MASTER

Action products at Jan Linders Supermarkets

a research to the current performance of and the possible improvements for the inventory management of action products

van den Heuvel, F.P.

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Action products at Jan Linders Supermarkets

by
F.P. (Frank) van den Heuvel

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Student identity number 0551338

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Supervisors:
dr. T. (Tom) van Woensel (TU/e)
prof. dr. ir. J.W.M. (Will) Bertrand (TU/e)
ing. M.P.G. (Ria) Bouten – van den Hombergh (Jan Linders Supermarkets)

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Author:	F.P. (Frank) van den Heuvel BSc
E-mail TU/e:	f.p.v.d.heuvel@student.tue.nl
E-mail:	fvdheuvel@yahoo.com
Telephone:	+31 (6) 15021281
First supervisor TU/e:	dr. T. (Tom) van Woensel
E-mail:	t.v.woensel@tm.tue.nl
Telephone TU/e:	+31 (40) 2475017
Second supervisor TU/e:	prof. dr. ir. J.W.M. (Will) Bertrand
E-mail:	j.w.m.bertrand@tm.tue.nl
Telephone TU/e:	+31 (40) 2472683
Supervisor Jan Linders:	ing. M.P.G. (Ria) Bouten – van den Hombergh
E-mail:	rbouten@janlinders.nl
Telephone Jan Linders:	+31 (485) 349983

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Abstract

In this master thesis project, research is conducted to the performance of the inventory management of action products at a specific Dutch grocery retailer, named Jan Linders Supermarkets. Analyses conducted during this project show that per action product too much items are supplied to the stores. This is mainly caused by the too high aggregate demand forecast. Furthermore, the current process of handling action products is very time-consuming. Recommendations are done to solve these two problems. First, an explanatory demand forecasting model was developed. Using this model, the lift factor in demand during the action week is forecasted based on specific information about the action product itself. Second, a process redesign for handling action products at Jan Linders Supermarkets was created.

Management Summary

In this research, conducted at Jan Linders Supermarkets, the following research question was investigated: “What are the relevant causes for the performance problem of the inventory management of the action products and how can this problem be solved?” The project consisted of two phases, namely an analysis phase and a design phase. In the analysis phase, the current performance of the inventory management of action products was researched and in the design phase, adaptations to this inventory management were proposed to improve the performance. The main outcomes of these two research phases can be summarized into three statements.

The aggregate demand forecast for action products has a poor performance.

A quantitative analysis was conducted on the service centre driven action products. For these products, the service centre determines an aggregate demand forecast for all stores. Thereafter, a general allocation rule is used to determine the proposed order per store. Store managers are enabled to change this proposed order to an initial order. Summing the initial orders of the stores results in a total order for the supplier of the action product. Since this total order must consist of a multiple packaging size, the initial orders are slightly changed to final orders. The inventory managers manually retype all adaptations to the orders in the ERP-system. Finally, the actual delivery of action products to the stores is slightly different from the final orders, mainly due to automatic changes to the final orders in the distribution centre.

Comparing these three different orders and the delivery with the actual sales in the action week results in a performance measure for the inventory management of action products. By comparing the action delivery with the actual sales, it can be seen that on average 0.70 case packs too much are supplied per action product per week per store. This is significantly too much. In searching for the cause for this performance problem, it turned out that the proposed order was on average 0.77 case packs too large. Therefore, it is concluded that the major cause of the surplus in supply of action products to the stores is the poor performance of the aggregate demand forecast. This is namely directly used for creating the proposed orders.

The purchasers determine the aggregate demand forecast. These employees only use their own experience to determine a demand forecast. The procedure used is called a judgemental forecasting method. This results in differently determined forecasts per product. Furthermore, the performance measures of the purchasers encourage them to supply more items per action product to the stores than necessary.

The answer to the research question is that the major cause of the performance problem of the inventory management of the action products is the judgemental forecasting method used to determine an aggregate demand forecast, resulting in a significantly too large proposed order of the service centre.

An explanatory forecasting model performs better than the currently used forecasting method.

The major improvement to the current process of handling action products is to develop a new method for forecasting aggregate demand. In this case an explanatory demand forecasting model is the best to use. In the developed model, the lift factor in demand during the action week is forecasted based on the average sales of the product in five previous non-action weeks, the number of actions in the product (sub)group of the action product, the normal price of the product, the price discount, and the action categorization (AAA, AA, or A). By multiplying this forecasted lift factor with the average

sales of the product in five previous non-action weeks, a demand forecast is created for the product in the action week.

The performance of the created model can only be measured as the number of product left after the action week in all stores together. The current performance was determined per store. Using the forecast of the explanatory demand forecasting model for supplying products to the stores results in a surplus in supply of 1.26 case packs per week for all stores. Dividing this by 53 results in a surplus in supply of 0.02 case packs per week per store. Although the comparison of this value with the current performance is not completely valid, this small surplus and the fact that a formal forecasting model in general will perform better than a judgemental method, validate the conclusion that the performance of the inventory management of action products is increased when this model is used.

To be able to reach this performance, the major prerequisite is to change the method of data storage. Both for the weekly creation of a demand forecast and for the regular update of the model, a significantly large amount of data is needed. To assure that these data can be gathered efficiently, the method of data storage has to be changed.

Redesigning the process results in significant performance improvements.

Based on two other conclusions of the analysis phase of the project, a redesign of the process of handling action products was developed. Besides the conclusion of the aggregate demand forecast being too large, the analysis phase also concluded that the total process was very time-consuming and that no difference was made between forecasts and orders during the process. The latter is a problem, since this results in no flexibility to react on actual sales. The process redesign solves these problems.

In this improved process, the above-described forecasting model is used to determine the aggregate demand forecast. Assuming that the performance of the created demand forecast is satisfactory, there is no need anymore for adaptation of the proposed orders by the store managers. Hence, this saves a lot of time and effort.

In the improved process, two action deliveries are used: one before the action week, initiated by the service centre, and one during the action week, initiated by the store managers. Using these two deliveries results in lowest costs and maximal flexibility to react on actual sales. The improved process starts with forecasting aggregate demand using the explanatory forecasting model developerd. Thereafter, an ordering policy is used to determine what part of the aggregate forecast is actually supplied to the stores with the first delivery. This policy determines that only a fixed part α of the forecasted aggregate demand is used for determining the orders for the stores. The remaining part ($1-\alpha$) of the forecast is used for a second delivery of action products during the action week. The store managers are responsible for determining the amount of action products extra needed during the action week. These managers have the experience to use the actual sales in the first part of the action week for determining their needs in the rest of the week and hence, the amount needed to be ordered extra.

Management Samenvatting

In dit, bij Jan Linders Supermarkten uitgevoerd, onderzoek is de volgende onderzoeksvraag onderzocht: “Wat zijn de relevante oorzaken van het prestatieprobleem van het voorraadbeheer van actieproducten en hoe kan dit probleem worden opgelost?” Het project bestond uit twee fasen, namelijk een analysefase en een ontwerpfase. Om een antwoord te kunnen geven op de onderzoeksvraag is in de analysefase de huidige prestatie van het voorraadbeheer van actieproducten onderzocht. In de ontwerpfase zijn verbetervoorstellen gedaan om deze prestatie te verbeteren. De belangrijkste uitkomsten van deze twee onderzoeksfasen kunnen worden samengevat in drie stellingen.

De prestatie van de vraagvoorspelling voor actieproducten op aggregaatniveau is slecht.

Op de actieproducten waarvoor de actie geïnitieerd wordt door het servicekantoor is een kwantitatieve analyse uitgevoerd. Voor deze actieproducten maakt het servicekantoor een vraagvoorspelling op aggregaatniveau voor alle winkels samen. Daarna wordt er een algemene verdeelsleutel gebruikt om het ordervoorstel per winkel te bepalen. Winkelmanagers krijgen dan de gelegenheid om dit ordervoorstel aan te passen tot een initiële order. De som van de initiële orders van alle winkels resulteert in een totale order voor de leverancier van het actieproduct. De initiële order van de winkels wordt nog lichtelijk veranderd in een uiteindelijke order, omdat de totale order voor de leverancier moet bestaan uit een volume van uitsluitend volle pallets. Alle orderwijzigingen worden handmatig ingevoerd in het ERP-systeem door het personeel van het servicekantoor. Uiteindelijk kan het werkelijk geleverde aantal actieproducten aan de winkels ook lichtelijk verschillend zijn van de uiteindelijke order. Dit wordt voornamelijk veroorzaakt door aanpassingen van de uiteindelijke orders in het distributiecentrum.

Het vergelijken van deze drie orders, de levering en de uiteindelijke verkopen in de actieweek resulteert in een prestatiemaat voor het voorraadbeheer van actieproducten. Door het vergelijken van de levering met de werkelijk verkochte actieproducten kan worden vastgesteld dat er per actieproduct per week per winkel gemiddeld 0.70 colli teveel wordt geleverd. Dit is significant teveel. Bij het zoeken naar de oorzaak van dit prestatieprobleem bleek dat het ordervoorstel gemiddeld 0.77 colli te hoog is. Geconcludeerd kan worden dat de belangrijkste oorzaak van het teveel leveren van actieproducten aan de winkels de slechte prestatie van de vraagvoorspelling op aggregaatniveau is. Deze vraagvoorspelling wordt namelijk direct gebruikt voor het creëren van de ordervoorstellen.

De inkopers zijn verantwoordelijk voor het bepalen van de vraagvoorspelling op aggregaatniveau. Deze werknemers gebruiken alleen hun eigen ervaring voor het bepalen van deze vraagvoorspelling. Er wordt geen gestandaardiseerde procedure gebruikt voor de vraagvoorspelling, wat resulteert in een op een steeds andere manier bepaalde voorspelling per product. Daarnaast moedigen de beoordelingscriteria van de inkopers hen aan om meer colli per actieproduct naar de winkels te sturen dan dat echt nodig is.

Het antwoord op de onderzoeksvraag is dat het prestatieprobleem van het voorraadbeheer van actieproducten wordt veroorzaakt doordat er een voorspelmethode op basis van ervaring wordt gebruikt om de vraagvoorspelling op aggregaatniveau te bepalen. Dit zorgt voor een significant te hoog ordervoorstel van het servicekantoor wat resulteert in te hoge leveringen aan de winkels.

Een verklarend voorspelmodel presteert beter dan de huidige voorspelmethode.

De belangrijkste verbetering om het huidige proces voor het verwerken van actieproducten te verbeteren is om een nieuwe methode te ontwikkelen voor het voorspellen van de vraag op aggregaatniveau. Het beste model wat gebruikt kan worden in deze situatie is een verklarend

voorspelmodel. In het ontwikkelde model wordt de liftfactor in de vraag gedurende de actieweek voorspeld op basis van de gemiddelde verkopen van het product in de laatste vijf niet-actieweken, het aantal acties in de product (sub)groep van het actieproduct, de normale prijs van het product, de korting en actiegroepering (AAA, AA of A). De voorspelling van de vraag van het product in de actieweek wordt verkregen door deze voorspelde liftfactor te vermenigvuldigen met de gemiddelde verkopen in de laatste vijf niet-actieweken.

De prestatie van het ontwikkelde model kan alleen worden gemeten als het aantal producten wat over is na de actieweek in alle winkels gezamenlijk. De huidige prestatie is bepaald op winkelniveau. Als de voorspelling van het verklarende voorspelmodel wordt gebruikt om producten naar de winkels te sturen resulteert dit in een overschot van 1.26 colli per actieproduct per week voor alle winkels gezamenlijk. Door dit te delen door 53 komt men op een overschot van 0.02 colli per actieproduct per week per winkel. Ondanks dat het niet helemaal geldig is om een vergelijking te maken tussen deze waarde en de huidige prestatie, resulteert deze lage waarde en het feit dat er een objectief voorspelmodel wordt gebruikt in de conclusie dat het gebruik van dit model zorgt voor een betere prestatie van het voorraadbeheer van actieproducten.

De belangrijkste voorwaarde om deze prestatie te behalen is een verandering in de manier van dataopslag. Op dit moment is het erg tijdrovend om de benodigde data te verzamelen. Voor de wekelijkse vraagvoorspelling en de regelmatige update van het model is een significant grote hoeveelheid data nodig. Om te verzekeren dat deze data efficiënt kunnen worden verzameld zal de manier van dataopslag moeten veranderen.

Het herontwerpen van het proces resulteert in significante prestatieverbeteringen.

Een herontwerp voor het proces voor het verwerken van actieproducten is ontwikkeld op basis van twee conclusies uit de analysefase van het project. Naast de conclusie dat de vraagvoorspelling op aggregaatniveau te hoog is, is er in de analysefase ook geconcludeerd dat het totale proces erg bewerkelijk is en dat er geen verschil wordt gemaakt tussen voorspellingen en orders gedurende het proces. Het laatste is een probleem, omdat dit veroorzaakt dat er geen flexibiliteit is om te reageren op de werkelijke verkopen. Het herontwerp voor het proces lost deze beide problemen op.

In het verbeterde proces wordt het verklarend voorspelmodel gebruikt om de vraagvoorspelling op aggregaatniveau te bepalen. Wanneer wordt aangenomen dat de prestatie van het gecreëerde voorspelmodel voldoende is, is er geen behoefte meer aan een aanpassing door de winkelmanagers van het ordervoorstel. Dit bespaart veel tijd en moeite.

In het verbeterde proces worden twee leveringen gebruikt voor het uitleveren van actieproducten aan de winkels: één voor de actieweek, geïnitieerd door het servicekantoor, en één tijdens de actieweek, geïnitieerd door de winkelmanagers. Het gebruik maken van deze twee leveringen resulteert in de laagste kosten en maximale flexibiliteit om op de gerealiseerde verkopen te kunnen reageren. In het verbeterde proces wordt eerst een aggregaat vraagvoorspelling gemaakt met behulp van het ontwikkelde verklarend voorspelmodel. Daarna wordt een bestelmethodiek gebruikt om te bepalen welk deel van de voorspelling op aggregaatniveau wordt gebruikt voor de eerste levering naar de winkels. Deze bestelmethodiek regelt dat een vast deel α van de vraagvoorspelling wordt gebruikt voor de bepaling van de orders voor de winkels. Het overgebleven deel $(1- \alpha)$ wordt gebruikt voor een tweede levering van actieproducten tijdens de actieweek. De winkelmanagers zijn verantwoordelijk voor het bepalen van de hoogte van deze extra actieorder gedurende de actieweek. Deze winkelmanagers hebben de ervaring om de werkelijke verkopen in het eerste deel van de actieweek te gebruiken voor het bepalen van de behoefte aan extra producten.

Preface

The research conducted at Jan Linders Supermarkets serves as the master thesis project related to my Master's study Operations Management and Logistics at the Eindhoven University of Technology. This multidisciplinary study comprises disciplines of product development, quality management, logistics, information systems, and human resources management. Within this multidisciplinary field, I chose to emphasize on the logistical part. In specific, I chose to relate my master thesis project to the research field of retail operations, in which research is done to the operational issues in the retail supply chain, like e.g. inventory management, distribution planning, and handling capacity planning.

At the start of my master thesis project, the logistical managers of Jan Linders Supermarkets offered me the opportunity to conduct my research at their company. I worked at this research from September 2008 to March 2009. In that period, I was an employee of Jan Linders Supermarkets, which resulted in many instructive and also enjoyable experiences.

Before starting to report the outcomes of this research study, I want to thank several people for their support during this project. First, I would like to thank all my colleagues at Jan Linders Supermarkets, and especially those of the inventory management department. In specific, I would like to thank Ria Bouten and Michael Ketelaars; Ria, since she made it possible for me to graduate at Jan Linders Supermarkets and because she was a real support for me during the complete project, both formal and informal, and Michael for the information he gave me during the project, both during working hours and our pleasant rides home.

Besides my colleagues at Jan Linders Supermarkets, I want to thank Tom van Woensel for his support during the project. Fortunately, our relationship made that our conversations were both very valuable for my project, but also pleasant, partly due to our joint hobby. Furthermore, I would like to thank prof. Bertrand for his critical approach to my progress during the project. In addition, I want to thank Rutger Stultiëns and Teun Burgers for checking this report on English.

In this list of thankful words, I cannot forget my parents. They were the ones giving me the opportunity to study at the TU/e and they were the ones supporting me in every decision I made during my study. Mum and dad, thanks!

Finally, this preface would not have been complete without thanking my girlfriend Marloes for her continues mental support during this project and part of my study.

Frank van den Heuvel
Nieuw Bergen, March 2009

Outline

List of abbreviations

AGF	Products from the product categories of potatoes, vegetables, and fruits (in Dutch: *Aardappelen, Groente en Fruit*)
AL	Administrative delivery warehouse (in Dutch: *Administratieve Levering*)
ANOVA	Analysis of variance
BO	Business Objects
DC	Distribution centre
DV	Freezer warehouse (in Dutch: *Diepvries*)
ERP	Enterprise Resource Planning
FnF	Food/non-food
KO	Cool warehouse (in Dutch: *Koel*)
KW	Food/non-food warehouse (in Dutch: *Kruidenierswaren*)
MAPE	Mean absolute percentage error
MSE	Mean squared error
SC	Service centre
SKU	Stock keeping unit
TR	Transit warehouse (in Dutch: *Transito*)
VBA	Visual Basics for Applications
VC	Fresh warehouse (warehouse of AGF products; in Dutch: *Verscentrale*)

Part I: Introduction

1. Problem environment and definition

"*A retailer is a business selling products and/or services to consumers for personal or family use. … This makes retailing a set of business activities adding value to the products and services sold to consumers for their personal or family use.*" (Levy and Weitz, 2007, page 7)

In this report, the business activities related to action products at a specific retailer, called Jan Linders Supermarkets, are researched. This chapter starts with an introduction of this research. Paragraph 1.1 describes the history and the organization of Jan Linders Supermarkets. Afterwards, paragraph 1.2 presents the actual problem of the current action products' process of Jan Linders Supermarkets. This problem is related to scientific literature in paragraph 1.3, and finally paragraph 1.4 clarifies the structure of this report.

1.1. Problem environment

The problem environment of this research is the organization of Jan Linders Supermarkets. The history of Jan Linders Supermarkets starts after the Second World War. Jan Linders worked as the local milkman in the neighbourhood of Gennep in that time. His entrepreneurial skills resulted in the first self-service shop in 1958. On December 18 1963, the first Jan Linders supermarket opened, still located in Gennep. During the years, the success of the organization resulted in the ability to open more and more stores. Since the mission of the organization is to become the best supermarket chain for all consumers in the southern part of the Netherlands, all new stores were opened in the southern provinces. Nowadays, the Jan Linders Supermarkets organization consists of 53 stores in the Dutch provinces Limburg, Noord-Brabant, and Gelderland. As part of the strategy, Jan Linders Supermarkets plans to have 60 outlets in the year 2010. In 2005, the turnover of Jan Linders Supermarkets was equal to 268 million euro.

Until 1999, Jan Linders himself was the director of the Jan Linders Supermarkets organization. In 1999, Jan Linders' son Leo took over this task. From that time, Leo Linders and his two sisters are the stakeholders of the organization. Appendix A1 presents a diagram of the current Jan Linders Supermarkets organization.

At a certain moment in the history of Jan Linders Supermarkets, it was needed to control the activities of the growing number of stores centrally. Therefore, headquarters were built in Nieuw Bergen. These consisted of a service centre (SC) and a distribution centre (DC). In 2006, the DC was needed to be modernized and the management decided to build an entirely new DC. In November 2007, this new DC was put into use. The difficulty of working with the completely new working methods resulted in many out-of-stock problems in the Jan Linders stores at that time, which had a negative influence on customer satisfaction (Lijftogt, 2007). At the moment of conducting this master thesis project, most of the problems are taken care of and customer satisfaction is again increasing. Nevertheless, this situation has to be kept in mind when judging the data used in this project, since it can result in biases.

At the start of this master thesis project, the goal was defined to research the process of the inventory management of action products at Jan Linders Supermarkets. Therefore, the emphasis of this project is on the activities of the inventory management department. This department is responsible for the planning of the inventories in the DC. This means that the inventory managers order products from the suppliers of Jan Linders Supermarkets and maintain contact with the employees at the different Jan Linders stores to coordinate the supply of products to the stores. For non-action products, the store managers themselves are responsible for the inventory level. These store managers use a computerized system in which they can specify how much items are needed of each stock keeping unit (SKU). The size of the order per SKU is based on the experience of the store managers. No standardized ordering procedure is used. An automatic ordering system is being developed, which probably will not be available soon. For non-action products, the task of the inventory management department is to assure that the right amounts of items are kept on stock in the DC. Also centrally, no standardized policies are used to determine the preferred amounts of items ordered from the suppliers. The inventory managers judge the sales history available in the ERP system, called DistRetail, to determine these amounts. A totally different process is used for the inventory management of action products. This process will be described in detail in chapter 2 of this report.

The scope of this project can be defined using the classification of products within different product departments. The following product departments exist:

- Food/non-Food (FnF)
- Freezer
- Cigarettes
- Potatoes, vegetables and fruits (AGF)
- Meat-products
- Fresh meat
- Cool
- Cheese boutique
- Bakery

In principle, products from all product departments are considered in this research. However, for the product category of cigarettes, no promotional actions are done. Therefore, this product department falls outside the scope of this research. Since products of all other departments are potential action products, all these products are considered in this report. The scope of this project is thus defined as action products within all product departments.

1.2. Problem definition

In this paragraph, the problems related to the action products are clarified. The management of Jan Linders wants to work with action products, due to the attractiveness of these products to the customers and the funds gained from the action products' suppliers for promoting their items. Nevertheless, the management also realises that it is very difficult to control the inventories of these products. The goal of this project is to determine the performance of the current procedure of the inventory management of action products and to propose improvements where possible.

The first step in a business problem solving project like this, is to formally describe the problem. Using the interview structure of Kempen and Keizer (2000), a cause-and-effect diagram could be created, as presented in appendix A2. Although this diagram should help with creating a more narrowed problem definition than originally presented by the project initiators, it was not possible to do so. No specific problem could be filtered out the problem mess to be the most important to analyse further. Therefore, the following broad problem statement was presented at the start of the project:

The current performance of the inventory management of action products is not sufficient.

Contiguously, the main research question of this project is: "What are the relevant causes for the performance problem of the inventory management of the action products and how can this problem be solved?" Based on the cause-and-effect diagram, this research question is subdivided in three more specific research questions:

1. Does Jan Linders Supermarkets use the correct inventory levels of action products in the stores? To answer this research question, an analysis is conducted on the incoming and the outgoing action products. Beforehand, the expectation of the management of Jan Linders Supermarkets is that too much action products are supplied to the stores, based on the observation of the number of action leftovers currently present in the small stockrooms of the stores.
2. What is the performance of the initial aggregate demand forecast made centrally? Employees of the service centre (SC) make an initial aggregate demand forecast for the largest group of action products. A comparison of this demand forecast with the actual sales creates the opportunity to judge the performance of this forecast.

3. Is the right allocation rule used, to allocate the initial aggregated demand forecast to the stores? After forecasting the aggregate demand, this forecast has to be allocated to the stores to be able to determine an order per store. A description of the current way of allocation and an analysis of the performance differences per store lead to a judgement about the validity of this allocation rule.

In addition, at the start of the project, a fourth and fifth research question were formulated. The fourth question was related to products discarded as a result of leftovers. Excess inventory for perishable items leads to extra costs, because these products have to be discarded sooner. During the analysis phase of this project, it was decided to skip the analysis to discarded products, since it would not add any more insights. The fifth research question was related to invisible action products: Can a difference be made in the performance of visible and invisible action products? The analysis to answer this question was actually conducted. Nevertheless, the outcomes of this analysis were less relevant for this study, since it was hard to prove that significant improvements could be made. Therefore, this analysis is only presented in appendix A3.

1.3. Relevant literature

To be able to relate the problems of Jan Linders Supermarkets with the inventory management of action products to scientific literature, this paragraph briefly summarizes the interesting topics of the literature study conducted in advance of this master thesis project (Van den Heuvel, 2008a). One of the topics presented is stock-out management in general. Corsten and Gruen (2003) researched stock-outs worldwide. Although retailers nowadays have sophisticated technological equipment available, these authors found an average out-of-stock rate of 8.3 percent in 40 studies.

Campo, Gijsbrechts, and Nisol (2000) present five different consequences of these out-of-stock situations by observing the customer reactions:

1. Buy the item at another store
2. Buy the item later at the same store
3. Buy a substitute for the product originally wanted of the same brand
4. Buy a substitute for the product originally wanted of a different brand
5. Do not purchase the item at all

Combining these studies, the conclusion is that stock-out management is an important aspect of a retailer's business, since out-of-stock situations result in an increase of the costs of a retailer, caused by lost sales (Corsten and Gruen, 2003). However, as the research conducted in this project shows, avoiding stock-outs can result in a significant amount of leftovers of products in the stores. Especially for action products, this also results in an increase in costs, caused by for instance the extra handling needed to get rid of these products. Therefore, the purpose is to determine the right amount of action products needing to be available in the stores.

To be able to determine this right amount, a demand forecast has to be made. Hence, the influence of promotions on the demand of products is a relevant research topic for this master thesis project. Van Heerde, Leeflang, and Wittink (2002) researched the influence of promotions on sales. These authors admit that sales increase when a product is promoted and state that these effects are only valid for the short run. Promotions do not result in surpluses in sales for the long run. It is therefore critical for a retailer to be aware of the causes of temporary sales improvements. Due to this temporariness, demand should no longer be forecasted using historical data, but marketing information should be used (Van Donselaar, Van Woensel, Broekmeulen, and Fransoo, 2004).

1.4. Structure of the report

Complementary to the research questions and the problem context, this paragraph describes the structure of the report. In this project, the regulative cycle of Van Strien (1997) elaborated by Van Aken, Berends, and Van der Bij (2005) as presented in appendix A4, was used. The first three paragraphs of this chapter already handled the first two steps of this cycle, containing the problem context and the problem definition. Afterwards, Van Aken et al. (2005) define an analysis phase, a design phase, an implementation phase, and an evaluation phase. Part II of this report describes the analysis phase of this project, in which the current performance of the inventory management related to action products is presented. Part III contains outcomes of the design and implementation phase, in which improvements to this inventory management are proposed. Due to the time-constraint of this project, only a proposal for the implementation of the redesigned process is made; the actual implementation and the evaluation have to be done by employees of Jan Linders Supermarkets.

Figure 1.1 shows the relationships between the different chapters within the two following parts of this report. For the analysis phase of the project, described in part II of the report, the funnel approach was used (Cooper and Schindler, 2003), meaning that in this project phase a procedure of moving from general to specific was used. Conducting several analyses, first all general processes related to action products were described. To quantify this analysis more, the executed process was monitored for ten specific action products. Finally, one specific performance measure was calculated for all action products in the first 41 weeks of 2008.

To be able to define the goals for the design phase of the project, first the results of the analyses had to be clear. Therefore, the next part of this report first describes the analysis phase of the project and afterwards part III continues with the clarification of the design and implementation phase of the project. Figure 1.1 already presents the subjects of the different chapters of part III of the report.

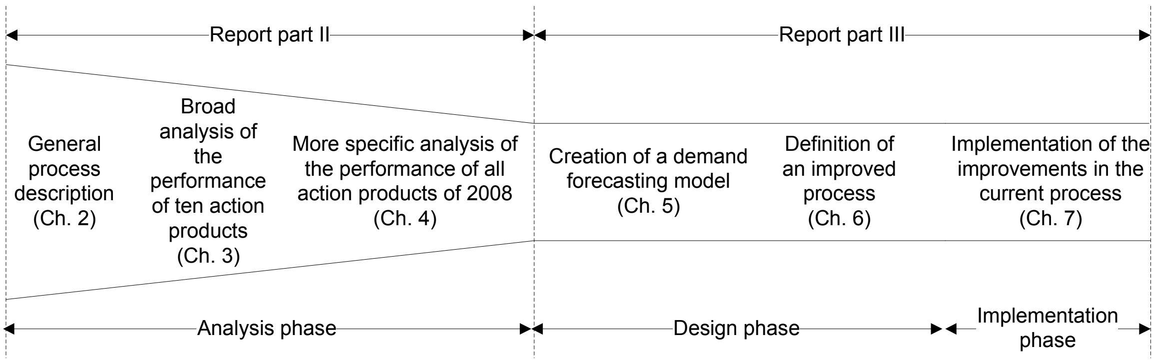

Figure 1.1: The structure of the report

Part IV of this report concludes the report by summarizing the main issues of the previous parts and gives recommendations for the future. Finally, the in part V presented appendices provide detailed information per chapter in the main text.

Part II: The current performance

2. Process description

This part of the report describes the outcomes of the analysis phase of the project. This chapter starts with a detailed description of the action products' process, based on qualitative data gathered from interviews with employees of Jan Linders Supermarkets. To get a complete overview of this process, ten specific action products were monitored. Chapter 3 presents the outcomes of this more specific analysis. Finally, an analysis is conducted to the performance of the inventory management system of action products, based on data of week 1 to week 41 of 2008. Chapter 4 presents the outcomes of that analysis.

This chapter starts with a description of the action products' process. First, an introduction is given on the part of the process that is common for all action products. Thereafter, a distinction is made between actions driven by the service centre (SC) centrally and action driven by the stores locally. Finally, the chapter ends with an overview of the complete process and a discussion about the problems indicated during the interviews.

Figure 2.1 presents the common start of the process for action products. It starts seven weeks before the action week with the purchasers of the commercial department that create the action package per week. This results in an action scheme, which is a list of all action products in a particular week, presented in a Microsoft Excel file. This file contains per action product information about the purchasing price, the regular selling price, the action selling price, and the action text in the promotional brochure.

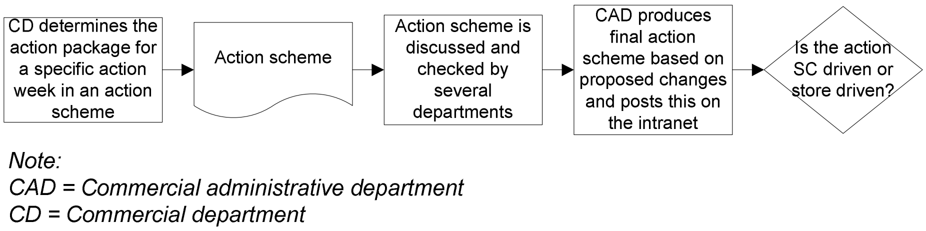

Figure 2.1: The for all action products common part of the action products' process

Within the action scheme, actions are categorized as AAA, AA, or A actions.[1] This categorization is based on the quality of an action, which can be characterized using the price discount and the exclusiveness of the discount. It also determines the amount of exposure the action product gets in the action week and therefore, probably affects the sales of the product in the action week.

The action scheme is revised several times, for instance after a discussion with the responsible members of the Jan Linders Supermarkets' board. When the final action scheme is presented, the marketing and communication department and the department of assortment management check the action scheme on for them relevant aspects. Due to the action scheme being an Excel file, these departments cannot make changes to it simultaneously. To overcome this problem, the commercial administrative department is responsible for adjusting the errors within the action scheme. Furthermore, this department also publishes the final action scheme on the intranet.

All other activities related to handling action products are different for actions that are SC driven and actions that are store driven. For actions that are SC driven, the employees of the SC initiate the orders of action products for the stores. For actions that are store driven, store managers themselves are responsible for ordering the action products from the DC. Paragraph 2.1 starts with describing the process related to SC driven action products. Thereafter, paragraph 2.2 elaborates on the store driven action products.

[1] From the start of the year 2009, another qualification is added, named AAAA actions.

2.1. Service centre driven actions

For the largest group of action products, employees of the service centre (SC) are responsible for the order initialisation. During the process, three different orders are created, as presented in figure 2.2. Afterwards, the final order results in a delivery of action products to the stores and finally in sold products to the customers. The following subparagraphs describe the different steps in figure 2.2.

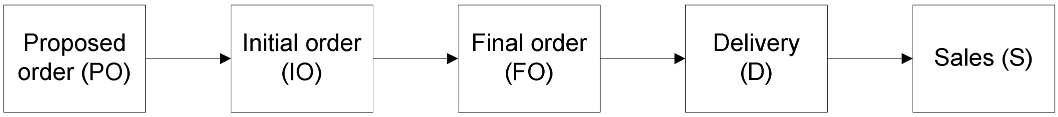

Figure 2.2: The global process of handling SC driven action products

2.1.1. Proposed order

The determination of the proposed order (PO) contains two different steps, executed by employees of the SC. First, the purchasers of the commercial department make an aggregate forecast for the total demand in the action week per action product. This forecast is made using a judgemental procedure, only based on the experience of the purchasers. Second, the employees of the inventory management department allocate this aggregate demand forecast to the 53 supermarkets, resulting in 53 proposed orders per action product. To do this, the inventory managers mainly use one general allocation rule prespecified in DistRetail.

2.1.2. Initial order

The list of all proposed orders is published on the intranet in an Excel file. The file is published to give the stores the opportunity to change the proposed order. This opportunity is given to the stores because of several reasons:

1. Regional information available. Information about planned activities in the environment, like for example fairs, is only available in the stores. These activities can have a significant effect on the demand of customers and are not known by the employees of the SC.
2. Leftovers of previous actions. When stores still have items of the action product left from previous action weeks, these can be used for the current action week.
3. Awareness of the forecasting procedure not being very sophisticated. Stores have to make changes due to the rather simple method of forecasting and the general allocation rule used.

Store managers make their adaptations to the proposed orders in the Excel file and return this file per e-mail to the inventory management department. These adaptations result in a new order, named the initial order (IO). The inventory managers print the returned files and retype the proposed orders in DistRetail based on the initial orders of the stores. However, not all changes are carried through, to limit the time needed for retyping the orders. Only corrections made by the stores of minimally three case packs are implemented in DistRetail. Furthermore, a change of a proposed order to zero is always allowed, to give the store managers the opportunity to sell out their leftovers.

2.1.3. Final order

Most SC driven action products are finally supplied to the stores in two deliveries. The first delivery is the biggest one. For food/non-food (FnF) products, this order contains the delivery of the products picked at the FnF action street in the distribution centre (DC). Most FnF action products are handled in the DC using a separate action products picking street. In this action street, the FnF action products are handled separately from the non-action products. Since only 110 SKUs can be handled in the action street, a small number of FnF action products is picked in the regular picking street in the DC.[2] The goal is that this action street is empty when all action products for the first delivery are picked. This means that the total order per action product of the SC to the supplier has to consist of multiple packaging sizes. The levelling of the total order causes that the initial orders again have to be changed. The inventory managers change these orders in DistRetail manually, resulting in a final

[2] During the analysis phase of this project, the size of the FnF action products picking street was changed from 110 SKUs to 135 SKUs. However, since all data are related to a boundary of 110 SKU, this boundary is used.

order (FO) per action product. The products for the second delivery are picked from the regular picking places and therefore, the orders for the second delivery do not have to be rounded to a multiple packaging size.

2.1.4. Delivery

Preferably, the delivery (D) of action products is equal to the final order. However, for large volume products, the final order per store is automatically changed to full pallets in the DC. Furthermore, picking faults also result in differences between the final orders and the deliveries.

2.1.5. Sales

Finally, customers sell (S) the products in the action week. During the first part of the action week, store managers are not allowed to order FnF products via the regular ordering procedure. This means that the first deliveries in the action week of products ordered by the store managers themselves are received on Thursday or Friday (depending on the delivery scheme of the stores). This procedure causes the store managers to make good demand forecasts in advance of the action week, since almost no extra items can be ordered, which creates the advantage of being able to correctly plan the supply of action products centrally. Nevertheless, as will be seen in this report, this procedure also contains several deficiencies.

Since sales are never equal to forecasts, someone has to monitor the actual sales to determine whether adjustments are needed. The inventory managers do this centrally. When the actual sales per SKU for all stores together are more than 1.15 times the forecasted sales, extra items available at the DC are supplied to the stores. The total amount of extra action items sent to all stores depends on the extra items available at the DC, and the difference between the sales and the forecast. Again, the allocation rule in DistRetail is used to allocate the extra supply to the stores. This means that all stores receive extra supply of the action SKUs that sell above expectations at all Jan Linders supermarkets in total.

The procedure related to SC driven action products was implemented in week 15 for FnF products. Since the logistics department was satisfied with this way of working, the procedure was also implemented for stock keeping cold storage products in week 36 of 2008. For these products, the procedure was partly changed. For cold storage products, stores are allowed to make any change to the proposed order of the SC. Furthermore, since no special action products picking street is present at the DC for these products, no multiple packaging sizes have to be ordered from the supplier for the first delivery of these action products to the stores. This means that the final orders are equal to the initial orders for the cold storage products.

2.2. Store driven actions

Due to product characteristics, not all products are handled using the procedure described in the previous paragraph. For these products, the store managers are responsible for the determination of the order.

The store driven action products are further divided into products having a barcode available in the action scheme and products not having a barcode available in the action scheme. For products having a barcode available in the action scheme, the stores have to place an order at the SC four weeks in advance of the action week. Therefore, for these products, predefined deliveries are present. The orders of all stores are added up and this summation is used to determine the size of the order of the SC for the suppliers. These products are supplied to the stores before the action week. In the action week, stores are still able to order extra action products. For AGF products, which do not have a barcode available in the action scheme, the procedure is almost the same. The only difference with these products is that the store managers do not have to place a definite order four weeks in advance. For these products, store managers have to forecast the amount they expect to order for the action week. However, stores are not obliged to order those products forecasted beforehand; in the action week itself, store managers can order whatever amount of products they want.

The last category that remains after deleting the SC driven action products, the products with predefined deliveries, and the AGF products, is the category of products that are ordered via the regular way, which only are FnF products not fitting in the action products picking street at the DC. When more than 110 SKUs have to be picked, these are picked from the regular picking location in the DC. Then, the action street is used for the most voluminous SKUs and the SKUs with the highest demand. For these FnF products not fitting in the action street in the DC, no activity is conducted beforehand and stores order these products the regular way.

2.3. Overview and discussion

Figure 2.3 presents an overview the complete process of handling action products. Although this figure is already simplified (appendix B1 contains an elaborate version), it still is concluded that the total process is very complex. This complexity should be reduced when improving the process in the design phase of this master thesis project.

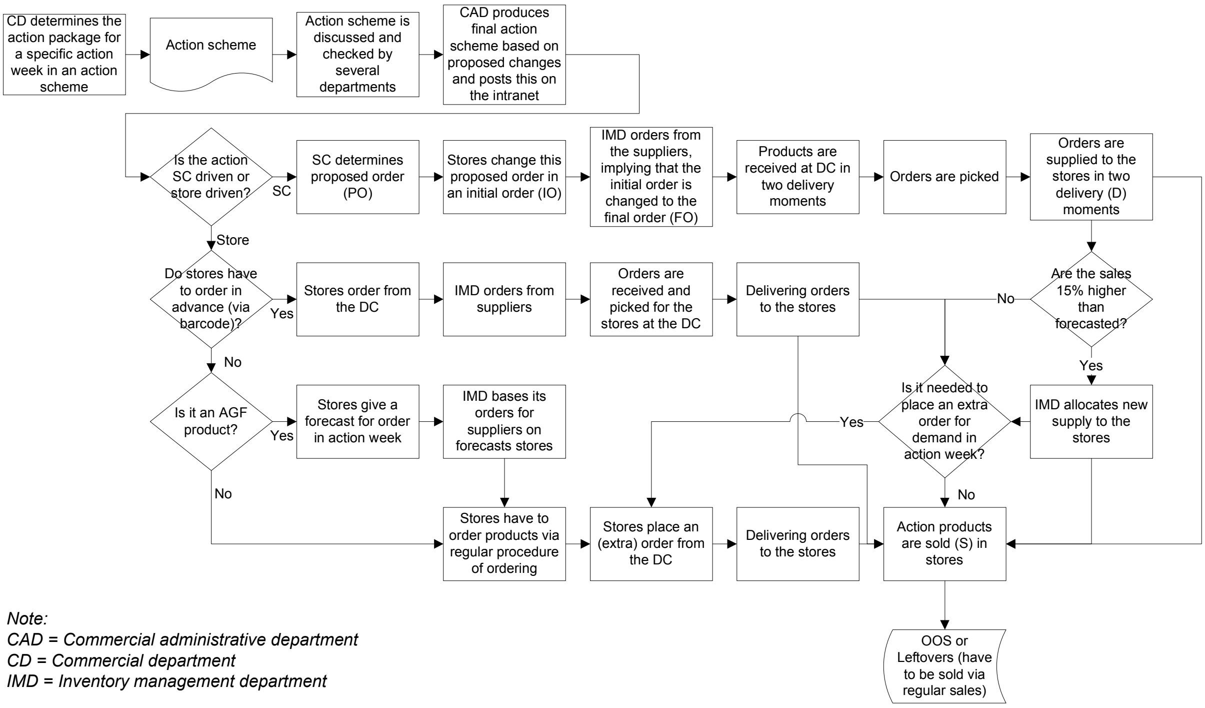

Figure 2.3: Flowchart of process used for action products within Jan Linders Supermarkets

Besides the complexity of the process, several other problems were found during the interviews conducted for describing the process. These are discussed in this paragraph.

The extensive use of the action scheme results in errors in this scheme

From the moment that the action scheme is available, many employees of both the commercial department and the commercial administrative department (equalling approximately 15 employees in total) use it. Since the action scheme only is an Excel file containing some macros in Visual Basic for Applications (VBA), this results in problems related to the functioning of this file. Partly due to this method, all faults in the action scheme found by the other departments have to be changed in the file by the commercial administrative department, since otherwise more versions of the file are created. This results in the commercial administrative department reading and changing every file approximately five times, which is very labour-intensive.

Purchasers still make changes on the final action scheme

The final action scheme has to be presented on Friday five weeks before the action week, because then the inventory management department determines the proposed orders, based on the aggregate demand forecasts available in the action scheme. However, the commercial department sometimes still makes changes to the action scheme after this moment in time. This would not be a problem when these changes were communicated well to the other departments. However, this is not always done, resulting in e.g. incomplete proposed orders.

The rule for adapting the proposed order is not valid for all products
Adaptations made to the proposed orders by the store managers are only implemented in DistRetail as initial orders when a change is made of three or more case packs. Store managers complain a lot about this rule, since from their perspective this rule is not valid. Every case pack ordered too much results in leftovers, needing space in the backroom of the store. One case pack does not make a large difference, but when for each action product per action week one case pack is left per store, this results in a significantly large amount of handling and space needed. Furthermore, the rule does not work due to the absolute amount of case packs that is used as a boundary: three case packs do not make a difference on an order of 50 case packs in total, but do on an order of one or two.[3]

Time-consuming procedure
After the purchasers made the aggregate demand forecast, four handling activities are executed before the final orders per store are known. Hence, the process is very time-consuming.

Furthermore, several process steps seem to be too much specified to the person that should execute this step. A good example is the member of the ICT-department making a csv-file containing the proposed orders from DistRetail and an inventory manager manually changing the lay-out of this file in Excel. In total, it would be less time-consuming to allocate both tasks to one of them and to make a standard VBA-macro to change the layout of the csv-file.

Reviewing the action products' sales is done for all stores together
To judge whether the stores received enough case packs of the action products, the inventory managers review the actual sales in the beginning of the action week and send extra case packs to all stores when total sales are 15 percent higher than expected. Two problems related to this procedure can be described:

1. Only when total demand is 15 percent higher than expected, extra supply is delivered to the stores. This means that one store that sells 20 percent more in the action week does not receive extra items, when this store is the only one that sells more than expected.
2. When extra items are supplied to the stores, all stores receive extra items. This means that also stores that sell less than or equal to the forecasted amount get extra items.

It would be ideal when only stores that need extra supply would get extra supply. This, however, results in more time needed at the service centre (SC) for determining which stores need extra supply and which do not. Another possibility is enabling store managers to order additional supply by themselves, which probably results in the store managers ordering fewer items in advance of the action week, because they know they can still order extra action items in the action week itself. Practice learns that this results in problems at the DC related to order picking and transport of the action products.

Concluding this chapter, several problems could be found within the currently used action products' process. To further research these problems and their causes, the process is monitored for ten specific SC driven action products in the next chapter.

[3] Due to complaints of the store managers, a new procedure was introduced in week 49 of 2008. From that time, changes are allowed of 50 or more percent, instead of changes of three or more case packs.

3. Performance of ten specific action products

In the former chapter, a general overview was given of the process related to action products at Jan Linders Supermarkets. This chapter elaborates on this process by following ten specific service centre (SC) driven action products of week 44 of 2008. This means that for all steps of the process of handling the SC driven action products, as again presented in figure 3.1, the involved people are asked to describe what they did and why they did it.

Proposed order (PO) → Initial order (IO) → Final order (FO) → Delivery (D) → Sales (S)

Figure 3.1: Global process of handling the SC driven action products

The goal of this chapter is to find out what the general performance is related to the inventory management system used for these ten action products and how this performance is affected by the size of the different orders. Paragraph 3.1 start with an introduction of the ten action products followed. Thereafter, paragraphs 3.2 to 3.6 each describe one of the steps presented in figure 3.1. Finally, paragraph 3.7 presents the answers to the research questions based on the analyses conducted in this chapter.

3.1. Introduction

For this detailed analysis, ten SC driven action products were chosen, since for these products the procedure is the newest and the most complicated. In addition, the goal is to handle all action products centrally in the future. Table 3.1 presents the products followed, together with the total volume of the first two orders in the process.

Article Nr.	Description	Brand	Total volume PO	Total volume IO	Difference between PO and IO
122033	Tomato cream soup 4 bowls	Unox	650	510	-21.54%
126543	Frankfurter 590gr	Limco	500	436	-12.80%
141585	Drinking yoghurt red fruits	Fristi	700	531	-24.14%
159258	Orange regular	Fanta	3500	3414	-2.46%
160806	Beer 30 cl bottle	Palm	4500	3412	-24.18%
161915	Cabernet sauvignon wine	African Dawn	1000	656	-34.40%
189186	Toilet paper soft	Edet	600	669	11.50%
201167	Washing-powder super compact	Ariel	400	330	-17.50%
254833	Soft curd cheese Spanish orange	Almhof	540	515	-4.63%
254835	Soft curd cheese vanilla	Almhof	440	448	1.82%

Table 3.1: Total volume of the first two orders for the ten followed action products

The main purpose of monitoring the process for ten specific action products was to find out the specific reasons of the store managers to adapt the proposed order of the SC. Therefore, products were picked for which many differences were found between the proposed orders and the initial orders; otherwise it is not possible to draw conclusions about the reasons for adapting. A disadvantage of this sampling method is that it is not random. Hence, it is not valid to generalize all outcomes of the in this chapter described analyses to all action products. Nonetheless, the analyses in this chapter are valuable, because these make clear why certain activities are performed this way. Table 3.1 shows that indeed some significantly large changes are made to the proposed orders of the ten action products. This already points out that the store managers had different views on the expected demand for week 44 than the purchasers, who are responsible for the total volume of the proposed orders. Appendix C1 provides some extra information about the adaptations made by the stores.

The in table 3.1 presented products were action products in week 44 of 2008. This week was chosen, because of the limited time span of this project, which caused that no weeks later could be chosen. Picking weeks further backwards was not preferred, since this meant that store managers only had to dig deeper in their minds to remember the cause of adaptation. It is assumed that week 44 is representative for other regular weeks during 2008.

Since the store in Geleen was going to close in week 44, to open a new store in week 45, the store manager of that store adapted almost all proposals to zero (he only ordered two case packs of both soft curd cheeses) and therefore, this store was deleted from the dataset. Except for the figures presented in table 3.1, no data presented in this chapter contains information about this store.

Before the differences between the proposed orders and the initial orders can be analyzed quantitatively, the performance measures of the employees of Jan Linders Supermarkets determining these orders are observed to find out whether these influence the order differences. First, one of the performance measures of the commercial department is the gross profit. Furthermore, the purchasers of this department are responsible for the relationship with the suppliers. Both these facts encourage the purchasers to ensure that enough products are available in the stores to fulfil demand: gross profit is increased when more products are sold and the relationship with suppliers is improved when the purchaser can guarantee that the suppliers' products are always available to the customers. Second, the three general performance measures of a supermarket manager are the turnover of the store, being equal to the sales multiplied by the selling price of the sold products, the products thrown away, because the best-before date was reached, and the staffing costs. The budgets for these performance measures are determined in cooperation with the supermarket managers themselves and therefore supermarket managers agree on these budgets. Hence, it may be assumed that they handle according to these measures. Observing these performance measures, supermarket managers are encouraged to order the products needed for the expected sales during the action week. When ordering more than needed, the staffing costs increase, since more handling activities are needed. Furthermore, in case of perishable items, the amount of products discarded increases. When ordering less than needed, sales are missed, resulting in a lower turnover than possible.

In conclusion, the performance measures of the store managers do not influence the amount of products ordered for the action week, but the performance measures of the commercial department do. Although the purchasers' performance is also measured with a measure based on the products thrown away in the supply chain of Jan Linders Supermarkets, this seems to have less influence than the above-mentioned factors. In the remainder of this chapter, it is analysed whether this influence indeed results in a poor performance of the order forecast of the commercial department.

3.2. Proposed order

This paragraph determines how the proposed orders (PO) for the ten products were created. As described in chapter 2, the purchasers first forecast the aggregate demand in all stores together. Thereafter, the inventory managers allocate this demand forecast to the stores, which directly results in 53 different proposed orders per product.

Five different purchasers, who all are responsible for one to three of the ten products, were asked to formulate why these products were action products in week 44 and how they determined the aggregate demand forecast. The general statement is that the action package is determined in cooperation with the supplier. For forecasting demand, all purchasers observe the sales of comparable historical actions and use these to forecast the demand in the upcoming action week. It is hard to find past actions similar to the current one. Therefore, the purchaser always has to estimate the effect of the different characteristics of the current action. According to the purchasers, the major variables to consider for this estimation are the action price, the action categorization (AAA, AA or A), and the seasonal effect. Purchasers determine their own way of working with these variables. Appendix C2 contains a detailed description of the working methods used for forecasting aggregate demand.

The examples given in appendix C2 make clear that no predefined procedure exists for determining a good demand forecast per action product. Basically, all purchasers only use their own experience, which does not have to be bad at all (Makridakis and Hibon, 1979). However, the procedure for determining this forecast is different per purchaser and it also varies per product. This has a bad influence on the performance of these forecasts.

To determine the proposed order based on the aggregate demand forecast, the inventory managers use standard available allocation rules in DistRetail. The forecast made by the purchasers is completely allocated to the stores and therefore, the total volume of the forecast is equal to the total volume of the proposed orders.

In practice, the same allocation rule is used for almost all food/non-food (FnF) products. This rule is determined at the start of the year 2008, based on the sales history of FnF action products of four weeks (week 5 to 8). It is clear that this is a very general rule, which may be not applicable for all FnF action products. Only for regional products, like beers and wines, other allocation rules are available. Furthermore, for these products, the inventory manager sometimes creates a new allocation rule for a particular action week. To do this, the inventory manager picks an old action of the specific product and uses the actual sales during that action to determine the new allocation rule for the new action. Table 3.2 confirms this general way of working for the ten followed products. Only for the wine and the cold storage products, other standard available allocation rules were used.

Article Nr.	Description	Brand	Allocation rule used
122033	Tomato cream soup 4 bowls	Unox	FnF General (actie KW algemeen)
126543	Frankfurter 590gr	Limco	FnF General (actie KW algemeen)
141585	Drinking yoghurt red fruits	Fristi	FnF General (actie KW algemeen)
159258	Orange regular	Fanta	FnF General (actie KW algemeen)
160806	Beer 30 cl bottle	Palm	Custom made
161915	Cabernet sauvignon wine	African Dawn	Wine General (actie KW wijn)
189186	Toilet paper soft	Edet	FnF General (actie KW algemeen)
201167	Washing-powder super compact	Ariel	FnF General (actie KW algemeen)
254833	Soft curd cheese Spanish orange	Almhof	Cold Storage General (alle fil x ds koeling)
254835	Soft curd cheese vanilla	Almhof	Cold Storage General (alle fil x ds koeling)

Table 3.2: The allocation rules used to determine the proposed orders per store (between brackets, the exact name of the allocation rule is displayed in Dutch)

3.3. Initial order

To find out why stores made changes to the proposed orders of the SC, store managers (or their assistants who changed the orders) were asked to give an explanation per product. Explanations were asked for all products, also when no change was made, because in that case also several reasons for not changing could exist (for example the proposed order was correct, the store manager did not have a clue himself, or he wanted to do a change, but this was smaller than three case packs). In total, 399 explanations were received.

The store managers were free to name any explanation they wanted. Therefore, no two explanations were the same. This way of gathering information about the reasons for changing results in the most reliable data, but makes the analysis more difficult. To be able to analyze these completely different explanations in a systematic way, the explanations were classified into different categories. Since some explanations were rather lengthy, one explanation could be classified to more than one category. Table 3.3 presents the number of explanations belonging to the different categories, classified based on the sign of the change made.

Categories	Negative change		No change		Positive change	
	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
Good proposed order	1	0.47%	191	53.95%		
Too high proposed order	81	37.85%	5	1.41%		
Too low proposed order			2	0.56%	15	30.00%
Considering historical data	49	22.90%	75	21.19%	13	26.00%
Inventory in store	34	15.89%	6	1.69%		
Local circumstances	9	4.21%	1	0.28%	5	10.00%
Multiple packaging size	2	0.93%	6	1.69%	14	28.00%
No data history			13	3.67%		
Preferred change < 3			4	1.13%		
Rather low order	5	2.34%	10	2.82%		
Season	3	1.40%	2	0.56%		
Sells poor	13	6.07%	3	0.85%		
Sells well			13	3.67%	2	4.00%
Substitution products in action	6	2.80%	2	0.56%		
Wrong adaptation			18	5.08%	1	2.00%
Other	11	5.14%	3	0.85%		
Total	214	100%	354	100%	50	100%

Table 3.3: Categories related to the explanations given by the store managers for changing the proposed orders

All explanations were tried to be classified in one of the first three categories, since then a judgement could be made about the proposed order of the SC. However, not all store managers made such a judgement. Complete explanations of the in table 3.3 presented categories can be found in appendix C3.

In total, 120 of the 399 explanations given were related to negative changes, 33 to positive changes, and 246 to orders that were not changed. Thus, 153 of the 399 explanations belong to adaptations made to the proposed order, resulting in a different initial order. The categories in which the explanations were classified were used to determine which of the adaptations could have been foreseen beforehand. In principal, all adaptations based on information also available at the SC could have been foreseen beforehand and hence, were not needed when the proposed order was better in the first place. Based on the categories presented in table 3.3, only adaptations classified into the following categories could not have been foreseen beforehand:

- Local circumstances
- Inventory in stores
- Sells poor
- Sells well

Concluding this categorization, in total 76 (50%) of the 153 changes could be cancelled out beforehand, because the explanation of the store managers was not classified in one of the four above-mentioned categories. Furthermore, when data about inventories in the stores are completely available at the SC, 108 (71%) changes could be cancelled out. Currently, these data are available centrally, but not in a proper format. When also data about products selling well or poor at specific stores are used centrally, 128 (84%) changes could be foreseen beforehand. For these data, it has to be analyzed per store which products sell well or poor. It is probably not possible to also make information about the local circumstances available at the SC. Therefore, based on this analysis, the conclusion is that at most 84% of the adaptations can be cancelled out by improving the proposed order of the SC.

3.4. Final order

When the initial orders are present in DistRetail, the inventory managers order the total amounts needed from the suppliers of the action products. As mentioned before, this ordering is restricted to prespecified rules, related to the total order size. These rules are present, because the first delivery of action products to the stores is picked at the special food/non-food (FnF) action street at the distribution centre (DC) that needs to be empty after picking all action products for all stores. Therefore, inventory managers change the sum of the initial orders for the first delivery moment to a multiple packaging size. Changing this sum of the initial orders, also results in small changes per initial order, resulting in a final order. The inventory managers were asked to describe their working method related to this step in the process. Appendix C4 presents a detailed description per product.

It is possible that the total amount ordered by a store does not have to be changed. For cold storage, this always is the case. For FnF products, this is only possible when products are delivered to the stores using two delivery moments. The order for the second delivery moment is picked from the regular picking place in the DC. Therefore, this order does not have to be rounded to a multiple packaging size, because this order can be filled up with products for non-action weeks. Hence, for the products with two action deliveries, a change in the total order size of the first delivery triggers a change in the opposite direction of the total order size of the second order. Examples clarifying this procedure are presented for the ordering procedure of the Ariel washing powder, the Fanta, and the African Dawn wine in appendix C4.

3.5. Delivery

When the supplier finally delivers the products at the DC, these products have to be supplied to the stores. Also in this process, things can go wrong, resulting in stores not getting their action products (on time) or stores not getting the amount they ordered. Hence, the amount delivered is not always equal to the size of the final orders. Another reason for a difference between the delivery and the final order is the automatic change to the final order made in the DC for fast moving products. For these products, final orders per store above half a pallet size are rounded off to a full pallet size.

3.6. Sales

Finally, in week 44 of 2008, the actual sales of the action products were registered. Using these sales data, analyses could be conducted on the performance of the inventory management of the ten action products followed. This paragraph presents the outcomes of these analyses.

3.6.1. Variables used

First, this paragraph introduces the variables used in the quantitative analyses. As already shown in figure 3.1, in total three different orders are made during the process. These orders result in a delivery of action products and finally in sales of action products in the stores:

$PO_{a,i,k}$ = proposed order of SC for product i for store k related to action week a

$IO_{a,i,k}$ = initial order of store k for product i related to action week a

$FO_{a,i,k}$ = final order for store k for product i related to action week a

$D_{a,i,k}$ = delivery of product i related to action week a at store k

$S_{a,i,k}$ = sales of product i in store k in action week a

In this paragraph, these three different orders and the delivery are compared to the actual sales, which results in a performance value for the different orders and the delivery. This can be done using several different performance measures. In principal, these performance measures compare a forecast with the demand of customers. In this case, this is not possible, due to two reasons. First, the demand of customers is not known. The only available information is based on actual action sales, defined as the sales of an action product in the action week. This results in a bias, since the sales of a particular product cannot be higher than the amount of items available for that product. However, in this case, not all items of a product available are considered. Only action deliveries are taken into account. These are the deliveries of specific action products to the stores; the products already available in the stores and the products ordered during the action week for the demand in the week after the action week, are not considered. Therefore, also action sales larger than the sum of the action deliveries can be observed. This partly solves the problem of having no demand data available. Second, no forecasts are known, since all forecasts are immediately transformed to orders in the case of Jan Linders Supermarkets. Therefore, orders are used, instead of forecasts. This working method is valid, since no ordering procedure exists that makes a difference between forecasts and orders; in the case of Jan Linders Supermarkets, the forecast per store immediately results in an order per store that is equal to the original forecast.

The first performance measure used is the number of items left of action product i in store k after action week a, $\overline{PL_a(D_{a,i,k})}$. This performance measure compares the action delivery with the action sales. This can be done for the three orders too. In general, the performance measure $\overline{PL_a(O)}$ is defined as the difference between an order/delivery and the sales in the action week:

$$\overline{PL_a(O)} = \frac{1}{10 \cdot 52} \cdot \sum_{i=1}^{10} \sum_{k=1}^{52} PL_{a,i,k}(O)$$

with: $PL_{a,i,k}(O) = O - S_{a,i,k}$

and O being equal to $PO_{a,i,k}$, $IO_{a,i,k}$, $FO_{a,i,k}$, or $D_{a,i,k}$

$PL_{a,i,k}(O)$ = items left of action product i in store k after action week a based on order/delivery O

$\overline{PL_a(O)}$ = average number of items left at the end of week a per product per store based on order/delivery O

Action products are placed on special shelves in the stores. These shelves are used to present the action products in a special way to the customers. The products supplied to the stores using the action deliveries are presented at these special shelves. Since these shelves have to be used by other products in the next week, these have to be as empty as possible at the end of the action week, otherwise the products left have to be removed by store personnel, resulting in extra handling costs. Obviously, this does not hold for the regular shelf of the action product in the store and therefore, the products at the regular shelf are not considered in determining the performance of the inventory management of action products. In addition, although it has never been investigated, it is generally assumed within Jan Linders Supermarkets that a significant part of the customers only buy the action products when the discount is given. This means that leftovers of action products are hard to get rid of after the action week, which is another reason to supply only the amount of action products extra that are expected to be sold extra in an action week.

Summing these considerations, the goal of the inventory management of action products is to have a neutral effect on the inventory available of an action product in the store. This means that the amount of items available of a particular action product after the action week is preferred to be equal to the amount of items available at the beginning of the action week, without considering the action delivery. Therefore, the difference between the action delivery and the action sales per product, defined as $\overline{PL_a(D_{a,i,k})}$, should be equal to zero.

A disadvantage of simply subtracting the sales from the order can be found in the method of calculating the average, where the positive values cancel out the negative values and vice versa. Therefore, the second performance measure that is presented is the mean squared error (MSE), which is calculated by taking the average of the squared differences between the actual sales and the delivery. By taking the square root of the differences, positive and negative values do not cancel each other out anymore.

Additionally, also the mean absolute percentage error (MAPE) is calculated, since for the actual value of the MSE it is hard to explain what it means in practice. A disadvantage of the MAPE-measure is that it is not applicable to cases having low demand values (Silver, Pyke, and Peterson, 1998). The formulas for calculating the MSE and the MAPE are presented in appendix C5.

One final remark has to be made regarding the performance measures. As presented above, all measures are related to the sales in store k of a specific product i being an action product in week a. In this chapter, a is equal to week 44, i is equal to product 1 to 10, and k is equal to store 1 to 52. For clarity reasons, these values are not presented in the rest of this chapter. This means e.g. that $\overline{PL_a(D_{a,i,k})}$ becomes $\overline{PL(D)}$.

3.6.2. General performance

Since inventories in the store before the start of the action week are not considered, it can be that more products are sold than delivered beforehand. This has as an advantage that also the amount of products short can be seen. The disadvantage is that store managers could have considered the already available inventory when ordering the action products, resulting in a biased performance measure. To see whether this has a significant effect on the performance, the $\overline{PL(D)}$ is calculated for products for which the store managers declared to have inventory left in their stores. This was equal to -0.21, being not significantly different from zero. Hence, the inventories in the stores do not have a significant effect on the performance analysis. Before calculating the performance of the ten action products, figure 3.2 gives an overview of the products left after the action week, the *PL(D)*-values.

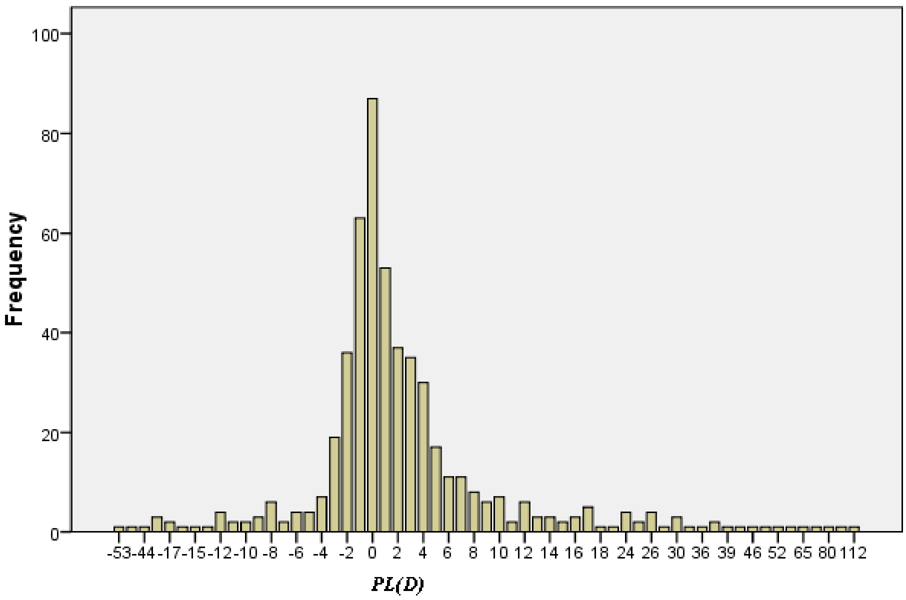

Figure 3.2: Overview of the PL(D)-values found in the dataset of the ten action products followed

Figure 3.2 shows that the *PL(D)*-values are concentrated around a peak at zero. In total 17% of the deliveries were exactly equal to the sales. Most bars can be found on the positive side; in total 52% of the differences were positive and 31% of the differences were negative. Some very large differences are observed. These need to be clarified. Most of them are caused by the automatic handling procedure used in the DC. For some products with a regularly high sales level, the orders per store are rounded to multiple pallet sizes. This is already done when an order is larger than half a pallet size. In this way, the final order related to the largest *PL(D)*-value was automatically increased from 61 case packs to a whole pallet, being equal to 120 case packs. These extreme values are not removed from the dataset, since these cannot be qualified as unaccountable outliers. Table 3.4 presents the descriptive values of the dataset used.

	Minimum	Maximum	Mean	Std. Deviation
PO	4	210	24.58	32.24
IO	0	185	20.99	27.54
FO	0	185	21.02	27.52
D	0	185	21.04	28.95
S	0	148	17.91	23.74
PL(D)	-53	112	3.13	12.69

Table3.4: General descriptive values related to the ten action products

Table 3.5 gives an overview of the three different performance measures for all orders calculated beforehand. $\overline{PL(D)}$ is equal to 3.13 case packs, meaning that on average a surplus of 3.13 case packs is sent to the stores. A one-sample t-test is used to determine whether this value is significantly different from the goal of zero. "A t-test is used to determine the statistical significance between a sample distribution mean and a parameter." (Cooper and Schindler, 2003, page 535) Conducting this test, the performance related to the ten followed action products turns out to be significantly different from zero (t = 5.626, df. = 519).

O	$\overline{PL(O)}$	MSE(O)	MAPE(O)
PO	6.67	234.78	80.21%
IO	3.08	125.12	45.67%
FO	3.11	124.13	45.54%
D	3.13	170.5	45.33%

Table 3.5: Performance of the different orders

Observing the three performance measures presented in table 3.5, comparisons can be made between the performance of the different orders and the delivery. All three performance measures conclude that the proposed orders (PO) of the SC perform worst. In addition, differences exist between the outcomes of the three different performance measures. The most striking difference is the MSE(D) being much worse than the MSE(FO) and the MSE(IO), while this effect cannot be seen using $\overline{PL(O)}$. This difference is caused by the large *PL(D)*-values presented in figure 3.2. When calculating the MSE, these large values are squared and therefore get more weight.

3.6.3. Orders compared

Table 3.5 already showed differences between the values of $\overline{PL(O)}$ for the different orders made. In this paragraph, these differences are compared to each other to find out which orders are significantly different from each other. Therefore, paired sample t-tests are conducted between the three different orders, the delivery, and the sales. In a paired sample t-test, the values of the tested variables are subtracted from each other. The actual t-test tests whether the average of this difference is significantly different from zero (Cooper and Schindler, 2003). The outcomes of these tests are shown is figure 3.6.

	PO	IO	FO	D	S
PO		3.5846	3.5558	3.5385	6.6692
IO	*6.663**		-0.0289	-0.0462	3.0846
FO	*6.626**	*-1.0280*		-0.0173	3.1135
D	*5.999**	*-0.0205*	*-0.0770*		3.1308
S	*11.014**	*6.5640**	*6.6300**	*5.6260**	
Note: Above the diagonal, absolute differences between the averages are presented. Below the diagonal, t-statistics of the paired sample t-tests are presented. All t-statistics that are significantly different from zero are marked.					

Table 3.6: Differences between the three different orders, the delivery, and the sales

In table 3.6, above the diagonal, the difference between the means of the different orders, delivery, and sales are presented in absolute values. Below the diagonal, the t-values of the paired sample t-tests are presented. Table 3.6 shows that all orders and the delivery are significantly different from the sales in the action week. Furthermore, the average value of the proposed order (PO) is also significantly different from the two other orders, the delivery, and the sales. This proves that the proposed order performs significantly worse than the other orders. Using this outcome, the presumption that the performance measures of the purchasers influence their behaviour is confirmed. Finally, the changes made to the initial orders at the SC and the DC that result in a delivery of action products to the stores, do not have a significant influence on the performance of the inventory management in this small dataset.

3.6.4. Differences between stores and products

To find out whether there is a significant difference in performance between the different stores, an analysis of variance (ANOVA) is conducted. This is a statistical method that can be used for testing whether the means of several populations are equal to each other (Cooper and Schindler, 2003). This analysis uses a single-factor, fixed-effects model to compare the effect of one variable (in this case the store) on a continuous dependent variable (in this case the *PL(D)*-values). Conducting a one-way ANOVA on the *PL(D)*-values using the factor stores, no differences were found in the performance of the stores ($F = 0.838$, df. = 51).

The same analysis is conducted based on the categorisation of article numbers, to see whether there are performance differences between products. Performance difference are found between different products ($F = 14.313$, df = 9). This test does not give a view on which product performs differently compared to the others. This can be found using a post-hoc test. Several of these tests exist. Following Cooper and Schindler (2003), the Games-Howell test is valid for this dataset. Using this test, it can be seen that especially the Fanta Orange regular has a poor performance; on average, the stores have 19.44 case packs too much of this SKU. Furthermore, it can be seen that the products allocated using the general allocation rule, as presented in paragraph 3.2, perform worse than the other products.

3.6.5. Comparison of the delivery and the proposed order

Paragraph 3.6.3 concluded that a significant difference exists between the proposed order and all other orders. In this paragraph, it is analysed where this difference comes from. To do this, ANOVAs are performed using the action delivery to the stores minus the proposed order as dependent variable:

$$\delta_{D,PO} = D - PO$$

with: $\delta_{D,PO}$ = difference between the action delivery and the proposed order

Several independent variables are used in these ANOVAs: store, product, purchaser, and gross profit. The gross profit is an ordinal variable, containing three classes, namely gross profit < 6 percent, 6 percent < gross profit < 15 percent, and gross profit > 15 percent. These classes are used, since store managers also receive the information about the gross profit in this way.

First, no significant differences exist between the performance values per store ($F = 0.965$, df = 51). This indicates that store managers do not change differently compared to each other. Second, significant differences exist between the performance values per product ($F = 19.27$, df = 9). In the post-hoc test, it turns out that the Palm beer is the product having a significant other $\delta_{D,PO}$-value than the other products. Table 3.7 shows that the amount of items delivered (D) for the Palm beer is much smaller than the proposed order (PO), meaning that for this product the PO was too high. This is caused by the purchaser, since he is the one determining the total forecasted demand. Third, significant differences also exist between the performance values per purchaser ($F = 27.11$, df = 4). Complementary to the ANOVA based on the performance values per product, the post-hoc test of the ANOVA based on the performance values per purchaser concludes that the purchaser that scores significantly different from the other purchasers is the one responsible for the beers and the wines.

Product	N	Mean of $\delta_{D,PO}$	Std. Deviation	95% Confidence Interval for Mean		Minimum	Maximum
				Lower Bound	Upper Bound		
Unox soup	52	-2.35	3.43	-3.30	-1.39	-11	1
Limco frankfurter	52	-1.79	3.08	-2.65	-0.93	-12	0
Fristi drinking yoghurt	52	-3.12	3.52	-4.10	-2.13	-12	1
Fanta orange	52	2.08	21.80	-3.99	8.15	-27	97
Palm beer	52	-22.67	27.77	-30.40	-14.94	-90	26
African Dawn wine	52	-6.71	7.04	-8.67	-4.75	-24	6
Edet toilet paper	52	0.69	4.54	-0.57	1.96	-10	18
Ariel washing-powder	52	-1.02	2.45	-1.70	-0.34	-14	0
Almhof soft curd cheese orange	52	-0.52	2.99	-1.35	0.31	-9	9
Almhof soft curd cheese vanilla	52	0.02	2.93	-0.80	0.84	-8	10
Total	520	-3.54	13.45	-4.70	-2.38	-90	97

Table 3.7: Difference between deliveries and proposed order, categorized by the products

Finally, also significant differences exist between the performance values per gross profit category (F = 19.639, df = 2). In the post-hoc test, it turns out that the lowest gross profit category scores significantly different from the other categories. Table 3.8 that the absolute $\delta_{D,PO}$-value decreases when the gross profit increases. Since the PO is significantly too high, it turns out that store managers do order excess supply of the products having a higher gross profit. Although no store manager did ground this in his explanation for the changes made and the performance measures of the store managers do not encourage to order more items of the products with a higher gross profit, the quantitative data presented in this paragraph indicates differently.

Gross profit classes	N	Mean of $\delta_{D,PO}$	Std. Deviation	95% Confidence Interval for Mean		Minimum	Maximum
				Lower Bound	Upper Bound		
< 6%	156	-8.94	18.856	-11.92	-5.95	-90	26
6 - 15%	260	-1.62	10.987	-2.96	-0.27	-27	97
> 15%	104	-0.25	2.962	-0.83	0.33	-9	10
Total	520	-3.54	13.451	-4.70	-2.38	-90	97

Table 3.8: Difference between deliveries and proposed order, categorized by the gross profit classes

3.7. Conclusion

This paragraph contains the conclusions based on the analyses conducted on the ten followed action products in this chapter. Paragraph 3.7.1 presents the answers on the research questions formulated in chapter 1, based on the analyses conducted in this chapter. In addition, paragraph 3.7.2 presents some other conclusions drawn, based on the analyses conducted in this chapter. It has to be kept in mind that all conclusions are not completely valid for all service centre (SC) driven action products, since the ten products were not sampled randomly from the total dataset of action products.

3.7.1. Answers to the research questions

1. Does Jan Linders Supermarkets use the correct inventory levels of action products in the stores?
No. Based on the average of 3.13 action case packs left per product per store after action week 44, it is concluded that too much action products are supplied to the stores.

2. *What is the performance of the initial aggregate demand forecast made centrally?*

Since it turns out that especially the proposed order of the SC is far too high, the current way of forecasting demand can be improved. Although all purchasers claim that they use a standard method for making a good forecast, all purchasers actually use their own working procedure. No standard procedure exists and all purchasers basically guess what the sales will be in the action week.

3. *Is the right allocation rule used, to allocate the initial aggregated demand forecast to the stores?*

By observing the performance measure of delivery (D) minus sales (S), it can be seen that products with the same general allocation rule negatively influence the performance. One general allocation rule is used for almost all products. Besides the fact that this rule is determined at the beginning of the year and therefore is probably not valid anymore, not all products sell equally well in a store. Because all stores are different, based on characteristics like size, place, and personnel, some products sell well and some products sell poor in particular stores compared to other stores.

3.7.2. Other conclusions

Furthermore, it turned out that 50 to 84 percent of the adaptations made by the store managers on the proposed order could be cancelled out beforehand, based on the explanations the store managers gave for their adaptations. Observing the actual performance of the inventory management system, it turns out that at this moment, the changes made by the store managers are needed to reach the performance, since the performance of the proposed order of the SC is much worse than the performance of the initial order. Therefore, when the goal is to simplify the process by skipping the step of the store managers adapting the proposed order, this order itself has to be improved.

4. Performance of all action products in 2008

Two major disadvantages of the detailed analyses of the ten action products of chapter 3 are the very small sample drawn from the complete population of action products and the non-randomness of this sample. Therefore, in this chapter, comparable analyses are presented based on data of all service centre (SC) driven action products from week 15 to week 41 of 2008.

To base this analysis on, a dataset was created containing information about the five different process steps of the handling of the SC driven action products, as again presented in figure 4.1.

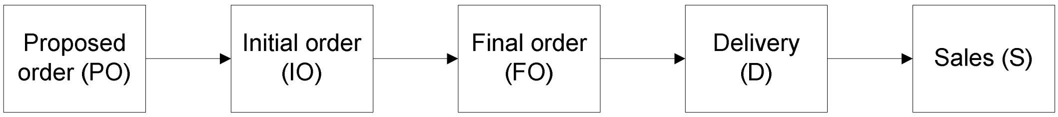

Figure 4.1: Global process of handling the SC driven action products

This elaborate dataset contains data for 51 of the 53 stores, since two were renewed during the period of data collection. In total, this dataset consists of 528,054 records, every record representing one action SKU per store per week. Due to many inconsistencies and outliers in this dataset, many of these records had to be removed. Furthermore, since the goal was to determine the performance of SC driven action products only, the dataset finally was reduced to 75,174 records. This dataset only contains records from week 15 to week 41 of 2008, since before week 15 no difference could be made between SC driven actions and store driven actions. A detailed description of the data collection and preparation can be found in appendix D1. Finally, a dataset was maintained containing the following data per action SKU:

- The week of the action
- The store, presented by the store number
- The warehouse: AL, DV, KO, KW, or TR
- Article number and product description
- The number of items delivered to the stores before the action week related to the action, separated in two delivery moments
- All sales in the action week

The data used in this chapter are collected from DistRetail, in which only the product classification based on the warehouses in the distribution centre (DC) is present. Hence, this product classification is used in this chapter to makes differences between products. Figure 4.2 presents this classification.

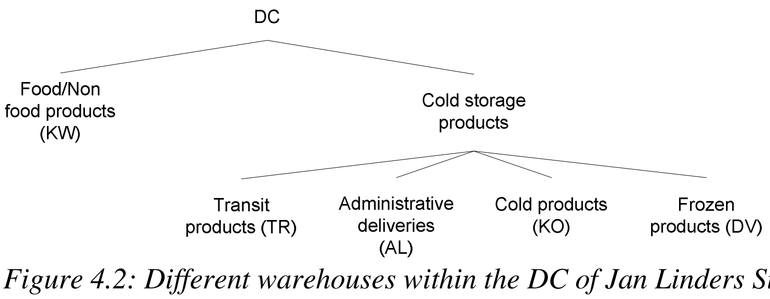

Figure 4.2: Different warehouses within the DC of Jan Linders Supermarkets

In the KW warehouse, the food/non-food (FnF) products are handled. This is the largest warehouse in the DC. The rest of the products are called cold storage products. These again are handled in different warehouses, based on the temperature needed for handling the products and the way of handling the products itself. The temperature is an issue, since some particular products need to be stored in a room with a certain temperature. Furthermore, a difference is made between products held on stock, transit products that are handled within the separate transit street, and products delivered cross dock or direct, named administrative deliveries.

4.1. General performance

As aforementioned, this chapter elaborates on only the SC driven action products. Consistently with the variables presented in paragraph 3.6.1, in this chapter a ranges from week 15 to week 41, i is equal to the number of action products present per week a, and k is equal to store 1 to 51. Again, these variables are not mentioned during this chapter, based on clarity reasons. Complementary to the analyses presented in this paragraph, appendix D2 presents the outcomes of comparable analyses conducted on the dataset containing all action products between week 1 and week 41 of 2008 with predefined action deliveries. This appendix also takes into account the store driven action products containing a barcode in the action scheme, together with the in this paragraph analyzed SC driven action products.

Since the dataset of all SC driven action products in week 15 to week 41 did not contain information about the initial order and the final order, the analyses in this paragraph are related to the process steps presented in figure 4.3. Table 4.1 presents the descriptive statistics of the proposed order, the delivery, the sales, and the performance measure for this dataset. Figure 4.4 gives an overview of the spread of the data.

Figure 4.3: Steps of the global process of handling the SC driven action products used in this paragraph

	Minimum	Maximum	Mean	Std. Deviation
PO	1	282	3.49	4.71
D	1	93	3.32	3.33
S	0.02	93	2.62	3.32
PL(D)	-1.07	3.05	0.70	0.93

Table 4.1: Descriptive statistics related to SC driven action products

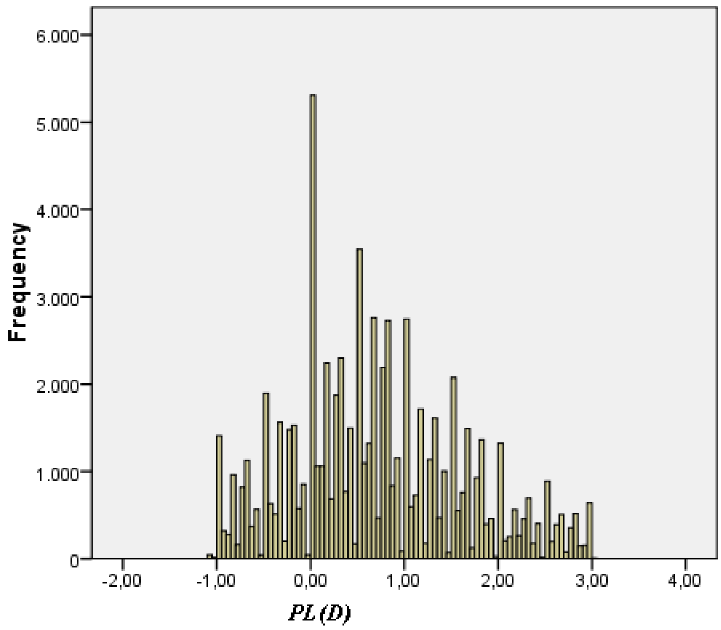

Figure 4.4: Overview of the PL(D)-values found in the dataset of all SC driven action products

Comparing table 4.1 with table 3.4, the conclusion is that indeed the ten products in chapter 3 were not randomly chosen. All figures presented in table 3.4 are higher than the ones presented in table 4.1. This was expected, since the products chosen had a relatively high demand level. Nevertheless, also table 4.1 and figure 4.4 give a distorted view, since from the dataset used to create this table and figure, all outliers were removed, which primarily influences the standard deviations. Not surprisingly, the performance of all SC driven action products is also significantly different from zero (t = 206). Therefore, the conclusion based on the analysis of the ten SC driven action products in the previous chapter, about the performance of the inventory management being not satisfactory, is also supported by the analysis on all SC driven action products. The MSE(D) of this dataset is also rather low (1.35). First of all, this means that the forecasts of the products in the dataset are not bad. However, it has to be kept in mind that all extreme values were removed from this dataset. The MAPE is not given anymore, since in this dataset many products were listed with a rather low sales level of one or two case packs. According to Silver et al. (1998), in this case the MAPE does not give a reliable value anymore.

Consequently, ANOVAs are performed to find out whether differences exist in products left after the action week between subgroups in the dataset of the allocated products. First, the ANOVA based on stores is performed. Now, the differences between the performance values per store are significant (F = 37.51). It can be seen that the minimum (and best) $\overline{PL(D)}$ per store is equal to 0.44 case packs for store 1600 and the maximum (and worse) is 1.00 case packs for store 6000. The ANOVA based on the article numbers, as conducted in the previous chapter, is uninteresting for this dataset, due to the large amount of article numbers. Instead, an ANOVA based on the warehouses is used. This gives a clue about the performance differences between the most general product groups to which the products belong. Table 4.2 presents the descriptive statistics of these subgroups.

Warehouse	N	Mean	Std. Deviation	95% Confidence Interval for Mean		Minimum	Maximum
				Lower Bound	Upper Bound		
AL	91	0.82	1.05	0.60	1.04	-1.00	3.00
DV	160	1.11	1.03	0.95	1.27	-1.00	3.00
KO	992	0.91	0.98	0.85	0.97	-1.00	3.00
KW	73,492	0.69	0.92	0.68	0.70	-1.07	3.05
TR	439	1.32	1.02	1.22	1.41	-1.00	3.00
Total	75,174	0.70	0.93	0.69	0.70	-1.07	3.05

Table 4.2: Difference between deliveries and sales, categorized by the warehouse

The F-value found with the ANOVA based on these subgroups is significantly different from zero (F = 72.11). This means that significant differences exist between the performances of the five subgroups. However, as can be seen in table 4.2, the sizes of the different subgroups are considerably different from each other and therefore it is hard to generalize this outcome.

4.2. Performance compared over time

The current procedure of SC driven action products was introduced in week 15 for food/non-food (FnF) products, due to problems with the old way of working. This was done quickly, to overcome the existing problems. Therefore, at Jan Linders Supermarkets it is not clearly known whether the performance has improved since then. In this paragraph, the performance before week 15 (characterized as $\overline{PL_{<15}(D)}$) and the performance from week 15 on (characterized as $\overline{PL_{>15}(D)}$) are compared to see whether there is an improvement.

Table 4.3 presents the differences between the statistics for FnF action products of the weeks before week 15 and the weeks after week 15. First, the increases in the averages of S and D are both significant (t = 6.63 and t = 14.28 respectively). Second, the $\overline{PL(D)}$ increase is also significant (t = 27.53) The $\overline{PL(D)}$-value is on average 1.27 times higher in weeks 15 to 41 compared to weeks 1 to 14.

	Week a	N	Mean	Std. Deviation
D	15 – 41	83,342	3.236	3.251
	1 – 14	41,511	2.960	3.206
S	15 – 41	83,342	2.540	3.238
	1 – 14	41,511	2.413	3.157
$\overline{PL(D)}$	15 – 41	83,342	0.696	0.919
	1 – 14	41,511	0.547	0.897

Table 4.3: Comparison between the performance of FnF products before and after week 15

It is not surprising that $\overline{PL_{>15}(D)} > \overline{PL_{<15}(D)}$, since the reason for changing the way of working was that the stores did not order the total amount wanted in advance of the action week. However, it seems that on average they already ordered enough to fulfil demand. Now, even more products are supplied to the stores, resulting in a higher surplus of inventories in the stores. Less easy to explain is why $\overline{PL_{>15}(D)} > \overline{PL_{<15}(D)}$ while $\overline{PL_{<15}(D)} > 0$, because the stores still have the final word in determining the order. An explanation may be that the changes of the stores are dependent on the proposed order of the SC. This is easily explained using an example. Assume that the SC proposed a total amount of 1000 case packs and the stores changed this to 600 case packs. If the SC proposed 1500 case packs, the stores would probably have decreased the amount too, but probably to approximately 900 case packs, instead of to 600. This example shows that the performance is highly dependent on the proposed orders of the SC. Since these are structurally too high, as can be seen in the next paragraph, the performance is not satisfactory.

4.3. Orders compared

To finish the analyses done in chapter 3 for all SC driven products, also the performance differences between the different orders and the delivery are analyzed. Unfortunately, the initial orders are only stored from week 25 of 2008 forward. Therefore, in this paragraph, a dataset is used containing 46,331 records of action SKUs for 51 stores. Final orders are not stored and hence not analyzed in this paragraph. Figure 4.4 presents the steps of the process of handling SC driven action products analyzed in this paragraph. Table 4.4 shows some general descriptive statistics of the data analysed.

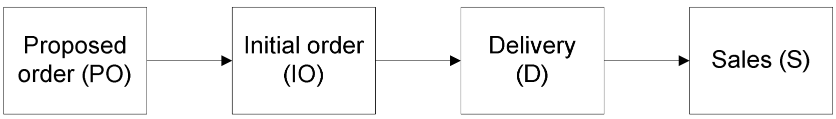

Figure 4.4: Steps of the global process of handling the SC driven action products used in this paragraph

	Minimum	Maximum	Mean	Std. Deviation
PO	1	97	3.42	3.83
IO	0	280	3.26	3.80
D	0.75	93	3.32	3.55
S	0.04	93	2.65	3.54
PL(D)	-1.07	3.04	0.67	0.93

Table 4.4: General descriptive statistics of data from week 25 to 41, 2008

Table 4.5 presents the differences between the different orders, the delivery, and the sales. Above the diagonal, the differences between the means of the different orders, the delivery, and the sales are presented in absolute values. The part of the table below the diagonal presents the t-values of the paired sample t-tests. It turns out that all differences are significant. This means that the stores would have attained a better performance if their initial orders were used for the delivery to the stores. Furthermore, table 4.5 again shows that the proposed order of the SC is too high.

	PO	IO	D	S
PO		0.1601	0.0955	0.7690
IO	*16.783**		-0.0646	0.6089
D	*12.349**	*-9.153**		0.6735
S	*88.969**	*75.237**	*156.435**	
Note: Above the diagonal, absolute differences between the averages are presented. Below the diagonal, t-statistics of the paired sample t-tests are presented. All t-statistics that are significantly different from zero are marked.				

Table 4.5: Differences between the three different orders, the delivery, and the sales

In addition, table 4.5 shows that the mean difference between the initial order and the proposed order is rather low; the mean change is equal to 0.16 case packs and the mean absolute change is equal to 0.31 case packs. This is caused by the fact that many proposed orders are not changed by the stores. In total 3,346 of the 46,331 proposed order were changed, equalling 7% of all orders. Table 4.6 presents the descriptive statistics of the dataset only containing records for which the initial order is different from the proposed order. This table presents that when a change is made to the proposed order, the average change is equal to 2.22 case packs. The average absolute change is equal to 4.27 case packs, being equal to 55% of the originally proposed order. Hence, when a change is made, this change is rather large.

	Minimum	**Maximum**	**Mean**	**Std. Deviation**
PO	1	97	7.50	7.76
IO	0	280	5.28	8.43
D	0.75	85	5.57	6.71
S	0.08	84	4.84	6.68
PL(D)	-1.05	3	0.74	1.05

Table 4.6: Descriptive statistics of records containing different values for IO compared to PO

4.4. Conclusion

In this paragraph, the research questions presented in chapter 1 are answered using the outcomes of the analyses based on all service centre (SC) driven action products in 2008. In these conclusions, also the main findings of chapter 2 and 3 are summarized to create a complete overview of the performance of the inventory management of action products at Jan Linders Supermarkets. Although it was expected that the outcomes of chapter 3 were not generalizable to all SC driven action products, it turned out in this chapter that almost all findings are also valid for the complete dataset.

1. Does Jan Linders Supermarkets use the correct inventory levels of action products in the stores?
No. Also based on the analyses conducted in this chapter, the conclusion is that on average too many items are supplied to the stores per action product. The actual average surplus in supply is equal to 0.70 case packs per product per store per week.

2. What is the performance of the initial aggregate demand forecast made centrally?
It turns out that the initial order performs best. Hence, the change made by the stores to the proposed order of the SC is needed to reach a better performance. The performance of the initial aggregate demand forecast thus is not satisfactory and has to be improved to be able to cancel out the need for adaptation of the proposed order of the stores.

3. *Is the right allocation rule used, to allocate the initial aggregated demand forecast to the stores?*
The fact that one general allocation rule, defined at the beginning of 2008, is used to allocate the total forecasted amount of action products to the stores, makes it obvious that a better performance could be reached when a more sophisticated rule would be used. What performance improvements are possible could not be analysed in detail, because the performance of this rule cannot be analysed separately from the performance of the aggregate demand forecast of the purchasers.

Using these outcomes, the research question ("*What are the relevant causes for the performance problem of the inventory management of the action products and how can this problem be solved?*") can be answered. The first, and most important, cause of the performance problem is the structurally too high aggregate forecast. Second, the general allocation rule also influences the performance. To be able to improve the performance of the inventory management, these causes have to be handled.

In the next part of this report, improvements are proposed for the inventory management of action products at Jan Linders Supermarkets. Since the most important improvement would be to increase the performance of the aggregate demand forecast of the SC, a more sophisticated demand forecasting model is created for structuring the way of demand forecasting. For the improvement of the allocation rule, many new data are needed. Therefore, the improvement of the allocation rule is analyzed in less depth.

In addition, the next part of this report also presents a redesign for the process of handling action products. The main reasons for this are the current process being very time-consuming and the fact that no difference is made between forecasts and orders in the current process, which also influences the performance negatively.

Part III: Improvements

5. Forecasting model

The main outcome of the analysis phase of this project is that the amount of action products supplied to the stores is too large. As concluded at the end of part II of this report, the most important improvement that can be made to decrease this amount is the improvement of the aggregate demand forecast. This is done in this chapter. Chapter 6 continues with the description of an improved process design. Finally, chapter 7 ends the description of the design phase of this project by presenting methods for implementation of the aforementioned improvements.

In this chapter, a model is developed for making a forecast for the aggregate demand of an action product in all Jan Linders stores. Paragraph 5.1 gives an overview of several demand forecasting models and determines which model is most useful in this case. Paragraph 5.2 continues with describing the different variables used in the model. Descriptive statistics of these variables are presented in paragraph 5.3. Paragraph 5.4 presents eight different models applicable to the demand forecasting of action products at Jan Linders Supermarkets and paragraph 5.5 presents the model most useful in practice. Finally, paragraph 5.6 concludes this chapter by summing up the main advantages of using the sophisticated model in practice.

5.1. Choice of the model

Demand forecasting can be done in several ways (Makridakis and Hibon, 1979). This paragraph elaborates on the different models and picks the one most applicable for forecasting action sales at Jan Linders Supermarkets.

5.1.1. Demand forecasting models

Figure 5.1 presents the classification of Makridakis and Hibon (1979) schematically.

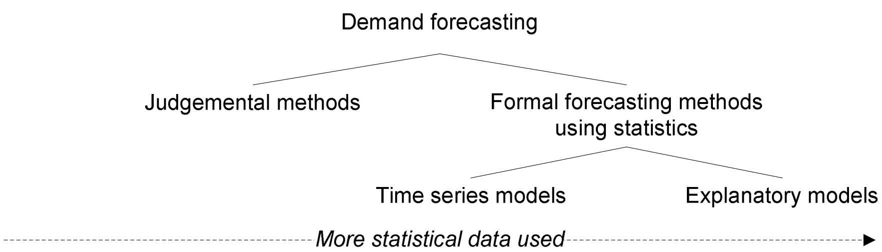

Figure 5.1: Classification of forecasting methods, as described by Makridakis and Hibon (1979)

A first distinction is made between judgemental methods and formal forecasting methods using statistics. In judgemental methods, the forecast is made using qualitative information available from employees in the organization. Formal forecasting methods use quantitative data to base a forecast on. These formal methods are further divided in time series and explanatory methods. In the first ones, only data of demand history are needed. The second methods also make use of marketing data.

A time series can be defined as “a collection of observations made sequentially through time” (Chatfield, 2004, page 1). According to Chatfield (2004), one of the objectives of time series analysis is predicting future. By analyzing several sources of variation in the time series, like seasonal variation, cyclic variation, trend, and other irregular fluctuations, future values of the time series are predicted using historical values of the time series. A common time series method is exponential smoothing (Silver et al., 1998). More sophisticated methods are the ARIMA models of Box and Jenkins (Chatfield, 2004), resulting in better forecasts when used by experienced users. Although these models are able to work with several sources of variation within the data, these models assume an underlying stationary pattern within the time series, when all these sources of variation are removed.

Explanatory forecasting methods are more accurate when non-stationary time series have to be forecasted (Fildes, 1985). These methods use several other variables to forecast future values in a particular time series. Factors that influence demand can be subdivided in internally determined characteristics, like e.g. the price discount and the way of promoting the action products, and externally determined factors, like e.g. the weather and promotional actions of competitors. Besides these factors, an influencing factor coming forward from the literature study (Van den Heuvel, 2008a) can be used, being the amount of products presented in the stores. Dana and Petruzzi (2001), Urban (2002), and Ouyang, Hsieh, Dye, and Chang (2003) present models for working with this inventory dependent demand. The general idea behind these models is that displaying more items of the same product in the store will result in a higher demand rate, since customers will see this product sooner. Unfortunately, none of these models are directly useful in this master thesis project, since promotional effects are not considered. Furthermore, the cost structures of these models do not cover all relevant costs, making them irrelevant for this study. Finally, the complex structure of these models complicates practical use.

According to Makridakis (1988), both judgemental and formal forecasting methods have their disadvantages. Disadvantages of judgemental methods are the ignorance of or overreaction to changes, the inconsistency in using historical data, and the high degree of influence of personal and political considerations. Disadvantages of formal models are the inability to predict changes, the inability to utilize all information available in historical data, and the underestimation of future uncertainty. These disadvantages make it preferable to combine both methods in specific situations, as suggested by Silver et al. (1998). These situations can be characterized by factors outside the company, like e.g. the economical situation, the legislation, and promotional actions of competitors, or by factors inside the organization, like e.g. price changes and promotions.

The time series that has to be forecasted at Jan Linders Supermarkets is the sales level of the products sold at Jan Linders Supermarkets, including all action sales. The inclusion of action sales in these data makes the data non-stationary, described by for instance Van Heerde et al. (2002). Therefore, the best method for forecasting sales containing action sales is an explanatory method (Van Donselaar et al., 2004). Afterwards, experienced employees have to judge the forecasts produced to overcome the disadvantages of the formal forecasting method. The most commonly used explanatory forecasting models are regression models. Appendix E1 explains these models. In this project, a multiple linear regression model is used to forecast demand for action products.

5.1.2. Relevant model

At this moment, two in scientific literature described models are relevant. The first is a multiple linear regression model in which the lift factor in demand during the action week is forecasted, as presented by Van Loo (2006)[4]. The second one is a model in which a forecast is made for demand in an action week using a regression tree, as presented by Ali, Sayin, Van Woensel, and Fransoo (2007).

To be able to make a choice between these models, first the lift factor has to be defined. The lift factor is defined as the sales in the action week divided by the average sales level, based on five previous non-action weeks:

$LF_{a,i} = {}^{S_{a,i}}\!\big/_{\overline{S_{a-5,a-1;i}}}$ and $\widehat{S_{a,i}} = \widehat{LF_{a,i}} \cdot \overline{S_{a-5,a-1;i}}$

with:

$LF_{a,i}$ = lift factor of sales of product i in action week a compared to the regular sales level

$\widehat{LF_{a,i}}$ = forecasted lift factor of sales of product i in action week a compared to the regular sales level

$S_{a,i}$ = sales of product i in action week a

[4] Van Loo (2006) presented that a regression model based on the lift factor performs better than the model of ACNielsen named SCAN*PRO (Van Heerde et al., 2002). Therefore, the latter model is not analysed in this chapter.

$\widehat{S_{a,i}}$ = forecasted sales of product i in action week a

$\overline{S_{a-5,a-1;i}}$ = average sales of product i in five regular weeks before action week a

Van Loo (2006) forecasts this lift factor using a multiple linear regression model containing the action characteristics of the product in the action week as dependent variables. This forecasted lift factor is used to forecast the demand for the action product. Since only forecasts are made for the sales in action weeks, the data used in the model of Van Loo (2006) cannot be characterized as a time series.

Ali et al. (2007) forecast the general demand per week using a regression tree based on data mining. In this model, the demand per week, for both action weeks and non-action weeks, is the dependent variable and again the variables related to the action characteristics are the independent variables. A tree is made based on all possible ways of categorization of the action products. For all subcategories present in the tree, separate regression models are made, which combined probably perform better than one regression model for the whole dataset. Since forecasts are made for demand per week, the dataset used for the model of Ali et al. (2007) can be characterized as a time series.

Whether one of the two ways of forecasting demand in an action week is better than the other one, remains to be determined. Therefore, the advantages and disadvantages of both models are considered to decide which model to use. Since the second model is rather new and complex, several criteria have to be met enabling the use of this method. Ali et al. (2007) use a dataset of 78 weeks containing data for 48 SKUs and four stores. The dataset used in this report contains 41 weeks, 3,484 different SKUs and 51 stores; when forecasting an aggregate forecast for all Jan Linders supermarkets together, only one store has to be considered. The difference in datasets is a problem for the usability of this model in this project. Since the model is very complex, it is expected that the number of weeks used by Ali et al. (2007) is minimally needed to create a valid model. Furthermore, the high number of different SKUs also is a disadvantage, causing it to become more complex and probably not even workable anymore. The objective for the design phase of this project is to create a model that can be used for an as large as possible group of SKUs. To start with, the model could be developed using only a small group of SKUs; however, in the future, the goal is to use the model for almost all action products, for which it is not yet known whether this is possible or not. A final disadvantage of the model of Ali et al. (2007) is the complexity itself; this is hard to handle within Jan Linders Supermarkets, since this organization already has problems with the implementation of a relatively simple model of simple exponential smoothing for the regular demand forecast of products.

To conclude, the model of Ali et al. (2007) is not useful for this project. Therefore, a multiple linear regression model based on the lift factor is worked out in detail in the design phase of this project, based on the model presented by Van Loo (2006).

5.2. Explanatory variables

To work out this regression model in detail, a new dataset had to be created, since the dataset already present does not contain information about non-action sales and the characteristics of the actions. Appendix E2 describes the data collection and preparation for the design phase. The newly created dataset contained 3,001 records. Table 5.1 presents the variables available in this dataset. All these variables, except the sales in the action week, are also used in the regression model. For clarity reasons, the subscripts a and i are not used in the names of the variables, except were differences have to be made between variables of the current week and the previous week. Variable a ranges from week 1 to week 41.

Variable	Variable description
S	Sales of the action product in the action week
LF	Lift factor of the action product in the action week
$\overline{S}$	Average sales of the action product in five non-action weeks before the action week (in case packs)
sp	Special week: weeks with special days (dummy variable): o 1: Action week is a special week; specials weeks are: • Week 1: New Year • Week 5-6: Carnival • Week 12-13: Easter • Week 18: Queens Day and Ascension Day • Week 19-20: Whitsun o 0: Action week is not a special week
Nd_a	Number of actions in the same department (as described in paragraph 1.1) in action week a
Nm_a	Number of actions in the same main product group in action week a, with a product group being a subset of a product department
Ns_a	Number of actions in the same product subgroup in action week a, with a product subgroup being a subset of a product group
Nd_{a-1}	Number of actions in the same department in the week before action week a
Nm_{a-1}	Number of actions in the same main product group in week before the action week a
Ns_{a-1}	Number of actions in the same product subgroup in week before the action week a
p	Regular price of the action product (in €)
d_{abs}	Absolute discount in the action week (in €)
d_{perc}	Discount in terms of percentage in the action week (in %)
B	Whether the product is promoted in the promotional brochure in the action week or not (dummy variable)
M	Whether the product is promoted in the magazine in the action week or not (dummy variable)
GP	Gross profit category of the gross profit of the action product in the action week: o 1: Gross profit < 6% o 2: 6% < Gross profit < 15% o 3: Gross profit > 15%
OO	Whether the product is completely out of stock when the product is out of stock in the store in the action week (dummy variable): o 1: Out is out o 0: Out is not out
F_l	The action consists of Y+Z items free, with $l = 1, \ldots, 5$ (five dummy variables): o 1: related to that sort of action o 0: not related to that sort of action
Np_h	Number of promotional items in the stores related to the action product in the action week, with $h = 1, \ldots, 6$: for two different store formulas the amounts of signs, A2 posters, and shelf cards used were registered (six variables)
V_j	Action is valid with j items of the action product bought in the action week: o 1: valid with j items of product i, with $j = 2, 3, 4, 5, 6$, and 8 o 0: not valid with j items of product i, with $j = 2, 3, 4, 5, 6$, and 8
Cat_s	Elaborate action category s in the brochure or the magazine to which the action product belongs, with $s = 1, \ldots, 10$ (ten dummy variables) o 1: the action product is presented in action category s o 0: the action product is not presented in action category s

Table 5.1: Variables used in the regression model

Variable	Variable description
C_r	Shortened action category r in the brochure or the magazine to which the action product belongs, with $r = 1, \ldots, 3$ (three dummy variables) o 1: the action product is presented in action category r o 0: the action product is not presented in action category r
NLA	Number of weeks until last action of the action product i, counted from the current action week backwards
SLA	Sales in last action week of the action product (in case packs)

Table 5.1 (continued): Variables used in the regression model

In table 5.1, two action categorizations are mentioned, namely an elaborate and a shortened categorization. These were collected using the general action schemes, in which action products are listed based on these categories. For the promotional brochure of Jan Linders Supermarkets, which is published weekly, standard categories exist. These are the A categorizations (AAA, AA, and A) and the categorizations theme, back, panel, and tasted. Furthermore, the magazine, which is only published once per month, also contains other action categories. These are less standard, meaning that purchasers name the categories per week. The elaborate action categorization (Cat_s) takes into account all ten different categorizations in total. To make the model more practicable in the future, also a shortened categorization (C_r) is made, in which only the three A categorizations are used. This means that the actions already scaled in one of these A categorizations keep this categorization and all other categories are scaled as A actions in this shortened action categorization, except the back categorization, which is scaled as AA action. The rescaling of the elaborate version to the shortened version is done in cooperation with an experienced purchaser.

Furthermore, the in table 5.1 presented variables contain several other exhaustive enumerations. All these need a reference variable. The first enumeration is whether the product is promoted in the brochure, magazine, or only in store. The list of variables in table 5.1 only contains a variable for the brochure (*B*) and for the magazine (*M*) and therefore, the reference variable is the promotion in store. This reference variable is most obvious, since now the extra effect of promoting a product in the brochure or magazine can be quantified. The second enumeration for which a reference variable is necessary is the characterization of Valid with j items (V_j). The most logical reference variable is the one with j = 1. The third enumeration needing a reference variable is the elaborate action categorization (Cat_s). For this categorization, also a variable exists of promoting the product in store. Therefore, this variable again is used as reference. This also holds for the shortened action categorization (C_r). With picking two times the same variable as reference, another problem is created. Now the *B* and *M* variables overlap the action categorization variables. Therefore, another variable has to be deleted, being *B*. Now the coefficient of variable *M* has to be analysed using the brochure variable as a reference.

In addition to the in table 5.1 presented independent variables, several other factors could be thought of to have influence on the sales of action products. First, the weather probably has a significant influence (Geurts and Kelly, 1986, and Bunn and Vassilopoulos, 1999). Second, the promotional actions of competitors influence the sales of action products (Cooper, Baron, Levy, Swisher, and Gogos, 1999). Both are hard to grasp in a forecasting model. Variables related to the weather can be inserted into the regression model, but the question remains how valuable they are when a forecast is made for the demand of action products for four weeks later. Therefore, the weather is not considered in the model. The promotional activities of competitors are simply not considered because of the lack of data for these actions.

5.3. Descriptive statistics

Table 5.2 starts with presenting the general descriptive values related to the dataset for the lift factor. Furthermore, figure 5.2 and appendix E3 give an overview of the spread in the dataset.

	Minimum	Maximum	Mean	Std. Deviation	Median
Average sales last 5 weeks ($\overline{S}$)	0.08	1280.33	29.45	53.14	17.60
Sales in the action week (*S*)	0.50	2232.75	125.72	185.67	69.17
Regular price (*p*)	0.35	13.14	2.06	1.49	1.59
Discount absolute (d_{abs})	0.02	3.26	0.48	0.46	0.33
Discount percentage (d_{perc})	0.02	0.60	0.22	0.10	0.23
Lift factor (*LF*)	1.00	14.28	4.59	2.80	3.94

Table 5.2: Descriptive values related to the dataset used in the design phase of this project

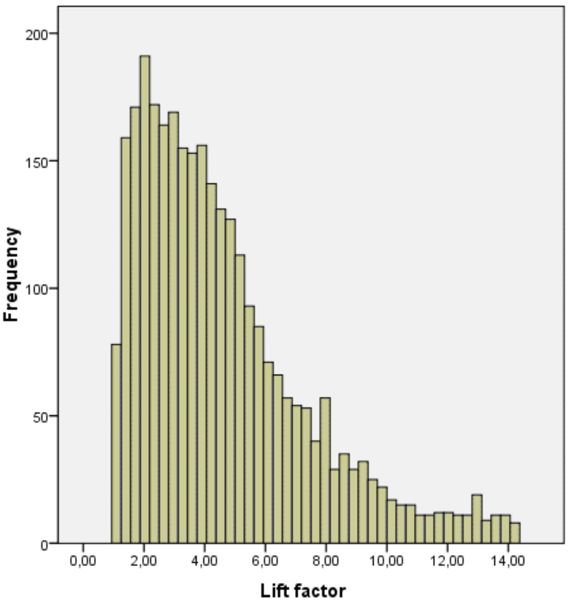

Figure 5.2: An overview of the lift factors found in the dataset

5.4. Linear regression models

To be able to forecast the lift factor in demand, first, several elaborate models are created. These models contain all possible independent variables, as presented in table 5.1. Using the performance of these models, an improved model is created. This model is not improved in the sense that the performance of the model itself is better than the performance of the elaborate models, but since it uses as little variables as possible to reach a satisfactory performance, it is better useful in practice.

5.4.1. Eight different models

Before the model can be formulated, decisions have to be made, which independent variable to use in the model, since not all variables can be inserted at the same time. Three decisions have to be made, before the detailed model can be formulated:

- *What action characterization is used: Valid with j items (V_j) or Action of Y+Z items free (F_l)?* Both categories of action characterization variables, V_j and F_l, contain conditions for the number of items that have to be bought to receive the promoted discount. Since an action product is either presented to the customer as a "Valid with j items"-action or as a "Y+Z items free"-action, only one of the action characterizations is considered per model.

- *What action categorization is used: the elaborate version (Cat_s) or the shortened version (C_r)?* Since it is not valid to use both action categorizations in a model, a choice has to be made between these two.
- *Are the data containing information about the previous action week considered in the model (NSA and SLA)?* The last two variables presented in table 5.1 contain information about the previous action of the product. For the first action in the dataset of a particular SKU, no history of previous actions is present in the dataset and hence, the variables *NLA* and *SLA* are not known. By including these variables in the regression model, the size of the dataset is further decreased to 1,454 records.

Instead of making a decision beforehand, eight models were developed using all possible combinations of independent variables, based on the above-formulated decisions. The complete regression model can be described as:

$$\widehat{LF} = c_0 + c_1 \cdot \overline{S} + c_2 \cdot sp + c_3 \cdot Nd_a + c_4 \cdot Nm_a + c_5 \cdot Ns_a + c_6 \cdot Nd_{a-1} + c_7 \cdot Nm_{a-1} + c_8 \cdot Ns_{a-1} + c_9 \cdot p$$
$$+ c_{10} \cdot d_{abs} + c_{11} \cdot d_{perc} + c_{12} \cdot M + c_{13} \cdot GP + c_{14} \cdot OO + c_{15,j} \cdot V_j + c_{16,l} \cdot F_l + c_{17,h} \cdot Np_h + c_{18,s} \cdot Cat_s$$
$$+ c_{19,r} \cdot C_r + c_{20} \cdot NLA + c_{21} \cdot SLA$$

All c_c values are the ones to be determined using linear regression. This is done in SPSS 16.0 for Windows. Table 5.3 presents the characterization of the eight models and the number of records used for calibrating the model. For the calibration of the model, only the first 24 weeks (week 6 to week 30) of the dataset were used. Afterwards, the validation of the models is done using the remaining weeks (week 31 to week 41).

Model	**Action characterization I**	**Action categorization II**	**NLA/SLA included**	**Number of records**
M1	Variables “Valid with j items” considered	Elaborate action characterization used	Data about previous action week (*NLA* and *SLA)* not considered	1861
M2	Variables “Valid with j items” considered	Elaborate action characterization used	Data about previous action week (*NLA* and *SLA)* considered	694
M3	Variables “Valid with j items” considered	Shortened action characterization used	Data about previous action week (*NLA* and *SLA)* not considered	1861
M4	Variables “Valid with j items” considered	Shortened action characterization used	Data about previous action week (*NLA* and *SLA)* considered	694
M5	Variables “Action of Y+Z items free” considered	Elaborate action characterization used	Data about previous action week (*NLA* and *SLA)* not considered	1861
M6	Variables “Action of Y+Z items free” considered	Elaborate action characterization used	Data about previous action week (*NLA* and *SLA)* considered	694
M7	Variables “Action of Y+Z items free” considered	Shortened action characterization used	Data about previous action week (*NLA* and *SLA)* not considered	1861
M8	Variables “Action of Y+Z items free” considered	Shortened action characterization used	Data about previous action week (*NLA* and *SLA)* considered	694

Notes:
I Action characterization: Variables “Valid with j items” considered = V_j variables used in the model, Variables “Action of Y+Z items free” considered = F_l variables used in the model
II Action categorization: Elaborate action characterization used in the model = Cat_s variables used, Shortened action characterization used = C_r variables used in the model

Table 5.3: Model characterizations

5.4.2. Performance of the models

Appendix E4 presents the coefficients for all variables included in the eight models characterized in table 5.3. Furthermore, it also presents the significance per coefficient by the p-value. The performance of these models is shown in table 5.4.

Model	R square	Adjusted R square	$MSE(\widehat{LF})$ [1]	$MSE(\widehat{LF})$ [2]	Products left after action week[1]	St. Dev. of products left [1]	Products left after action week [2]	St. Dev. of products left [2]
M1	0.28	0.27	5.78	6.63	-0.02	141.37	-13.33	310.54
M2	0.46	0.44	3.95	6.85	-0.11	224.31	-10.71	279.65
M3	0.27	0.26	5.86	6.52	0.01	141.33	-10.65	294.24
M4	0.45	0.42	4.05	6.73	-0.16	229.61	-10.74	299.39
M5	0.27	0.26	5.90	6.59	-0.02	136.17	-7.51	290.95
M6	0.45	0.43	4.07	6.87	-0.10	227.53	-11.62	282.69
M7	0.26	0.25	5.98	6.43	0.00	134.94	-3.91	269.40
M8	0.44	0.41	4.15	6.68	-0.15	231.21	-8.25	294.78
Notes: [1] Values calculated for the calibration phase (week 6 to week 30) [2] Values calculated for the validation phase (week 31 to week 41)								

Table 5.4: Performance of the models

Per model, six performance variables are given. Appendix E5 clarifies these. The R square values presented in table 5.4 may seem to be low. However, these are not lower than expected, keeping in mind that this dataset is not a time series. The R square values for the models containing the variables related to the previous action week perform much better than the models without those variables. This is probably caused by the reduction in data. Other differences between the R square values of the different models are small.

The second performance measure used is the mean squared error of the forecasted lift factor compared to the realised lift factor ($MSE(\widehat{LF})$).For the data used in the calibration phase, the MSE is lowest (and best) for the models containing the information about the previous action of the action product. In contrast, for the validation phase, the models without these variables perform best, although this performance difference is very small.

The third and last performance measure is the products left after the action week in all stores, when the lift factor was used to determine the order to the stores ($PL(\widehat{LF})$). Using this measure, the performance of the models can be compared with the current performance of Jan Linders Supermarkets. In the validation phase, model M7 performs best on this measure. This is the model using the variables of Y+Z products free, the shortened action categorization, and not including the variables related to the previous action week. This performance has to be compared to the in chapter 4 presented current performance of 0.70 case packs left after the action week per product per store. The data presented in table 5.4 is aggregated for all stores together, meaning that the performance of these models has to be related to a current performance of $53 \cdot 0.70 = 37.1$ case packs left after the action week per product in all Jan Linders stores. It can be concluded that all models perform better than the current process, since all PL-values are lower than the current one. This conclusion is not completely valid, since the performance of the models is not determined in the same way as the aggregate performance of the current process. In calculating the performance of the models, the negative and positive performance values per store cancel out each other, while this is not the case in calculating the aggregate performance of the current process. Nonetheless, the performance difference is large enough to conclude that the explanatory forecasting model proposed in this paragraph performs better than the currently used judgemental method. Finally, all models result in a forecast below the realised sales, meaning that not enough products are supplied to the stores. Obviously, this is not preferred (Corsten and Gruen, 2003). Therefore, it may be necessary to adapt the lift factors forecasted by the models. Before doing this, the number of variables in the models is reduced, since this is preferred when implementing the model in practice at Jan Linders Supermarkets.

5.5. Improved model

As presented above, the performance of the explanatory forecasting models is much better than the performance of the currently used judgemental method. A disadvantage of these forecasting models is that these make use of many variables. In practice, this results in time-consuming data collection, especially at Jan Linders Supermarkets, where the data management is not organized to collect these data easily. Therefore, this paragraph presents an improved model. Compared to the models presented in the previous paragraph, this model uses far less explanatory variables to forecast the lift factor. Hence, the R square values will be decreased. However, since the practical usefulness of this model is increased, this model is an improvement for Jan Linders Supermarkets.

Because the models using the shortened action categorization perform better than those using the elaborate one do, the improved model uses the shortened version. Furthermore, the contribution of the variables related to the action characterization is very low and hence, these variables are not included in the improved model. Since inclusion of the variables related to the previous action week of the action product significantly reduces the dataset, these are also not included. Finally, whether all other variables are considered in the improved model is determined per variable, using its contribution, significance, and performance improvement. The final model contains eight explanatory variables, presented in table 5.5.

Variable	Variable description	Coefficient	Value of coefficient	Significance (p-value)
C	Constant	c_0	3.6390	0.0000
$\overline{S}$	Average sales last 5 weeks	c_1	-0.0068	0.0000
Nm_a	Actions in same main group	c_4	-0.0261	0.0034
Ns_a	Actions in same group	c_5	-0.1451	0.0000
p	Regular price	c_9	0.1673	0.0003
d_{perc}	Discount percentage	c_{11}	3.9853	0.0000
C_1	Category AAA	$c_{19,1}$	6.5733	0.0000
C_2	Category AA	$c_{19,2}$	2.9421	0.0000
C_3	Category A	$c_{19,3}$	1.1562	0.0000

Table 5.5: Variables and their coefficients used in the final model

Using the coefficients in table 5.5, the final recommended model is the following:

$$\widehat{LF} = C - 0.0068 \cdot \overline{S} - 0.0261 \cdot Nm_a - 0.1451 \cdot Ns_a + 0.1673 \cdot p + 3.9853 \cdot d_{perc}$$

with:
C = 10.2123, if the action product can be characterized as an AAA action,
C = 6.5811, if the action product can be characterized as an AA action product,
C = 4.7952, if the action product can be characterized as an A action product, and
C = 3.6390, if the action product can be characterized as an in store action product.
As aforementioned, this model uses the shortened action categorization.

Using this forecasting model results in the performance values presented in table 5.6. First, it can be seen that the fit of the improved model, presented by the R square values of the model, is worse than the fit of the elaborate models, being as expected. Second, the MSE values of the improved model are comparable with the elaborate models. Third, and more surprisingly, the performance measured by the amount of products left at the end of the action week is better using the improved model compared to using the elaborate models. To conclude, it is better to use the improved model, both because of the decreased number of variables used and the increased performance.

R square	0.22
Adjusted R square	0.21
MSE lift factor (calibration)	6.32
MSE lift factor (validation)	6.43
Products left after action week (calibration)	0.00
St. Dev. Of products left (calibration)	109.96
Products left after action week (validation)	1.26
St. Dev. Of products left (validation)	175.50

Table 5.6: Performance of the downscaled model

Finally, it has to be analyzed whether the coefficients of the variables used in the improved model behave as expected. Observing the coefficients in table 5.5, this is the case. The average sales in non-action weeks have a negative effect, meaning that when the regular sales level is higher, the sales in an action week will be lower. The numbers of actions in the same main group and the same subgroup also have a negative effect. As expected, this means that the more actions are done within a certain group of products, the lower the lift factor per product will be. The lift factor of e.g. the Perfekt soups in the product group of all soups, probably is lower when the Unox soups and the Perfekt soups are discounted, compared to the situation in which only the Perfekt soups are discounted. Not surprisingly, all remaining coefficients in the model are positive. When the regular price is higher, the lift factor is also higher; expensive products sell relatively more in action weeks than cheaper products. The sales of products with a high discount also lift more in an action week, compared to the sales of products that are discounted less. Finally, all extra promotions in the brochure and the magazine result in a higher lift factor compared to only promoting the action products in store (being the reference variable of the coefficients with number 19). Furthermore, the coefficients increase when the categorization increases: the more exposure, the higher the lift factor.

5.6. Conclusion

The conclusion of this chapter is that it indeed is possible to increase the performance of the inventory management of action products at Jan Linders Supermarkets when an explanatory forecasting model is used. The main improvement actually is that the forecasting of the demand in the action week is based on a formal, prespecified model, instead of the judgement of a particular employee, which is highly influenced by many environmental factors. Furthermore, the performance measured as the amount of items left of an action product at the end of the action week in the stores also increases when the explanatory forecasting model is used.

The main prerequisite for a successful implementation of this model in practice is the change of the method of data storage. Chapter 7 elaborates on this and other prerequisites. First, chapter 6 presents a redesign for the total process of inventory management of action products at Jan Linders Supermarkets.

6. Process redesign

The analysis phase of this project made clear that the main improvement is to implement a more sophisticated method for forecasting the aggregate demand. In addition, it was concluded that the total process is very time-consuming and that no difference is made between forecasts and orders at Jan Linders Supermarkets. Therefore, this chapter presents improvements for the process itself, which especially take away these two disadvantages of the current process. Since the process still has to be useful for Jan Linders Supermarkets, paragraph 6.1 presents the boundary conditions for the improved process. Paragraph 6.2 continues with a description of the process redesign and paragraph 6.3 ends this chapter with giving an overview of the process.

6.1. Boundary conditions

The following assumptions underlie the proposition for the improved process:

- The action package, as determined by the purchasers, is a given.
- The current structure of Jan Linders Supermarkets, containing 53 stores, one service (SC), and one distribution centre (DC) cannot be changed.
- The improved process is only related to action products. As described before in chapter 3, the goal is to have no action products left in the stores at the end of the week. This does not mean that the regular shelves of the action products in the stores are also empty. It is assumed that the there available items are ordered using the regular ordering procedure.
- The process described can be used for all action products. Due to difficulties with the best before-date of particular products (for especially AGF products), it is probably not possible to use the same procedure for all products. It goes beyond this research to develop an action products' handling procedure for all different classes of products. It is recommended to first change the current process of handling SC driven action products to the proposed process. When the results of this process change are satisfactory, the process can also be used for other products.
- The forecasting model is used efficiently. To assure that the new process indeed is less time-consuming than the actual process, data needed for the forecasting model has to be stored efficiently. This assures that data needed to make a forecast and to update the model regularly can be collected easily. Chapter 7 presents recommendations for the method of data storage.
- The allocation of total forecasted demand to the stores is done effectively. Due to lengthy data collection for proposing an improvement for the allocation rule used to divide total demand over the stores, no concrete recommendations for this rule are done in this report. The improvement of this rule has to be done by employees of Jan Linders Supermarkets itself. To start, the allocation rule has to be updated more regularly. Furthermore, an allocation rule has to be more product (group) specific. Preferably, standardized software is created (or bought) to assure that the allocation of demand is executed efficiently.

6.2. Process description

As presented in chapter 2, a difference can be made between service centre (SC) driven actions and store driven actions. In literature, a similar classification can be seen: an action is coordinated centrally (at the SC) or locally (at the stores). By using scientific literature, it can be determined what is optimal. De Leeuw, Van Goor, and Van Amstel (1999) divide this decision into two sub-decisions: whether to use a central or a local distribution control technique, and whether to use a centrally or locally initiated allocation of products. According to De Leeuw et al. (1999), it is optimal to work with a central distribution control technique and a central initial allocation when working with action products. This paragraph analyzes these decisions for the handling of action products at Jan Linders Supermarkets.

The decision about the distribution control technique handles the decision about where to hold inventory. Two options exist: holding inventory only locally in the stores, and holding inventory both centrally and locally. Due to high demand uncertainty and high customer service level requirements, the optimal choice for the distribution control technique obviously is to hold inventory of action products both centrally and locally.

The second decision concerns the choice between a locally initiated allocation, in which the stores are able to order the products they need from the DC, and a centrally initiated allocation, in which the SC allocates supply to the stores. Before this decision can be made, it has to be decided how many deliveries are used to supply the action products to the stores. This decision is based on an analysis of the action products' handling and transportation costs. According to Van Zelst, Van Donselaar, Van Woensel, Broekmeulen, and Fransoo (2004), handling costs make up 66% of the operational logistical costs in the retail supply chain for food/non-food (FnF) products, compared to 12% inventory holding costs and 22% transportation costs. Hence, handling costs can be characterized as important costs to control. This results in two implications for the design of the action products' process. First, the optimal amount of action products sent to the stores is less than or equal to the actual demand. In that case, no handling is needed for emptying the special action shelves at the end of the week. Second, the total amount of action products sent to the stores is supplied in as less deliveries as possible. In that situation, the shelf is (re)filled as less as possible, which also decreases the handling costs. Furthermore, a minimal number of deliveries also minimizes the handling costs made at the DC. Transportation costs are primarily dependent on the number of deliveries used for the action products. To minimize these costs, the number of deliveries has to be minimized

Considering these costs, it is optimal to work with two deliveries of action products to the stores. To minimize the handling costs, it has to be assured that the supply of action products is close to the demand. Using one delivery before the action week and one or more deliveries during the action week makes it possible to observe actual sales during the first part of the action week and adapt the orders in the action week to this observation. This working method results in a better performance of the delivery of action products to the stores, than a method with only one delivery before the action week (Fisher, Rajaram, and Raman, 2001). An assumption related to this working method is that the sales in the beginning of the week are representative for the sales in the rest of the week. At Jan Linders Supermarkets, percentages are known of the division of sales over the days of the weeks, assuring that this assumption is valid.

On the other hand, handling costs are minimized when the action products are sent to the stores in as less deliveries as possible. Then, the amount of products per delivery is the highest, which results in efficiency in handling the products. In addition, for products for which the action sales per store are lower than the capacity of one truck, transportation costs are also minimized when the number of deliveries is minimized. Combining the requirement that a minimal number of two deliveries is needed and the requirement that the total number of deliveries has to be minimized, the optimal amount of deliveries for action products is equal to two: one delivery before the action week and one delivery during the action week. Exceptions are products with a very high sales level in action weeks, as e.g. particular beers. These products probably need more deliveries per action week.

Now, for both deliveries it has to be determined whether these will be allocated locally or centrally. De Leeuw et al. (1999) propose to use a central allocation for the first delivery and a local allocation for the second delivery. This recommendation is also valid in the case of Jan Linders Supermarkets. When the first delivery is allocated centrally, this means that the demand forecast is made centrally using the forecasting model presented in the previous chapter. This centrally made forecast results in a better forecast than summing 53 forecasts for 53 stores (Silver et al, 1998). Thereafter, the largest part of this forecast is supplied to the stores. Since action products are characterized by a short period of high sales, it is preferred to coordinate this allocation centrally, assuring a good planning for handling these extra sales.

Preferably, the store managers themselves initiate the second delivery, since this is the only way to assure that extra supplies are only delivered to the stores when these are actually necessary (De Leeuw et al., 1999). The alternative is to adapt to actual sales centrally. This is not optimal, because the experience needed to make a good judgement based on the early sales is not available centrally.

Finally, it has to be determined what part of the forecasted action sales is used for the actual supply of products to the stores. Currently, Jan Linders Supermarkets allocates the total forecast to the stores. This is not preferred, since flexibility is reduced this way. Preferably, the total forecasted amount plus some extra safety stock is ordered from the supplier and stocked at the DC. After that, only a part of this stock is allocated to the stores for the first delivery. De Leeuw et al. (1999) describe this as the α-policy; a fraction α of the forecast will be allocated directly to the stores and the remaining fraction (1- α) is used for the locally allocated orders. Using this policy, a difference is made between the forecast and the actual supply of products to the stores, which creates flexibility in the reaction on actual sales and assures that not too much products are supplied to the stores. Therefore, it is highly recommended for Jan Linders Supermarkets to use this policy, since the problem presented in the analysis part of this report was that too much action products were sent to the stores. Obviously, with the first delivery, enough products have to be supplied to the stores to be able to fulfil demand in the first part of the action week. Therefore, α is probably equal to 70 to 80 percent (Van Donselaar et al., 2004). The remaining 20 to 30 percent can be supplied during the week, when more is known about actual sales.

In practice, this means that the following formulas are used to determine the amount of items needed of the action product from the supplier and the amount of items supplied to the stores:

$$Q = \widehat{LF} \cdot \overline{S} \cdot \beta + SS$$

$$D_1 = \widehat{LF} \cdot \overline{S} \cdot \beta \cdot \alpha$$

with

Q = size of the order of the SC to the supplier of the action product related to the demand forecast in the action week

D_1 = total amount of items supplied to the stores of the action product with the first delivery before the action week

β = correcting factor on statistically determined forecast of an experienced employee

SS = safety stock for the action product

The safety stock can be determined in several ways. Commonly used methods, as described by for example Silver et al. (1998), are not useful in this case, since these assume stationary time series data. At this moment, for Jan Linders Supermarkets preferably uses a judgemental procedure to base a safety stock on. In the future, this decision should also be supported by a more statistically grounded method.

6.3. Overview and discussion

Figure 6.1 summarizes the process redesign description for the inventory management of action products at Jan Linders Supermarkets.

The improved process is less time-consuming than the current process. This is mainly caused by a good forecast made in advance of the action week, since then adaptations to the centrally determined forecast are not needed anymore. Another reason is that the store managers are able to order the action products during the action week. Both are not true in the current situation.

With the implementation of the in chapter 5 described forecasting model, the performance of the demand forecast is improved. Furthermore, the complete forecasted amount of products needed to fulfil demand is not directly sent to the stores. Instead, a fixed part α of the forecast is actually used for the supply of action products to the stores to decrease the chance that too much products are sent to the stores.

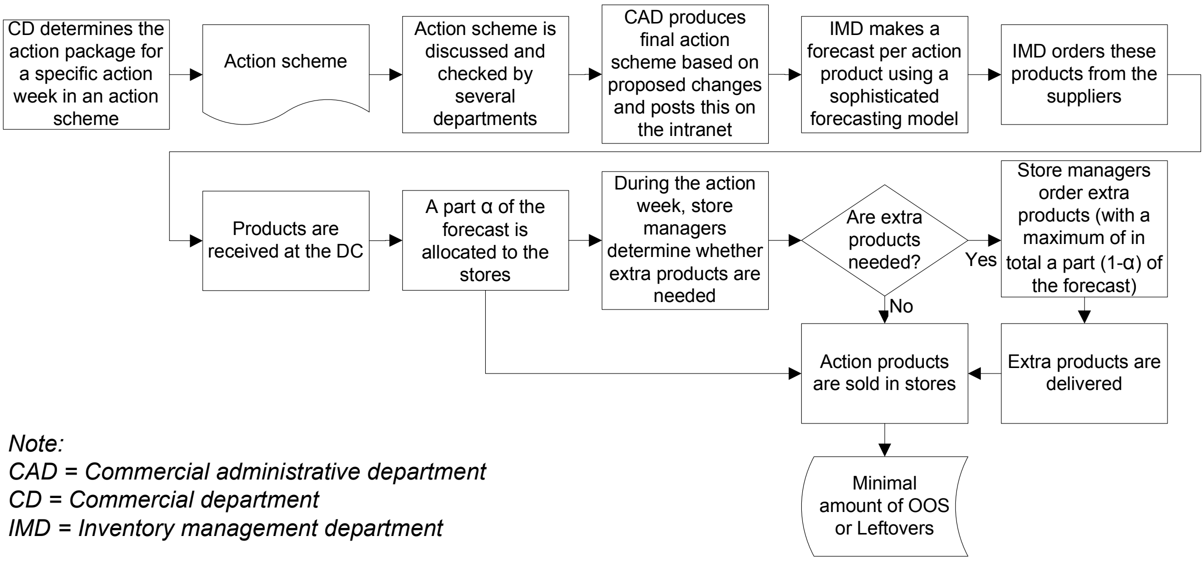

Figure 6.1: Flowchart of the improved aggregated process related to action products

Finally, during the action week, store managers are still able to order additional action products, which is not possible in the current situation. Since the first delivery is lower than the actual forecast made, store managers will probably order extra items during the action week. At the DC, only an amount of items equal to (1- α) times the forecast plus a safety stock is available. This amount of products may not be high enough to fulfil all extra demand of the stores. To assure that all stores get extra supply when needed, a fixed moment during the action week has to be planned at which the store managers have to evaluate how much extra supply they need of the action products of that week. When the additional supply needed per SKU is more than the actual available inventory at the DC, the supply is allocated according to the relative size of the orders of the store managers.

When Jan Linders Supermarkets uses the above-presented process, together with the in chapter 5 presented forecasting model, the current problem of supplying too much action products to the stores is taken care of. How to implement this process, and especially the sophisticated forecasting model, in the current processes of Jan Linders Supermarkets is described in the next and final chapter of the third part of this report.

7. Implementation

This chapter elaborates on the implementation phase of the project by describing how to implement the forecasting model into the current process used for handling action products at Jan Linders Supermarkets. The implementation issues handled in this chapter are primarily based on the current process of Jan Linders Supermarkets, but are also prerequisites for a successful implementation of the process redesign presented in the previous chapter. First, paragraph 7.1 again describes the boundary conditions that have to be kept in mind with implementing the forecasting model in practice and thereafter, paragraph 7.2 describes the actual implementation. To able to use the forecasting model on the long run, it has to be updated regularly. Paragraph 7.3 presents the requirements for doing this successfully. Paragraph 7.4 presents a short implementation plan for the process redesign at Jan Linders Supermarkets. Finally, paragraph 7.5 concludes this chapter.

7.1. Boundary conditions

For using the forecasting model in practice, several conditions have to be kept in mind:

- The forecasting model can only be used for food/non-food (FnF) action products. Since the model is based on the FnF products only, the model can only be used for forecasting action sales of these products. For other products, like e.g. cold storage products, another model has to be created.
- The forecasting model cannot be used for in-out products. In-out products are defined as products that are only sold once. No sales and action history are present for these products. Kurawarwala and Matsuo (1996) presented a framework for forecasting sales of short-cycle products in general. Their framework uses the history of comparable products for the demand forecasting of the in-out product. Since this is a time-consuming and error-sensitive procedure, Jan Linders Supermarkets probably prefers to forecast the sales of in-out products using the judgements of experienced employees. In addition, the already in DistRetail available action module can be used to forecast sales for in-out products, when qualitative judgements are hard to make. Although the use of this module is very time-consuming, it can be used for a small number of in-out action products.
- For composite products, this model makes only one forecast. For a composite product, defined as a product sold with different packaging sizes (see appendix D1), only the total sales of all SKUs with different package sizes are forecasted. Mostly, one of these package sizes is the action SKU, which is probably the only package size sold in the action week (Huchzermeier, Iyer, and Freiheit, 2002). Hence, the total forecast has to be attributed to that package size.
- The final action scheme cannot be changed anymore. The determination of the number of actions within a certain (sub)group is only valid when no action products are added to or deleted from the action package in that particular week.

7.2. Implementation plan for the forecasting model

The main prerequisite for a successful implementation of the forecasting model in practice is the change of the method of data storage. Per week per action product, it is necessary to know the values of the in the model included variables: $\overline{S}$, Nm_a, Ns_a, p, and d_{perc}. Furthermore, one should know to what action category of the shortened action categorization (AAA, AA, or A) the action product belongs.

Preferably, all data are collected using DistRetail, because this system includes a database structure in which the information can easily be saved. Nowadays, the action selling price and the action categorization are not present in DistRetail. Both can be found in the action scheme in Excel. In the future, it is preferred to include the action scheme in DistRetail. At the moment of finishing this project, plans existed to do this. How long this will take is unclear. Another incompleteness of the necessary data in DistRetail is that not all FnF action products in a particular action week are characterized in DistRetail as action products; store driven FnF action products do not get an action code. To assure that all FnF action products are considered in determining the number of actions within a particular product (sub)group, all FnF action products should get an action code in DistRetail. For the other variables, it does not seem to be a problem to gather the information using DistRetail; the average sales of the last five non-action weeks can easily be determined and the regular selling price is currently available in DistRetail.

When all data are available in DistRetail, the forecasting model also has to be implemented in DistRetail, making the ERP-system able to produce a forecast for all action products. This minimizes the number of manual steps needed. However, it probably takes a lot of time before Jan Linders Supermarkets will be able to implement this model in DistRetail.

Until DistRetail can be used for making a demand forecast, it is preferred to make all information available in Excel, in which specialised macros in Visual Basics for Applications (VBA) can be run to make a forecast. To start with, the data present in DistRetail, being the regular selling price and the average sales in the last five non-action weeks, are gathered using Business Object (BO) and transported to Excel. BO is software that is able to create reports from information in DistRetail. The number of actions in a particular (sub)group has to be determined using a complete list of FnF action products within one action week. The most reliable list is the action scheme in Excel. A VBA macro can be used to determine the number of actions within certain (sub)groups, based on the action scheme and a list of article numbers per (sub)group. Furthermore, also the action categorization (AAA, AA, or A) and the action selling price have to be collected from the action scheme. To be able to use the action scheme as a data source, the layout of the action scheme has to be changed and more important, the employees of the commercial department and the commercial administrative department have to use a more structured way of entering the information in the action scheme. The main prerequisite for this scheme is that per SKU only one record is used and that this record always contains one article number.

Summarizing, the following procedure has to be used to implement the forecasting model within the current Jan Linders Supermarkets' process:

1. The purchasers determine the action package, containing all action products within one week. This is done in a structured way in Excel.
2. When the final action scheme is presented, a VBA macro is run to create a list of all FnF action products in the action week. Per product, this list also contains the action selling price and the action categorization.
3. Per action product the average sales of the last five non-action weeks, the regular selling price, and the product (sub)group are gathered from DistRetail using BO. Afterwards, this BO-report is transported to Excel.
4. Both Excel files are combined. Simultaneously, the number of products within a certain (sub)group and the discount in terms of percentages are calculated.
5. Finally, the forecast for the lift factor is created, also using a VBA macro in Excel. Thereafter, the forecast for the action sales is directly calculated using the forecasted lift factor and the average sales level.

7.3. Regularly update of the forecasting model

Although the described procedure seems practical on the short run, it is definitely preferred to implement the action scheme in DistRetail, since this also brings advantages for updating the model regularly. Updating the model is necessary on the long run, since the coefficients of the regression model are not valid on a long-term basis, due to changes to products and procedures. The interval for updating has to be determined by employees of Jan Linders Supermarkets. The easiest way is to update the model every fixed period. Another way to define the updating interval is to measure the performance of the model every week and define a threshold, which triggers the model to be updated when the performance is lower than this value.

When all data are present in DistRetail, a new dataset can be created. This dataset can be used to determine the new parameters of the updated model. Any application that can conduct a regression analysis, e.g. SPSS or Excel, is feasible for this. Until all data are present in DistRetail, the Excel files created to make the forecast have to be saved in a structured way, to assure that these data can be used again for updating the model. The most obvious way to do this is making a Microsoft Access database, to which the Excel files are transported weekly. A disadvantage of this method is that only the same independent variables can be used in the updated model as currently used in the model. On short term, this is no problem, but on long-term basis, this probably is. Again, the DistRetail database is preferred, since then all data are saved.

Updating the variables in the model is already needed at the end of this project. This is caused by the implementation of a new action categorization. From January 2009, a fourth action category AAAA is used, which is not included in the model. In the new categorization, the A and AA actions did not change. The old AAA categorization is now called AAAA. The new category is the AAA action. The proposal for using the developed model also for this categorization is to scale all new AAA and AAAA classifications to AAA actions in the model.

7.4. Implementation plan for the process redesign

The in the previous chapter redesigned process of handling action products cannot be implemented at once. It goes too far for this project to develop a detailed plan for the implementation of this improved process design at Jan Linders Supermarkets. This paragraph describes a short implementation plan for the process redesign. The most difficult will be to convince the store managers that no change is needed anymore to the proposed order of the service centre (SC). The good performance of the forecasting model finally has to convince them of this.

The following implementation plan is proposed:

1. The current way of forecasting the aggregate sales is changed to the proposed way, using the explanatory forecasting model created during this project. To be able to adapt the procedures to a formally created forecast, other processes do not have to change in this phase. This means that still a forecast is made at the SC and that the store managers are still able to change this forecast. Whether the forecast will be made and slightly adapted by the purchasers has to be discussed, since at this moment the purchasers are encouraged to send more products to the stores than actually needed.
2. Together with the implementation of the formal forecasting model, the structure of the current action products' process has to be discussed. A rescheduling of activities among employees assures that several process steps are not needed anymore. Furthermore, the ICT-experts should create some standardized VBA macros for executing standard tasks automatically.
3. When implementing the formal forecasting method, data has to be gathered about the performance of the forecast. This performance has to be communicated to all involved employees regularly. When the performance is satisfactory, store managers will agree that their adaptation to the proposed order is not needed anymore. When this is the case, the improved process design, as presented in chapter 6, can be implemented.
4. For implementing the process redesign, a value for the part α of the forecast that finally has to be send to the stores, has to be determined. The employees that are already familiar with the new forecasting procedure can do this. Furthermore, these employees are probably also made responsible for updating the model regularly.
5. Finally, the total process structure can be changed to the one proposed in the previous chapter.

In this short implementation plan, it is not stated whether DistRetail is used for making the demand forecast or not. Obviously, this is preferred, but not required for the successful implementation of the process redesign. Furthermore, when it is expected that the improved process design is implemented soon, step 2 of the action plan is not needed. Nonetheless, since it is expected that a significant amount of time is needed for employees to get used to the new forecasting model, it is recommended to take some time between the implementation of the new forecasting model and the implementation of the complete new process. Hence, slight improvements to the current process are valuable to consider.

7.5. Conclusion

In this chapter, the implementations of both the explanatory forecasting model and the improved process design were discussed. For the implementation of the explanatory forecasting model, it is most important to create a database in which the data needed for making forecasts is stored. Preferably, this is done in the already available ERP-system, called DistRetail. Since the implementation of the new forecasting model is the major change to the currently used process, it is recommended to first enable employees to get used to this change. Thereafter, the complete process can be changed to the process described in chapter 6. The most difficult will be to convince the store managers that no change is needed anymore to the proposed order of the service centre (SC). However, when the forecasting model performs well, they finally will realize that it indeed saves a lot of time when they agree on the proposed order of the SC.

Part IV: Conclusions

8. Conclusions and recommendations

This final chapter concludes the research conducted by summarizing the main results of the different phases of the project. Paragraph 8.1 presents the main results of the analysis phase and paragraph 8.2 presents the main results of the design and implementation phase. Besides these conclusions, several recommendations are done for further research, presented in paragraph 8.3. Finally, paragraph 8.4 describes the main problems during the realization of this project

8.1. Conclusions of the analysis phase

In the first phase of this master thesis project, several analyses were conducted to determine what the current performance is of the inventory management of action products at Jan Linders Supermarkets. First, a qualitative analysis was conducted, to be able to make a description of the current process, using the outcomes of interviews with several employees of Jan Linders Supermarkets. Thereafter, the total process was monitored for ten specific service centre (SC) driven action products. Finally, the performance of the inventory management of action products was quantitatively analyzed, based on data of SC driven action products in week 15 to week 41 of 2008. First, the research questions formulated in paragraph 1.2 are answered.

1. Does Jan Linders Supermarkets use the correct inventory levels of action products in the stores?
No. Based on the quantitative analysis of SC driven action products in week 15 to week 41, it is concluded that on average too many items are supplied to the stores per action product. On average 0.70 action case packs per SKU per store per week are left after the action week.

2. What is the performance of the initial aggregate demand forecast made centrally?
The performance of the proposed order of the SC is bad. In the analyses of the SC driven action products, three different orders, the delivery to the stores, and the actual sales were compared to each other. The orders compared were the proposed order, the initial order, and the final order. The proposed order is determined by using a standard allocation rule on the aggregate demand forecast of the purchasers. The initial order contains the changes of the store managers on the proposed order. The final order differs from the initial order of the stores due to the need for rounding off the action orders for the supplier. The conclusion of the analysis on the differences between these orders, the delivery, and the sales is that the proposed order is the major cause of the poor performance of the inventory management of action products. The difference between the proposed order and the actual sales was on average equal to 0.77 case packs per SKU per store per week. The cause of this proposed order performing worst is the aggregate demand forecasting method used. The demand forecast of an action product is determined based on a judgement of the purchaser of the product. Besides that these purchasers are encouraged by their performance measures to supply more items of action products to the stores than actually needed, this judgemental approach is dependent on the experience of the purchasers and the extent of extern factors influencing them. At Jan Linders Supermarkets, these disadvantages of the judgemental forecasting method used result in significantly too large aggregate demand forecasts.

3. Is the right allocation rule used, to allocate the initial aggregated demand forecast to the stores?
No, probably not. One general allocation rule is used for allocating aggregate demand of almost all SC driven action products to the stores. Besides that this allocation rule is determined at the beginning of 2008 and hence is probably not valid anymore, the allocation rule is not product (group) specific. The distribution of total action sales over the different action products is different per store. Some products sell well in a particular store, while other products do not. It does not mean that the well selling products of one store also sell well in another store. This is assumed when only one general allocation rule is used. Since this assumption is not valid, the performance of allocation rule is bad. No hard conclusions can be drawn about this performance, since the actual performance of this allocation rule could not be separated from the performance of the aggregate demand forecast.

Second, the main research question (*"What are the relevant causes for the performance problem of the inventory management of the action products and how can this problem be solved?"*) can be answered. The main causes for the performance problem of the inventory management system can be found in the following problems:

- The aggregate demand forecast is significantly too high
- The process of handling action products is very time-consuming and error-sensitive
- No difference is made between forecasts and orders

The first conclusion directly follows from the answer on the second research question presented above. The second conclusion is based on the qualitative analysis of the process, in which the process was described in detail. The problem of the third conclusion is that the amount of products supplied to the stores is equal to the demand forecast, which means that no ordering policy is used to determine the size of the orders of the stores based on the forecast. This also causes the significantly large amount of leftovers after the action week in the stores. These three problems were tried to be solved in the design phase of the project.

8.2. Conclusions of the design phase

Based on the outcomes of the analysis phase of the project, the major improvement for the inventory management of action products were determined to be the improvement of the aggregate demand forecasting method and the improvement of the total process of handling action products.

First, the demand forecasting method was improved by developing an explanatory demand forecasting model. In this model, the lift factor in demand during the action week is forecasted based on the average sales of the product in five previous non-action weeks, the number of actions in the product (sub)group of the action product, the normal price of the product, the price discount, and the action classification (AAA, AA, or A). By multiplying this forecasted lift factor with the average sales of the product in five previous non-action weeks, a demand forecast is created for the product in the action week. Since this model creates an aggregate demand forecast, it is hard to compare the performance of the model with the current performance. The performance of the model can only be measured as the number of product left after the action week in all stores together, while the current performance was measured per store. Using the forecast of the model for supplying products to the stores results in an average surplus in supply of 1.26 case packs per week for all stores. This small amount and the fact that a formal forecasting model generally performs better than a method only based on experience, validate the conclusion that the performance of the inventory management of action products is increased when this model is used.

Second, an improved process design was developed based on findings in literature. In this improved process, the forecasting model is used to determine the aggregate demand forecast. Thereafter, an ordering policy is used to determine what part of this forecast is actually supplied to the stores. This policy determines that only a fixed part α of the forecasted aggregate sales is supplied to the stores. The remaining part $(1-\alpha)$ of the forecast is used for an extra delivery of action products during the action week. In the improved process, two action deliveries are used: one before the action week, initiated by the SC, and one during the action week, initiated by the store managers. Using these two deliveries results in lowest costs and maximal flexibility to react on actual sales.

Finally, an implementation plan was developed for implementing the improvements into the current process. The main prerequisite for a successful implementation of the forecasting model is a proper way of data storage.

8.3. Recommendations for further research

Before the proposed process can work properly, some other research has to be done within Jan Linders Supermarkets, based on this research project. Paragraph 8.3.1 presents recommendations for these research studies. In addition, paragraph 8.3.2 presents further opportunities for scientific research.

8.3.1. Recommendations for further research within Jan Linders Supermarkets

At Jan Linders Supermarkets, the research still needed to be conducted is based on the allocation rule and on an ABC analysis for action products.

Allocation rule(s)
The most important research that has to be conducted concerns the improvement of the allocation rule(s) used. For this research, similar data are needed as used for the determination of the aggregate forecasting model, but then data are needed on a store level. This means that 53 times the amount of data used in the design part of this project is needed. Due to the amount of time needed to collect these data using the current database structure of Jan Linders Supermarkets, this could not be done within the time span of this project.

ABC analysis for action products
In this report, it is recommended to use the improved process design for the handling of all action products. However, this probably is not possible, due to problems with best-before dates. Besides, the question remains whether it is needed to use this process for all action products. It would be wise to research the possibility of making an ABC classification for action products (Silver et al., 1998, and De Leeuw et al., 1999). This way, it is determined whether it is profitable to use a sophisticated forecasting model for all action products. The forecasting model presented in this report already uses some sort of classification based on the action categorization. It has to be investigated whether this subjectively determined classification is as good as a more objectively determined classification based on for example price discount, regular sales, product characteristics, gross profits, and/or seasonal influences. As a result of this ABC analysis, different handling procedures would be used for different classes of action products. Obviously, the A-products will get most attention, while C-products will be handled using rather unsophisticated techniques.

8.3.2. Recommendations for further scientific research

Besides these specific recommendations for further research for Jan Linders Supermarkets, also recommendations can be done for further scientific research, based on this master thesis project. These are related to the use of inventory dependent demand in forecasting action sales and substitution effects found with action products.

Inventory dependent demand
Dana and Petruzzi (2001), Urban (2002), and Ouyang, Hsieh, Dye, and Chang (2003) present models for taking into account inventory dependent demand in forecasting demand. However, none of these models also takes into account promotional effects, while the issue of inventory dependent demand is especially observable with action products. Therefore, it is recommended to develop a demand forecasting model for action products in which the issue of inventory dependent demand is considered.

Substitution effects
Completely different from the analyses conducted in this project is the analysis to the substitution effects of the action products. As Huchzermeier et al. (2002) conclude, smart customers switch between different package sizes of the same product, due to price differences caused by promotional actions of one particular package size. How to take these substitution effects into account with determining the demand forecast of both the action products and the substitution products of the action products is not researched in scientific literature.

8.4. Experiences during the project

With presenting the conclusions of this research and some recommendations for further research, this project is finished. This paragraph finally presents some experiences during the process, which can be useful when a similar project is executed.

Following the planning made in advance of this master thesis project (Van den Heuvel, 2008b), the major difficulty was collecting the data needed. As explained by several people within Jan Linders Supermarkets, all data could be collected. The problem was to collect these data in the correct format to be valuable for the analyses. This took more time then expected. Almost all data gathered needed extra handling using Visual Basic for Applications (VBA) within Excel. Partly due to the limited knowledge of the present writer of the programming language used within VBA, this resulted in long periods of data preparation.

In addition, at the start of the project, only a detailed planning was available for the analysis part of the master thesis project, since Jan Linders Supermarkets' first need was to determine the current performance of the process related to action products. When this performance was known, it was probable that something could be improved and therefore, the design part of the project was planned later on. The disadvantage of this way of working is that the dataset collected in the analysis phase of this project turned out to be of no value anymore in the design phase of the project. Therefore, in the design phase, again a complete new dataset had to be created, which again took a lot of time.

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Part V: Appendices

Outline appendices

Note: The appendices are related to the chapters in the main text: appendix A belongs to chapter 1, appendix B belongs to chapter 2, etc.

Appendix A. Problem context

Appendix A1. Organization diagram

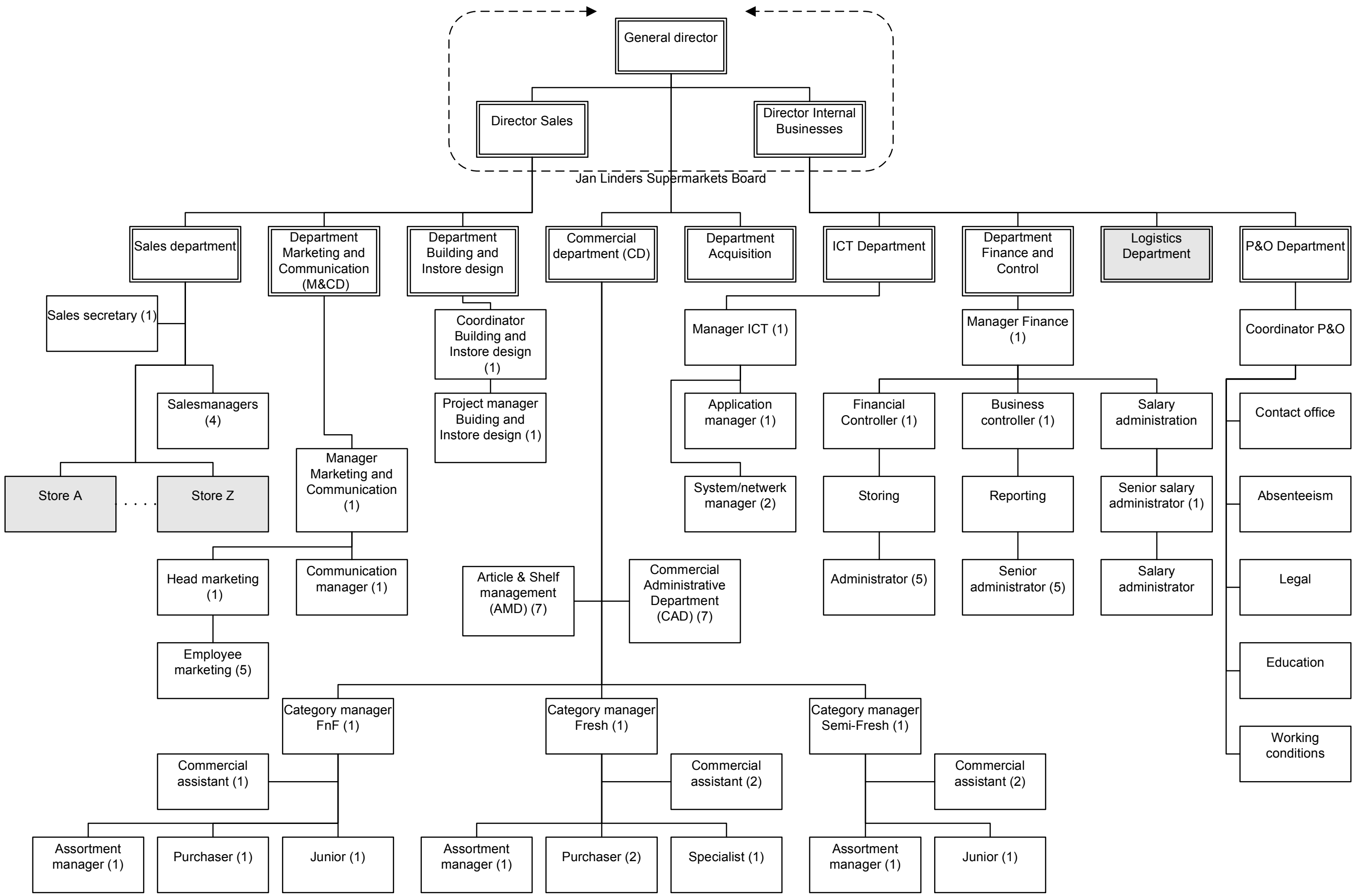


Figure A1: Diagram of the Jan Linders Supermarkets organization

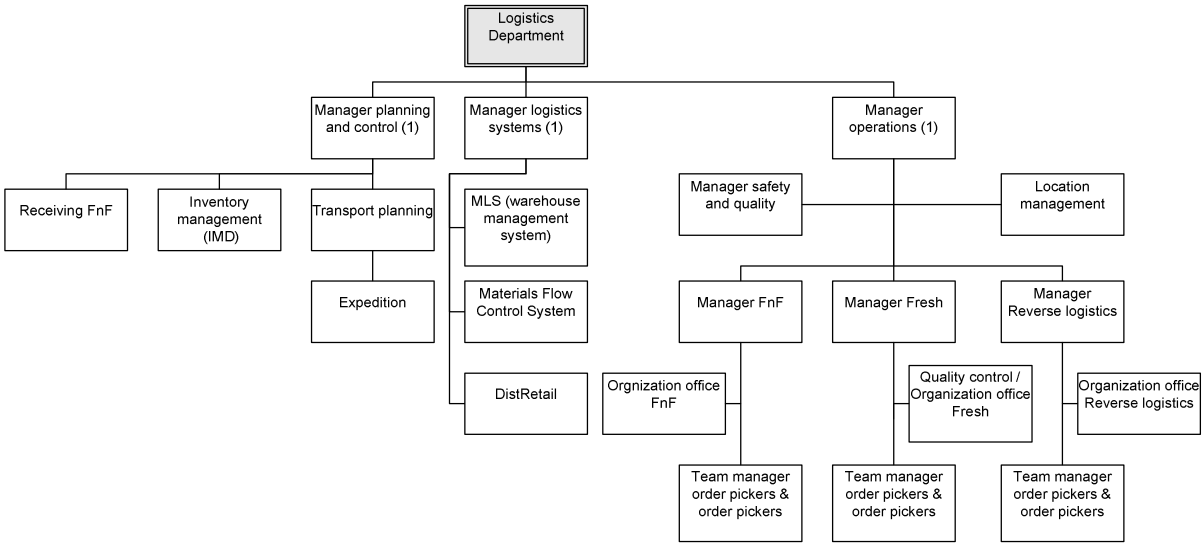


Figure A2: Diagram of the logistics department

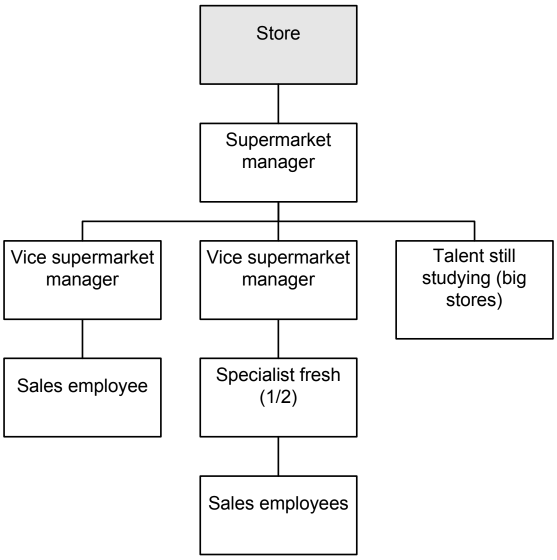


Figure A3: Diagram of the organization in a store

Appendix A2. Cause-and-effect-diagram

This appendix presents the problem structure related to action products within Jan Linders Supermarkets. Figure A4 presents the cause-and-effect diagram, created in the orientation phase of this project. On the right side of figure A4, problems, or effects, are presented. The boxes left to these problems are their causes, which become more and more concrete when going further to the left. This means that the statements in the boxes at the left hand side are easier observable. The shaded boxes are related to the research questions explained in paragraph 1.2.

Some general statements have to be made about the selection of these topics to analyse. First, the focus of this project is on action products. However, figure A4 also contains some problems related to action products but directly found at non-action products, like the problem with the inventories of substitution products of action products. This problem can only be observed using the data of non-action products too. Since this broadens the analyses too much, no data of non-action products are used, which means that the problem of substitution products falls outside the scope of this project. Second, some problems are related to the general problems caused by the new distribution centre (DC) used by Jan Linders Supermarkets. Since these are operational problems, these also fall outside the scope of this master thesis project.

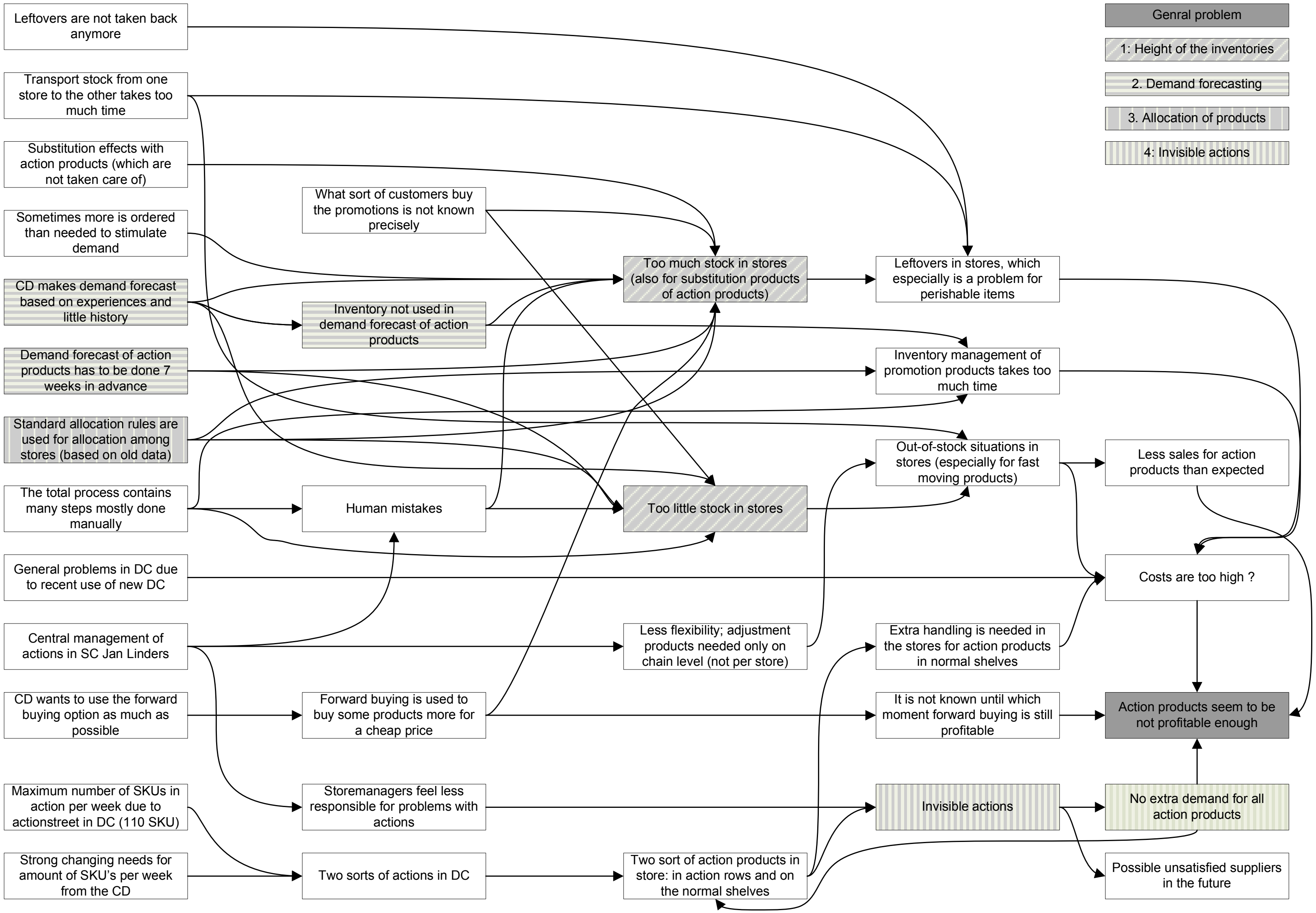


Figure A4: Cause-and-effect diagram related to action products within Jan Linders Supermarkets

Appendix A3. Invisible actions

A supplementary analysis also conducted in this project, is the analysis to invisible actions. Due to the size of the action street in the distribution centre (DC), there is a boundary on the amount of food/non-food (FnF) actions per week, which is set on 110 SKUs. However, the commercial department often wants to present more actions. This results in the so-called invisible action products, which are placed on the regular shelves in the store. This means that customers do not see these actions as soon as they see the special presented action products, which probably results in lower lifts in demand for these invisible actions. To determine whether the performance of action products is highly dependent on the performance of these invisible actions, an analysis is conducted regarding the lift factor of FnF action products, differentiating between visible and invisible actions.

An assumption for testing this is that service centre (SC) driven FnF action products, picked using the action street in the DC, are also presented at special action shelves in the stores. By interviewing some supermarket managers, it became clear that it is not per definition the case that products picked at the action street are also placed at special shelves in the stores. Nevertheless, this is regularly the case, since most products picked in the action street are volume products, meaning that these products are rather large in size or large in customer demand. These are exactly the products that the supermarket manager wants to present well, to encourage sales.

To determine the influence of the so-called invisible action products, the lift factor is analyzed. This lift factor is defined as the sales in the action week divided by the average sales level.[5]

First, usable data had to be prepared. Therefore, the total dataset available for the analyses is taken as a starting point. After removing records with total sales being negative or equal to zero, average sales being negative or equal to zero, and total deliveries equal to zero, 348,428 records remained. Complementary to the data presented in paragraph 4.1, per record also an average sales value was given. The preparation of this value is described in appendix D1. Most important is that the average was calculated using only week 31 to 46. Therefore, only data from week 31 onwards could be used. This resulted in only 101,837 records available. By only picking the FnF products and products with a lift factor above 1, a dataset of only 45,935 records was maintained. Nonetheless, this seems enough to base sound conclusions on.

The average lift factor of this dataset is equal to 14.59, meaning that on average the sales in the action week are 14.59 as high as in a regular week. Discussing this average with the manager of the inventory management department, large lift factors are probably found because also in-out products are maintained in the dataset. These are products sold only once, meaning that their average sales are really low. To overcome this problem, also for this dataset an outlier analysis is done using the borders of 1.5 times the interquartile range below and above the first and third quartile respectively. A new dataset was created only containing the records with lift factors between 1 and 21.61, resulting in a dataset with 40,669 records. Table A1 presents the descriptive values of these records.

	Minimum	Maximum	Mean	Std. Deviation
Total Sales	0.04	237.25	3.54	6.16
Average Sales / Week	0.00	59.75	0.75	1.72
Lift factor	1.00	21.60	6.19	4.35

Table A1: Descriptive values of the dataset containing FnF products in week 31 to 41 without outliers

[5] An elaborate description of the lift factor can be found in chapter 5 of the main report.

An independent samples t-test was performed to find out whether there is a difference between the mean of the lift factor of SC driven action products and the mean of the lift factor of store driven action products. The descriptive values related to this test are presented in table A2. The difference between the means presented in table A2 is significantly different from zero (t = 43.215, not assuming equal difference).

	Actions	N	Mean	Std. Deviation
Lift factor	SC driven	34,830	6.52	4.45
	Store driven	5,839	4.25	3.58

Table A2: Descriptive statistics of the dataset containing FnF products in week 31 to 41 categorized by whether the actions are SC driven or store driven

The question remains whether it is possible to raise the lift factor for the store driven action products. By interviewing several people within Jan Linders Supermarkets, it became clear that this would be rather difficult. The difficulty lies in the stores. Special places in the stores are dedicated to present the action products. The commercial department makes a proposal for the presentation of the action places; however, the store manager is responsible for what products to present at these special places. Due to the large amount of action SKUs, not all action products can be placed at these special product locations. Both in the proposal and the actual presentation, only products that are expected to sell significantly more in the action week are placed at the various special action places. This has two reasons, namely the space that is needed for these extra selling products besides the regular shelf space and the commercial effect of presenting these products separately. Nonetheless, this also means that some action products are only sold via the regular shelf space, which means that the customer does not see these products sooner than normal, although these products still have a special promotion card presented at the shelf. Although not analyzed quantitatively, probably a high correlation exists between the products picked at the action street in the DC and the products presented at a special place in the store.

It is assumed by the commercial department that when all FnF products will be picked in the action street in the DC, these will all be presented on a special place in the stores. Whether this is true, is arguable. Furthermore, the question remains whether the customer sales of all specially presented action products in the action week still increase, when the number of these products increases. Therefore, it is hard to conclude that more sales can be gained by making all FnF action products SC driven and therefore picking them in a special picking street in the DC.

Appendix A4. Regulative cycle

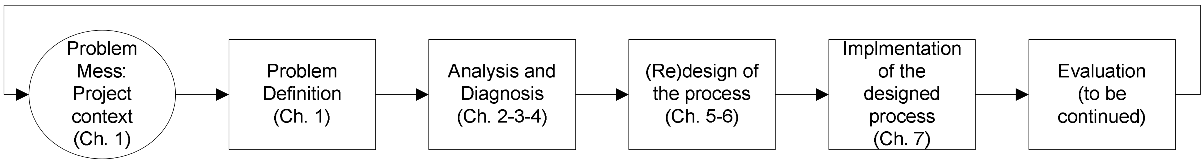
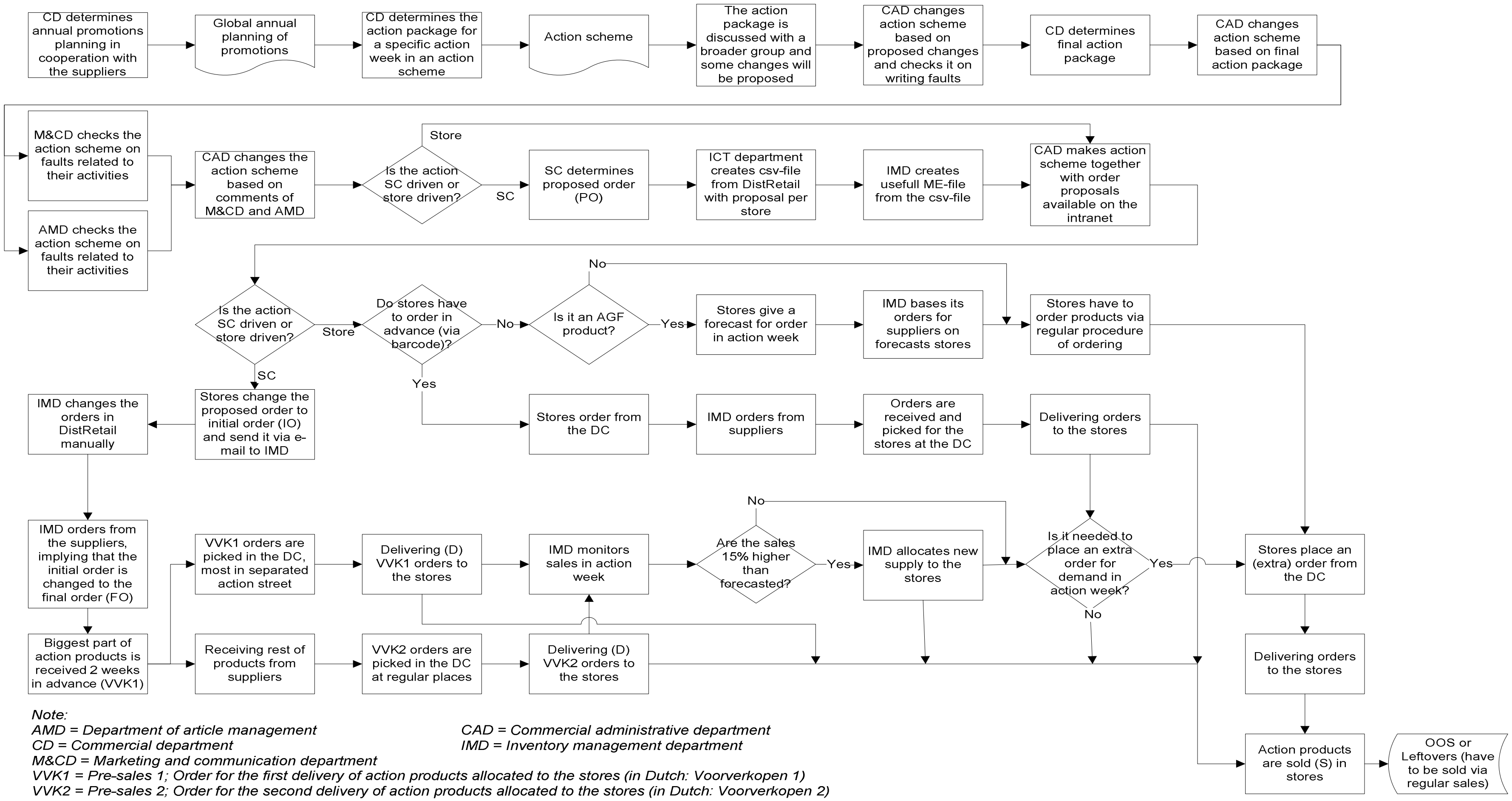


Figure A5: Regulative cycle of Van Aken et al. (2005) applied to this project

Appendix B. Process description

Appendix B1. Elaborate process description



Note:
AMD = Department of article management
CAD = Commercial administrative department
CD = Commercial department
IMD = Inventory management department
M&CD = Marketing and communication department
VVK1 = Pre-sales 1; Order for the first delivery of action products allocated to the stores (in Dutch: Voorverkopen 1)
VVK2 = Pre-sales 2; Order for the second delivery of action products allocated to the stores (in Dutch: Voorverkopen 2)

Figure B1: Elaborate flowchart of process used for action products within Jan Linders Supermarkets

Appendix C. Performance of ten specific action products

Appendix C1. Differences between the proposed orders and the initial orders

Article Nr.	Description	Brand	Number of stores that adapted	% of stores that adapted	% that adapted positively	% that adapted negatively
122033	Tomato cream soup 4 bowls	Unox	21	40%	0%	100%
126543	Frankfurter 590gr	Limco	13	25%	0%	100%
141585	Drinking yoghurt red fruits	Fristi	25	48%	0%	100%
159258	Orange regular	Fanta	19	37%	20%	80%
160806	Beer 30 cl bottle	Palm	29	56%	3%	97%
161915	Cabernet sauvignon wine	African Dawn	34	65%	6%	94%
189186	Toilet paper soft	Edet	14	27%	93%	7%
201167	Washing-powder super compact	Ariel	10	19%	0%	100%
254833	Soft curd cheese Spanish orange	Almhof	28	54%	29%	61%
254835	Soft curd cheese vanilla	Almhof	28	54%	43%	50%
	Total		221			

Article Nr.	Description	Brand	Lowest absolute change	Highest absolute change	Average absolute change
122033	Tomato cream soup 4 bowls	Unox	27%	75%	49%
126543	Frankfurter 590gr	Limco	17%	100%	49%
141585	Drinking yoghurt red fruits	Fristi	27%	100%	46%
159258	Orange regular	Fanta	6%	90%	37%
160806	Beer 30 cl bottle	Palm	7%	100%	40%
161915	Cabernet sauvignon wine	African Dawn	23%	100%	57%
189186	Toilet paper soft	Edet	14%	300%	67%
201167	Washing-powder super compact	Ariel	25%	100%	64%
254833	Soft curd cheese Spanish orange [1]	Almhof	6%	82%	29%
254835	Soft curd cheese vanilla [1]	Almhof	13%	100%	33%
	Total		6%	300%	45%

[1] For the cold storage products, changes of 0% were done, since some stores changed both deliveries, but in total changed nothing. These are not taken into account in determining the lowest absolute change

Appendix C2. Action initialisation

This appendix describes the working methods of the purchasers related to the action initialisation of the ten in week 44 followed products and the demand forecast of these products.

Special actions in week 44 of 2008, in the sense that these are initialized in another way than described generally, were the actions of the Edet toilet paper and the Ariel washing powder. These actions were part of the overall action, named Animal World. This is an action initialised by the seven supermarket members of Superunie[6] and contains an action with animal cards, which customers receive when they buy special action products. This overall action also was a reason to start an action with the African Dawn wine. However, for this product the most important reason was the amount of leftovers available at the distribution centre (DC) due to the former action of this product. This wine was the wine of the month September. Due to the disappointing sales of this wine in that period, many items were left.

The forecasting of the action volume is mostly based on historical data. However, the details are quite different. For example, the purchaser of the Limco frankfurter first looked at the regular weekly sales. For this product, these are approximately 28 case packs per week. The most recent action of this product was in week 24. In that week, the sales were increased to 343 case packs. Furthermore, the sales in week 25 and 26 were also increased to around 50 case packs per week. Due to this increase after the action week and the fact that the supplier gives discounts for the products bought, the purchaser of this product also took these latter weeks into account to determine the action volume. This finally resulted in a forecast of 500 case packs.

Another purchaser, the one responsible for the Fristi and Almhof products, first uses the action schemes of action weeks in which the current action product also was discounted. For the Fristi drinking yoghurt, this meant that the action schemes of week 26, 21, and 13 were used. In principle, the most recent action is used; however, in this case, the most recent action was not comparable to the current action. The actions in week 13 and 44 both were 2+1 items free actions. Therefore, the sales volume in week 13 could be used to make a forecast. The sales were equal to 368 case packs and the purchaser made a forecast for week 44 of 700 case packs. The purchaser cannot tell anymore why he increased this amount. It may be that rising non-action sales played a role.

The forecasted action volumes of the Edet toilet paper and the Ariel washing powder products were determined using a comparable overall action in the spring of 2008, namely the Jetix action, at which customers received marbles with the action products. For the Edet toilet paper, the sales of week 16 could be used. The sales in that week were equal to 407 case packs. However, the action in that week was unsuccessful. Furthermore, the discount given in week 44 was better than the one in week 16 (the regular price is €7.89; in week 16 the action price was €6.49 and in week 44 €5.99). Hence, the purchaser of this product predicted to sell 600 case packs in week 44. With regard to the Arial washing powder, the sales history of week 13 had to be used, in which the action selling price was equal to the action selling price in week 44. However, for week 44, the purchaser chose to allocate more volume of the fast moving SKUs and less of the slow moving SKUs of this product group. The reason is that leftovers of fast movers are sold out sooner in non-action weeks than leftovers of slow movers. Since this SKU is a fast mover, the predicted volume for week 44 was equal to 400 case packs, compared to 324 case packs sold in week 13.

Finally, the forecasted volume of the wine was primarily based on the inventory left at the DC. However, the purchaser emphasized that this also was a realistic amount to sell.

[6] Since Jan Linders Supermarkets is a relatively small player on the supermarkets market, part of its purchasing activities are done by Superunie. This purchasing organization buys products for 16 independent retailers in the Netherlands.

Appendix C3. Categories for the explanations of the changes to the proposed orders

Category	Explanation
Considering historical data	The store manager made a forecast by himself using data of the past, available in Oscar, the software programme available at the checkouts in the stores.
Good proposed order	Store managers agreed with the proposed order of the SC, not meaning that they did not adapt this. The adaptation could have other reasons, like e.g. the inventory left.
Inventory in store	There was still inventory left in the store, due to earlier actions.
Local circumstances	The proposed order had to be changed due to local circumstances. Some local circumstances mentioned were a fair, a competitor opening or closing his store in the neighbourhood, and the road in front of the store being replaced.
Multiple packaging size	The order was rounded to a multiple packaging size, being preferred for logistical activities or the presentation of the action product in the store.
No data history	Store managers did not have any action history to base the order on. A good example is the new store in Herkenbosch.
Preferred change < 3	No change was made, since the change would have been lower than three case packs.
Rather low order	The store manager realised that the initial order has a large chance to be too low to fulfil all demand in the action week, but he also knew that he could order more at the end of the action week by himself.
Season	The proposed order was changed based on the selling season.
Sells poor	This product sells poor in this store.
Sells well	This product sells well in this store.
Substitution products in action	The proposed order was changed considering other products in action this week or in recent history.
Too high proposal	The proposed order of the SC was too high.
Too low proposal	The proposed order of the SC was too low.
Wrong adaptation	At the time they had to give an explanation, some store managers realised that the adaptation they did was wrong (although no actual sales were known at that moment in time).

Appendix C4. Determination of the final orders

This appendix describes the way of determining the final orders based on the initial orders for the ten followed action products in detail. The change to the initial orders is made during the process of ordering the products from the suppliers.

<u>Unox tomato cream soup</u>
This SKU has to be ordered per pallet layer, meaning that the sum of all final orders has to be dividable by 21. Since the stores in total ordered 510 case packs in their initial orders, the inventory manager of this product changed this total amount to 525 case packs. The extra 15 case packs were allocated to the stores manually, meaning that the relatively high orders per store where increased by one.

<u>Limco frankfurter</u>
The inventory manager of this product already considers the ordering rules when allocating the products to the stores. According to this inventory manager, this results in a volume of the initial orders being close to a multiple packaging size. The demand forecast for this product was equal to 500 case packs, which means that 490 case packs were allocated to the stores in the proposed orders, since this is equal to five whole pallets. After the stores made their changes to the proposed orders, the sum of the initial orders was equal to 436 case packs. This had to be rounded to whole layers, which meant that 434 case packs are ordered. In this case, two products were ordered less, so two stores got one case pack less of this SKU. The inventory manager does this manually, taking into account to not change the orders of the same stores every time and to not change the orders of the relatively small stores.

<u>Fristi drinking yoghurt</u>
Of this product, the stores ordered 531 case packs. This SKU also has to be ordered from the supplier in multiples of whole layers. Therefore, the sum of the final orders was changed to 540. The inventory manager allocated the nine case packs extra to the stores using the same general food/non-food (FnF) allocation rule as used to allocate the items in the first place. This also results in giving the relatively large stores one case pack extra.

<u>Fanta regular orange</u>
For this product, two delivery moments were chosen. For the first moment, the stores ordered 2832 case packs and for the second 582 case packs. Here the first order has to be rounded to whole pallets. This means that for the first delivery 2880 case packs were ordered. This increase is also allocated to the stores. However, in this case, no extra case packs are sent to the stores; the increase for the first delivery triggers a decrease for the second one. Therefore, the order for the second delivery was decreased from 582 to 525 case packs. There is no explanation for the total decrease of nine case packs. Normally, the two changes to the total orders should cancel out each other (as can be seen with the washing powder). The order for the second delivery does not have to be rounded to whole pallets, since this order is picked from the regular picking place in the DC and therefore, the order can be filled with case packs for non-action weeks.

<u>Palm beer</u>
The ordering of this SKU is rather simple, since no restrictions are present for the order size. The reason for this is that this SKU is picked in the packaging hall of Jan Linders Supermarkets, which is a separate hall only used for retour deliveries of packaging materials of the sold drinks, and the storage and picking of most of the to sell drinks. Since both the non-action orders and the action orders are handled here, action orders again can be filled with non-action orders to obtain whole pallets. Hence, for this SKU the final orders were equal to the initial orders of the stores.

African Dawn wine
As aforementioned in appendix C2, the leftovers at the DC initialized this action. Therefore, no items had to be ordered from the supplier, since enough inventories were still available at the DC (881 case packs were still available, where 656 case packs were needed in total). Nevertheless, since this SKU is picked from the action street in the DC, all orders for the first delivery moment in total still had to be changed to fill full pallets. Therefore, the first order was changed from 504 to 500 case packs. It is expected that the order for the second delivery was increased with four case packs. However, this was not done; the second order remained equal to 152 case packs. Again, no explanation could be given.

Edet toilet paper
The inventory manager of this SKU also already changes the forecast of the purchaser to an amount dividable by the number of products on a pallet. In this case, the forecasted amount was equal to 600 case packs, being exactly equal to 25 pallets. The stores changed this amount to 658 case packs, resulting in 28 full pallets containing 672 case packs. The extra items were again allocated to the largest stores.

Ariel washing powder
The forecast of the purchaser of this SKU was again adapted to a multiple pallets size, which resulted in 384 case packs allocated to the stores. These ordered in total 330 case packs, resulting in an order of 320 case packs. The other ten items were supplied to the stores using the second delivery moment, so in sum no changes were made to the initial orders of the stores.

Almhof soft curd cheeses
Since these SKUs are cold storage products, no action street has to be considered. Therefore, the final orders for these products are in principal equal to the initial orders. In this case, the final orders were slightly different from the initial orders, for which the reason was unclear (for both products the order for the second delivery is changed minimally).

Appendix C5. MSE and MAPE calculation

$$MSE(O) = \frac{1}{A \cdot I \cdot K} \sum_{a=1}^{A} \sum_{i=1}^{I} \sum_{k=1}^{K} (PL_{a,i,k}(O))^2 = \frac{1}{A \cdot I \cdot K} \sum_{a=1}^{A} \sum_{i=1}^{I} \sum_{k=1}^{K} (O - S_{a,i,k})^2$$

with:
$MSE(O)$ = mean squared error of order O

$$MAPE(O) = \frac{1}{A \cdot I \cdot K} \sum_{a=1}^{A} \sum_{i=1}^{I} \sum_{k=1}^{K} \left(\left| \frac{O - S_{a,i,k}}{S_{a,i,k}} \right| \right) \cdot 100$$

with:
$MAPE(O)$ = mean absolute percentage error of order O

Furthermore, O is equal to $PO_{a,i,k}$, $IO_{a,i,k}$, $FO_{a,i,k}$, or $D_{a,i,k}$. A is the number of weeks used, I the average number of action products, and K the number of stores used.

Appendix D. Performance of all action products in 2008

Appendix D1. Data collection and preparation for the analysis phase

This appendix clarifies the different steps needed to gather the data from week 1 to 41 of 2008 used in the analysis phase of this project.

First, a list was needed of all action products per week. As aforementioned, all actions are demonstrated in the action scheme produced weekly. However, this Excel file does not contain the data in such a manner that analyses can be conducted. Therefore, another way had to be found to get a list of all action products. Eventually, this list is produced using Oscar and Business Object (BO). Oscar is the software used at the checkouts of the supermarkets and BO is software usable for creating reports out of DistRetail and Oscar. Using these software applications, a list is created of all action products for which sales were registered during the action week. Later on, it turned out that this way of creating a list of action products does have a disadvantage, which is explained later.

All other data were gathered using DistRetail. Since the data needed were not available in the proper format, a specialized software application had to be created by one of the DistRetail experts of Jan Linders Supermarkets. When all data were collected, it turned out that an error was present in this application, causing that the inventory data collected were unreliable. Therefore, these data could not be used. Furthermore, since at the moment of collecting these data the stores with number 2518 and 3107 in respectively Herkenbosch and Geleen were not present anymore in DistRetail, no data were collected for these stores. At the moment of data collection, these stores were replaced by new stores in the same places with respectively the store numbers 7300 and 7400, for which no data was present for week 1 to week 41 of 2008. Therefore, the dataset contains 51 stores. In total, this elaborate dataset contains 528,054 records, every record representing one action SKU per store per week.

Per action SKU, the following data were collected:

- The week of the action
- The store, presented by the store number
- The warehouse: AL, DV, KO, KW, TR, and the Fresh warehouse (VC, *in Dutch*: Verscentrale)
- Article number and product description
- Commencing date of the product in the assortment
- The number of consumer units in a case pack
- The number of items delivered to the stores before the action week related to the action
- The number of items delivered to the stores in the action week
- All sales in the action week
- The average sales per week, determined over the last fifteen weeks

Some characteristics of these data cause that extra handling is needed to make the data usable for the analyses. First, all data were gathered in consumer units, since this results in the most accurate data. However, all other data already present, like the proposed orders and the initial orders, were given in case packs. Therefore, first all numbers had to be divided by the number of consumer units in a case pack. Second, the average sales given are just the sum of the sales of the last fifteen weeks divided by fifteen. For products being less than fifteen weeks part of the assortment, this does not give the correct average. Hence, the commencing dates are used to determine the correct sales averages. Another disadvantage of these average sales is that these are related to the last fifteen weeks from the moment of data collection backwards. It is not said that this average is also valid for the first weeks of 2008. Therefore, these data have to be handled carefully.

When doing a first check on the performance of these action products, a measure of goods in minus goods out was calculated summing all action deliveries and extracting the total sales in that week. Observing these values, some turned out to be extremely low or high, suggesting some errors in the data. Several inventory managers at Jan Linders Supermarkets clarified that these poor performances were related to so called composite products (in Dutch: *samengestelde artikelen*). A good example is a crate of beer. This is sold to the customers per crate and per bottle, but only ordered and bought from the supplier per bottle. Therefore, on the article number of the crate, only sales can be found and no deliveries; on the article number of the bottle, only marginal sales are recorded and many deliveries can be found. This results in an extreme value for the measure of goods in minus goods out for both article numbers, which does not give a valid value for the actual performance of the product. To solve this problem, sales of these products have to be summed. Here, the disadvantage of the aforementioned creation of the list of action products becomes clear: for products with no sales in the action week, the article number is not present in the list. Therefore, for many composite products, only the article number related to the sold item (being the crate in the example) is present on the list. When this is the case, this article number is removed from the list. Otherwise, distorted performance measures are created. Another problem is the determination of the composite products. When searching for a list of these products, the only list found was dated at February 2007. To deal with the composite products within the dataset, this list was used. By observing the striking SKUs in the dataset, this list of composite products was extended and attempted to be completed. By using this extended list, it is assumed that most composite products were adapted or removed from the list.

Finally, the following data were deleted from the dataset, since these would otherwise have resulted in a distorted view:

- SKUs for which the sum of the deliveries is equal to zero and the sales are equal to zero. These would have a perfect performance, but are not handled at all. Together with handling the composite products, this resulted in a dataset of 455,144 records.
- SKUs for which the predefined deliveries are equal to zero. Products with predefined deliveries are all service centre (SC) driven action products and all store driven action products with a barcode in the action scheme. All other products do not have a predefined delivery. For these products, only regular deliveries are present in the dataset. These deliveries contain some products for the week after the action week and miss some products delivered before the action week. Therefore, these products are not considered in the determination of the performance of the inventory management of action products.
- SKUs for which the total sales in the action week are equal to zero.
- SKUs with negative total sales in the action week or negative average sales.

Despite all these deletions, the dataset still contained outliers. How many is determined using a boxplot method, meaning that the interquartile range is determined and used to determine the outliers. This is a common method to delete outliers from a dataset (Cooper and Schindler, 2003). The interquartile range was determined to be 1.033, since the first quartile corresponds to a performance of 0.4667 case packs and the third quartile to 1.5 case packs. The borders for determining the outliers then are -1.1083 (being equal to $0.4667-1.5\cdot 1.033$) and 3.0495 (being equal to $1.5+1.5\cdot 1.033$) case packs. When records with a performance below the first border and above the second were deleted, 198,128 records were left. In total 329,926 records were deleted, representing 62% of the starting dataset. This is a very high number, but this had to be done to ensure data reliability.

In the design phase of this project it turned out that only quantitatively founded improvements could be determined for the process related to the SC driven action products. Therefore, chapter 4 only includes analyses for these products. Now, only data could be used from week 15 to week 41. This reduced the dataset to 75,174 records. Appendix D2 contains an analysis of all action products with predefined action delivery.

Appendix D2. Performance analysis for all products with a predefined action delivery

In this appendix, the analyses done in paragraph 4.1 for the service centre (SC) driven action products are conducted for all products having predefined action deliveries, meaning that besides the SC driven action products also the store driven action products containing a barcode in the action scheme are considered. Table D1 presents the descriptive statistics of the delivery, the sales, and the performance measure for this dataset. Figure D1 gives an overview of the spread of the data.

	Minimum	Maximum	Mean	Std. Deviation
D	0.50	150.00	3.45	3.74
S	0.01	149.67	2.78	3.71
PL(D)	-1.08	3.05	0.67	0.95

Table D1: Descriptive statistics related to the total dataset

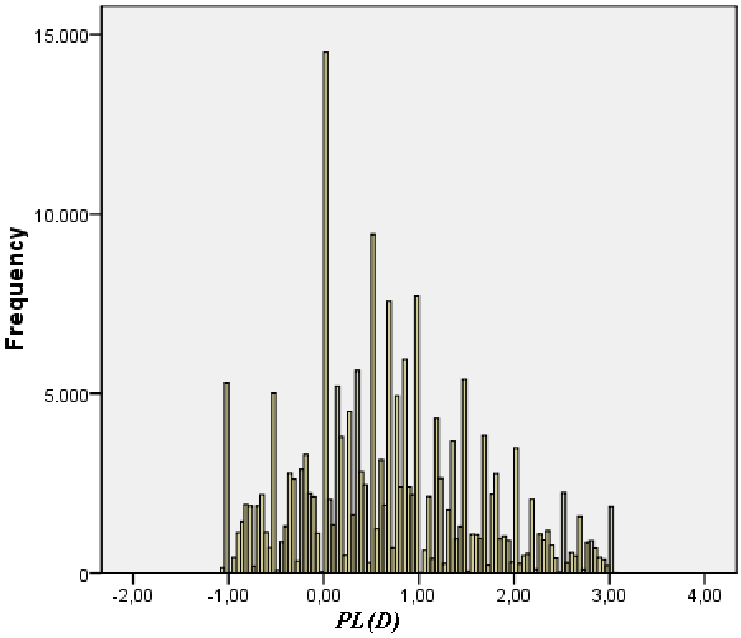


Figure D1: Overview of the PL(D)-values found in the dataset of the all action products with a predefined action delivery

Compared to the value found in paragraph 3.6.2 for ten food/non-food (FnF) products, the performance of all products together is much better. This is not surprising, since the ten products used in chapter 4 were not chosen randomly and had relatively high sales levels, which implies that errors also will be higher. Although the overall performance of the complete dataset is much better than the one of the ten FnF products, it is still significantly different from zero (t = 319).

To find out further whether performance differences can be found between several groups based on other characteristics of the action products, several ANOVAs can be conducted. Using such an analysis, significant differences were found between the performance values per store (F = 34.58). A post-hoc test cannot be executed due to the large number of groups, which was equal to 51. It can be seen that the minimum (and the best) $\overline{PL(D)}$ per store is 0.4893 case packs for store 205 and the maximum (and the worst) is 0.8970 case packs for store 7200. In addition, the ANOVA based on the warehouses is conducted. Again, classes could be made labelled AL, DV, KO, KW, and TR. Table D2 presents the descriptive values of these subgroups.

	N	Mean	Std. Deviation	95% Confidence Interval for Mean		Minimum	Maximum
				Lower Bound	Upper Bound		
AL	14,851	0.64	1.01	0.63	0.66	-1.00	3.00
DV	22,221	0.86	1.03	0.84	0.87	-1.08	3.00
KO	21,038	0.68	0.96	0.67	0.69	-1.06	3.04
KW	124,853	0.65	0.91	0.64	0.65	-1.08	3.05
TR	15,165	0.63	0.96	0.62	0.65	-1.05	3.00
Total	198,128	0.67	0.95	0.67	0.68	-1.08	3.05

Table D2: Difference between delivery and sales, categorized by warehouse

Significant differences also exist between the performance values per product group ($F = 245$). The outcome of the Games-Howell post-hoc test concludes that the means of AL, KW, and TR are not significantly different from each other. All other means differ significantly from each other. By observing the actual values of these means in table D2, it can be seen that these differences are minimal.

Appendix E. Forecasting model

Appendix E1. Regression model

To use a regression model, one has to assume relationships between the independent variables and the dependent variable (Montgomery and Runger, 2003). When these relationships are expected to be linear, a linear regression model can be used. In the following model, it is assumed that a simple linear relation exists between the independent variable x and the dependent variable Y:

$$Y = \beta_0 + \beta_1 x + \varepsilon$$

with ε being the random error with mean zero and (unknown) variance σ^2. Suppose that n observations are done in the past, which resulted in n combinations of x and y: (x_1, y_1), (x_2, y_2), …, (x_n, y_n). The coefficients β_0 and β_1 should be estimated in such a way that a line is created which has the best fit with the n observations done. In regression analysis, the best fit is determined by minimizing the sum of the squared errors of the estimated line with the actual observations (Cooper and Schindler, 2003). To find out whether indeed a relationship exists between the independent variable x and the dependent variable y, a t-test is conducted for the significance of the model, in which the hypotheses are:

$$H_0 : \beta_1 = 0$$

$$H_1 : \beta_1 \neq 0$$

When the null hypothesis is rejected, it can be concluded that a relationship exists between the two tested variables. Extending this model with more independent variables results in a multiple regression model.

Appendix E2. Data collection and preparation for the design phase

This appendix clarifies the data collection and preparation for the design phase. Two types of data had to be collected, namely sales data and data about action characteristics. Both are explained separately.

Sales data collection
The new sales dataset was gathered using BO and DistRetail. This dataset contained sales for all SKUs sold. Furthermore, per SKU the action sales were gathered, which are equal to zero when the SKU is not an action SKU in a specific week. Finally, per SKU three product group categorizations were added. The first was already described in paragraph 1.1 as the product departments. Furthermore, within these departments main product groups and product subgroups are defined.

Using several VBA macros in Excel, a dataset was created of 41 weeks, containing per action SKU per week the following data:

- Product groups: department, main group, and subgroup
- Average sales in non-action weeks for the complete period of 41 weeks
- Average sales in the previous five non-action weeks before the current action week
- Sales in the current action week
- Lift factor: Sales in current action week divided by the average sales in the previous five non-action weeks before the current action week

The lift factor can be defined in several ways. For determining the lift factor used in the regression model, the average sales of the previous five non-action weeks were used in the denominator. This means that when the last five weeks before the current action week were non-action weeks for the current action product, the average of the sales in these weeks was used. When these weeks also contained an action week, this one was deleted and, when possible, one week further backwards was used to determine an average sales level. A similar procedure was used when two weeks of the last five weeks were action weeks. A disadvantage of this way of the determination of the lift factor is that it causes a data reduction, since for the action products in the first five weeks of the dataset no average of the last five weeks could be determined. Due to this disadvantage, only the previous five weeks are used to calculate the average. Furthermore, going more weeks backwards in time makes the model less applicable in the future. Since five weeks seems to be the minimal number of weeks to use, it is the most obvious number of weeks to use.

Action characteristics collection
Since an explanatory forecast model is chosen, descriptive data were needed to base the model on. The action schemes made by the commercial department are not made in such a format that data can be gathered easily. However, these are the only files containing the relevant characteristics of the actions. Hence, it is needed to use these files to get these action characteristics. Furthermore, also the action schemes made by the marketing and communication department contain valuable information, like the way of promoting the items in the stores. Therefore, these files and the general action schemes had to be combined to have all valuable data.

Both these action schemes are not created to be used as datasets to get data from. This means that again several VBA macros had to be written to get all data in the right format. Finally, per action SKU per week the following variables were collected:

- Regular selling price (in €)
- Action selling price (in €)
- Discount, both absolute (in €) and in terms of percentage (in %)
- Whether the product is promoted in the promotional brochure or the magazine (two dummy variables):
    - 1: promoted in folder or magazine
    - 0: not promoted in folder or magazine

- Gross profit categorization:
    - 1: Gross profit < 6%
    - 2: 6% < Gross profit < 15%
    - 3: Gross profit > 15%
- Elaborate categorization within the brochure and magazine: AAA, AA, A, in store, theme, back, panel, festive tasty, tested, new, tasted, editorial, coupon, and wine (14 dummy variables):
    - 1: product is presented in action category within the brochure or magazine
    - 0: product is not presented in action category within the brochure or magazine
- Shortened categorization within the brochure and magazine: AAA, AA, A, and in store (four dummy variables):
    - 1: product is presented in action category within the brochure or magazine
    - 0: product is not presented in action category within the brochure or magazine
- Whether a product is completely out of stock when the product is out of stock in the store (dummy variable):
    - 1: Out is out
    - 0: Out is not out
- From which amount of items the action is valid (nine dummy variables):
    - 1: valid with k items, with k = 1, 2, 3, 4, 5, 6, 8, 10, and 12
    - 0: not valid with k items, with k = 1, 2, 3, 4, 5, 6, 8, 10, and 12
- What sort of action it is: 1+1 free, 2+1 free, 2+2 free, 3+1 free, 4+1 free, 5+1 free, 4+4 free, 4+2 free, 6+2 free, 7+2 free, 5+5 free, and second item half price (twelve dummy variables):
    - 1: related to that sort of action
    - 0: not related to that sort of action
- Number of promotional items at the stores: for two different store formulas the amounts of signs, A2 posters, A3 posters, A4 posters, and shelf cards used were registered (ten variables)

Using these variables, it has to be kept in mind that the last four variable categories mentioned are made using the marketing action schemes, meaning that these variables were created based on marketing purposes. This means that whether a products is e.g. an out is out product does only mean that the product is promoted this way. It could be the case that a product is an out is out product, since no more products can be bought after the action week, but this is, for whatever reason, not communicated to the customer this way. Although these variables are thus not really indicating the truth, the customer perceived these actions this way and therefore, these variables are valid to use for forecasting the lift factor of sales in the action week.

The number of variables used in the model, as presented in table 5.1, is smaller than the number of variables available in the data of action characterization. The reason for this is the dataset reduction described next, resulting in dummy variables that only contain zero values.

Data reduction

The total dataset contained products of all departments. However, it turned out that this dataset still contained very high lift factors for several products. Analyzing these high lift factors, many products were found not belonging to the food/non-food (FnF) product department, like e.g. bread products, with changing packaging sizes in the action week, meaning that the lift factor was not based on all non-action sales. Since the goal was to build a reliable model, it was decided to only take into account the FnF products. Within the product grouping of Jan Linders Supermarkets, this meant that only products from the first department with an article number below 700000 were considered. Still, the data contained several low and high lift factors. Lift factors below one are characterized as low, since this means that the sales in the action week are lower than the average sales in regular weeks. These records were deleted from the dataset. For the high values, it was hard to judge whether these were outliers or valid lift factors. Hence, the same outlier deletion method was used as described in appendix D1, based on the interquartile range of the lift factor. This means that the dataset was reduced to records containing a lift factor between 1 and 14.36. This resulted in a total dataset of 3,001 records.

Appendix E3. Spread in the sales data used in the design phase

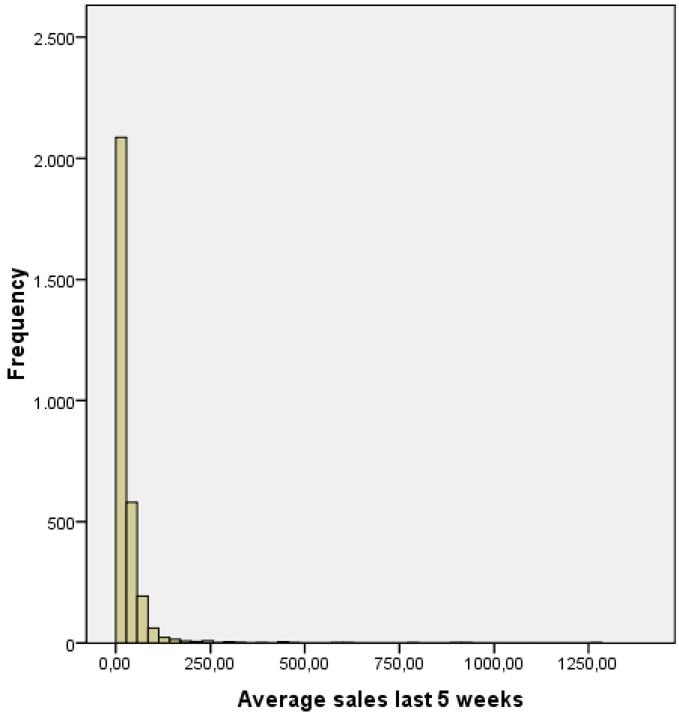


Figure E1: An overview of the average non-action sales found in the dataset used in the design phase

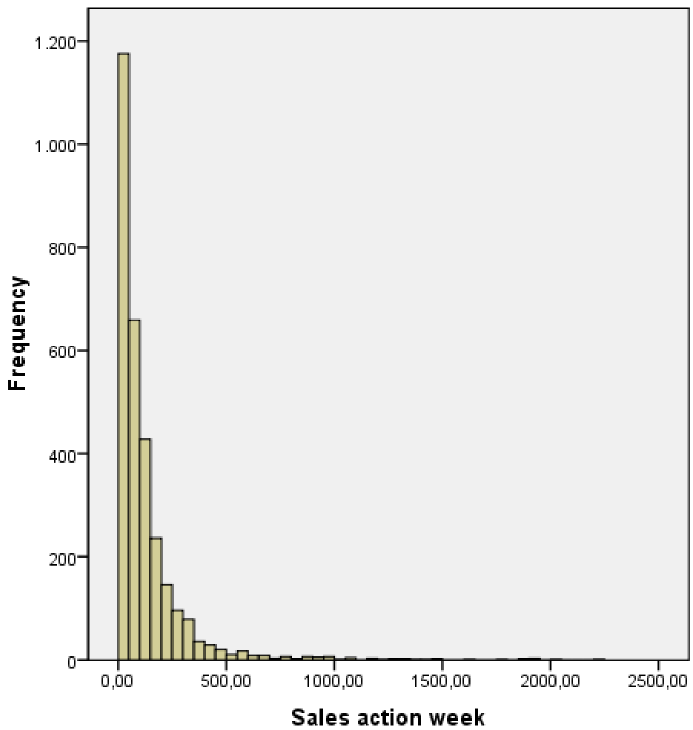


Figure E2: An overview of the sales in the action weeks found in the dataset used in the design phase

Appendix E4. Coefficients of variables in the eight models

Coeffi-cient	Variable description	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8	
		c	p	c	p	c	p	c	p	c	p	c	p	c	p	c	p
c_0	Constant	4.305	0.000	4.372	0.000	4.402	0.000	4.914	0.000	4.219	0.000	3.919	0.000	4.267	0.000	4.334	0.000
c_1	Average sales last 5 weeks	-0.009	0.000	-0.012	0.000	-0.008	0.000	-0.012	0.000	-0.008	0.000	-0.012	0.000	-0.008	0.000	-0.012	0.000
c_2	Special week	-0.174	0.234	-0.927	0.000	-0.181	0.219	-0.953	0.000	-0.092	0.520	-0.705	0.003	-0.093	0.517	-0.696	0.003
c_3	Actions in same department	-0.001	0.602	-0.002	0.637	-0.001	0.507	-0.002	0.549	0.000	0.934	-0.002	0.639	0.000	0.868	-0.001	0.848
c_4	Actions in same main group	-0.026	0.013	-0.034	0.075	-0.025	0.016	-0.038	0.062	-0.025	0.014	-0.022	0.243	-0.024	0.021	-0.027	0.191
c_5	Actions in same group	-0.150	0.000	-0.107	0.000	-0.134	0.000	-0.085	0.003	-0.157	0.000	-0.128	0.000	-0.143	0.000	-0.108	0.000
c_6	Actions in same department last week	0.001	0.729	0.003	0.149	0.000	0.820	0.001	0.737	0.001	0.683	0.003	0.255	0.001	0.729	0.000	0.897
c_7	Actions in same main group last week	-0.019	0.110	-0.047	0.007	-0.022	0.059	-0.047	0.008	-0.017	0.148	-0.045	0.010	-0.021	0.079	-0.045	0.012
c_8	Actions in same group last week	0.044	0.072	0.026	0.416	0.036	0.150	0.021	0.520	0.051	0.040	0.031	0.336	0.042	0.087	0.023	0.476
c_9	Regular price	-0.097	0.411	0.430	0.045	-0.065	0.578	0.436	0.065	-0.124	0.294	0.488	0.021	-0.092	0.428	0.495	0.032
c_{10}	Discount absolute	1.197	0.008	-0.594	0.421	0.948	0.036	-0.749	0.375	1.200	0.008	-0.831	0.256	0.966	0.033	-1.010	0.224
c_{11}	Discount percentage	0.985	0.389	4.985	0.010	2.428	0.046	7.303	0.000	1.190	0.296	5.421	0.005	2.558	0.034	7.898	0.000
c_{12}	Magazine	0.648	0.017	-0.581	0.271	0.720	0.009	-0.214	0.687	0.186	0.388	-0.530	0.134	0.157	0.468	-0.515	0.149
c_{13}	Gross profit category	-0.241	0.032	-0.489	0.004	-0.362	0.001	-0.767	0.000	-0.306	0.006	-0.488	0.003	-0.412	0.000	-0.776	0.000

Table E1: Coefficients of the different models made

Coeffi-cient	**Variable description**	**Model 1**		**Model 2**		**Model 3**		**Model 4**		**Model 5**		**Model 6**		**Model 7**		**Model 8**	
		c	**p**	**c**	**p**	**c**	**p**	**c**	**p**	**c**	**p**	**c**	**p**	**c**	**p**	**c**	**p**
c_{14}	Out is out	0.183	0.353	0.104	0.731	0.098	0.625	0.110	0.721	0.165	0.405	0.155	0.608	0.090	0.651	0.153	0.619
$c_{15,2}$	Valid with 2	0.236	0.139	0.199	0.453					0.195	0.222	0.198	0.453				
$c_{15,3}$	Valid with 3	0.295	0.158	-0.222	0.481					0.275	0.184	-0.200	0.523				
$c_{15,4}$	Valid with 4	-0.197	0.551	-1.593	0.001					-0.100	0.764	-1.622	0.001				
$c_{15,5}$	Valid with 5	-1.085	0.233							-1.721	0.059						
$c_{15,6}$	Valid with 6	2.211	0.048							2.206	0.050						
$c_{15,8}$	Valid with 8	3.661	0.000	4.315	0.000					3.527	0.000	4.350	0.000				
$c_{16,1}$	1+1 free					0.308	0.575	-0.636	0.456					0.254	0.645	-0.587	0.493
$c_{16,2}$	2+1 free					-0.384	0.102	-0.671	0.047					-0.416	0.075	-0.735	0.028
$c_{16,3}$	3+1free					-0.613	0.146	-2.238	0.001					-0.475	0.261	-2.243	0.001
$c_{16,4}$	5+1 free					-0.010	0.992							0.049	0.959		
$c_{16,5}$	Second half price					-0.815	0.000	-1.065	0.000					-0.752	0.001	-1.128	0.000
$c_{17,1}$	Sign (not pilot)	-0.264	0.779	2.007	0.143	-0.627	0.510	2.425	0.085	-0.422	0.656	1.852	0.180	-0.845	0.377	2.133	0.133
$c_{17,2}$	A2 (not pilot)	0.558	0.000	0.472	0.033	0.687	0.000	0.638	0.004	0.565	0.000	0.479	0.028	0.677	0.000	0.611	0.005
$c_{17,3}$	GS (not pilot)	1.405	0.001			1.375	0.001			1.598	0.000			1.562	0.000		
$c_{17,4}$	Sign (pilot)	-0.107	0.802	0.120	0.834	-0.276	0.524	-0.245	0.680	-0.084	0.845	0.245	0.671	-0.219	0.616	-0.083	0.889
$c_{17,5}$	A2 (pilot)	-0.053	0.778	-0.413	0.137	-0.116	0.537	-0.479	0.085	-0.027	0.887	-0.485	0.079	-0.064	0.735	-0.516	0.062
$c_{17,6}$	GS (pilot)	-1.060	0.008	-0.084	0.624	-0.994	0.013	-0.055	0.755	-1.164	0.004	0.082	0.624	-1.098	0.006	0.116	0.496

Table E1 (continued): Coefficients of the different models made

Coefficient	**Variable description**	**Model 1**		**Model 2**		**Model 3**		**Model 4**		**Model 5**		**Model 6**		**Model 7**		**Model 8**	
		c	**p**	**c**	**p**	**c**	**p**	**c**	**p**	**c**	**p**	**c**	**p**	**c**	**p**	**c**	**p**
$c_{18,1}$	Elaborate Cat AAA	5.163	0.000			5.665	0.000										
$c_{18,2}$	Elaborate Cat AA	1.903	0.000	2.250	0.000	2.238	0.000	2.245	0.000								
$c_{18,3}$	Elaborate Cat A	1.092	0.000	1.116	0.000	1.150	0.000	1.145	0.000								
$c_{18,4}$	Elaborate Cat Theme	0.134	0.595	1.011	0.033	0.093	0.714	0.688	0.152								
$c_{18,5}$	Elaborate Cat Back	2.056	0.403	0.526	0.804	2.022	0.414	0.596	0.781								
$c_{18,6}$	Elaborate Cat Panel	1.114	0.112	1.571	0.282	1.145	0.105	1.656	0.263								
$c_{18,7}$	Elaborate Cat Festive Tasty	1.276	0.192	3.225	0.001	0.969	0.325	2.478	0.011								
$c_{18,8}$	Elaborate Cat Tested	2.853	0.001			2.508	0.003										
$c_{18,9}$	Elaborate Cat New	1.393	0.092	-1.221	0.348	1.257	0.131	-1.479	0.261								
$c_{18,10}$	Elaborate Cat Wine	2.222	0.016	5.416	0.000	2.153	0.021	5.293	0.000								
$c_{19,1}$	Shortened Cat AAA									5.082	0.000			5.621	0.000		
$c_{19,2}$	Shortened Cat AA									1.865	0.000	2.321	0.000	2.204	0.000	2.371	0.000
$c_{19,3}$	Shortened Cat A									0.966	0.000	1.184	0.000	1.006	0.000	1.196	0.000
c_{20}	Number of weeks until last action			-0.011	0.473			-0.007	0.671			-0.011	0.481			-0.008	0.620
c_{21}	Sales last action week			0.003	0.000			0.004	0.000			0.004	0.000			0.004	0.000

Note: significance p-values of < 0.05 are tinted, c = coefficient of the variable in the regression model, p = p-value of the significance of the coefficient in the model

Table E1 (continued): Coefficients of the different models made

Appendix E5. Performance measures of the forecasting models

An R square value (or coefficient of multiple determination) is used as a global statistic to assess the fit of a multiple regression model (Montgomery and Runger, 2003). This value represents the part of the variability of the data that is accounted for by the model. In calculating the adjusted R square value, the number of variables being part of the model is considered. This means that this statistic penalizes the analyst for adding more variables into the model.

The $MSE(\widehat{LF_{a,i}})$ is calculated using the following formula:

$$MSE(\widehat{LF_{a,i}}) = \frac{1}{\overline{I} \cdot (A_2 - A_1 + 1)} \sum_{i=1}^{I} \sum_{a=A_1}^{A_2} \left(\widehat{LF_{a,i}} - LF_{a,i} \right)^2$$

with:

$\widehat{LF_{a,i}}$ = forecasted lift factor

$LF_{a,i}$ = realised lift factor

A_1 = first week used, being 6 in the calibration phase and 31 in the validation phase

A_2 = last week used, being 30 in the calibration phase and 41 in the validation phase

The $PL_{a,i}(\widehat{LF_{a,i}})$ performance measure calculated is the same as the one presented in chapter 4, namely the average amount of products left in the stores after the action week, which is determined using the following formulas:

$$PL_{a,i}(\widehat{LF_{a,i}}) = \widehat{LF_{a,i}} \cdot \overline{S_{a-5,a-1;i}} - S_{a,i}$$

$$\overline{PL(\widehat{LF_{a,i}})} = \frac{1}{\overline{I} \cdot (A_2 - A_1 + 1)} \sum_{i=1}^{I} \sum_{a=A_1}^{A_2} PL_{a,i}(\widehat{LF_{a,i}})$$

For clarity reasons, the subscripts are removed from the variables in the main text. Hence, $MSE(\widehat{LF_{a,i}})$ is presented as $MSE(\widehat{LF})$ and $PL_{a,i}(\widehat{LF_{a,i}})$ is presented as $PL(\widehat{LF})$.