MASTER

Design of the periodic weekly delivery schedule at Jumbo Supermarkten
a store-oriented approach

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Design of the Periodic Weekly Delivery Schedule at Jumbo Supermarkten: a store-oriented approach

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Abstract

This report describes a master thesis conducted at Jumbo Supermarten B.V. The master thesis considers the design of an approach to generate the periodic weekly delivery schedule, a schedule that determines:

- At what time a store manager is required to order at the distribution centre for its various categories of products;
- At what time (corresponding to a certain moment of ordering) the store will receive the ordered goods at their store.

An integrated supply chain planning approach is presented that makes use of a hierarchical planning framework based on Schneeweiss (2003). The model which is formulated by Broekmeulen and Van Donselaar (2012) makes use of a store oriented approach, where each individual store is able to locally choose a schedule based on an anticipated base model that contains expected costs for transportation and for the distribution center (DC). By influencing the anticipated base model, we can smooth the supply chain workload and generate a set of schedules which has a good supply chain performance.

Preface and acknowledgements

The report is the result of my graduation project for the master Operations Management and Logistics (OML), at the sub department Operations Planning and Control (OPAC). The project was conducted at Jumbo Supermarkten B.V., more specifically at the Supply Chain Management department.

First of all, I would like to thank my two university supervisors. I thank Karel van Donselaar for his guidance during the last one and a half year of my master. I appreciated his flexibility in making appointments and his enthusiastic attitude towards the project. Furthermore I would like to thank Rob Broekmeulen for his large contribution to this project, in which he invested more time than he was obliged to do as a second supervisor.

Second, I would like to thank my two company supervisors, Jan and Guido. The continuous interest and support throughout the project, the help with finding the right persons and data in such a large organization and the honest and critical look at my work were inevitable to this project. Apart from this project related aspect, I would like to thank you and all the other colleagues at Jumbo Supermarkten for the pleasant company during the past months. Ad, Albert, Cornée, Enrico, Peter, Sander, Pier and the Supply Chain Operators; thank you for the nice working environment in the past months!

Finally, I would like to thank my friends and family. Your unconditional support and your ongoing encouragement have helped through the whole project. In particular, I would like to thank my parents: not only for their contribution to my master thesis as such, but for the relentless support in the past 24 years.

Management summary

This report is the result of a master thesis conducted at Jumbo Supermarkten B.V., a grocery retail chain in the Netherlands. Over the past years the company has expanded rapidly and with the acquisition of the Dutch supermarket chain C1000 in 2012, the company will have an estimated turnover of 7,0 billion euro per year, a market share of 20 percent and 600 stores.

Analysis of the problem context

This master thesis considers the periodic weekly delivery schedule (PWDS), a schedule which determines at what time a store manager is required to order at the distribution center and at what time (corresponding to a certain moment of ordering) the store will receive the ordered goods at the store. Figure 3 in chapter 1 shows that regarding this process, store handling costs and costs for the distribution center both comprise about 40 % of the total relevant cost distribution. Transportation accounts for the remaining 20 %. From these results it was concluded that in contrast to the current process which is based on a sub optimization per step in the supply chain, a supply chain integrated planning approach is needed. The current process is labor intensive and the outcome of the process is a result of multiple iterations between the stakeholders in the process. This leads to the problem statement as follows:

How can Jumbo Supermarkten B.V. generate a Periodic Weekly Delivery Schedule that has the lowest total cost for the supply chain and takes into account all constraints?

This question is accompanied by two sub questions:

1. *How can Jumbo Supermarkten B.V. simplify the process of designing a Periodic Weekly Delivery Schedule?*
2. *How can Jumbo Supermarkten B.V. increase the performance (i.e. reduce costs) of the Periodic Weekly Delivery Schedule, and what is the influence of the backroom on this performance?*

Conceptual model

Based on the analysis, a model is developed that is based on the hierarchical planning framework of Schneeweiss (2003). The model consists of a top level (a store) and a base level (transportation and DC), where the top model makes decisions based on an anticipated base model. Thus, each store individually makes the choice for a schedule based on an instore cost model and the anticipated costs for the remainder of the supply chain (the anticipated base level). By means of influencing the antipated base level costs, we can influence the schedule choice and thereby, the workload for transportation and the distribution center.

The anticipated base model contains the anticipated base costs and capacities for transportation. To avoid stores to be privileged or prejudiced based on the distance to the distribution center, we include a parameter in the model which resembles the costs per drop which is the same for all stores.

To account for the costs of the distribution center in the anticipated base level, we introduce a smoothing tariff. Changing the smoothing tariff (per roll container per timeslot) gives the opportunity to smooth the workload since top level decisions by the store can be influenced by changing the smoothing costs.

Analytical model

This master thesis makes use of the analytical model of Broekmeulen and Van Donselaar (2012). The model is deterministic and makes use of the framework of Schneeweiss (2003).

Beta(it)

The model of Broekmeulen and Van Donselaar (2012), contains a parameter beta(it) which resembles the fraction of total sales for store i and timeslot t which are sold from shelves requiring concurrent replenishments.

When beta is equal to one, the complete expected delivery volume does not fit in the shelves in the timeslot of delivery. Hence, the expected delivery volume needs to be placed in the backroom. The volume will be stacked during remaining timeslots in the review period and the concurrent volume in the backroom decreases in line with the sales pattern.

In contrast, when beta is equal to zero, the store can stack the complete expected delivery volume in the shelves immediately. Hence, this leaves more room for instore optimization. Hence, the parameter has two effects:

- First, beta (it) has direct influence on the schedule choice in combination with handling costs due to the fact that the fraction concurrent is stacked in the model by means of fulltime workers.
- Second, beta(it) has an indirect influence on the schedule choice in combination with handling costs due to the fact that the fraction concurrent determines the constraining effect of the backroom.

Chapter 3 of this master thesis specifically focuses on the analysis of the parameter beta(it). The analysis firstly showed that the quality of the SAP shelf capacity data was not as good as expected, at least for very fast moving products. A data quality check for 18 stores and 3 very fast moving products per store, showed that for these products the actual shelf capacities are on average 116 % higher than the shelf capacities in SAP. Due to the fact that SAP shelf capacity is used to perform an instore logistical optimization, an improvement of data quality can lead to a more smoothed store demand and thereby to large cost savings in the remainder of the supply chain.

Secondly, after a choice for the definition of beta as described in section 4.1, the analysis focuses on approximation of beta(it). The original computation of beta(it) according to the definition occurs per product per store which causes a very high demand for computational resources. Approximation by means of readily available data increases the efficiency of the model. The approximation was split up in two parts: approximation of gamma(i), which represents the average of beta(it) over all timeslots, and an approximation of the seasonal effect of beta(it) represented by alpha(it).

The approximation of the two parameters yielded three conclusions:

- Regression analysis does not show a significant relationship between turnover pressure (turnover in Euros per square meter store floor area) and gamma(i).
- Regression analysis showed a significant relationship between turnover share beer and turnover share coke and soda.
- Approximation of alpha(it) by means of a store dependent seasonal index parameter of the consumer turnover per day does not yield a good approximation. Beta(it) has a much larger amplitude and a generic correction for the difference in amplitude does not yield better results than approximation of beta(it) by means of time independent parameter gamma(i).

Numerical study

To start with the numerical study of the approach of Broekmeulen and Van Donselaar (2012), chapter 5 considers the input data of the model. An important conclusion is that although the approach of Broekmeulen and Van Donselaar assumes that the (expected) delivery volume is equal to the sum of sales during the review period, data analysis shows that stores make use of order advancement. This means, stores order more at the beginning of the week and stores order less at the end of the week leading to an over- or underestimation of the expected delivery volume for a certain store and a certain schedule.

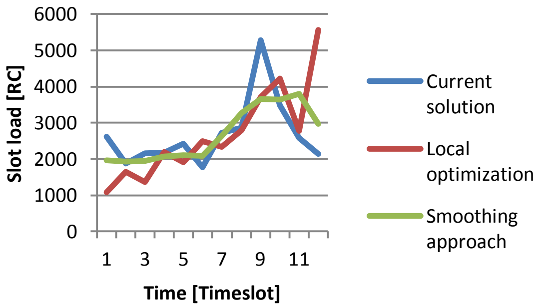

Figure 1: Aggregated load per timeslot

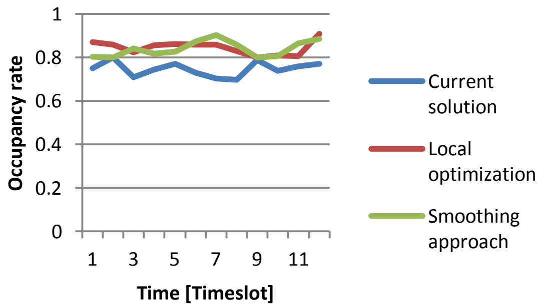

Figure 2: Occupancy rate per timeslot

Regarding the output of the model of Broekmeulen and van Donselaar (2012), we can draw five conclusions.

First, the approach of Broekmeulen and Van Donselaar (2012) is able to reduce the peak load in the distribution center as is shown in figure 1. Reduction of peak loads is beneficial for the distribution center in two manners:

- First, the reduction of peak loads leads to a lower demand for (flexible) temporary workers.
- Second, a peak load causes a reduction of the labor productivity due to congestion in DC corridors which indirectly increases costs.

Second, the approach of Broekmeulen and Van Donselaar (2012) is able to decrease Jumbo's transportation costs by means of a better matching of supply and demand as shown in figure 2, for respectively truck capacity and roll containers. In contrast to the current situation at Jumbo Supermarkten, the approach takes into account the expected delivery volume versus truck capacity at the moment of schedule selection instead of conducting a sub optimization later in the process.

Third, allocation of a relatively small tariff can already provide an incentive to the stores that is large enough to balance the DC workload to a large extent. A maximum smoothing tariff of € 2 per roll container per timeslot showed a much more smoothed workload distribution.

Fourth, the distribution of the number of delivery days which is obtained by the approach of Broekmeulen and van Donselaar (2012) is comparable on average with the current distribution of the number of delivery days used by Jumbo Supermarkten. However, the result per store obtained from Broekmeulen and Van Donselaar (2012) showed a much larger standard deviation.

Fifth, for 117 out of 122 stores the delivery frequency is equal to the minimal delivery frequency. The 5 stores with a deviating delivery frequency showed an increase of the delivery frequency with exactly one delivery. Hence, regarding the fact that delivery frequencies are more or less fixed, the approach of Broekmeulen and Van Donselaar (2012) mainly contributes by optimizing the distribution of delivery days.

Conclusion and recommendations

The research question consists of two sub questions. The first research question considers how Jumbo Supermarkten can simplify the process of designing a periodic weekly delivery schedule (PWDS). The current schedule generation process consists of many steps and many stakeholders which leads to a labour intensive and time consuming process. The model has shown to provide good results where the time needed for schedule generation is limited to about 40 minutes. Thus, the introduction of an integrated schedule generation system can shorten the lead-time of the schedule generation process and reduce the (human) resources needed to generate the schedule.

The second research question considers how Jumbo Supermarkten can increase the performance of the PWDS. As shown in chapter 6, the approach of Broekmeulen and Van Donselaar (2012) has the potential to improve the performance of the model output. The integrated approach leads to a better match between supply and demand of respectively capacities and roll containers. This has the potential to reduce peak loads for the DC, costs for transportation and yield better schedules for stores.

Recommendations for Jumbo Supermarkten

The supply chain cost composition discussed in chapter 1 gives evidence for the introduction of a supply chain oriented planning process. Regarding the improvement that can be made on both process and performance, one recommendation for Jumbo Supermarkten is to implement a new supply chain planning system which aims at the generation of an integrated planning with benefits both for process and for schedule performance.

Second, chapter 4 showed that the quality of the SAP shelf capacity data of very fast moving prodicts is lower than expected. Hence, it is recommendable to investigate:

- To what extent this sample size is representative for all products and all stores;
- To what extent the workload balancing for transportation and for the DC can be improved by an improvement of the data quality within the stores;

Subsequently, it can be beneficial to provide incentives for stores to increase the SAP data quality. Stores show large differences in terms of variability of store demand. Hence, it is recommendable for Jumbo to investigate the extent to which it is possible to influence store order behavior.

Table of contents

List of figures

List of tables

List of abbreviations

Abbreviation	Variable definition
(s,nQ)	Inventory policy where the AOS orders if the inventory position is lower than a predefined order level s. The ordered quantity is always a multiple n of a certain quantity Q (e.g. a casepack).
ABL	Anticipated Base-Level
AOS	Automated Order System
BRC	Backroom Capacity
CU	Consumer Unit
CV	Coefficient of variation
DC	Distribution Center
KPI	Key performance indicator
MAD	Mean absolute difference
MST	Maximum smoothing tariff
NDC	National Distribution Center
PWDS	Periodic Weekly Delivery Schedule
RC	Roll-containers
RDC	Regional Distribution Center
SCM	Supply Chain Management
SKU	Stock Keeping Unit
TB	Time block
TWL	Target Workload

Introduction

The current retail environment can be characterized as extremely competitive. High customer expectations combined with intense competition lead to the difficult task of achieving high (logistical) performance while selling products with low margins. To guarantee this high performance, an effective and efficient retail supply chain is of vital importance. To realize this cost effectiveness, a supply chain-broad view on planning is necessary.

The basis for this report is a project at Jumbo Supermarkten, the second largest supermarket chain in the Netherlands. Subject of the project is the Periodic Weekly Delivery Schedule (or in Dutch: Bestel- en Afleverschema), determining *which* product categories have to be ordered and *when* to be delivered on a certain moment in time. More about the Periodic Weekly Delivery Schedule (PWDS) will be explained in chapter 1.

The master thesis should both contribute to the research available on retail supply chain planning and it should yield an approach for the generation of periodic weekly delivery schedules. This can provide a basis for an integrated planning system that could be implemented at Jumbo Supermarkten. Given these goals, the following chapters will provide such an approach which allocates the delivery of stores to a certain timeslot.

This report consists of seven chapters. Chapter 1 introduces the problem context and formulate the research question. Chapter 2 and chapter 3 consider the formulation of the conceptual and analytical model, respectively. Chapter 4 focuses on the analysis on the analysis of one specific parameter of the model, beta(it). Chapter 5 contains a numerical study of the analytical model. Chapter 6 addresses the implementation of the model. Finally, chapter 7 concludes the report and formulates recommendations for Jumbo Supermarkten.

Chapter 1: Introduction of the research context

To start with, this chapter focuses on a delineation of the research context. The purpose is to get an idea of the problem context and to show understanding on this topic (van Aken et al., 2007). For the sake of structure, this chapter is separated in four parts. The first part mainly focuses on the internal context of the problem within the company and it contains a brief view on the company's history, organizational issues and the distribution structure. The second part treats the external problem context which embraces the positioning and developments of the supermarket chain. The third part addresses the direct problem context of the problem. Finally, the fourth part considers the problem definition.

1.1 Internal problem context

1.1.1 Company establishment

The master thesis has been carried out at Jumbo Supermarkten, a grocery retail chain in the Netherlands. Originated as a family owned wholesale company in 1921, the transition to self service supermarket created the opportunity for the wholesale company (by that time still known as the van Eerdt groep) to vertically integrate by acquiring several supermarkets. After trying several formulas the "Jumbo" formula, acquired by the company in 1983, has proven great success in the past decades. Especially over the past years the formula has expanded rapidly and the recent acquisition of the Dutch C1000 supermarkets in 2012 will lead to an almost doubling of the number of supermarkets owned by the company. The takeover is approved by the Netherlands Competition Authority, and at the end of the integration process Jumbo Supermarkten will become the second largest grocery retail chain in the Netherlands. The new combination will have an estimated turnover of 7,0 billion Euro per year and a market share of about 20 percent generated in more than 600 stores supplied by 5 distribution centers. The company is still wholly owned by the van Eerd family.

Currently, Jumbo Supermarkten is in the middle of the integration process with C1000. This has implications for, for example, the number of distribution centers and the number of stores although the logistical structure as such will remain unchanged. To avoid confusion, we will consider the situation prior to the integration of C1000 in the remainder of this report.

1.1.2 Mission & vision

The mission of the company is clear, the company aims at acquiring a permanent market leader position in every place where a "Jumbo"-store is located. The formula is well known for the fact that it promises to provide "customer service to the extreme" combined with an Every-Day-Lowest-Price guarantee. With this formula the company operates on the edge, providing unique value to their customers. The company enforces this customer-minded culture with its "seven daily securities" (in Dutch: "zeven dagelijkse zekerheden"), seven rules that guarantee good service to customers every day.

1.1.3 Internal structure

Within Jumbo Supermarkten B.V. basically all parties relevant for the problem fall under the responsibility of the Supply Chain Management director, apart from the Store Operations department. Apart from three facilitating departments, the Supply Chain Management department is split up in four sub departments:

- Department *"Logistiek"* which is responsible for the functioning of the distribution centers;
- Department *"Productie"* which is responsible for the two production departments, the butchery and the flowers & plants department;
- Department *"Transport"* which is responsible for planning and operationalization of the transportation function;
- Department *"Replenishment"* which is responsible for the replenishment of the DC's and stores.

The organizational chart is shown in appendix i. Schedule generation is done by the (tactical) replenishment department, in consultation with the stores, the Logistical Planning department, the DC-managers and Transport.

1.1.4 Logistical structure

Jumbo Supermarkten works with a distribution structure consisting of Regional Distribution Centers (RDCs) which are used for fast moving products, and National Distribution Centers (NDCs) for slow moving products. Within these two types of distribution centers there is a difference in conservation circumstances needed, which results in a distinction between DC's for dry groceries, fresh goods and frozen goods.

Geographically, the stores of Jumbo Supermarkten are more concentrated in the south of the Netherlands although the chain is moving more northwards over the past years, especially after the acquisition of the supermarket chains Super de Boer and C1000. The 300 stores of Jumbo Supermarkten prior to the integration of C1000 are currently supplied by two DCs: one DC in the north of the Netherlands (DC North) and one DC in the south of the Netherlands (DC South).

The distribution center in the south of the Netherlands is about twice or triple as large as DC north, depending on the unit of measurement. DC South is currently working in a two shift structure and operates at nearly full capacity. DC North is currently working in a one shift structure and has capacity to expand and to handle more stores than the DC is doing at the moment.

All stores are allocated to either DC North or DC South for a certain product group (dry groceries, fresh produce, frozen goods). The allocation of stores to distribution centers is done based on both cost and capacity considerations. Certain stores which should be allocated to DC South regarding transportation costs are currently allocated to DC North for capacity reasons.

1.1.5 Supply chain cost analysis

A supply chain cost analysis gives an indication of the cost-based influence of the three supply chain steps on the periodic weekly delivery schedule. An estimation of the relevant cost per chain which is elaborated in appendix iii leads to an overall view on supply chain costs for the PWDS, shown in figure 3.

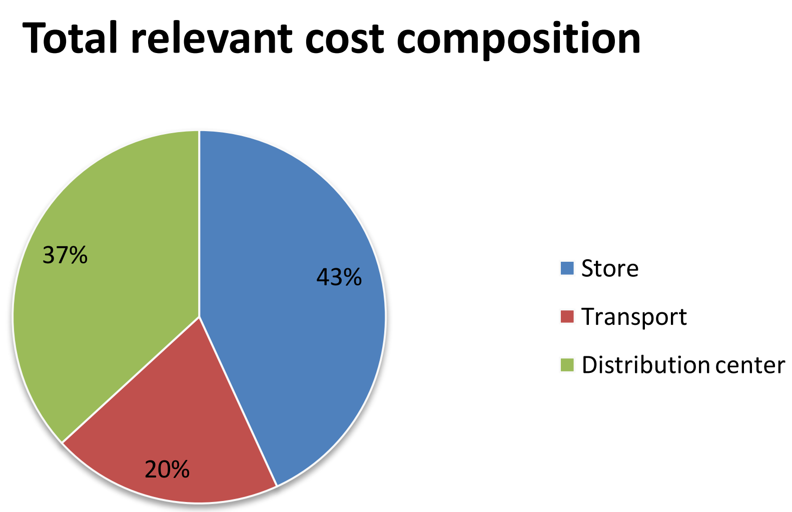

Figure 3: Total relevant cost composition

This result matches the supply chain cost composition as given by Broekmeulen (2004). Although the costs included in the cost composition are all relevant to the PWDS, it is not possible to draw a conclusion about the extent to which these costs can be influenced as such. Based on the cost composition one can conclude however, that a planning system which is purely aimed at minimizing transportation costs is likely to produce inferior results compared to a system that takes into account the other supply chain steps as well.

1.2 External context

Jumbo Supermarkten B.V. is acting in an environment which is very dynamic. With a fast growth over the past decades the challenges are high for the company and the logic/supply chain department in particular. The takeover of other supermarket chains combined with an autonomous growth causes an almost continually changing logistical structure and an increasing demand for capacity for transportation and distribution centers.

The most recent data available, the market shares of supermarkets in 2010 shown in table 1, show the stepwise growth of Jumbo Supermarkten in the past years. On top of this, the takeover of Super de Boer in 2009 and of C1000 in 2012 will make Jumbo Supermarkten the second largest supermarket chain in the Netherlands. Jumbo Supermarkten tries to find the combination between high service and low prices (EDLP) which leads to the positioning of the supermarket chain in the middle segment as shown in figure 4. Locally, the main competitors on price are the price discounters in the middle segment. Albert Heijn, the largest supermarket chain of the Netherlands, is the largest player on national level with the largest buying power.

		2007	2008	2009	2010
1	Albert Heijn	29.5%	31.3%	32.8%	33.6%
2	C1000	14.3%	13.2%	11.7%	11.5%
3	Aldi	8.9%	8.5%	8.3%	7.9%
4	Plus	6.0%	6.1%	6.0%	6.0%
5	Lidl	4.0%	4.8%	5.4%	5.6%
6	Super de Boer	7.3%	6.8%	6.5%	5.5%
7	Jumbo	4.4%	4.8%	4.9%	5.5%
8	Detailconsult	-	-	4.2%	4.2%
9	Coop	2.4%	2.5%	2.4%	2.5%
10	Spar	1.9%	2.2%	2.3%	2.2%

Table 1: Top 10 market shares Dutch supermarket chains, chain structure start of 2011 (Nielsen,2011)

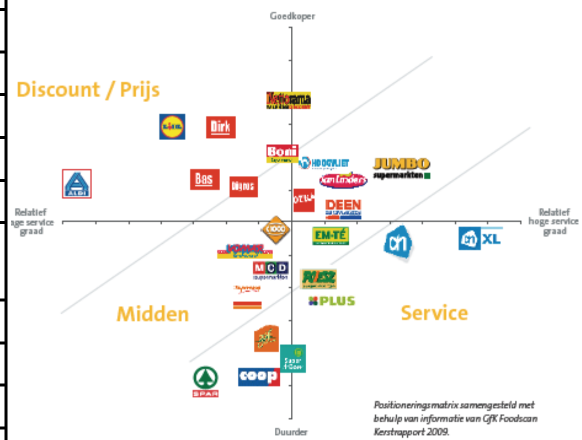

Figure 4: Positioning of Jumbo Supermarkten (GfK-Foodscan, Kerstrapport 2009)

1.3 Direct problem context

Subject of the master thesis involved is the Periodic Weekly Delivery Schedule (or in Dutch: Bestel- en Afleverschema) of which an example is shown in appendix ii. In short, the Periodic Weekly Delivery Schedule (PWDS) determines:

- At what time a store manager is required to order at the distribution centre for its various categories of products;
- At what time (corresponding to a certain moment of ordering) the store will receive the ordered goods at their store.

Due to this central role in the retail supply chain, the planning and execution of this schedule has consequences for four different steps in the supply chain:

- The schedule influences the *stores*. The PWDS determines the daily operations at the store, which influences factors such as workforce scheduling, shelf stacking efficiency and available backroom capacity;
- The schedule influences *transportation*. The schedule determines the frequency and time of delivery which influences for example, occupancy rates and hiring decisions for extra truck capacity in terms of quantity and type.
- The schedule influences the *distribution centers*, both regional and national. The PWDS almost completely determines the workload at a given moment in time and thereby, it influences factors such as workforce hiring, the degree of congestion caused by a certain workload and dock planning constraints;
- The schedule influences *manufacturers*, primarily in an indirect manner. As described before, the PWDS determines the workload at the dock station and in the distribution center. Since retail chains demand high logistical performance from their suppliers, such as high speed delivery with high reliability, the schedule determines the (cross) docking constraints for manufacturing. However, since the PWDS is designed by the retailer, the costs factors involved at the supplier are often left out of scope by the retail chain when developing the schedule.

Concluding, one can say that the PWDS is the logistical thread through the company involving a large number of stakeholders inside and outside the company. Since all these parties claim their influence on the schedule, the establishment of such a schedule is not an easy process and time is needed to accomplish this. At the moment, the Periodic Weekly Delivery Schedule of Jumbo Supermarkten is developed involving a total number of 74 steps, according to a process description. The process can roughly be grouped in the following steps:

- Determining the supply chain characteristics; Acquiring the characteristics of stores, transport and DC such as opening times and storage capacities;
- Generation and communication of the conceptual version;
- Adjusting schedule to comments if needed and communicating the final version;
- Operationalizing the PWDS: generating the workload schedule, personnel planning, dock planning, wave planning, etc.;
- Evaluation.

The current process is the result of a constant adaptation of the planning process, which eventually results in a solution that works. Some factors not taken into account in the process; others are taken into account in a simplified manner. For example, variation in the store demand forecast is taken into account by adding a certain percentage to each forecast and using this as the input demand data for the logistical planning program which makes use of artificially enlarged truck capacities.

The process makes (direct or indirect) use of several different systems (store replenishment system, DC WMS system, tactical transport planning system) and these different systems are coupled via handmade excel spreadsheets. The current process takes into account different types of capacities and the solution looks reasonable.

1.4 Problem definition

The goal of this paragraph is to formulate the research question, based on two parts. First, it will be formulated based on gaps in the literature on the topic of the PWDS as formulated in the literature review and second, the company's problem statement.

1.4.1 Literature review

In the literature review conducted prior to this master thesis (van Dun, 2012), several areas were identified as suitable for further research. The integration of all supply chain cost factors in one approach was identified as the main gap in the literature and suitable for further research. Research on the topic of the PWDS was mainly concentrated by transportation issues, thereby leaving the other steps of the supply chain out of scope (e.g. Gaur, 2004). The inclusion of workload balancing in the distribution center and store costs and capacities will ultimately lead to the best supply chain planning.

1.4.2 Company problem definition

An intake meeting and interviews with several employees of Jumbo Supermarkten B.V. supplied information for the cause and effect tree. All interviewees were somehow related to the Periodic Weekly Delivery Schedule. The general conclusion is that the current process of generating a set of schedules works, but it is more the result of an incremental development than an integrated supply chain approach. The large number of steps in the process, the large number of stakeholders and the large number of workarounds leads to a labor-intensive and time consuming process. In addition, interviewees indicate that an integrated supply chain approach that makes use of an integrated approach has the potential to yield a better set of schedules. The information gathered during the interviews leads to the cause-and-effect diagram shown in figure 5.

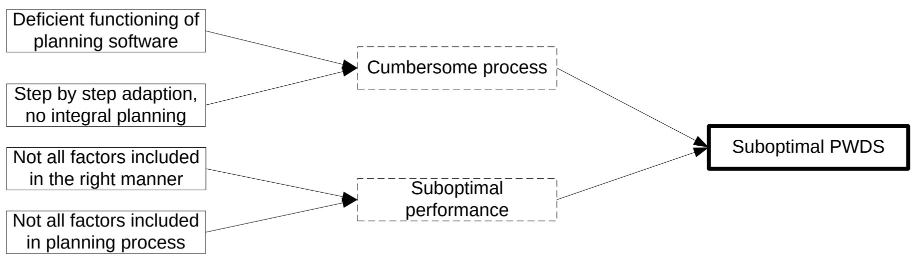

Figure 5: Cause-and-effect diagram

The fact that the two sub problems, process and performance, go hand in hand when (re-) designing the solution, makes the choice for "suboptimal PWDS" a sound starting point of the project with the following problem statement:

The current procedure for generating the PWDS at Jumbo Supermarkten is inefficient and, presumably, also ineffective.

1.4.3 Research question formulation

The preceding section aligned the problem statement at Jumbo Supermarkten and section 1.4.1 showed a summary of the literature review conducted for this study. The combination of these two is combined into the following research question:

How can Jumbo Supermarkten B.V. generate a Periodic Weekly Delivery Schedule that has the lowest total cost for the supply chain and takes into account all constraints?

This question is accompanied by two sub questions:

1. *How can Jumbo Supermarkten B.V. simplify the process of designing a Periodic Weekly Delivery Schedule?*
2. *How can Jumbo Supermarkten B.V. increase the performance (i.e. reduce costs) of the Periodic Weekly Delivery Schedule, and what is the influence of the backroom on this performance?*

The first goal of this master thesis preparation is to make a contribution to academic literature available on this topic. This goal will be achieved by the focus of the thesis on integrated supply chain planning, instead of limiting the focus to transport planning. In this supply chain focus on planning, the analysis of the influence of the backroom capacity on this schedule and on the in store logistics is interesting for academic literature, due to the limited amount of research available and the large potential influence on handling costs. The second goal is to yield an approach for the generation of periodic weekly delivery schedules.

Chapter 2: Conceptual model

The prior chapter considers the introduction of the research context. This chapter outlines the development of a conceptual model. Section 2.1 considers the discussion of cost factors involved with the schedule generation. Section 2.2 outlines the problem context. Section 2.3 describes the current conceptual model and section 2.4 considers the development of a new conceptual model. Finally, section 2.5 describes the final conceptual model.

2.1 *Cost factors*

This section outlines the cost composition per supply chain step; the detailed modeling of each cost component will be treated later in more detail.

2.1.1 Store

Within a store, the largest fraction of costs such as salary costs for cashiers and housing costs has to do with daily operations which are independent from the delivery schedule. For the model, we will only consider costs that are dependent on the selection of the delivery schedule.

When a delivery arrives at a store, in general products are placed in the backroom and these products can be stacked during planned replenishment. However, when the delivery volume does not fit in the backroom this requires immediate shelf stacking which affects handling costs. Hence, the influence of the periodic weekly delivery schedule will be assumed to be limited to handling costs. Store handling costs will be modeled by means of a cost and capacity model which depends on arrival time block of a delivery at the store.

2.1.2 Transport

The transportation supply chain step within Jumbo uses a cost realization composition which contains [redacted] components: [redacted] The first [redacted] cost components are variable in a linear manner [redacted]. The last cost component [redacted]

The [redacted] costs components consider the costs for planned routes where the expected delivery volume does not exceed the truck volume. However, to penalize for the exceedance of truck capacity and to take into account extra overhead costs that need to be made operationally, a [redacted] cost component must be included which consists of the extra operational costs for route overflow.

2.1.3 Distribution Center

The performance of the distribution center is based on the aggregated number of containers of all routes departing from the distribution center within a certain time slot. Therefore, the costs for the distribution center per time block are dependent on the aggregated set of routes that depart from the distribution center during that time block.

2.2 Problem context

The prior section illustrated the cost composition of the three supply chain steps involved. However, all three supply chain steps' costs depend on a different timeslot:

- DC costs depend on the DC departure timeslot;
- Transportation costs depend on the clustering of stores, i.e. the extent to which deliveries for multiple stores are combined in one route;
- Store handling costs depend on the store arrival timeslot;

Figure 6 illustrates the difficulty of the problem: the factors are linked, since the lead-time from the moment of departure at the DC until the moment of arrival at the store is variable due to clustering. In other words, the dependency has a hierarchical form as shown in figure 7 which depends on the definition of either the store as the starting point of the hierarchy or the definition of the DC as the starting point of the hierarchy.

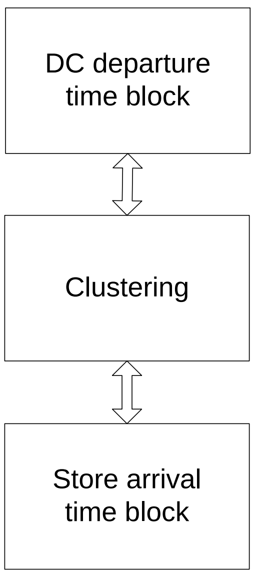

Figure 6: Supply chain cost dependency

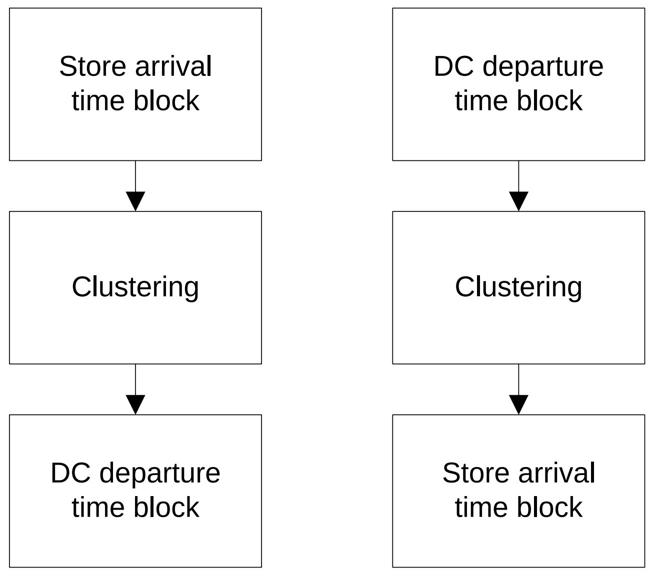

Figure 7: Hierarchical supply chain dependency, Option 1 (left) and Option 2 (right)

The choice for the store arrival time block or the DC departure time block as the starting point of the model has large implications on the (conceptual) modeling, since it defines the mutual dependency within the supply chain. Hence, two options are possible:

- Define store arrival time block as the starting point, as shown in option 1 in figure 7. This would define the delivery schedule at the store first, based on the time block of arrival, followed by clustering and consideration of the DC workload.
- Define the DC departure time as the starting point, as shown in option 2 in figure 7. This would define the delivery schedule at the distribution center first, based on the DC departure time block, followed by clustering routes and consideration of the store costs.

Since costs for the store are more influenced by time block variability than costs in the DC which are based on aggregated volumes, we will continue under the definition of the time block of arrival at the store as the starting point of the model. Thus, the hierarchical structure is defined as shown in option 1 of figure 7. A schedule will give an overview of the time slots in which a store will receive a delivery, and in which time slots it does not.

The interdependence of the supply chain steps has a hierarchical form, as shown in figure 7. To model this dependence the hierarchical planning framework as introduced by Schneeweiss (2003) is used, which is shown in figure 8. This model makes use of an anticipated base model, a model which anticipates on the reaction of the base model. An example of this hierarchical structure is the instruction of the operational production department by the strategic production planning department. The anticipated base model here resembles the anticipated reaction of the operational production department.

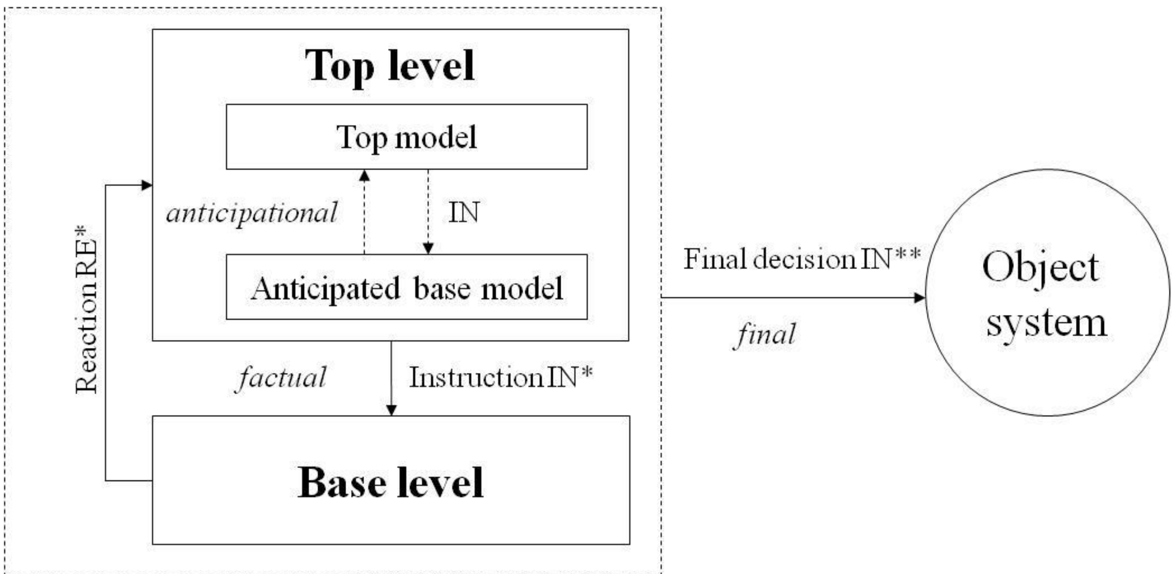

Figure 8: Interdependency of hierarchical levels, planning concept based on Schneeweiss (2003)

The hierarchical problem context defined in the prior section can be defined in terms of this framework as well. In line with the hierarchal dependency as discussed in the prior section, the store supply chain step forms the top level. Based on a cost and capacity model, the top model defines can calculate costs for each of the optional schedules.

In addition, the store will consider the anticipated supply chain costs per schedule for transportation and handling in the distribution center. The combination of the instore handling costs and the anticipated base level costs eventually leads to the local choice for the schedule with the lowest combined supply chain costs as shown in figure 9. The following two sections describe the current conceptual model of Jumbo Supermarkten and the design of a new conceptual model.

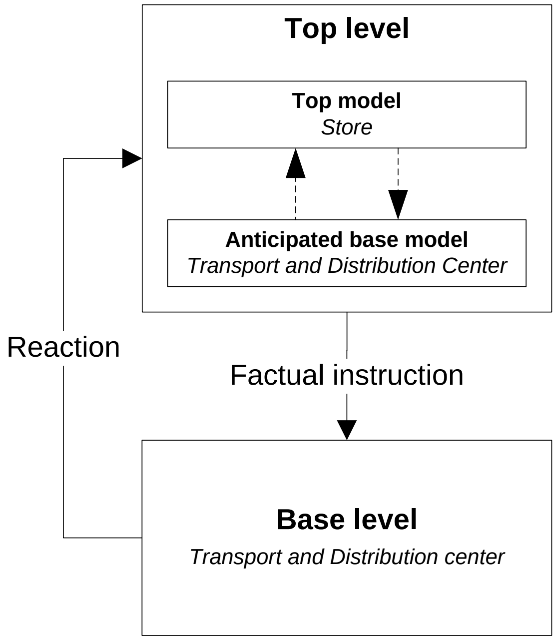

Figure 9: Conceptual model description

2.3 Current conceptual model

Currently at Jumbo Supermarkten, a hierarchical decompositioning approach is used in which candidate schedules are selected based on a combination of company rules, based on turnover and turnover pressure, and an instore capacity simulation.

Based on the output of this step, the set of schedules with the minimal store handling costs is used to determine a transportation clustering and finally to calculate the influence of this candidate on the DC. Figure 33 in appendix iv resembles this process. A result of the design of this conceptual model is that candidates for the base model are “biased”, since the current “top level” selects only one candidate schedule per store. This constraints the optimization by transportation and the distribution center to sub optimization given a certain set of schedules, instead of influencing the schedule choice.

Although the current solution can be improved by means of iterations after feedback of the base model, the end result is likely to improve at a slow pace since the candidates’ priority is still based only on store costs and capacities.

2.4 Anticipated base model with supply chain costs

As explained above, the inclusion of an estimation of transportation and distribution center costs gives the best anticipation for the base model. To define the model, the first step is to cope with the dependency of supply chain costs on the cluster’s lead time of the distribution center, the store and transportation. To cope with the lead-time dependency on clustering of stores in one route, constant lead-time is assumed. Furthermore, we assume that all routes depart from the DC and arrive at the store within the same time block. This is realistic due to the close proximity of stores relative to the DC. Hence, we assume a lead-time which is equal to zero for all stores. Based on the assumption of a constant lead-time which is equal to zero, an anticipated base model can be formulated which estimates the transportation and distribution center's costs.

2.4.1 Transportation costs

As discussed in section 2.1.2, the cost composition for transportation within Jumbo Supermarkten is based on [redacted] cost components [redacted] To incorporate the costs in the model that need to be made in case of route overflow (i.e. sum of delivery volumes for stores in a route exceeds truck capacity), expected overflow costs need to be included. Based on these [redacted] components the expected transportation costs for a delivery from the DC to a certain store can be estimated, by assuming a single store route.

However, when we include a store dependent estimation of the expected transportation costs in the anticipated base model, this will prejudice stores with a large distance and privilege stores with a relatively small distance to the DC. In practice, this will lead to a situation where for two comparable stores in terms of consumer turnover, the delivery frequency for a store near the distribution center will be high and the delivery frequency of a store relatively far from the distribution center will be low. This is not in accordance with the equality principle which is used within Jumbo Supermarkten considering the equal treatment of stores. Hence, instead of using an estimation of the actual transportation in the ABL, a new parameter is introduced which represents the costs per drop. These drop cost should give an indication of the costs per drop, but the value of the parameter does not differ per store.

2.4.2 Distribution center

As can be seen in the prior section, the costs for transportation in the anticipated base model can be estimated by assuming a single store delivery or by means of including drop cost in the model. Since costs for the distribution center are completely based on the aggregated volumes, it is not possible to determine the exact expected costs for a certain schedule in the DC. However, if we do not introduce costs in the model for the distribution center, it is likely that the distribution center will experience extremely volatile workload distribution.

Thus, in order to result in a supply chain wide optimization, certain stores will have to have a schedule which is not per definition optimal as such for that specific store. The introduction of a fictitious cost parameter is a manner to balance the workload and by means of adapting the parameter we can influence the workload for a certain timeslot. Hence, the store is "compensated" to receive a sub optimal schedule, which incorporates the sensitive subject of the distribution of earnings in the model.

Since decisions on the top level will be taken based on the anticipated base model, the next step is to further specify this model.

2.5 Final conceptual model definition

When we aggregate the results of the discussion in the prior section, the formulation of the anticipated base model leads to the scheme as shown in table 2.

	Store	Transport	DC
Top level	- Handling costs		
Anticipated base level		- Drop cost* - Expected overflow costs* * *Assumptions:* *Single store route*	- Fictitious fee* * *Assumptions:* *Lead-time is constant and equal to zero*
Base level		[redacted]	- Aggregated container costs

Table 2: Formulation of the base level and the anticipated base model costs, Schneeweiss (2003)

The anticipated base model ultimately gives an anticipation for the reaction of the base model on a certain set of schedules. With this anticipated based model, we come to the final conceptual model as displayed schematically in figure 10.

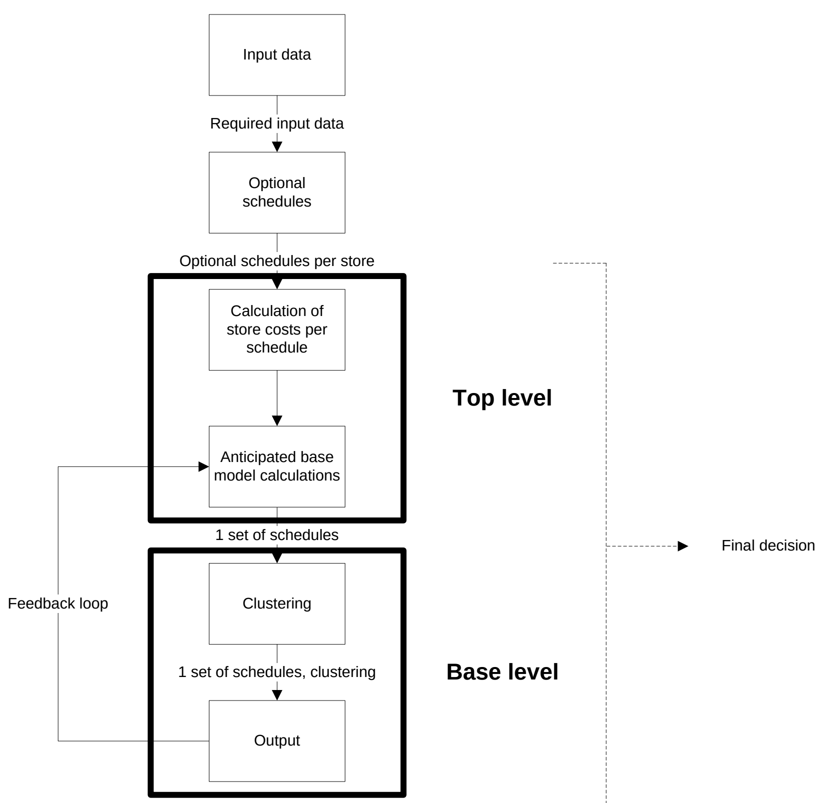

Figure 10: Design of the conceptual model

The final conceptual model has 6 phases represented as blocks in figure 10, which we will elaborate in this paragraph.

Phase 1: Input data

In phase 1 all input data is gathered or estimated which is needed in the following phases of the model.

Phase 2: Optional schedules

This phase includes the demarcation per store of schedules which are optional or not. This decision can be based on several factors such as a minimum delivery frequency depending on truck capacity or on agreements between the store and Jumbo Supermarkten. Output of this phase is the collection of schedules which are an option to become the delivery schedule for a specific store, per store.

Phase 3: Calculation of store handling costs per schedule

Phase 3 considers the calculation of the handling costs per schedule based on a cost and capacity model. This is the output of this phase.

Phase 4: Anticipated base model calculations

This phase comprises the calculation of the costs of the anticipated base model. Combined with the store costs calculated in the prior phase, all stores (or Jumbo on behalf of the store) choose one particular delivery schedule. The set of schedules is output of the model, with one schedule per store for all stores.

Phase 5: Clustering

In the clustering phase, the combination takes place of multiple deliveries in one truck within the same timeslot based on a certain clustering algorithm. Output of this model is a clustering of stores per route per time block.

Phase 6: Output

By means of the output of the clustering phase, this phase calculates the full expected supply chain costs for a specific candidate set of schedules.

Feedback loop

The feedback loop, or the “reaction” in the concept of Schneeweiss (2003), gives the bottom-up feedback on the candidates. This may be the adaption of the smoothing tariffs.

Final decision

The final decision to choose a certain set of schedules will be based on a stop-criterion to be specified later. The set of schedules with the minimum costs will be the output of the model.

Chapter 3: Analytical model

For the assignment of a delivery schedule to all stores allocated to a distribution center at the tactical level, we will make use of the model formulated by Broekmeulen and Van Donselaar (2012) which is shown in appendix v. This chapter will give a short qualitative description of the model. This model makes use of a hierarchical planning structure as described in chapter 2, where the top level consists of store costs. Per store, the set of optional schedules can be constrained for example due a minimal delivery frequency constraint regarding the weekly volume relative to the truck capacity. For each of the optional schedules the top level calculates the instore handling costs.

The model distinguishes two types of handling costs: costs for regular shelf stackers and costs for fulltime shelf stackers where the available capacity of regular shelf stackers is limited depending on store and timeslot. The eventual employment of these two types of workers is influenced by the available backroom capacity.

The model of Broekmeulen and Van Donselaar (2012) assumes a difference between two filling regimes: concurrent and nonconcurrent replenishment. Nonconcurrent replenishment considers the shelf stacking of products at first replenishment (usually once per day), concurrent replenishment considers the shelf stacking of products during the day due to the fact that these products cannot be stacked during first replenishment due to the fact that the demand per timeslot is large than the available shelf capacity. Thus, nonconcurrent products can be stacked at the moment of delivery while concurrent products have to be placed in the backroom.

Within the model of Broekmeulen and Van Donselaar (2012) each store has a basic available backroom storage capacity, which is already corrected for returnables such as returned packaging and remaining inventory of broken case packs. In addition, the backroom capacity is corrected for the storage of concurrent volume during the remainder of the review period by means of the parameter β_{it}. This parameter accounts for the fraction of total sales for a certain store within a certain timeslot which are sold from shelves requiring concurrent replenishments, i.e. where shelf capacity is insufficient for sales corresponding with this timeslot. Based on this capacity model, the top level's store handling costs can be calculated based on an LP-formulation. The calculated instore handling costs need to be outweighed by costs for the anticipated base model which contains two elements.

First, the anticipated base model includes a generic parameter U which represents the average cost per drop and which is the same for all stores.

Second, the model of Broekmeulen and Van Donselaar (2012) introduces smoothing tariffs which represents costs per roll container per timeslot. By changing the smoothing tariffs we can minimize the workload range by the assignment of additional costs to undesirable schedules for the distribution center.

Thus, the model changes the smoothing tariffs in an iterative manner until a desired workload range for the DC is reached or when the additional costs for local stores become too high. In addition, the model of Broekmeulen tries to reduce transportation costs for a given set of schedules by combining multiple stores in one truck with a maximum of two stores per route.

Chapter 4: Analysis of beta(it)

Chapter 3 of this report contains the qualitative description of the analytical model which will be used to determine a delivery schedule per store. In this section we focus on the calculation and analysis of the beta parameter specifically. This chapter starts with the discussion of the definition of beta in section 4.1, followed by an analysis of the input data in section 4.2. Section 4.3 shows the results and section 4.4 describes an approach to approximate the results by means of readily available data.

4.1 Definition

This section considers the definition of the beta parameter. When we refer to "the beta parameter" this considers the parameter β_{it} which is included in the model of Broekmeulen and Van Donselaar (2012) defined as:

β_{it}: fraction of total sales for store i during time slot t which are sold from shelves requiring concurrent replenishments, i.e. shelf capacity insufficient for sales corresponding with this time slot;

Thus, Broekmeulen and Van Donselaar (2012) make a distinction between two product groups.

First, a product group for which demand corresponding to a certain timeslot is smaller than shelf capacity. Thus, these products can be stacked during planned replenishments and are considered as nonconcurrent products. It is reasonable to assume that during this planned replenishment, the shelf capacity is fully stacked and the remaining inventory is placed in the backroom.

Second, the model defines a product group for which the demand corresponding with a certain timeslot is larger than the product's shelf capacity. These products require an extra replenishment moment during the timeslot and the products stacked during this extra replenishment are considered as concurrent products.

Broekmeulen and Van Donselaar (2012) assume that the net available backroom capacity is already adjusted for empty roll-cages and remaining inventory after first replenishment, but not yet for the volume needed for concurrent replenishment. Instead, the net available backroom capacity is corrected for the fraction of the sales during the review period which is sold from shelves requiring concurrent replenishments. Hence,

$$B_{ijt} = \bar{B}_i - \sum_{k=t+1}^{t+R_{jt}} \beta_{it} \cdot E[S_{ik}] \quad [1]$$

The available backroom capacity needs to be respected for all stores and all timeslots for the nonconcurrent volume, as shown in [ITP 5] and [ITP 6] of the model of Broekmeulen and Van Donselaar (2012).

This section considers the definition of beta(it). To acquire a value for store i and timeslot t, we will consider the fraction concurrent on an SKU level. D_{ikt} is defined as the random variable for the demand in consumer units for product k in store i and timeslot t. C_{ik} is the shelf capacity for product k in store i. We assume that shelves are fully stacked after first replenishment.

The on-shelf inventory of fast-moving products has influence on the extent to which products can be stacked and thus on the instore operations. Considering the on-shelf inventory at the moment of first replenishment, store supervisors within Jumbo Supermarkten state that it is almost impossible to make a reasonable assumption on the on-shelf inventory just before first replenishment due to the fact that, for fast moving products, the on-shelf inventory depends on both the ratio between demand and shelf capacity and the moment of concurrent replenishment.

Due to the fact that it is hard to make a reasonable assumption on the on shelf inventory, we will consider a lower bound and an upper bound to the fraction concurrent.

In the following three paragraphs, we will consider two formulations of beta(it). The first paragraph considers the definition of the lower bound for the fraction concurrent for store i in timeslot t. The second paragraph considers the definition of the upper bound for the fraction concurrent for store i in timeslot t. Finally, the paragraph considers the choice for a definition and the interpretation at that definition.

4.1.1 Lower bound

This section considers a lower bound for the fraction concurrent of sales for store i in timeslot t. As described above, products require concurrent replenishment when the demand during a certain timeslot exceeds the shelf capacity of the corresponding product, i.e. when $D_{ikt} > C_{ik}$. Hence, the situation where the on shelf inventory just before first replenishment is equal to zero maximizes the number of products that will be stacked by means of first replenishment. Thus, the number of products that need to be filled by means of concurrent replenishment is minimized and the lower bound for the number of products measured in consumer units that need to be filled by means of concurrent replenishment is equal to $(D_{ikt} - C_{ik})^{+}$. Subsequently, this leads to a definition of the lower bound of beta(it):

$$\beta_{it} = \frac{\sum_{\forall k} E[I_{ikt} \cdot (D_{ikt} - C_{ik})]}{\sum_{\forall k} E[D_{ikt}]} = \frac{\sum_{\forall k} E[(D_{ikt} - C_{ik})^{+}]}{\sum_{\forall k} E[D_{ikt}]} \qquad [2]$$

Where:

D_{ikt}	:	Random variable for the demand in store i for product k in time block t
I_{ikt}	:	1 if $D_{ikt} > C_{ik}$ in store i for product k in time block t in week x and 0 otherwise
C_{ik}	:	Shelf capacity in store i for product k

4.1.2 Upper bound

This section considers the determination of the upper bound for the fraction concurrent of sales for store i in timeslot t. During timeslot t the demand for product k in store i is equal to the random variable D_{ikt} in consumer units and the shelf is fully stacked during first replenishment. Therefore, at maximum D_{ikt} consumer units can be stacked by means of concurrent replenishment. Hence, given a certain demand in consumer units D_{ikt} for store i, product k in timeslot t and a corresponding shelf capacity C_{ik}, the upper bound to the number of products that need to be stacked by means of concurrent replenishment is equal to $D_{ikt} \cdot I_{ikt}$ where $I_{ikt} = 1$ when $D_{ikt} > C_{ik}$. This leads to the definition of beta(it):

$$\beta_{it} = \frac{\sum_{\forall k} E[I_{ikt} \cdot D_{ikt}]}{\sum_{\forall k} E[D_{ikt}]} \qquad [3]$$

Where:

D_{ikt}	:	Random variable for the demand in store i for product k in time block t
I_{ikt}	:	1 if $D_{ikt} > C_{ik}$ in store i for product k in time block t in week x and 0 otherwise
C_{ik}	:	Shelf capacity in store i for product k

4.1.3 Choice of definition3

The prior two sections considered the determination of a lower and an upper bound. The use of a lower bound for the fraction concurrent for store i and product k would yield a lower bound for the concurrent volume during the remainder of the review period $\sum_{k=t+1}^{t+R_{jt}} \beta_{it} \cdot E[S_{ik}]$. Subsequently, due to the fact that this concurrent volume for the remainder of the review period is deducted from the net available backroom capacity, the use of a lower bound for the fraction concurrent β_{it} would yield an upper bound for the available backroom storage capacity B_{ijt} for first replenishment items in store i following schedule j during timeslot t. However, due to the fact that B_{ijt} is used as a constraint for the backroom inventory at the end of timeslot t, the use of a lower bound value for β_{it} does not make sense. Instead, the use of an upper bound value for β_{it} yields a lower bound value for the available backroom capacity B_{ijt} for first replenishment items.

For the sake of interpretation, we can assume the set of schedules with insufficient shelf capacity to be exactly the same during each timeslot. In this case, the approach makes a distinction between two categories of products:

- One category of products for which the demand for the remaining review period is included in the backroom;
- One category of products for which it is either possible to stack the demand for the remaining review period in the shelves, or where exceeding products can be placed in the backroom;

Regarding the correlation of the demand of products in subsequent timeslots, it is reasonable to assume that the set of products with insufficient shelf capacity remains more or less the same throughout the planning period.

4.2 Data

This section addresses the nature of the input data which is used for the analysis.

4.2.1 Sample size

Prior to this analysis, we used a small sample of three stores (low/medium/high shelf pressure) to gain an estimation of the pattern to be expected. The results for the three stores gave reason to expect a beta parameter which is dependent on turnover pressure.

Hence, we initially expect the beta parameter to be negligible for stores with a relatively low shelf pressure and a beta parameter which is linearly increasing with shelf pressure after a certain cutoff point. For this analysis we will therefore make use of a larger subset of 19 stores where these stores are equally distributed between the store if the subset with medium shelf pressure and the store with a large shelf pressure.

Data is available for five weeks; stores are open six or seven days per week. However, to be able to compare beta-parameters based on their average value, especially for section 4.4.1, we will neglect the demand for Sunday openings and compare the stores on the demand during the first six days of the week in the remainder of the report. Eventually, we would like to do the comparison twice to avoid this negligence, once for stores with six opening days and once for stores with seven opening days, but the sample size is too small to do this.

4.2.2 Demand data

The demand data that is used for the calculations is point-of-sales data measured in consumer units. The demand data for all stores in the sample set considers demand data which excludes promotions. It is not reasonable to include promotions, since usually shelf capacity is temporarily enlarged for weeks in which promotions take place. In the point-of-sales data, the consumer unit for beer is defined as one bottle.

4.2.3 Shelf capacity data

The source of the shelf capacity data used for the calculation of the beta parameters is the SAP system which is used for automated store replenishment. This system generates an order advice based on demand data and shelf capacities. The result of the system should provide store managers an incentive to update the shelf capacities: not setting the shelf capacities too low (which results in too many orders) and not too high (which results in too much backroom inventory). Given this feedback loop, we initially expect the quality of the data to be of sufficient quality

Data check

To perform an extra check for the quality of the data, we take a sample to verify whether the SAP shelf capacity C_{ik}^{SAP} for store i and product k is consistent with the actual instore shelf capacity C_{ik}^{Actual} for store i and product k. The actual shelf capacity is gathered for the stores in the sample set by telephone. One (franchise) store did not want to participate, for the remaining 18 stores the shelf capacity was checked for the three products which have the highest contribution to the beta parameter, i.e. the three products within store i for which $\sum_{\forall t} E[D_{ikt} \cdot I_{ikt}]$ had the largest value. Consequently, we can calculate the shelf index parameter SI_{ik} for each of the 54 observations:

$$SI_{ik} = \frac{C_{ik}^{Actual}}{C_{ik}^{SAP}} \quad [4]$$

This represents the actual shelf capacity relative to the SAP shelf capacity for store i and product k. Characteristics of these 54 shelf index parameters are shown in table 3. As shown in the table, we differentiate between indexes for products in stores for which the actual shelf capacities are equal to shelf capacities in SAP for all three products which were checked, and for indexes for products in stores where this is not the case.

	All stores	Products in stores where $C_{ik}^{SAP} = C_{ik}^{Actual}$ for $\forall k$	Products in stores where $\exists k$ for which $C_{ik}^{SAP} \neq C_{ik}^{Actual}$
Frequency	54	12	42
Average	2.16	1.00	2.79
Standard deviation	2.53	0.00	2.91
Coefficient of variance	1.17	0.00	1.05
Median	1.10	1.00	1.88
Min	0.17	1.00	0.17
Max	13.71	1.00	13.71

Table 3: Data description of SI_{ik}, for 3 products with largest contribution beta(it), for 18 stores

Based on the sample, actual shelf capacities are on average more than twice as high as the shelf capacity in SAP. One of the products even showed a shelf capacity which is almost 14 times as high as the shelf capacity registered in SAP. Thus, the actual shelf capacity clearly deviates from the shelf capacities which originate from the SAP system. Thus, it is relevant to know whether these results eventually lead to a change in beta(it). To compare the values of beta(it) across different stores, we define γ_i as the average value per store for beta(it) within the planning horizon P, hence:

$$\gamma_i = \frac{\sum_{\forall t} \beta_{it}}{P} \qquad [5]$$

Table 4 shows a data description of the index parameter $\gamma_i^{Actual3P}/\gamma_i^{SAP}$ per store, which represents the average beta parameter after adjustment of the three products' shelf capacities $\gamma_i^{Actual3P}$ relative to the average beta parameter based on the original SAP shelf capacity data γ_i^{SAP}. As can be seen, the value for gamma(i) based on the original SAP shelf capacities decreases with 14 % on average after adaption of the three products' shelf capacities. Furthermore, we can see that the minimum value for $\gamma_i^{Actual3P}/\gamma_i^{SAP}$ is equal to 0.52 with a maximum value of 1.17. In other words, the checking of the shelf capacity of only three very fast moving products per store leads to a reduction of gamma(i) with 48 %.

	All stores	Stores where $C_{ik}^{SAP} = C_{ik}^{Actual}$ for $\forall k$	Stores where $\exists k$ for which $C_{ik}^{SAP} \neq C_{ik}^{Actual}$
Number	18	4	14
Average	0.86	1.00	0.82
Standard deviation	0.18	0.00	0.18
Coefficient of variance	0.21	0.00	0.22
Median	0.88	1.00	0.78
Min	0.52	1.00	0.52
Max	1.17	1.00	1.17

Table 4: Data description for $\gamma_i^{Actual3P}/\gamma_i^{SAP}$

The results show clear difference for the values of gamma(i) prior to and after adaption of the three products' shelf capacity values. Regarding these results, it is relevant to consider whether a decrease or an increase of gamma(i) eventually influences the choice of a delivery schedule for a store. To test for the relevance of the difference between $\gamma_i^{Actual3P}$ and γ_i^{SAP}, we consider the multiplication of the difference between $\gamma_i^{Actual3P}$ and γ_i^{SAP} with the average daily demand, relative to the backroom capacity. Hence, we formulate a backroom fraction BF_i,

$$BF_i = \frac{|\gamma_i^{Actual3P} - \gamma_i^{SAP}| \cdot D_i}{BRC_i} \qquad [6]$$

where D_i is the average daily demand for store i measured in containers and BRC_i represents the backroom capacity for store i. Thus, the comparison is done based on the assumption of having a daily delivery for each store which is reasonable as will be shown in table 14 . Hence, this will estimate the fraction of the backroom that is wrongly estimated by using the SAP data for the three products instead of actual shelf capacities. Increasing the assumed review period, will cause an increase for BF_i .

To make a reasonable conclusion on the result of shelf capacity data, we introduce an arbitrary threshold value of 0.05. When BF_i exceeds this value, we consider the difference between $\gamma_i^{Actual3P}$ and γ_i^{SAP} not to be negligible.

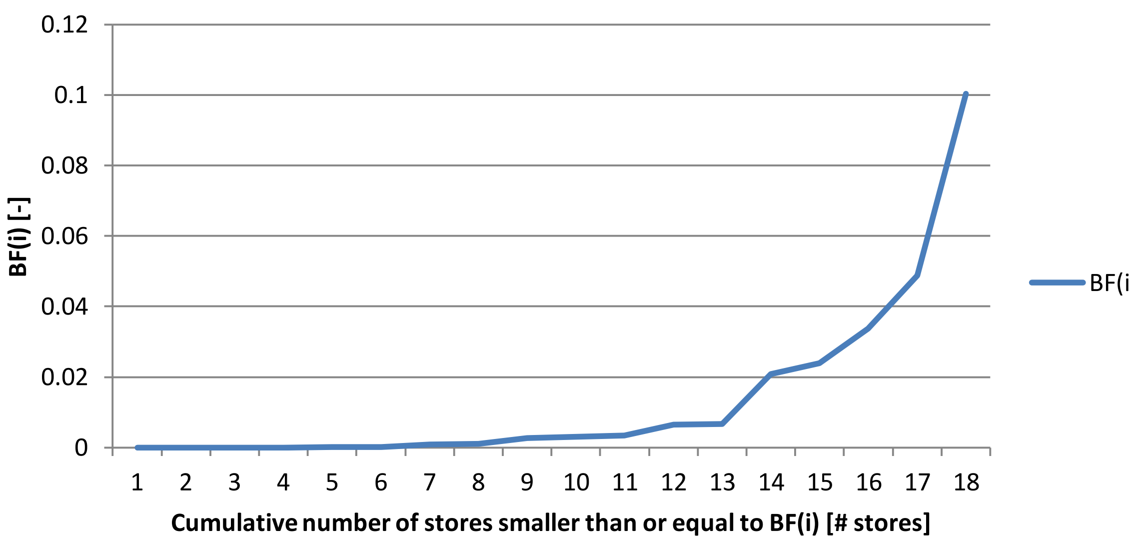

Figure 11: Cumulative number of stores versus BF_i

If the values for BF_i would be negligibly small, it is reasonable to continue with the shelf capacity data which is adapted for the three products. However, the results in figure 11 show that 1 of the 18 stores exceeds the threshold value of 0.05 and that two stores have values which approximate the threshold value of 0.05. Hence, the difference between $\gamma_i^{Actual3P}$ and γ_i^{SAP} comprises a reasonable fraction of the backroom.

Thus, the effect on the schedule choice is relatively large although we have limited the sample size to only three products. To estimate what the effect is if we would extend the sample size of three products for which we checked shelf capacities, we extrapolate the results for the first three products with the largest contribution to definition A to the first twenty products with the largest contribution to definition A. Hence, we define a new parameter ASI_{ik} which is the average shelf index parameter per store for the three products for which the shelf capacity was checked. Hence:

$$ASI_i = \frac{1}{3} * \sum_{k=1}^{3} SI_{ik} \qquad [7]$$

Where products $k = 1,2,3$ are the three products for which the shelf capacity was checked and possible adapted. We can extrapolate the results per store by multiplying the shelf capacity of the first twenty products with the largest value for $\sum_{\forall t} E[D_{ikt} \cdot I_{ikt}]$ (excluding the first three products) by the index parameter ASI_i and consequently we can recalculate gamma(i) after adaption of the shelf capacity of these twenty products $\gamma_i^{Actual20P}$ to check the effect of the extrapolation of results.

	All stores	Stores where $C_{ik}^{SAP} = C_{ik}^{Actual}$ for $\forall k$	Stores where $\exists k$ for which $C_{ik}^{SAP} \neq C_{ik}^{Actual}$
Number	18	4	14
Average	0.64	1	0.53
Standard deviation	0.41	0	0.41
Coefficient of variance	0.65	0	0.77
Median	0.55	1	0.37
Min	0.05	1	0.05
Max	1.33	1	1.33

Table 5: Data description for $\gamma_i^{Actual20P}/\gamma_i^{SAP}$

As shown in table 5, the multiplication of the shelf capacity of the first twenty products with the largest contribution value for $\sum_{\forall t} E[D_{ikt} \cdot I_{ikt}]$ with the index parameter leads, on average, to a further decrease of the parameter of gamma(i). With an average decrease compared to the initial gamma(i) of 36 %, these results show that extrapolation of the results found for the first three products per store leads of a further decrease of gamma(i). However, although these results give evidence to state that the data quality is relatively low and to state that the influence of this data quality is large, there are three reasons to mitigate this conclusion:

- First, the sample size of three products is relatively small. For example, one of the three products for store 14 has a shelf index parameter SI_{ik} which is equal to 13.71. It is not likely that this effect is representative for the remainder of the products of that store.
- Second, it is reasonable to assume that fast moving products have more relative deviation in shelf capacities than slow(er) moving products, which makes the extrapolation contestable.
- Third, we consider a store where all shelves have sufficient actual shelf capacity to cover the daily demand for that product in that store. In this store, it is reasonable to assume that the products with the largest contribution to beta(it) are precisely those products for which the actual shelf capacities deviates from the shelf capacities in SAP. Concluding, the selection of products for which the shelf capacity is checked can be biased due to the fact that these products have a high contribution to beta(it) can be caused by the inaccurate SAP shelf capacity itself. This limits the extent to which it is reasonable to extrapolate the shelf capacity of the first three products to the first twenty products.

4.2.4 Conclusion

In first instance, we assumed the SAP shelf capacity data to be of relatively good quality due to the fact that the store has an incentive to update the shelf capacity: a SAP shelf capacity which is higher than the actual shelf capacity should lead to an automated order advice which is too high, which subsequently leads to excessive leftovers. This should provide an incentive to stores to update the shelf capacity. When the SAP shelf capacity is lower than the actual shelf capacity this should lead to a too high order frequency for first replenishment. This increases handling costs and this should provide an incentive to stores to update the shelf capacity. Hence, shelf capacity is used to perform an instore logistical optimization.

However, if sales volumes for extremely fast moving products are constantly larger than or at least quite near to the actual shelf capacity, the extent to which order advancement and workload smoothing is possible is limited since the automated ordering system will always order the projected demand during the review period.

Furthermore, the benefit for the store of a smoothed workload is rather small due to the fact that for large volumes, ordering more at once does not create a significant increase in productivity since volumes are already large and setup costs (such as costs related to searching for the right location to stack a certain product) are negligible. In other words, the store does not have a significant incentive to adapt shelf capacities for extremely fast moving products.

Hence, shelf capacity data quality is not as good as expected and shelf capacities in SAP are most likely to deviate from the actual shelf capacity for fast moving products. This conclusion has two implications:

- First, it has an implication for the store replenishment in general. Within the automated ordering system, shelf capacity data is used for logistical optimization within the store and smoothing of the workload within the store. Hence, the fact that this smoothing does not take place within the store will have consequences on an aggregate level. Improvement of quality of the data can cause a more leveled workload not only for the store, but for the transportation function and for the distribution centers as well.
- Second, the data inaccuracy influences the outcome of this research.

Data analysis showed that data quality is insufficient. However, we continue with the shelf capacity data after adaption of the three products' shelf capacities, for three reasons:

- To start with, it is reasonable to assume that for fast-moving products the shelf capacity data is more inaccurate then for slow moving products due to the difference in incentives for the store to update the shelf capacity. This reduces the data quality issue to a limited set of products.
- Second, after adaption of the shelf capacities, only 2 of a total of 18 stores showed an increase of gamma(i) while the remainder of the values of gamma(i) showed a decrease or did not change. Furthermore, the increase for the two stores was relatively small where $\frac{\gamma_i^{Actual3P}}{\gamma_i^{SAP}} = [1.08, 1.27]$. Hence, it is reasonable to state that the gamma(i) parameter after adaption of the three products' shelf capacities provides an upper bound of the actual gamma(i). Thus, the gamma(i) parameter is likely to overestimate the fraction concurrent but unlikely to underestimate the fraction concurrent.

Considering the model formulation of Broekmeulen and Van Donselaar (2012), the overestimation of gamma(i) will lead an overestimation of the requirement for backroom capacity which can subsequently lead to an increase of costs. Thus, although the data inaccuracy can lead to a cost increase, it will not result in an impossible schedule for a store.

- Third, due to the fact that it is not practically possible to check all actual shelf capacities, the SAP shelf capacity data is the best data source available.

Concluding, although there are limitations to the use of the data, we will continue with the shelf capacity data after adaption of the three products' shelf capacities in the remainder of this report, with a sample set of 18 stores. For further research it is recommendable to extend both the number of stores and the number of products.

4.3 Results

In the prior sections, we showed the influence of the decrease or increase of gamma(i) by means of an adaption of the SAP shelf capacity data. This section considers the results for the parameter beta(it) which is split in four paragraphs for the sake of structure. The first paragraph considers whether beta(it) indeed has influence on the schedule as such. The second paragraph considers the seasonality of the parameter. Paragraph three considers the sensitivity of the measure and finally, paragraph four concludes this section.

4.3.1 Influence of beta(it)

This section considers the influence of beta(it) on the eventual schedule choice. When the parameter is infinitely small, the parameter is unlikely to influence the choice of a store for a schedule. In contrast, when beta(it) is equal to one, this influence is large. To consider the influence of beta(it), a new parameter is introduced:

$$BRF_i = \frac{\gamma_i \cdot D_i}{BRC_i} \tag{8}$$

Where D_i is the average daily demand per store and BRC_i represent the backroom capacity per store. The parameter represents fraction of the backroom capacity that is used for storage of concurrent products, if we assume a review period of one day. This parameter gives an indication of the concurrent volume relative to the backroom capacity and hence, an indication of the influence on the choice of schedule. As for BF_i, we will make use of an arbitrary threshold value of 0.05. Values for BRF_i which are larger than 0.05 can be assumed to be negligibly small and values larger than 0.05 can be assumed not to be negligible.

When we check this parameter for the 18 stores in the sample set, BRF_i has an average value of 0.054 with a standard deviation of 0.075. The maximum value is 0.24 and the minimum value is 0.002. Hence, with an average that is larger than the threshold value of 0.05 and a maximum value of 0.24 this supports the conclusion that beta(it) is likely to have influence on the choice of a delivery schedule.

4.3.2 Seasonal effect of beta(it)

To compare the effect of the seasonal demand data on beta(it), we define a new parameter SE_t which represents the average beta(it) parameter for timeslot t. Hence:

$$SE_t = \frac{\sum_{\forall i} \beta_{it}}{n} \qquad [9]$$

where n is the number of stores in the subset. Figure 12 shows SE_t for beta(it) as defined in formula [9]. Values for SE_t vary between 0.02 and 0.10 which shows a large variation in the parameter value per timeslot.

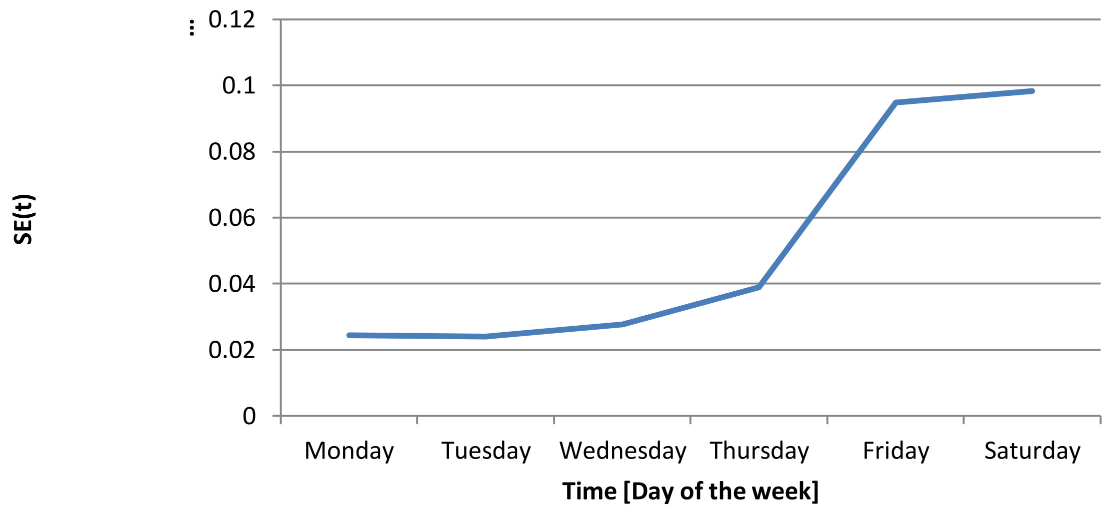

Figure 12: SE(t) for each day of the week, averaged over all 18 stores

4.3.3 Sensitivity analysis

This section considers a sensitivity analysis which investigates the sensitivity of beta(it) to shelf capacity data. To explore this sensitivity, we will multiply all shelf capacities with a fraction p and then compare the result with the results for $p = 1$, based on the change in the average gamma(i) across all stores $\bar{\gamma}_i$, and the change in the average standard deviation of beta(it) across all stores, $\bar{\sigma}(\beta_{it})$. Due to the fact that for most of the products the average demand is lower than the shelf capacity, we expect that if we decrease shelf capacities with α %, the beta parameter will increase with at least α %. In reverse, we expect that if we increase shelf capacities with α %, the beta parameter will decrease with at least α %.

$p = 0.8$		$p = 0.9$		$p = 1$		$p = 1.1$		$p = 1.2$	
$\Delta\bar{\gamma}_i$	$\Delta\bar{\sigma}(\beta_{it})$	$\Delta\bar{\gamma}_i$	$\Delta\bar{\sigma}(\beta_{it})$	$\Delta\bar{\gamma}_i$	$\Delta\bar{\sigma}(\beta_{it})$	$\Delta\bar{\gamma}_i$	$\Delta\bar{\sigma}(\beta_{it})$	$\Delta\bar{\gamma}_i$	$\Delta\bar{\sigma}(\beta_{it})$
66.0%	44.8%	26.4%	14.6%	0.0%	0.0%	-17.0%	-9.6%	-32.7%	-23.2%

Table 6: Comparison of gamma(i) and sigma(beta(it)) after a change in shelf capacities

As can be seen in table 6, this indeed is the case. As for most supermarkets in the Netherlands, sales volumes are high and for most products demand is large relative to shelf capacity. Thus, a small decrease ($p = 0.8$) already causes a large increase of beta(it) due to the fact that a large number of products does have insufficient shelf capacity. For a small increase ($p = 1.2$), a number of fast moving products now does fit in the shelf capacity which leads to a drop of beta(it). Apart from the sensitivity to aggregate changes, section 4.2.3 showed that the change of the shelf capacity of three fast-moving products causes a 14 % decrease on average of γ_i. As discussed in paragraph 4.2 we will continue with the data after adaption of the three products' shelf capacities, although beta(it) is sensitive to this data quality.

4.3.4 Conclusion

Concluding, we have drawn several sub conclusions in this section:

- Beta(it) comprises a reasonable fraction of the backroom and hence, the parameter is likely to have influence on the choice of schedule;
- Beta(it) shows a clear seasonal pattern, caused by the seasonal effect that is present in the demand data;
- Beta(it) is sensitive to changes in shelf capacities, both on aggregate level as on SKU-level.

We will continue with the sample set of 18 stores with a possibly adapted value for the three products for which the shelf capacity was checked.

4.4 Approximation

In the prior sections, we discussed the calculation and use of beta(it). However, the extensive calculation comes has three disadvantages:

- The calculation requires demand data. The combination of more than 300 stores, about 30.000 SKU's and multiple weeks of data, leads to a very large data set which is too large to export via the regular data export process within Jumbo Supermarkten. A data request is needed, and the extra delay of up to one week that is caused by this extra step is a direct delay in the schedule development process.
- The calculation requires shelf capacity data. As discussed in section 4.2, shelf capacity data quality is not sufficient and it requires much time to check a sample set of products for all stores.
- The calculation of beta(it) parameters takes a considerable amount of time due to the fact that two large databases need to be combined.

Hence, although the effectiveness of the calculation of beta(it) is sufficient, the efficiency considering the use of resources such as time and computational power for determining the parameter leaves room for improvement. This section aims to approximate beta(it) by means of readily available data, in order to approximate beta(it) of a large set of stores by means of readily available data. We will consider two approximations:

- Gamma(i): Average value per store for beta(it) within the planning horizon P
- Gamma(i)*Alpha(it): average value per store for beta(it) within the planning horizon P multiplied by a seasonal index

The definition of the approximating parameters will be treated in more detail in the following sections.

4.4.1 Approximation by means of Gamma(i)

This section considers the approximation of beta(it) by means of γ_i as formulated in formula [5]. The parameter represents the average per store of β_{it} regarding the planning horizon P. As shown earlier in this report, the beta(it) parameter shows a clear seasonal effect throughout the week. Although a seasonal effect is present in the data it needs to be considered whether it is accurate enough to approximate beta(it) with a parameter that is not time-dependent. The difference between gamma(i) and beta(it) is relevant if the difference between the two parameters beta(it) and gamma(i) in combination with the expected delivery volume comprises a reasonable fraction of the backroom capacity. Hence, we apply the same logic as for formula [8] by considering the fraction of the difference between gamma(i) and beta(it) multiplied with the average demand D_{it} relative to the backroom capacity.

$$BF_{it} = \frac{|\gamma_i - \beta_{it}| \cdot D_{it}}{BRC_i} \qquad [10]$$

As can be seen in table 7, the average value of BF_{it} for all stores and all timeslots is equal to 0.04. Although this is below the threshold value of 0.05, the maximum value of 0.80 and the standard deviation 0.11 give reason to expect a regular exceedance of the threshold value. Data analysis shows that 13 % of all measurements (for all i and all t in the subset) exceed the cutoff value.

Calculation of the maximum value of BF_{it} per week per store, yields an average value across all stores equal to 0.12. Hence, although on average the approximation of β_{it} by means of γ_i can be assumed to be negligible, the maximum value for BF_{it} and the average of the maximum values per store show that approximation of β_{it} by means of γ_i is contestable.

Average	Median	Standard deviation	Min	Max
0.04	0.01	0.11	0.00	0.80

Table 7: Data description for BF_{it}

4.4.2 Approximation of Beta(it) by means of readily available data

Given the reasons mentioned in the introduction of this paragraph, we would like to approximate beta(it) by means of a store-dependent average parameter γ_i (which can be acquired by a small sample size of SKU data or by aggregate measures) possibly multiplied by a seasonal factor $\propto_{it}$, as is shown in formula [11].

$$\beta_{it} = \gamma_i \cdot \alpha_{it} \qquad [11]$$

In this section, we will consider the approximation of γ_i and α_{it} by means of readily available data.

Gamma(i)

This section considers the approximation of γ_i by means of a regression analysis on readily available data to increase the efficiency of the process. At first instance, turnover pressure defined as the weekly turnover in Euros per square meter store floor area was expected to be a good predictor of γ_i. However, it can be seen in appendix vi that no linear relationship between turnover pressure and γ_i can be found. Data analysis showed that in most stores in the sample set, the products with the largest sales quantities relative to the shelf capacity were beer, coke and sodas. Hence, appendix vii shows a potential relationship between the turnover share for beer, and for coke and soda. To approximate gamma(i), we conduct a linear regression analysis on the share of beer and soda in the total turnover per store. As can be seen in appendix viii, the approximation by means of the turnover share of beer and the turnover share for coke and soda provides a relatively good fit with an R^2_{adj} equal to 0.502. Introduction of the turnover pressure as an additional predictor in the model decreases both R square and the Adjusted R square. This implies that shelf pressure is, in contrast to what was expected, not a good predictor of gamma(i).

Application of regression result to the sample set of 122 stores, this results in the data characteristics as shown in table 8.

Average	Median	Standard Deviation	Min	Max
0.056745	0.054798	0.023669	0.012308	0.156546

Table 8: Data characterization of gamma(i)

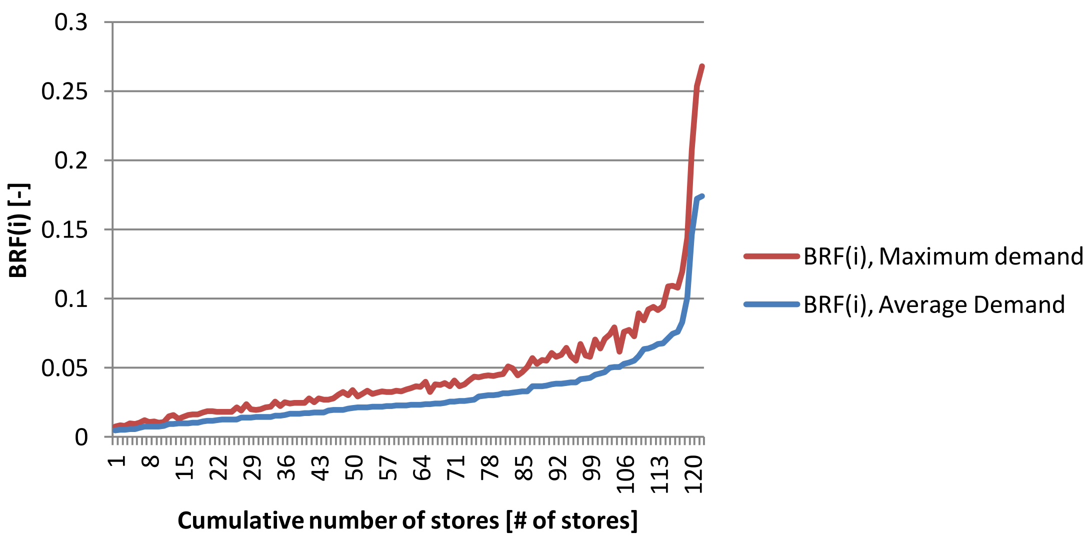

Figure 13: Cumulative number of stores versus BRF(i)

To put the values of gamma(i) in perspective, figure 13 shows the cumulative number of stores versus two definitions:

- $BRF_i = \frac{\gamma_i \cdot D_i}{BRC_i}$ where D_i is defined as the average demand for store i during the planning horizon P

- $BRF_i = \frac{\gamma_i \cdot D_i}{BRC_i}$ where D_i is defined as the average demand of the timeslot during planning horizon P with the highest average demand per timeslot for store i

What can be seen in the figure is that for about 70-80 % of the stores, if we use a threshold value of 0.05, the fraction concurrent is not expected to have influence on the choice of schedule. However, for the top 20-30 % the value is significantly large to have an impact on the eventual schedule choice.

Alpha(it)

Given the relatively good approximation of gamma(i), we would like to improve the approximation by correcting the (approximation of) gamma(i) for the seasonal effect which is present in the data. As specified earlier, alpha(it) resembles the seasonal index for gamma(i). To approximate the seasonal effect of beta(it), we will assume that the seasonal pattern is defined by the turnover distribution over the week. Although this considers the total consumer turnover per day instead of only the dry groceries turnover per day, it is reasonable to assume that the share of dry groceries turnover in the total turnover differs per store but, for a certain store, does not differ during the week. Hence, the seasonal pattern $\propto_{it}$ is dependent on this distribution, while we will consider the approximation of the gamma parameter where:

$$\propto_{it} = \frac{Turnover_{it}}{\sum_t \frac{Turnover_{it}}{P}} \qquad [12]$$

To compare the seasonality of beta(it) and alpha(it), we introduce two parameters IB_t and IA_t which respectively represent the seasonal effect of Beta(it) and Alpha(it) where n represents the number of stores and P represents the planning horizon.

$$IB_t = \frac{\sum_{\forall i} \beta_{it}}{\frac{\sum_{\forall i,t} \beta_{it}}{n \cdot P}} \qquad [13]$$

$$IA_t = \frac{\sum_i \propto_{it}}{n} \qquad [14]$$

Figure 14 shows IB_t and IA_t. As can be seen, the seasonal pattern for the two parameters is similar but the amplitude differs due to the fact that beta(it) is mainly based on fast-moving products which show an enforced seasonal effect.

Figure 14: IB_t and IA_t

The difference in the amplitude of the seasonal parameters leads to a bad approximation of beta(it). In order to correct for the enforced seasonal effect, we will test whether a correction of the original alpha(it) for the amplitude enhances the approximation. Hence, we correct the amplitude of the turnover distribution by means of an overall average ratio per timeslot t of IB_t relative to IA_t. This parameter is time-dependent but not store dependent and ultimately leads to an estimation of alpha(it) for each store and for each timeslot which is equal to:

$$\propto_{it} = \frac{Turnover_{it}}{\sum_t \frac{Turnover_{it}}{P}} \cdot \left(\frac{IB_t}{IA_t}\right) \qquad [15]$$

However, a time-varying estimation based on the actual value of gamma(i) and the estimated values for alpha(it) $\hat{\beta}_{it} = \gamma_i \cdot \hat{\alpha}_{it}$ eventually showed values for BF(i) which are on average equal to 0.05, with a maximum value of 0.35. Hence, compared to the results that we acquired earlier for gamma(i), the introduction of an additional parameter does not improve the solution due to the fact that the ratio between IB_t and IA_t shows much variation per store and due to the fact that the amplitude correction does not guarantee the fact that $\sum_t \propto_{it} = P$.

4.5 Conclusion

Due to the fact that the introduction of a seasonal pattern does not yield improvements of the estimation of beta(it), we will continue with the approximation of beta(it) by means of gamma(i). Approximation of alpha(it) can be considered as a topic for future research.

Subsequently, we will approximate gamma(i) by means of the regression analysis on the store dependent turnover share for beer and the store dependent turnover share coke and soda. Concluding, gamma(i) will be approximated by means of the regression formula:

$$\gamma_i = -0.096 + 0.716 \cdot TurnovershareBeer_i + 1.610 \cdot TurnovershareCoke\&Soda_i \qquad [16]$$

Chapter 5: Numerical study

This chapter contains the numerical study of the model. Section 5.1 covers the selection and analysis of input data. Section 5.2 is aimed at checking the assumptions of the model. Section 5.3 analyses the performance of the model. Section 5.4 considers a sensitivity analysis and section 5.5 adresses the verification and validation of the model. Section 5.6 specifically considers the analysis of the parameters U, γ_i and handling costs. Finally, section 5.7 concludes this chapter.

5.1 Input analysis

Chapter 3 specifies the model of Broekmeulen and Van Donselaar (2012). This section considers the selection and analysis of the input data required for this model.

5.1.1 Sales data

Basis for the model is the estimation of the expected delivery volume. To calculate this volume for store i in time slot t for schedule j, Broekmeulen and Van Donselaar (2012) assume that the delivery volume is equal to the sum of the consumer sales volumes during the review period measured in roll containers. However, data on these sales quantities does not exist as such, due to the fact that consumer demand is realized in consumer units and existing historical delivery volumes in containers are realized per delivery moment instead of per timeslot.

Concluding, the expected sales volume in roll containers needs to be approximated by combining these two data sources. Due to the recent development of Jumbo Supermarkten the company has grown with a large number of new stores that entered the Jumbo formula. Therefore, we will only include “stable” stores that are delivered by DC South and which have delivery data for one year (stores which have demand data for at least 49 weeks) starting at week 21 of 2011. To estimate the expected sales volumes, we have to relate the sales in consumer units with the container quantities. We will first describe the acquisition of the input data in the following paragraphs.

Consumer demand (Consumer units)

Consumer demand in consumer units can be expressed in several levels of aggregation:

- Per product group: either dry groceries, fresh produce or frozen products;
- Per presentation group: e.g. baby food or coffee milk;
- Per products: e.g. Becker Hamburger 12ST.

Ultimately data per product group is required, but within Jumbo Supermarkten data is only available either per presentation group or per product. Thus, aggregation is required. If we can use presentation group data for this aggregation, this saves computation time. However, this assumes that the quality of the underlying SKU data is sufficient and a check is required to confirm this quality. The data quality check is elaborated in appendix ix from which we can conclude that the data quality on an SKU level is relatively good after exclusion of other product groups than the dry groceries product group and exclusion of the “restgroep” presentation group. Subsequently, we can use the presentation group data as a basis to acquire the number of consumer units per product group per time slot t for store i.

Container volumes (Containers)

Container volumes are registered per delivery moment, but can be aggregated to weekly container volumes. Weekly aggregated container volumes are shown in figure 15, where the data in the figure is running for one year, starting at week 21 of 2011. The figure clearly shows a number of peaks such as Christmas and New Year in week 51/52 and Easter in week 14. The variation coefficient is more or less constant through the year.

[redacted]

Figure 15: Average and standard deviation of the weekly demand for all Jumbo stores in the subset

Approximation of sales volumes

Now that both the container quantities and the consumer sales quantities are known, we can combine these data sources to approximate the expected sales volumes by dividing the sales volumes in consumer units by a store-dependent number of consumer units per container.

To determine this number of consumer units per container, the yearly demand per store in consumer units is divided by the yearly number of containers. This results in an average number of consumer units per container equal to [redacted]. Given the realization of an average number of [redacted] case packs per container this implies [redacted] consumer units per case pack. Given the fact that experts on Jumbo Supermarkten's automated order system expected a value between [redacted] in advance, this is realistic. The number of consumer units per container per store shows limited variation across all stores in the subset, with a coefficient of variation of [redacted]. Given the allocation of container volumes to week days, the following step is to forecast sales volumes for the period for which the schedule that is to be developed will hold. However, for now we will leave the forecasting step out of scope. We will assume a stationary demand and develop a schedule for the period of one year, based on available data for one year.

5.1.2 Distance

Within the algorithm as developed by Broekmeulen and Van Donselaar (2012), an estimation of the actual distance is calculated based on the Euclidian distance. This is calculated by the Haversine formula multiplied by a multiplication factor 1.34 which is a reasonable approximation of the average of actual distances divided by the Euclidian distances between two random locations within the Netherlands. The distance is used to estimate the expected actual transportation costs.

5.1.3 Beta parameter

Beta(it) was discussed extensively in chapter 4. As was concluded in that chapter, we will continue with an approximation of beta(it) by gamma(i), which is subsequently approximated by turnover share beer and turnover share coke and soda.

5.1.4 Backroom capacity

The backroom capacity is defined in the model as the available backroom capacity (excluding returnables such as empty roll cages and remaining inventory after first replenishment) in store i during timeslot t. Within Jumbo Supermarkten, separate capacities are defined per store for all product groups. Furthermore, the company defines a fixed inventory per product group which accounts for (regular and promotional) leftovers. The predefined fixed inventory for dry groceries is deducted from the original backroom capacity for dry groceries. This is used as the net available backroom capacity which is input for the model.

5.1.5 Drop cost

To represent the costs per drop, the parameter U considers a generic estimation of the costs per drop for all stores. Based on a financial cost realization, costs per delivery by means of charter trucks equal [redacted]

5.1.6 Truck capacity

Jumbo Supermarkten uses trucks with a range of capacities. To cope with the heterogeneity of the truck fleet, a fixed truck capacity is assigned per store. Hence, we assume that the loads for a certain store are always delivered by one truck type.

[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]

Table 9: Frequency table of the deliveries per week

As shown in table 9, truck capacity can roughly be divided in two capacities: [redacted] (which we will all consider as [redacted]) and [redacted] with a total of [redacted]% share in the total capacity. Stores which are normally delivered by a large capacity truck will have a store dependent capacity equal to [redacted].

As can be seen in data analysis, there are two reasons to deliver a store by a large capacity truck. The store can either have relatively large volumes which save on the delivery frequency, or the store can have a relatively large distance to the distribution center which (in combination with another store) can lead to a large saving on transportation costs. The stores that will be delivered by a large capacity truck are selected based on the criterion of having more than two deliveries per week by a truck with large capacity based on previous schedules. This leads to a total of 25 stores within a total of 122 stores in the sample size.

5.1.7 Further parameter estimates

Further parameter estimates were based on present data and/or determined in consultation with experts within Jumbo Supermarkten.

Parameter	**Value**	**Origin**
Truck speed [Km/Hr]	[redacted]	*Based on average realized truck speed*
KM transport cost [€/Km]	[redacted]	*Based on cost realization*
Hourly transport cost [€/Hr]	[redacted]	*Based on cost realization, combined with setup costs/day*
Load time [Hr]	[redacted]	*Based on current plan value*
Unload time [Hr/RC]	[redacted]	*Based on current plan value*
Handling cost fulltime [€/Hr]	[redacted]	*Based on available data*
Handling cost stackers [€/Hr]	[redacted]	*Based on available data*
Extra drop cost multiplier [-]	[redacted]	*Parameter setting*
Longitude DC [-]	[redacted]	*Based on geographical location*
Latitude DC [-]	[redacted]	*Based on geographical location*
Max smoothing tariff [€]	[redacted]	*Parameter setting*
Target MAD workload [RC]	[redacted]	*Parameter setting*

Table 10: Parameter setting

The maximum smoothing tariff is set very high to be able to compare solutions with a comparable DC load. These parameter settings will be used as input for the remainder of the report.

5.2 Model assumptions

In this paragraph we will check the assumptions of the model of Broekmeulen and Van Donselaar (2012).

5.2.1 Demand is equal to the sum of demand during review period

The model of Broekmeulen and Van Donselaar (2012) assumes that the expected delivery volume is equal to the sum of the demand during the review period. It is possible to check this assumption by comparing the calculated quantity with the realized container quantities for the current schedule. This result is shown in figure 16, where the left axis resembles the average difference across all measurements between the calculated expected delivery volume based on consumer demand and the realized delivery volumes. The right axis shows the relative average distance in percentages compared to the average number of containers across all measurements.

The figure had two important attributes. First, the shape of the graph provides evidence for order advancement in the store. Thus store managers order relatively more at the beginning of the week to balance the workload for instore operations. Second, the average difference is considerable compared to the average expected delivery volume of about 37 containers. Although the difference limits the validity of the model, we will continue under the assumption that the expected delivery volume is equal to the sum of the demands during review period.

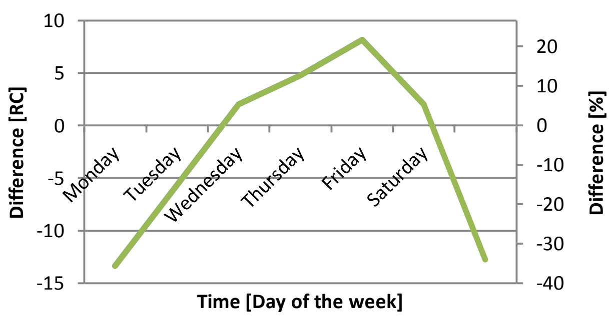

Figure 16: Average nominal and relative difference between actual delivery volumes and calculated delivery volumes

[redacted]

Figure 17: Frequency diagram of all the coefficients of variation per store, per day

5.2.2 Deterministic quantities

In the model of Broekmeulen and Van Donselaar (2012), delivered quantities are assumed to be deterministic. Figure 17 displays the frequency diagram of the coefficient of variation of the consumer demand in consumer units, per day for all stores in the subset (n=122). As can be seen, the daily demand during the year has a relatively low variation since the highest frequencies occur at a coefficient of variation value of [redacted] and [redacted]. Given this result, we conclude that it is legitimate to approximate demand as being deterministic. However, inclusion of variability in the model remains an important aspect for future research.

5.2.3 At most two deliveries per truck route

As mentioned in the model description, the model assumes a maximum of two deliveries per truck route based on Gaur (2004). Figure 18 shows the current route composition within Jumbo Supermarkten. Of all routes conducted on a weekly basis, only [redacted] of all routes that deliver only dry groceries contain three stores in that route.

[redacted]

Figure 18: Frequency diagram for route composition

Regarding the fact that this research is limited to dry groceries, the assumption of having clusters with at maximum two stores seems reasonable and we will continue under this assumption. As can be seen in the graph, the assumption of maximum two routes is less plausible for the other two product groups, fresh produce and frozen products.

5.2.4 Close proximity

The model assumes close proximity of the stores to the DC, such that loading at the DC and unloading at the store always takes place within the same time slot. The stores included in the subset have coordinates as shown in figure 19 which brings forward the outline of the south of the Netherlands. As is clearly visible, most stores are relatively close to the distribution center.

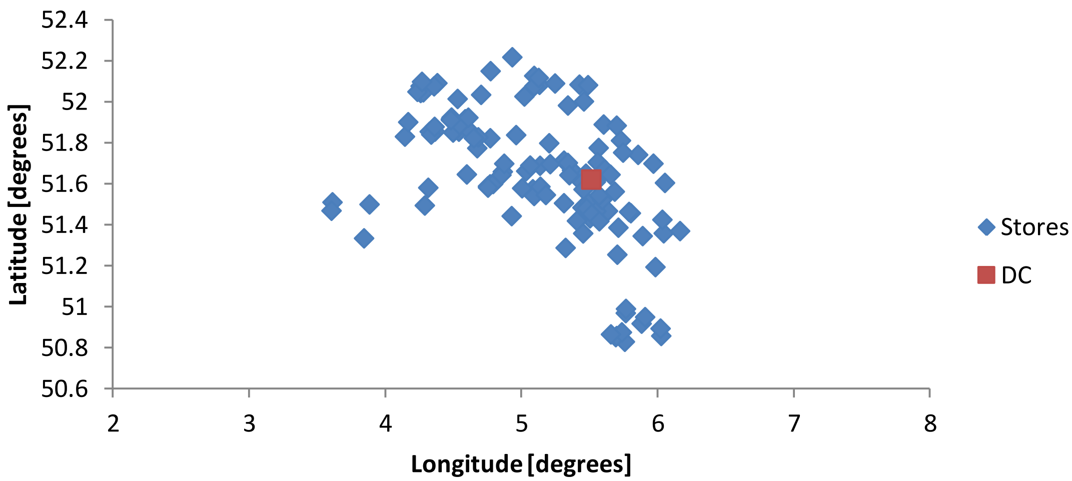

Figure 19: Geographical location of stores, based on geographical coordinates

When we assume a time window of 12 hours per day, this leads to the time per time block as indicated in figure 37 in appendix x. However, this only includes driving time while the loading time at the DC and unloading time at the store is relevant as well. We approximate this by assuming a load time and unload time as described in the parameter setting. This results in figure 38 in appendix x. It can be seen that the assumption of departure from the DC and arrival at the store within one time block is reasonable if at maximum two time blocks per day are used.

5.2.5 Fixed truck capacity per store and ample trucks available

The approach of Broekmeulen and Van Donselaar (2012) assumes a fixed truck capacity per store. As can be seen in table 11, [redacted] of the stores are delivered by trucks of more than one type of capacity if we consider only dry groceries deliveries in a one week schedule. Hence, the approximation by means of a fixed capacity is arguable. Experts on transportation indicate that usually the availability of trucks is not a problem, which makes the availability of ample trucks a reasonable assumption.

[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]

Table 11: Fraction of the stores delivered by a certain number of different capacities within one week

5.2.6 Expected sales are independent of the delivery schedule

The results in figure 16 showed that order advancement has influence on the realized delivery volume. The fact that store managers order more than the projected sales during the review period at the beginning of the week, implies that the presence of more inventory will lead to a fill rate which is higher at the beginning of the week than at the end of the week. However, given the relatively small fraction of out-of-stocks during the week and the use of an automated store ordering system which makes use of an adapted version of an (s,nQ)-policy, it is reasonable to assume that the fill rate is fixed and constant during the week and that the influence of the delivery schedule on the expected sales is negligible.

5.2.7 Backroom capacity

The model makes two assumptions regarding the backroom capacity;

- The backroom capacity is respected at the end of a time slot;
- Net available backroom capacity is already adjusted for empty roll cages and remaining inventory after first replenishment.

The first assumption guarantees that containers for example, do not remain in the stores' corridors overnight. This assumption is realistic as long as time slots are large enough.

The second assumption implicitly assumes that the returnables backroom capacity available is constant and is not being influenced by the delivery schedule. With a capacity demand for returnables which is equal to about 20 percent of the original delivered number of containers, it is not possible to neglect the influence of returnables. We can conclude as well that it is not desirable to collect returnables at each delivery since the collection of returnables comes with extra costs as indicated in table 12 which is equal to a [redacted] increase of route costs. Moreover, a fraction of all stores (9.05 %) is not the last store in the route in the current schedule, where it is not possible to collect returnables since this would hinder the next delivery.

[redacted]	[redacted]
[redacted]	[redacted]
[redacted]	[redacted]
[redacted]	[redacted]

Table 12: Extra costs for collecting returnables

To incorporate returnables in the model, we make use of a fixed number of containers in the backroom to account for remaining inventory and returnables as indicated by the stores. If capacity becomes a bottleneck, trucks are always able to collect returnables at the moment of delivery, thereby preventing capacity issues. Although this leads to a cost increase, it is expected that this "emergency" solution is not frequently needed. In addition, if stores are not the last store in the route, the delivery sequence can be changed.

Concluding, returned packaging is not expected to have influence on the process. Moreover, employees of Jumbo Supermarkten indicate that is that the available backroom capacity for the storage of nonconcurrent dry groceries containers can be approximated by a constant capacity. We will continue under this assumption.

5.2.9 Two types of workers, where available capacity is limited for regular shelf stackers

Although it is possible to distinguish more types of workers based on age and hourly wage as shown in table 13, a rough distinction between two groups is reasonable to include the difference. Interviews with store supervisors confirm this, and indicate that most of the regular shelf stackers can be assumed to be of class 1. A limitation of the shelf stacker capacity is reasonable to model for example, the unavailability of young shelf stacking capacity during the day and thereby, it is a suggestion for improvement of the model. A general restriction on the overall shelf stacking capacity is not included in the current model. If timeslots become very small, the number of containers that is stacked eventually is capacitated due to the availability of space in the store corridor and due to the nuisance that is caused by customers by shelf stacking during opening hours.

Class	Hourly wage
1: < 18 years	[redacted]
2: < 20 years	[redacted]
3: < 23 years	[redacted]
4: < chef	[redacted]
5: Specialist	[redacted]

Table 13: Hourly wage per labor class, rounded in whole Euros

5.2.10 General conclusion

Based on the assessment of the model's assumptions, it can be concluded that the model's assumptions seem reasonable although limitations are observed for:

- The observed order smoothing by store managers;
- The fixed truck capacity per store;
- The uncapacitated shelf stacking capacity.

Although these assumptions will have influence on the model's output, we will continue under these assumptions.

5.3 Model performance and output analysis

This paragraph analyzes the output of the model. During this paragraph we will generally compare three situations:

- "Current situation", which represents the effect of the current schedules given the parameter setting defined earlier;
- "Local optimization", which represents the effect of the set of selected schedules before applying the smoothing approach;
- "Smoothing tariff", which represents the effect of the set of selected schedules after applying the smoothing approach;

What needs to be noted is that for the "current situation", the output will be based on the calculated demand for capacity instead of on the realized demand. This excludes the presence of order smoothing by store managers. Although this limits the exact comparison with the actual current situation, it creates the possibility to compare the current situation given the model of Broekmeulen and Van Donselaar (2012) with the model's output.

5.3.1 Data set and model performance

The data set consists of 122 stores, for all of which the parameter settings as mentioned in paragraph 5.1.7 are available. Running the PWDS optimizer takes about 40 minutes.

5.3.2 Key performance indicators

In essence, the optimal solution should provide the solution with the lowest costs given the capacities in the model. To provide a more in-depth view on the results, we will compare the solutions based on several aspects with one or multiple KPIs:

- Distribution center performance
    - DC costs;
        - Average smoothing tariff
    - Aggregated volume per timeslot;
        - MAD: Mean Absolute Difference between the target workload $\overline{w}_t$ and the aggregated workload after smoothing, across all t
        - Minimal workload, measured in roll containers
        - Maximum workload, measured in roll containers
    - Number of routes: determines both the dock load (DC) and the number of required trucks per timeslot (transportation);
        - Minimal number of routes
        - Maximum number of routes
- Transport performance
    - Transportation costs;
        - Average transportation costs for the DC
        - Average transportation costs for the store
    - Occupancy rate;
        - Average occupancy rate
    - Number of stops;
        - Total number of stops
    - Number of combinations, i.e. number of routes with more than one stop;
        - Average number of combinations/Number of stops
- Store performance
    - Handling costs;
        - Average store handling costs
    - Delivery frequency;
        - Average delivery frequency

The output analysis will consider the measures in more detail. For the sensitivity analysis, verification and validation, we will make use of the KPIs as such. It is important to note is that cost analyses can only be considered for the local optimization solution and for the solution after smoothing. The current solution cannot be evaluated in terms of costs, due to the fact that the model of Broekmeulen and Van Donselaar (2012) makes use of an LP-formulation. Hence, where the current solution can be less strict considering the availability of backroom capacity, this is a hard constraint in the analytical model. For 39 stores of the total of 122 stores (32 %), the current schedules are not included as an optional schedule and costs are not calculated.

5.3.3 Output analysis

This paragraph outlines the results of the analytical model of Broekmeulen and Van Donselaar (2012) given the data input as described prior in this report. This leads to the cost balance as presented in figure 20. As can be seen, the costs for handling in the store represent the largest share in the cost pie. In accordance with the supply chain cost composition in figure 3, the store handling costs are about twice as high as transportation costs. The costs in the distribution center are much lower, due to the fact that this figure considers the smoothing tariffs instead of actual DC costs.

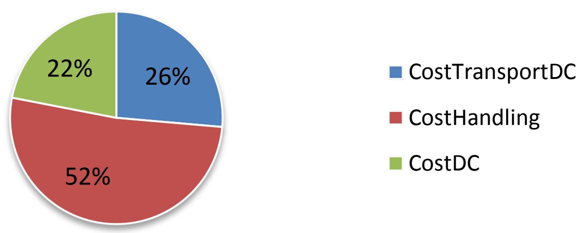

Figure 20: Share in total costs in the model

Given this cost output, we will describe the consequences of the solution per step of the supply chain.

Distribution center

In this section we will consider the implications of the output for the distribution center. The performance of the distribution center mainly depends on the aggregated number of roll cages per timeslot that need to be processed by the DC, which is determined by [IPL 7]. We will consider the distribution of these loads and we will consider the smoothing tariffs that are used to smooth the solution after local optimization.

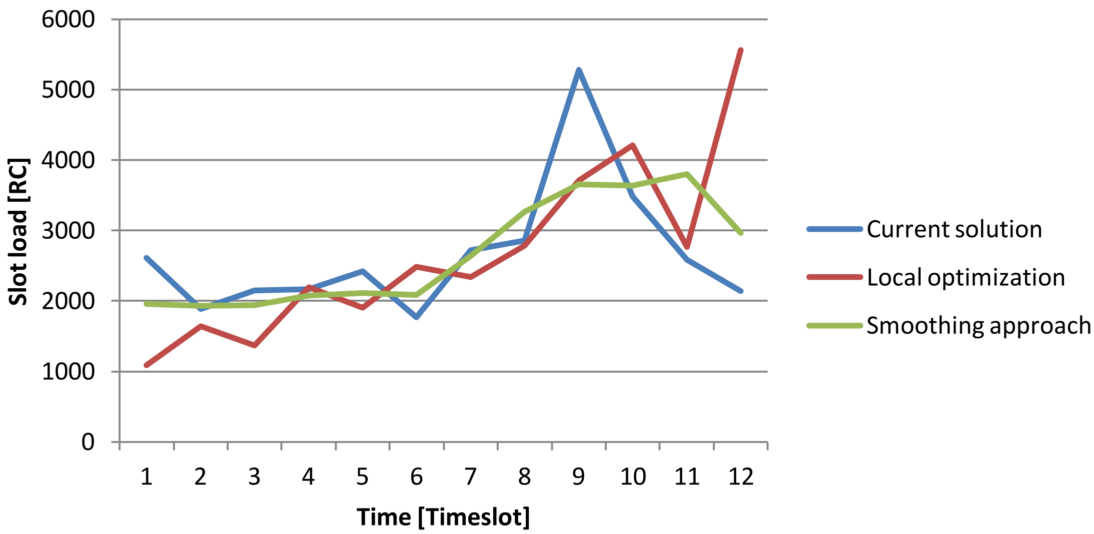

Figure 21: Aggregated number of containers per timeslot

Figure 21 shows the distribution of roll-containers over the week. Firstly, it can be seen that during the beginning of the week (timeslots 1 to 8), the slot load of the current solution is comparable with the solution after applying the smoothing approach. However, timeslot 9 shows a large peak for the current solution while the solution after applying the smoothing approach shows a more smoothed pattern. As was discussed in section 5.2.1, the execution of order smoothing by store managers is not included in this model. Hence, this indicates that due to the overestimation of the demand during peak periods in the current demand model, the actual peak in slot loads will be lower than indicated. Nevertheless, due to the fact that earlier results in figure 16 showed that the overestimation of delivery volumes was limited to about 20 % on Friday, we can still state that the results of the current solution show potential to reduce the peak load. The number of routes departing from the DC per timeslot showed a pattern which is comparable with the smoothed workload distribution. Thus, no capacity problems are expected considering the dock capacity or truck availability.

The smoothing of the solution after local optimization occurs by means of the introduction of smoothing tariffs in the anticipated base level according to figure 22 on the next page. The seasonal pattern in the demand data creates an incentive for stores to receive a delivery at the end of the week. Hence, to smoothen the initially large aggregated expected sales volumes during these last timeslots of the week the smoothing tariffs show a large peak at the end of the time horizon. However, due to the cyclic time window and the interaction between stores, the reduction of the local demand for deliveries at the end of the week (timeslots 10-12) will lead to an increase in the demand for deliveries during timeslots at the beginning of the week. Thus, to balance the demand the smoothing tariff needs to be increased at the beginning of the week to compensate the flow of demand from the end of the week.

The initial solution with local optimization shows an alternating pattern where within one day the slot load in the afternoon timeslot (2,4,6…,12) is higher than the morning timeslot (1,2,…,11) for all delivery days. This pattern is explainable due to the availability of cheap labor in the afternoon time slot which gives stores an incentive to choose for a delivery in the afternoon timeslot, combined with the fact that the model assigns (very low) holding costs to the backroom inventory at the end of period t. The alternating pattern after the local optimization is cancelled out after applying the smoothing algorithm of Broekmeulen and Van Donselaar (2012). Although figure 21 showed an alternating pattern for the slot load after local optimization, there is not a clear alternating pattern visible in the graphical representation of smoothing tariffs in figure 22.

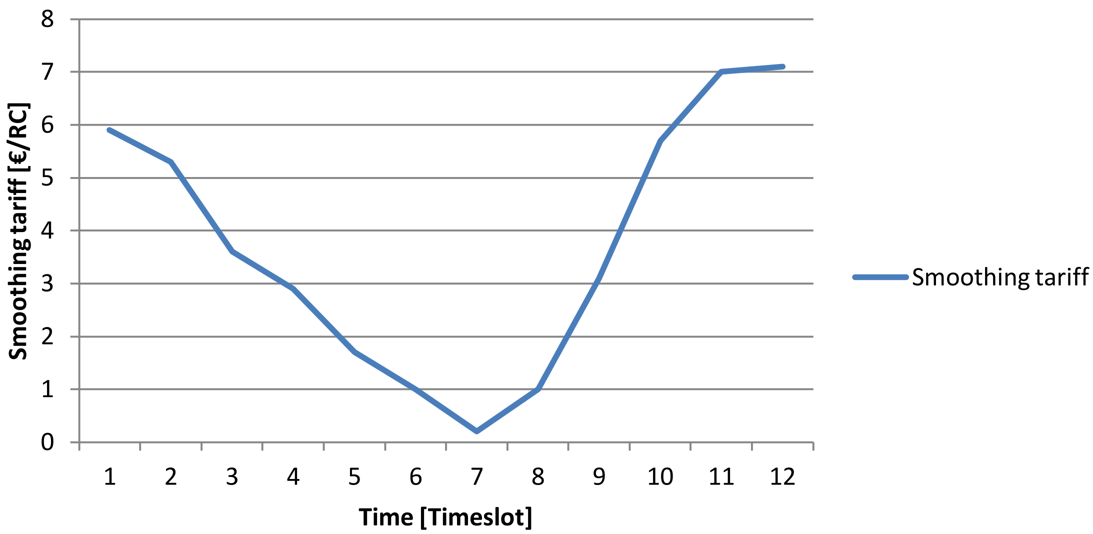

Figure 22: Smoothing tariff per timeslot

The conclusion that only a small tariff is required to smooth workload to a large extent is supported by figure 23 as well. The allocation of small smoothing tariffs is already able to outperform the store benefit of the availability of cheap labor availability in the afternoon slots for stores with a relatively large backroom capacity.

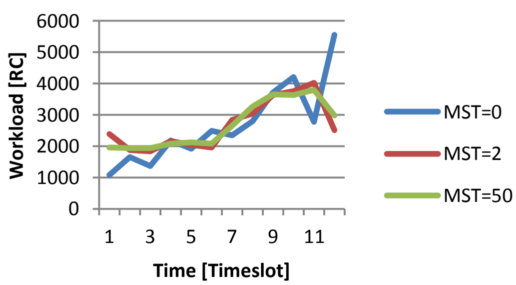

Figure 23: Workload after smoothing, for three values of the maximum smoothing tariff

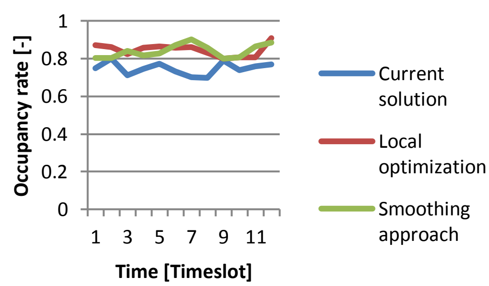

Figure 24: Occupancy rate throughout the week

Transportation

The performance of the transportation function ultimately depends on the [redacted] This leads to a share in the total supply costs as indicated in figure 20. Hence, although the relative cost share of transportation is small compared to the other steps in the supply chain, the extent to which the costs can be influenced is relatively high. To put these financial measures in perspective we will consider the occupancy rate and the number of loads and combinations.

The occupancy rate per timeslot, depicted in figure 24, shows a relatively flat pattern over the week. However, the occupancy rate of the current solution is considerably smaller than the occupancy rate for the solution as generated by the algorithm of Broekmeulen and Van Donselaar (2012). This result can be explained by two factors.

First, the model of Broekmeulen and Van Donselaar (2012) includes truck capacity in the anticipated base model for the selection of schedules. However, in the current process within Jumbo Supermarkten, the schedule selection is based on store costs and capacities and this set of schedules is only sub optimized for transportation and DC at the end of the process. Hence, the observed difference in figure 24 between the current solution and the solution after smoothing is mainly due to the fact that in the model of Broekmeulen and Van Donselaar (2012) truck capacity is part of the anticipated base model while in the current situation this is not the case.

Second, the model of Broekmeulen and Van Donselaar (2012) assumes a fixed truck capacity per store. However, almost [redacted] of the stores is delivered by more than one truck capacity per week. Hence, in reality the truck capacity differs per delivery which directly leads to an over- or underestimation of the delivery volume compared to the truck capacity. This implies an underestimation of the occupancy rate and an overestimation of the transportation costs for the current situation.

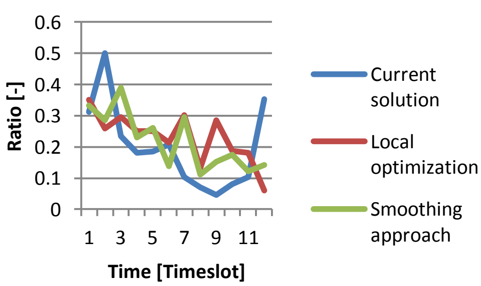

Figure 25: Nr. of combinations/Nr. of stops

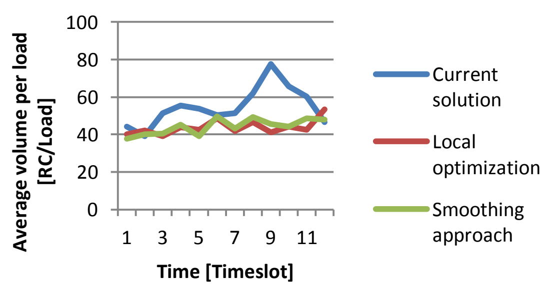

Figure 26: Average nr. of roll-containers per stop

Thus, the occupancy rate makes a statement considering the use of capacity at the moment of departure at the DC. In addition, it is relevant to consider the extent to which multiple loads can be combined into one truck. A larger ratio of combinations relative to the number of stops indicates a less efficient use of trucks per route as such, although savings on instore operations may outweigh these extra costs. Figure 25 depicts the number of combined routes for the three different situations relative to the number of loads. For all three solutions, the relative number of combinations is decreasing as the week progresses, which is mainly influenced by the average number of roll containers per stop in figure 26, due to the fact that combining two loads in one truck is easier when loads are small.

Store operations

In the current schedule generation process within Jumbo Supermarkten, stores are assigned to a delivery day and a time block. Hence, in this situation stores can be delivered in at maximum 6 time blocks per week and this schedule is input to the allocation of transportation material. If the expected delivery volume according to Jumbo's forecast exceeds the assigned truck capacity, the store will receive an additional delivery with the remainder of the products within the same timeslot.

In contrast, in the analytical model of Broekmeulen and Van Donselaar (2012), the assignment of a store to a timeslot has a restricted truck capacity and the model allocates a penalty cost if the expected delivery volume exceeds this capacity. Hence, it is not possible to compare the solution after smoothing based on the frequency as such. However, it is possible to compare based on the number of delivery days on which a store receives a delivery.

	[redacted]		[redacted]
[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]
[redacted]		[redacted]	
[redacted]		[redacted]	
[redacted]		[redacted]	
[redacted]		[redacted]	
[redacted]		[redacted]	
[redacted]		[redacted]	

Table 14: Delivery days and delivery frequency for the current situation and for the smoothing solution

Table 14 shows the results for the smoothing approach and the current solution. The current solution has total of [redacted] delivery days per week with an average of [redacted] delivery days per week per store, while the smoothing solution has 584 delivery days per week and an average of 4.79 delivery days per week per store. Thus, the solution of Broekmeulen and van Donselaar (2012) is comparable with the current situation regarding the number of days at which a store is delivered. The main difference is the fact that while the current solution has a standard deviation of [redacted], the smoothing solution has a standard deviation of 1.19. Hence, while the average number of delivery days is comparable, the deviation the number of delivery days is much higher for the smoothing solution.

Furthermore, data analysis showed that for most of the stores the eventual delivery frequency of the approach of Broekmeulen and van Donselaar (2012) was equal to the minimal delivery frequency which is possible regarding delivery frequency and backroom constraints. Only five stores in the sample set of 122 deviated from their minimal delivery frequency and these five stores showed an increase of the delivery frequency with one delivery per week. Hence, we can conclude that due to the relatively high costs per drop relative to the handling costs, the main contribution of the approach of Broekmeulen and Van Donselaar (2012) is to determine the days of delivery instead of the determination of the delivery frequency.

5.4 Sensitivity analysis

In this section, we will conduct a sensitivity analysis by adapting parameter values with an increase or decrease of 12.5% or 25 %. We will compare the results based on the key performance indicators as described in section 5.3.2. The results of the sensitivity analysis as shown in appendix xi yielded three conclusions:

- There is a clear separation between two types of parameters in the model of Broekmeulen and van Donselaar (2012)
    - Parameters which only have an influence on the eventual expected transportation costs for the DC;
    - Parameters which have direct or indirect influence on all schedule parameters, due to the fact that the parameters affect the top level or anticipated base level;
- For the parameters which only have effect on the eventual transportation costs for the DC, hourly transportation costs have the largest influence on the eventual costs. However, the influence of these costs is limited due to the fact that these parameters do not influence schedule selection but only the eventual schedule costs.
- Parameters which directly or indirectly affect all schedule parameters do have influence on the schedule choice. From these parameters, the target MAD of the workload and handling costs are most sensitive to changes in input data.

5.5 Verification and validation

This section first considers the verification of the model, which checks whether the results of the model are in accordance with what was programmed. Second, this section considers the validation of the model which checks whether results are in line with reality.

5.5.1 Verification

Verification checks whether results are in accordance with the expected reaction of the model. We will do a verification by means of an extreme value test. In this test, we vary the parameter settings between extreme values to check the effect on the outcome of the model. As can be seen in appendix xii, insertion of the extreme values does not yield unexpected outcomes.

5.5.2 Validation

As discussed prior in this report, there are two main issues regarding the validity of the model. First, the difference between the expected delivery quantity and the realized delivery quantity based on historical data and second, the difference regarding the truck capacity and occupancy rate.

The inaccurate estimation of the expected delivery volumes reduces the validity of the model. The inclusion of order advancement by store managers should improve the validity of the model and thereby is suitable for further research. However, even if we can acquire a good approximation of order advancement in the model, it is arguable to what extent it is possible to yield an accurate estimation of the expected delivery volume for all delivery moments and all delivery schedules.

The second issue regarding the validity of the model was the difference between the current delivery of one store by trucks with more than one type of capacity while the model which assumes a single truck capacity per store. Although this limits the validity of the model, the delivery of a store by one truck type is not per definition worse than the current solution at Jumbo Supermarkten. Furthermore, the future harmonization of the truck fleet will increase the validity of this assumption.

Concluding, these two issues affect the validity of the model. However, we will leave these two topics for future research and these issues are taken for granted.

5.6 Discussion of U, Gamma(i) and handling costs

In the introduction of this report, we addressed the influence of the backroom as an important topic for future research. In this section, we will consider the interaction between three model parameters U (which represents the costs per drop for all stores) gamma(i) (which represents the fraction concurrent) and shelf stacking costs. As can be seen in the model of Broekmeulen and Van Donselaar (2012), these parameters have an interaction via the store's backroom.

First of all, given a fixed set of capacity parameters the drop cost parameter U and the handling costs jointly determine the costs during local optimization and the schedule choice is purely based on the balance between these costs. The model of Broekmeulen and Van Donselaar (2012) selects a schedule per store. Due to the fact that regardless of the schedule the delivered volume per week in terms of roll containers is fixed, all containers will have to be stacked and only the difference between regular shelf stackers and full time employees is relevant. Hence, when we lower the difference between the shelf stacking costs (for regular and fulltime employees) and U with the same percentage, the solution remains exactly the same after local optimization. The same holds for the solution after smoothing, although due to the presence of rounding effects the smoothing tariffs and the resulting schedule selection can slightly differ.

Apart from the drop cost U and the difference between handling costs, the fraction concurrent which is represented in the model by gamma(i) influence the schedule choice as well. This can be subdivided in two effects:

- First, gamma(i) has direct influence in combination with handling costs due to the fact that the fraction concurrent is stacked in the model by means of fulltime workers.
- Second, gamma(i) has indirect influence in combination with handling costs due to the fact that the fraction concurrent determines the constraining effect of the backroom.

Hence, gamma(i) influences both the fraction of the demand which is stacked by fulltime employees relative to the regular shelf stackers.

Concluding, gamma(i) and the backroom capacity jointly determine the available backroom capacity which is available per store to store nonconcurrent backroom inventory. Subsequently, the balance between the drop cost parameter U and the difference between the two handling cost parameters determine the eventual store handling costs per schedule per store.

5.7 Conclusion

The numerical study in this chapter considered the use of the analytical model of Broekmeulen and Van Donselaar (2012). We can draw multiple conclusions on this chapter:

- Analysis of the demand data showed that store managers make use of order advancement. This is an area for future research.
- Although the model assumes a fixed truck capacity per store, table 11 showed that almost [redacted] of the stores is delivered by trucks of more than one different capacity.
- Based on the expected delivery volume available, the approach of Broekmeulen and Van Donselaar (2012) is able to reduce the peak load. Reduction of peak loads is beneficial for the distribution center in two manners:
    - First, the reduction of peak loads leads to a lower demand for (flexible and more expensive) temporary workers.
    - Second, a peak load causes a reduction of the labor productivity due to congestion in DC corridors. This increases costs as well.
- To be able to compare different solutions with a similar MAD, we have set the maximum smoothing tariff to a very large value in the standard parameter settings. However, figure 23 showed that allocation of a relatively small tariff can already provide an incentive to the stores that is large enough to balance the DC workload to a large extent. Thus, stores do not necessarily need to receive a schedule which deviates much from their optimal schedule.
- The approach of Broekmeulen and Van Donselaar (2012) shows an improvement of the occupancy rate which is mainly due to the fact that this analytical model makes a comparison with truck capacity in the anticipated base model. Hence, the approach has the potential to decrease Jumbo's transportation costs by means of a better matching of demand and supply of respectively, roll containers and (truck) capacities.
- As shown in table 14, the average number of delivery days that result from the model of Broekmeulen and Van Donselaar (2012) are comparable to the number of delivery days for the current actual situation. Due to the fact that the model makes use of hard backroom constraints, the average of delivery days of the model is slightly higher than the current delivery frequency. The number of delivery days of the model showed a much larger standard deviation than the number of delivery days for the current actual situation.
- For 117 out of 122 stores the delivery frequency is equal to the minimal delivery frequency. The 5 stores with a deviating delivery frequency showed an increase of the delivery frequency with exactly one delivery. Hence, the approach contributes by optimizing the distribution of delivery days more than by optimization of the delivery frequency.

Chapter 6: Implementation

This chapter discusses the final phase of this project, the implementation of a new approach for the development of a periodic weekly delivery schedule (PWDS), in the form of a supply chain planning system.

In the current situation, the design of a PWDS is a stepwise process; the coordinator supply chain planning assigns one schedule per store based on certain store characteristics, subsequently the transportation function assigns trucks to deliveries and the distribution center checks whether the workload distribution is feasible. A supply chain planning system can improve both process and performance of the current schedule generation. This chapter considers the advantages regarding both process and performance in paragraph 6.1 and paragraph 6.2. Furthermore, this chapter considers the possibilities of the implementation of the smoothing tariff in paragraph 6.3.

6.1 Performance

A new supply chain planning system is able to contribute to a better schedule performance on three aspects.

First of all, the use of such a system gives clarity to all the stakeholders in the process. Due to the importance of the schedule for day-to-day operations, the development of such a schedule can lead to an emotional and political discussion. A scheduling approach can concentrate these discussions on a rational discussion on parameter values and the introduction of a scheduling approach can contribute to the discussion as such, due to the fact that it is possible to calculate the additional costs for the change of the set of schedules.

Secondly, a new supply chain planning system can result in a better set of schedules as such for the whole supply chain. For example, taking into account truck capacity during the choice of a schedule can lead to a reduction of the number of routes and a reduction of instore handling costs due to the delayed delivery. Or for example, taking into account store specific demand variability can prevent overload or partly empty trucks.

Thirdly, a supply chain planning system gives the opportunity to conduct “what if..?”-analyses on a strategic level. For example, it can be used to study a possible reallocation of stores to a distribution center or to consider the option to increase the distribution center’s production capacity.

6.2 Process

Within Jumbo Supermarkten, it can be expected that the largest benefit of the introduction of a supply chain planning system will be in the process improvement. Currently, the process contains numerous manual data adaptations which makes the process slow and labor intensive. An integrated supply chain planning system is able to contribute to a better schedule generation process on three aspects.

Firstly, the introduction of a supply chain planning system can make the process less labor intensive. The current process contains several manual executions of data adaptations, which can be automated.

Secondly, the introduction of a supply chain planning system can make generation of a set of schedule faster. This decreases the lead-time of the generation of a schedule which gives the opportunity to adapt the schedule more often to changing demand during the year. Furthermore, a decrease of the schedule generation lead-time gives the opportunity to use more recent data and even to respond faster to emergencies, such as for the reallocation of stores during a (partial) breakdown of a distribution center.

Thirdly, it is possible to couple the supply chain planning system with, amongst others, SAP. This reduces the amount of errors which currently occur due to inaccurate data entry.

6.3 Implementation of a tariff structure

The resulting tariff structure that results from the model of Broekmeulen and van Donselaar (2012) provides incentives for stores to use schedules which are sub optimal as such for that specific store. However, this does not require the full incentive needs to be paid out to the stores.

Regarding the use of these incentives, two different systems are possible: a bonus system or a penalty system. The first system considers the smoothing tariffs to be additional income for the store to compensate for extra costs. The second system assumes worst-case costs for the store, and stores can acquire a better schedule by paying a certain fee to Jumbo Supermarkten. In both cases, not the full smoothing tariff needs to be paid out to the stores. Jumbo Supermarkten can determine a threshold value that needs to be reached before a store is paid out the difference between this threshold value and the smoothing costs. Due to differences in store size this value should be determined per roll container and this value can, for example, be determined by the store with the lowest average smoothing costs.

6.4 Conclusion

One of the two aims of this master thesis to provide an approach for the generation of the periodic weekly delivery schedule. Eventually, this can be used as a basis for a future integrated supply chain planning system for Jumbo Supermarkten. Based on the findings, we can conclude that the introduction of a supply chain planning system can make the current process both more effective and efficient and the introduction of smoothing tariffs can structure the political discussion.

Chapter 7: Conclusion and recommendations

This chapter contains the main conclusions and recommendations that resulted from the research project. In paragraph 7.1, general conclusions will be drawn regarding the different phases of the project. Paragraph 7.2 addresses two recommendations for Jumbo Supermarkten. Paragraph 7.3 considers the academic relevance of this thesis and finally, paragraph 7.4 considers limitations and areas for future research.

7.1 General conclusions

Within this section conclusions will be drawn regarding the different phases of the research project.

7.1.1 Analysis of the problem context

The introduction of this master thesis indicated yielded that the current process for generating the periodic weekly delivery schedule at Jumbo Supermarkten is inefficient and, presumably, also ineffective. To improve the schedule generation, Jumbo aims at an integrated supply chain planning which was supported, amongst others, by a supply chain cost analysis which illustrates the importance of a supply chain approach instead of a focus which is limited to a sub optimization of for example, transportation.

7.1.2 Conceptual model

To improve the current process, chapter 2 considers the development of a new conceptual model. Regarding the conceptual model the following main conclusions were made:

- The conceptual model is based on a hierarchical planning framework based on Schneeweiss (2003). This framework consists of a top model which decides based on the anticipated base model.
- The top level consists of a local store cost model. Only handling costs are taken into account.
- The anticipated base level contains the anticipated transportation costs for the store. To avoid stores to be privileged or prejudiced based on the distance to the distribution center, we include a parameter in the model which resembles the costs per drop and which is the same for all stores.
- The anticipated base level contains the expected DC costs for the store. To level the DC workload, smoothing tariffs are introduced which have influence on the aggregated result after local optimization by the store.

7.1.3 Analytical model

This master thesis makes use of the analytical model of Broekmeulen and Van Donselaar (2012). The model is deterministic and makes use of the framework of Schneeweiss (2003).

7.1.4 Beta

This master thesis specifically considers the analysis of the parameter beta(it), which is a parameter of the analytical model of Broekmeulen and van Donselaar (2012). The analysis firstly showed that the quality of the SAP shelf capacity data was not as good as expected, at least for very fast moving products. After a data quality check for 18 stores and 3 products per store, actual instore shelf capacities showed to be on average 116 % higher than the shelf capacities in SAP. Due to the fact that SAP shelf capacity is used to perform an instore logistical optimization, an improvement of data quality can lead to a more smoothed store demand and thereby to large cost savings in the remainder of the supply chain.

Secondly, after a choice for the definition of beta as described in section 4.1, the analysis focuses on approximation of beta(it). The computation of beta(it) according to the definition is done per product per store which causes a very high demand for computational resources. Approximation by means of readily available data increases the efficiency of the model. The approximation was split up in two parts: approximation of gamma(i) which represents the average of beta(it) and approximation of the seasonal effect by means of alpha(it). The approximation of the two parameters yielded three conclusions:

- Regression analysis does not show a significant relationship between turnover pressure (i.e. turnover in Euros per square meter store floor area) and gamma(i).
- Regression analysis showed a significant relationship between turnover share beer and turnover share coke & soda.
- Approximation of alpha(it) by means of a store dependent seasonal index parameter of the consumer turnover per day does not yield a good approximation. Beta(it) has a much larger amplitude and a generic correction for the difference in amplitude does not yield better results than approximation of beta(it) by means of gamma(i).

7.1.5 Numerical study

Chapter 5 considers a numerical study of the research context. The numerical study yields the following conclusions:

- Stores make use of order advancement, the (expected) delivery volume is not equal to the sum of sales during the review period. This is an area for future research.
- Almost half of all stores is delivered by more than one type of truck capacity.
- Based on the expected delivery volume available, the algorithm of Broekmeulen and Van Donselaar (2012) is able to reduce the peak load. Reduction of peak loads is beneficial for the distribution center in two manners:
    - First, the reduction of peak loads leads to a lower demand for (flexible) temporary workers.
    - Second, a peak load causes a reduction of the labor productivity due to congestion in DC corridors. This increases costs as well.
- Allocation of a relatively small tariff can already provide an incentive to the stores that is large enough to balance the DC workload to a large extent.
- The approach of Broekmeulen and Van Donselaar (2012) is able to decrease Jumbo's transportation costs by means of a better matching of supply and demand or respectively, roll containers and capacities.
- The average number of delivery days which is obtained the approach of Broekmeulen and Van Donselaar (2012) is comparable with the average number of delivery days for the current situation, although the distribution of the number of delivery days per store of the model showed a much larger standard deviation.

- For 117 out of 122 stores the delivery frequency is equal to the minimal delivery frequency. The five stores with a deviating delivery frequency showed an increase of the delivery frequency with one delivery. Hence, regarding the fact that delivery frequencies are more or less fixed, the approach of Broekmeulen and Van Donselaar (2012) mainly contributes by optimizing the distribution of delivery days.

7.1.6 Answer to the research question

In the introduction in chapter 1, we addressed the following research question:

How can Jumbo Supermarkten B.V. generate a Periodic Weekly Delivery Schedule that has the lowest total cost for the supply chain and takes into account all constraints?

In the chapter, the research question is split up in two sub questions. The first research question questions how Jumbo Supermarkten can simplify the process of designing a PWDS. As was concluded in the first chapter, the current schedule generation process consists of many steps with many different departments which leads to a labor intensive and time consuming process. The model has shown to provide good results where the time needed for schedule generation is limited to about 40 minutes. Thus, the introduction of an integrated schedule generation system can shorten the leadtime of the schedule generation process and reduce the (human) resources needed to generate the schedule.

The second sub question questions how Jumbo Supermarkten can increase the performance of the PWDS. As shown in chapter 6, the approach of Broekmeulen and Van Donselaar (2012) has the potential to improve the performance of the model output. The integrated approach leads to a better match between demand (in roll containers) and supply (of capacity) which is able to reduce peak loads for the DC, costs for transportation and yield better schedules for stores.

7.2 Recommendations for Jumbo Supermarkten

The section addresses the recommendations for Jumbo Supermarkten. As shown in chapter 1, the supply chain cost composition gives evidence for the introduction of a supply chain oriented planning process. For the reasons explained in the prior paragraph, one recommendation for Jumbo Supermarkten is to implement a new supply chain planning system which aims at the generation of an integrated planning.

Second, chapter 4 showed that the quality of the SAP shelf capacity data is lower than expected. Hence, it is recommendable to investigate :

- To what extent this sample size is representative for all products and all stores;
- To what extent the workload balancing for transportation and for the DC can be improved by an improvement of the data quality;

Subsequently, it can be beneficial to provide incentives for stores to increase the SAP data quality. Apart from the shelf capacity data, stores show large differences in terms of variability of store demand. Hence, Jumbo should investigate the extent to which it is possible to influence store order behavior.

7.3 Academic relevance

In the first chapter we discussed the fact that one of the two goals is to contribute to the literature available on the topic of the PWDS. This thesis contributes to this topic on two aspects.

To start with, this master thesis contributes to the academic literature available by the fact that in contrast to the literature available, this thesis takes into account the whole supply chain while prior research was mostly limited to transportation costs (van Dun, 2012). The approach of Broekmeulen and Van Donselaar showed to be able to balance supply chain costs and capacities.

Furthermore, this master thesis contributes to the academic literature available with the fact that in contrast to the literature available the approach of Broekmeulen and Van Donselaar (2012) focuses on stores instead of on transportation. The introduction of an anticipated base level based on the framework of Schneeweiss (2003), is able to represent the often political process that comes with the distribution of costs. This makes the approach especially useful in case of franchise stores.

7.4 Limitations and areas for future research

This section shows some limitations of the model, which are suggested for areas suitable for future research:

- The current formulation of the model assumes delivery volumes to be equal to the sum of sales during the review period. The inclusion of order advancement by store managers can yield a better approximation. Therefore, this is an area for future research.
- The current model assumes deterministic demand. The inclusion of stochasticity in the model is an area which is important for future research.
- The inclusion of a heterogeneous truck capacity can improve the model's validity and therefore, is an area for future research.

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Appendices

Appendix I

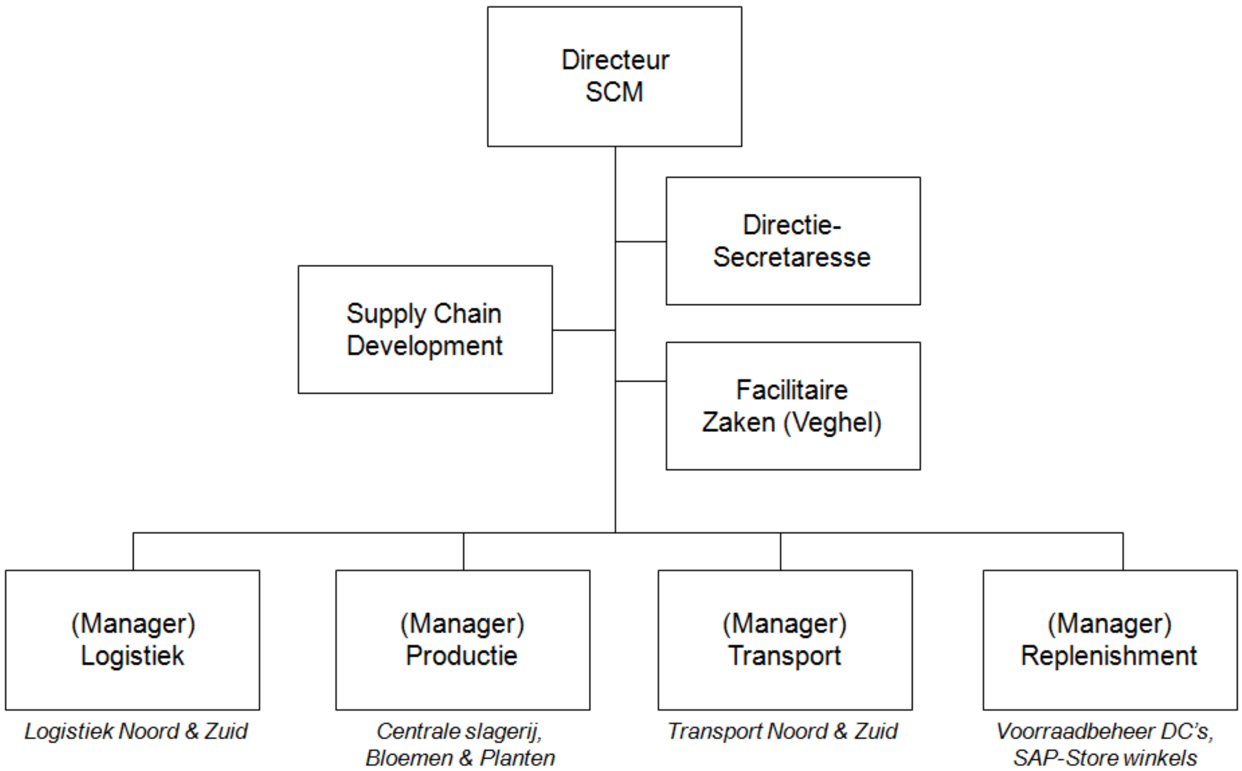

Figure 27: Organization chart of Jumbo Supermarkten's Supply Chain Management department

Appendix II

Bestel en Afleverschema

VERSIE: RE1016-WK18

JUMBO supermarkten

Winkel nr 56154 J SCHIJNDEL ROOISEHEIDE

ingangsdatum : **Afleverdatum 02 mei 2011**

Groep	OSG	Omschrijving Groep	Besteldag	Besteltijd	Leverdag	Levertijd* Hoofdvracht	Levertijd*2e hoofdvracht	Levertijd* Restant
						van - tot	van - tot	van - tot
VERS 1	VERS	Vleeswaren, Kaas, Brood,	maandag	9:00	maandag	19:00 - 21:00		
		Salade, Vis en vegetarisch,	dinsdag	9:00	dinsdag	19:00 - 21:00		
		Slagerij / grill corner	woensdag	9:00	woensdag	19:00 - 21:00		
	ZUIVEL	Zuivel / Boter	donderdag	9:00	donderdag	19:00 - 21:00	19:00 - 21:00	
	KRICO	Convenience	vrijdag	9:00	vrijdag	19:00 - 21:00	19:00 - 21:00	
	AGF WARM	AGF Warm	zaterdag	9:00	zaterdag	19:00 - 21:00		
VERS 2	AGF KOUD	AGF koud	maandag	9:00	maandag	19:00 - 21:00		
		AGF Kriel	dinsdag	9:00	dinsdag	19:00 - 21:00		
			woensdag	9:00	woensdag	19:00 - 21:00		
			donderdag	9:00	donderdag	19:00 - 21:00		
			vrijdag	9:00	vrijdag	19:00 - 21:00		
			zaterdag	9:00	zaterdag	19:00 - 21:00		
XDOCK VERS	AGF PBL 0	Stoomgroenten	zaterdag	10:00	maandag	19:00 - 21:00		
			maandag	10:00	dinsdag	19:00 - 21:00		
			dinsdag	10:00	woensdag	19:00 - 21:00		
			woensdag	10:00	donderdag	19:00 - 21:00		
			donderdag	10:00	vrijdag	19:00 - 21:00		
	XDBACU_K	BACU Banket	zaterdag	9:00	maandag	19:00 - 21:00		
			maandag	15:00	dinsdag	19:00 - 21:00		
			dinsdag	15:00	woensdag	19:00 - 21:00		
			woensdag	15:00	donderdag	19:00 - 21:00		
			donderdag	15:00	vrijdag	19:00 - 21:00		
			vrijdag	15:00	zaterdag	19:00 - 21:00		
	XDBACU_W	BACU warme stroom	vrijdag	15:00	dinsdag	19:00 - 21:00		
			maandag	15:00	woensdag	19:00 - 21:00		
			dinsdag	15:00	donderdag	19:00 - 21:00		
			woensdag	15:00	vrijdag	19:00 - 21:00		
			donderdag	15:00	zaterdag	19:00 - 21:00		
	SANDWPBL	Sandwiches	maandag	8:00	dinsdag	19:00 - 21:00		
			woensdag	8:00	donderdag	19:00 - 21:00		
			vrijdag	8:00	zaterdag	19:00 - 21:00		
	XDGROENTEH	Groentehof / Hessing	maandag	9:00	maandag	19:00 - 21:00		
			dinsdag	9:00	dinsdag	19:00 - 21:00		
			woensdag	9:00	woensdag	19:00 - 21:00		
			donderdag	9:00	donderdag	19:00 - 21:00		
			vrijdag	9:00	vrijdag	19:00 - 21:00		
			zaterdag	9:00	zaterdag	19:00 - 21:00		
	XDBELIMP	Bel-Impex Indo	zaterdag	20:00	maandag	19:00 - 21:00		
			dinsdag	20:00	woensdag	19:00 - 21:00		
			donderdag	20:00	vrijdag	19:00 - 21:00		

* Levertijd geeft zowel het vroegst mogelijk geplande levermoment als het uiterste levermoment aan.

1 van 3

Figure 28: Example of a Periodic Weekly Delivery Schedule (page 1/3)

Appendix III

The operational logistical costs in the supply chain can be subdivided per link in the supply chain.

Store operational costs

Store operations comprise the largest share of the logistical cost pie, which is mainly determined by labor costs. For company owned stores these costs are exactly known and can be found in the cost realization, which resembles the total wage costs including gross wages as well as other expenses such as social security charges. In contrast to company owned stores, wage costs for franchise stores are only partially retrievable since franchisers do not have the duty to report their exact cost composition. Since the total turnover for franchise store is known, we can estimate the total salary cost realization of franchise stores by estimating the percentage of the turnover that is spent on store salary costs. Thus, we now have an estimation of the total salary costs of all stores.

However within the total salary costs for stores, a clear distinction has to be made within relevant costs and irrelevant costs (e.g. cashier salary costs). Within the total salary costs, only costs related to shelf stacking are considered as relevant. An estimation of these costs can be gained by combining two parts. First, an estimation of hours (per product category) by means of a predetermined overview of store hour norms. These norms specify exactly the number of hours per sub activity per week. Second, an estimation of the hourly wage per product category. This can be gained by dividing the store's salary costs realization by the number of hours.

Based on these results, we can determine the fraction of the total wage costs estimation that is spent relevant for the periodic weekly delivery schedule. This is based on franchise stores ([redacted]) and company owned stores ([redacted]).

Distribution center costs

Costs for the distribution center can be split in fixed costs for amongst other housing and depreciation and variable costs such as costs for handling and inventory waste. Within these costs, handling costs is the largest share within the total costs. Only handling costs are considered relevant for the problem and are included as relevant costs in the total cost composition.

[redacted]

Figure 29: Distribution Center cost distribution

Transportation costs

As well as in the store operations, transportation costs can be split in two parts: charter routes and routes by company owned trucks. Charter costs are based on [redacted]

[redacted]

Figure 30: Charter cost distribution

Although actual costs for company owned trucks consist of cost realizations such as fuel and maintenance costs, the financial realization used within Jumbo Supermarkten is split in the same [redacted] parameters as used for the charter trucks: [redacted] The composition of the total costs for the company owned transportation is shown in figure 31.

[redacted]

Figure 31: Transportation costs company owned fleet

Total cost composition

Aggregating the results, results in the overall view on supply chain costs for the PWDS, which is displayed in figure 32.

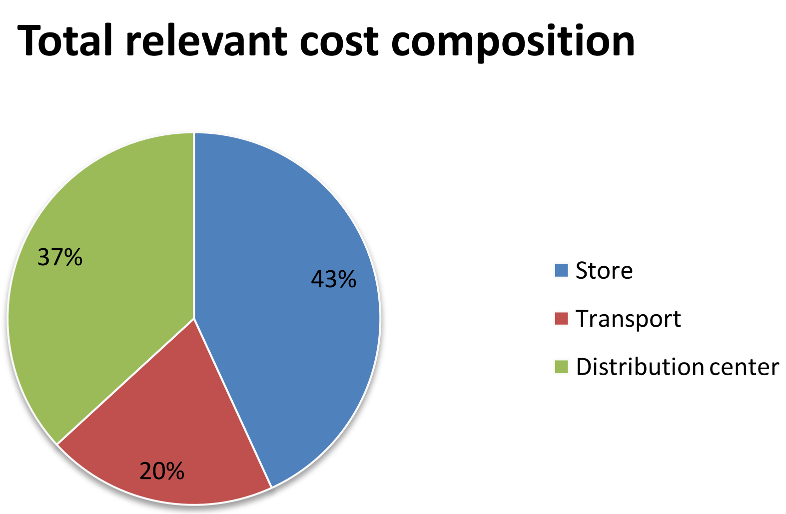

Figure 32: Total relevant cost composition

This result matches the supply chain cost composition as given by Broekmeulen (2004). Although the costs included in the cost composition are all relevant to the PWDS, one cannot draw a conclusion about the extent to which these costs can be influenced as such. Based on the cost composition one can conclude however, that a planning system purely aimed at minimizing transportation costs is likely to produce inferior results compared to a system that takes into account the other supply chain steps as well.

Appendix IV

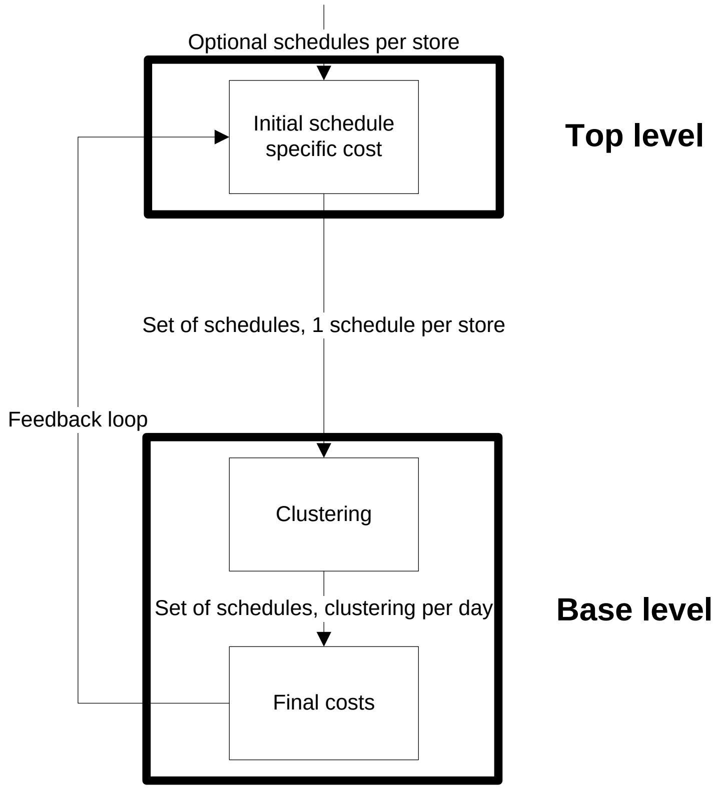

Figure 33: Current conceptual model at Jumbo Supermarkten

Appendix V

This section describes the model of Broekmeulen and Van Donselaar (2012).

We will first introduce an integral tactical planning (ITP) model, in which the planning department has the authority to assign delivery schedules to stores, regardless of the cost impact on the local store. Next, we assume that store managers are more or less independent from the retailers headquarter and therefore need an incentive to assist the central planning department to level the workload at the DC. The decision by the store manager on the delivery schedule has a large effect on the operations of the distribution center, but we assume that the local manager will always select the delivery schedule with the lowest cost. Based on the framework of Schneeweiss (2003), we formulate an anticipated base-level (ABL) model for the distribution planning department at the DC which deals with this decentralized decision making.

The basic input parameters for both the ITP and the ABL are the set of stores, the handling and storage capacities per store and the expected sales per weekday per store.

Notation

- x_{ij} : store *i* uses schedule *j*;
- P : number of time slots;
- $\overline{w}_t$: average expected workload at the DC [RC];
- w_t^+ : maximum expected workload at the DC in time slot *t* [RC];
- T_{jt} : time table of schedule *j* in time slot *t* (1=delivery, 0=no delivery);
- R_{jt} : time to next delivery according to schedule *j* in time slot *t*;
- V_i : truck capacity assigned to store *i* [RC];
- $\overline{B}_i$: basic available backroom storage capacity (independent of the delivery schedule, excluding returnables such as empty roll cages, and remaining inventory of broken case packs after stacking) in store *i* [RC];
- B_{ijt} : available backroom storage capacity for first replenishment items in store *i* following schedule *j* during time slot *t* [RC];
- α_{it} : seasonal index of sales in store *i* during time slot *t*;
- γ_i : fraction of total sales for store *i* which are sold from shelves requiring concurrent replenishments (e.g. determined by sales rank);
- β_{it} : fraction of total sales for store *i* during time slot *t* which are sold from shelves requiring concurrent replenishments, i.e. shelf capacity insufficient for sales corresponding with this time slot;
- W_{it} : available handling capacity of regular shelf stackers in store *i* during time slot *t* [RC/slot];
- s_{it} : use of regular shelf stackers in store *i* during time slot *t* [RC/slot];
- f_{it} : use of full time staff for shelf stacking in store *i* during time slot *t* [RC/slot];
- I_{it} : backroom inventory in store *i* at the end of time slot *t* [RC];

- $C^B < C^S < C^F$: storage penalty cost in the backroom, handling cost for using shelf stackers, and handling cost full time staff [€/RC];
- U : tariff for a visit at a store [€];
- $E[C_{it}^T]$: expected transportation cost for store *i* in time slot *t* [€];
- $E[S_{it}]$: expected sales volume in store *i* in time slot *t (*independent from other stores) [RC/slot];
- $E[D_{ijt}]$: expected delivery volume to store *i* using schedule *j* in time slot *t* [RC/slot];

We start with a basic deterministic model. Gaur & Fisher (2004) showed that for deliveries to grocery stores, we have at most two deliveries per truck route. As an initial estimate for C_{it}^T, we will assume that each truck visits a single store for each delivery and that the retailer has ample trucks available on each weekday. We assume a close proximity of stores to the DC, such that loading at the DC and unloading at the store always takes place within the same time slot.

We assume that the expected sales are independent of the delivery schedule, which is reasonable with a fixed and constant fill rate during the week. We approximate the delivery volume by assuming that the expected delivery volume is equal to the expected sales during the next review period:

$$E[D_{ijt}] = \sum_{k=t+1}^{t+R_{jt}} E[S_{ik}]$$

We further assume that at the end of a time slot, the backroom capacity is respected and the net available backroom capacity is already adjusted for empty roll-cages and remaining inventory after first replenishment (not yet the volume needed for concurrent replenishment). We assume that $\beta_{it} = \alpha_{it} \cdot \gamma_{it}$, i.e. the fraction for concurrent replenishments depends on the fraction of sales generated by SKU's with insufficient shelf space, corrected by the seasonal index for the time slot.

$$B_{ijt} = \overline{B}_i - \sum_{k=t+1}^{t+R_{jt}} \beta_{it} \cdot E[S_{ik}]$$

The target workload $\overline{w}_t$ in the DC for a time slot *t* depends on the expected sales of all allocated stores during the next two time slots:

$$\overline{w}_t = \frac{1}{2} \sum_i \sum_{k=t+1}^{t+2} E[S_{ik}]$$

ITP

In the ITP, we search for an assignment of delivery schedules to stores, such that

$$z_{ITP} = \lambda \cdot \sum_t w_t^+ + \sum_i \sum_j \sum_t C_{it}^T \cdot T_{jt} \cdot x_{ij} \\ + \sum_i \sum_t \left(C^S \cdot s_{it} + C^B \cdot I_{it} + C^F \cdot \left(f_{it} + \beta_{it} \cdot E[S_{it}] \right) \right) \quad \text{[ITP 1]}$$

is minimized, subject to the following constraints:

1. Each store is assigned to exactly one schedule
   $$\forall i: \quad \sum_j x_{ij} = 1 \quad \text{[ITP 2]}$$
2. The delivery volume depends on the schedule assignment and is restricted by the truck capacity V_i
   $$\forall i,t: \quad \sum_j E[D_{ijt}] \cdot T_{jt} \cdot x_{ij} \le V_i \quad \text{[ITP 3]}$$
3. The availability of regular (low cost) workers is limited.
   $$\forall i,t: \quad s_{it} \le W_{it} \quad \text{[ITP 4]}$$
4. The balance in the backroom for each slot. We only need to consider the non-concurrent volume.
   $$\forall i,t: \quad I_{it} = I_{i,t-1} + \sum_j (1-\beta_{it}) \cdot E[D_{ijt}] \cdot T_{jt} \cdot x_{ij} - s_{it} - f_{it} \quad \text{[ITP 5]}$$
   and $I_{i,0} = I_{i,P}$
5. The backroom capacity is respected at the end of each slot.
   $$\forall i,t: \quad I_{it} \le \sum_j B_{ijt} \cdot x_{ij} \quad \text{[ITP 6]}$$
6. The workload in the DC depends on the schedule assignment
   $$\forall t: \quad \sum_i \sum_j E[D_{ijt}] \cdot T_{jt} \cdot x_{ij} \le \overline{w}_t + w_t^+ \quad \text{[ITP 7]}$$
7. The schedule assignment variable is binary, i.e., $x_{ij} \in \{0,1\}$.

To solve the ITP, we use a column generation procedure. Each store-schedule combination has an associated local cost

$$C_{ij}^L = \sum_t \left(U \cdot T_{jt} + C^S \cdot s_{it} + C^B \cdot I_{it} + C^F \cdot (f_{it} + \beta_{it} \cdot E[S_{it}]) \right)$$

This local cost is determined by optimizing the local store operations based on constraints ITP3-6 for the given delivery schedule. We generate all columns for which the delivery schedule is greater or equal to the minimal delivery frequency *M*, with

$$M = \frac{1}{V_i} \sum_{t=1}^{P} E[S_{it}]$$

We initially restrict the number of columns further to delivery frequencies less or equal to *M+2* if we can generate more than 1 feasible alternative.

We only need a very small penalty $C^B = \varepsilon$ to ensure that the backroom inventory is moved to the sales area. Only a value higher than $C^F - C^S$ (the difference between full time staff cost and regular stackers cost) will eliminate the backroom inventory.

ABL

We can change the integral ITP model into a decentralized ABL model by introducing the penalty C_t^W as an incentive to order less RC's in busy slots.

$$\forall t: \quad \lambda \cdot w_t^+ \approx C_t^W \cdot \sum_i \sum_j E[D_{ijt}] \cdot T_{jt} \cdot x_{ij} \qquad \text{[ABL 0]}$$

This changes the objective function of the ITP into:

$$z_{ABL} = \sum_i \sum_j \left(C_{ij}^L + \sum_t \left(C_t^W \cdot E\left[D_{ijt}\right] \cdot T_{jt} \right) \right) \cdot x_{ij} \qquad \text{[ABL 1]}$$

Next to the original ITP constraints, we have to add a constraint to ensure that the store selects the delivery schedule with the lowest cost:

$$\forall i, j: \quad \left(C_{ij}^L + \sum_t \left(C_t^W \cdot E\left[D_{ijt}\right] \cdot T_{jt} \right) \right) \geq \sum_k \left(C_{ik}^L + \sum_t \left(C_t^W \cdot E\left[D_{ikt}\right] \cdot T_{kt} \right) \right) \cdot x_{ik} \qquad \text{[ABL 2]}$$

In the ABL, we need to find values for C_t^W that minimize the workload range in the DC by penalizing undesired schedules. We will do this in an iterative way until the desired workload range is reached or the additional cost for the local stores becomes too high. We could use (ABL 0) to calculate the initial values for C_t^W.

Combined deliveries

After the smoothing, we will try to combine deliveries to reduce the transportation cost by solving a maximum weighted matching problem for each time slot *t* with $N_t = \sum_i \sum_j T_{jt} \cdot x_{ij}$.

Objective:

$$Min\left\{ z_{WM} = \sum_{i=1}^{N_t} \sum_{k=1}^{i} C_{ikt}^{TC} \cdot y_{ik} \right\}$$

Subject to

$$\forall i: \quad \sum_{k=1}^{i} y_{ik} + \sum_{k=i+1}^{N_t} y_{ki} = 1$$

With tour cost $C_{iii}^{TC} = C_{it}^T$ for $i = k$ and $C_{ikt}^{TC} = \infty$ for combinations that exceed the assigned truck capacity, i.e., $\sum_j \left(E[D_{ijt}] + E[D_{kjt}] \right) \cdot T_{jt} \cdot x_{ij} \geq Max\{V_i, V_k\}$.

Appendix VI

The analysis of a small data set of three stores, indicated that turnover pressure (i.e. turnover in Euros per square meter store floor area) can yield a reasonable approximation. However, as can be seen in figure 34 the relation between turnover pressure and the beta parameter does not show a clear linear pattern and measurements show a pattern which is comparable to random noise.

Figure 34: Turnover pressure versus Gamma(i)

Hence, linear regression analysis of the turnover pressure on gamma(i) does provide a bad model fit.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.105[a]	.011	-.055	.032311973012023

Table 15: Regression results, dependent variable Gamma(i) and predictor Turnover Pressure

Appendix VII

[redacted]

Figure 35: Turnover share Beer versus Gamma(i)

[redacted]

Figure 36: Turnover share Coke & Soda versus Gamma(i)

Appendix VIII

R	R Square	Adjusted R Square	Std. Error of the Estimate
.749[a]	.561	.502	.021953157844579

Table 16: Regression result, dependent variable Gamma(i) and predictors Turnover share Coke&Soda, Turnover share beer

	Sum of Squares	df	Mean Square	F	Sig.
Regression	.009	2	.005	9.580	.002[a]
Residual	.007	15	.000		
Total	.016	17			

Table 17: Analysis of variance

	Unstandardized coefficients		Standardized coefficients		Sig.
	B	Std. Error	Beta	t	
(Constant)	-.096	.036		-2.633	.019
Turnover Share Beer	.716	.196	.632	3.652	.002
Turnover Share Coke and Soda	1.610	.548	.509	2.940	.010

Table 18: Coefficients

Appendix IX

To analyze the quality of the point-of-sales data on an SKU level, a sample set of point-of-sales data is analyzed for three example stores for a time span of one week. The resulting 117.022 records contain 41 records with a negative value. These records represent a “negative demand” of 3664 products, most of which is “demand” for returned products and recycled packaging. Of all records, 31 records contain a value larger than 500 products, and most of these exceptionally large demands consider sales values for the sales of stamps. A characterization of the input data is shown in table 19.

[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]

Table 19: Data characterization of consumer demand data

Within all records available, we only consider dry groceries. Within the dry groceries product group, most outliers form part of the presentation groups which are classified as a “restgroep”. This contains, amongst others, returned packaging bookings and products for in-store use such as bags and stamps. Since these products are not actual consumer sales and are not likely to influence the expected delivery volume, we remove this presentation group and continue with the dry groceries sales data. The characterization of the dry groceries product group without the “restgroep” is shown in table 20.

[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]

Table 20: Characterization of consumer demand data of dry groceries, without the “restgroep”

The data characterization still contains two remarkable points. First, what is remarkable in the data characterization are the relatively high maximums. These maximums consider beer, where a consumer unit is defined as one bottle instead of one crate. Data quality will be used to link consumer sales and delivery volumes, and it is plausible to assume that the volume of a bottle does not deviate much from other consumer units' volumes. Therefore, this does not cause a data problem.

Second, the dataset still contains negative values. These consider negative sales of slow-moving products, which is caused by the booking of returned products as negative sales. Although negative sales should not be included since they do not influence the delivery volume in a negative manner, the number of products in consideration is negligible compared to the total number of products and thus does not have a large influence on the data quality.

Concluding, the data quality on an SKU level is relatively good after considering if other product groups than the dry groceries product group and the "restgroep" presentation group are excluded. Therefore, we can use the presentation group data as a basis to acquire the number of consumer units per product group per time slot t for store i.

Appendix X

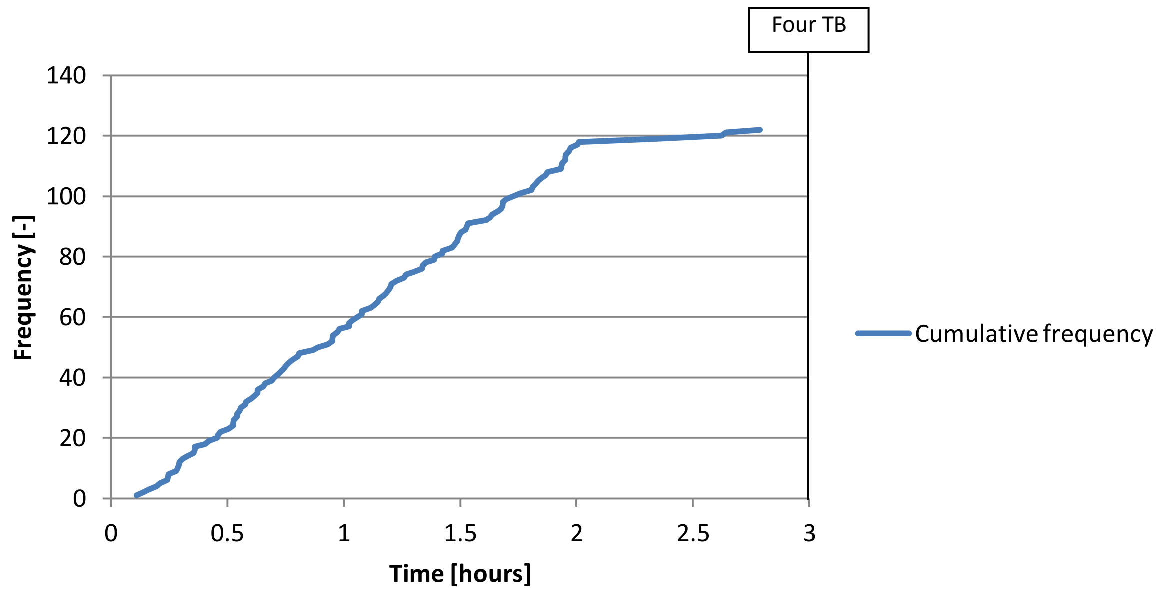

Figure 37: Cumulative frequency diagram for driving time, with an indication for time slot length

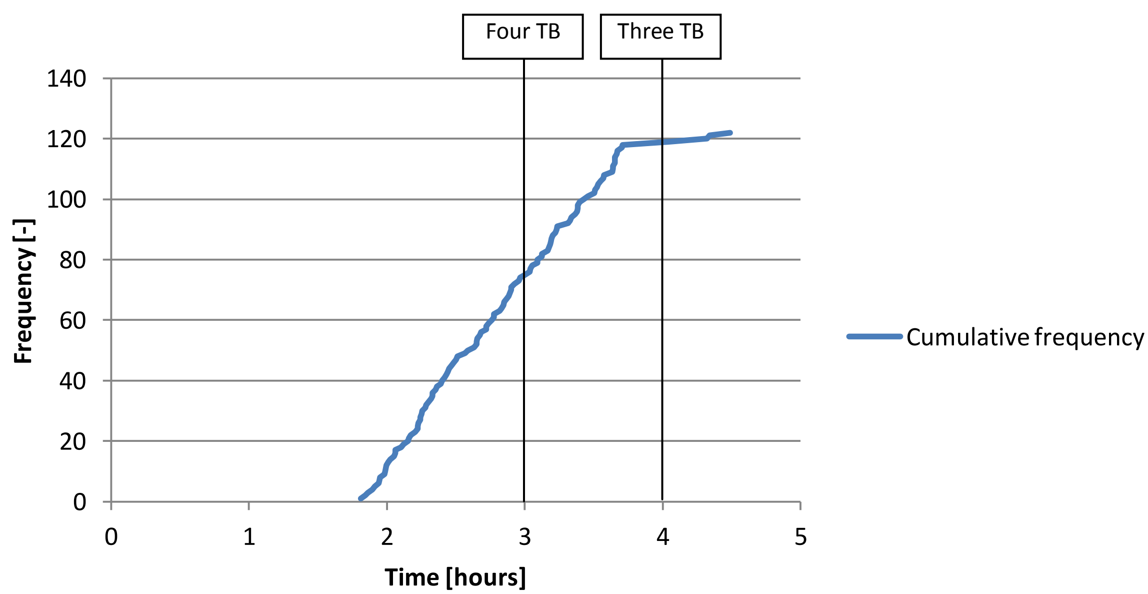

Figure 38: Cumulative number of store versus lead-time, with an indication for time slot length

Appendix XI

	Standard value	Test value	Average smoothing tariff	MAD DC-load	Minimal slot load	Maximum slot load	Min NrRoute s	Max NrRoutes	Average Transportation CostsDC	Average Transportation Costs Store	Average Occupancy Rate	Total NrLoads	Average NrCombis/NrLoad s	Average Handlingcosts	Average Delivery Frequency
Standard, after smoothing			3.7	299.9	1928	3802	37	70	1220.7	1033.5	0.83	719	0.17	2391.0	5.9
Drop tariff	167	125.3	5.1	297.3	1873	3697	36	71	1231.8	783.3	0.83	727	0.17	2389.9	6.0
		146.1	4.5	295.8	1881	3778	36	72	1196.7	907.9	0.84	722	0.17	2389.8	5.9
		187.9	5.9	299.7	1804	3734	35	71	1223.2	1165.7	0.84	721	0.17	2391.4	5.9
		208.8	6.0	291.0	1825	3782	36	71	1221.6	1293.6	0.84	720	0.17	2392.7	5.9
Truck speed	65	48.8	3.7	299.9	1928	3802	37	70	1371.2	1033.5	0.83	719	0.17	2391.0	5.9
		56.9	3.7	299.9	1928	3802	37	70	1285.2	1033.5	0.83	719	0.17	2391.0	5.9
		73.1	3.7	299.9	1928	3802	37	70	1170.6	1033.5	0.83	719	0.17	2391.0	5.9
		81.3	3.7	299.9	1928	3802	37	70	1130.4	1033.5	0.83	719	0.17	2391.0	5.9
Km transport costs	0.46	0.35	3.7	299.9	1928	3802	37	70	1121.5	1033.5	0.83	719	0.17	2391.0	5.9
		0.40	3.7	299.9	1928	3802	37	70	1171.1	1033.5	0.83	719	0.17	2391.0	5.9
		0.52	3.7	299.9	1928	3802	37	70	1270.3	1033.5	0.83	719	0.17	2391.0	5.9
		0.58	3.7	299.9	1928	3802	37	70	1320.0	1033.5	0.83	719	0.17	2391.0	5.9
Hourly transport costs	34	25.5	3.7	299.9	1928	3802	37	70	1014.8	1033.5	0.83	719	0.17	2391.0	5.9
		29.8	3.7	299.9	1928	3802	37	70	1141.7	1033.5	0.83	719	0.17	2391.0	5.9
		38.3	3.7	299.9	1928	3802	37	70	1323.7	1033.5	0.83	719	0.17	2391.0	5.9
		42.5	3.7	299.9	1928	3802	37	70	1426.7	1033.5	0.83	719	0.17	2391.0	5.9
Load time	1.25	0.94	3.7	299.9	1928	3802	37	70	1155.0	1033.5	0.83	719	0.17	2391.0	5.9
		1.09	3.7	299.9	1928	3802	37	70	1187.8	1033.5	0.83	719	0.17	2391.0	5.9
		1.41	3.7	299.9	1928	3802	37	70	1280.9	1033.5	0.83	719	0.17	2391.0	5.9
		1.56	3.7	299.9	1928	3802	37	70	1286.5	1033.5	0.83	719	0.17	2391.0	6.3
Unload time	0.0114	0.009	3.7	299.9	1928	3802	37	70	1220.7	1033.5	0.83	719	0.17	2391.0	5.9
		0.010	3.7	299.9	1928	3802	37	70	1207.1	1033.5	0.83	719	0.17	2391.0	5.9
		0.013	3.7	299.9	1928	3802	37	70	1234.4	1033.5	0.83	719	0.17	2391.0	5.9
		0.014	3.7	299.9	1928	3802	37	70	1220.7	1033.5	0.83	719	0.17	2391.0	5.9
Handling cost fulltime	16	12	5.5	294.7	1902	3729	36	71	1219.8	1032.1	0.84	718	0.17	2310.0	5.9
		14	4.0	297.2	1849	3765	36	69	1219.5	1032.1	0.83	718	0.17	2350.7	5.9
		18	6.5	285.7	1857	3778	36	72	1232.6	1044.4	0.83	727	0.17	2431.2	6.0
		20	4.9	299.2	1912	3753	36	71	1224.0	1037.6	0.84	722	0.18	2472.3	5.9
Handling cost stackers	8.5	6.4	6.0	293.6	1879	3778	36	72	1225.3	1039.0	0.83	723	0.17	1875.8	5.9
		7.4	5.9	299.2	1837	3778	36	72	1225.3	1039.0	0.83	723	0.17	2132.7	5.9
		9.6	5.8	298.6	1862	3756	36	71	1223.2	1036.2	0.84	721	0.17	2648.7	5.9
		10.6	4.9	295.6	1832	3782	34	69	1221.6	1034.9	0.84	720	0.18	2906.7	5.9
Drop cost multiplier	2	1.5	3.7	299.9	1928	3802	37	70	1209.8	1021.2	0.83	719	0.17	2391.0	5.9
		1.75	3.7	299.9	1928	3802	37	70	1215.3	1027.3	0.83	719	0.17	2391.0	5.9
		2.25	3.7	299.9	1928	3802	37	70	1226.2	1039.6	0.83	719	0.17	2391.0	5.9
		2.5	3.7	299.9	1928	3802	37	70	1231.6	1045.8	0.83	719	0.17	2391.0	5.9
Max smoothing tariff	50	37.5	3.7	299.9	1928	3802	37	70	1220.7	1033.5	0.83	719	0.17	2391.0	5.9
		43.8	3.7	299.9	1928	3802	37	70	1248.0	1033.5	0.83	719	0.17	2391.0	5.9
		56.3	3.7	299.9	1928	3802	37	70	1220.7	1033.5	0.83	719	0.17	2391.0	5.9
		62.5	3.7	299.9	1928	3802	37	70	1248.0	1033.5	0.83	719	0.17	2391.0	5.9
Target MAD	300	225	12.9	214	1773	3636	36	70	1295.1	1100.6	0.81	768	0.20	2392	6.3
		262.5	8.3	259	1762	3644	34	69	1249.6	1058.1	0.82	737	0.17	2392	6.0
		337.5	1.3	337	1864	3832	33	73	1217.0	1030.4	0.83	717	0.17	2391	5.9
		375	0.6	355	1828	4030	35	71	1217.0	1030.4	0.84	717	0.17	2391	5.9
Fraction concurrent	Var	-25%	5.7	291.1	1799	3770	34	71	1224.0	1037.6	0.84	722	0.18	2356.2	5.9
		-12.5%	4.9	295.1	1870	3734	37	71	1223.2	1036.2	0.83	721	0.17	2372.8	5.9
		12.5%	5.5	294.1	1843	3778	35	72	1224.0	1037.6	0.83	722	0.17	2408.2	5.9
		25%	5.5	295.5	1837	3805	36	70	1223.2	1036.2	0.83	721	0.17	2426.5	5.9

Table 21: Sensitivity analysis, absolute results

	Standard value	Test value	Average smoothing tariff	MAD DC-load	Minimal slot load	Maximum slot load	Min NrRoutes	Max NrRoutes	Average Transportation CostsDC	Average Transportation Costs Store	Average Occupancy Rate	Total NrLoads	Average NrCombis/NrLoads	Average Handlingcosts	Average Delivery Frequency
Standard, after smoothing			3.7	299.9	1928	3802	37	70	1220.7	1033.5	0.83	719	0.17	2391.0	5.9
Drop tariff	167	125.3	37.3%	-0.9%	-2.9%	-2.8%	-2.7%	1.4%	0.9%	-24.2%	-0.9%	1.1%	-1.1%	0.0%	1.1%
		146.1	21.3%	-1.4%	-2.4%	-0.6%	-2.7%	2.9%	-2.0%	-12.2%	0.5%	0.4%	0.4%	-0.1%	0.4%
		187.9	59.1%	-0.1%	-6.5%	-1.8%	-5.4%	1.4%	0.2%	12.8%	0.3%	0.3%	2.2%	0.0%	0.3%
		208.8	61.8%	-3.0%	-5.4%	-0.5%	-2.7%	1.4%	0.1%	25.2%	0.3%	0.1%	-0.1%	0.1%	0.1%
Truck speed	65	48.8	-	-	-	-	-	-	12.3%	-	-	-	-	-	-
		56.9	-	-	-	-	-	-	5.3%	-	-	-	-	-	-
		73.1	-	-	-	-	-	-	-4.1%	-	-	-	-	-	-
		81.3	-	-	-	-	-	-	-7.4%	-	-	-	-	-	-
Km transport costs	0.46	0.35	-	-	-	-	-	-	-8.1%	-	-	-	-	-	-
		0.40	-	-	-	-	-	-	-4.1%	-	-	-	-	-	-
		0.52	-	-	-	-	-	-	4.1%	-	-	-	-	-	-
		0.58	-	-	-	-	-	-	8.1%	-	-	-	-	-	-
Hourly transport costs	34	25.5	-	-	-	-	-	-	-16.9%	-	-	-	-	-	-
		29.8	-	-	-	-	-	-	-6.5%	-	-	-	-	-	-
		38.3	-	-	-	-	-	-	8.4%	-	-	-	-	-	-
		42.5	-	-	-	-	-	-	16.9%	-	-	-	-	-	-
Load time	1.25	0.94	-	-	-	-	-	-	-5.4%	-	-	-	-	-	-
		1.09	-	-	-	-	-	-	-2.7%	-	-	-	-	-	-
		1.41	-	-	-	-	-	-	4.9%	-	-	-	-	-	-
		1.56	-	-	-	-	-	-	5.4%	-	-	-	-	-	6.8%
Unload time	0.0114	0.009	-	-	-	-	-	-	-	-	-	-	-	-	-
		0.010	-	-	-	-	-	-	-1.1%	-	-	-	-	-	-
		0.013	-	-	-	-	-	-	1.1%	-	-	-	-	-	-
		0.014	-	-	-	-	-	-	-	-	-	-	-	-	-
Handling cost fulltime	16	12	49.4%	-1.7%	-1.4%	-1.9%	-2.7%	1.4%	-0.1%	-0.1%	0.3%	-0.1%	-1.5%	-3.4%	-0.1%
		14	9.2%	-0.9%	-4.1%	-1.0%	-2.7%	-1.4%	-0.1%	-0.1%	0.0%	-0.1%	-0.7%	-1.7%	-0.1%
		18	74.4%	-4.7%	-3.7%	-0.6%	-2.7%	2.9%	1.0%	1.1%	-0.3%	1.1%	3.0%	1.7%	1.1%
		20	31.7%	-0.2%	-0.8%	-1.3%	-2.7%	1.4%	0.3%	0.4%	0.8%	0.4%	5.3%	3.4%	0.4%
Handling cost stackers	8.5	6.4	61.6%	-2.1%	-2.6%	-0.6%	-2.7%	2.9%	0.4%	0.5%	0.0%	0.6%	0.3%	-21.5%	0.6%
		7.4	59.3%	-0.3%	-4.8%	-0.6%	-2.7%	2.9%	0.4%	0.5%	0.2%	0.6%	1.9%	-10.8%	0.6%
		9.6	56.4%	-0.4%	-3.4%	-1.2%	-2.7%	1.4%	0.2%	0.3%	0.3%	0.3%	1.4%	10.8%	0.3%
		10.6	32.4%	-1.4%	-5.0%	-0.5%	-8.1%	-1.4%	0.1%	0.1%	0.9%	0.1%	5.6%	21.6%	0.1%
Drop cost multiplier	2	1.5	-	-	-	-	-	-	-0.9%	-1.2%	-	-	-	-	-
		1.75	-	-	-	-	-	-	-0.4%	-0.6%	-	-	-	-	-
		2.25	-	-	-	-	-	-	0.4%	0.6%	-	-	-	-	-
		2.5	-	-	-	-	-	-	0.9%	1.2%	-	-	-	-	-
Max smoothing tariff	50	37.5	-	-	-	-	-	-	-	-	-	-	-	-	-
		43.8	-	-	-	-	-	-	2.2%	-	-	-	-	-	-
		56.3	-	-	-	-	-	-	-	-	-	-	-	-	-
		62.5	-	-	-	-	-	-	2.2%	-	-	-	-	-	-
Target MAD	300	225	249.3%	-28.6%	-8.0%	-4.4%	-2.7%	-	6.1%	6.5%	-2.5%	6.8%	16.4%	-	6.7%
		262.5	124.5%	-13.5%	-8.6%	-4.1%	-8.1%	-1.4%	2.4%	2.4%	-1.7%	2.5%	0.6%	-	2.4%
		337.5	-63.6%	12.4%	-3.3%	0.8%	-10.8%	4.3%	-0.3%	-0.3%	0.6%	-0.3%	-2.2%	-	-0.3%
		375	-83.4%	18.5%	-5.2%	6.0%	-5.4%	1.4%	-0.3%	-0.3%	1.3%	-0.3%	0.3%	-	-0.3%
Fraction concurrent	Var	-25%	53.7%	-2.9%	-6.7%	-0.8%	-8.1%	1.4%	0.3%	0.4%	1.2%	0.4%	7.0%	-1.5%	0.4%
		-12.50%	32.6%	-1.6%	-3.0%	-1.8%	-	1.4%	0.2%	0.3%	0.1%	0.3%	0.5%	-0.8%	0.3%
		12.50%	47.6%	-1.9%	-4.4%	-0.6%	-5.4%	2.9%	0.3%	0.4%	0.2%	0.4%	1.2%	0.7%	0.4%
		25%	47.6%	-1.5%	-4.7%	0.1%	-2.7%	-	0.2%	0.3%	0.1%	0.3%	2.2%	1.5%	0.3%

Table 22: Sensitivity analysis, relative to the standard situation

Appendix XII

	Standard value	Extreme value	Average smoothin tariff	MAD DC load	Minimal slotload	Maximum slotload	MinNrRoutes	MaxNrRoutes	AverageTPCostsDC	AverageTPCostsStore	AverageOccupancyRate	TotalNrLoads	AverageNrCombi/NrLoads	AverageHandlingcosts	AverageDeliveryFrequency
Standard, after smoothing			3.7	299.9	1928	3802	37	70	1220.716	1033.5	0.83	719	0.17	2391.0	5.9
Drop tariff	167	1	1.5	589.1	829	4023	16	73	1412.3	7.3	0.82	854	0.29	2390.5	7.0
		1000	8.6	296.0	1872	3700	35	68	1213.0	6147.5	0.84	714	0.17	2406.2	5.9
Truck speed	65	1	3.7	299.9	1928	3802	37	70	30110.7	1033.5	0.83	719	0.17	2391.0	5.9
		500	3.7	299.9	1928	3802	37	70	828.0	1033.5	0.83	719	0.17	2391.0	5.9
Km transport	0.46	10^(-6)	3.7	299.9	1928	3802	37	70	823.7	1033.5	0.83	719	0.17	2391.0	5.9
costs		20	3.7	299.9	1928	3802	37	70	18083.4	1033.5	0.83	719	0.17	2391.0	5.9
Hourly	34	1	3.7	299.9	1928	3802	37	70	422.0	1033.5	0.83	719	0.17	2391.0	5.9
transport costs		500	3.7	299.9	1928	3802	37	70	12510.9	1033.5	0.83	719	0.17	2391.0	5.9
Load time	1.25	0.01	3.7	299.9	1928	3802	37	70	959.8	1033.5	0.83	719	0.17	2391.0	5.9
		20	3.7	299.9	1928	3802	37	70	5165.9	1033.5	0.83	719	0.17	2391.0	5.9
Unload time	0.0114	10^(-6)	3.7	299.9	1928	3802	37	70	1111.4	1033.5	0.83	719	0.17	2391.0	5.9
		1	3.7	299.9	1928	3802	37	70	10701.5	1033.5	0.83	719	0.17	2391.0	5.9
Handling cost	16	8.5	7.4	272.0	1873	3741	37	69	1229.6	1040.3	0.83	724	0.17	2234.4	5.9
fulltime		100	6.5	296.6	1846	3691	35	71	1232.1	1044.4	0.83	727	0.17	4121.0	6.0
Handling cost	8.5	0.1	5.1	297.3	1878	3728	36	71	1224.0	1037.6	0.83	722	0.17	355.6	5.9
stackers		16	4.7	293.9	1885	3720	35	69	1215.0	1028.0	0.84	715	0.17	4206.1	5.9
Drop cost	2	1.1	3.7	299.9	1928	3802	37	70	1201.1	1011.3	0.83	719	0.17	2391.0	5.9
multiplier		10	3.7	299.9	1928	3802	37	70	1395.3	1230.6	0.83	719	0.17	2391.0	5.9
Max smoothing	50	1	0.5	470.3	1314	3967	26	72	1217.4	1030.7	0.85	717	0.18	2391.5	5.9
tariff		100	3.7	299.9	1928	3802	37	70	1220.7	1033.5	0.83	719	0.17	2391.0	5.9
Target MAD	300	240	7.4	214.3	1773	3636	36	70	1229.6	1040.3	0.83	768	0.20	2234.4	6.3
		400	0.6	355.3	1828	4032	35	71	1217.4	1030.7	0.84	717	0.17	2391.8	5.9
Fraction	Var	0 for all i	4.5	297.4	1870	3828	37	73	1224.0	1037.6	0.83	722	0.17	2249.9	5.9
concurrent		1 for all i	Error, does not satisfy LP-constraint												
Stacker	Var	max(D(t))	4.7	293.9	1885	3720	35	69	1215.0	1028.0	0.84	715	0.17	4206.1	5.9
capacity		10000	3.7	299.9	1928	3802	37	70	1220.7	1033.5	0.83	719	0.17	2391.0	5.9

Table 23: Extreme value test, absolute results

	Standard value	Extreme value	Average smoothin tariff	MADDCload	Minimal slotload	Maximum slotload	MinNrRoutes	MaxNrRoutes	AverageTPCostsDC	AverageTPCostsStore	AverageOccupancyRate	TotalNrLoads	AverageNrCombi/NrLoads	AverageHandlingcosts	AverageDeliveryFrequency
Standard, after smoothing			3.7	299.9	1928	3802	37	70	1220.716	1033.5	0.83	719	0.17	2391.0	5.9
Drop tariff	167	1	-60.9%	96.4%	-57.0%	5.8%	-56.8%	4.3%	15.7%	-99.3%	-1.5%	18.8%	73.3%	0.0%	18.8%
		1000	131.5%	-1.3%	-2.9%	-2.7%	-5.4%	-2.9%	-0.6%	494.8%	1.0%	-0.7%	2.4%	0.6%	-0.7%
Truck speed	65	1	-	-	-	-	-	-	2366.6%	-	-	-	-	-	-
		500	-	-	-	-	-	-	-32.2%	-	-	-	-	-	-
Km transport	0.46	10^(-6)	-	-	-	-	-	-	-32.5%	-	-	-	-	-	-
costs		20	-	-	-	-	-	-	1381.4%	-	-	-	-	-	-
Hourly	34	1	-	-	-	-	-	-	-65.4%	-	-	-	-	-	-
transport costs		500	-	-	-	-	-	-	924.9%	-	-	-	-	-	-
Load time	1.25	0.01	-	-	-	-	-	-	-21.4%	-	-	-	-	-	-
		20	-	-	-	-	-	-	323.2%	-	-	-	-	-	-
Unload time	0.0114	10^(-6)	-	-	-	-	-	-	-9.0%	-	-	-	-	-	-
		1	-	-	-	-	-	-	776.7%	-	-	-	-	-	-
Handling cost	16	8.5	100.0%	-9.3%	-2.9%	-1.6%	-	-1.4%	0.7%	0.7%	-0.3%	0.7%	1.8%	-6.5%	0.7%
fulltime		100	76.0%	-1.1%	-4.3%	-2.9%	-5.4%	1.4%	0.9%	1.1%	-0.8%	1.1%	-0.3%	72.4%	1.1%
Handling cost	8.5	0.1	36.9%	-0.9%	-2.6%	-1.9%	-2.7%	1.4%	0.3%	0.4%	0.2%	0.4%	0.4%	-85.1%	-
stackers		16	27.9%	-2.0%	-2.2%	-2.2%	-5.4%	-1.4%	-0.5%	-0.5%	0.6%	-0.6%	0.6%	75.9%	-0.6%
Drop cost	2	1.1	-	-	-	-	-	-	-1.6%	-2.1%	-	-	-	-	-
multiplier		10	-	-	-	-	-	-	14.3%	19.1%	-	-	-	-	-
Max smoothing	50	1	-87.6%	56.8%	-31.9%	4.3%	-29.7%	2.9%	-0.3%	-0.3%	1.9%	-0.3%	7.7%	0.0%	-0.3%
tariff		100	-	-	-	-	-	-	-	-	-	-	-	-	-
Target MAD	300	240	100.0%	-28.6%	-8.0%	-4.4%	-2.7%	-	0.7%	0.7%	-0.3%	6.8%	17.6%	-6.5%	6.8%
		400	-83.4%	18.5%	-5.2%	6.0%	-5.4%	1.4%	-0.3%	-0.3%	1.3%	-0.3%	0.3%	0.0%	-0.3%
Fraction	Var	0 for all i	21.1%	-0.8%	-3.0%	0.7%	-	4.3%	0.3%	0.4%	0.0%	0.4%	-1.2%	-5.9%	0.4%
concurrent		1 for all i	Error, does not satisfy LP-constraint												
Stacker	Var	max(D(t))	27.9%	-2.0%	-2.2%	-2.2%	-5.4%	-1.4%	-0.5%	-0.5%	0.6%	-0.6%	0.6%	75.9%	0.4%
capacity		10000	-	-	-	-	-	-	-	-	-	-	-	-	-

Table 24: Extreme value test, relative to the standard situation