my life is ending: student life. This chapter was diverse and is characterized by making many new friends, personal development, being an entrepreneur and an international experience in Singapore. The master thesis at Sligro Food Group provided me with the excellent opportunity to close this chapter and make a step towards a new phase: working life.

To perform this project I was dependent on the help and support of a few people.

At first I would like to express my gratitude to my supervisors Bart Takkenkamp, Peter Siemons, Karel van Donselaar and Ad de Jong. Bart, thank you for giving me the opportunity to conduct my master thesis at Sligro Food Group and giving me flexibility and trust during the project. Peter, thank you for always being interested and helping me with obtaining the information at the time I needed it. Karel, thank you for your well directed feedback and being always critical and open towards my academic and personal attitude. I really appreciated this way of working. Ad, thank you for providing me with feedback, it resulted in new insights and improved the quality of this master thesis.

At second I would like to thank my family and friends for the support and the pleasant time during my student life in Eindhoven. In special I would like to thank my parents for giving me the opportunity to finish this study successfully. At last I would like to thank my girlfriend for the love and inspiration you gave me the last five years.

Ward van Dinter

Veghel, March 2011.

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Part 1: Problem situation

In this part the aim of the project is defined. In the first chapter the problem is introduced. In the second chapter, a problem analysis is given and a research question is defined. Finally, the research boundaries are presented in chapter 3.

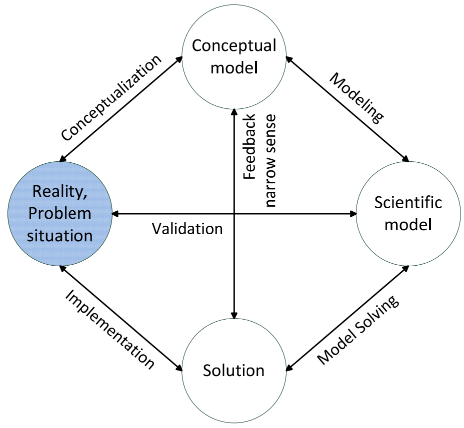


Figure 1-1: Methodological Foundation

1 Introduction

1.1 Report structure

The report is structured in 6 parts. The parts are based on the methodological foundation to guide empirical operational research which is developed by Mitroff, Betz, Pondy, & Sagasti (1974). In the methodological foundation four different parts are distinguished: 1) Reality, Problem situation, 2) Conceptual model, 3) Scientific Model and 4) Solution (Figure 1-1). Since the methodology is described as circularity it does not have a predefined starting or end point.

The report starts with a description of the **problem situation of EMTÉ**, which is outlined in this part. Furthermore, in this part the research question is defined and scoping decisions are made. In the second part **a conceptual model** is developed to address the research question. In the third part the conceptual model is translated to a **scientific model.** In this part, variables, constraints and the objective function of the scientific model are defined. The fourth part elaborates on the model **solution**. In this part different scenarios for the research model are tested. Finally the best scenario is chosen. In the fifth part an existing demand forecasting model is **validated**. At last, in the sixth part, a brief plan for **implementation** is presented and an overall **conclusion** is drawn.

1.2 Problem environment

Sligro Food Group is a large food retailer in the Netherlands. The Sligro Food Group delivers its products via two different distribution channels to its customers; Food retail and Food service (wholesale market). Within the Food retail division a distinction can be made between regular EMTÉ supermarkets and Golff franchise supermarkets. Only the EMTÉ supermarket division is within the scope of this research project. An overview of the company structure is given in Figure 1-2.

Headquarter and central Distribution Center located in Veghel			
Food retail		**Foodservice**	
EMTÉ 78 supermarkets	**Golff (franchise)** 45 supermarkets	**Sligro** Wholesale markets	**Van Hoekcel** Institutional
2 retail distribution centers		Nationwide network of 45 self service and 11 delivery wholesale markets	1 distribution center

Figure 1-2: Company structure

EMTÉ is a small and relatively new player in the competitive Dutch market. Since 2002, EMTÉ is part of the Sligro Food Group and claims a market share of 1,8 % in this market. In 2009 EMTÉ employed 5.316 people and realized a turnover of 727 million euro's. In total a profit of 5,5 million is realized, this indicates that profit margins are relatively small and under pressure in this industry. A primary goal stated by the management team of EMTÉ is to realize an annual increase in turnover of 6 %. Furthermore, EMTÉ has the ambition to become the best fresh-food and most personal supermarket in the Netherlands. The core values of EMTÉ are; fresh products, low prices and cosy supermarkets.

At the moment of writing, the grocery supply chain of EMTÉ consists out of 78 supermarkets. Most of these supermarkets are located in the south of the Netherlands (Figure 1-3). These supermarkets are supplied from three distribution centers (DC's) located in Putten, Kapelle and Veghel. The DC's in Putten and Kapelle are exclusively used for the food retail division of the Sligro Food Group. The DC in Veghel can be regarded as the main logistic hub. This hub is primarily used to supply the whole-sale channel. In some cases this hub is used as a cross-docking point to supply the DC's in Putten and Kapelle.

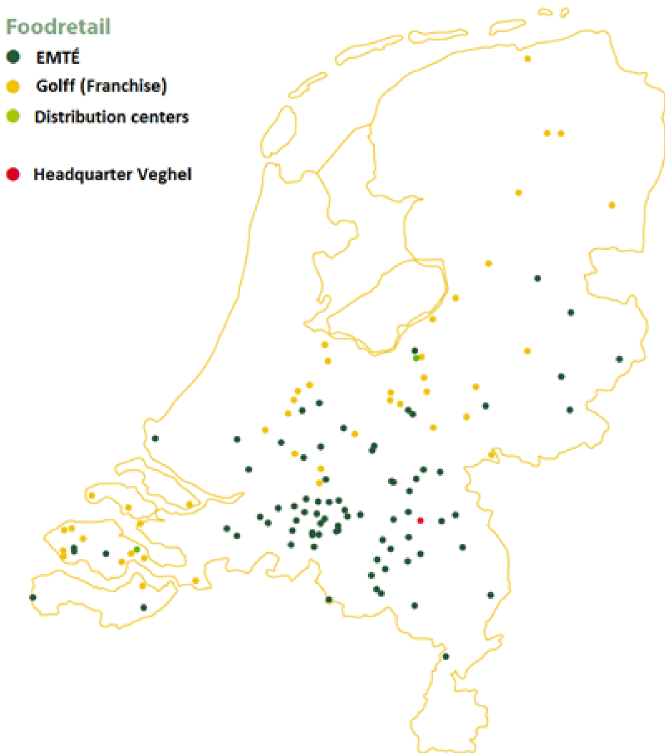


Figure 1-3: Location overview

1.3 Problem introduction

In the last two decades promotions in the fast moving consumer goods (FMCG) industry have become more important. Promotion activities of companies within this industry claim currently the main share of the total marketing budget (Srinivasan et al., 2004). Moreover, promotional sales were responsible for about 14,7% of all sales in Dutch supermarkets in 2009 (Appendix 1). It is expected that this promotional pressure will rise in the next years to 20% (Source: GFK Service Panel 2010).

The management of EMTÉ noticed this trend, and realized that the current promotion process has to be reconsidered. Currently EMTÉ is coping with the consequences of an inaccurate functioning promotion process. The consequences are either leftovers after a promotion week at the supermarkets or a shortage of promotion products. Since leftovers are returned from the supermarkets to the related DC's this results in extra handling and transportation costs. On the other hand, a shortage of promotion products leads to lost sales. This is in contradiction to the main strategy of EMTÉ; maximize turnover. Based on a qualitative analysis is concluded that there are two main reasons which are responsible for this inaccurate promotion process. The first reason is the way in which forecasting of promotional sales is organized. There are currently too many stakeholders actively involved in making forecasts. Moreover, these forecasts are mainly based on personal experience. The second reason is the current distribution mechanism that is used to distribute promotion products. Most promotion products are distributed in one delivery from the DC's to the stores which results in inflexibility. More details about the qualitative analysis are discussed in depth in chapter 2.

1.4 Overview literature

In this paragraph the findings of the literature study (Van Dinter, 2010a) are briefly reported. These findings will be related to the problems where EMTÉ is coping with and function as a starting point to make scoping decisions.

Most attention within this research field is drawn by the forecasting of promotion products. In literature promotion forecasting is argued to be one of the improvement opportunities in retail logistics (Donselaar et al., 2006). Recently, several studies have been conducted to research the power of more advanced forecasting techniques. Based on a trade-off between forecast accuracy and data preparation multiple regression is thought to be the most appropriate method to forecast promotional sales. In 2006, Van Loo developed a lift-factor (LF) model. In this model a multiplier is computed which forecasts promotional sales based on the average sales in recent non-promotion weeks. The LF model has been applied recently in several researches (Van Loo, (2006), Van de Heuvel (2009) and Van der Poel (2010). In each of the conducted researches substantial improvements in forecast accuracy have been realized. As indicated in the literature study (Van Dinter, 2010a), the setting of an appropriate aggregation level is an elementary decision in the model development of a forecasting model. However, the aggregation decision is generally subject to data availability within the research context.

In the FMCG industry different types of promotions are being used by retailers to promote their products. These promotion types have been used as predictive variables in recently developed forecasting models. Although there are common findings with regards to the significance of variables, every variable has to be tested in each specific setting since the predictive power might differ. Typically the following variables have been used to forecast promotional sales; price-cut, regular price, promotional sales history, perishability, fast or slow-movers, product group characteristics, advertising medium (e.g. TV or folder), number of items on promotion in a product category, promotion frequency, promotion mechanism (e.g. 2 for 1), seasonality and the number of selling points.

Besides an accurate forecasting system, Van Loo (2006) and Van de Heuvel (2009) stressed the need for an appropriate distribution and control mechanism for promotion products. They suggested to use a distribution system in which promotion products are distributed in multiple deliveries. With regards to the impact of handling costs and the goal of reduction of out of stocks they concluded that two deliveries to distribute promotion products is optimal. In this way it is possible to react on early discrepancies between forecasted demand and actual sales during a promotion week. Leeuw et al. (1999) proposed to coordinate the first delivery of promotion products to the stores centrally. The second delivery should be coordinated decentrally by the store managers. These store managers can initiate the second delivery if more information about actual sales becomes available. Unfortunately, a decentral coordination mechanism of the second delivery has never been compared to a central coordination mechanism. When the second delivery is coordinated centrally information about actual inventory levels and early sales information can be used to determine the second delivery systematically. In the fashion industry a research has been conducted to analyze the predictive power of early sales data (Fisher et al., 1996). Based on the results Fisher et al. (1996) concluded that retailers, especially retailers of short life cycle products, can significantly improve their forecast accuracy by adapting forecasts based on early sales data. Large retailers in the fashion industry, who analyze early sales data structurally, achieved a substantial improvement in their inventory management. Although the power of early sales forecasting has never been tested in the FMCG industry, it might be interesting to use early sales forecasting to determine the second delivery of promotion products centrally.

Since forecasts can result in an overestimation of customer demand, it can lead to leftovers at the supermarkets. Van de Heuvel (2009) concluded that it is possible that there is a significant amount of leftovers available in the supermarkets after a promotion period which can result in unnecessary handling costs. In literature, though, this topic remains fairly undiscovered.

1.5 Gaps in literature

In the literature review (Van Dinter, 2010a) multiple gaps in literature have been discussed. The gaps which are denoted here are directly related to the problem definition that is presented in the next chapter. In this research the following gaps in literature will be addressed:

1. **Product aggregation in the domain of promotional products.** This research is conducted in a multi-product environment. It is expected that products with different characteristics will react differently to promotions. Hence, it can be beneficial to take these characteristics into account when forecasting and/or distribution decisions are made. The effect of product aggregation has currently not been investigated in this research domain.

2. **Application of early sales forecasting at a retailer in the FMCG industry**. In literature it is suggested that early sales data can be a powerful predictor for future sales of products with short life cycles (Fisher et al., 1996). This conclusion is based on a study in the fashion industry. Within EMTÉ is argued that the first days of demand in a promotion week are a good indicator for the demand in the remaining part of the promotion week. Therefore it is interesting to investigate if early sales forecasting can be applied at a food retailer in the FMCG industry.

3. **Coordination of the second delivery of promotion products**. According to Leeuw et al. (1999) the second delivery of promotion products should be coordinated by store managers (decentrally). However, the decentral coordination for this second delivery has never been compared to a central coordination.

2 Problem definition

In this chapter the problem situation of EMTÉ is discussed in more detail. In the first paragraph background information about the complete promotion process is given. In the second paragraph the problems of EMTÉ are discussed in detail and a problem chart is presented. In the last paragraph of this chapter the research questions are defined.

2.1 Process description

To get more insights in the current promotion process several interviews have been conducted with stakeholders of the process (Appendix 2). These stakeholders approach the promotion process from their own perspective. Stakeholders of the following departments have been interviewed: Stores, DC's, Inventory management, Forecasting, Purchasing, Operations and Marketing & Sales. These different perspectives are combined to make a process description and to outline the problem where EMTÉ is coping with. In this paragraph the process description is presented. The process is started with the development of a promotion plan and ends with the returns of leftovers after a promotion week. In total eight different process steps can be distinguished. A complete graphical overview of the complete process and its stakeholders is presented in Figure 2-1.

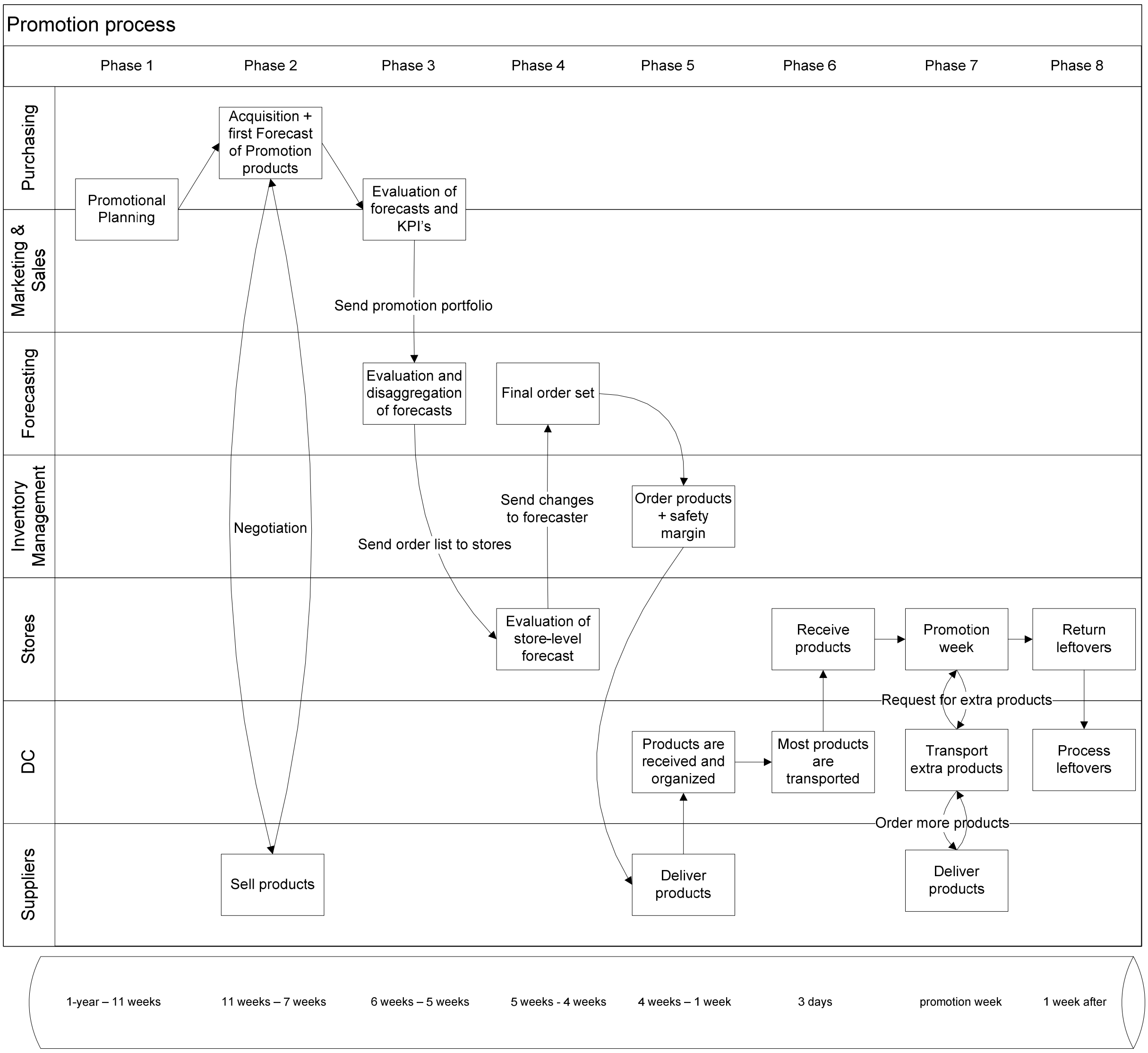


Figure 2-1: Complete promotion process

1. Promotion plan. A promotion is initiated 1 year upfront in the Marketing & Sales and Purchasing department. In collaboration between these two departments an annual campaign list is developed. This list describes periodical campaigns that will be held during the next year. In a more detailed plan a grid is defined that organizes the promotion plans on week level. The amount of promotions in different product categories is defined in this plan. About 11 weeks before the promotion week starts a concept promotion plan is composed in the Marketing & Sales department. Important key performance indicators (KPI's) of this completed concept promotion plan are product margins and expected sales. Eventually, the promotion plan is finished and sent to the Purchasing department.

2. Acquisition plus first demand forecast for promotion products. When the Purchasing department receives the promotion plan, acquisition for promotion products is started. A major objective in this acquisition process is searching for products that lead to interesting profit margins and possibilities to apply forward-buying[1]. Subsequently, a demand forecast is made for the promotion products by members of the Purchasing department. Accuracy of this demand forecast is important to create a reliable promotion portfolio which results in a minimum expected turnover. The forecast which is made by the members of the Purchasing department is mainly based on experience. The complete acquisition process takes three to four weeks and the results are reported to the Marketing & Sales department.

3. Evaluation of forecasts and KPI's. Every three weeks a meeting between the Marketing & Sales and Purchasing department is scheduled. In this meeting the forecasts and deals that have been made by the members of the Purchasing department are evaluated. Two important KPI's in this evaluation are expected turnover and profit margins. After this meeting an order set for all promotion products is created. This order set is sent to a forecaster who evaluates this order set comprehensively. Eventually, the order set is disaggregated on supermarket level based on a preset allocation rule. This disaggregated order set is sent to the supermarket managers.

4. Supermarket ordering. Four weeks before the promotion week starts, the supermarkets receive an order set from the forecaster. Supermarket managers have the opportunity to adapt this order set. However, it is only allowed to adapt this order set with a minimum of two packages. Finally, the supermarket returns a definitive order set to the forecaster located at the headquarter. The forecaster evaluates this order set again and informs inventory management of the DC's about the amount of products that have to be purchased. In some cases Marketing & Sales makes last-minute changes in the marketing-portfolio. These changes are not always incorporated in the final order set due to time constraints.

5. Delivery to the DC's. Inventory management of the DC's orders the products that are listed on the final order set. In addition to this final order set they order on average 25 % extra products. These extra products function as a inventory buffer. The inventory buffers at the DC's are set manually and based on the following criteria: price, sales in previous promotion periods, promotion characteristics, reliability of the forecast, perishability, supplier characteristics, personal experience and a reasonable risk factor. Suppliers deliver the promotion products generally 1 to 4 weeks before

[1] Forward-buying can be defined as the practices in which retailers stock up products that are temporarily offered by a manufacturer at a better deal to create extra profit margins.

the promotion week starts. Also the products that are normally cross-docked from the central DC located in Veghel, are delivered in this week. For this reason the central DC located is in this process description regarded as a supplier of the other two DC's. In total, about 15% of the promotion products are delivered from the central DC. The major part (85%) is directly delivered by external suppliers to the two retail DC's. One week before the promotion week starts products are collected and prepared for transportation to the supermarkets.

6. **Delivery to the supermarkets.** Promotion products are generally delivered from the DC to the supermarkets in the end of the week before the promotion week starts. The precise date and time of a delivery to a supermarket depends on the transportation schedule. Most products are supplied in one delivery to the supermarkets. Except for bulky products like; toilet paper, beer, frozen products, soft drinks, chips and perishable items. These products are usually delivered in two or three deliveries to the supermarkets. This decision is determined by the supermarket managers. The supermarket manager can decide to split the order set in different deliveries (e.g. Monday 20%, Wednesday 30 % and Friday 50 %).

7. **Promotion week.** Supermarkets attempt to sell all promotion products in the promotion week. The most important KPI of supermarkets is turnover. If a supermarket expects to have a substantial risk to run out of stock it is possible to place an extra order during the promotion week. These extra orders are fulfilled by the inventory buffer that is located at the DC's. If the DC is running out of stock they can ask for an extra replenishment by a supplier. Besides this, they can request for products located at the other two DC's. Unfortunately it is not always possible to fulfill the market demand. In case of an overall shortage, a first come first serve policy is applied by the DC's. Consequently, it occurs that some supermarkets have a shortage and other supermarkets have an abundant amount of products available. In some cases it is possible to exchange products between supermarkets; this process is coordinated by the related DC.

8. **Returned products.** After a promotion week it is possible to return unsold promotion products. The forecaster at the headquarter informs all supermarkets about the products that can be returned. Generally, non-perishable bulky products can be returned. For other products a return request can be sent to the related DC. If products are returned to the DC there are three options: 1) products are put in the regular assortment and stay on the DC, 2) products are sent to the central DC located in Veghel, 3) products are disposed. Since returned products require several handlings they are considered to be very costly.

2.2 Problem analysis

The problem overview which is presented here is also based on interviews with several stakeholders of different departments within EMTÉ. To present the findings of this analysis a fishbone (cause and effect) diagram is used. In this diagram the challenges that are currently faced in the promotion process are outlined in a structural manner.

The general problem that has been denoted in the interviews with several stakeholders of the promotion process is:

The performance of the promotion process is not sufficient.

Sales of promotion products account for 17,5% of all sales of EMTÉ and this promotional pressure is expected to rise in the future. Therefore, this problem can be regarded as a critical issue for EMTÉ. Two frequently mentioned consequences of this problem are "**lost sales"** and **"too much costs".**

Based on the conducted analysis, three major root causes of the general problem can be differentiated. The first root cause can be related to the first four steps in the process description is: *"***the forecasting process is not optimal".** The second root cause is related to the process steps five, six and seven. This cause is defined as: the **"distribution and control mechanisms are inappropriate".** The third root cause can be found in the last process step: there is **"lack of a formal return policy".** In the fishbone diagram (Figure 2-2) depicted below the general problem and all (sub-) causes are outlined. More details about this fishbone diagram are given in the remaining part of this paragraph.

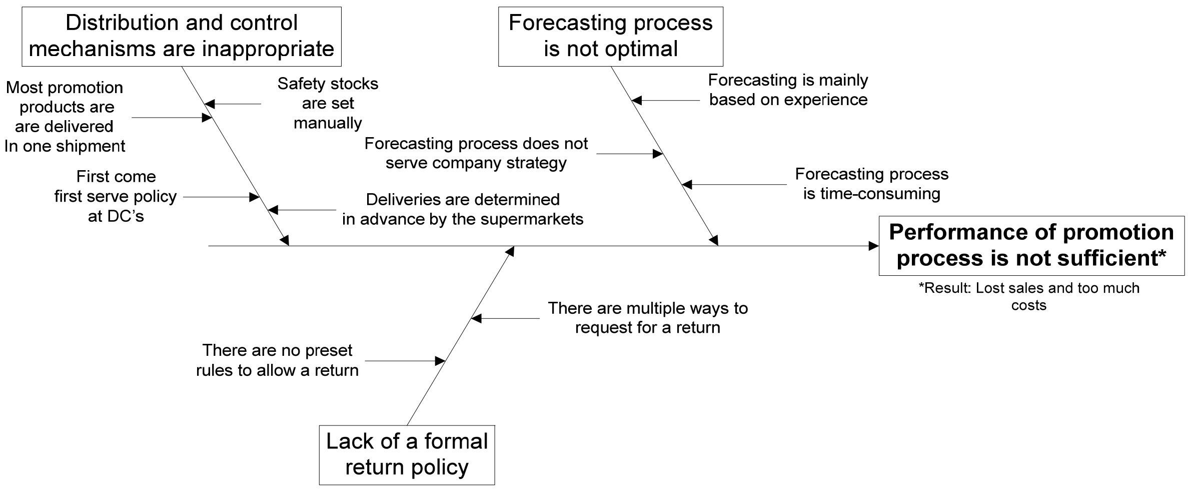


Figure 2-2: Fishbone diagram

A. Forecasting process is not optimal. Currently "forecasting is mainly based on experience". Forecasters, purchasers and supermarket managers use their personal experience to forecast sales. Although this way of forecasting has benefits, it is recommended to use this personal experience in addition to statistical forecasts (Goodwin & Fildes, 1999). Furthermore, the current forecasting process is expensive since the "forecasting process is time-consuming". As indicated in the process description, multiple stakeholders are involved in the forecasting process. In total four different stakeholders forecast sales of promotion products and/or evaluate the forecasts of others. These stakeholders are: a specialized demand Forecaster, the Purchasing department, the store managers and the inventory managers of the DC's. With regards to the company goals can be said that the current forecasting process "does not serve company's strategy". It is clearly stated in the mission statement that maximizing turnover is a major goal of EMTÉ. However, this goal is not served by the current forecasting process since lost sales are not being analyzed. Furthermore, the sequence in which the forecasting process is performed is ineffective. After the evaluation of the promotion plan, the expected sales are radically changed by forecasters and supermarket managers. This indicates that the KPI's of the Marketing & Sales strategy which are used to evaluate the promotion portfolio are critically endangered. Hence, it is difficult to control the overall profit margin of promotion products. This can be dangerous in an industry where profit margins are low and will decrease further due to an expected rise of the promotion pressure. Another cause is that some products are displayed in the folder while they are only sold in the regular assortment of a limited amount of supermarkets. The consequence of this action is customer dissatisfaction. Namely, customers expect that a product which is displayed in the folder is available in every supermarket. As indicated in the process description Marketing & Sales can make last-minute changes in the promotion plan. This will affect the operational performance of the promotion process negatively. It is unclear if a trade-off is made between commercial incentives and customer dissatisfaction when these changes are made.

B. The distribution and control mechanisms are inappropriate. The distribution mechanisms that are currently used can be classified as inflexible. Most "promotion products are delivered in one shipment", except for a few products as mentioned in the process description. These products are shipped in multiple "deliveries that are determined in advance by the supermarkets". Hence, there are few opportunities to react on actual sales since all products have already been allocated or sent to the supermarkets. If supermarkets are running out of-stock they can place an extra order at the DC. The DC uses a "first come first serve policy" to process these extra orders. The result of this policy is that supermarkets tend to reorder as much as possible in the beginning of the week. In case of paucity, the promotion products are not equally distributed. Products that are reordered are generally fulfilled from the extra stock that is available at the DC's. This amount of "safety margin that is available to fulfill this extra demand is set manually". Since this margin is determined according to criteria like past sales and promotion characteristics it cannot solely be seen as a safety margin. It is rather a positive adaption of the demand forecast plus some safety stock.

C. Lack of a formal return policy. After a promotion week, products can be returned to the DC's. However, it is often not clear which products can be returned. There is a lack of a formal return policy. Currently, every week a list is published which contains the promotion products that can be returned. Although there are some criteria to determine this list, "there are no fixed rules to allow a return". Furthermore, when products are not on the return list a supermarket managers "has multiple other ways to request for a return". Namely, it is possible to make a request for a return at the related DC or at the Headquarter. Hence, an unnecessary amount of products is returned from the supermarkets to the DC's.

2.3 Potential research directions

In the research proposal that is made in preparation of this research an analysis is made of the expected impact of three potential research directions (Table 2-1). Based on a trade-off has been decided to define a major and a minor research direction. It has been decided to put the primary focus of this research on the distribution and control problem since it is relatively undiscovered in literature. Furthermore, it is expected that this research direction will resolve a major part of the problems where EMTÉ is coping with. The forecasting problem will be addressed in the minor research direction since it is also a major issue for EMTÉ and expected to reduce costs. However, in literature more is known about this direction. Therefore, this direction which will contain only a validation phase; the exact approach is described in the next paragraph.

Research question	Expected impact on lost sales	Expected impact on costs	Potential contribution to literature
Forecasting	Unclear	Positive	Minor
Distribution and Control	Positive	Positive	Major
Return policy	None	Positive	Minor

Table 2-1: Impact potential research directions.

2.4 Research questions

In this paragraph the aim of the research is defined. Based on the problem analysis and evaluation of potential research directions a major research question is defined:

How can the current distribution and control mechanism of promotion products be improved considering both costs and lost sales?

In addition to this research question the following sub-questions are used:

1. Which distribution and control mechanism should be used to distribute promotion products?
2. How should the first and second delivery of promotion products be determined?
3. How should the second delivery of promotion products be coordinated?

As concluded in the research proposal (Van Dinter, 2010b), solely addressing the distribution and control problem is not sufficient and will lead to a sub optimization. To provide an integrated solution also the aggregated demand forecast on company level has to be improved. Therefore, in a minor research direction an existing forecast model will be validated in this research environment. The model that is tested in this research is the LF – model developed by Van Loo (2006). For this minor research direction the following minor research question can be defined:

4. Does the demand forecasting model of Van Loo (2006) lead to an accurate forecast of promotional sales in this research context?

2.5 Practical requirements

Besides the research questions it is important to formulate practical requirements to fulfill also the objectives of the Sligro Food Group. Three practical requirements are formulated:

1. Simplicity
2. Operational limitations
3. Data availability

The most important practical requirement is *simplicity*. It is important that the concepts that will be developed in this research are understandable for stakeholders within the Sligro Food Group. This will enhance the potential for future implementation. Besides this it is important to take *operational limitations* into account. This assures that the proposed concepts can be implemented from a practical point of view. Finally, the concepts that will be developed are dependent on historic data. To make potential concepts operational Sligro Food Group is dependent on this *data availability*. For this reason availability of data in the current information systems is a key element to consider.

2.6 Problem scoping

The major and minor research questions are indicated in the fishbone diagram (Figure 3-1). The fishbone diagram shows that the major research direction will address the distribution and control problem. The forecasting of promotion products will be addressed in the minor research direction.

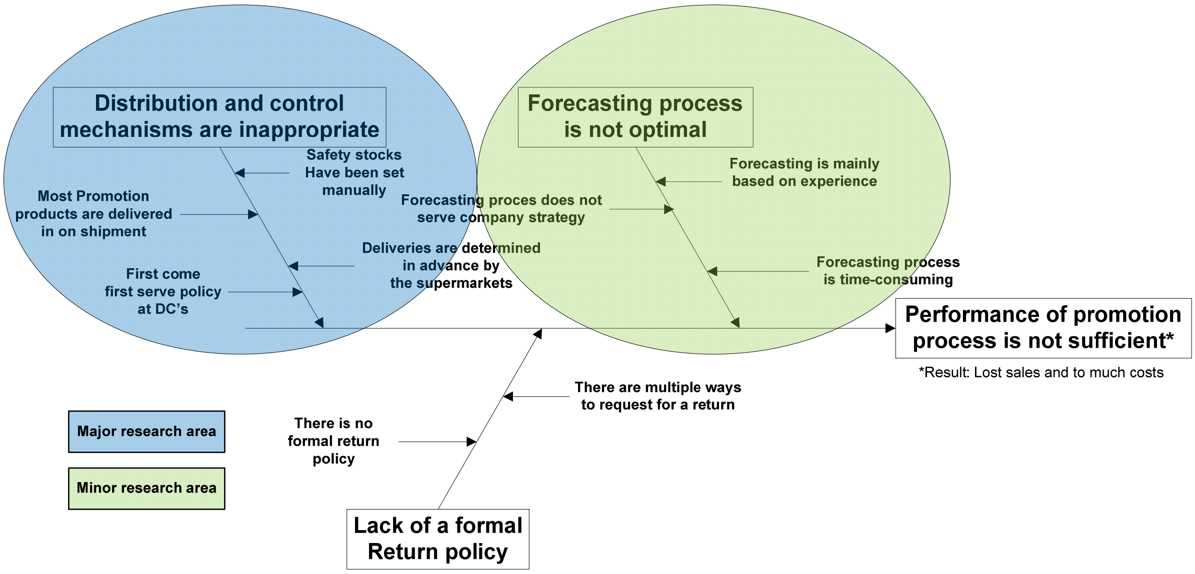


Figure 2-3: Restructured Fishbone Diagram

2.7 Product scoping

In this paragraph product scoping decisions are made with regards to project feasibility. Currently, EMTÉ lacks a useful product categorization. Different stock keeping units (SKU's) are organized in different hierarchies (Appendix 3). This product hierarchy will not be used in this research for practical reasons. It is decided to create a new and more useful product categorization. The new product categorization is a combination of the product categories that are currently used by EMTÉ and a product categorization that has been used by Van Loo (2006). The final product categorization is presented on product group level in Appendix 4.

Next to a product categorization, a differentiation is made between fast and slow moving products. As indicated by Cooper (1999), fast and slow moving products will react differently to promotions. Moreover, it is expected that fast moving products are responsible, due to their large product volumes, for the major part of the operational problems where EMTÉ is coping with. To differentiate between slow and fast moving products the Pareto principle is applied. According to the Pareto principle 20 % of the events are responsible for 80% of the results. The Pareto rule is used to make a classification based on the annual sales of year 2009 (Appendix 5). In the graph can be seen that 20% of all SKU's is responsible for 84% of the total absolute sales. These SKU's are classified as fast moving products. Both research directions will only focus on these **fast moving products**.

Furthermore, it is decided to focus only on **non-perishable items**. As indicated in a previously conducted study perishable items are different with regards to key sales and logistic product characteristics (Donselaar et al., 2006). Moreover, inventory management for these products is likely to be different due to a high risk of having waste.

Next to perishable products also In/Out[2] products are excluded in this research since they are purchased based on purchasing considerations (discount offers) rather than demand forecasting (Donselaar et al., 2006). Furthermore, it is expected that these products require a different supply strategy since they become obsolete after a promotion week.

Based on these two scoping decisions, two product categories remain in the focus of this study. These are the fast moving products within the product categories "DKW" and "Frozen Food". The scoping decisions for all product categories are summarized in Table 3-1.

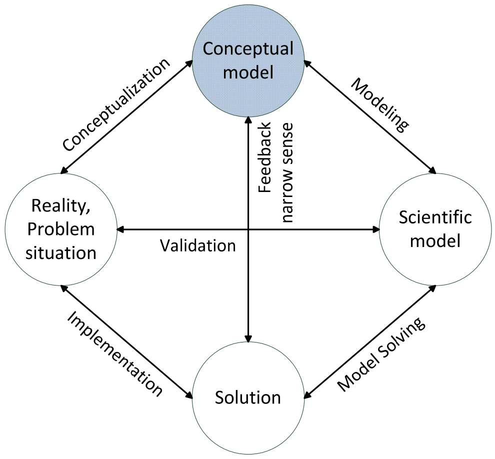
Product category[3]	In scope of this research	Argumentation
DKW	Yes	-
Frozen Food	Yes	-
Meat and Salads	No	Perishable products
Milk Products	No	Perishable products
Bread	No	Perishable products
WRCP	No	Mainly slow moving products
In/Out	No	Become obsolete after a promotion week

Table 2-2: Product scoping decision

Results Part 1: *In this part two key problems are identified: the forecasting process is not optimal and the current distribution and control mechanisms are inappropriate. These two problems will be addressed in a minor and major research direction. Furthermore, it is decided to focus in this research solely on fast moving products within the product groups "DKW" and "Frozen Food".*

[2] In/Out products can also be defined as one-time-items. These are promotion products, generally presented in a special package, which are temporarily offered by a manufacturer.
[3] In Appendix 2 is indicated which products belong to these product categories.

Part 2: Conceptual model



This part translates the actual problem "the distribution and control mechanism is inappropriate" to a conceptual model. Important characteristics of the design of an appropriate distribution and control system are discussed. In this discussion important cost drivers in grocery supply chains are considered. To conclude this part a concrete research design is presented.

3 Design of a distribution and control system

In this chapter the design of a distribution and control system for promotion products is discussed. Distribution control has been defined as:

"All activities taking place to coordinate the place and timing of demand over a finite horizon with the supply of products and capacities, in such a way that the objectives of the distribution process are met, given the characteristics of the product and the requirements of the market (Leeuw, 1996)."

Two design decisions which are defined by Leeuw et al. (1999) are used as major input for the design of a new distribution and control system for promotion products. These are the **allocation coordination decision** and the **central stock function decision** (Table 3-1).

Design Decision	Description
Allocation Coordination	Having a centrally or a decentrally coordinated allocation
Central stock function	Having both central stock and local stock or only local stock

Table 3-1: Design Decisions

Before these two design decisions are discussed in more detail it is essential to incorporate important KPI's in this design phase. As indicated in the problem analysis, costs and service levels (lost sales) are the two most important KPI's. In a recently conducted study is found that of all operational costs in grocery supply chains 66% of the costs are caused by handling (Van Zelst et al., 2009) (Figure 3-1). The capital costs that are involved with holding a sufficient amount of inventory claim only 12 % of total costs. Transportation costs account for 22% of all costs that are made. These findings are important since handling costs appears to be the main cost driver within this industry.

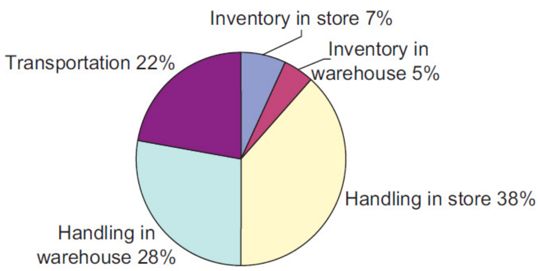


Figure 3-1: Cost drivers in Grocery Supply Chains (Van Zelst et al., 2009)

3.1 Design decision 1: Allocation coordination

The allocation decision is about who is controlling the inventory of products in a supply chain. Basically, the allocation decision can be coordinated centrally (at the DC's) or de-centrally (at the stores). In literature it is argued that central control leads to a better customer service, moreover inventory costs are lowered (Leeuw et al., 1999). Next to this, the workload at the DC is easier to manage which results in lower handling costs at the DC.

Another argument to coordinate the allocation decision centrally is the need for control of profit margins. Since promotional pressure is expected to rise in the next years, control of profit margins of promotion products will become more important. When deliveries are coordinated centrally the management of EMTÉ is able to control the goods flow of promotion products better. Hence, it is possible to be more conservative by sending promotion products with low (or negative) profit margins to the stores. In particular since store managers are assessed on the KPI turnover and not on profit margins, a decentral coordination can critically endanger the overall profit margin.

One of the main advantages of a decentral coordination is that responsibility is delegated to the store managers. Store managers are able to order more if they expect to have the opportunity to sell more products. In this way the entrepreneurial attitude of the store manager is stimulated. Store managers are also expected to take more responsibility for the leftovers after a promotion week if their orders were too high. However, a decentral coordination will also result in more handling costs since orders have to be initiated for multiple products manually. Next to this the handling costs at the DC will rise due to coordination problems of decentral initiated orders. For these reasons it is unclear if the benefits of a decentral coordination mechanism outweigh the increase of other handling costs. Also the impact of the decentral coordination mechanism on customer service level is undiscovered. Since store managers are currently assessed on the KPI turnover, it is expected that customer service levels will rise.

Based on the discussion in this paragraph it is difficult to conclude if the allocation decision should be coordinated centrally or decentrally for promotion products. As argued by Leeuw et al. (1999) it is recommended to coordinate the first delivery of promotion products centrally to be able to manage the workload at the DC. When stores are running out of products during the promotion week, extra deliveries can be initiated. It is unclear if store managers (decentrally) are able to coordinate these extra deliveries, especially in a multi-product environment. For this reason **the coordination mechanism of deliveries during the promotion week is introduced as decision variable** in this research.

3.2 Design decision 2: Central stock function

In this design decision is decided whether to keep stocks centrally or de-centrally. In the Leeuw et al. (1999) is argued that the most important reason to keep stock centrally is demand uncertainty. In case of high demand uncertainty it is beneficial to keep stock longer at the DC (centrally) to postpone the allocation decision. When the allocation decision is postponed the inventory will be distributed better across all stores since more more sales information becomes available. This information can be used to allocate the centrally located inventory more effectively to the stores.

Other reasons for keeping stock centrally in this specific setting are:

- High product volumes of promotion products
- Limited storage space in stores
- High number of stores which increases the potential for a second allocation

Based on these arguments it is recommendable to keep inventory during promotion weeks longer at the DC's. The most important determinant of the stock function is the number of deliveries that are performed to distribute promotion products. Obviously, if more deliveries are performed during the promotion week the stock can be withheld longer at the DC. Therefore it is important to question in how many deliveries promotion products should be shipped. At least two deliveries are needed to create a flexible distribution system. However, more deliveries can lead to even more flexibility. Two other indicated benefits of more frequent deliveries are; less local storage capacity is needed and inventory costs are lower (Van der Vorst, 2000). However, more frequent deliveries will also lead to extra costs. Namely, transportation costs and handling costs at the DC's and stores will rise. Since more frequent deliveries result in more and smaller order sets the mode of transportation and order-picking will become less efficient. Moreover, the shelves in the stores have to be stacked more often.

It remains difficult to say how many deliveries should be performed from a cost point of view. This is a trade-off between an increase in flexibility and extra handling and transportation costs that are made due to smaller order sets. Furthermore, the number of deliveries that can be performed is generally dependent on delivery schemes. However, when the savings of more deliveries of promotion products are so significant it might even be worthwhile to reconsider the delivery schemes. In this research it is decided to **deliver promotion products in two shipments**. With regards to *operational limitations* can be said that it is not possible to create more than two synchronized decision moments to initiate deliveries for all stores. Therefore, to provide EMTÉ with a feasible solution, promotion products are delivered in two shipments.

4 Research design

In order to discover the gaps in literature (see 1.5) and to answer the research question (see 2.4) a new distribution model will be developed. In this distribution model promotion products are delivered in two shipments. In the distribution model different scenarios are tested. These different scenarios are based on different settings for two decision variables. The first decision variable is the **coordination mechanism of the second delivery**. As indicated in the previous chapter, it is unclear if a decentral coordination mechanism can outperform a central coordination mechanism during the promotion week. The second decision variable in this research is the **setting of an appropriate aggregation level**. Since this research is conducted in a multi-product environment the setting of the right aggregation level on which decisions are made is expected to be important.

In this chapter the rationales behind the two decision variables are explained in more detail. For each decision variable different settings are pointed out. These different settings for the decision variables result in unique and comparable scenarios which can be tested with a scientific model. In the final research design which is presented in paragraph 4.3 the different test scenarios are summarized.

4.1 Decision variable 1: Coordination mechanism of the second delivery

The second delivery can be coordinated centrally or decentrally. A major characteristic of this research environment is that there are many different products involved. It is expected that this characteristic influences the complexity of the second delivery. Namely, it will be more difficult to coordinate the second delivery for multiple products than for one product. In order to test if a central or decentral coordination mechanism leads to a different performance both scenarios will be modeled. This results in two different settings for the first decision variable:

4.1.1 Central coordination mechanism

To test the central coordination mechanism a second demand forecast will be made upon early sales data during the promotion week. In this way the principle of early sales forecasting which is proposed by Fisher et al. (1996) is applied in the FMCG industry. Based on this second forecast and information about stock levels the second delivery of promotion products can be determined. In this way the second delivery of promotion products is coordinated centrally.

4.1.2 Decentral coordination mechanism

Store managers are actively involved to test if the second delivery can be coordinated decentrally. In a questionnaire store managers are asked to determine a fictive second delivery based on actual stock levels and early sales information. Store managers will also receive an advice for the second delivery which is initiated centrally. Hence, store managers have the opportunity to improve this advice.

4.2 Decision variable 2: Aggregation level of decision making

In this research multiple stores and many different products are involved. It is likely that the demand week patterns of products will vary across stores and products. Stores located in city centers are expected to have a stable demand week pattern. This stable demand week pattern can be explained by the customer buying behavior. Customers visit stores in cities frequently and buy relatively less per visit. On the contrary, stores located in smaller places will have more demand pressure in the end of the week. Customers visit these stores only once or twice a week and purchase a relatively large amount of products per visit. Generally, one of these visits will take place in the end of the week. An example between differences between stores is illustrated in Figure 4-1. In this Figure also the average demand week pattern of all stores is depicted.

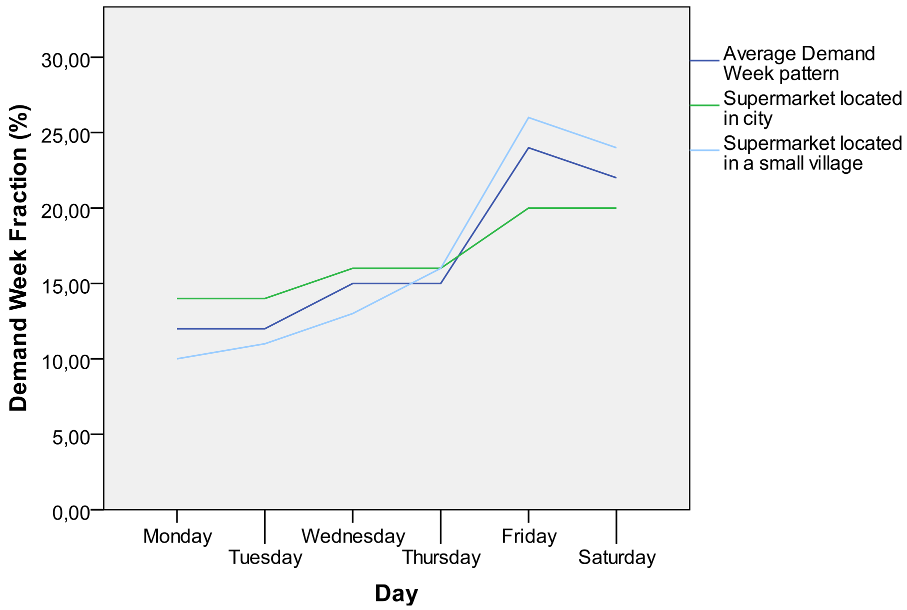


Figure 4-1: Demand week patterns of stores

Besides differences between stores, also products are expected to follow a different demand week pattern. It is likely that goods like “Beer” will be purchased more often in the end of the week. On the contrary, goods like “Coffee” are expected to have a more stable demand week pattern.

Hence, in this environment it might be beneficial to make decisions on a more disaggregated level. In order to assess the effect of the applied aggregation level, two different aggregation settings are tested.

4.2.1 Aggregation on store level

In the highest aggregation level the first and second delivery of each store will be determined based on the demand week pattern on store level. The first delivery will be based on the fraction of the total week demand of a store that is expected to be sold in the beginning of the promotion week till the second delivery arrives. To determine the second delivery a forecast based on early sales data is made for each store to cover demand at the end of the week. This demand forecast is also based on demand week patterns on store level.

4.2.2 Aggregation on store-product group level

In this aggregation level the first and second delivery will be determined based on the demand week pattern per store-product group combination. Examples of product groups are “Beer” and “Coffee”. In total there are 30 product groups involved in this research.

4.3 Modeling scenarios

The modeling scenarios that are designed are based on the settings of the two decision variables (Table 4-1). The different settings of the decision variables result in three unique modeling scenarios. In an additional scenario the performance of the current distribution system is measured.

These four scenarios function as research design and are able to assess the impact of:

- The aggregation level of decision making (comparison scenario 1 and 2)
- The coordination mechanisms of the second delivery (comparison scenario 1 and 3)
- The performance of the developed distribution model compared to the current way of distributing promotion products (comparison between best performing scenario and scenario 4)

The comparison between scenario 1 and 2 will be made in the calibration period. Due to the data-collection costs of the questionnaires the comparison between scenario 1 and 3 will be made in the validation period. In the validation period the best performing scenario will be compared to the current way of distributing promotion products (scenario 4).

It is important to notice that in scenario 3, in which store managers are actively involved, the decision making for the second delivery is performed on store-product level. Namely, from a practical point of view a store manager will always order per product and not per product group. It is decided to not apply this aggregation level in another scenario because it is expected that this extra layer of complexity will not add value compared to decision making on store-product group level. It is assumed that decision making on store-product group level is able to explain differences between products sufficiently.

<table>
<tr><th>Delivery</th><th>Scenario 1</th><th>Scenario 2</th><th>Scenario 3</th><th>Scenario 4 (current)</th></tr>
<tr><td>1st Delivery</td><td>Central coordination on store level</td><td>Central coordination on store-product group level</td><td>Central coordination on store level</td><td rowspan="2">Most promotion products are delivered in one shipment which is coordinated centrally. Extra deliveries are coordinated decentrally.</td></tr>
<tr><td>2nd Delivery</td><td>Central coordination on store level</td><td>Central coordination on store-product group level</td><td>Decentral coordination on store-product level</td></tr>
<tr><td colspan="5">Performance Measures:
1) Amount of returned packages
2) Customer service Level</td></tr>
</table>

Table 4-1: Research Design

4.4 Performance measures

To make a clear tradeoff between costs and customer service level two performance measures are selected: **customer service level** and the **amount of returned packages**[4].

To measure **customer service level** the fill-rate is used as defined in Silver et al. (1998). According to Kaipia & Tanskanen (2003) the service level of the DC to the stores is not relevant. Therefore only the service level of the stores to the customer is measured. This measure represents the overall performance of the grocery supply chain. To transform the customer service level to a cost measure the number of out-of stocks (OOS) will be counted. For each OOS stock a penalty cost has to be paid. This penalty cost is basically a representation of the weight of a disappointed customer and a lost profit margin of an OOS. The penalty cost has to be determined by the management team of EMTÉ.

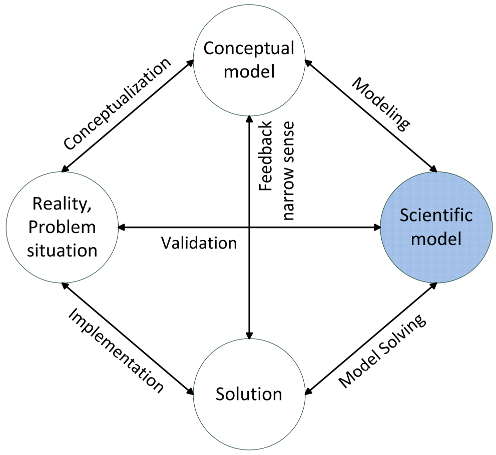
Currently, there is no formal rule that allows the return of promotion products from a store to the DC. In order to measure the **amount of returned packages** equally across all models a new rule is

[4] A package contains multiple products. Since products are always processed and transported in packages it is decided to use this as performance measure.

developed. In collaboration with inventory management and operations management is decided that 2 weeks of inventory for bulky products is acceptable. Bulky products are products like: "Chips, Beer, Softdrinks, Pizzas and Wines". For other products 4 weeks of inventory is accepted. If this inventory allowance is exceeded the complete inventory of a product can be returned except for one week of store inventory. When a promotion product is returned several handling costs are made at the DC's and in the stores.

Result Part 2: *It is decided to deliver promotion products in two deliveries. The first delivery is recommended to be coordinated centrally (Leeuw et al., 1999). The coordination mechanism of the second delivery is introduced as decision variable in this research. Furthermore, the setting of the aggregation level on which decisions are made in a multi-product environment is expected to influence the performance of the distribution model. This resulted in a concrete research design in which different testing scenarios are pointed out.*

Part 3: Scientific Model



In this part the scientific distribution model is built.

5 Definition of the Distribution Model

In this chapter at first a description of the scientific distribution model is given to increase understandability of the mathematical model. Thereafter, performance measures and the complete mathematical distribution model is defined.

5.1 Model description and assumptions

In the distribution model an entire grocery supply chain consisting of ***j*** retail DC's and ***i*** stores is considered. The planning horizon of the distribution model is 1 week. Within this week multiple promotions of multiple products take place. The customer demand per store for each promotion product is variable. When customer demand cannot be filled from the stock that is available in the store the demand is considered as lost. In the distribution model promotion products are delivered to the stores in two deliveries. The first delivery takes place before the promotion week starts. The second delivery moment takes place during the promotion week. After the promotion week, the remaining inventory in the stores can be returned if a formal return is satisfied.

The second delivery in the distribution model is initiated after the second day of the promotion week. At this moment early sales information about two sales days is available. This information in combination with actual inventory levels is used to forecast the amount of products that have to be shipped in the second delivery. This delivery is constrained by the amount of promotion products that is available at the DC. The second delivery will arrive on the fourth day of the promotion week just before store opening. Hence, the time between the initiation of the second delivery and the actual delivery is assumed to be one day (= lead-time). This assumption is acceptable since in practice more than 70% of all involved stores will meet this assumption. These are generally the large stores which have a substantial impact on the total performance of the distribution model.

The forecasts that are made in the model are based on the demand week patterns of non-promotion products. Due to the lack of *data availability* it is not possible to use the demand week patterns of promotion products. Therefore is assumed that the demand week patterns of non-promotion products are similar to the demand week patterns of promotion products.

Since the second delivery is initiated on the second day of the promotion week two days of sales data are available for early sales forecasting. Bartezzaghi et al. (1999) argued that more early sales information leads generally to a better and more reliable forecast. In this research setting, where times series are short (promotions last for 1 week) it is expected to be optimal to apply early sales forecasting based on the first two sales days of the promotion week. In this way the flexibility of the distribution system is conserved and a reliable forecast can be made. When the early sales period becomes longer more products have to be shipped in the first delivery. This will reduce the flexibility of the distribution system substantially.

To cope with demand variability a safety factor k will be introduced in the model. This safety factor is set equal across all stores and product groups and can be used to determine the customer service level that will be achieved. For the first and second delivery a separate safety factor is available. **The safety factors for both deliveries function as model parameters.**

5.2 Performance measures

To make the performance measures which are defined in the conceptual model comparable they are translated to one criterion; costs. The first performance measure is the service level. To translate this measure to costs the amount of lost sales is counted. For each lost sale a **penalty cost C_p** is charged. Based on productivity and labor cost information an estimate can be made for the cost of each returned package. In this estimation only the handling costs are considered. Transportation and inventory costs are neglected. **The cost per returned package** is denoted with C_r.

5.3 Formulation of the mathematical model

The mathematical distribution model which is defined in this paragraph uses demand week patterns on store level as proposed in scenario 1. All variables that are used in the model are introduced in this paragraph. For the complete overview of the definitions the reader is referred to Appendix 6.

In the mathematical model time is denoted with *t,* which stands for the weekday. A promotion week starts on the first day (*t = 1)* and ends on sixth day *(t = 6)*. The day before the promotion week starts is denoted with *t = 0*.

The major input of the distribution model is a demand forecast of a promotion product for all stores. This central forecast is disaggregated on store level by the current information system and is denoted with: A_{xi}. In the first delivery of promotion products only a part of this forecast is shipped to the stores to postpone the allocation decision. The first delivery of product *x* from DC *j* to store *i* is indicated with $D1_{xij}$. Every store is supplied by one DC, this store-DC relationship is defined as (i, j).

To compute the amount of products that have to be shipped in the first delivery, the A_{xi} is multiplied with the fraction of the week demand $\sum_{t=1}^{3} F_{i,t}$ of a store that is normally sold in the first three days of the week ($F_{i,t}$ is the demand fraction at store *i* at day *t*). Due to demand variability a safety factor for the first delivery is introduced; k_1. This results in the following equation for the first delivery (1).

$$D1_{xij} = (1 + k_1) \cdot A_{xi} \cdot \sum_{t=1}^{3} F_{i,t} \tag{1}$$

The second delivery is initiated on second day of the promotion week. At this time early sales information about the first two sales days is available $\sum_{t=1}^{2} S_{xi,t}$ and stock levels of stores are known; $I_{xi,2}$. This information is used to propose the second delivery. Based on the demand week pattern of a store a forecast is made for the expected stock level at the time the second delivery arrives. This expected inventory level is deducted from the forecast for the demand at the days after the second delivery arrived. A detailed explanation of the derivation of this formula can be found in Appendix 7. Finally, it results in the following definition (2):

$$D2P_{xij} = MAX\left\{(1 + k_2) \cdot \left[\frac{\sum_{t=4}^{6} F_{i,t}}{\sum_{t=1}^{2} F_{i,t}} \cdot \sum_{t=1}^{2} S_{xi,t}\right] - MAX\left\{I_{xi,2} - (1 + k_2) \cdot \left[\frac{F_{i,3}}{\sum_{t=1}^{2} F_{i,t}} \cdot \sum_{t=1}^{2} S_{xi,t}\right], 0\right\}, 0\right\} \tag{2}$$

As aforementioned, the second delivery is constrained by the inventory that is available at the DC. The inventory that is available for the second delivery at the DC is the starting inventory $I_{xj,0}$ minus the first delivery to all related stores:

$$I_{xj,2} = I_{xj,0} - \sum_{\forall i \epsilon (i,j)} D1_{xij} \quad (3)$$

Whether the proposal for the second delivery can be satisfied depends on the inventory level at the DC. If the sum of all proposed deliveries is higher than the current inventory level the products will be equally divided over the proposed orders. When there is sufficient inventory available the proposal is directly turned into an actual delivery; $D2A_{xij}$. This delivery arrives before *t = 4*.

$$D2A_{xij} = MIN\left\{D2P_{xij}, \frac{D2P_{xij}}{\sum_{\forall i \epsilon i,j} D2P_{xij}} \cdot I_{xj,2}\right\} \quad (4)$$

Every store is able to fulfill customer demand as long as inventory is available. The starting inventory of a store $I_{xi,0}$ is the inventory that is part of the regular store inventory plus the first delivery of promotion products. The customer demand, denoted with $D_{xi,t}$, that is fulfilled on day *t* in a promotion week is defined as sales; $S_{xi,t}$. The demand that can is fulfilled during the first three days of the week is limited by the starting inventory of a store ($I_{xi,0}$). For the demand on the last three days of the promotion week the inventory that is available after the second delivery arrived ($I_{xi,3}$) is limiting. The total demand of a product at a store that is fulfilled can be defined as:

$$\sum_{t=1}^{6} S_{xi,t} = MIN\left[I_{xi,0}, \sum_{t=1}^{4} D_{x,i,t}\right] + MIN\left[I_{xi,3}, \sum_{t=4}^{6} D_{x,i,t}\right] \quad (5)$$

After the promotion week the inventory $I_{xi,6}$ that is left can be returned if the new return policy is satisfied. A return is in the objective function denoted with R_{xi}, this is the number of packages of product *x* at store *i* that is returned. In the return policy two product subsets are differentiated: a subset for bulky products denoted with *b* and a subset for regular products denoted with *r*. For bulky and regular products it is allowed to keep two and four weeks of inventory respectively. When this inventory level is exceeded all products can be returned except for one week of inventory. The average week inventory of a product at a store is denoted with T_{xi}. Since the R_{xi} is measured in packages, the number of products has to be corrected with the pack-size per product denoted with P_i. This leads to the following formulation for the return rule of the two product subsets:

$$\forall x \epsilon b \qquad R_{xi} = \frac{I_{xi,6} \cdot \left[MAX\left[\frac{I_{xi,6}}{T_{xi}} - 2, 0\right] + 1\right]}{P_i} \qquad \text{if} \qquad \frac{I_{xi,6}}{T_{xi}} > 4 \quad (6)$$

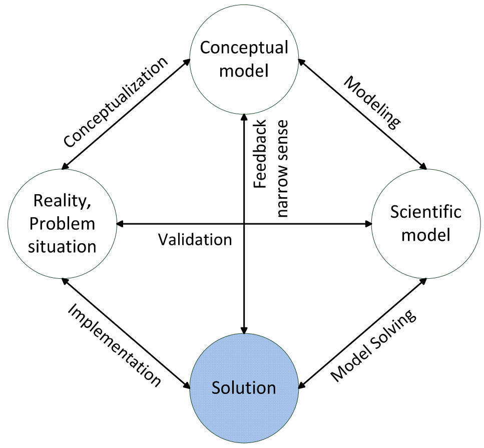
$$\forall x \epsilon r \qquad R_{xi} = \frac{I_{xi,6} \cdot \left[MAX\left[\frac{I_{xi,6}}{T_{xi}} - 4, 0\right] + 3\right]}{P_i} \qquad \text{if} \qquad \frac{I_{xi,6}}{T_{xi}} > 2 \quad (7)$$

The primary objective of the mathematical model is to gain more insights in the trade-off between the costs of returned packages and lost sales. This trade-off can be defined in the following objective function:

Minimize: $$Total\ Costs = C_p \cdot \sum_{t=1}^{6}\left(D_{xi,t} - S_{xi,t}\right) + C_r \cdot \sum R_{xi} \qquad \forall x, \forall i \quad (8)$$

Result Part 3: *This part resulted in a clear definition of the distribution model.*

Part 4: Solution



In this part of the research the point of sales data that is used in the model solving is collected and extensively researched. Thereafter the model solving starts. The 3 different research scenarios are simulated in the distribution model. To conclude this part the distribution model is compared to the current distribution of promotion products (scenario 4).

6 Data collection and analysis of point of sales data

The distribution model will be tested on point of sales data collected over the first half year of 2010. In this period 1165 promotions have taken place in the subset Fastmovers "DKW" and "Frozen Food" across 78 stores. These stores are related to 2 retail DC's. Sales data for the promotions are available on day level per product per store. It is important to notice that in this period stores have been closed during the following holidays: Eastern, Ascension Day and Whitsun. These records are removed from the dataset since they negatively affect the forecasts that are made based on the demand week patterns. For these weeks an adaption in the models is demanded. In total the dataset is split into a calibration and a validation period (Table 6-1). It is difficult to determine how much data should be used exactly for each period. Since in the calibration period, next to the model calibration, also an extra analysis is performed it is decided to use the largest extent (2/3) of the dataset for this period. The remaining part (1/3) is used to validate the distribution model.

Besides point of sales data also data to determine start inventory levels at the DC's and stores are collected. Since there is no information about historic inventory levels these values are estimated. Details about the data collection process are given in Appendix 8.

	Data collection period	Number of records
Total	Week 1 2010 – Week 26 2010	79086
Calibration Period	Week 1 2010 – Week 18 2010	56056
Validation Period	Week 19 2010 – Week 26 2010	23030

Table 6-1: Dataset

Before the distribution model is tested an extra analysis is conducted on the collected point of sales data. As aforementioned the distribution model makes use of demand week patterns of non-promotion products. To test the assumption that demand week patterns of promotion and non-promotion products are similar **an analysis to the demand week patterns** is conducted. In this analysis also the **impact of OOS's on the point of sales data** is investigated. According to Fisher et al. (2000) many retailers lack knowledge about lost sales since they do not track OOS's. The fact that OOS's are currently not tracked might indicate that the point of sales data does not represent real customer demand since lost sales are not recorded.

To investigate the demand week patterns and the impact of OOS's a scatterplot analysis is performed. In this analysis forecasts based on early sales information and actual sales are plotted. The early sales forecast is based on the first two sales days and forecasts demand for the remaining four days of the promotion week. When the forecast is accurate it is expected that the two variables are positively correlated.

The following two variables are plotted:

$$Forecast = \frac{\sum_{t=3}^{6} F_{i,t}}{\sum_{t=1}^{2} F_{i,t}} \cdot \sum_{t=1}^{2} S_{xi,t} \quad \text{(Forecast for the last four days of the promotion week)} \quad (9)$$

$$Actual\ Sales = \sum_{t=3}^{6} S_{xi,t} \quad \text{(Actual sales in last four days of the promotion week)} \quad (10)$$

In the next four paragraphs the scatterplot analysis is applied on four different aggregation levels: company level, store level, product group level and store-product group level. In the scatterplot analysis the demand data of 78 stores, collected in the calibration phase, is used.

6.1 Scatterplot analysis on company level

In Figure 6-1 the relation between the "Actual Sales" and the "Forecast" is plotted for all stores and all product groups. As expected, there exists a positive relation between the "Forecast" and "Actual Sales". Although the relationship is positive, the slope of the trendline (0,79) is smaller than 1 which indicates that the forecasts are on average higher than the actual sales. There are two potential explanations for these over-forecasts. The first explanation might be that promotions products have more demand pressure in the beginning of the week compared to non-promotion products. Therefore the forecasts based on the demand week patterns of non-promotion products are too high compared to the actual sales. Consequently, the trendline in the scatterplot is pulled down.

Another explanation might be the occurrence of OOS's. In Figure 6-1 potential OOS's are indicated (see marked area). The dots that lie in the marked area represent a relatively high forecast, caused by high sales values in the first two days, and low actual sales values in the end of the week. The fact that less product are sold in the end of the week might be caused by OOS's. To gain more insights in these two potential explanations the same analysis is applied on lower aggregation levels in the next paragraphs.

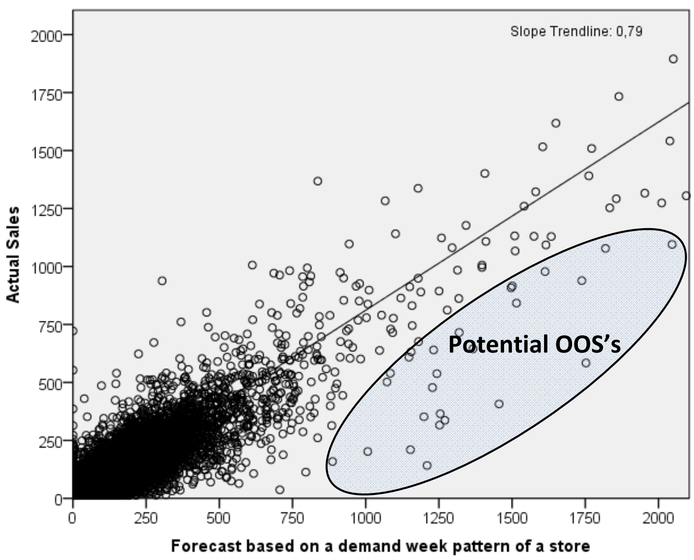


Figure 6-1: Scatterplot analysis on company level

6.2 Scatterplot analysis on store level

In this paragraph the scatterplot analysis is conducted on store level. In Figure 6-2, six scatterplots of six different stores are depicted. In the scatterplots differences can be noticed between the six stores with regards to the slopes of the trendlines and the number of potential OOS points.

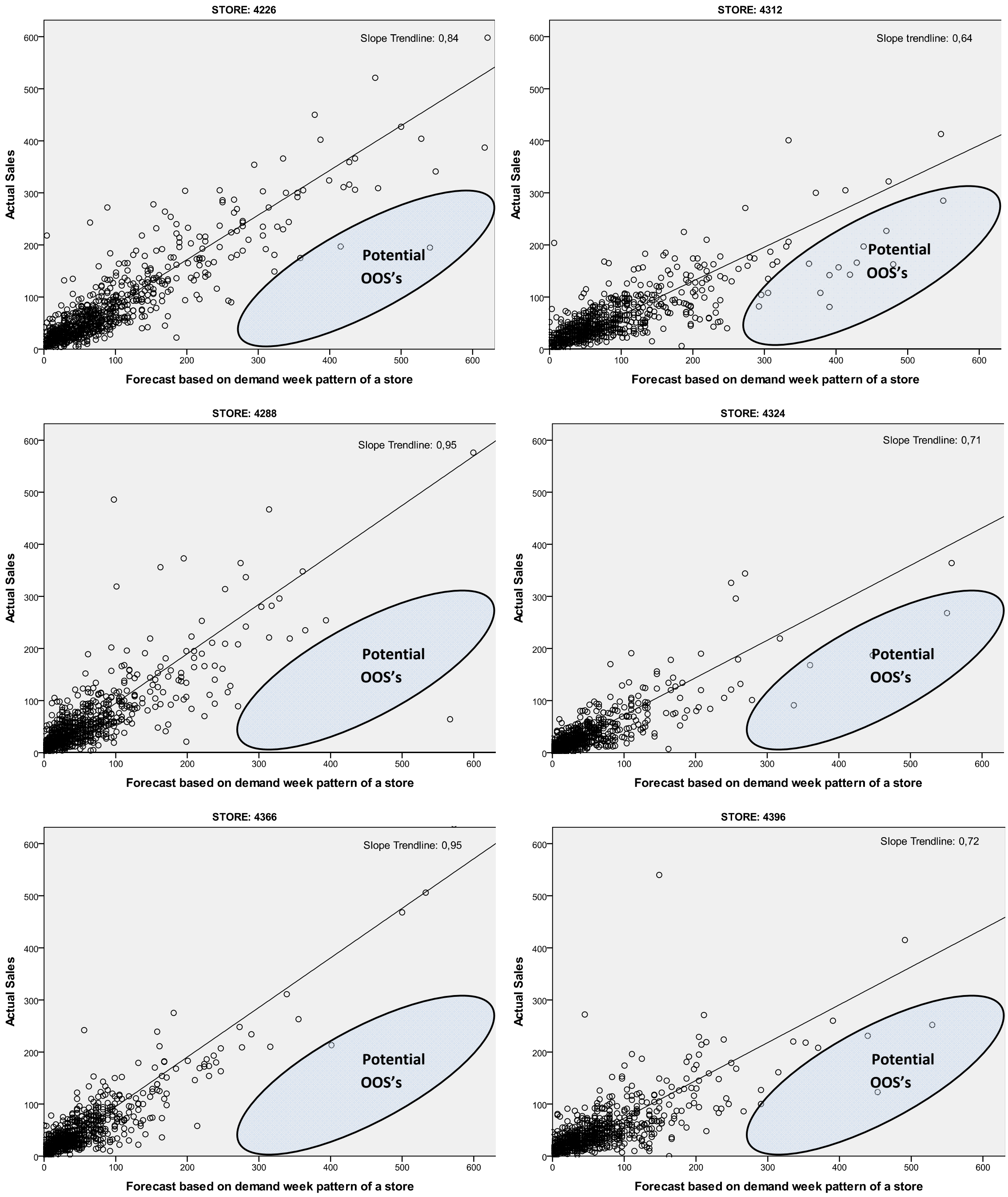


Figure 6-2: Scatterplot analysis of six stores

The differences between the stores might be explained by the performance of the inventory management of promotion products in the stores. For instance, it is possible that stores 4324, 4312 and 4396 have more difficulties with managing their inventory levels than stores 4226, 4288 and 4366. This is suggested by the relatively low slope of the trend line in the scatterplots of the low performing stores. The low slope of the trend line might be caused by OOS's. Moreover, the scatterplots of these stores contain more potential OOS points (high forecast and low actual sales) than the well performing stores. This suggests that relatively more sales are lost in the stores 4324, 4312 and 4396 than in the stores 4226, 4288 and 4366. The observation that store 4288 appears to perform well in the scatterplot analysis can be supported by the fact that this store was the best performing store of year 2010 from an economic point of view.

6.3 Scatterplot analysis on product group level

In this paragraph the scatterplot analysis is performed on product group level. In total 30 scatterplots are made for 30 different product groups. The scatterplots for 6 product groups are depicted in Figure 6-3, the remaining scatterplots can be found in Appendix 9.

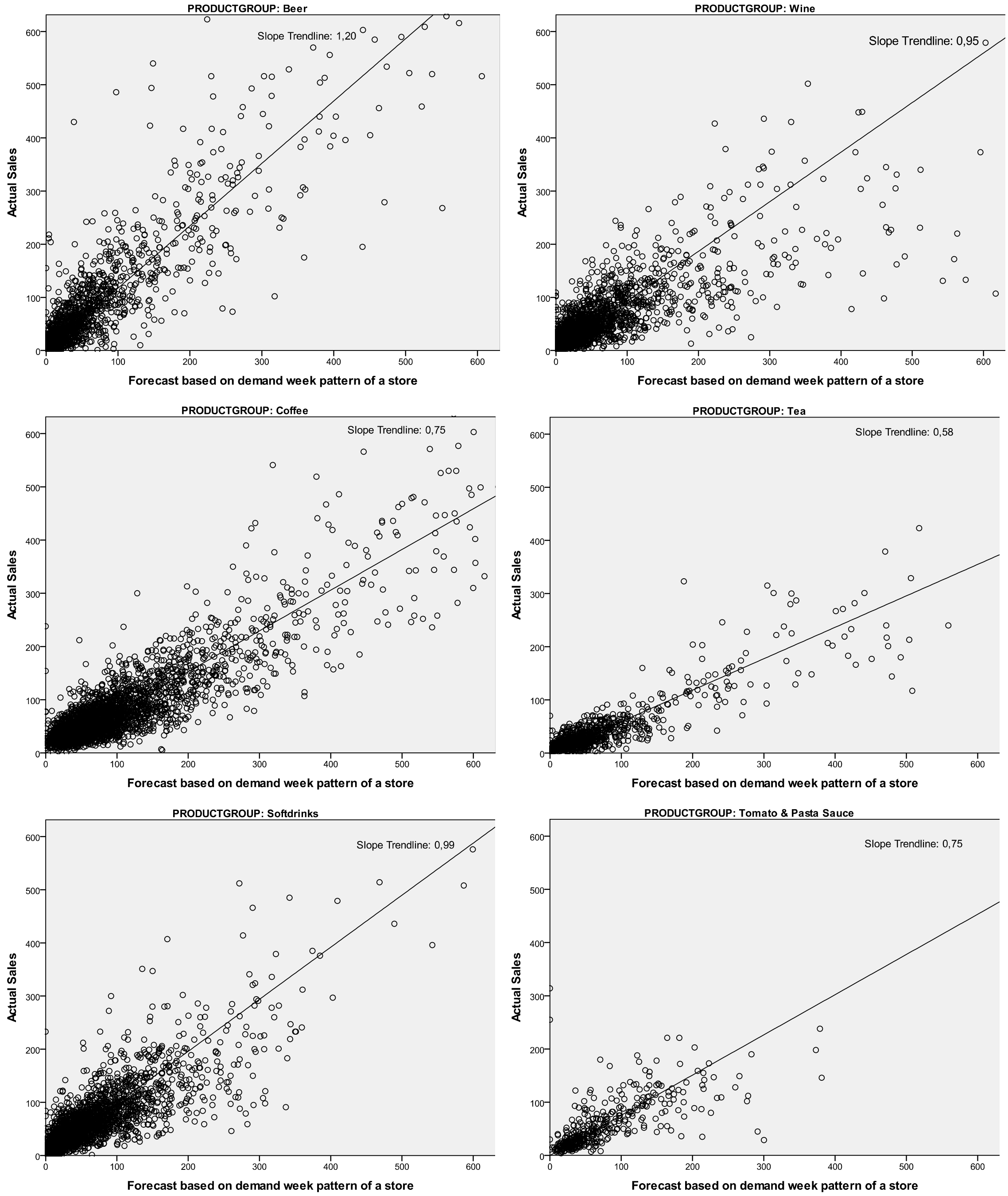


Figure 6-3: Scatterplot analysis of six product groups

As aforementioned, products like “Coffee” and “Beer” are expected to follow a different demand week pattern. This expectation is confirmed in Figure 6-3. The trendline in the scatterplot of the product group “Beer” is steeper than the trendline of the product group “Coffee”. This implies that “Beer” has compared to “Coffee” more demand pressure in the end of the promotion week (weekend). In Table 6-2 a ranking is presented of the product groups with the highest and lowest slopes. In this Table it can be seen that there are typical weekend products which are in particular sold in the weekend. These are products like: “Beer and Nuts”. Other products like “Tea and Pasta & Tomato sauce” have more demand pressure in the beginning of the week. Compared to the demand week patterns of non-promotion products it is likely that most product groups have more demand pressure in the beginning of the week. Namely, the slope of only two product groups is larger than 1.

Ranking of 30 product groups	Product group	Slope Trend line
1	Beer	1,20
2	Nuts	1,02
3	Softdrinks	0,99
4	Wine	0,95
5	Chips	0,94
..... AVERAGE	..... AVERAGE	0,79
26	Meal sauces & mixes	0,65
27	Canned vegetables	0,65
28	Snacks	0,65
29	Pasta & Tomato sauce	0,63
30	Tea	0,56

Table 6-2: Slope ranking of several product groups

The differences between the demand week patterns of some product groups can be regarded as substantial. For instance, the slopes of the trendlines of the product groups “Chips” and “Canned Vegetables” are 0,95 and 0,65 respectively. This implies that the product group “Chips” has based on the first two sales days on average 42% more demand in the end of the week compared to the product group “Canned Vegetables”. Hence, it is promising that these differences exist between product groups. Because of these differences, applying decisions on a lower aggregation level (product group level) has the potential to improve the performance of the distribution model.

Next to the differences in demand week patterns, also differences in difficulty of inventory management between product groups can be discovered. Since the scatterplot of the product group “Beer” shows relatively more potential OOS points, inventory management for this product group might be more difficult than for “Coffee”. To gain more insights in the potential OOS points, the product group “Beer” is investigated further. As indicated in the problem description the return flow of products after a promotion week is currently a major issue. It is likely that when a return flow occurred stores have been “over-supplied”. Therefore, the effect of OOS’s in these situations is expected to be negligible. To see if this can be confirmed in a scatterplot the promotions of the product group “Beer” are filtered on return flows: only points that contain a return flow are plotted. The results are plotted in Figure 6-4. The scatterplot shows a clear demand pattern. All points that could have been classified as a potential OOS point in Figure 6-3 are disappeared in the new scatterplot. Hence, it is likely that in the product group “Beer” a serious amount of sales is lost. Since similar potential OOS points can be found in scatterplots of other product groups it is possible that also for these product groups sales is lost. Moreover, this evidence proves that the scatterplot method to detect potential OOS’s is a simple and powerful tool. It is important to notice that this method is especially appropriate to detect OOS's of products with large sales volumes. When sales volumes are lower the probability that an OOS is detected correctly is lower since demand variability plays than a relatively more important role.

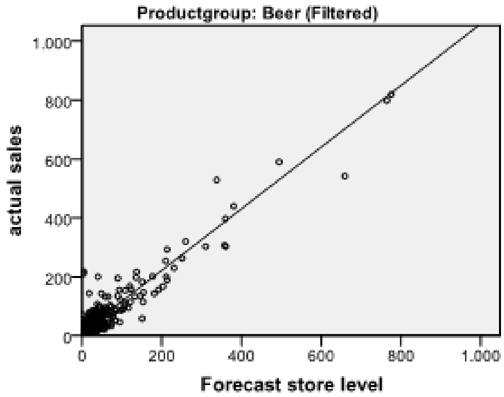
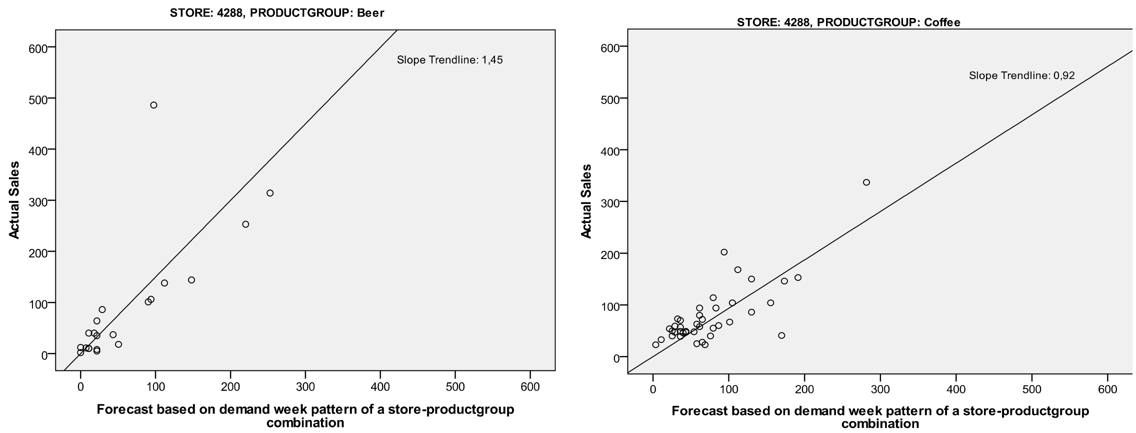


Figure 6-4: Scatterplot analysis of product group "Beer" (filtered)

6.4 Scatterplot analysis on store-product group level

In the scatterplots which are presented up to here a certain amount of noise can be observed. The noise in the scatterplots might be reduced by disaggregating these scatterplots to a store-product group level. Also the forecast will be applied on a more disaggregated level. The forecast will be based on the demand week pattern of a store-product group combination. It is expected that this forecast will take the differences between product groups better into account. In total six scatterplots are made for six different product groups of a well performing store (4288) (Figure 6-5).

The first thing that can be noticed is that there exists a clear demand pattern on store-product group level. This is shown by the fact that the points in the scatterplots deviate relatively less from the trend line. This suggests that on this aggregation level it is possible to make a quite accurate demand forecast based on the first two sales days for the end of the promotion week. The second thing that can be remarked is that even when a forecast is applied based on demand week patterns of non-promotion products on store-product group level some product groups stay under- or over forecasted. This implies that for product groups like "Beer, Pastry and Tea" the demand week patterns change substantially when the products are in promotion. Hence, the assumption regarding the similarity of demand week patterns of promotion and non-promotion products is in these cases violated.



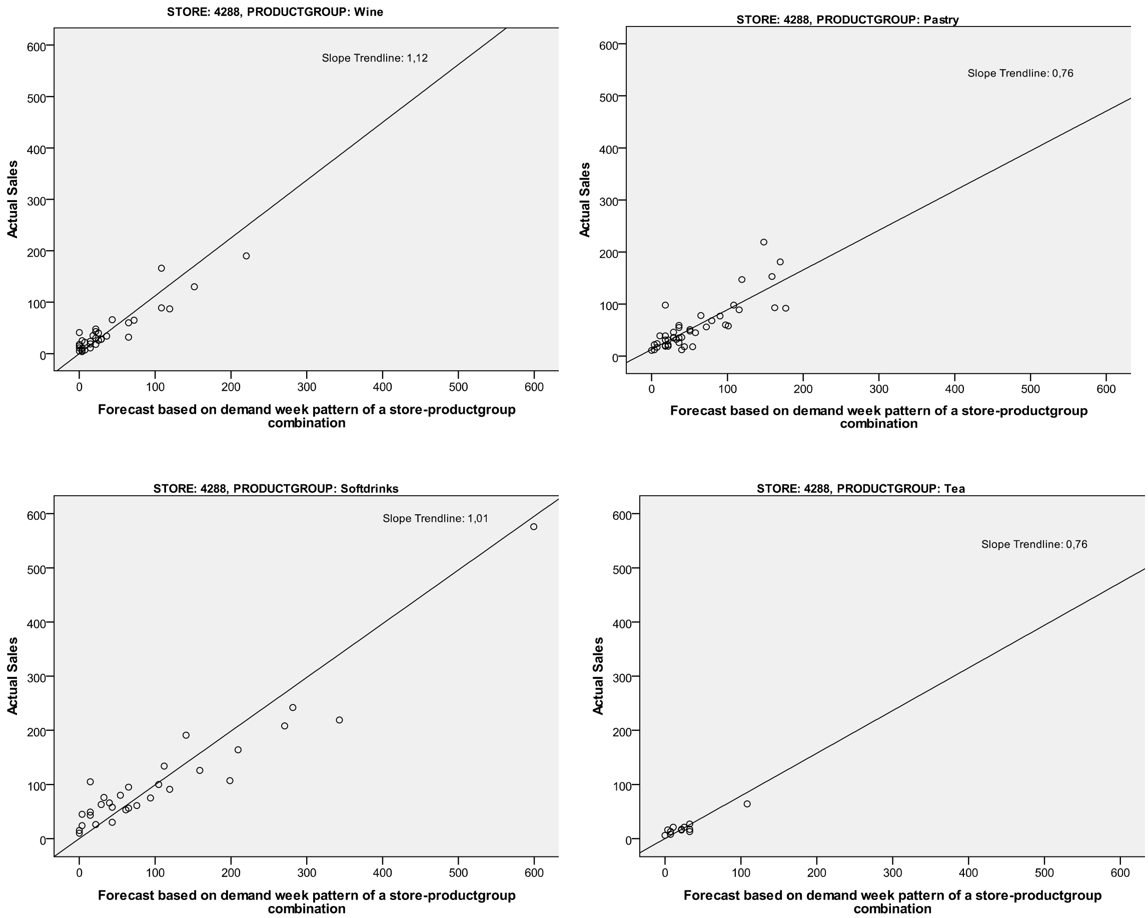


Figure 6-5: Scatterplot analysis of six product groups of store 4288

6.5 Conclusion Scatterplot analysis

It is likely that potential OOS's have affected the point of sales data. This means that the point of sales data might not always represent real customer demand. The impact of the potential OOS´s on the point of sales data is expected to differ between stores and product groups. Furthermore, the scatterplot analysis has lead to the following insights in the demand patterns of promotion products:

1. There exist substantial differences in the demand week patterns of promotion products between product groups. There are typical weekend promotion products and promotion products which are generally sold in the beginning of the week.
2. Compared to the demand week patterns of non-promotion products it is likely that the demand week patterns of promotion products of most product groups have more demand pressure in the beginning of the week.
3. The demand week patterns of products can change when products are in promotion. Therefore demand week patterns of promotion and non-promotion products are not always similar.
4. There is a clear demand week pattern of promotion products on store-product group level.

7 Calibration of the Distribution model

In this chapter the first simulations are performed to calibrate the distribution model. An illustration of the simulation model built in Microsoft Excel is shown in Appendix 10. At first an overview is given of the performance of scenario 1. Thereafter, scenario 1 and 2 are compared. After this comparison one scenario is selected to test an improvement suggestion.

7.1 Simulation of scenario 1

In this paragraph scenario 1 (central coordination of both deliveries on store level) is tested in the developed distribution model. In the distribution model promotion products are delivered in two shipments. It is expected that OOS's occur at two moments; just before the second delivery arrives and at the end of the promotion week. This can be seen when the service level is plotted over the weekdays (Figure 7-1) for two different settings of the safety factor parameters (k_1 and k_2). In this Figure can also be seen that when the safety factor parameters are increased a higher service level is achieved. In Table 7-1 the results for multiple settings of the safety factor parameters are reported. The results show that most uncertainty is related to the first delivery since the value of k_1 appears to be more important than the k_2. The uncertainty that is related to the k_1 can be described as the reaction of customers to a particular promotion. If more information about the reaction of customers to a particular promotion becomes available this uncertainty is reduced since the value of k_2 appears to be less important. This is a first sign that early sales forecasting has benefits within this domain. In Table 7-1 is shown that more than 70% of all products have to be shipped in the first delivery to achieve a minimum service level of 95% without having many returned packages.

When the best results with respect to the two defined performance measures are plotted can be seen that the number of returned packages dramatically increases when a higher service level is desired (Figure 7-2). This stresses the need for a careful trade-off between penalty costs of OOS's and the costs of returned packages. More about this trade-off is discussed in the validation phase.

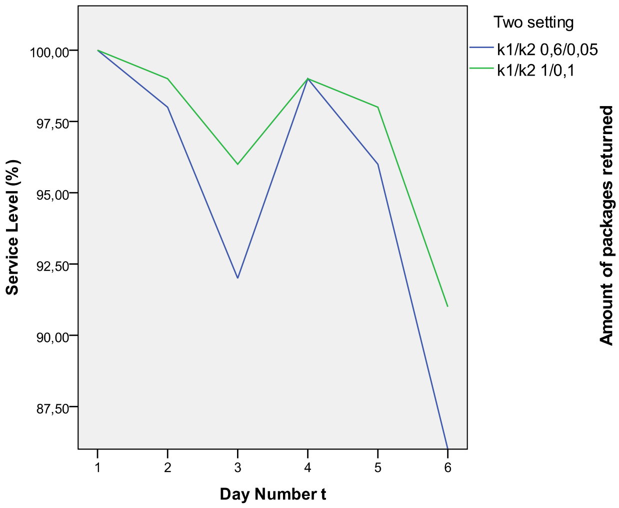


Figure 7-1: Service level over the weekdays

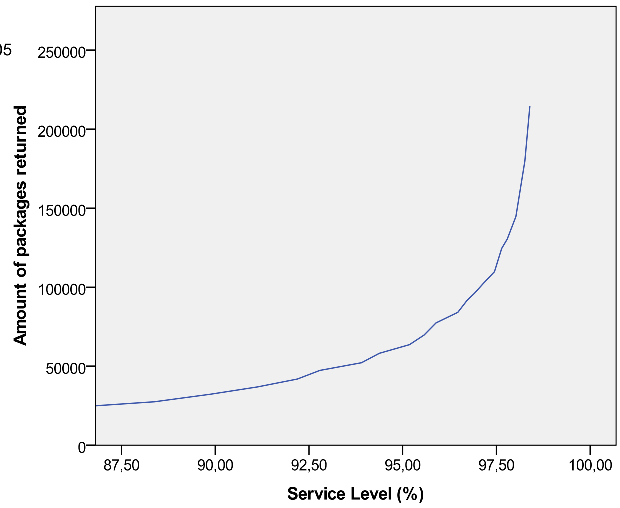


Figure 7-2: Relation Service level (%) and Returned packages

Setting parameter k1	Performance measure	Setting parameter k2: 0	0,05	0,1	0,2	0,4	0,6	% Shipped in the first delivery
0	Service level	85,56	86,53	88,31	89,52	91,00	91,81	39%
	Returned packages	22985	27193	32467	45092	83338	128210	
0,1	Service level	88,38	89,21	89,85	90,97	92,28	92,99	43%
	Returned packages	27477	32453	38020	52287	91314	135662	
0,2	Service level	89,87	91,09	91,32	92,18	93,33	93,98	47%
	Returned packages	32246	40527	43270	58476	98032	142092	
0,3	Service level	91,13	91,79	92,34	93,19	94,21	94,79	51%
	Returned packages	36881	42437	49405	64294	104591	147801	
0,4	Service level	92,19	92,79	93,28	94,03	94,95	95,46	55%
	Returned packages	41854	47357	54569	70261	110395	153342	
0,6	Service level	93,90	94,38	94,78	95,38	96,10	96,50	62%
	Returned packages	52207	58186	65660	81102	121427	163258	
0,8	Service level	95,18	95,57	95,89	96,37	96,93	97,24	70%
	Returned packages	63601	69697	77431	92799	132136	173194	
1	Service level	96,16	96,47	96,72	97,1	97,53	97,77	78%
	Returned packages	77822	84079	91685	106723	145130	184986	
1,2	Service level	96,91	97,15	97,45	97,64	97,96	98,14	86%
	Returned packages	95987	102263	109742	124432	161744	199310	
1,4	Service level	97,45	97,61	97,79	98,02	98,26	98,39	94%
	Returned packages	117143	125161	130453	144742	179863	214452	

Table 7-1: Simulation results Scenario 1 (best settings with respect to both performance measures are colored blue)

7.2 Comparison between scenario 1 and scenario 2

The difference between scenario 1 and 2 is that forecasts are based on different aggregation levels. In the first scenario forecasts are based on store demand patterns, in the second scenario forecasts are based on store-product group demand patterns. This comparison is made in order to test if the **aggregation level on which decisions are made in a multi-product environment influences the performance of the distribution system.**

To assess the impact of a more disaggregated approach the $F_{i,t}$ is transformed to $F_{i,p,t}$ in scenario 2. The $F_{i,p,t}$ stands for the fraction of the week demand of product group *p* in store *i* that is normally sold at day *t*. To test the performance of scenario 2 different settings for the two safety factor parameters k_1 and k_2 are simulated again. The simulation results for scenario 2 are reported in Appendix 12. The best values of both scenarios are plotted in Figure 7-3 to make a comparison. The results are surprising and counterintuitive: a more disaggregated approach does not lead to a net improvement. Although there are differences between product groups, a forecast applied on store-product group level is not able to explain these differences. This might be explained by the finding that demand week patterns of promotion and non-promotion products are not always similar. Therefore a more disaggregated approach based on the demand week patterns of non-promotion products might not be able explain the differences between product groups better than a more aggregated approach.

Based on the results of the simulation can be concluded that applying decisions on a more disaggregated level in the 2nd scenario does not lead to a model improvement. **This implies that in this situation the aggregation level on which decisions are made does not influence the performance of the distribution system**. Hence, it is decided to continue with the more aggregated approach **(scenario 1)** since it fits the practical requirement *simplicity* better.

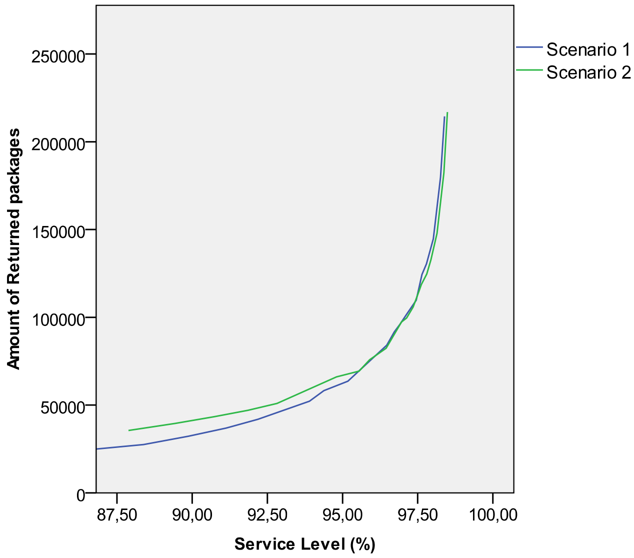


Figure 7-3: Comparison between Scenario 1 and 2

7.3 Improvement suggestion for scenario 1

Despite the attempt to lower the aggregation level in scenario 2, no improvements are realized. As observed in the scatterplot analysis, the demand week patterns of promotion and non-promotion products can differ. In this paragraph a new attempt is performed to include the differences between promotions across different product groups in the distribution model. For this improvement, scenario 1 is used as the scenario to improve.

The early sales forecast that is made in the distribution model is adjusted per product group for the demand week pattern of a product group when it is in promotion. This is done by using the slopes of the trend lines of the scatterplots that are made in Appendix 9 of all product groups. As indicated, the trend lines in these scatterplots can be used to assess if demand of a product group is under- or over forecasted. When the slope of the trend line is larger than 1 the demand of a product group is under-forecasted. For a slope of the trend line which is lower than 1, demand of a product group is over-forecasted. To compensate for this under- and over forecast, the early sales forecast of a product group is multiplied with the slope of the trend line of the product group. The slope of the trend line is denoted with β_p for each product group *p*. The values of the β_p that are used for the included product groups can be found in Appendix 11. To see if the forecast accuracy of the adjusted early sales forecast is increased a scatterplot is made. The relation between the following two variables is plotted:

$$Adjusted\ Forecast = \beta_p \cdot \frac{\sum_{t=3}^{6} F_{i,t}}{\sum_{t=1}^{2} F_{i,t}} \cdot \sum_{t=1}^{2} S_{xi,t} \quad (11)$$

$$Actual\ Sales = \sum_{t=3}^{6} S_{xi,t} \quad (12)$$

In Figure 7-4 is shown that the adjusted forecast effectively corrects the bias in the forecast (the slope is of the trend line is almost 1). When the average absolute deviation of the forecast from the actual sales is measured an increase in forecast accuracy of more than 20% is realized. This result is promising and is expected to improve the proposed distribution model.

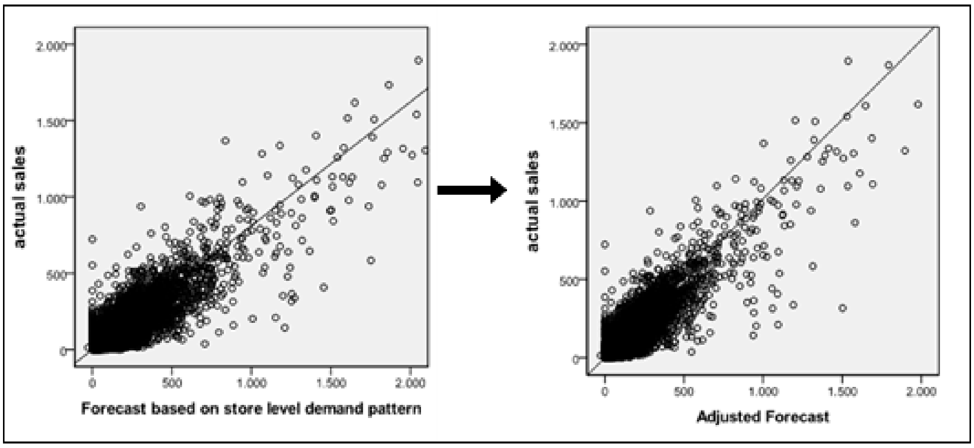


Figure 7-4: Normal forecast compared to adjusted forecast

Before this suggestion for improvement can be tested in the simulation model the notation of the second delivery has to be rewritten. When the β_p is added to the formula $D2P_{xij}$, the following definition is the result:

$$D2P_{xij} = MAX\left\{(1+k_2)\cdot\left[\beta_p \cdot \frac{\sum_{t=4}^{6} F_{i,t}}{\sum_{t=1}^{2} F_{i,t}} \cdot \sum_{t=1}^{2} S_{xi,t}\right] - MAX\left\{I_{xi,2} - (1+k_2)\cdot\left[\beta_p \cdot \frac{F_{i,3}}{\sum_{t=1}^{2} F_{i,t}} \cdot \sum_{t=1}^{2} S_{xi,t}\right], 0\right\}, 0\right\}$$

To test if the adjusted forecast leads to an improvement of the distribution model new simulations are performed. The results of the simulations are reported in Appendix 12 and the best values are plotted in Figure 7-5. Surprisingly an improvement in forecast accuracy does not lead to a model improvement. The model with the adjusted demand week pattern is outperformed for all service levels by scenario 1.

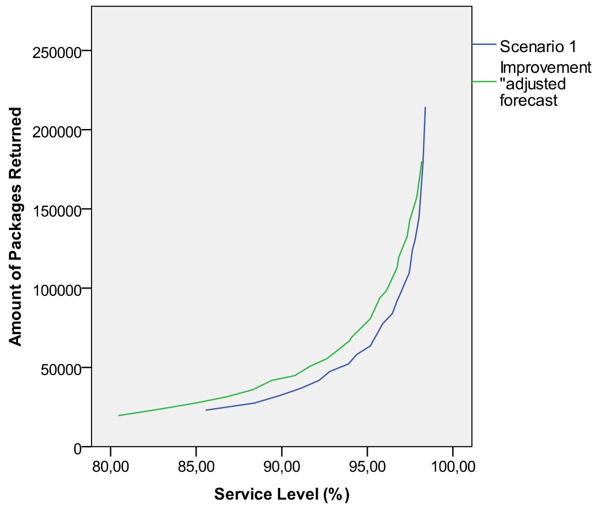


Figure 7-5: Improvement suggestion "Adjusted forecast"

To see why the adjusted scenario is underperforming the performance of the first and the latter scenario are compared. To make a valid case comparison, the safety factor parameter (k_1) of the first delivery is set equal for both scenarios (Table 7-2). This safety factor is set on 100%. It is important to notice that the difference between the two models lies in the second delivery. Since most promotion products have demand pressure in the beginning of the week the value of β_p is for most product groups lower than 1. Consequently, the forecast for most product groups is decreased. Therefore a larger value for the safety factor parameter of the second delivery (k_2) is needed in the adjusted model to achieve the same service level as in scenario 1. In order to achieve a service level of 96,16% a safety margin of 23,4% is required for the second delivery. The amounts of products that are shipped in the second delivery are almost similar in both scenarios. However, the amount of returned packages increases with 25%.

	Scenario 1	Improvement “adjustment week patterns”
k_1	100%	100%
k_2	0%	23,4%
Service Level	96,16 %	96,16%
First delivery	3701129	3701129
Second Delivery	1446046	1431414
Amount of returned packages	77822	101095

Table 7-2: Case comparison scenario 1 and improvement suggestion "adjusted forecast"

The amount of returned packages of both scenarios is compared on product group level in Appendix 13. In this diagram can be seen that in 65% of all product groups a small reduction in the amount of returned packages is realized. However, the total result is outweighed by a few product groups that behave differently as expected. These are in particular the typical weekend products. One product group clearly sticks out above the rest; this is the product group “Beer”. Apparently this product group is responsible for more than 50% of the total return flow in both scenarios. The product group “Beer” is also responsible for the major increase in the amount of returned packages in the adjusted scenario. When the “adjusted forecast” of the product group “Beer” is plotted against the actual sales a clear bias can be seen for promotions with large product volumes (Figure 7-6). The values in the marked area represent potential OOS points which are substantially over-forecasted by the

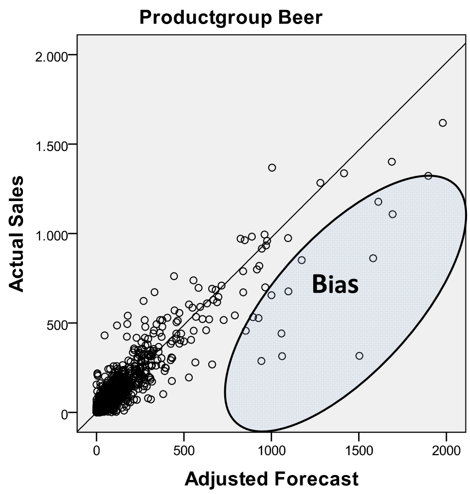


Figure 7-6: Forecast Bias in product group "Beer"

adjusted forecast. This bias will also affect the performance of the first scenario. Nevertheless, the effect is strengthened in the model improvement scenario due to a large value of the β_p (= 1,2) of the product group "Beer". This explains the decrease in performance of the adjusted scenario compared to the first scenario to a large extent. A possible explanation why this bias is occurring for "Beer" - promotions with large volumes might be that store managers treat large volumes with more caution.

Since the product group "Beer" is biased and has a large impact on the total performance of the distribution model it is decided to run the simulations again without the product group "Beer". The results of the simulations are depicted in Figure 7-7 and the complete overview can be found in Appendix 12.

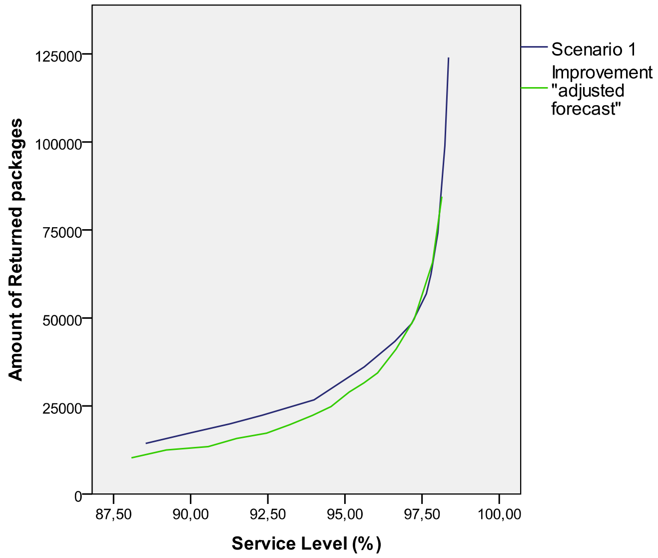


Figure 7-7: Improvement suggestion "Adjusted forecast" without product group "Beer"

When the product group "Beer" is excluded an improvement is realized. The improved scenario leads to a further reduction of the returned packages with about 10% when the service level is lower than 97%. Although it is a slight improvement, it indicates **that product aggregation can be beneficial in a distribution model for promotion products**. To reap the full benefits of product aggregation more knowledge about demand week patterns of promotion products is needed. In the remaining part of this thesis is decided to continue with scenario 1. Namely, in this scenario a solution is provided in which all product groups are incorporated. It is suggested to test decision making on product group level in practice when the distribution model is operational.

8 Validation of the Distribution model

In this chapter the performance of the distribution model in scenario 1 is validated on an independent part of the dataset. Thereafter, a central and a decentral coordination mechanism of the second delivery are compared (scenario 1 versus scenario 3). In the third paragraph of this chapter the design decision to deliver promotion products in two deliveries instead of one or even more deliveries is evaluated. Afterwards, the developed distribution model is compared to the current way of distributing promotion products (scenario 4). At last the limitations of the use of the developed distribution model in practice are discussed briefly.

8.1 Validation of scenario 1

To see whether the distribution model in scenario 1 performs as expected it is tested on an independent part of the dataset: week 19 till week 26. It is important to remark that within this period two weeks of data are deleted due to holiday periods. The results of the simulation are depicted in Figure 8-1. For the complete overview of the results the reader is referred to Appendix 12. Figure 8-1 shows that the distribution model performs as expected in the validation phase[5]. This indicates that the results of the distribution model are robust when it is used for other promotions than the original dataset.

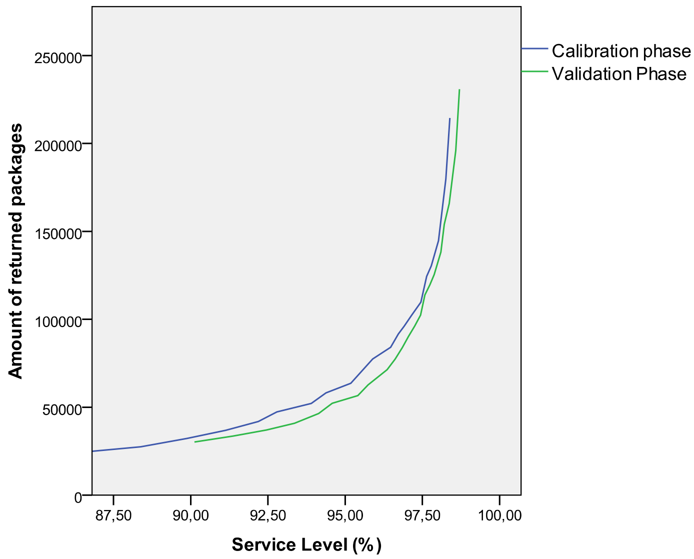


Figure 8-1: Performance of the distribution model in the Calibration and Validation phase

To understand the performance of the distribution model in more detail a specific setting for the safety factor parameters k_1 and k_2 is discussed. When the k_1 and k_2 are set on 80% and 10% respectively an overall service level of about 97% is achieved. This service level fluctuates across the week (Figure 8-2). In the beginning of the week the service level is high, but downfalls on Friday and Saturday. Especially on Saturday, where the service level is 90%, a considerable amount of sales is lost. However, since this is the last day of the promotion week and the overall service level is high, the amount of lost sales seems to be acceptable. Nevertheless, if the management team decides that a higher service level on Saturday is desired a substantial increase in costs (returned packages) can be expected.

[5] Since the calibration and the validation phase concern a different amount of promotions the amount of packages returned in the validation phase is corrected for the number of promotions in the calibration phase.

In Figure 8-3 the good flows in the distribution model before and during the promotion week is illustrated. On average 70% of the total forecast is shipped to the stores in the first delivery. Hence, of the 2,2 million products that are initially forecasted only 1,55 million products are delivered in the first shipment to the stores. After two days of sales the second delivery is initiated, less than 50% of all promotions require a second delivery. This result confirms the benefits of a flexible distribution system since more than 50 % of all promotions do not need a second delivery. In total 0,56 million products are shipped in the second delivery to stores where extra products are needed. After the promotion week 0,18 million products are returned to the DC's, which is about 8% of all promotion products that are shipped to the stores.

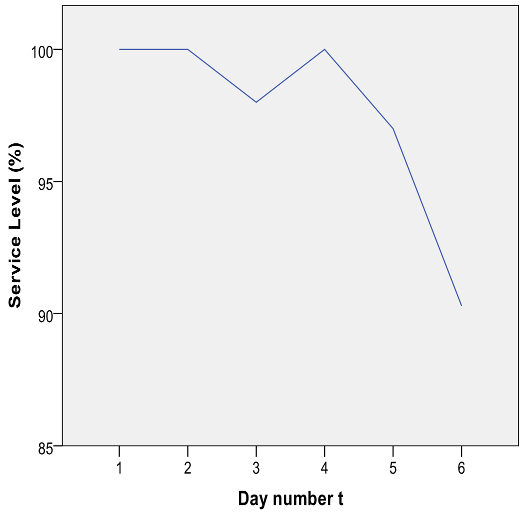


Figure 8-2: Overview of the service level across the weekdays

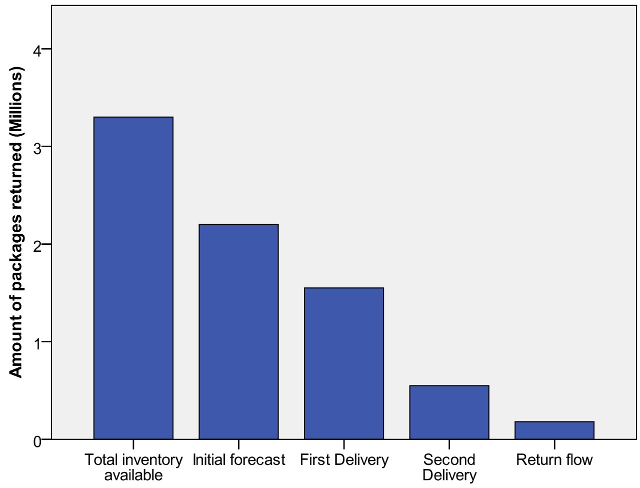


Figure 8-3: Overview of goods flow and initial forecast

8.2 Comparison between scenario 1 and scenario 3

In literature it is suggested that the second delivery should be coordinated decentrally. However, it is unclear if store managers, in a multi-product environment, are able to coordinate this delivery. It is expected that, due to many sources of information that have to be consulted, a store manager cannot outperform a centralized coordination mechanism. For this reasons it is expected that **the coordination mechanism of the second delivery influences the performance of the distribution system.**

To test the performance of a decentral coordination mechanism of the second delivery **(scenario 3)**, 78 store managers are actively involved. Each store manager received a questionnaire that is specifically related to his/her store. The questionnaire consists basically out of two parts; an order list for the second delivery of multiple products and a few open questions. In the order list an order for the second delivery of 55 promotions has to be determined (see example of the order list in Appendix 14). These 55 promotions are randomly selected in the dataset of the validation phase.

To determine an order for the second delivery the following information is given to the store managers:

- Week in which the promotion takes place
- Name of the promotion product
- Customer demand on the first two days of the promotion week
- Inventory level on Tuesday evening
- Advice for the second delivery[6]

The advice for the second delivery is given to see the additional value that a store manager can have in developed distribution model. Since store managers possess knowledge of the local market they are able to take external factors into their consideration. To gain more insights in the order behavior of the store managers open questions are used. In these questions store managers are asked to explain which factors they consider before placing an order. In total 62 store managers responded in time, which means that the response rate of the questionnaire is 80%. Filling in the form took on average 15 minutes time per store manager. When all the questionnaires were collected a total dataset of 3337 promotions was created to compare the central **(scenario 1)** and decentral **(scenario 3)** coordination mechanism of the second delivery.

In the open questions store managers indicated that several factors influence their order decisions. The most frequently mentioned factor is sales in the first two days of a promotion week. Store managers frequently argue that; “sales on the first two days of a promotion week give a good indication of the total week sales”. However, there are also store managers that say that “two days of information is not enough to determine an order for the second delivery”. These stores require more information like: seasonality, current inventory levels, market conditions, type of promotion, weather, location of the promotion in the store, promotions of competitors and the type of product. Especially the type of product is frequently cited by store managers. Namely “a product like Chips is more frequently sold in the weekend than during normal weekdays”. Besides these factors, store managers also adjust advices for products that are typically sold in their local market. One store manager mentioned: “most advices are correct; I only made adjustments for fast-moving products in my store”. Although some store managers argue that “there are many factors which influence the sales of a promotion product”, it remains unclear how all these factors are turned into an actual order. To see the difference between a central and decentral coordination mechanism the returned order lists are injected in the simulation model.

On average 25% of all advices in the order list are adjusted by store managers. In 72% of these adjustments the order volume is increased. This effort, did not lead to an increase in performance. When the central and the decentral coordination mechanism of the second delivery are compared, the amount of returned packages increases with 30% from 5486 to 7120 packages (Table 8-1). This indicates that the order behavior of a store manager is optimistic. The optimistic order behavior can be explained by the fact the most important KPI for a store manager is turnover. Therefore, ordering more products than essential is from their point of view justified. In a recently conducted research to the order behavior of retail store managers is also found that the order behavior of store managers leads to extra store inventory in the stores (Donselaar et al., 2010). Despite the increase in inventory levels, Donselaar et al. (2010) argued that store managers can improve upon an automated

[6] The advice for the second delivery is based on the order that the developed distribution model has generated.

replenishment system by better balancing the workload in the stores. However, it is expected that in this setting the benefits of a better distributed workload are outweighed by an increase in workload caused by returned packages.

At first sight the optimistic behavior appears to run counter to the finding that OOS's are occurring. However, since the DC's are currently using a "first come first serve policy" this behavior can lead to an unequal distribution of the available promotion products. Consequently, stores that order their products later in the promotion week run the risk of having OOS's. Especially for products which have a relatively low inventory buffer at the DC's. Next to this effect, an effect that is filtered out in the questionnaire is that store manager can forget to reorder extra products. This might result in practice also in OOS's.

Conclusively can be said that a decentral coordination mechanism leads to an unnecessary return flow of promotion products. Moreover, extra costs are made in the stores since every advice for each promotion product has to be checked manually. **Thus, in a multi-product environment, it is better to coordinate the second delivery centrally (scenario 3 is outperformed by scenario 1).**

	Coordination mechanism of the second delivery	
	Scenario 1 Central coordination mechanism	Scenario 3 Decentral coordination mechanism
sample size	3337	3337
Sales	288073	288204
OOS's	6942	6811
Returned Packages	5486	7120
Service Level	97,59 %	97,62 %

Table 8-1: comparison between a central and decentral coordination mechanism

8.3 Evaluation design decision: central stock function

In the conceptual design of this research is discussed how many deliveries should be performed to distribute promotion products. If more deliveries are performed the stock can be withheld longer at the DC (centrally) during the promotion week. Due to operational limitations has been decided to perform two deliveries. It is interesting to assess the effect of this design decision on the performance of the distribution model. For this reason two new settings are simulated. In the first setting only one delivery is used to distribute promotion products. In the second setting promotion products are delivered in three shipments. The third shipment is initiated on the fourth day of the promotion week and arrives just before the last day of the promotion week starts.

The results are depicted in Figure 8-4, the complete simulation results can be found in Appendix 12. In this Figure can be seen that the more deliveries are performed, the better the performance of the distribution model is. This can be explained by an increase in flexibility. The diagram shows clearly that when only one delivery is used the amount of returned packages increases dramatically. The initial demand forecast disaggregated on store level is apparently not accurate enough to ship promotion products in one delivery. The difference between two and three deliveries is smaller but there is still a difference of about 10.000 returned packages in a period of 6 weeks. However, as indicated in the conceptual design more handling costs will be made in the stores and DC's due to a decrease in order sizes if more deliveries are performed. For this reason more research is needed to make a trade-off between an increase in handling costs caused by smaller order sizes and a reduction in the amount of returned packages. As aforementioned, in this research is decided to solely focus on a feasible solution for EMTÉ: deliver promotion products in two shipments.

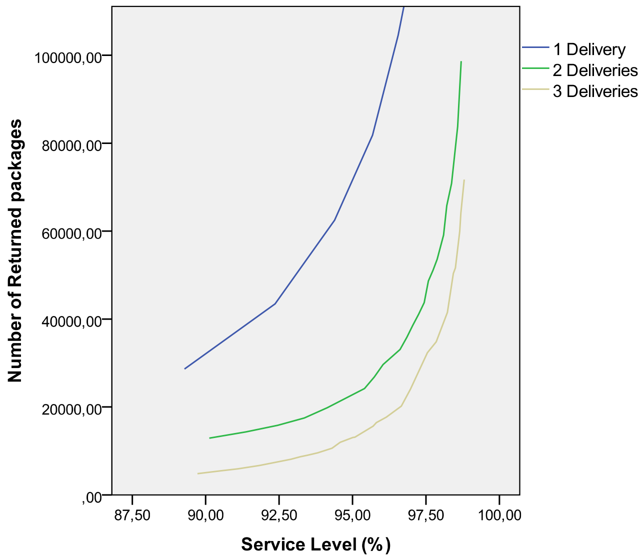


Figure 8-4: Number of deliveries comparison

8.4 Comparison between scenario 1 and scenario 4 (current)

In this paragraph the performance of the distribution model in **scenario 1** is compared to the performance of the current way of distributing promotion products in **scenario 4**. In the current distribution system the first delivery is coordinated centrally. Extra deliveries during the promotion week are coordinated to a large extent decentrally: store managers have the opportunity to place extra orders. To measure the performance of the current distribution system historic goods flow information and point of sales data are combined. Based on this information the current distribution system is rebuilt. Since the demand data which is used to measure the performance of the developed distribution model is influenced by OOS's it is complex to make valid a comparison between both scenarios. Namely, lost sales that could have been fulfilled by the developed distribution model are not taken into account since these are not recorded. Therefore an assumption has to be made for the service level that is achieved in the current distribution system. Since demand uncertainty is high in presence of promotions a service level of 97 % is assumed to be realistic. It is expected that this assumption is rather optimistic than pessimistic. Namely, a study that analyzed worldwide average losses in retail due to OOS's, concluded that about 4% of the total sales is lost (Corsten & Gruen, 2003).

To make the comparison the setting of the distribution model that is described in paragraph 8.1 is used here again[7]. At first the differences in good flows between the current and the new distribution model are investigated (Figure 8-5). Since deliveries in the current distribution system can be performed on all weekdays, they are summed up as deliveries during the promotion week. In Figure 8-5 can be seen that in the current distribution system almost the complete initial forecast is shipped in the first delivery. In addition to this delivery, also the deliveries during the promotion week tend to be larger than in the new distribution model. This implies that store managers are

[7] The realized service level for this setting was also 97 %.

optimistic in reordering extra promotion products during the promotion week. The optimistic order behavior of store managers has already been noticed in the previous paragraph. Since as well the first delivery as the deliveries during the promotion week are larger, it is likely, that more returned packages are the result.

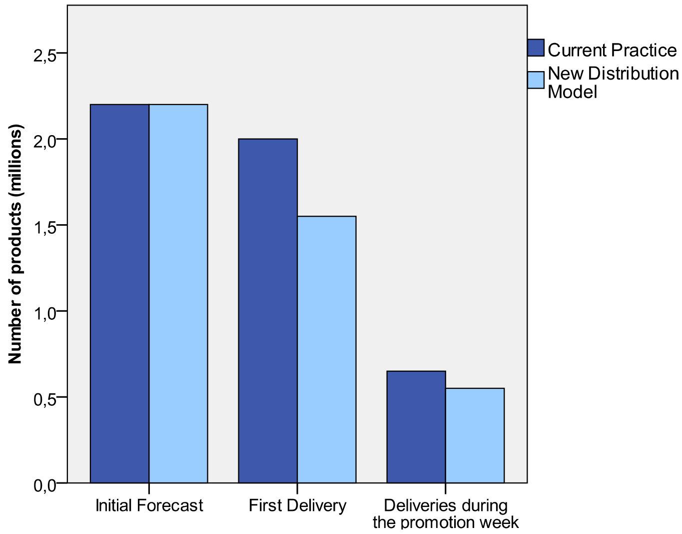


Figure 8-5: Goods flow comparison

Based on the new return rule and the inventory levels of stores after the promotion week the amount of returned packages can be computed. Since the product group "Beer" is expected to have a significant influence on the total number of returned products the results for this product group are reported separately. In Figure 8-6 the results are presented. As expected, the new distribution model outperforms the current way of distribution **(scenario 4 is outperformed by scenario 1)**. The reduction of the return flow is large. Compared to the current practice the distribution model is able to reduce the return flow for all product groups (without Beer) with 60%. The return flow for the product group "Beer" is reduced with 40%. The two main arguments, based on the goods flow analysis, that the new distribution model outperforms the current practice are: 1) in the current distribution model more products are withheld at the DC during the promotion week, 2) the second delivery is coordinated centrally which filters out the optimistic order behavior of store managers.

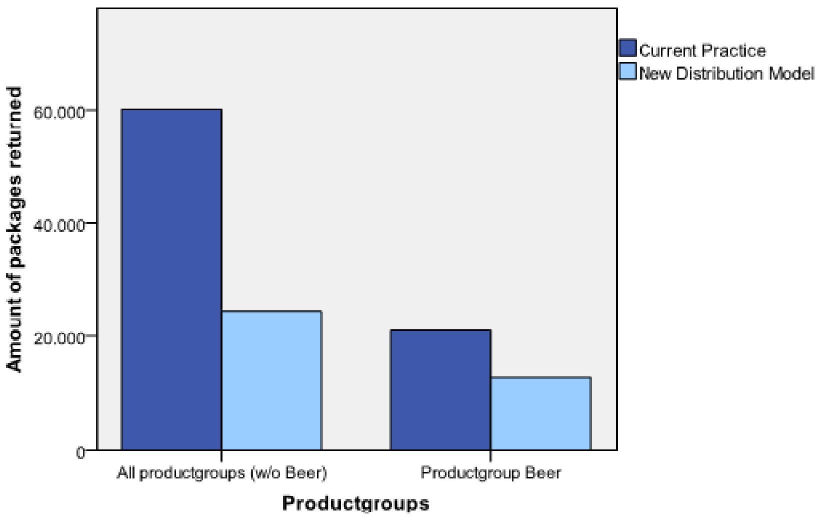


Figure 8-6: Comparison of returned packages

Based on Figure 8-6[8] can be said that the weekly return flow can be reduced with 7500 packages with the developed distribution model. To assess the total impact of this improvement the cost of a returned package is estimated (Appendix 15). In this estimation actual labor cost and productivity information are used. Based on this estimate it is expected that the handling cost of a returned package is €0,80. Hence**, the developed distribution system can reduce the handling costs caused by the return flow with €312.000 annually**. With regards to the total company profit that is realized in 2009 (5,5 million) this cost saving can be regarded as substantial. In particular because this cost saving is pessimistic since only handlings costs to process the return flow are incorporated in this estimate. Besides this also the following savings will be realized with the centrally coordinated distribution model:

1. Transportation costs will decrease since less products have to be transported.
2. Store operations will be enhanced since inventory levels of promotion products in stores, even after a return flow, are reduced with more than 25%. Netessine (2005) concluded that fewer leftovers in the backroom of a store have a positive effect on the reduction of OOS's.
3. No time is needed in the stores to initiate orders since all orders are coordinated centrally.
4. The workload of promotion products is easier to manage at the DC's since all orders are coordinated centrally.
5. The Marketing & Sales department of EMTÉ is able to control the profit margins of its promotion products since the total good flow is coordinated centrally.

8.5 Trade-off between service level and handling costs

The most important management decision that has to be made in the promotion process is the trade-off between customer service level and costs. This decision is closely aligned to the business strategy of a retail organization. Since EMTÉ desires to be a full-service supermarket it is not possible to compete on costs. Moreover, in one of the company statements is mentioned that product availability is a core element of the current business strategy. Hence, a high service level is for EMTÉ of major importance to achieve customer loyalty. Therefore the penalty cost that EMTÉ is willing to pay for an OOS is more than solely the profit margin that is related to a particular product. Nevertheless, it is not possible to guarantee a 100% service level. Therefore it is important to carefully consider what the value of an OOS is. In this consideration it is important to distinguish two elements; the lost profit margin and customer responses to OOS's. The customer responses to OOS's are extensively researched in literature (Emmelhainze et al., 1991; Schary et al., 1979 & Campo et al., 2000). In total 5 primary customer responses are indicated which are summarized by Corsten & Gruen (2003) in Figure 8-7. The most common response of a consumer response to an OOS is store switching. This is also the most harmful response for a retailer since besides a lost profit margin a retailer runs the risk to lose this customer in the long term. Besides this effect, also substitution effects (buy another item, buy another brand, and buy a different brand) occur frequently. However, it is unclear if this effect is also strong for promotion products since the ability to switch between promotion products is limited.

[8] The results in this diagram are based on 6 promotion week (validation phase).

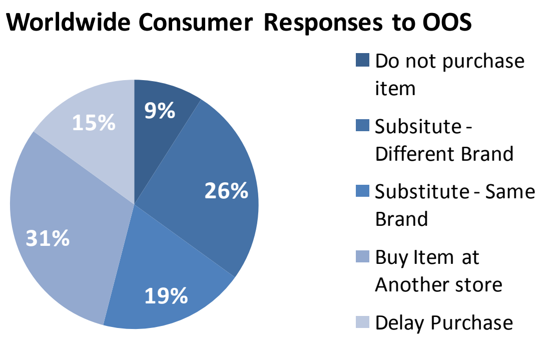


Figure 8-7: Worldwide consumer responses to OOS's.

To shed more light in the trade-off between service level and handling costs two realistic scenarios are pointed out. In these scenario's the overall cost[9] of a returned package (a package contains multiple products) is assumed to be €1,00 per package. In the first and the second scenario the penalty cost of an OOS are set on €1,00 and €0,50 per product respectively (Figure 8-8 and Figure 8-9). In these Figures can be seen that the cost optimal point changes when the penalty costs are increased. In both settings the cost optimal point lies between service levels of 96% and 97,5%.

Unfortunately, in practice it not possible to determine the cost optimal point on forehand since customer demand is uncertain. Moreover, the exact penalty cost of an OOS is difficult to determine rationally. Nevertheless, it is important to be aware that this trade-off between customer service level and costs is made indirectly in many business processes. Therefore it is important to monitor the results of this process (OOS's and return packages) continuously to see if it is aligned with the business strategy.

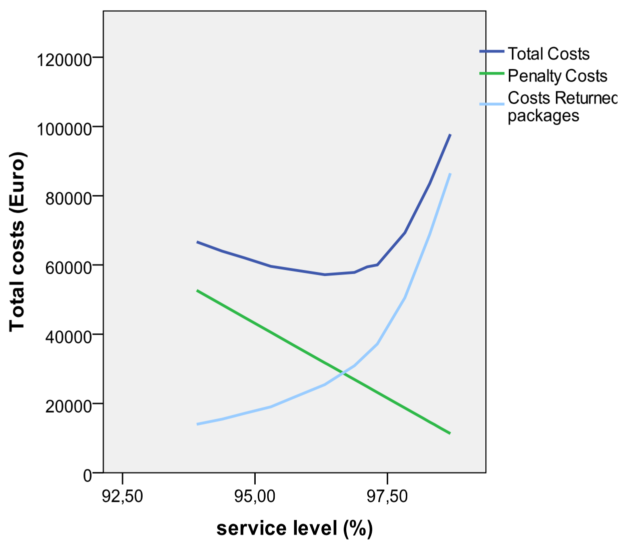


Figure 8-8: Trade-off between penalty costs (€ 0,50) and costs of returned packages (€ 1,00)

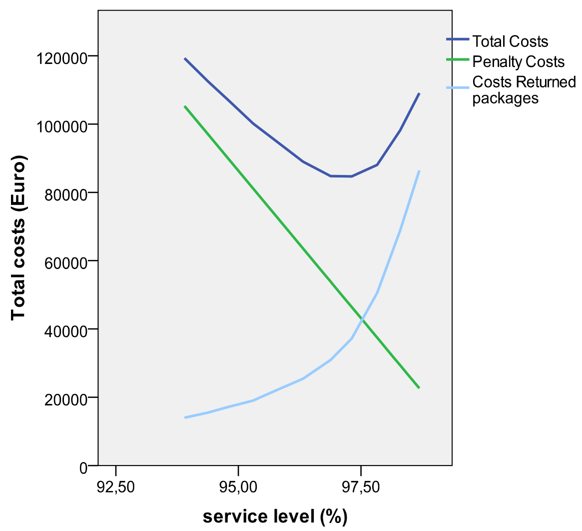


Figure 8-9: Trade-off between penalty costs (€ 1,00) and costs of returned packages (€ 1,00)

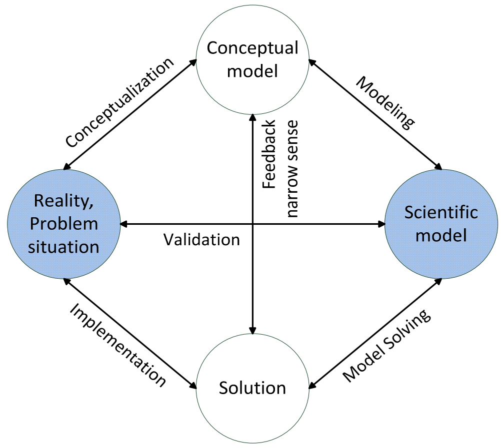
[9] Handling costs plus other savings as mentioned in 8.3.

8.6 Limitations of the distribution model in practice

Although the developed distribution model leads to an interesting cost-saving it is important to be aware of the limitations of the model in practice. The first limitation of the model is that it makes use of inventory data. As indicated by Raman et al. (2001), retailer inventory data is known to be very inaccurate. This might lead to an inaccurate demand forecast for the second delivery. At second, the model is prone to errors that are caused by mistakes made by suppliers or the DC's. For instance, when a promotion product is accidently not delivered to a store, sales of this product in the first days of a promotion week will be zero. Hence, also no second delivery for this product will be initiated. At last, extra store openings (e.g. Sunday opening) or closures due to special events (e.g. Eastern) require an adapted approach. For these events it is important to change the moments on which decisions are made. For instance, when a store is closed on Monday on Eastern it is important that in the early sales forecasting only Tuesday sales is used to make a forecast.

Results Part 4: *In this part is shown that it can be beneficial to make different distribution decisions for different product groups. Furthermore, it is demonstrated that both deliveries of promotion products should be coordinated centrally. When the distribution model is compared to the current practice a significant improvement is realized. The distribution model is able to reduce the total return flow of promotion products substantially, which will result in a minimum annual cost saving of €312.000.*

Part 5: Validation of Forecasting Model



In this part the major input for the developed distribution model is addressed: the aggregated demand forecast. An existing demand forecasting model developed by Van Loo (2006) is validated in this research environment.

9 Definition of the Forecasting model

Two major steps in the promotion process are the distribution and the forecasting of promotion products. As concluded in the problem analysis, solely improving one process step will not lead to an integrated solution. Therefore in this part of the research, the major input of the distribution model, the aggregated demand forecast ($\sum A_{xi}$) for all stores, is addressed. To improve the accuracy of the initial demand forecast the Lift-Factor Model developed by Van Loo (2006) is tested in this research environment.

9.1 Definition of the LF-model

Van Loo (2006) developed a Lift-Factor model (LF-Model) which is based on multiple regression. The LF-model basically forecasts the lift-factor in demand during a promotion week compared to the baseline sales (average sales during non-promotion weeks). The lift-factor is defined as:

$$Lift - Factor = \frac{Sales\ in\ the\ promotion\ week}{Baseline\ sales}$$

The lift-factor (LF) is estimated by using multiple independent variables which have an explanatory relationship with the LF. These independent variables are described in paragraph 9.2. To compute the baseline sales, the average sales in the last five non-promotion weeks are used. Since high and low values of the LF's are generally under- and over estimated van Loo (2006) decided to apply a lognormal transformation on the dependent variable (LF). In this research also the lognormal transformation of the LF (LN(LF)) is used as dependent variable.

9.2 Independent variables

Based on the marketing data that is currently available a variable framework is created (Appendix 16). The variable types that are used are compared to the variable types that are used in previously developed forecasting models in Table 9-1. All independent variable types that are used in this research have also been found good predictors in previous studies. It is important to notice that the total number of variables that is used in this study is limited compared to other studies.

Variable types used in the LF-model	Van der Poel (2010)	Van Loo (2006)	Van de Heuvel (2009)	Promocast (1999)
Price variables	x	x	x	x
Promotion mechanisms	x		x	x
Number of products on promotion in product group	x		x	
Holidays		x	x	x
Previous LF	x			x
Product group dummy variables	x	x	x	

Table 9-1: Variable overview

9.3 Research design

In literature it is mentioned that the aggregation level of the dependent variable in a forecasting model can be set on three different dimensions; market (location), product and time-frame (Zotteri & Kalschmidt, 2007). Although Van Loo (2006) analyzed the impact of location aggregation, less is known about product aggregation. Since in this research is indicated that different products react in a different way to promotions it could be beneficial to create different aggregation settings to test in the forecasting model. In total three aggregation settings in the forecasting model are tested:

1. Total setting: in this setting forecasts are made for all promotion products of all product groups within the product categories “DKW” and “Frozen Food”
2. DKW setting: in this setting forecasts are made for all promotion products of all product groups within the product category “DKW”
3. Frozen Food setting: in this setting forecasts are made for all promotion products of all product groups within the product category “Frozen Food”

9.4 Data collection

A database is created by linking point of sales data with promotion data of the Marketing & Sales department. The promotion data is obtained by collecting promotion information which is stored in separate excel files. Sales data is obtained by collecting the sales data on week level that are available in the current information system. Finally, a database is generated for the period of week 1 (2009) - week 37 (2010). This database contains 18008 records which represent promotions for all products groups. In this dataset there is a subset of 4129 records available that represent the promotions of fast moving products within the product categories “DKW” and “Frozen Food”. In total 2/3 and 1/3 of the dataset will be used to calibrate and validate the forecasting model respectively. With regards to other studies that applied the LF-model the size of the dataset is extensive.

Before a regression model can be build outliers have to be removed. As indicated by Van Loo (2006) lift factors with values lower than 1 have to be excluded since:

1. Product was not in promotion
2. The average sales were relatively high in the previous weeks
3. The supplier was not able to deliver the promotion products
4. Not enough products are ordered by inventory management

Outliers with extremely high lift factors can be traced by making box plots. Lift-factors with values farther than 3 interquartile ranges from the box edge are defined as extreme outliers (Montgomery & Runger, 2003). These records are excluded from the dataset that is used in the calibration period. In the dataset of the validation period these extreme outliers are conserved. Otherwise a comparison with the performance of the current forecasts is not valid. The records which contain missing values for the LF’s are replaced with the average LF of a product group. Since group-dummies are included to represent the different product groups one product group has to function as reference group. This reference group is selected randomly. As aforementioned, the lognormal transformation of the LF (LN(LF)) is used as dependent variable. Based on the normality plots that are made of this transformation can be concluded that the LN(LF) leads to a better normality fit (Appendix 17). The complete data collection process is summarized in Appendix 18.

10 Calibration of the Forecasting Model

In this chapter the LF model is calibrated. A stepwise multiple regression method is used to test the predictive model. At first, the performance indicators that are used to evaluate the three settings are defined. Secondly, the assumptions that have to be satisfied before multiple regression can be used are tested. Finally, the results of the forecasting model in the calibration period and the significant variables are presented.

10.1 Performance measures

Before the forecasting model can be evaluated it is important to specify the performance indicators. Totally, two different performance measures are used. These are widely accepted measurement indicators which have been used in similar studies. The two performance measures are:

1. MAPE: Mean absolute percentage error.

$$\frac{1}{\mathrm{n}} \cdot 100\% \sum_{1}^{\mathrm{n}} \frac{|\mathrm{actual\ LF} - \mathrm{forecasted\ LF}|}{\mathrm{actual\ LF}}$$

2. Adjusted R-square: Indicator of the goodness of fit of a regression model

$$\mathrm{R}^2 = \frac{\mathrm{SS}_{\mathrm{model}}}{\mathrm{SS}_{\mathrm{regression}}} \qquad \mathrm{Adjusted\ R}^2 = 1 - (1 - \mathrm{R}^2)\frac{\mathrm{nr.\,of\ cases} - 1}{\mathrm{nr.\,of\ cases} - \mathrm{nr.\,of\ predictors} - 1}$$

It is important to notice that the MAPE is an asymmetric performance measure. This means that in this functional form an underestimation of a forecast has more impact on the MAPE than an overestimation.

10.2 Assumptions

Before a regression model can be build some assumptions have to be met. According to Field (2005) the following assumptions have to be satisfied:

1. All predictor variables must be quantitative or categorical
2. The predictors should have some variation in value
3. No perfect multicollinearity
4. Homoscedasticity
5. Independent errors
6. Normally distributed errors
7. Linearity: the modeled relationship is linear

All these assumptions are satisfied; in Appendix 19 the assumptions are tested.

10.3 Calibration

The three settings of the forecasting model are calibrated over the period week 1 2009 till week 8 2010. The results are presented in Table 10-1.

	Calibration period		
	Total	DKW	Frozen food
sample size	2632	2433	209
Adjusted R-square	0,378	0,342	0,705
MAPE	37,2%	37,0%	27,4%

Table 10-1: Results calibration period

In this Table can be seen that the disaggregated setting “Frozen Food” has a high MAPE compared to the other two settings. Moreover this setting has an extremely high model fit (Adjusted R-square which might be explained by the heterogeneity of the setting. Although the results of the “Frozen Food” setting are promising, it is important to assess the robustness of this setting in the validation phase since this setting is based on a relatively small dataset.

Based on the results obtained in the calibration period can be concluded that product aggregation can be beneficial in a forecasting model. Since the MAPE of the “DKW” and “Frozen Food” setting are both lower than in the “Total” setting indicates that it is better to make forecast on a lower aggregation level. However, it is important to remark that the differences between the settings appear to be relatively small.

10.4 Significant variables

In Appendix 20 the values of the significant variables in the three settings are pointed out. Within this Table can be seen that price variables like; absolute discount, relative discount and regular price have an important impact on the final forecast. Due to multicollinearity it is not possible to include both the variables relative and absolute discount in one regression model. Besides price variables the previous LN(LF) proves to be an important predictive variable. The impact of this variable on the dependent variable is comparable with the result that has been found by Van der Poel (2010). Furthermore, the price mechanisms “2nd half price” and “3rd for free” appear to have a negative impact on the LF. This negative impact indicates that these price mechanisms are considered as less attractive than other price mechanisms by customers.

Since the forecasting model, in particular in the settings “Total” and “DKW”, attempts to forecast demand for a wide variety of product groups, product group dummies have been included in the regression models. These variables are used to explain the differences between the product groups. Based on the results (Appendix 20) can be concluded that many product group dummies are significant and increase the predictive power of the forecasting model. This indicates that different product groups react differently to promotions.

11 Validation of the Forecasting Model

To assess the predictive power of the forecasting model it is essential to validate the performance on an independent part of the dataset. This is done in the first paragraph of this chapter. Besides this validation phase it is interesting to compare the forecast accuracy with the accuracy of the forecasts that are currently made within EMTÉ. In the second paragraph of this chapter this comparison is presented.

11.1 Validation

In total 1/3 of the dataset is used to validate the three different settings of the forecasting model. The results are reported in Table 11-1. When these results are compared to the results that are achieved in the calibration period a substantial difference can be noticed with regards to the “Frozen Food” setting. The MAPE of this setting is changed dramatically from 27% to 34%. This instability might be explained by the small dataset on which the “Frozen Food” setting is based. The other two settings which are based on a larger dataset can be regarded as stable with regards to the MAPE.

In practice it is possible to use two more disaggregated settings "DKW" and "Frozen Food" instead of one aggregated setting "Total" in the forecasting model. The use of the two more disaggregated settings improves the overall forecast accuracy slightly compared to the "Total" setting. This confirms again that product aggregation in the domain of promotional forecasting can be beneficial. However, the differences between the two disaggregated settings and the aggregated setting are small (+/-1%). Therefore it is recommended to EMTÉ to use the "Total" setting. Namely, only one setting is needed to make forecasts for a wide range of SKU's which fits the requirement "*simplicity"* better. In the next paragraph the "Total" setting is compared to the current forecasting performance.

Although the differences between the settings are small, the outcome of the effect of product aggregation in the domain of promotional forecasting is fruitful. Especially since the development of a forecasting model is only a minor part of this research. To reap the full benefits of product aggregation in forecasting models for promotion products it is recommended to conduct in the future more extensive research to this topic.

	Validation period		
	Total	DKW	Frozen food
sample size	1349	1242	107
MAPE	36,4%	35,6%	34,2%

Table 11-1: Results validation period

11.2 Comparison with the current forecasting performance

Currently, forecasts are made by several stakeholders within EMTÉ. The two most important forecasters in the forecasting process are a specialized demand Forecaster and the Purchasing department. To gain more insights in the performance of the LF-model it is compared to the current forecast accuracy. For this comparison historic information about forecasts of the Purchasing department and the Forecaster is collected. In total 1300 complete records are collected to make a comparison. The results of the comparison are presented in Table 11-2. This Table shows that the LF-model outperforms the forecasts that are currently made with regards to the MAPE. The members of the Purchasing department achieve currently the lowest forecasting accuracy. The fact that Table 11-2 shows values of the MAPE ranging from 35% to 41% indicates that forecasting promotional demand is difficult. Namely, in the LF-model every forecast deviates on average 35% from the actual sales.

	Comparison in the validation period
sample size	1300
MAPE "Purchasing department"	41,3%
MAPE "Forecaster"	38,4%
MAPE "LF-Model"	35,5%

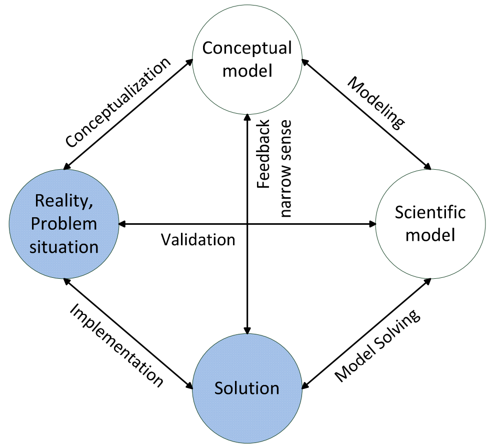
Table 11-2: Comparison with current forecasting performance

To gain more insights in accuracy of the three forecasts, a comparison is made on product group level (Appendix 21) with regards to the MAPE. This overview demonstrates that the developed forecasting model is able to make an accurate forecast for multiple product groups. For more than 50% of all product groups the forecast accuracy is higher than whether it is forecasted by the Forecaster or the Purchasing department. For some product groups, though, the performance is substantially lower. Also in this overview the performance of the product group “Beer” is low compared to the forecasts that are made by the Forecaster. However, as concluded before, the demand for this product group is biased by a certain amount of OOS’s. It is likely that the forecasts that are made in with the LF-model are also biased by these OOS’s. Therefore the performance of the LF-model is disadvantaged in this comparison. Hence, it is possible that the forecast accuracy of the LF-model is even higher in practice.

Next to this, it is important to notice that the LF-model is a fully automated forecasting model. This will result in a reduction of the amount of human resources that are needed to make demand forecasts. Although the model is automated, it is recommended to use human judgment (with the elaborate experience of the specialized demand Forecaster) in addition to this statistical forecast to increase the performance of the forecasts further (Goodwin & Fildes, 1999).

Result Part 5: *The LF-model is able to make an accurate forecast for promotion products in this research environment. Although the forecast deviates on average 36% from the actual sales, the performance of the forecast is in comparison with the forecasts that are currently made quite accurate. To increase the accuracy of the forecasting model further it is recommended to use human judgment in addition to the statistical forecasts.*

Part 6: Implementation and Conclusions



In this part a suggestion for implementation is presented for the deliverables of this research. Next to this, overall conclusions are drawn and the obtained insights are placed in a broader context. At last the contributions to literature are pointed out.

12 Implementation

In this research the complete promotion process of EMTÉ ranging from an initial demand forecast to the actual distribution of promotion products is considered. The major focus of this research is put on **the sell-side of the supply chain** of EMTÉ: how can we get the right product at the right place at the right time to service customers? Next to this, it is also important consider profit opportunities like forward-buying on **the buy-side of the supply chain**. Lee (2003) argued that not exploiting these buy-side profit opportunities is one of the pitfalls of demand chain optimization. Therefore is decided to formulate, next to the deliverables of this research, the role of forward buying explicitly in the final advice for EMTÉ to redesign of the promotion process. In the first paragraph of this chapter the reconsidered promotion process is presented. At second, a brief implementation plan is presented to adapt the current promotion process.

12.1 Reconsidered promotion process

In this paragraph a reconsidered promotion process is presented in which the deliverables of this research are included (Figure 12-1). The promotion process consists out of 8 phases:

1. **Promotional Planning.** A promotion plan is developed by the Marketing & Sales department annually.
2. **Acquisition & Demand Forecasting.** Acquisition for promotion products is started and a demand forecast is made by Purchasing department. The demand forecast will be made with the developed forecasting model which increases the accuracy of the forecast. Finally the selected promotion products are summarized in a promotion portfolio.
3. **Evaluation of promotion portfolio.** The promotion portfolio is evaluated with respect to the KPI's expected turnover and profit margin. The increased forecast accuracy in the previous step will improve the quality of this evaluation. Hence, Marketing & Sales will be better able to control the KPI's of the promotion portfolio. Next to this, it is important that Marketing & Sales indicates on which promotion products forward-buying can be applied. When the promotion portfolio is finished it is sent to the Forecaster.
4. **Brief evaluation of forecasts.** The role of the Forecaster is to evaluate the forecasts in the promotion portfolio briefly and make adaptions only when necessary. It is important that the Forecaster makes a clear discrimination between a clean demand forecast and a safety margin. The Forecaster is solely responsible for the demand forecast. The final forecast is defined in a final order set and sent to the Inventory management of the retail DC's.
5. **Order products.** Inventory management of the DC's has to order the promotion products on the order set plus about 25% extra to function as inventory buffer. When is indicated that forward-buying can be applied, even more products have to be ordered to function as extra inventory

buffer and result in extra profit margins. The ordered products are delivered about four weeks before the promotion week starts. These products are organized at the DC's and made available for transportation one week before the promotion week starts.

6. **First delivery.** A few days before the promotion week starts the first delivery of promotion products is performed. In the new distribution model about 70% of the demand forecast is shipped in the first delivery to the stores. The remaining part is withheld at the DC.
7. **Second delivery.** During the promotion week an algorithm, based on early sales forecasting, determines the amount of promotion products that are delivered in the second delivery to each store. When Inventory management expects to run out of stock based on the first sales day an order for an extra replenishment should be placed at a supplier. However, when forward-buying is applied correctly the risk of running out of stock will be negligible.
8. **Process leftovers and evaluate.** After the promotion week products can be returned that satisfy the new return rule. These products are processed at the DC. After the promotion week it is important to monitor potential OOS's and return flows. This can be done by involvement of store and DC managers. The major objective of this feedback loop is to improve the promotion process and to align it better to the business strategy of EMTÉ. It is especially important to calibrate the distribution model further on store and product group level in practice.

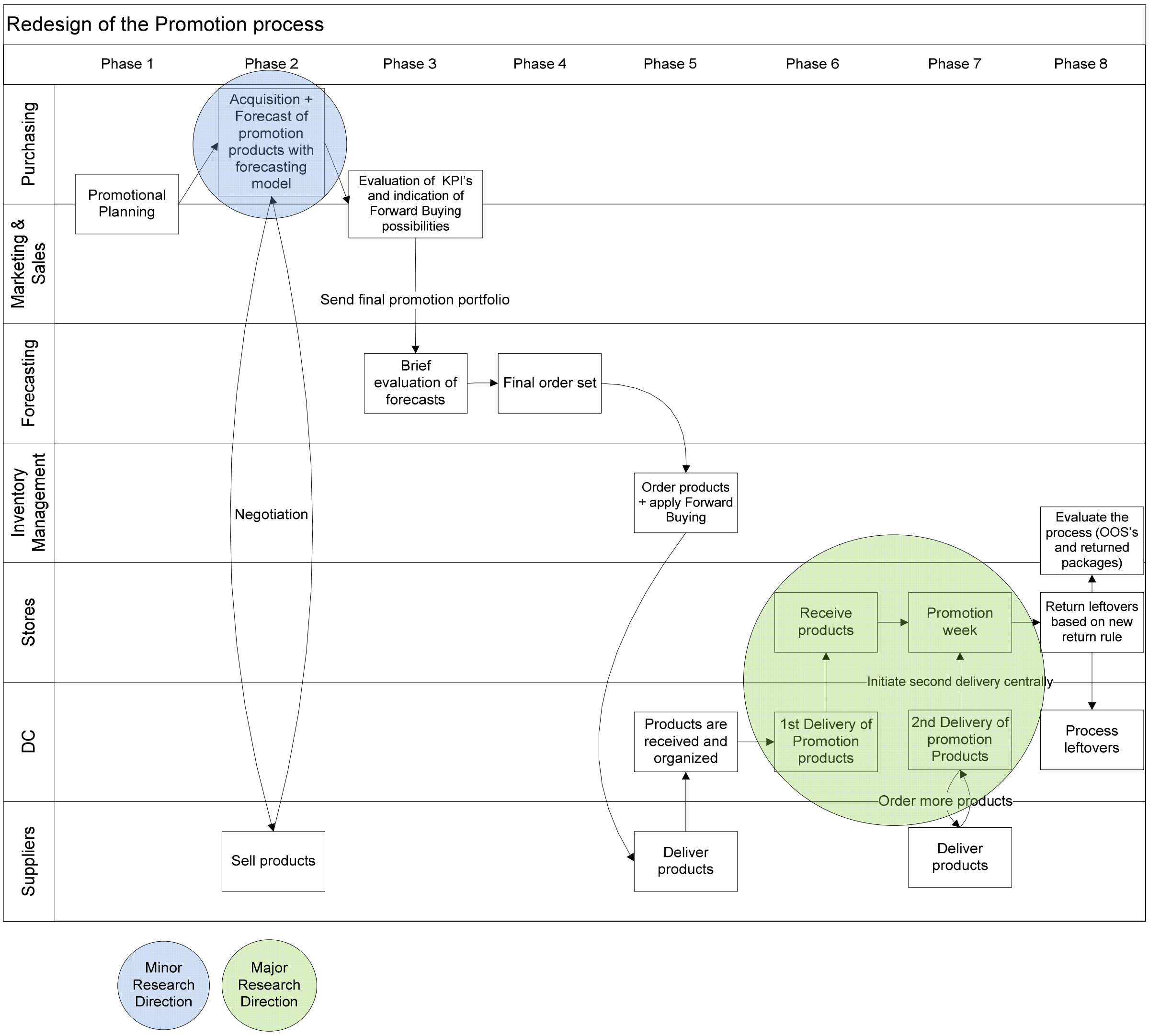


Figure 12-1: Reconsidered promotion process

12.2 Brief implementation plan

To adapt the current promotion process several adaption's have to be made in the **information systems** and **planning of operational activities**. Next to this it is important that **stakeholders** are informed about the proposed changes.

To foster the implementation of the proposed concepts it is important to create a solid base in the **information systems**. A product hierarchy which is useful from an operational point of view has to be developed. Furthermore, it is important that the information systems integrate the concepts that are developed in a separate information platform for promotion products. The demand forecasting model and the distribution model have to be incorporated in this platform. Since these two models make use of different sources of information, it is essential that the availability of this information is guaranteed by the current information systems. Next to this, it is important to close the information platform for store managers to make sure that orders during the promotion week cannot be initiated decentrally.

At second, changes have to be made in the **planning of operational activities** in the DC's and in the stores. Since deliveries of promotion products will take place on two fixed moments in the week, resources have to be made available to process these good flows.

Thirdly, it is essential to assign **responsibilities** clearly to the stakeholders of the reconsidered promotion process. Rules of the process have to be outlined and the stakeholders have to be informed about their role in the process.

13 Conclusion

In the last chapter of this research an overall conclusion is drawn. To gain more insights in the applicability of the deliverables of this research findings are placed in a broader context. To conclude, the contributions to literature are pointed out briefly.

13.1 Overall Conclusion

In this master thesis a mathematical distribution model is developed to distribute fast-moving non-perishable promotion products in a multi-product environment. This model is developed to improve the current distribution system of EMTÉ. Based on different testing scenarios the major research question of this thesis can be answered: **How can the current distribution and control mechanism of promotion products be improved considering both costs and lost sales?**

With regards to the impact of handling costs in grocery supply chains and the need for a flexible distribution system to cope with demand uncertainty, promotion products should be delivered in two deliveries. To analyze how these deliveries should be determined, the impact of two decision variables is tested:

1. The setting of the aggregation level on which decisions are made

In this thesis is demonstrated that product groups react differently to promotions. A slight improvement has been achieved by lowering the aggregation level of decision making from store-level to store-product group level in the distribution model. However, this result should be interpreted with caution since product aggregation does not work for all product groups. Therefore more future research is needed to the demand week patterns of promotion products on product group level before this approach can be used in practice.

2. The setting of the coordination mechanism of the second delivery

With the use of a questionnaire a decentral (store manager) and a central (based on early sales forecasting) coordination mechanism of the second delivery have been compared. Whereas the customer service level stays equal in both settings, the amount of returned packages after a promotion week increases with 30% when the store manager coordinates the second delivery. Since returned packages are expensive, optimistic order behavior of the store managers results in extra costs. Therefore, it is better to coordinate the second delivery centrally based on early sales forecasting.

Next to the analysis of the impact of the two decision variables the developed distribution model is compared to the performance of the current distribution system. The improvement that the developed distribution system can realize under the condition that the service level is equal, is a reduction of handling costs caused by returned packages with € 312.000 annually. Other savings that will be realized by the centrally coordinated distribution model are:

1. Reduction of transportation costs since less promotion products have to be transported
2. Improvement of store operations due to lower inventory levels of promotion products
3. Reduction of human resources needed to initiate orders of promotion products
4. Improvement of DC operations since the workload of promotion products is easier to manage since all orders are coordinated centrally
5. The Marketing & Sales department is able to control profit margins of promotion products better since all good flows are controlled centrally

The two main factors which are responsible for these improvements are: 1) in the distribution model more promotion products are withheld at the DC during the promotion week. 2) the second delivery in the distribution model is coordinated centrally which excludes optimistic order behavior of store managers.

In an additional part of this research the aggregated demand forecast which is responsible for the major input of the developed distribution model is addressed. This done by testing an existing demand forecasting model developed in this research environment. Based on this test the following minor research question can be answered: **Does the demand forecasting model of Van Loo (2006) lead to an accurate demand forecast of promotional sales in this research context?**

The demand forecasting model of Van Loo (2006) leads to a quite accurate forecast in this research environment. The demand forecasting model is able to forecast promotional demand with a mean absolute percentage error of about 36%. This means that each forecast deviates on average 36% from the actual sales. Compared to the current forecast that are made by the Purchasing Department and a specialized Demand forecaster this result is satisfactory. Nevertheless, the fact that each forecasts deviates 36% from the actual sales stresses the need for a flexible distribution system to cope with this forecasting bias.

13.2 Generalizability of insights for other food retailers

The insights generated in this master thesis can also be used by other food retailers. The insights are in particular useful for full-service food retailers. It is likely that they face the same problem characteristics as EMTÉ because of four reasons:

1. Full-service food retailers have every week **many different products** in promotion.
2. The time in which a product is in promotion at a full-service food retailer is in general one week which makes the **time span** of the problem similar.
3. Full-service food retailers do not want to compete solely on costs, they also desire a **high service level** which requires a flexible distribution mechanism in two shipments.
4. All food-retailers are expected to face **high demand uncertainty** of promotion products.

13.3 Generalizability of insights for other product groups

In this master thesis the promotion process of fast-moving non-perishable products is addressed. The decision to focus solely on these products is made since different product types require a different supply chain strategy. In this paragraph the insights generated in this thesis are used to discuss the most appropriate strategy for other product types. In total four product types are discriminated; **fast-movers** (non-perishable), **slow-movers** (non-perishable), **in/out products** and **perishable products**. In the reconsidered promotion process four methods are indicated to cope with demand uncertainty of promotion products (Figure 13-1):

1. Accurate demand forecasting
2. Deliver promotion products in multiple deliveries based on early sales forecasting
3. Forward-buying possibilities to create an inventory buffer
4. Replenishment opportunities by a supplier

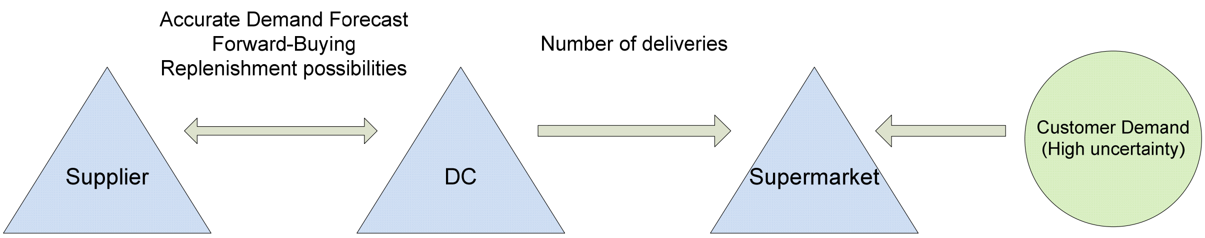


Figure 13-1: Methods to cope with demand uncertainty of promotion products

As shown in chapter 5 it is difficult to forecast promotional sales accurately since forecasts deviate on average 36% from the actual sales. Furthermore, to achieve an accurate forecast, availability of historic sales information is essential. Therefore it is in particularly difficult to forecast demand for **in/out products** since no historic data is available since this are one-time items. Moreover, these products are purchased rather based on purchasing considerations than on demand forecasting.

Fast-movers can be classified as low risk products. Since sales volumes of these products are high, the time that these products are in the supply chain is short. Moreover, these products are non-perishable which means that they can be stocked up at the DC for a long period. These circumstances are ideal to apply forward-buying. Especially in an environment which is characterized by high demand uncertainty and low inventory holding costs. This can result in an inventory buffer to cope with demand uncertainty and result in extra profits. Hence, the probability that there will be shortage of these products should be negligible. Nevertheless, when there is a shortage it might be possible to demand for an extra replenishment by a supplier. To avoid that stores are over-supplied with this type of promotion products (high product volumes), it is recommended to distribute these products in two centrally coordinated deliveries to the stores.

Slow-movers are represented by multiple SKU's which have in total a relatively low contribution to the overall sales volume. Handling costs per product are relatively high since DC and store operations are less efficient for these products which are characterized by low sales volumes. Hence, it is better to deliver these products in one delivery to the stores with regards to the impact that handling costs have. Furthermore, forward-buying is not beneficial since the throughput time of inventory is high and product volumes are low. Although there are less ways to cope with demand uncertainty of this product type, this product type is considered as less risky for the total supply chain since the impact is due to low sales volumes limited (see Pareto analysis in appendix 5).

The major risk of **In/out products** is that they become obsolete after a promotion week. Moreover, the supply chain is heavily dependent on the amount of products that are purchased. Namely, there are no replenishment possibilities because these products are temporarily offered by suppliers. Therefore it is important to deliver these products in at least two centrally coordinated deliveries. In this way the probability that the promotion products are distributed equally across all stores is improved. This will reduce the costs of having obsolete products after a promotion week.

Also **perishable products** can be classified as high risk products since waste can have a significant impact on costs. An advantage of perishable products compared to other product types is that these products are delivered from the DC's to the stores more frequently to guarantee freshness. This enhances the potential to apply early sales forecasting to determine deliveries during the promotion week. However, it is important to take in mind that inventory control for perishable products is difficult. Hence, Donselaar et al. (2006) argued that visual inspection of inventory levels is especially crucial for perishables because of the risk of getting too much waste. This implies that the second delivery of perishable promotion products should be coordinated decentrally. Next to frequent deliveries in the internal supply chain, also suppliers of perishable products will replenish more frequently to guarantee freshness of their products. This supplier flexibility can be used to cope with demand uncertainty of perishable promotion products. However, before this supplier flexibility can be utilized a good collaboration between supplier and retailer is essential. This collaboration can be supported by creating a business link with concepts like vendor managed inventory. In this concept the supplier is responsible to manage the inventory of the retailer which can lead to an improvement of overall supply chain performance (Disney,2003). In this collaboration, it is important to notice that the short-term flexibility of the supplier will be limited by its production capacities.

In Table 13-1 the generalizability made in this paragraph is summarized for the four product types.

	Fast-movers	Slow-movers	In/out products	Perishable products
Product Risk	Low (high product volumes)	Low (low throughput time)	High (obselete products)	High (waste)
How to cope with demand uncertainty?	(1) Demand forecasting (2) Two deliveries (3) Replenishment possibilities (4) Forward-buying	(1) Demand forecasting	(1) Two deliveries	(1) Demand forecasting (2) Multiple Deliveries (3) Replenishment possibilities

Table 13-1: Product risk related to methods to cope with demand uncertainty per product type.

13.4 Contribution to literature

In the beginning of this report three gaps in literature are indicated. These three gaps are:

1. **Product aggregation in the domain of promotional products.**

In this research is demonstrated that different product groups react differently to promotions. A slight improvement has been realized in the developed distribution model by applying product aggregation. Also the use of product aggregation in the forecasting model has lead to a slight improvement in forecasting accuracy. To reap the full benefits of product aggregation in a multi-product environment more research is needed to assess if product aggregation can lead to a further improvement of distribution and forecasting models. Especially in the area of demand week patterns of promotion products more research has to be conducted.

2. **The application of early sales forecasting at a retailer in the FMCG industry.**

The power of early sales forecasting at a retailer in the FMCG industry is proved in this research. Early sales forecasting is successfully applied in a newly developed distribution model for promotion products. In this thesis is demonstrated that an early sales forecast in the distribution model outperformed a forecast that is made by a store manager considering both costs and lost sales. In future research it is important to assess the reliability of early sales forecasts in practice.

3. **The coordination mechanism of the second delivery of promotion products.**

With the use of a questionnaire in which 62 store managers were actively involved it is shown that it is better to coordinate the second delivery of promotion products centrally. Optimistic order behavior of store managers and the inability to transfer many environmental factors in an accurate order for multiple products leads to unnecessary costs. Thus, in a multi-product environment, the second delivery of fast-moving non-perishable promotion products should be coordinated centrally.

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List of abbreviations

LF: Lift-Factor

KPI: Key Performance Indicator

DC: Distribution Center

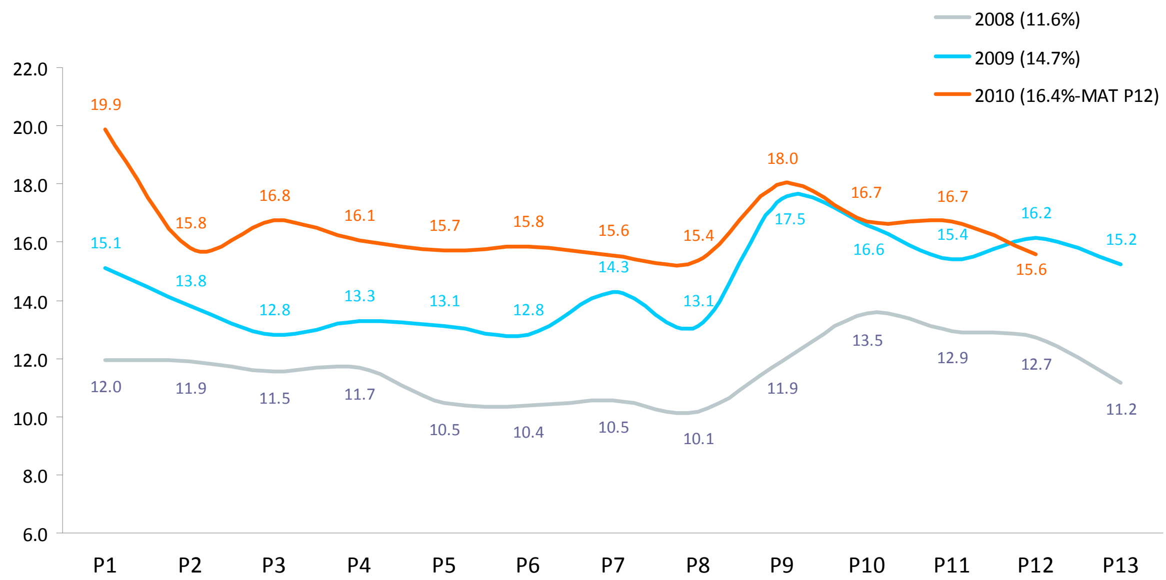
SKU: Stock Keeping Unit

OOS: Out-of-stock

FMCG: Fast Moving Consumer Goods

Appendix

Appendix 1 - Promotional pressure in the Dutch food retail market (GFK, 2010)



Appendix 2 - Interviewees

Department	Function
Store	3 Supermarket managers
DC	2 Manager of the retail DC's
Purchasing	Director Purchasing Sligro Food Group
Marketing & Sales	Director Marketing & Sales ÉMTE
Marketing & Sales	Coordinator promotion activities
Forecasting	Specialized Demand Forecaster
Inventory Management	Manager Inventory Management
Inventory Management	2 ABS Planners
Logistics	Project Manager Logistics
Operations	3 Operational Managers
Operations	Director Operations ÉMTE
Management Team	Director Retail Sligro Food Group
Management Information systems	Business Analyst

Appendix 3 - Current product hierarchy

Department code (DCODE)

AGF
BAKKERIJ
ZELFBEDIENING
KASSA & SERVICES
SLAGERIJ
VLEESWAREN/KAAS

MAIN CATEGORIES

VERSE MAALTIJDEN
AGF
VERSE SAPPEN
BROOD/GEBAK-ZELFBEDINING
BAKE-OFF/VERS GEBAK
DKW/MARGARINES/VETTEN/BOTER/EIEREN
DAGVERSE ZUIVEL
DIEPVRIES
NON FOOD
WRCP
ROOKWAREN/TABAK
BLOEMEN/PLANTEN
GENEESMIDDELEN/OTC
GEDISTILLEERD
SERVICE ARTIKELEN
LOTERIJ VERKOOP
VERS VLEES/KIP - VVP
VERSE VIS - VVP
VLEESWAREN/ SALADES - VVP
KAAS - VVP
KAAS - SEMI BEDIENING
VLEESWAREN/SALADES/SEMI- BEDIENING

ARTICLE GROUPS

10 - KOEK & BANKET RETAIL
11 - KOEK & BANKET GROOTVERBRUIK
12 - BROODVERVANGERS
13 - TOAST
.....
.....
343 - COSMETICA

SKU

1102 - VVP NOTENKAAS CA. 125 G
1213 - BIO+ SHOARMAREEP CA. 250G30626
1216 - BIO TARTAARTJES 2ST30617
1218 - BIO GEHAKT HALF OM HALF 30615
.....
.....
99306 - ZUURKOOL NATUREL 500G

Appendix 4 - New product categorization

DKW
10 - Koek en Banket retail
14 - Ontbijtkoek
15 - Noten
16 - Chips en snacks
19 - Bars en tabletten
25 - Suikerwerk
33 - Tussendoortjes
37 - Koffie, cacao & oploskoffie
40 - Thee
43 - Groenteconserven en peulvruchten
45 - Dier
55 - Soepen en bouillons nat
56 - Soep droog & smaakversterkers
58 - Vleesconserven
67 - Oosterse Keuken*
73 - Kindervoeding
86 - vlees, vis en groentesauzen
87 - Maaltijdsauzen en mixen
88 - Cereals
89 - Boterhamartikelen
91 - Snack- en tafelsauzen
96 - Pasta
98 - Tomaten en pasta sauzen
121 - Fris water & sap kleinverapkking
124 - Vruchtenwaters
125 - Vruchtensappen
127 - Margarine
128 - Siropen
130 - Zuivel houdbaar
133 - Frisdrank
134 - Bieren
206 - Gedistilleerd
208 - Wijnen

Bread
199 - Brood/gebak - zelfbediening

In/Out products
999 -Temporarily offered disc. products

Meat and Salads
123 - vleeswaren vers verpakt
154 - vleeswaren bulk retail
165 - vers vlees retail
169 - verse kip en gevogelte ret.
170 - salades
178 - maaltijden en comp. koel

Frozen Products
146 - Diepvries pizza
185 - Aardappelpr. diepvries
203 - Broodproducten diepvries*
224 - Retailsnacks diepvries
226 - Groente en fruit diepvries

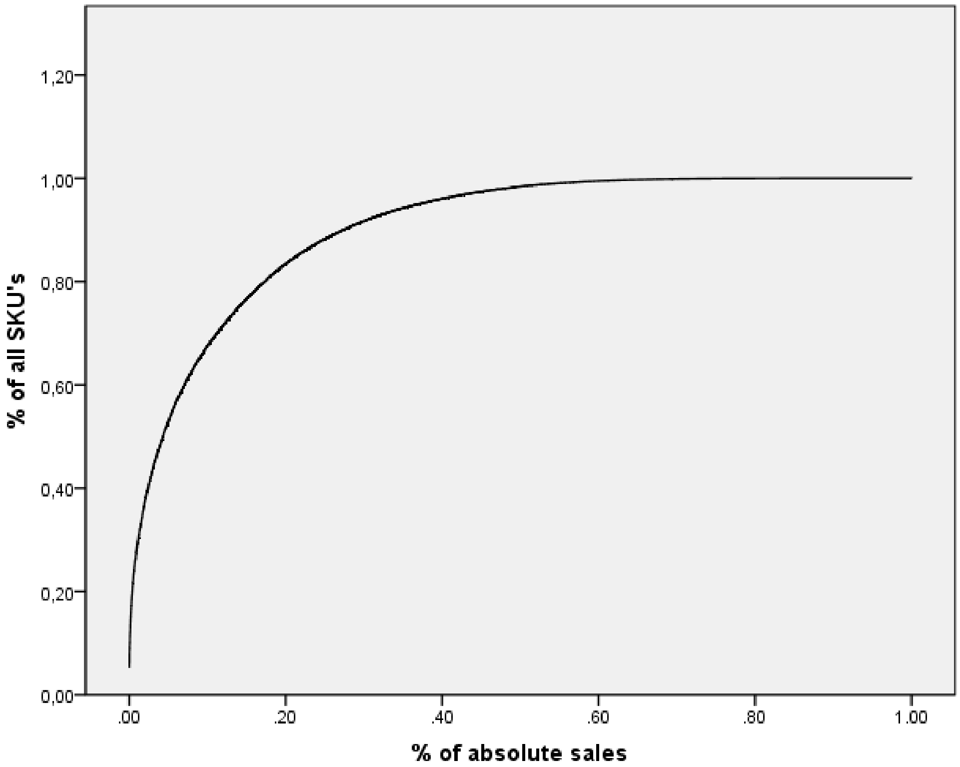
Milk products
168 - Kaas Buitenland verpakt
177 - Melkproducten dagvers
220 - Kaas Holland uitsnij
227 - Kaas Holland verpakt
182 - IJs en Pudding

WRCP
144 - Luiers & Babydoekjes
148 - Afwas en Vaatmiddelen
147 - Wasmiddelen
149 - Reinigingsmiddelen
150 - Toiletverfrissers
151 - Damesverzorging
343 - Cosmetica

AGF
223 - Verse sappen
192 - Groenten en fruit dagvers

Appendix 5 - Pareto analysis

The Pareto analysis is based on all sales of all SKU's in year 2009.



Appendix 6 - Definitions

Variables:

$I_{xi,t}$: Inventory of product *x* at store *i* at the end of day *t*

$I_{xj,t}$: Inventory of product *x* at DC *j* at the end of day *t*

$D1_{xij}$: 1st delivery of product *x* from DC *j* to store *i*

$D2P_{xij}$: Proposed 2nd delivery of product *x* from DC *j* to store *i*

$D2A_{xij}$: Actual 2nd delivery of product *x* from DC *j* to store *i* (limited by inventory on the DC)

$F_{i,t}$: Fraction of the week demand of store *i* that is sold at day *t (*based on non-promotional sales)

$F_{i,p,t}$: Fraction of the week demand of product group *p* in store *i* that is sold at day *t* *(*based on non-promotional sales)

$D_{xi,t}$: Demand of product *x* at store *i* at day *t*

$S_{xi,t}$: Sales of product *x* at store *i* at day *t*

k_1: Safety factor for the first delivery

k_2: Safety factor for the second delivery

A_{xi}: Forecast of product *x* for store *i* that is made by the central forecast

R_{xi}: Returned packages after a promotion week of product *x* at store *i*

T_{xi}: The average week inventory of product *x* at store *i*

Subsets:

b: Set of all bulky products

r: Set of all non-bulky products

(i,j): Set of all store *i* – DC *j* combinations

Appendix 7 - Derivation of equation (2)

Equation (2) which determines the amount of products that are shipped in the second delivery consists basically out of two parts; a demand forecast for the days after the second delivery arrived and a demand forecast to determine the expected inventory position at the moment the second delivery arrives. All forecasts that are made in this equation use the demand week patterns on store level ($F_{i,t}$).

The expected inventory position at the moment the second delivery arrives (*t=3)* is the inventory level at the moment the second delivery (*t=2)* is initiated minus the expected demand during the lead-time (the time between the initiation and the actual arrival of the second delivery). This equation is multiplied with the safety factor of the second delivery to take demand variability into account. Since it is not possible to place backorders the inventory position can never become smaller than zero, therefore a MAX function is used.

Inventory level at *t=2*: $I_{xi,2}$ (2a)

Expected demand during lead-time: $(1+k_2)\cdot\left[\frac{F_{i,3}}{\sum_{t=1}^{2}F_{i,t}}\cdot\sum_{t=1}^{2}S_{xi,t}\right]$ (2b)

Expected inventory level at *t=3*: $MAX\left\{I_{xi,2}-(1+k_2)\cdot\left[\frac{F_{i,3}}{\sum_{t=1}^{2}F_{i,t}}\cdot\sum_{t=1}^{2}S_{xi,t}\right],0\right\}$ (2c)

The demand forecast for the days after the second delivery has arrived (*t=4 till t=6)* is based on the sales in the first two days of the promotion week (*t=1 and t=2)* multiplied with the safety margin*:*

Demand forecast for days after the second delivery arrived:

$$(1+k_2)\cdot\left[\frac{\sum_{t=4}^{6}F_{i,t}}{\sum_{t=1}^{2}F_{i,t}}\cdot\sum_{t=1}^{2}S_{xi,t}\right] \quad (2d)$$

Since it is not possible to generate a negative order, the order minimum is set on zero. To include this in the simulation model again a MAX function is used. The result is the complete equation for the second delivery:

$$D2P_{xij} =$$
$$MAX\left\{(1+k_2)\cdot\left[\frac{\sum_{t=4}^{6}F_{i,t}}{\sum_{t=1}^{2}F_{i,t}}\cdot\sum_{t=1}^{2}S_{xi,t}\right]-MAX\left\{I_{xi,2}-(1+k_2)\cdot\left[\frac{F_{i,3}}{\sum_{t=1}^{2}F_{i,t}}\cdot\sum_{t=1}^{2}S_{xi,t}\right],0\right\},0\right\} \quad (2)$$

Appendix 8 - Dataset major research direction

In total 1165 have taken place in the first 26 weeks of 2010. For each of these promotions a forecast is made by the forecaster. Each forecast is disaggregated to store level; this is in fact the promotion inventory that is available for each store. This fraction denoted with A_{xi} is used as input for the determination of the first delivery.

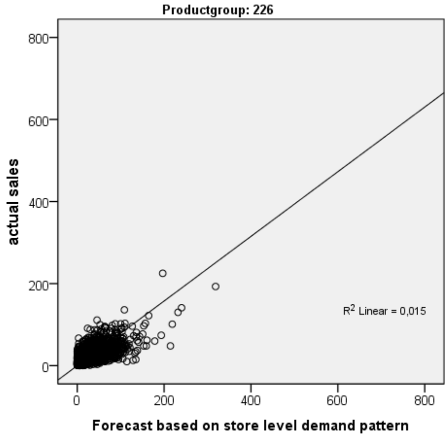
Besides this promotion inventory there is normal inventory available in the shelves of the stores. Since no historic information about these inventory levels is available an estimate is made. This estimate is based on the average demand in the last 6 weeks before the promotion took place. According to inventory management one week of inventory is on average available in the stores.

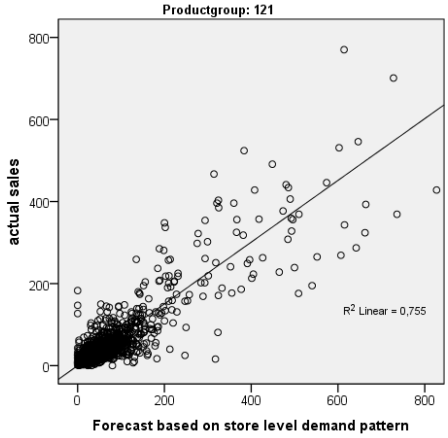
In most promotions forward-buying is applied. This means that there are generally more products purchased than is actually forecasted. Based on ingoing and outgoing product flows and historic information of the DC's an estimate is made for the starting inventory that is available at the DC's for each promotion product in the dataset.

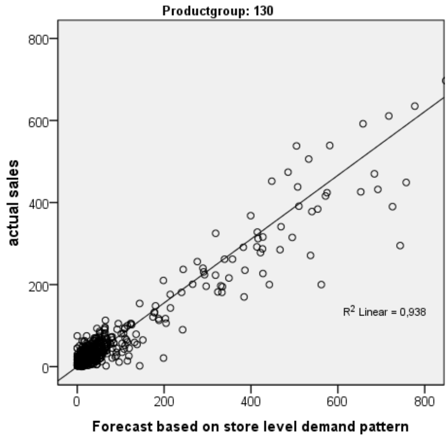
In the data collection process some information about promotions was unavailable. These missing values have been deleted from the data set, in total 21 promotions are deleted. Besides these missing values also weeks which contain holidays are deleted. It is expected that these weeks, which have gaps in the demand week pattern, will affect the forecasting process negatively. These weeks demand for an adapted approach. In the end 1021 promotions are available for the simulation model.

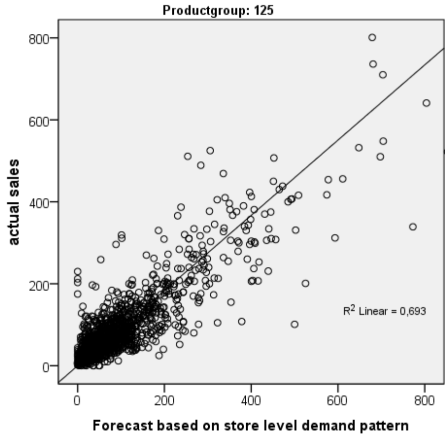
	Number of Promotions	Number of records	Promotions deleted
Number of promotions available	1165	90036	-
Delete missing values	1143	88403	21
Delete holidays	1021	79086	122

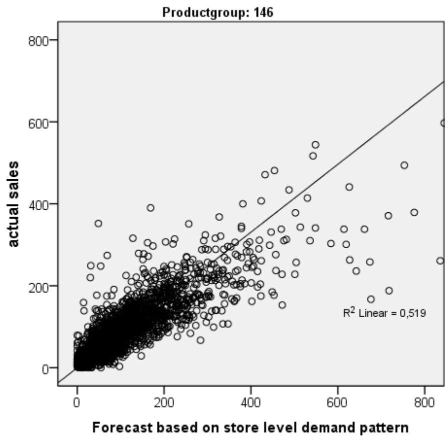
Appendix 9 - Scatterplot analysis on product group level

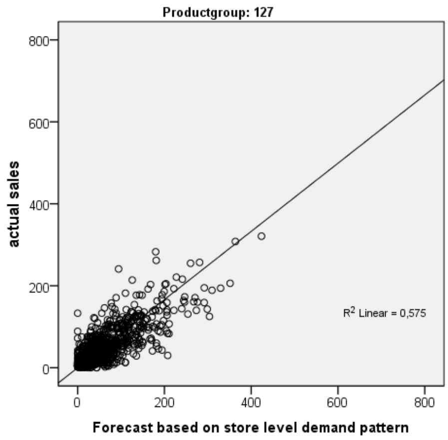


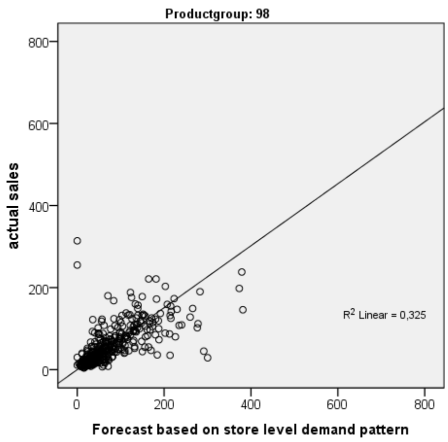


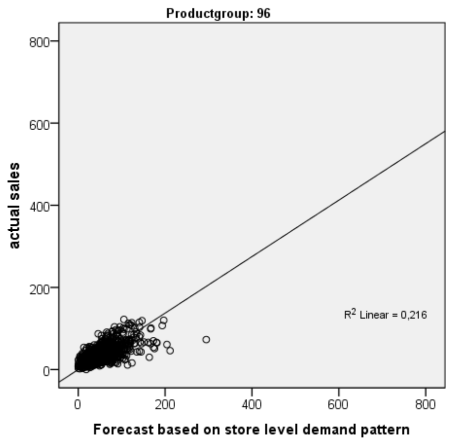


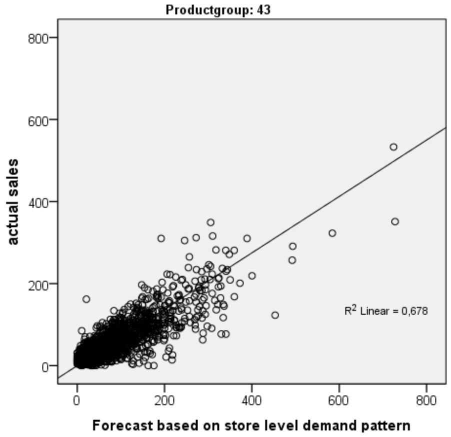


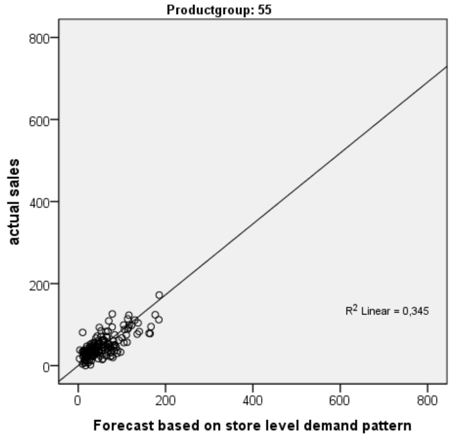


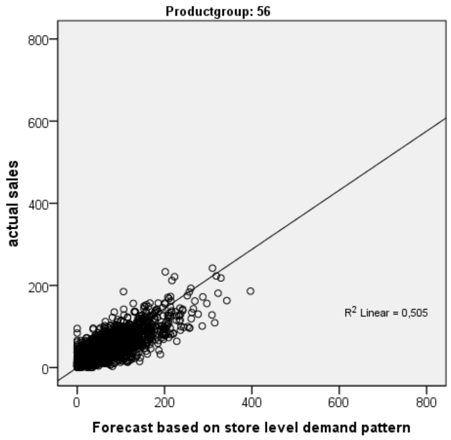


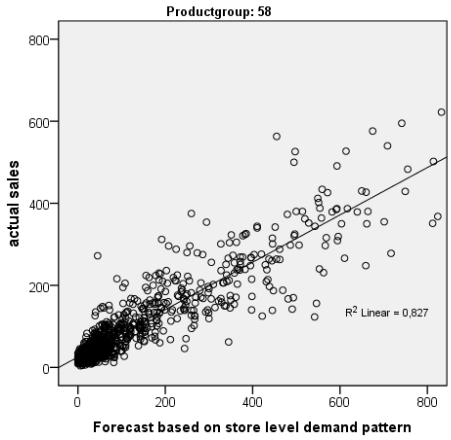


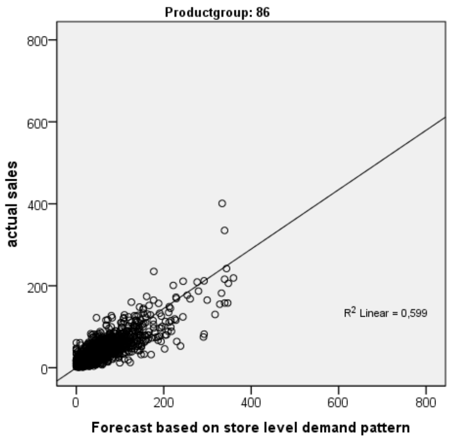


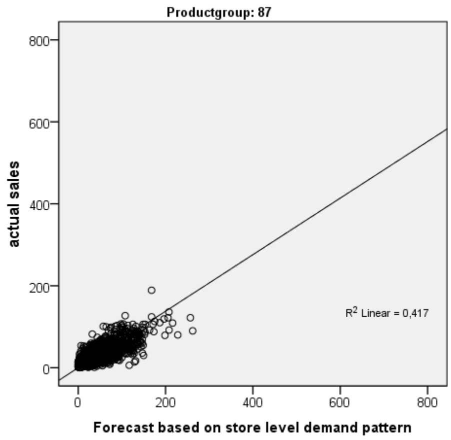

Productgroup: 43
actual sales
800
600
400
200
0
R² Linear = 0,678
0
200
400
600
800
Forecast based on store level demand pattern

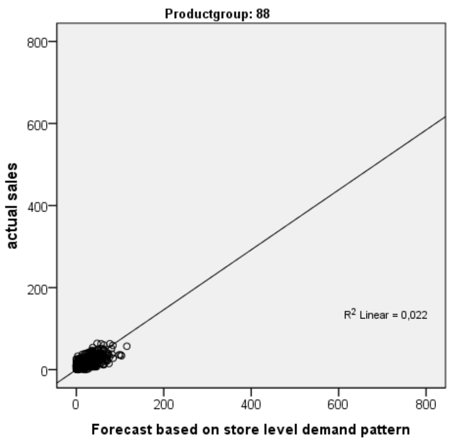

Productgroup: 55
actual sales
800
600
400
200
0
R² Linear = 0,345
0
200
400
600
800
Forecast based on store level demand pattern

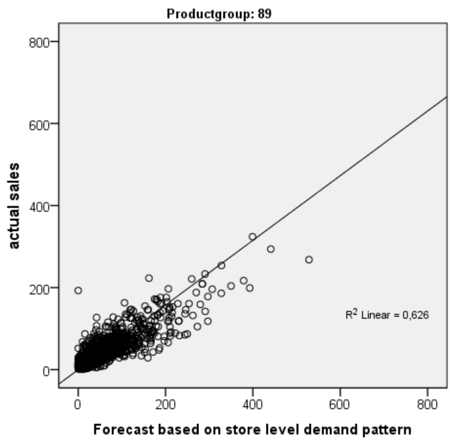

Productgroup: 56
actual sales
800
600
400
200
0
R² Linear = 0,505
0
200
400
600
800
Forecast based on store level demand pattern

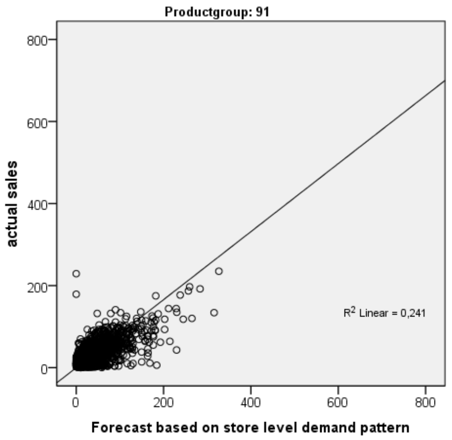

Productgroup: 58
actual sales
800
600
400
200
0
R² Linear = 0,827
0
200
400
600
800
Forecast based on store level demand pattern

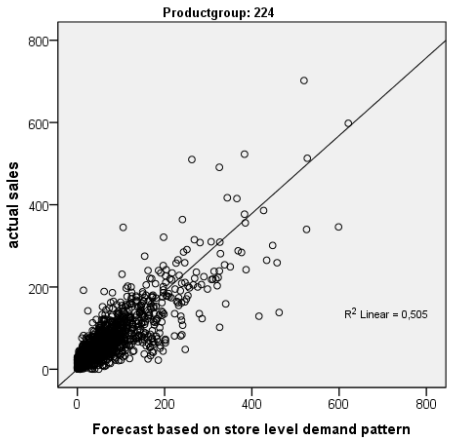

Productgroup: 86
actual sales
800
600
400
200
0
R² Linear = 0,599
0
200
400
600
800
Forecast based on store level demand pattern

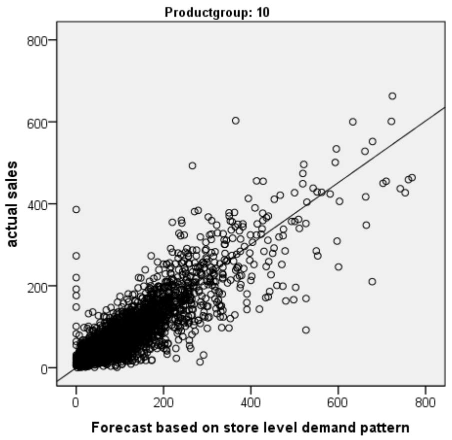

Productgroup: 87
actual sales
800
600
400
200
0
R² Linear = 0,417
0
200
400
600
800
Forecast based on store level demand pattern

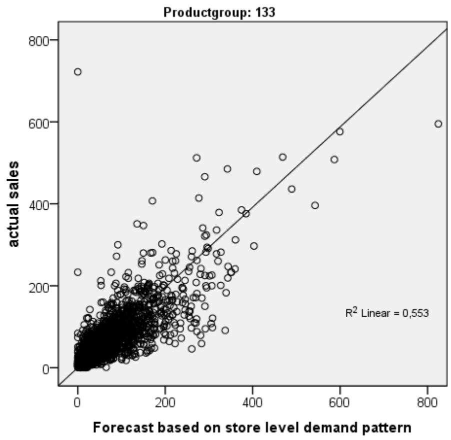

Productgroup: 88
actual sales
800
600
400
200
0
R² Linear = 0,022
0
200
400
600
800
Forecast based on store level demand pattern

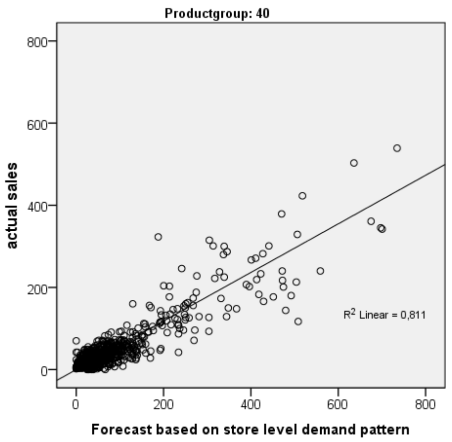

Productgroup: 89
actual sales
800
600
400
200
0
R² Linear = 0,626
0
200
400
600
800
Forecast based on store level demand pattern

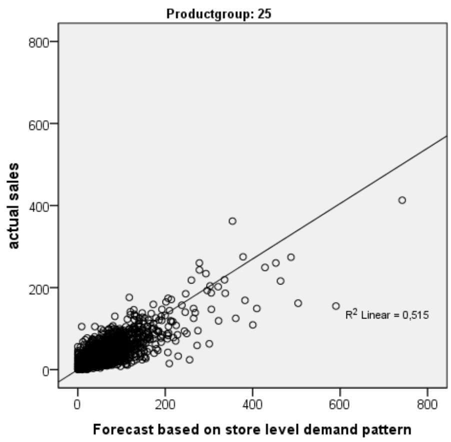

Productgroup: 91
actual sales
0
200
400
600
800
Forecast based on store level demand pattern
R2 Linear = 0,241

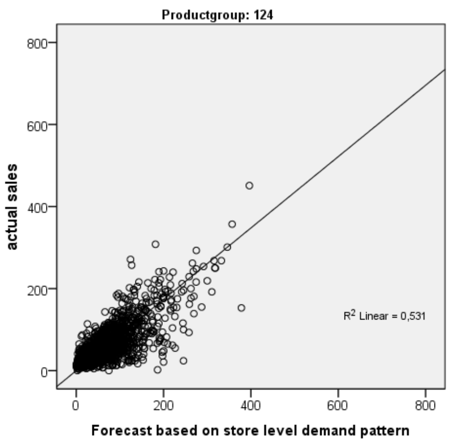

Productgroup: 224
actual sales
0
200
400
600
800
Forecast based on store level demand pattern
R2 Linear = 0,505

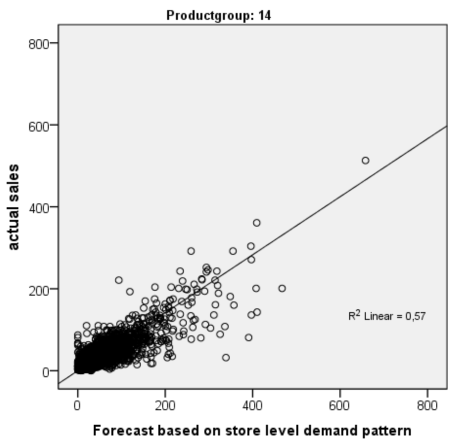

Productgroup: 10
actual sales
0
200
400
600
800
Forecast based on store level demand pattern

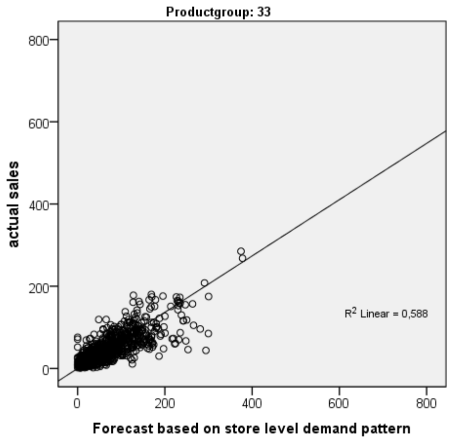

Productgroup: 133
actual sales
0
200
400
600
800
Forecast based on store level demand pattern
R2 Linear = 0,553

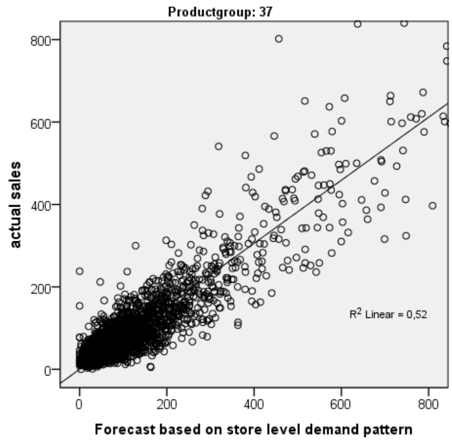

Productgroup: 40
actual sales
0
200
400
600
800
Forecast based on store level demand pattern
R2 Linear = 0,811

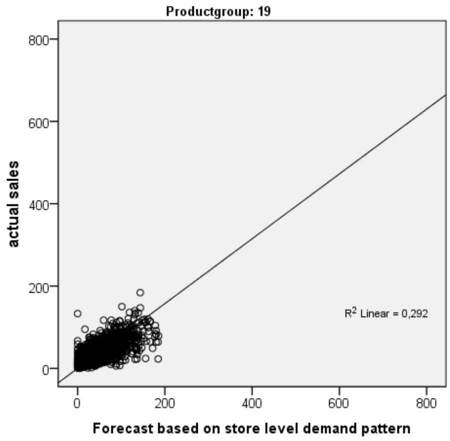

Productgroup: 25
actual sales
0
200
400
600
800
Forecast based on store level demand pattern
R2 Linear = 0,515

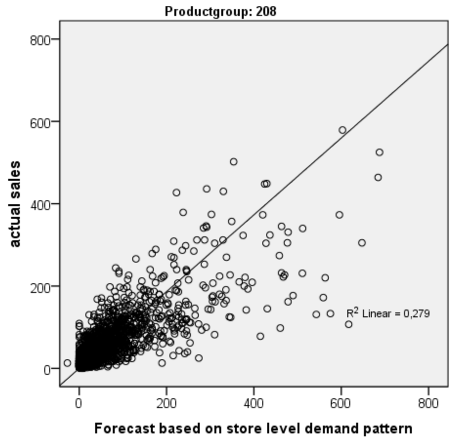

Productgroup: 124
actual sales
0
200
400
600
800
Forecast based on store level demand pattern
R2 Linear = 0,531

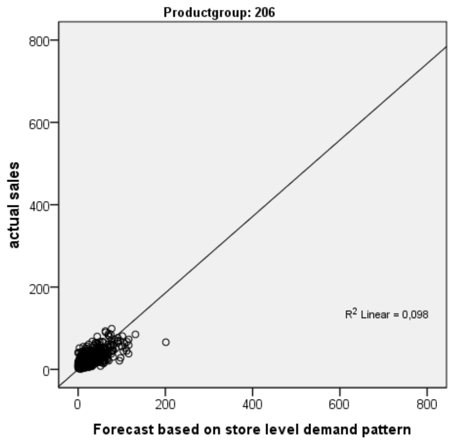

Productgroup: 14
actual sales
0
200
400
600
800
Forecast based on store level demand pattern
R2 Linear = 0,57

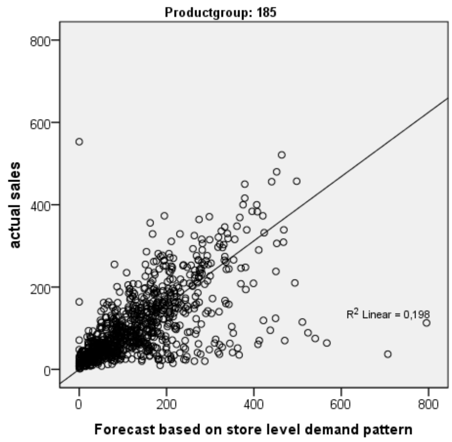

Productgroup: 33
actual sales
Forecast based on store level demand pattern
R2 Linear = 0,588

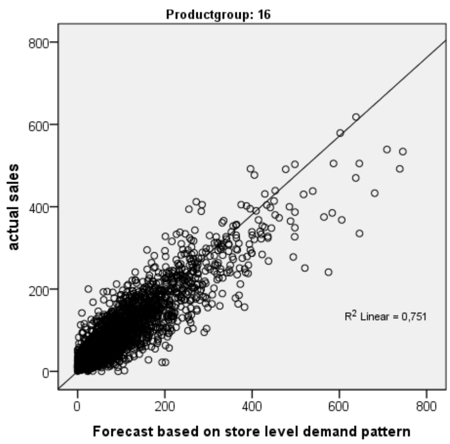

Productgroup: 37
actual sales
Forecast based on store level demand pattern
R2 Linear = 0,52

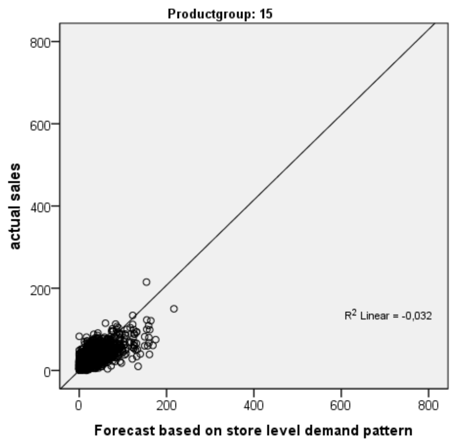

Productgroup: 19
actual sales
Forecast based on store level demand pattern
R2 Linear = 0,292


Productgroup: 208
actual sales
Forecast based on store level demand pattern
R2 Linear = 0,279


Productgroup: 206
actual sales
Forecast based on store level demand pattern
R2 Linear = 0,098


Productgroup: 185
actual sales
Forecast based on store level demand pattern
R2 Linear = 0,198

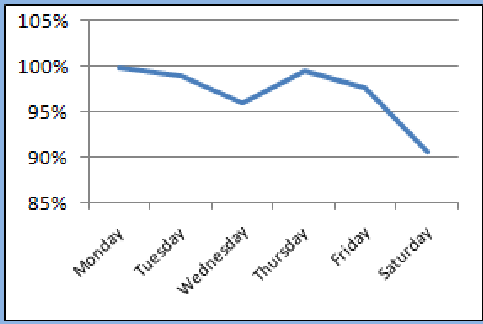

Productgroup: 16
actual sales
Forecast based on store level demand pattern
R2 Linear = 0,751


Productgroup: 15
actual sales
Forecast based on store level demand pattern
R2 Linear = -0,032

Appendix 10 - Illustration of the simulation Model built in Microsoft Excel

Settings	
Safety factor parameter second delivery	**10%**
Safety factor parameter first delivery	**100%**
Early sales (1 day/2 days/3 days/ delivery	**2**
Delivery 1	
aggregation level (store or store/productgroup	**store**
Delivery 2	
coordination mechanism	**central**
aggregation level	**store**
KPI'S	
service level	**96,72%**
number of promotions	**56056**
sales	**4418658**
oos	**144811**
number or returned packages	**91685**

Details oos	
OOS	
Monday	**100%**
Tuesday	**99%**
Wednesday	**96%**
Thursday	**99%**
Friday	**98%**
Saturday	**91%**



Appendix 11 - Slopes of trendlines of different product groups

Productgroup number	Productgroup	β_p
10	koek& banket	0,75
124	vruchtenwaters	0,85
125	vruchtensappen	0,89
121	Fris Water & Sap Kleinverpakking	0,75
127	Margarine	0,83
130	Zuivel Houdbaar	0,76
133	Frisdrank	0,99
134	Bier	1,20
14	Ontbijtboek	0,73
146	Diepvries Pizza	0,81
15	Noten	1,03
16	Chips& Snacks	0,94
185	Aardappelproducten diepvries	0,78
19	Bars&Tabletten	0,78
206	Gedestilleerd	0,88
208	Wijn	0,95
224	Retailsnacks diepvries	0,93
226	Groente & Fruit Diepvries	0,78
25	Suikerwerk	0,66
33	Tussendoortjes	0,65
37	Koffie	0,75
40	Thee	0,56
43	Groenteconserven & Peulvruchten	0,65
55	Soepen & Bouillons nat	0,88
56	Soep droog & smaakversterkers	0,70
58	Vleesconserven	0,75
86	Vlees, Vis- en Kaassauzen	0,75
87	Maaltijdsauzen & mixen	0,65
88	Cereals	0,75
89	Boterhamartikelen	0,78
91	Snack- en Tafelsauzen	0,81
96	Pasta	0,63
98	Tomaten & Pasta Sauzen	0,75

Appendix 12 - Simulation results

Setting parameter k1	Performance measure	Setting parameter k2: 0	0,05	0,1	0,2	0,4	0,6	% Shipped in the first delivery
0	Service level	85,56	86,53	88,31	89,52	91,00	91,81	39%
	Returned packages	22985	27193	32467	45092	83338	128210	
0,1	Service level	88,38	89,21	89,85	90,97	92,28	92,99	43%
	Returned packages	27477	32453	38020	52287	91314	135662	
0,2	Service level	89,87	91,09	91,32	92,18	93,33	93,98	47%
	Returned packages	32246	40527	43270	58476	98032	142092	
0,3	Service level	91,13	91,79	92,34	93,19	94,21	94,79	51%
	Returned packages	36881	42437	49405	64294	104591	147801	
0,4	Service level	92,19	92,79	93,28	94,03	94,95	95,46	55%
	Returned packages	41854	47357	54569	70261	110395	153342	
0,6	Service level	93,90	94,38	94,78	95,38	96,10	96,50	62%
	Returned packages	52207	58186	65660	81102	121427	163258	
0,8	Service level	95,18	95,57	95,89	96,37	96,93	97,24	70%
	Returned packages	63601	69697	77431	92799	132136	173194	
1	Service level	96,16	96,47	96,72	97,1	97,53	97,77	78%
	Returned packages	77822	84079	91685	106723	145130	184986	
1,2	Service level	96,91	97,15	97,45	97,64	97,96	98,14	86%
	Returned packages	95987	102263	109742	124432	161744	199310	
1,4	Service level	97,45	97,63	97,79	98,02	98,26	98,39	94%
	Returned packages	117143	125161	130453	144742	179863	214452	

Simulation results Scenario 1 (best settings with respect to both performance measures are colored blue)

Setting parameter k1	Performance measure	Setting parameter k2: 0	0,05	0,1	0,2	0,4	0,6	% Shipped in the first delivery
0	Service level	87,88	88,65	89,29	90,29	91,53	92,22	39%
	Returned packages	35553	41592	48476	66450	106310	152740	
0,1	Service level	89,43	90,12	90,70	91,60	92,73	93,36	43%
	Returned packages	39559	45719	53350	71104	110635	156730	
0,2	Service level	90,73	91,37	91,9	92,71	93,74	94,31	47%
	Returned packages	43337	49799	57538	75079	114470	160462	
0,3	Service level	91,85	92,43	92,91	93,65	94,57	95,09	51%
	Returned packages	46983	53602	61374	78988	118548	163756	
0,4	Service level	92,82	93,34	93,77	94,44	95,27	95,74	55%
	Returned packages	50888	57516	66049	83162	122575	167250	
0,6	Service level	94,37	94,8	95,16	95,7	96,36	96,72	62%
	Returned packages	59478	66041	74700	91555	130868	175163	
0,8	Service level	95,55	95,9	96,19	96,62	97,14	97,42	70%
	Returned packages	69307	75798	84334	100837	139507	183279	
1	Service level	96,45	96,67	96,96	97,3	97,7	97,91	78%
	Returned packages	82417	88830	97348	113275	150890	193421	
1,2	Service level	97,13	97,35	97,53	97,79	98,1	98,25	86%
	Returned packages	99596	105887	114247	129738	166439	206794	
1,4	Service level	97,62	97,80	97,94	98,14	98,37	98,49	94%
	Returned packages	118640	124671	132831	147794	182394	216919	

Simulation results Scenario 2 (best settings with respect to both performance measures are colored blue)

Setting parameter k1	Performance measure	Setting parameter k2: 0	0,05	0,1	0,2	0,4	0,6	% Shipped in the first delivery
0	Service level	80,45	82,14	83,6	85,94	88,94	90,54	
	Returned products	19543	25389	28973	41447	71722	107238	39%
0,1	Service level	82,96	84,47	85,77	87,85	90,47	91,88	
	Returned products	23796	29164	33755	46499	77770	114667	43%
0,2	Service level	85,04	86,4	87,57	89,44	91,73	93	
	Returned products	27621	32941	37945	51386	83627	120882	47%
0,3	Service level	86,80	88,03	89,08	90,75	92,78	93,91	
	Returned products	31539	37381	42223	56067	88933	126800	51%
0,4	Service level	88,31	89,41	90,36	91,85	93,68	94,68	
	Returned products	35889	41761	46865	60900	94326	131791	55%
0,6	Service level	90,76	91,66	92,42	93,61	95,08	95,88	
	Returned products	44828	50817	56096	70971	104809	139936	62%
0,8	Service level	92,62	93,35	93,97	94,94	96,12	96,75	
	Returned products	55448	61533	66885	81911	115674	148236	70%
1	Service level	94,09	94,67	95,17	95,95	96,9	97,39	
	Returned products	69152	75270	80686	95589	128537	157788	78%
1,2	Service level	95,26	95,73	96,12	96,74	97,48	97,86	
	Returned products	87240	93828	98537	113028	142865	167834	86%
1,4	Service level	96,08	96,52	96,83	97,32	97,89	98,18	
	Returned products	108548	114448	119479	132438	157533	180058	94%

Simulation results model improvement suggestion "adjusted forecast" (best settings with respect to both performance measures are colored blue)

Setting parameter k1	Performance measure	Setting parameter k2: 0	0,05	0,1	0,2	0,4	0,6	% Shipped in the first delivery
0	Service level	90,12	90,83	91,46	92,46	93,75	94,51	
	Returned packages	12909	15227	17735	23702	39201	56444	39%
0,1	Service level	91,37	92,01	92,56	93,45	94,60	95,30	
	Returned packages	14356	16704	19392	25441	40905	58170	43%
0,2	Service level	92,45	93,01	93,50	94,30	95,31	95,93	
	Returned packages	15848	18328	20934	26995	42601	59815	47%
0,3	Service level	93,36	93,68	94,30	95,00	95,89	96,45	
	Returned packages	17493	19937	22708	28788	44154	61452	51%
0,4	Service level	94,14	94,58	94,97	95,59	96,38	96,87	
	Returned packages	19831	22328	25182	31257	46682	63866	55%
0,6	Service level	95,41	95,74	96,04	96,52	97,13	97,52	
	Returned packages	24204	26813	29662	35694	50907	68016	62%
0,8	Service level	96,36	96,62	96,95	97,21	97,68	97,98	
	Returned packages	30516	33075	35872	41820	56646	73533	70%
1	Service level	97,05	97,25	97,44	97,71	98,07	98,3	
	Returned packages	38537	41087	43750	49550	63953	80199	78%
1,2	Service level	97,58	97,74	97,88	98,10	98,37	98,54	
	Returned packages	48653	51106	53596	59087	72892	88508	86%
1,4	Service level	97,98	98,10	98,21	98,37	98,58	98,7	
	Returned packages	61276	63552	65815	70845	83778	98670	94%

Simulation results validation phase (best settings with respect to both performance measures are colored blue)

Setting parameter k1	Performance measure	Setting parameter k2: 0	0,05	0,1	0,2	0,4	0,6	% Shipped in the first delivery
0,4	Service level	88,08	89,21	90,18	91,69	93,54	94,56	55%
	Returned packages	10278	12511	15005	20923	37135	57261	
0,6	Service level	90,57	91,49	92,27	93,49	94,98	95,79	62%
	Returned packages	13470	15788	18277	24907	41852	62076	
0,8	Service level	92,46	93,21	93,24	94,84	96,04	96,68	70%
	Returned packages	17266	19696	22437	29370	46324	81873	
1	Service level	93,95	94,55	95,06	95,86	96,83	97,33	78%
	Returned packages	22325	24830	27742	34685	51518	71163	
1,2	Service level	95,14	95,62	96,06	96,66	97,42	97,81	86%
	Returned packages	28988	31578	34390	41141	57757	76976	
1,4	Service level	96,05	96,43	96,75	97,25	97,84	98,14	94%
	Returned packages	37965	40417	43105	49754	65769	84459	

Simulation results model improvement suggestion "adjusted forecast" without product group "Beer" (best settings with respect to both performance measures are colored blue)

Setting parameter k1	Performance measure	Setting parameter k2: 0	0,05	0,1	0,2	0,4	0,6	% Shipped in the first delivery
0,1	Service level	88,54	89,35	90.01	91,03	92,98	93,14	43%
	Returned packages	14374	18708	23518	34393	55283	89323	
0,2	Service level	90,02	90,74	91,33	92,25	93,33	93,92	47%
	Returned packages	17412	21802	26784	38172	66010	95627	
0,3	Service level	91,27	91,91	92,44	93,25	94,22	94,75	51%
	Returned packages	19921	24565	29777	41525	69678	98884	
0,4	Service level	92,32	92,90	93,37	94,10	94,96	95,44	55%
	Returned packages	22371	27043	32348	44650	72665	101544	
0,6	Service level	94,00	94,47	94,85	95,43	96,11	96,48	62%
	Returned packages	26756	31504	37147	49744	77724	105750	
0,8	Service level	95,25	95,63	95,94	96,40	96,93	97,22	70%
	Returned packages	31240	36113	42015	54618	81934	109282	
1	Service level	96,19	96,5	96,75	97,11	97,52	97,74	78%
	Returned packages	36638	41661	48465	59897	86558	113625	
1,2	Service level	96,62	97,16	97,35	97,64	97,95	98,11	86%
	Returned packages	43344	48374	54065	66180	92065	117873	
1,4	Service level	97,46	97,64	97,79	98,01	98,24	98,36	94%
	Returned packages	52051	56872	62380	74159	98925	123982	

Simulation results scenario 1 without product group "Beer" (best settings with respect to both performance measures are colored blue)

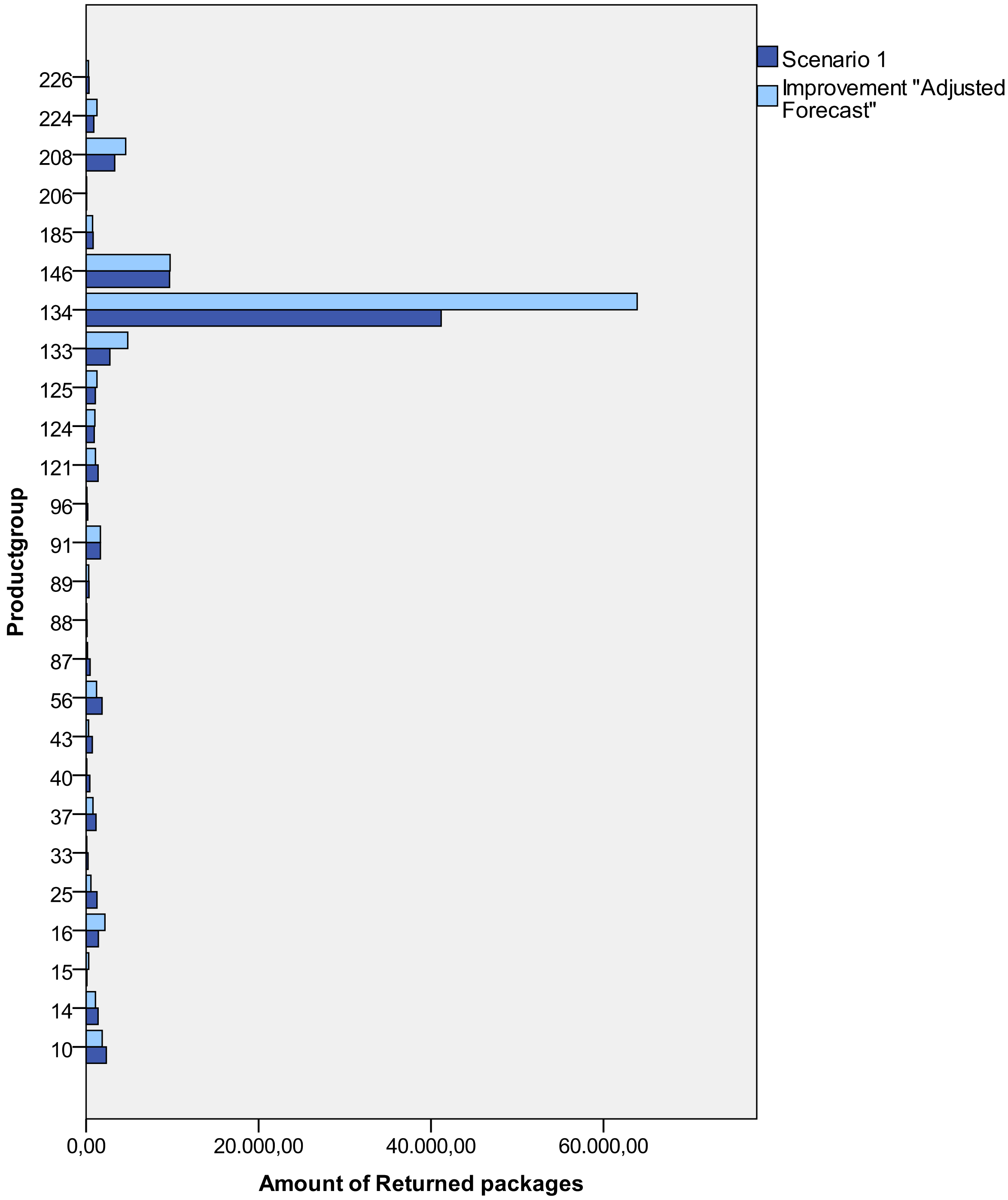
Setting parameter k1	Performance measure	Setting parameter k2 and k3						% Shipped in the first delivery
		0	0,05	0,1	0,2	0,4	0,6	
0	Service level	89,72	90,57	91,04	92,44	93,93	94,74	39%
	Returned packages	4830	5521	6334	8403	13983	22409	
0,1	Service level	91,09	91,83	92,47	93,48	94,80	95,52	43%
	Returned packages	5947	6715	7575	9824	15751	24474	
0,2	Service level	92,24	92,9	93,46	94,35	95,52	96,15	47%
	Returned packages	7235	8100	9013	11455	17578	26523	
0,3	Service level	93,23	93,81	94,30	95,08	96,09	96,65	51%
	Returned packages	8711	9590	10625	13143	19570	28576	
0,4	Service level	94,08	94,58	95,01	95,7	96,57	97,06	55%
	Returned packages	11041	11980	13083	15654	22217	31308	
0,6	Service level	95,42	95,81	96,15	96,66	97,32	97,68	62%
	Returned packages	15743	16447	17671	20205	27051	36053	
0,8	Service level	96,41	96,71	96,97	97,36	97,86	98,12	70%
	Returned packages	22031	22987	24073	26604	33505	42651	
1	Service level	97,13	97,35	97,55	97,85	98,23	98,43	78%
	Returned packages	30383	31242	32366	34814	41540	50373	
1,2	Service level	97,67	97,84	97,99	98,22	98,5	98,65	86%
	Returned packages	40881	41704	42811	45170	51628	59962	
1,4	Service level	98,06	98,20	98,31	98,48	98,69	98,8	94%
	Returned packages	53966	54690	55770	57977	64073	71749	

Simulation results validation phase "3 – deliveries" (best settings with respect to both performance measures are colored blue)

Setting parameter k1	Performance measure		% Shipped in the first delivery
-0,2	Service level	89,28	80%
	Returned packages	28646	
-0,1	Service level	92,36	90%
	Returned packages	43467	
0	Service level	94,39	100%
	Returned packages	62502	
0,1	Service level	95,68	110%
	Returned packages	81828	
0,2	Service level	96,55	120%
	Returned packages	104539	
0,3	Service level	97,17	130%
	Returned packages	125112	
0,4	Service level	97,62	140%
	Returned packages	143559	
0,6	Service level	98,2	160%
	Returned packages	173085	
0,8	Service level	98,56	180%
	Returned packages	196673	
1	Service level	98,78	200%
	Returned packages	213548	

Simulation results validation phase "1 – delivery" (best settings with respect to both performance measures are colored blue)

Appendix 13 – Case comparison on product group level



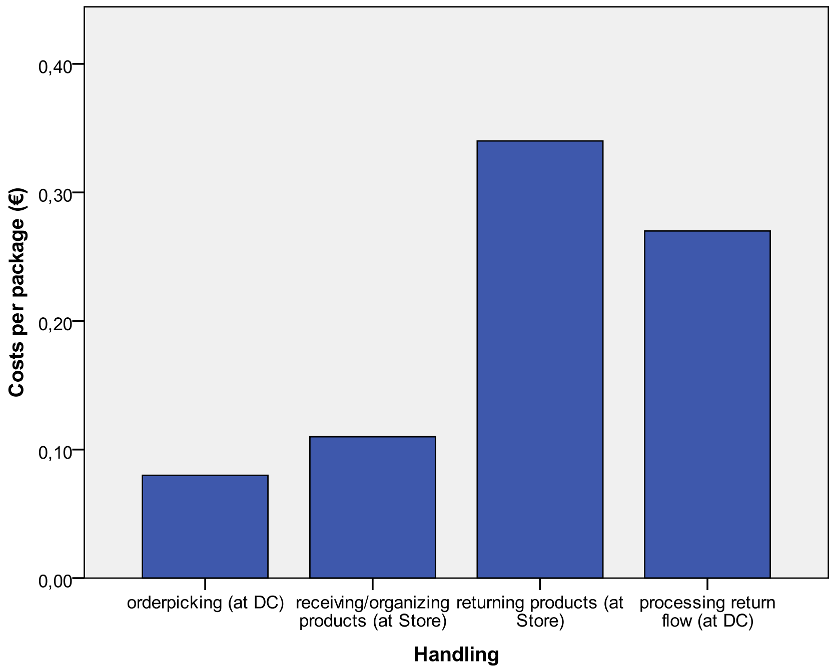
Appendix 14 – Illustration of the orderlist (questionnaire)

STORE NUMBER	ARTICLE NAME	WEEK NUMBER	Sales Monday + Tuesday	Inventory Level at Tuesday evening	Order advice	TO FILL IN Your order
4288	Rosé D'anjous couron Lions 75 CL	20	18	26	44	
4288	HONIG KIPPENSOEP 6B60G15412	20	4	21	0	
4288	HONIG TOM-GROENTESP 6BRD 15814	20	14	46	9	
4288	MAGGI BRAADS.KIP KNOFL36G83826	20	2	39	0	
4288	MARK.KIPSATE M.STOK 280G 1091	20	12	17	29	
4288	Rummo spire pasta 500G12054	20	10	42	0	
4288	MAGGI OVENSCH.BLOEMK 100G67236	20	7	48	0	
4288	WICKY AARDB.DRINK 10X20CL	20	7	42	0	
4288	SISI SIN/MANGO NB PET1,5L 2140	20	10	20	20	
4288	SEVEN-UP FREE PETFL. 1,5L 2093	20	19	61	14	
4288	HAK HOLL.BRUINE BONEN37CL01700	22	8	52	0	
4288	HAK RD.KOOL+ST.APPEL 37CL06600	22	42	65	102	
4288	HONIG MACAR.VLUGK. 250GR 43500	22	5	174	0	
4288	KKR PILS 12X30CL03956	22	0	106	0	
4288	D.E.ROODM SNELF. 500GR 324	22	132	228	296	
4288	AVIKO AARD.SCH/HONG. 450G52700	22	36	11	88	
4288	GD AAR JAVAWAFELS 250G13530	22	23	59	32	
4288	GD AAR ZEEUWSE RONDJE250G41073	22	19	46	30	
4288	HARIBO KERSEN 300G30971	22	19	27	46	
4288	HERO CASSIS LIGHT 1,25L19554	22	12	39	8	
4288	KNORR MIX SPAGHETTI 76G 32620	23	4	48	0	
4288	UNOX C-A-S CHAMPIGNON 51G03904	23	11	80	0	
4288	UNOX C-A-S CHIN.KIP 44G03912	23	2	40	0	
4288	TWIX MINI 375G I4834	23	16	42	21	
4288	BAVARIA PILS BLIK 6X33CL 02151	23	5	32	0	
4288	UNOX C-A-S TOM.CREME 58G03921	23	7	62	0	
4288	MARK.PATATES FRITES 1KG20083	23	52	131	75	
4288	JUPILER BIER 24X25CL 7216	23	21	91	0	
4288	DUBFR.APP/PERZIK 1,5L 4243	23	93	130	227	
4288	DUBFR.DRUIF/CITR.L. 1,5L 4263	23	16	93	0	
4288	DUBFR.APP/ZW.BES 1,5L 4245	23	27	125	0	
4288	RV ROODFRUIT 50/50 1,5L30700	24	11	42	2	
4288	MARK.PADS CAFVRIJ 36X7G	24	5	54	0	
4288	MARK.PADS MOCCA 36X7G	24	6	61	0	
4288	MARK.PADS DARK ROAST36X7G	24	6	26	0	
4288	RV MULTIV.PERZIKEN. 1,5L31500	24	13	38	14	

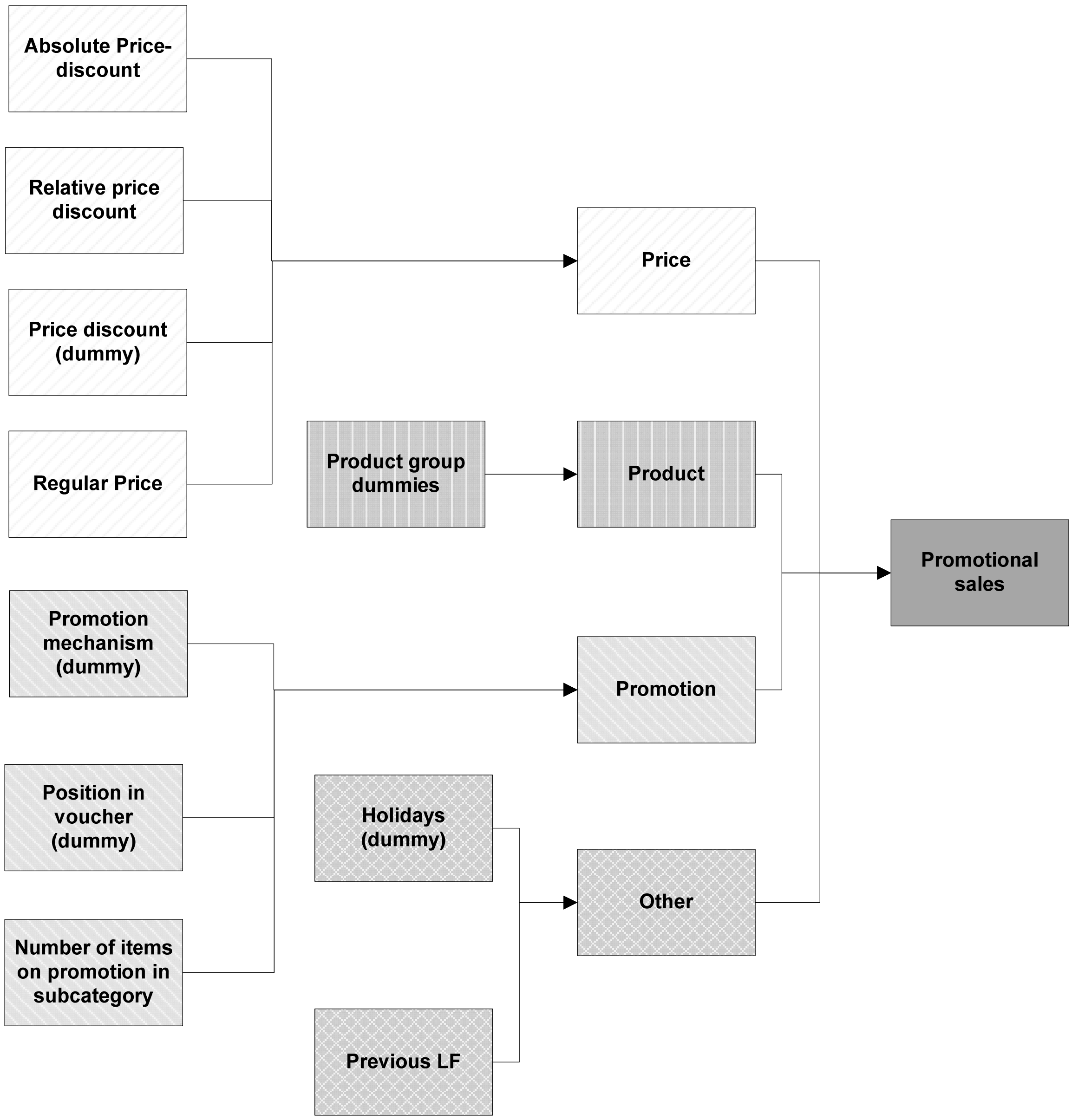
Appendix 15 - Cost estimation of a returned package

In this estimation actual labor cost and productivity information are used. With regards to labor costs a differentiation is made between labor costs in stores and in the DC. The productivity numbers are determined in collaboration with the DC's which have a detailed productivity analysis. Since no productivity information about the stores is available is assumed that store operations are less efficient than DC operations. Hence, stores operations are expected to be 33% less efficient than DC operations.

	Potential Cost Savings		
	Productivity Packages/hr	Labor Costs €/hr	Costs per package €/package
1. Order picking products at the DC	240 packages/hr	€ 20,00	€ 0,08
2. Receiving and organizing products at Store	160 packages/hr	€ 17,00	€ 0,11
3. Returning products at store (requesting for a return/ filling in forms/scanning products/organizing products on a pallet)	50 packages/hr	€ 17,00	€ 0,34
4. Processing return flow at the DC (checking and scanning the return flow/organizing products on pallets/putting products back in the shelves)	75 packages/hr	€ 20,00	€ 0,27
5. TOTAL	-	-	€ 0,80

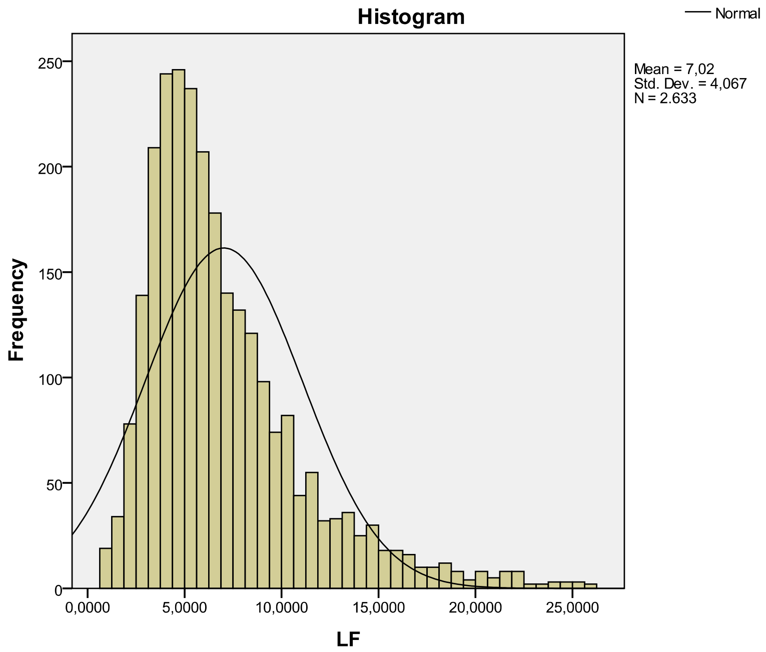


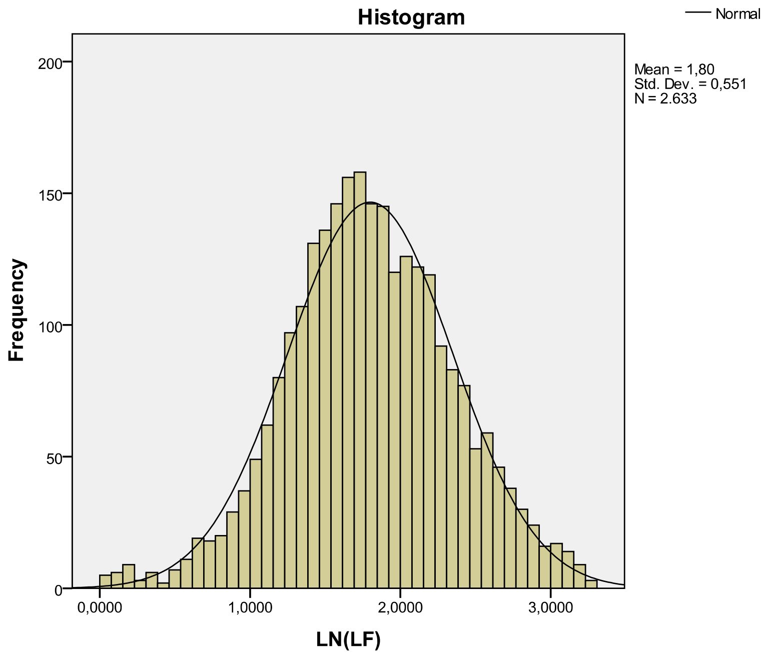
Appendix 16 - Independent variable framework used in the LF-model



Appendix 17 - Transformation dependent variable

To assess the normality of the dependent variable the LF and the LN(LF) two histograms are created. Based on these graphs can be concluded that the lognormal transformation of the dependent variable leads to a considerable improvement in normality.





Appendix 18 - Summary data collection minor research direction

	Data.reduction		
	Total	DKW	Frozen food
Starting dataset	4129	3794	335
LF smaller than 1	88	81	11
LF larger than 3*interquartile range	60	38	8
Final dataset for calibration	2632	2433	209
Final dataset for validation	1349	1242	107

	Data.creation		
	Total	DKW	Frozen food
Remove outliers	4%	3%	6%
Set reference groups	group 10	group 10	group 146
Compute average LF's per product group to replace missing values	15%	15%	19%

Appendix 19 - Test of assumptions

a. All predictor variables must be quantitative or categorical

All predictor variables that have been used in the regression models are either quantitative or categorical.

b. The predictors should have some variation in value

All used predictors have some variation in value. If there was no variation (the value was constant) the predictor variable has been excluded from the regression model.

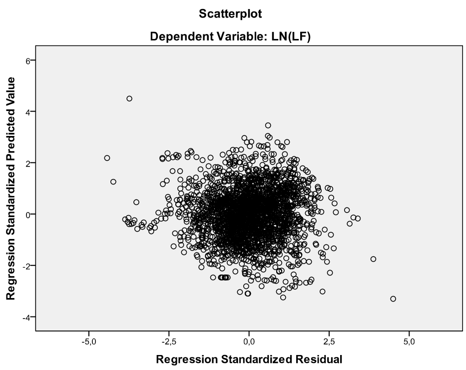
c. No perfect multicollinearity

To assess the multicollinearity of a regression model the VIF factor can be used. If the VIF value is greater than 10 for a particular variable or if the average VIF is substantially greater than 1 there is a cause for multicollinearity (Bowerman & O'Connel, 1990). Since the maximum VIF of the settings is not larger than 10 and the average VIF's are considerably small there is no cause for multicollinearity.

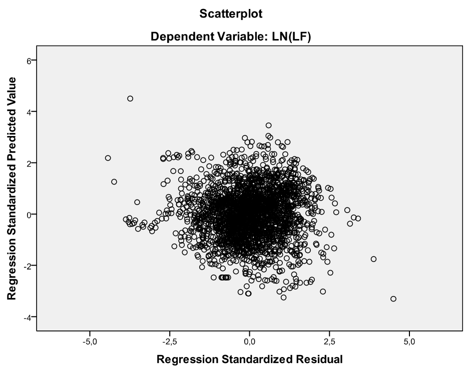
	Total setting	DKW setting	Frozen Food setting
	VIF	VIF	VIF
Maximum	1,642	4,186	3,980
Minium	1,037	1,038	1,041

d. Homoscedasticity

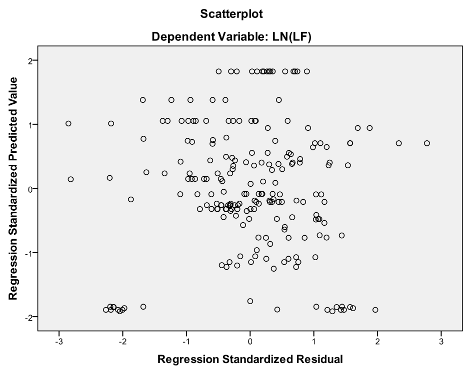
To test the homoscedasticity assumptions the regression standardized predicted values are plotted against the standardized residuals. Based on the plots can be concluded that there is no risk for homoscedasticity based on the plots for the "DKW" and "Total" settings. It is difficult to draw a conclusion upon the "FROZEN" model since it includes less data-points.



"Total" setting



"DKW" setting



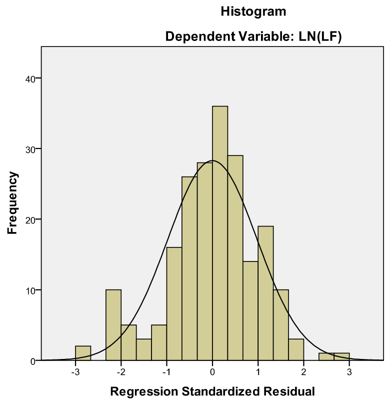
“Frozen Food” Setting

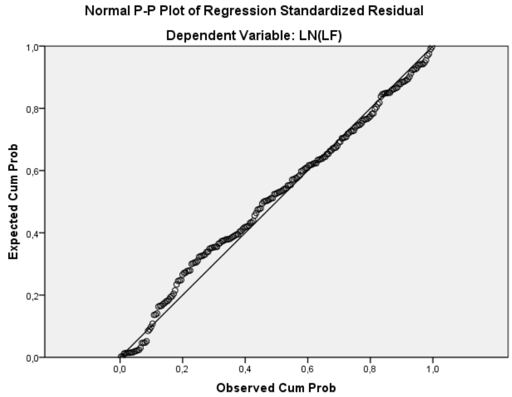
e. Independent errors

To test if there exists correlation between the errors of the residuals in a regression analysis the Durbin-Watson statistic can be used. The value of this test lies always between 0 and 4. If the Durbin-Watson test is substantially smaller than 2 there is a concern for a positive correlation. As a rule of thumb can be said that a value less than 1 and larger than 3 causes a serious concern for correlation between errors of residuals. Since the Durbin-Watson statistic of the “TOTAL”- model has a value of 1,808 this assumption is satisfied.

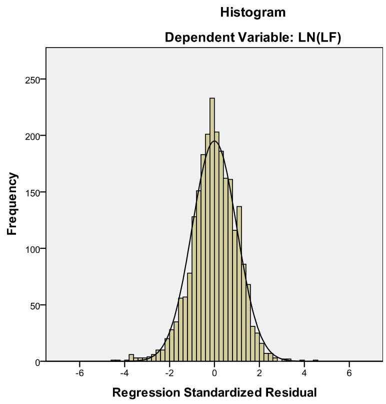
f. Normally distributed errors

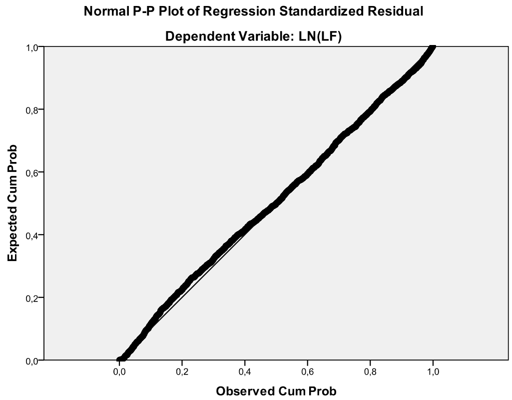
In the histograms and normal probability plots of all three settings can be seen that the normality assumption is satisfied.



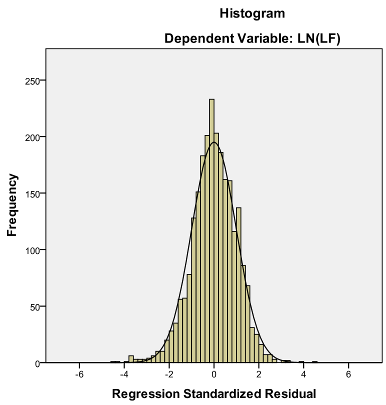


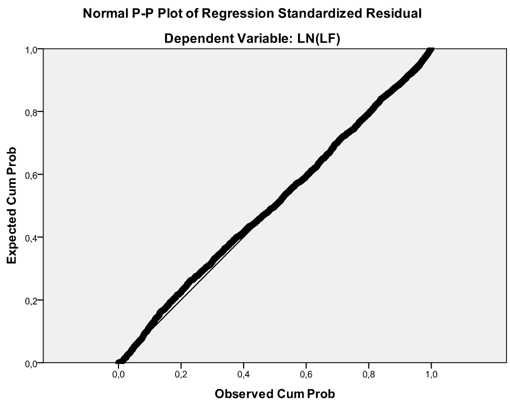
"Frozen Food" setting





"DKW" setting

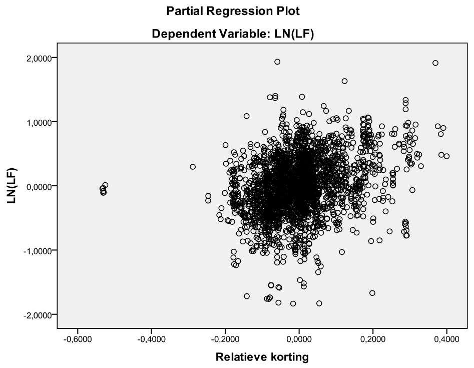


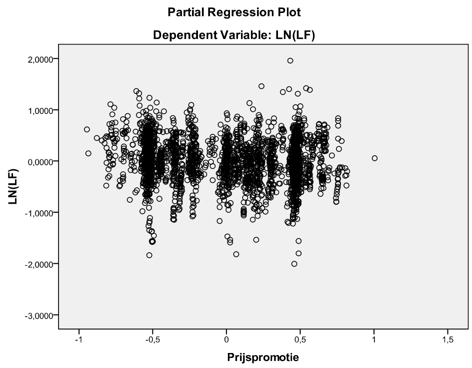


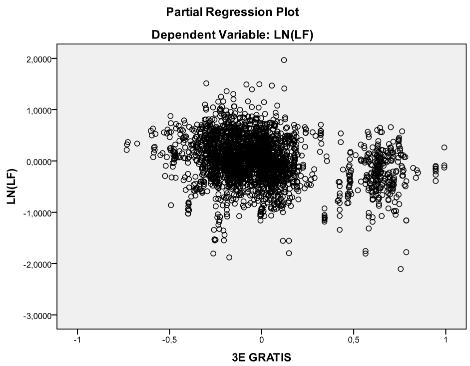
"Total" setting

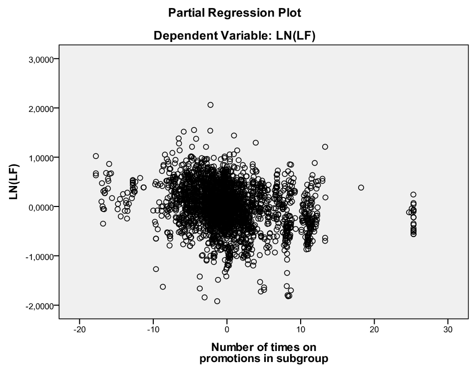
g. Linearity: the modeled relationship is linear

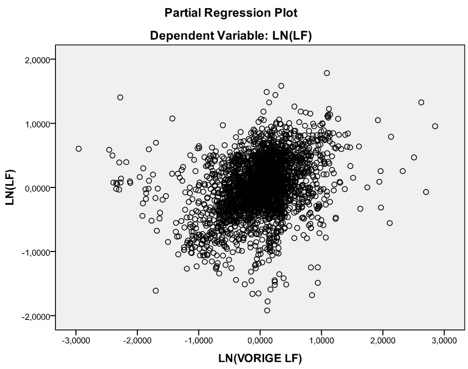
To assess if the relationship between the multiple variables and the dependent variable (LN(lf)) can be considered as a linear relationships, partial regression plots have been made. The plots of the significant variables (except for the product group variables) in the "TOTAL"-model are depicted below. Based on these plots no non-linear relationships can be explored, therefore can be concluded that the linearity assumption is approached.

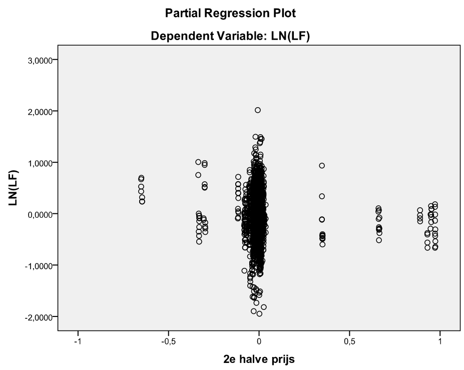


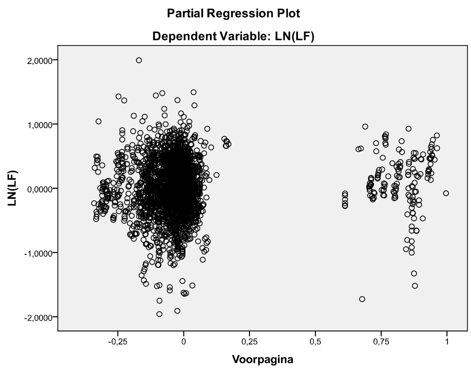












Appendix 20 - Coëfficients Regression model

	Total Model		DKW Model		Frozen Food Model	
	B	Beta	B	Beta	B	Beta
Constant	1,37*		1,33*		3,003*	
LN(vorige LF)	0,268*	0,292	0,267*	0,29		
Absolute discount					1,012*	0,6
Regular price			0,017**	0,067	-0,435*	-0,466
Relative discount	1,405*	0,291	1,46*	0,297		
Price promotion	-0,129*	-0,117	-0,138*	-0,128		
Number of items on promotion in subgroup	-0,021*	-0,258	-0,02*	-0,256	-0,065*	-0,276
2nd half price	-0,286*	-0,071	-0,29*	-0,07		
3rd for free	-0,39*	-0,243	-0,394*	-0,244	-0,443*	-0,262
Frontpage	0,124*	0,052			0,22**	0,105
Last page					-1,487*	-0,146
Product group Dier	-0,809*	-0,127	-0,781*	0,112		
Product group Frisdrank	-0,275*	-0,136	-0,254*	-0,132		
Product group Noten	-0,336*	-0,109	-0,349*	-0,119		
Product group Margarine	-0,357*	-0,088	-0,378*	-0,098		
Product group Groente en fruit diepvries	-0,381*	-0,08			-0,8*	-0,428
Product group Pasta	-0,275*	-0,073	-0,283*	-0,079		
Product group Suikerwerk	0,123*	0,049	0,125*	0,052		
Product group Cereals	-0,342*	-0,062	-0,397*	-0,077		
Product group Diepvries Pizza	0,12**	0,035				
Product group Siropen	-0,264*	-0,056	-0,271*	-0,061		
Product group Soep droog & smaakversterkers	0,111*	0,048	-0,083**	0,038		
Product group Soepen en bouillons nat	0,144**	0,03	0,155**	0,035		
Product group Boterhamartikelen	0,109**	0,031				
Product group Koffie, cacao & oploskoffie	-0,154*	-0,064	-0,152*	-0,068		
Product group vruchtensappen	-0,181*	-0,053	-0,175*	-0,053		
Product group Bieren	-0,168*	-0,054	-0,28*	-0,096		
Product group Aardappelpr. Diepvries	-0,202*	-0,047			-0,486*	-0,268
Product group Chips en Snacks	-0,128*	-0,053	-0,104*	-0,046		
Product group Vleesconserven	-0,175*	-0,044	-0,161**	-0,043		
Product group Gedestilleerd	-0,186**	-0,039	-0,358*	-0,078		
Product group Zuivel houdbaar	-0,174**	-0,036	-0,233*	0,081		
Product group Retailsnacks diepvries					-0,303*	-0,172
Product group Thee	-0,15**	-0,034	-0,155**	-0,037		

Product group Vruchtenwaters			0,098**	0,062		

*   Significant at a 0,01 level

** Significant at a 0,05 level

Appendix 21 - Comparison of forecast accuracy on product group level