MASTER

Replenishment strategy for supply chain collaboration under pull control policy in the fast moving consumer goods industry

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Replenishment Strategy for Supply Chain Collaboration under Pull Control Policy in the Fast Moving Consumer Goods Industry

by

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Abstract

In this thesis research is conducted to analyse replenishment strategies for the company Mars Nederland B.V. in collaboration with its customer Jumbo in order to eliminate the Bullwhip effect. First, an analysis is made for the current way of pull replenishment within Mars. Using three types of available data (supplier delivery, retailer orders, and point of sale data), the possibilities of replenishment improvements are researched. This study gives insight to the multi echelon replenishment policy with service level constraint. Besides that, this policy relates to a collaboration model between Mars and its customers in order to promote future collaborations.

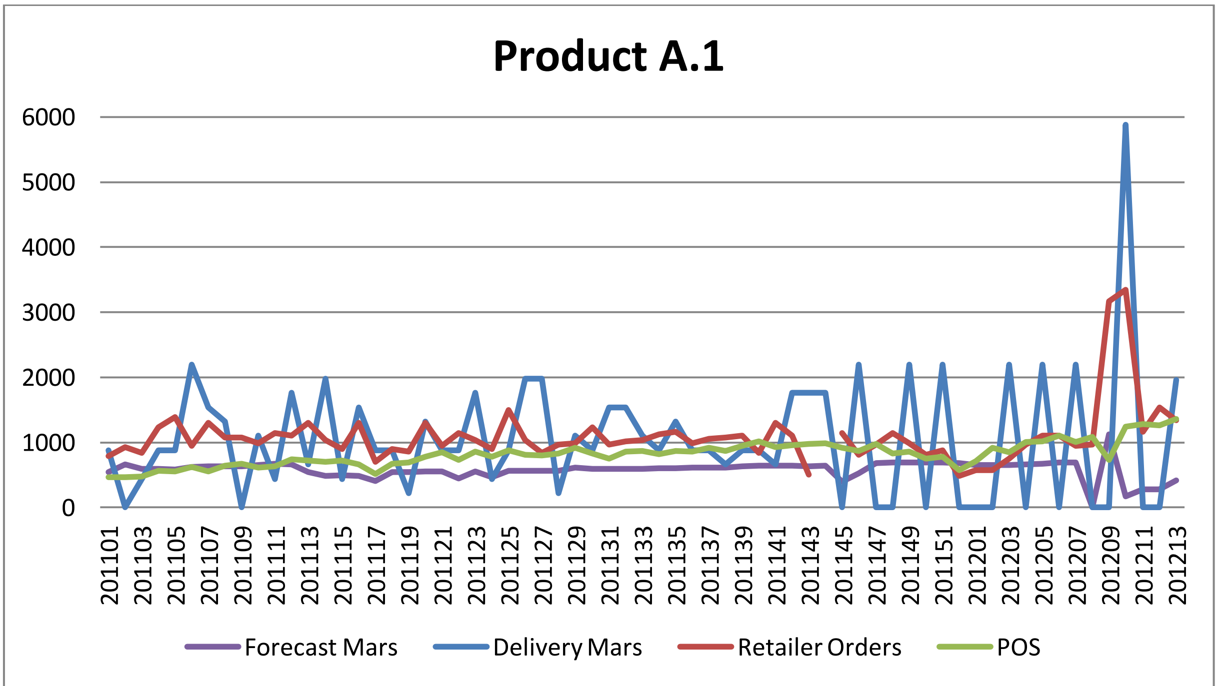
Management Summary

Mars Nederland B.V. is part of Mars Incorporated, one of the most prominent producers of chocolates, confectionery, food, and pet care products in the world. For Mars Nederland B.V., where this research is performed, stock and lead-time reduction are important issues. This is directly linked to freshness as Mars strives to have their products consumed at an optimal age of the product. Moreover, Mars is always looking for new ways to improve its current processes.

This master thesis elaborates on a previous project performed at Mars, which was the so-called pull project. Within this pull project Mars started piloting its replenishment based on a pull strategy for the production line X. This strategy is based on an “if something goes out, it must be replaced” principle on a first in first out basis, mirroring the actual demand having the ultimate goal of removing the Bullwhip effect.

The current operations of the pull project are translated into working with Kanban cards. These Kanban cards results into a steady work in process. All demands are translated directly to production, and productions will be scheduled accordingly taking into account the manufacturing frequency index and the Kanban urgency levels. For exceptional processes such as promotions, forecasting is still used to indicate the level of needed stock building.

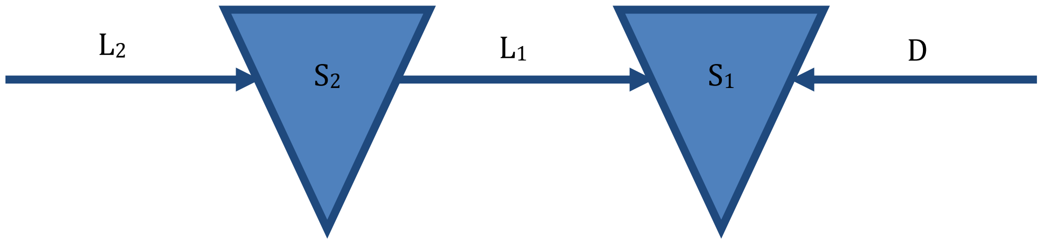
The next step in the pull project is the involvement of Mars’ customers. Having already a supply chain collaboration between Mars and Jumbo, the data from Mars and Jumbo are analysed. Three types of data, Mars delivery, Jumbo retailer orders, and point of sale (POS) data are analysed.



It is noticeable that as demand is measured closer to the end consumer, the data appears to be more stable. The effects of the different types of demand are caused by the Bullwhip effect with the presence of the following four symptoms.

- *Demand signal processing*
  If demand increases, firms order more in anticipation of further increases, thereby communicating an artificially high level of demand.
- *Rationing game*
  There is, or might be, a shortage so a firm orders more than the actual forecast in the hope of receiving a larger share of the items in short supply
- *Order batching*
  Fixed cost at one location lead to batching of orders
- *Manufacturer price variation*
  Price reductions encourage forward buying of bulk orders

The variability of the different data differs from 2 to 15 times. More variability means a higher stock level is needed in order to attain a certain service level. The different levels of data are compared and substantial reductions varying from 21.4% up till 41.2% in stock reduction can be reached when Mars uses the POS data. However, the focused should shift to the possibilities of a supply chain wide optimization, thus with the inclusion of Jumbo the system of replenishment can be viewed as a multi echelon base stock system.

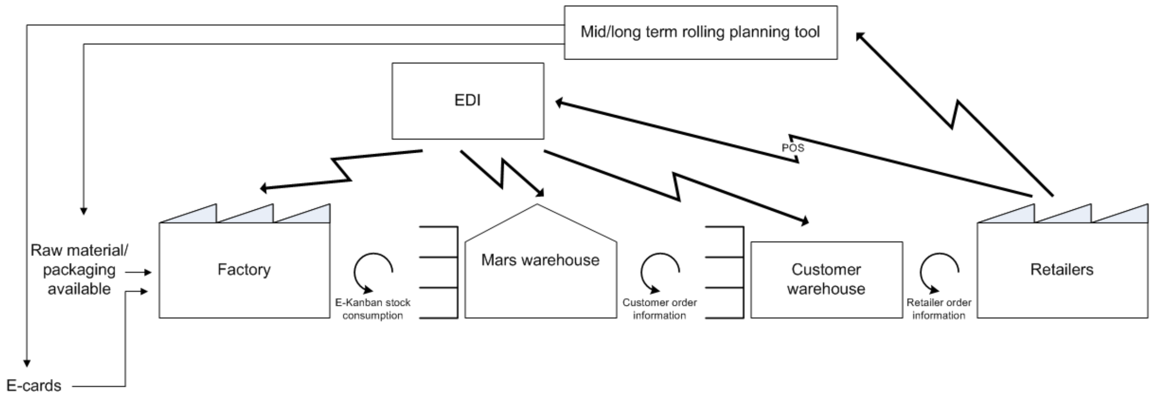


Quantitative analyses indicate that the local optimization of the different links within the supply chain results in suboptimality compared to having the whole supply chain in scope. Although the base stock policy requires more base stock at the Mars warehouse (from a supply chain wide perspective) than the current pull project; it is still an improvement compared to the original push situation. The stock level for the total supply chain is reduced from 11% to even 68% using POS data. For the Jumbo warehouse, large reductions are obtained when complying with the base stock policy. Moreover, a part of the collaboration between Mars and Jumbo is to order in full pallet (layers) and trucks. The order quantity restriction is shown to increase the needed base stock level and a trade-off should be made against the benefits.

Considering the lead-time analysis, it is shown that the biggest reduction in base stock is obtained when lead-time reduction can be obtained from the Mars warehouse to the customer warehouse. Next, the assumption of the holding cost for Jumbo warehouse and the demand distribution for base stock computation are relaxed. It is shown that variation in the holding cost for Jumbo has little to no effect on the required base stock level. However, larger differences appear when comparing the assumption of Normal distribution with Erlang distribution. When the base stock levels are considered throughout the supply chain, it is noticed that the data with lower standard deviation exert less difference between the two distributions.

For the analysis of products in a push replenishment situation, a test case is taken to analyse on the Product B. It appears that for this particular product, the delivery data from Mars results in the lowest needed base stock levels with a total base stock level of 433.5 cases compared to 458 from the current total needed stock. However, the data of delivery from Mars shows substantial smaller averages than the retailer order and POS data, suggesting out of stock may have occurred. The reduction in variability in demand while moving to the use of POS data is still present. With the addition of other customers the needed base stock could be lowered as variability could be pooled.

Finally, the design of the supply chain collaboration model is given where a central independent entity is suggested that collects and analyses the data and distributes it to the links within the supply chain that should replenish according in a base stock manner.



An important addition, in order to create the optimal flow, is a central electronic data interchange system that distributes data to every link of the supply chain as soon as it is available or measured, most preferable in real time. In order to implement this data for real time reactiveness from the links within the supply chain, a central data sharing system is required where a central planner knows information for the entire system. Thus, the view is not on each company separately. Instead, the supply chain is seen as a one single organization. According to the pull principle as well as the base stock policy, the demanded amount at the next link (preferably from the end consumer) is then replenished. This results into a smaller amount of stock needed as it will only need to cover the replenishment time and a certain variance instead of the forecasted demand. For the mid/long term planning as well as the promotions agreed with the sales team, data still needs to be transferred to the mid/long term planning tool in order to forecast periods where stock building is required.

Preface

This report is the result of my graduation project conducted at Mars Nederland B.V. in order to finalize the Master Operations Management and Logistics. During my project many helpful people have directly and indirectly supported me. First of all, I would like to thank my university supervisors Henny van Ooijen and Rob Broekmeulen for the interesting discussions and advices. I am fortunate enough to perform this project at a very interesting company. To the company supervisors Daniel Morgan and Houkje Zwinkels-Janssen, thank you for your support and guidance throughout the project.

To my parents, I would like to thank you for your continuous and unconditional support with every decision I have ever made and above all, your believe in me. I would also like to thank my friends that have been there for me during my study showing me support and motivation, and especially besides my study, having a great time together enjoying life as students.

Finally, I would also like to thank everyone at the inbound logistics department of Mars Nederland B.V. for making me feel at ease and like a true member of the team. The many insider jokes and the Friday afternoons (including the weekly lunches at the "fish farmer") were the least productive but regardless the most fun part of the week. So thank you Anke, Ashley, Daniel, Lida, Lieke, Linda, Natascha, Nathalie, and Yvonne. You definitely made my stay at Mars a pleasant one.

Concluding this project also marks the end of my student life. The past six years were a wonderful part of my life and I can look back with joy and contentment to a period where I have learned and experienced more than I could have expected.

Thank you all for the unforgettable time!

Ying

Contents

Introduction

This report is a result of a project conducted at Mars Netherlands B.V. in partial fulfilment of the master's program Operations Management and Logistics at Eindhoven University of Technology.

The structure of this report is constituted as follows. Chapter 1 illustrates the description of the company and the department at which the project is conducted. This research is part of two ongoing projects within Mars. Chapter 2 explains the description of the two projects, the problem statement and the proposed research questions.

Chapter 3 contains a description of the current mathematical method within Mars with regards to the pull project and its exception process. Chapter 4 contains the data analysis of the different data levels obtained. Comparisons are made within the current process.

Chapter 5 takes the view of the supply chain in greater perspective and gives the heuristics in reviewing the multi echelon system and thus providing the new replenishment model. Chapter 6 will provide results for the calculations and the possible improvements are reviewed.

In chapter 7, sensitivity and scenario analyses are made in order to check certain assumptions made. Chapter 8 discusses possible extensions of this project to other products and collaborations with more retailers. Finally in chapter 9 the conclusion is given together with the recommendations for Mars Netherlands as well as the recommendations for future research.

1. Company overview

In this chapter, an introduction is given to the company Mars. First, a description of Mars in the Netherlands is given in chapter 1.1. Secondly, the Dutch market will be discussed in chapter 1.2. The inbound logistics department will be explained in chapter 1.3 and finally the production planning will be briefly discussed in chapter 1.4.

1.1. Mars Nederland B.V.

Mars Nederland B.V. is part of Mars Incorporated, one of the most prominent producers of chocolates, confectionery, food, and pet care products in the world. This family-owned company generates more than 28 billion dollars in sales every year. Mars is a global leader in chocolate, selling seven of the world's 20 best selling chocolate snacks. Furthermore, Mars has been feeding pets since 1935 and is a leading provider in pet care. The Mars Food business segment produces rice, entrees, sauces and condiments under a number of well-known brand names. Wrigley is a leading manufacturer and marketer of chewing gum and a leader in confections. As one of the leading food manufacturers in the world, Mars has a significant international presence in more than 70 countries and has around 70,000 employees. For a list of Mars brands see appendix I.

Mars operates according to The Five Principles of Mars: Quality, Responsibility, Mutuality, Efficiency, and Freedom. It gives purpose and direction to business and makes it unique as a company.

In The Netherlands, more than 1450 associates secure the success of Mars: 1200 associates in Veghel and 250 associates in Oud-Beijerland. The Veghel and Oud-Beijerland factories in the Netherlands enjoy success because of their modern and efficient production processes.

The town of Veghel in the Noord-Brabant region is home to one of the biggest chocolate-producing factories in the world. Here, Mars produces chocolates for the brands Mars, Bounty, Twix, Snickers, Milky Way, Maltesers, Celebrations, and Mars Planets.

The factory in Veghel not only produces for the Dutch market, it also provides many other Mars factories with semi-finished products such as chocolate and peanuts. Mars Nederland B.V. has three types of distribution channels; grocery, out of home, and non-food retail. The grocery channels entails supermarkets, the biggest customers are Albert Heijn, Jumbo (with C1000), SuperUnie, Sperwer, and DetailResult. The out of home channels consists of all customers that make sure that chocolates are provided in places out of home. No direct delivery is provided to all sport canteens, gas stations and such. Instead, the products are delivered to wholesalers. The biggest clients within this channel are Lekkerland, Sligro, Makro, and DeliXL The third channel is the non-food retail. This channel entails retailers that do not belong in the first two channels. The main clients are Kruidvat and Action.

Within Mars Europe, the Veghel factory has occupied a leading position for years as one of the most efficient production sites for chocolate products. It ranks as one of the most efficient production plants for chocolate bars. Veghel is an example for other factories; associates from the plant are often involved in the start-up of new Mars factories elsewhere.

1.2. Dutch market (Veghel)

The headquarter for the marketing and sales of Mars snack food and pet care in The Netherlands is also located in Veghel. From here Mars sells, besides the chocolates it produces, M&M's, Dove, and Balisto. The petcare brands are Pedigree, Frolic, and Cesar for dogs; Whiskas, Sheba, Kitekat, Catsan and Perfect Fit for cats.

1.3.Inbound Logistics Department

The inbound logistics department is responsible for the daily availability of products to its customers. It captures the needed demand by demand forecasting and informs the production department about these forecasts. The demand planners use an in house forecasting program called Apollo Demand, which uses a nationwide base level. Inbound logistics operates in close coordination with the sales and marketing department. This is to ensure the availability of products during promotions and listings and delistings of products.

1.4.Production (planning)

Within the factory of the Mars plant there are 11 production lines (Appendix II). Once the forecasted demand from inbound logistics is available, it will be send to the production planner. The production planner will make a planning requirement that will be send to the scheduler that plans the weekly production shifts of the production lines.

2. Description of the problem

In order to explain the aim of the research project, first the pull project history will be described in chapter 2.1. Next, the collaboration between Mars and Jumbo will be described in chapter 2.2. In chapter 2.3 and 2.4, respectively the scope of the problem and the expansion of the scope of the current project will be given.

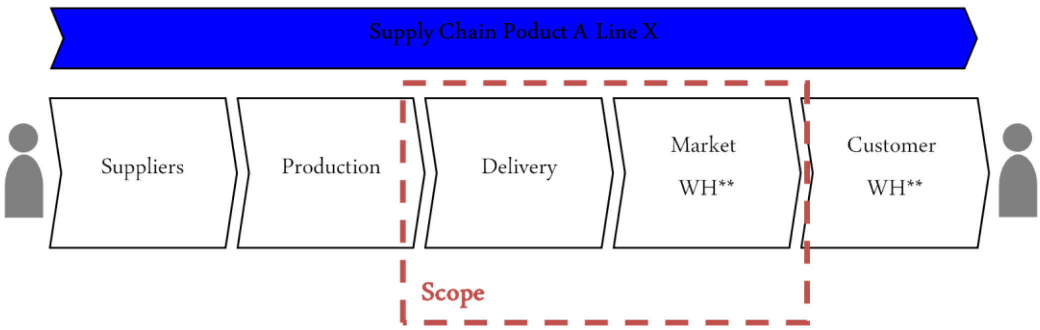
2.1. Pull project history

This master thesis elaborates on a previous project performed at Mars, which was the so-called pull project. Within this pull project Mars started piloting its replenishment based on a pull strategy for production line X. This strategy is based on an “if something goes out, it must be replaced” principle on a first in first out basis, mirroring the actual demand. The volume depends on the demand and the replenishment time.

The goal of the initial project was to define and implement a pull system for six items of product group A for the Dutch and German market. One of the focus points of pull was to lower the Bullwhip effect in the supply chain by taking out the human behaviour influencing (amplifying) the demand planning. The key performance indicators of the project were:

- Cash in stock
- Pipeline stock
- Case fill
- Manufacturing Frequency Index (MFI)

The pilot has been run with the following scope (Figure 1).



Market WH** = warehouse Mars

Figure 1 **Scope of the pull project**

This scope includes a part of production planning as the way lead time is determined is dependent on the planning of production. The pull project has influence on production planning, as manufacturing frequencies are checked and emergency runs can be enforced when a shortage might occur. This will distort the normal cycle of production and requires the flexibility of the production line.

The focus was on the physical and the information flow of the seven Product A items of production line X in Veghel. No focus was laid on the performance improvements of current production line X and/or suppliers or on related implementation of other lean tools. The pilot pull project is run with the following products (Table 1) on production line X. The distinction in products is based on different sizes and different way of packaging.

Table 1 Pull Product A products

Pull pilot items line X	
1	[redacted]
2	[redacted]
3	[redacted]
4	[redacted]
5	[redacted]
6	[redacted]
7	[redacted]

In order to implement the pull project, an electronic Kanban system was used in the pilot for several different packaging of Product A. This electronic Kanban system uses an Excel file to keep track of the stock instead of physical cards. In the Excel file the stock and production were kept up to date. There are three coloured regions that indicates how far down the stock level is. The coloured Kanban levels are illustrated per product and calculated with the average demand during lead-time and the days needed to replenish a certain product. This will be explained in more detail in chapter4.

This Kanban system is not exactly the same as the traditional Kanban principle, where after physical removal of one product, this removal is communicated after which the production of a new product of the same type is started. Instead, the stock level at the market warehouse is sent through every day and adjustments on the stock level are made accordingly. From the Kanban principle this amount is made. However, the Kanban method from Mars is not completely driven on pull. The in house forecasting system Apollo Demand is used to forecast a certain demand. When this forecast deviates from the base line (above a certain standard deviation) for two consecutive weeks due to, among others, promotions and introductions, the Kanban levels are adjusted. This will lead to an adjustment of products in the pipeline to cope with this uplift (or downfall). For example, consider the case where the average demand is 100,000 cases per period. Derived from forecasting there are two consecutive periods of demand of 130,000 cases. Therefore this uplift will be adjusted in the number of Kanbans. Thus, more stock will need to be within the pipeline to cover the uplift in demand. This situation can be seen as a hybrid kind of Kanban system.

After phase 1 (using physical Kanban cards) and 2 (using electronic Kanban system), the key performance indicators were measured in order to test whether the transition to the pull project had an impact. Strong decreases in stock in cash (-26%) and pipeline stock (-30%) in the first phase were observed. In the second phase, relatively less reduction has been observed due to the improvements made earlier in phase 1 (-15% for stock in cash and -22% for pipeline stock).

2.2. Project History Mars & Jumbo

At the second half of 2011, Mars and Jumbo started a project in order to create the value chain of the future. Both Mars and Jumbo have stakes in shortening the supply chain and the reduction of stock. The pilot of the project is on Collaborative Planning and Forecasting in order to prove the benefits. This collaboration initiative is funded by Brabants Ontwikkelings Maatschappij (BOM) and is led by the consultancy firm Eye On.

Within the project the emphasis is laid on four aspects; planning together, order & delivery, value chain dashboard, and a pilot in flowcasting. These four aspects will be briefly explained. For the aspect of planning together, Mars and Jumbo have made agreements in having a planning of information sharing and ordering. A standardized sheet is created for both Mars and Jumbo in order to check up on the progress of ordering. The promotions, listing (introductions of new products), and delisting (removals of products) of products are also shared several weeks ahead.

The order & delivery aspect is based on the commitment from both parties to have faster delivery to the shelf. Currently, Mars is delivering products to Jumbo in two working days because orders of different sizes (parts of a pallet) are made and an order does not always contain a full truck. The idea is proposed that if Jumbo accepts to order full pallets and full truckloads from Mars, Mars could deliver within one working day.

The third aspect is the value chain dashboard. The performance information between Mars and Jumbo is kept in this value chain dashboard to provide insight and keep track on each other's performances. At the moment the case fill, on time delivery, and on shelf performance (out of stocks based on actual out of stock and stock in transit) can be improved.

The last aspect is the pilot flowcasting. The goal of this part is to kill the bullwhip effect by planning together. The current situation is that each player in the supply chain makes its own forecasting as information from each step is passed back into the supply chain (Figure 2).

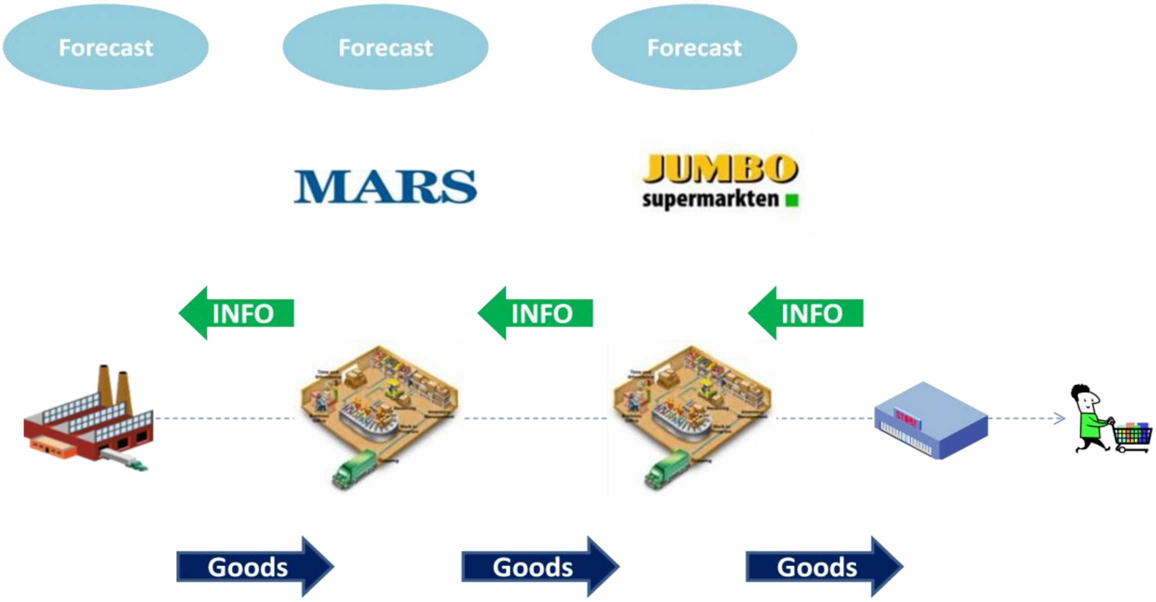


Figure 2 Current forecasting process Mars & Jumbo

The proposed improvement is that information should be shared throughout the supply chain and the demand can be forecasted accordingly (Figure 3).

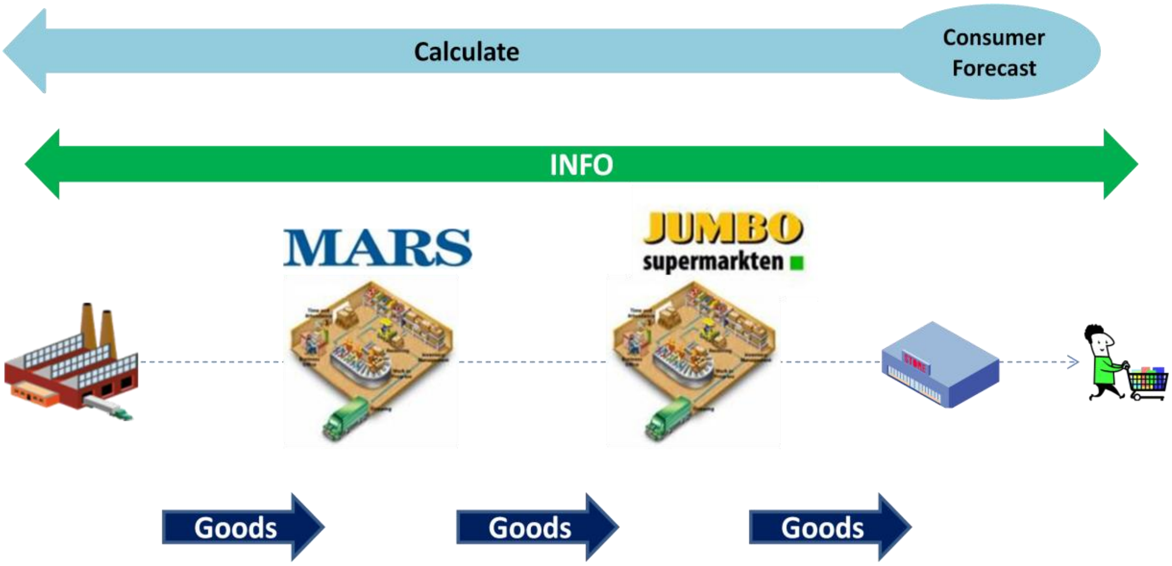


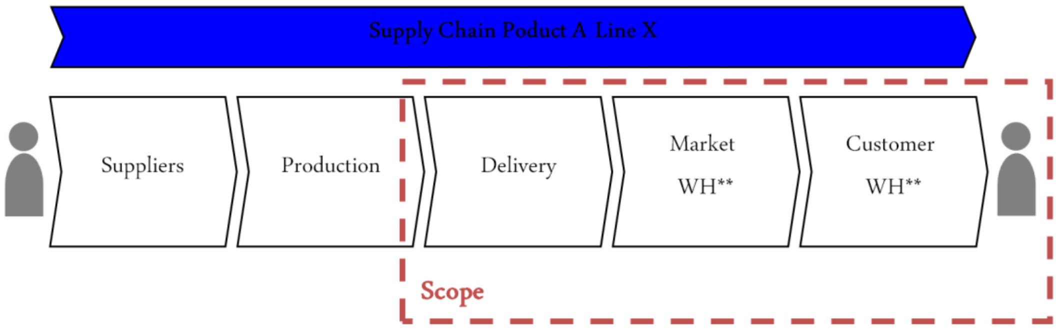
Figure 3 Improved forecasting process Mars & Jumbo

Within the flowcasting project there are many factors taken into account in order to make the best prediction. Consultancy firm Eye On made a forecasting tool based on Jumbo's point of sale data. Moreover, this tool is created with input of promotional actions and many other parameters. This resulted in a significantly better forecasting for sales by Jumbo.

In order for Mars to take advantage of the better forecasting using point of sale data, Jumbo has to keep ordering the exact numbers forecasted and Mars should also stick to producing this amount for Jumbo. However, because of human judgment and the doubt that Mars cannot reliably meet its targets regarding case fill, Jumbo orders more than needed. The planners at Mars who anticipate uplift in demand also amplify these orders.

2.3. Scope of problem

Within the current pull project at Mars, besides the aspects given in chapter 2.2, it is interesting to extend the scope, including retailer's data and POS data, in order to improve the KPI's. However, it is unknown what is needed in order to extend this scope including the customers and which data provides better performance (Figure 4).



WH** = warehouse

Figure 4 Proposed scope of the problem

The new scope to be considered will be from production until the final consumers. In the previous scope (of the pull pilot project) the scope runs until the market warehouse. The question can be asked whether widening the scope leads to other control mechanisms throughout the supply chain or whether the current pull pilot already leads to the optimal stock level and can be extended.

Although production is not taken as a main focus due to own optimization cycles, a short description is provided. In Appendix II the overview is given for the production lines at Mars. Line X is the subject of interest within this research. Within this line both Product A Milk as well as Product A Dark products (different recipes) are produced. The Product A chocolates are made on 1 central and continuous flow line for all Product A products within one recipe. Among others, cocoa powder, milk powder, sugar and coconut extract are used as raw materials for the products. Within the Product A Milk products there are many machine changeovers as each different packaging is a different product. However, this specialisation to different products is only dependent on the last step of production, the packaging step. Changeover times are four hours for recipe changes (dark and milk chocolate). The changeover for different products within the same recipe is primarily change in packaging and it takes 24 hours to get the packaging material delivered from Kuehne + Nagel.

Within a production run of for example Product A Milk are a lot of set ups as around 70 products are made on line X. The set up times for the products are not really an issue time wise as the packaging machine processes at a higher rate than the chocolate producing machines. For instance, if 100 bars can be produced per minute, the packaging machine can wrap 130 bars. In this way, the machine can be set up while production is ongoing.

On the basis line X is flexible enough to produce each product each week. However, due to the demand of certain products, not all of them need to be produced every week such as the Product A Dark chocolates. To start production the factory needs to have the packaging material delivered from Kuehne + Nagel. The packaging is transferred to and from the Mars factory each time a certain product needs to be produced, as there is no storage room available at the factory.

2.4. Expansion of the current project

In order to manage production, in the current pull project with the Kanban system, data of demand need to be used. The market warehouse will give a daily update of their stock to the inbound logistics department. Here the demand planner will transfer the data into an excel sheet with stock and Kanban levels. The required amount that needs to be produced is then known and will be corrected with a certain volatility factor that is derived from the in house forecasting system that takes promotions into account. The ultimate figures will be send to production planning that also has to implement the requested amounts. It is noticeable that the amount of manual labour that accompanies this process is large. This is the main reason that the pull project has not been expanded onto other products/production lines, as there is a lack of an IT system that links the information.

The collaboration with the supermarket chain Jumbo is an on-going process. The addition of the retailer's and point of sale data is key to extend the scope of the project. However, a platform to use the data is yet unknown. What kind of aggregation of data is needed (whether daily, weekly or monthly demand), to implement into the operations of Mars in order to reduce costs and obtain the optimal stock level, is yet unknown. For the next step in the pull project it is also not clear how to deal with volatility of the new data.

For Mars Nederland B.V. stock and lead-time reduction, and thus freshness, are still important issues. Freshness is an issue as Mars strives to have their products consumed at an optimal age of the product. This is especially significant for candy bars that contain biscuits that will perish earlier than other candy bars. Moreover, Mars is always looking for new ways to improve its current processes.

The average cycle time within Mars after the pull pilot for the Product A is 12 days, while the average cycle time from the customer warehouse to the final customers is 4 to 8 weeks (Figure 5). This cycle time implies the stock cover that is needed. Thus the biggest reduction in stock cover seems to be within the latter part. However, the complete scope from the factory until the final consumer will be considered to see whether overall improvements could occur.

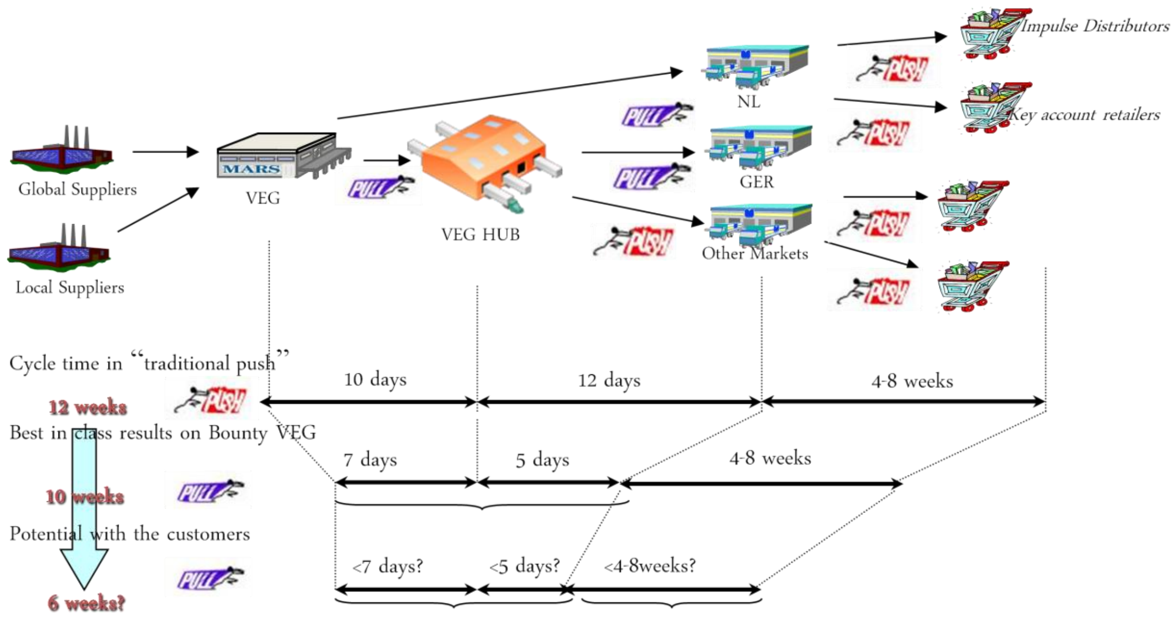


Figure 5 **Cycle time reductions**

Considering what the current project has achieved, the scope can be extended to get commitment from Mars' customers. This commitment is in the form of provision of retailer's demand and POS data. However, in which manner that the available information can be used remains unanswered. With the expansion of scope of the pull project, an analysis can be made whether more advantages can be obtained with respect to an optimized stock level. Other control methods to be considered might lead to more reduction in costs. In case this occurs, the trade-off between the methods should be made.

Past literature has promoted supply chain collaboration and the use of customer warehouse data and point of sale data, in which each has its own favourable conditions (Ye, 2012a). According to Hopp and Spearman (2003) a pull production system is one that explicitly limits the amount of work in process (WIP) that can be in the system. This implies that a push production system is one that has no explicit limit on the amount of work in process that can be in the system. In this way, the inventory in a pull system would be considerably lower because of the capacitated WIP.

Pull is a part of the Lean concept. The Lean principles are as follows (Lian & Landeghem, 2007):

1. Define 'Value' from the perspective of the customer.
2. Identify the 'Value Streams', and eliminate 'Waste' from them.
3. Create 'Flow'.
4. Introduce 'Pull'.
5. Strive to 'Perfection'.

Flow is a key aspect within Lean. It comprises the synchronization of activities and effective process management to keep a product moving through the system at the rate of the customer demand. Once this flow has been created, a system is put in place to control the movement of finished goods with the underlying idea of replacing what has been used when there is a demand signal for more products. The intent is to remove unnecessary inventories and activities out of the system (Kahn & Mello, 2005).

Although many conceptual literatures exist on Lean and pull on a strategic level, there are still little publications on the implementation of pull. As discussed, the execution of the principles of pull within literature is not always consistent and sometimes contradicting. Thus, there is still a need to define a clear implementation of pull. Furthermore, as Lean and pull are originated from the automotive industry and spread across some other industries such as the process industry; little is known about pull within the Fast Moving Consumer Goods industry. As the FMCG industry has different kind of products that are produced in bigger batches than the automotive industry, pull is not commonly used as a replenishment mechanism. Furthermore the practical interpretation within this field of subject and industry is combined a gap within literature that is interesting to research (Ye, 2012b). This leads to the following assignment:

> *'Design a collaboration model for Fast Moving Consumer Goods companies to control information sharing onto the involvement of customers in order to optimize stock levels and replenishment time.'*

Within this collaboration model the emphasis is laid on the use of different types of data. The project has several research questions.

1. What kind of information exchange model is needed in order to design the framework of the new collaboration?
2. Which aggregation level of shared demand data is needed to have more accuracy to control the supply chain?
3. What will be the total replenishment lead-time in the new collaboration, considering Figure 5 specifically from the Mars factory to the Dutch warehouse and from the Dutch warehouse to the Jumbo warehouse?
4. What are the possibilities to focus on other chocolates?
5. How can the collaboration with Jumbo be generalized in order to be applicable for other collaborations?

To research the questions above a deeper look into the literature on the different pull control policies and the nature of POS data is required. In Appendix III the different types of pull control systems are explained to have insight into the way pull systems work. Prior to conducting the research and during the actual research, a number of interviews and meetings were held in order to gain knowledge into the problem and the project history. Moreover, sufficient documentations have been made available in the form of presentations and data. A list of key resources from which information is obtained is illustrated in Appendix IV.

3. Current operations pull project

This chapter is dedicated to the current operations for the pull project at Mars. The operations around line X and replenishment of the line X products under pull control are described. The Kanban calculation will be discussed in chapter 3.1. During times of peak demand that exceeds the Kanban levels stock building is required. The rules behind the exception process called the volatility translator are explained in chapter 3.2.

3.1. Kanban calculations

According to Silver, Pyke and Peterson (1998, p. 640) the formula of the number of Kanbans is given by

$$N_i = \frac{D_i * t_i * (1 + SF)}{n_i}$$

Where

D_i = demand or usage rate for part i

t_i = total lead time

n_i = number of parts per container

SF = safety factor

The safety factor is used to buffer for uncertainty. In case of the Mars safety factor, this is used to buffer uncertainties such as late signal to the warehouse, scrap during physical distribution, impact of quality incidents, and MFI deviation. This factor is not the same as the factor k (a safety factor that leads directly to a value of safety stock by multiplying with the standard deviation) as the safety factor here is not a multiple of the measure of uncertainty. Silver, Pyke and Peterson (1998) suggests that the safety factor of 0.25 is somewhat higher than is often recommended. As uncertainty is reduced, this safety factor should be lowered.

For the current pull project at Mars, the Kanbans represent inventory that must buffer for demand during time spent in transportation and production. The Kanban calculation for the current pull project is made with the following model:

$$K_i = D_i * T_{L,i} * (1 + S_{f,i})$$

Where:

K_i = Number of Kanbans for product i

D_i = Expected weekly demand of item i in cases

$T_{L,i}$ = Replenishment time of product i

$S_{f,i}$ = Safety factor of product i

The Kanban numbers in pallets can then be derived and is in line with the model given by Silver, Pyke, and Peterson (1998).

$$K_{P,i} = \frac{D_i * T_{L,i} * (1 + S_{f,i})}{KU_i}$$

Where:

KU_i = Kanban units in a pallet for product i.

In order to determine the Kanban level, the expected weekly demand of product i (D_i) is used. This expected demand is derived from historical demand. D_i constitutes of either the maximum weekly demand of product i ($D_{max,i}$) or an adjusted value of $D_{max,i}$ due to forecast (see Table 2, the exception process will be explained in the next paragraph). The maximum weekly demand (D_{max}) is taken from an in-house tool called Value Added Planning Matrix. This tool takes historical data into account and calculates the capped maximum and minimum demand taking out the outliers. However, this value can be adjusted when peaks in forecast occur, thus resulting into the adjusted value of $D_{max,i}$. At this moment, the maximum weekly demand used is based upon calculations in the past, due to the fact that the Value Added Planning Matrix doesn't function anymore.

Using D_i, the Kanban level has been calculated. This Kanban level indicates a maximum number of work in process that the pipeline stock from the production to the Mars warehouse has to contain.

The replenishment time ($T_{L,i}$) can have one of the two values; the normal replenishment time ($T_{L,i}$) and the emergency replenishment time ($T^*_{L,i}$). When the stock of a certain product falls below a critical boundary, a new production is started within 24 hours. Therefore, the emergency replenishment time is used. Otherwise the normal replenishment time holds.

$$T_{L,i} = MFI_i + P_i + T_f + MH_r$$

$$T^*_{L,i} = ES + P_i + T_f + MH_r$$

Where:

MFI_i =	Manufacturing Frequency Index, this implies the number of hours between two consecutive production runs of the same product.
ES =	Emergency start time needed to get wrapping material in from Kuehne + Nagel.
P_i =	Production time of product i. The production time needed for product i is the maximum weekly demand observed in the past of product i divided by the operating capacity for that product.
T_f =	Transportation time from factory to Mars market warehouse.
MH_r =	Remaining micro hold time, including time for micro biotic research and maturation needed for all products. As the transportation of the products take

place during the micro hold time, the transportation time is subtracted from the total micro hold time.

In the past a project was performed for determining the MFI's. These values are used here. Only when emergency productions are enforced, would the production deviate from the manufacturing frequency index. This MFI value is set for all the Product A products at the beginning of the pull pilot project and shall be used as a constant during the calculations.

The safety factor is a correction percentage for the demand during replenishment time. This factor has been obtained by means of trial and error during the pilot phase (and thereafter adjusted each half year) and varies for the different products between 0.15 and 0.30.

The stock level at the Mars Dutch market warehouse is sent to the demand planner at Mars on a daily basis. The level of stock can then be reviewed and this level can fall within three parts (red, yellow, and green). The ranges of the three parts are defined as follows:

$$Total_i = K_i = D_i * T_{L,i} * (1 + S_{f,i})$$

$$Red_i = [0\,, D_i * T^*_{L,i}]$$

$$Yellow_i = \left[D_i * T^*_{L,i}\ , \left(\frac{Total_i - D_i * T^*_{L,i}}{2}\right) + D_i * T^*_{L,i}\right]$$

$$Green_i = \left[\left(\frac{Total_i - D_i * T^*_{L,i}}{2}\right) + D_i * T^*_{L,i}\ , \ Total_i\right]$$

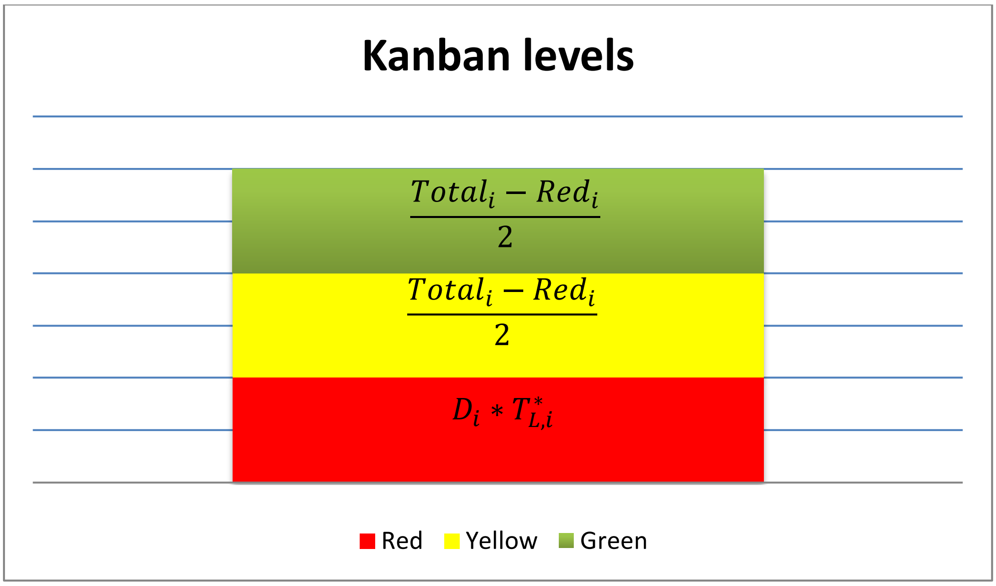


Figure 6 **Kanban level values**

Figure 5 illustrates the values of the different Kanban levels. As can be seen the green and yellow region are both of equal value. This is taken as an initial value for both and can be adjusted through trial and error. Up until now, no adjustments have been made for these values. For a detailed description of the process and the process model, see Appendix V (Heuvelmans, 2011).

3.2. Exception process/Volatility Translator

During periods with exceptional peaks in demand (these are mainly caused by promotions and listings) the Kanban level is changed. This change is originated from the adjustments in D_i. Mars came up with the volatility translator in order to calculate the needed adjustment.

The volatility translator will adjust the D_i when there is a period of exceptional demand. With the Kanban calculation the Yellow Green Barrier (YGB, see Appendix IX) is set. This comprises the demand covering the yellow and green region. Thus when demand exceeds this barrier the stock level will fall within the red area and emergency production will be enforced.

From the forecasting tool Apollo Demand, the weekly demand forecast (D_f) is made. The height of this forecast will trigger the needed adjustments. Table 2 shows the conditions and rates of adjustment. Here, the $D_{max,i}$ is the maximum weekly historical demand and the $D_{min,i}$ the minimum weekly historical demand.

Table 2 Adjustment conditions for Di

Condition of $\boldsymbol{D_{f,i}}$	Adjustment of $\boldsymbol{D_i}$
$\boldsymbol{D_{max,i} < D_{f,i} < YGB_i}$	$D_i = D_{max,i} * \left(\frac{(D_f - D_{max,i}) * 0.5}{D_{max,i}} + 1\right)$
$\boldsymbol{D_{f,i} > YGB_i}$	$D_i = D_{max,i} * \left(\frac{(D_f - D_{max,i}) * 0.5}{D_{max,i}} + 1\right)$
$\boldsymbol{D_{min,i} < D_{f,i} < D_{max,i}}$	$D_i = D_{max,i}$
$\boldsymbol{D_{f,i} < D_{min,i}\ for\ 1\ week}$	$D_i = D_{max,i}$
$\boldsymbol{D_{f,i} < D_{min,i}\ for\ 2\ weeks\ in\ a\ row}$	$D_i = D_{min,i}$

The D_i can then be used in the Kanban calculations in order to determine the Kanban level of the coming weeks.

At first glance, the current system from the pull pilot project has similarities to the Generalized Kanban system (see Appendix III); the replenishment is not directly linked to the demand, as it first needs an authorization Kanban (the demand planner would first receive the stock level and adjusts it in Excel, then this is sent to the production planner). However, when considering the Generalized Kanban system, if the number of finished inventory level is equal to the Kanban size, the system will be a Kanban system.

The stock level at the Mars market warehouse is send once each day instead of real time as the stock level changes. However, the current model links the replenishment with several stock level urgencies. It also has adjustments to the maximum demand taking forecasting into account. Thus it may not completely be a Generalized Kanban system, but a hybrid form of this system that takes the forecasted demand into account. The process model is illustrated in Appendix VI (Heuvelmans, 2011).

3.3. Summary

In summary, the current operations of the pull project are translated into working with Kanban cards. These Kanban cards indicate a certain work in process. This results in a steady work in process. All demands are translated directly to production, and productions will be scheduled accordingly taking into account the MFI and the Kanban urgency levels. For exceptional processes such as promotions, forecasting is still used to indicate the level of needed stock building.

This pull replenishment process and the forecasting are based on delivery data from Mars to its customers. However, other demand information could lead to other values of decision variables and could affect the way of working within the current operations. According to the assignment formulation in chapter 2.4, research will be conducted to see the effect of the different types of data and the consequences in obtaining and using other data. In the next chapters the use of the different data will be analysed using it in the current pull project (chapter 4), taking a supply chain wide view (chapter 5) and the comparison against the former push replenishment system (chapter 6.3).

4. Data Analysis and current model

After the analysis of the current process, others types of data will be researched and the way these data influence the current calculations will be given. Thus this chapter focuses on the current models with new data. First the definition and nature of POS data will be introduced in chapter 4.1. Then the different levels of data will be explained in chapter 4.2. Next, the data will be cleaned using Wisorization in chapter 4.3. Forecasts can be made in the program Apollo Demand; this will be explained in chapter 4.4. Finally, in chapter 4.5, the comparison of the Kanban calculations on different levels of data will be made.

4.1. POS data and factors that influence its effectiveness

Point of sale data is data measured at the consumer level, also known as scanner data. It is a direct measure of consumption. It shows independent demand whereas other types of data in the supply chain are dependent demand. POS is not dependent on inventory levels, ordering processes at the customer and such.

A study of Williams and Waller (2010) show that in 65% of the cases POS data outperformed order history data used for forecast. For high volume products, POS is more effective than for low volume products.

Top down forecasting represent more aggregate level. The forecast is made at a higher level and disaggregated into item level. The bottom up forecasting forecasts at item level and roll these together to brand or category forecast. From a top down perspective, POS data is not so effective. Within the bottom up forecast approach POS data outperforms order data significantly (Williams & Waller, 2011).

The most effective data are the real time data. However, this is often not possible to be offered. Therefore there is a need to consider aggregated data on a weekly or monthly basis. Temporal aggregation is the aggregation of demand over time. POS data can be used aggregated at for example weekly level or on a 4 weeks basis. As aggregation starts to occur, forecast error increases with POS data. POS and order data can be used simultaneously. As the forecast horizon is shorter, both data together leads to better forecast. With seasonal effects, POS was found less useful (Williams B. , 2012).

4.2. Data levels overview

The following data are acquired with respect to three Product A chocolates as this is offered at Jumbo.

- Forecast data from Mars for Jumbo
- Delivery data from Mars to Jumbo
- Order data from the Jumbo supermarkets to it distribution centre
- Point of sale data of the Jumbo customers

The forecast data from Mars to Jumbo are the last made weekly forecast.

After the first analysis it is visible that the data closest to the final customers exerts less fluctuation. As an example the Product A.1 is illustrated in Figure 7. The graphs of the remainder of the products are illustrated in Appendix VII.

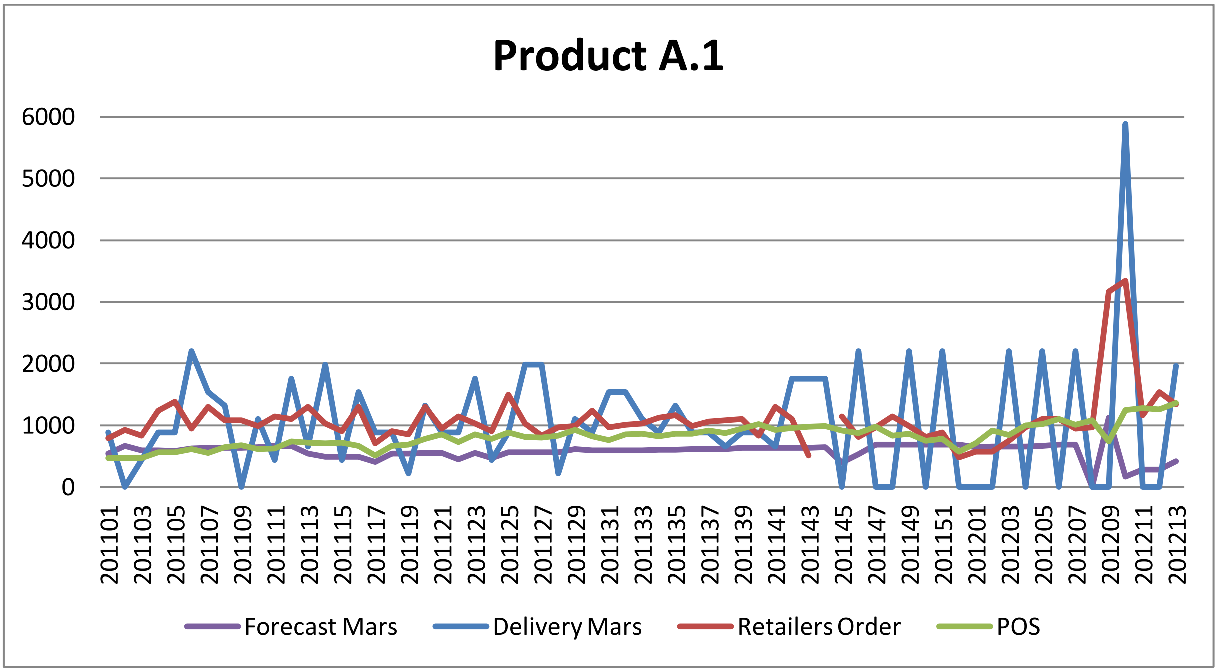


Figure 7 **Product A.1 in consumer units**

It is interesting to see that the forecast and POS data are least variable. An aspect of the existing collaboration with Jumbo is very visible. From week 201145 the Product A.1 is being replenished with a full pallet in a full truck. This restriction contributes to the high fluctuation in the delivery data from Mars to Jumbo.

Now that the forecast, delivery, retailer order, and POS data are available; one can consider which data can have influence on the Kanban level. There are several levels of data that can be used to determine D_i. This is depicted in Figure 8.

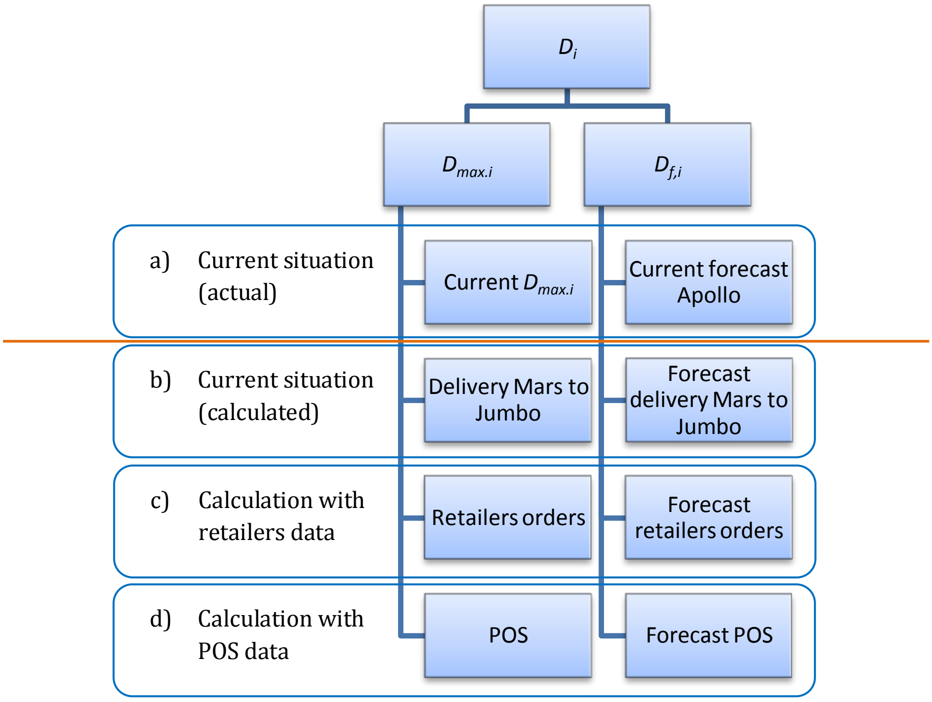


Figure 8 Comparison possibilities

The current situation actual (a) can be compared with the different levels of data (b, c, and d). The current situation calculated is based on the delivery data from Mars to its customers (b). The calculations with the delivery data should approach the current situation actual (a). The $D_{f,i}$ can be forecasted with Apollo Demand. The forecast data will be used to check if adjustment of the maximum demand is needed in the volatility translator.

4.3. Winsorization and data trimming

As the Value Added Planning Matrix tool does not appear to be functioning anymore due to technical reasons, a new way should be searched in order to calculate the $D_{max,i}$. To exclude the extreme peaks in data, literature suggests that one can either trim the data or use Winsorization. Winsorization adjusts some data points to make them less extreme, whereas trimming eliminates those data points entirely (Jose & Winkler, 2008). Determining the cut off point at each end can involve sophisticated approaches, yet it often is designated as the most extreme five percent, or all observations beyond a certain multiple of standard deviations from the mean. Usually, this would be 2 to 4 standard deviation.

For the data of Mars and Jumbo, Winsorization is used to adjust the values above or below two standard deviations from the mean. The basis for the Value Added Planning Matrix is the mean plus one standard deviation. Thus, this is applied after Winsorization. The values from this method appear to be closest to the current values. Moreover, to deal with the exceptional demand during promotion, the volatility translator tool explained in chapter 3.2 will take care of the uplift, thus the adjustment to high demand with Winsorization seems less appropriate.

4.4. Apollo Demand

The in house forecasting program Apollo Demand is used to determine the weekly forecast. The program is based on the Lewandowski method in which the combination of linear regression and exponential smoothing is used. The Lewandowski method is a special form of the Holt-Winter exponential smoothing method. In general, the Lewandowski method is a more practical method that is widely adopted by many European firms. It allows the user to incorporate judgmental elements into the forecasting model (Lewandowski, 1982). There is an important difference between the Lewandowski method and the Holt-Winter method. Lewandowski's method dampens the trend as the forecast lead-time increases. The level of dampening increases with the level of noise in the series (Silver, Pyke, & Peterson, 1998).

In this research the testing space of Apollo Demand is used to investigate the effects of the different types of available data. This forecasting can be used for the volatility manager to foresee future demand that needs stock building.

The parameters are kept the same for all Product A products except for the seasonality impact that is adjusted to best fit the data. However, this seasonality impact is also kept constant for each type of data per product. The obtained forecast is illustrated in Appendix VIII. This forecasting can then be used to see whether stock building is required. The conditions for adjustment are explained in chapter 3.2.

4.5. Comparison

Recall Figure 8 with the different levels a, b, c, and d of comparison. The data of Mars and Jumbo can be reviewed to see the effects of demand on different levels. First the current $D_{max,i}$ values at Mars used for the three Product A items at national level are depicted in Table 3. Next the percentage of the Product A products that are allocated to Jumbo can be used to compute the part of the overall products for the Dutch market.

Table 3 **Percentages delivered accounted for Jumbo**

	$D_{max,i}$ National (cases/week)	% accounted for Jumbo	$D_{max,i}$ Jumbo (cases/week)
Product A.1	529	11.153	59.00
Product A.2	1593	7.432	118.40
Product A.3	707	1.621	11.46

The current values are given on a national level. Taken from the actual delivery data from Mars to Jumbo, the percentages of the different Product A products for the whole Dutch market accounted for Jumbo are also depicted. The Product A.2 is a big item as it is sold much more than the other Product A items. Furthermore, the Product A.3 is a small item especially for the percentage accounted to Jumbo. This is explained as the Product A.3 is sold more at "out of home" spots such as gas stations as impulse products rather than supermarkets.

From the available data the values for $D_{max,i}$ and $D_{min,i}$ are calculated. This is done by determining the D_{avg} and D_{sigma} from Winsorization and adding (or subtracting in case of D_{min}) one standard deviation to D_{avg} (Table 4). The current calculations (see Figure 8, a) are made on a national level based on the delivery data from Mars. These values are adjusted for Jumbo with regards to the percentages given in Table 3.

Table 4 **Descriptive statistics of demand accounted for Jumbo**

		Current $D_{max,i}$ (cases/week)	*$D_{avg,i}$ (cases/week)*	*$D_{sigma,i}$ (cases/week)*	*$D_{avg,i}$ + $D_{sigma,i}$ (cases/week)*
Product A.1	a)	59.00			
	b)		45.16	35.35	80.50
	c)		46.71	10.23	56.93
	d)		37.08	8.04	45.12
Product A.2	a)	118.40			
	b)		55.11	45.25	100.35
	c)		67.66	26.51	94.18
	d)		57.60	12.47	70.07
Product A.3	a)	11.46			
	b)		5.55	4.17	9.72
	c)		6.29	3.15	9.44
	d)		5.87	2.87	8.75

4.5.1. Comparison Kanban sizes

Using the determined values of $D_{max,i}$ the Kanban levels can finally be calculated by multiplying the demand with the safety factor and replenishment time. The safety factor ($S_{f,i}$) is the factor currently in use at Mars. The replenishment time ($T_{L,i}$) depends on the variables MFI, SOC, T_f, and MH explained in chapter 5.1. The values of the variables are depicted in Table 5.

Table 5 **Decomposition of replenishment time**

	MFI_i (hours)	*SOC (cases/hour)*	*T_f (hours)*	*MH (hours)*
Product A.1	168	110	13	72
Product A.2	168	101	13	72
Product A.3	84	131	13	72

For Jumbo, the effects that arise with regards to the Kanban size are given in Table 6. To calculate the Kanbans needed for the Dutch market, the weekly demand ($D_{max,i}$) of Jumbo and the percentage it accounts for the products on national level is used. For $D_{max,i}$ the average of the data plus one standard deviation is used.

Table 6 Kanban calculations for Jumbo

Jumbo		$D_{max,i}$ (cases/week)	$T_{L,i}$ (weeks)	$S_{f,i}$	K_i (cases)	% reduction in K_i
Product A.1	a)	59.00*	1.4318	0.3	110	0.0%
	b)	80.50	1.4329	0.3	150	-36.4%
	c)	56.93	1.4317	0.3	106	3.6%
	d)	45.12	1.4310	0.3	84	23.6%
Product A.2	a)	118.40*	1.4356	0.2	204	0.0%
	b)	100.35	1.4345	0.2	173	15.2%
	c)	94.18	1.4341	0.2	162	20.6%
	d)	70.07	1.4327	0.2	120	41.2%
Product A.3	a)	11.46*	0.9291	0.3	14	0.0%
	b)	9.72	0.9290	0.3	12	14.3%
	c)	9.44	0.9290	0.3	11	21.4%
	d)	8.75	0.9290	0.3	11	21.4%

* These values are taken as the sales accounted for Jumbo from the actual values used on national level

From Table 6 one can observe that the values for the delivery data from Mars (b) deviates slightly, and stronger in case of the Product A.1, in comparison to the actual data. However, using the retailer order data (c) leads to a reduction in Kanban sizes varying from 3.6 percent up till 21.4 percent. Furthermore, using POS data (d) will even lead to a higher reduction in Kanban size varying from 21.4 percent up till 41.2 percent. These reductions are also considerable when compared to the calculations with delivery data (b).

Table 7 Kanban calculations on national level

National level		$D_{max,i}$ (cases/week)	$T_{L,i}$ (weeks)	$S_{f,i}$	K_i (cases)	% reduction in Ki
Product A.1	a)	529*	1.4572	0.3	1002	0.0%
	b)	722	1.4676	0.3	1377	-37.4%
	c)	510	1.4562	0.3	966	3.6%
	d)	405	1.4505	0.3	763	23.9%
Product A.2	a)	1593*	1.5226	0.2	2911	0.0%
	b)	1350	1.5082	0.2	2444	16.0%
	c)	1267	1.5033	0.2	2286	21.5%
	d)	943	1.4842	0.2	1679	42.3%
Product A.3	a)	707*	0.9606	0.3	883	0.0%
	b)	600	0.9558	0.3	745	15.6%
	c)	582	0.9550	0.3	723	18.1%
	d)	540	0.9531	0.3	669	24.2%

* These values are the actual values used for the national level

From Table 6 one can observe that the values for the delivery data from Mars (b) deviates slightly, and stronger in case of the Product A.1, in comparison to the actual data. However, using the retailer order data (c) leads to a reduction in Kanban sizes varying from 3.6 percent up till 21.4 percent. Furthermore, using POS data (d) will even lead to a higher reduction in Kanban size varying from 21.4 percent up till 41.2 percent.

These reductions are also considerable when compared to the calculations with delivery data (b).

Table 7 gives the results assuming that the effect of stability in demand of the data from Jumbo is also present for other customers of Mars in the Dutch market. As expected, the results in reduction are similar to the values allocated for Jumbo. Reductions at level c, retailer order data, vary from 3.6 percent up till 21.5 percent. For level d, POS data, the reductions vary from 23.9 percent up till 42.3 percent.

As can be seen from the results, the closer to the end consumer the data is measured; the less Kanbans are needed because the demand shows less variance as an input parameter (D_{max}) in the Kanban calculation is dependent on the variance. This effect was also confirmed by the graphs of the data (Appendix VII). The effect on the replenishment time is small due to little time saving of production relative to the Micro Hold (MH) time and the manufacturing frequency index (MFI). The lead-time will be discussed more extensively in chapter 8.4. The excel calculations and electronic representation of the Kanban file can be found in Appendix IX.

4.6. Summary

In this chapter the method of comparing the different types of data has been addressed. First, a data analysis has been made and then the method of data trimming and Winsorization is discussed. It is concluded that the current $D_{max,i}$ values are based on the average value plus one standard deviation after data trimming. Subsequently, the different levels of data are compared and substantial reductions varying from 21.4 percent up till 41.2 percent in stock reduction can be reached when Mars uses the POS data. This chapter has focused on the optimization within the company Mars. However, one should look at the possibilities of a supply chain wide optimization, thus with the inclusion of Jumbo. The new model of replenishment control for both Jumbo and Mars will be discussed in the next chapter.

5. Supply chain scope and multi-echelon serial system

In supply chain perspective one should consider the possible collaboration model to broaden its scope. A value chain to provide service to the end consumer will require more than local optimality. That is why this chapter is devoted to the inclusion with a customer of Mars. First the existence of the Bullwhip effect within the supply chain is discussed in chapter 5.1. Then, the use of forecast versus actual data is discussed in chapter 5.2. Next, an analysis of the influence of lead-time is given in chapter 5.3. Next, the multi-echelon serial system is discussed with its heuristics to calculate the optimal base stock level in chapter 5.4. Finally, the design of the supply chain collaboration model is given in chapter 5.5.

5.1. Bullwhip effect

As the production at line X is quite flexible and able to produce each product every week, production line X is stable. Moreover, the final demand (POS) is considered to be stable. However, the links within the supply chain acts in such a way that an amplification of demand exists. This can be considered as the Bullwhip effect. This effect is subjected to four rational factors. According to Silver, Pyke, and Peterson (1998) these are as follows:

Demand signal processing
If demand increases, firms order more in anticipation of further increases, thereby communicating an artificially high level of demand.
In practice, as can be seen from the graphs of the three Product A products (Appendix VII), this is the case.

Rationing game
There is, or might be, a shortage so a firm orders more than the actual forecast in the hope of receiving a larger share of the items in short supply
In practice, as explained before, because of human judgment and the doubt from Jumbo that Mars cannot reliably meet its targets regarding case fill, Mars' customers order more than needed. Right after an out of stock occurred, the demand increases above regular level.

Order batching
Fixed cost at one location lead to batching of orders
In practice, due to the collaboration project with Mars and Jumbo, appointments are made to order in full pallets and truckloads in trade for faster delivery. This leads to order batching. Moreover, not only does this encourage order batching, it will also facilitate buying products to fill a truck when this product is not needed. This results into higher stock levels and is detrimental to the demand signals.

Manufacturer price variation
Encourage forward buying of bulk orders
In practice, at Mars, promotions are discussed beforehand and the amount of discount is also agreed upon. There are different promotional agreements with the different customers and deviations from the discussed outtake seem to appear. Thus everyday low pricing is not in order.

The latter two factors generate large orders that are followed by small orders, which imply increased variability at upstream locations (Silver, Pyke, & Peterson, 1998).

Whenever out of stocks occurs, Mars will deliver the product shortages upon the next delivery moment after the product becomes available again. However, the forecast of Mars is still based upon delivery data and not demand. This is amongst others because of automatic ordering systems from customers that order the shortage again the period after out of stock, and it is noticed that the demand of a certain product is higher than normal right after a period of out of stock. The Veghel plant is the only Mars plant in the world that produces Product A. So in occurrence of an out of stock, there is no substitution possibility to supplement the order.

5.2. Forecast versus actual data

In order to react to the actual demand in the market, the Kanban calculations have been using actual historical demand to determine an expected maximum demand for the future. For the collaboration between supply chain links, it needs be decided whether the obtained data should be used for forecast or as actual demand.

Fransoo and Wouters (2000) describe one of the causes of the Bullwhip effect as demand forecast updating. This explains that that the links in the supply chain base the expectations about future demand on orders they receive from the succeeding link. An increase in orders leads to higher demand forecasts, which is transferred to the next link by increased order quantities. That link also sees an increase in demand, updates its forecast and distorts information for the subsequent link, thus making it unfavourable to for each link in the supply chain to use its own forecasting.

Moreover, a test case analysis is made to examine the mean square errors based upon simple forecasting techniques compared to the expected demand that would arise when the data is used in a pull manner. The historical data is used and the expected demand for a given week is the actual demand of a week earlier. Next, methods such as simple exponential smoothing and linear exponential smoothing are used to forecast.

Silver, Pyke, and Peterson (1998) explained the underlying demand model of simple exponential smoothing as follows.

$$x_t = a + \varepsilon_t$$

The simple exponential smoothing model assigns a weight to historical data. The estimate of a is the following formula.

$$\hat{a}_t = \alpha x_t + (1 - \alpha)\hat{a}_{t-1}$$

Where α is obtained from the following. It can be noticed that as N becomes bigger (we go further back in time), less emphasis will be laid on the previous demand values.

$$\alpha = {}^{2}\!/_{(N + 1)}$$

The estimate of x from time t until $t + \tau$ is therefore

$$\hat{x}_{t,t+\tau} = \hat{a}_t$$

The linear exponential smoothing model is based on a model with a trend. The underlying model of demand is the following.

$$x_t = a + bt + \varepsilon_t$$

The a and b can be estimated by using

$$\hat{a}_t = \alpha_{HW} x_t + (1 - \alpha_{HW})\left(\hat{a}_{t-1} + \hat{b}_{t-1}\right)$$

$$\hat{b}_t = \beta_{HW}(\hat{a}_t - \hat{a}_{t-1}) + (1 - \beta_{HW})\hat{b}_{t-1}$$

Where α_{HW} and β_{HW} are Holt-Winters smoothing constants

$$\alpha_{HW} = [1 - (1 - \alpha)^2]$$

$$\beta_{HW} = \frac{\alpha^2}{1 - (1 - \alpha)^2}$$

In order to determine the accuracy of the predictions, the mean square error (MSE) measure is used.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_t - \hat{x}_{t-1,t})^2$$

Where $x_1, x_2, \dots, x_n$ is the actual demand and $\hat{x}_{0,1}, \hat{x}_{1,2}, \dots, \hat{x}_{n-1,n}$ the one period ahead forecasted demand. Using these methods resulted in the following MSE.

Table 8 Mean square errors of usage actual demand and forecasting

MSE	Actual demand 1 week delayed	Simple exponential smoothing	Linear exponential smoothing
Product A.1			
Delivery data	3357.68	1272.08	1301.29
Retail orders	135.33	135.86	105.08
POS	23.50	96.45	86.38
Product A.2			
Delivery data	2710.77	2852.11	2055.65
Retail orders	1190.32	889.10	715.90
POS	160.93	248.81	163.08
Product A.3			
Delivery data	24.98	19.82	17.87
Retail orders	3.24	9.09	10.30
POS	0.62	7.23	8.43

Table 8 shows that POS data obtain the lowest MSE when actual demand is used at a week delay. For other types of data, linear exponential smoothing mostly seems to have the lowest MSE when comparing the use of actual data and forecast. Because of the fact that using individual forecast would increase the Bullwhip effect and the better performance of actual POS data with regards to the MSE, the research will be continued using actual data for the average demands under pull control.

5.3. Supply chain lead time

Considering the total supply chain having in mind the persuasion of Mars customers to share their data, the priorities of customers are the length of the supply chain and stock level.

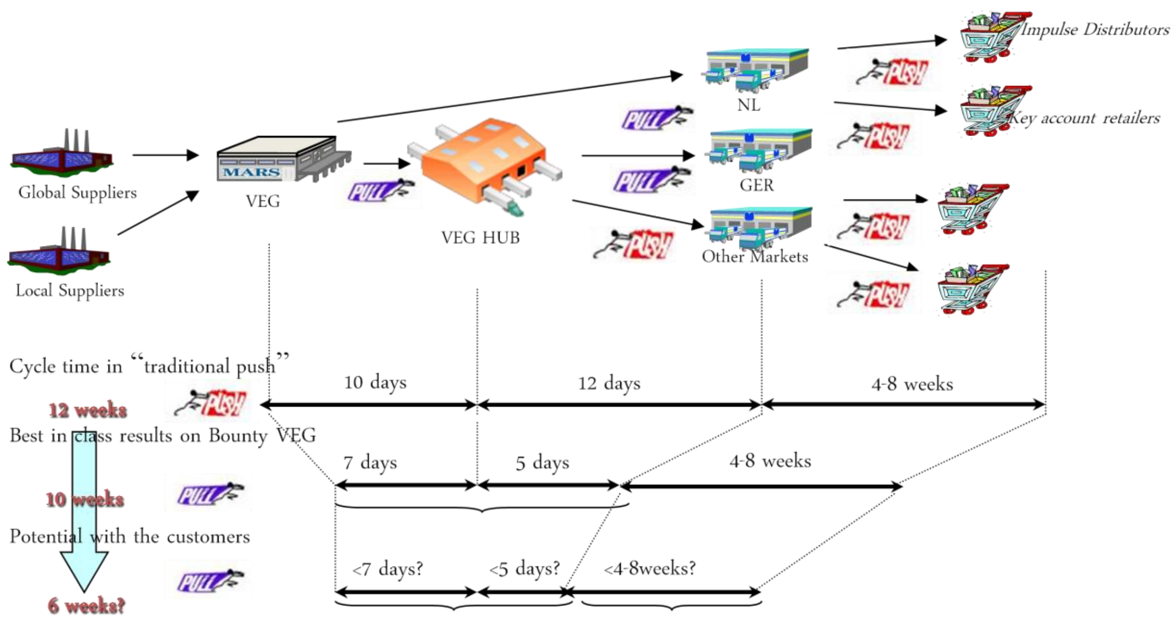


Figure 9 Stock cover throughout supply chain

The cycle time in Figure 9 constitutes the stock cover of the Product A products in the traditional push situation, after the pull pilot project and the potential with customer inclusion. Considering the left part of the chain, from the factory to the Mars warehouses, improvements are already obtained in the cycle time. It is however the right part of the chain where great reductions can be made as the cycle time is 4 to 8 weeks from the customer warehouse to the end consumer.

Nevertheless, replenishment time at the left part will be considered first. From the current Kanban calculations it is noticed that the replenishment time is as follows:

$$T_{L,i} = MFI_i + P_i + T_f + MH_r$$

$$T_{L,i}^{*} = ES + P_i + T_f + MH_r$$

Where:

- MFI_i = Manufacturing Frequency Index, this implies the number of hours between two consecutive production runs of the same product.
- ES = Emergency start time needed to get wrapping material in from Kuehne + Nagel.
- P_i = Production time of product i. The production time needed for product i is the maximum weekly demand of product i divided with the operating capacity for that product.
- T_f = Transportation time from factory to Mars market warehouse.
- MH_r = Remaining micro hold time, including time for micro biotic research and maturation needed for all products. As the transportation of the products take place during the micro hold time, the transportation time is subtracted from the total micro hold time.

It is noticeable that the effect of less variable data on the replenishment time is small due to little time saving of production relative to the Micro Hold (MH) time and the manufacturing frequency index (MFI). Thus, these “bottlenecks” should be addressed. In order to achieve reduction in the supply chain one should pay attention to the micro hold and research whether this hold could be reduced.

The right part of the supply chain is large due to the case sizes of the different products. The Dutch market is small relative to other countries. This is noticed considering the amount of a product that is sold at a random supermarket. For the Product A products, an average of 4 to 5 consumer units is sold per week per supermarket for a certain product. Thus a case of 22 consumer units of a product at a supermarket implies that this would be on shelf (or at least within the supermarket) for 4 to 6 weeks. Mars could take a closer look at the case sizes of the products, especially the ones allocated to the Dutch market. Furthermore, with the base stock calculations one can demonstrate the needed base stock given a certain service level for both Mars and Jumbo. This will be discussed in the next chapter.

5.4. Multi-echelon serial system

Considering the Mars operations with the addition of the Jumbo warehouse, the system can be viewed as a serial multi echelon system. Such a system assumes the following: the different demand levels are independent and identically distributed with the normal distribution, out of stocks are fully back ordered, whenever the inventory position is below the optimal base stock level, one orders up to the optimal base stock level. Otherwise, no order is placed. Moreover, an outside supplier has ample stock to supply material to the factory. To order at the Jumbo warehouse, the order quantity is multiples of cases. To order at Mars, the order quantity is multiples of pallet layers. Furthermore, the average ordering, shipping and processing cost are excluded from consideration.

This system has been studied by Clark and Scarf (1960) who showed that an echelon base stock policy is optimal for the finite horizon problem. The inclusion of Jumbo as a supply chain collaborator is considered as multi-echelon serial system with two echelon stock points (Figure 10).

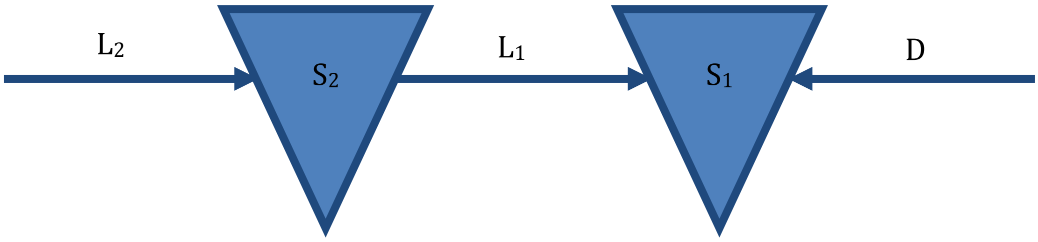


Figure 10 **Two echelon serial system**

The multi echelon systems studied by Clark and Scarf (1960) can be characterized as a centralized control mechanism. This means that a central planner or owner knows the information for the entire system and calculates the optimal base stock level for each stage. Operating according to local optimal policies may not lead to optimal system performance. It is important to identify incentive-compatible schemes to facilitate coordination.

To calculate the optimal base stock level for both stock points the lower and upper bounds of the optimal base stock level equations from Shang and Song (2003) are used. The heuristics of Shang and Song (2003) is practical as it allows studying the effects of system parameters on the optimal costs and policies analytically. The relative error of the heuristic is less than 0.05 percent. It is an easy to implement, near optimal heuristic, while the exact formula for the optimal base stock levels provided by van Houtum et. al (1996) requires heavy computation.

The following parameters are defined:

λ = demand arrival rate

L_1, L_2 = lead times

h_1, h_2 = echelon inventory holding cost rate at stage $j = h'_j - h'_{j+1}$; $(h'_{N+1} = 0)$

h'_1, h'_2 = installation (local) inventory holding cost at stage j

b = unit backordering costs

s_1^*, s_2^* = optimal base stock levels

s_j^α = the approximation for s_j^*

β = fill rate at the most downstream echelon

Within the heuristics the demand is supposed to follow a Normal distribution. This is decided upon an analysis of the distribution (see Appendix X) of the demands based upon the Chi-squared test that takes into account the squared differences between the predicted and observed value. The Normal distribution is assumed as in most cases this is a fairly good fit compared to other distributions. Moreover, for computational purposes, the parameters for the Normal distribution are straightforward and obtained easily. The normal distribution is usable as the coefficient of variation for most demand data is less than 0.5 (van Houtum, 2007). For expansion purposes, this distribution is assumed.

This serial system will be implemented in Excel with the different parameters from Mars and Jumbo. Under a normal distributed demand the following applies. Z denotes the demand with mean μ and variance σ^2. Then

$$\widetilde{D}_j = \sum_{k=1}^{N(\tilde{L}_j)} Z_k$$

Where $N(\tilde{L}_j)$ is the total number of demand arrivals during lead-time $\tilde{L}_j (= \sum_{i=1}^{j} L_i)$ which has a Poisson distribution with mean $\lambda \tilde{L}_j$. The sum of these demands for stock point j is thus the total number of demand arrived during lead-time.

This leads to

$$E[\widetilde{D}_j] = \lambda \mu \tilde{L}_j$$

$$Var[\widetilde{D}_j] = \lambda(\mu^2 + \sigma^2)\tilde{L}_j$$

The lower and upper bound cost ratios are

$$\theta_j^l = \frac{b + \sum_{i=j+1}^{N} h_i}{b + \sum_{i=1}^{N} h_i}$$

$$\theta_j^u = \frac{b + \sum_{i=j+1}^{N} h_i}{b + \sum_{i=j}^{N} h_i}$$

Let $z_j^l = \Phi^{-1}(\theta_j^l)$ and $z_j^u = \Phi^{-1}(\theta_j^u)$. Where $\phi(\cdot)$ and $\Phi(\cdot)$ denote standard normal pdf and cdf, respectively, and define $s_j^l = F_j^{-1}(\theta_j^l)$ and $s_j^u = F_j^{-1}(\theta_j^u)$, with j=1, ... , N.

Following the standard procedure

$$s_j^l = \lambda\mu\tilde{L}_j + z_j^l\sqrt{\lambda(\mu^2 + \sigma^2)\tilde{L}_j}$$

$$s_j^u = \lambda\mu\tilde{L}_j + z_j^u\sqrt{\lambda(\mu^2 + \sigma^2)\tilde{L}_j}$$

$$s_j^a = \lambda\mu\tilde{L}_j + \frac{1}{2}(z_j^l + z_j^u)\sqrt{\lambda(\mu^2 + \sigma^2)\tilde{L}_j}$$

$$C_j^l(s_j^u) = \left(b + \sum_{i=j}^{N} h_i\right)\phi(z_j^u)\sqrt{\lambda(\mu^2 + \sigma^2)\tilde{L}_j} + \sum_{i=1}^{j-1}(h_{i+1}\lambda\mu\tilde{L}_i)$$

$$C_j^u(s_j^l) = \left(b + \sum_{i=1}^{N} h_i\right)\phi(z_j^l)\sqrt{\lambda(\mu^2 + \sigma^2)\tilde{L}_j} + \sum_{i=1}^{j-1}(h_{i+1}\lambda\mu\tilde{L}_i)$$

For stock point 1 (the Jumbo warehouse) the following holds.

$$z_1^l = \Phi^{-1}\left(\frac{b + h_2}{b + h_1 + h_2}\right)$$

$$z_1^u = \Phi^{-1}\left(\frac{b + h_2}{b + h_1 + h_2}\right)$$

$$s_1^l = \lambda\mu L_1 + z_1^l\sqrt{\lambda(\mu^2 + \sigma^2)L_1}$$

$$s_1^u = \lambda\mu L_1 + z_1^u\sqrt{\lambda(\mu^2 + \sigma^2)L_1}$$

$$C_1^l(s_1^u) = (b + h_1 + h_2)\phi(z_1^u)\sqrt{\lambda(\mu^2 + \sigma^2)L_1}$$

$$C_1^u(s_1^l) = (b + h_1 + h_2)\phi(z_1^l)\sqrt{\lambda(\mu^2 + \sigma^2)L_1}$$

For stock point 2 (the Mars warehouse) the following holds.

$$z_2^l = \Phi^{-1}\left(\frac{b}{b + h_1 + h_2}\right)$$

$$z_2^u = \Phi^{-1}\left(\frac{b}{b + h_2}\right)$$

$$s_2^l = \lambda\mu(L_1 + L_2) + z_2^l\sqrt{\lambda(\mu^2 + \sigma^2)(L_1 + L_2)}$$

$$s_2^u = \lambda\mu(L_1 + L_2) + z_2^u\sqrt{\lambda(\mu^2 + \sigma^2)(L_1 + L_2)}$$

$$C_2^l(s_2^u) = (b + h_2)\phi(z_2^u)\sqrt{\lambda(\mu^2 + \sigma^2)(L_1 + L_2)} + (h_2\lambda\mu L_1)$$

$$C_2^u\left(s_2^l\right) = (b + h_1 + h_2)\phi\left(z_2^l\right)\sqrt{\lambda(\mu^2 + \sigma^2)(L_1 + L_2)} + (h_2\lambda\mu L_1)$$

As all information is given in weekly data no specific information is known about the number of orders within a week. Thus the λ is considered to be one per week. To implement this heuristic, input parameters from Mars and Jumbo are used. All input parameters are present except for the back ordering costs. It appears that no back ordering cost is applied during out of stocks. The drawbacks are the loss in service and possible sales but this is cumbersome to quantify.

While the heuristic of Shang and Song (2003) uses the back order costs as a given, one can search for alternatives in order to approach this cost. This is found in the research by Boyaci and Gallego (2001). They researched the serial inventory systems under service constraint, which is given (as fill rate) at the current parameters. The connection with the back order cost system is given as

$$Fill\ rate = \beta = P\left(\widetilde{D}_J(s) < s_j\right) = b/(b + h_j')$$

Suppose that $\left(s_1^*, s_2^*, \ldots, s_{J-1}^*\right)$ are the optimal local base stock levels for the back order cost model for stages $j = 1, \ldots, J-1$ where J represent the last stage as opposed to the heuristic by Shang and Song (2003) where stage 1 represent the last stage. Then in the back order cost model, s_{J-1}^* is chosen to minimize

$$h_j' E\left[s_J - \widetilde{D}_J(s)\right]^+ + bE\left[s_J - \widetilde{D}_J(s)\right]$$

This is a newsvendor problem with the optimal solution given as

$$s_J^* = \{\min_{s_J}: P\left(\widetilde{D}_J(s) \le s_J\right) \ge b/(b + h_j')\}$$

Recall that the fill rate is defined as the limit probability of positive inventory $P\left(\widetilde{D}_J(s) < s_j\right)$. The slight variation of the fill rate, the probability of nonnegative inventory (PONI) is defined by $P\left(\widetilde{D}_J(s) \le s_J\right)$. The PONI and the fill rate service measures differ only when demands are discrete.

By substituting b with $\beta h_1'/(1 - \beta)$ the heuristic of Shang and Song (2003) is usable with the given parameters in order to calculate the optimal base stock level. This means the following change in θ:

$$\theta_j^l = \frac{\beta h_1'/(1-\beta) + \sum_{i=j+1}^{N} h_i}{\beta h_1'/(1-\beta) + \sum_{i=1}^{N} h_i}$$

$$\theta_j^u = \frac{\beta h_1'/(1-\beta) + \sum_{i=j+1}^{N} h_i}{\beta h_1'/(1-\beta) + \sum_{i=j}^{N} h_i}$$

$$z_1^l = \Phi^{-1}\left(\frac{\beta h_1'/(1-\beta) + \mathrm{h}_2}{\beta h_1'/(1-\beta) + \mathrm{h}_1 + \mathrm{h}_2}\right)$$

$$z_1^u = \Phi^{-1}\left(\frac{\beta h_1'/(1-\beta) + \mathrm{h}_2}{\beta h_1'/(1-\beta) + \mathrm{h}_1 + \mathrm{h}_2}\right)$$

$$z_2^l = \Phi^{-1}\left(\frac{\beta h_1'/(1-\beta)}{\beta h_1'/(1-\beta) + \mathrm{h}_1 + \mathrm{h}_2}\right)$$

$$z_2^u = \Phi^{-1}\left(\frac{\beta h_1'/(1-\beta)}{\beta h_1'/(1-\beta) + \mathrm{h}_2}\right)$$

The use of the fill rate (P2-measure) is justified when no emergency runs will be initiated. At the current pull project, it is measured that 10 percent of the productions runs are initiated by an emergency run. This, however, is not desired as emergency runs should only be possible whenever problems occur. This might indicate that the parameter setting was not completely set right as 10 percent emergency runs is quite high. The base stock model is set up as such that no emergency runs are required.

5.5. Design of the supply chain collaboration model

The multi echelon serial system leads to optimal control in terms of stock keeping of the supply under optimal conditions. In order to explain the current state compared to the possible future state value stream mapping visuals are created. A value stream mapping is a technique used to design the flow of materials and information required within a value chain. It is also known as the material and information flow mapping. At the moment the replenishment is controlled as follows.

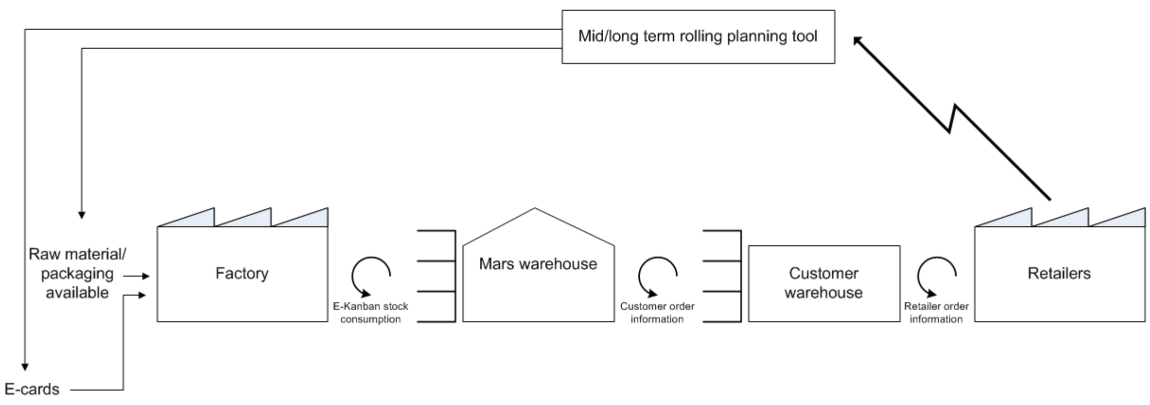


Figure 11 Value stream mapping current replenishment situation

Figure 11 illustrates that the replenishment process is triggered by the orders from each link in the supply chain separately. Each link contains its own replenisher that order with the help of a forecasting system, cooperation with the sales team and its own judgement. Moreover, the available information from the retailers are analysed in the form of Nielsen data (data that gives insight to consumer behaviour), that in part contains the POS data. However, this data is not directly available to the supplier.

From the efforts of the pull system and the new possibilities of cooperation the replenishment process should transform into the following value stream mapping depicted in Figure 12.

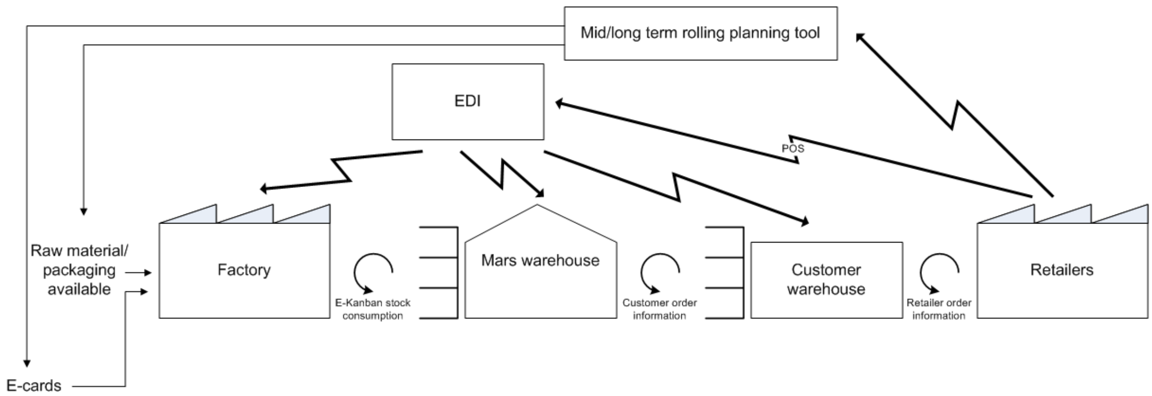


Figure 12 Value stream mapping possible future situation

The most important addition is a central electronic data interchange system that distributes data to every link of the supply chain as soon as it is available or measured. According to the pull principle as well as the base stock policy. The demanded amount at the next link (preferably from the end consumer) is then replenished. This results into a smaller amount of stock needed as it will only need to cover the replenishment time and a certain variance instead of the forecasted demand. For the mid/long term planning as well as the promotions agreed with the sales team, data still needs to be transferred to the mid/long planning tool in order to forecast periods where stock building is required.

5.6. Summary

In this chapter, we broadened the scope of the view of the project. A closer look at the current operations throughout the supply chain for Mars and Jumbo revealed that the actual data is needed for the replenishment of products in a pull fashion. Supply chain lead-time is an important factor in planning and replenishment. The quantitative effect of this lead-time will be demonstrated in the next chapter. Finally a multi echelon serial system has been described along with its heuristics in a manner that the heuristic is possible to be used for calculation on the base stock level. The cleaned data (explained in chapter 4) on the three different data levels will be used to implement this heuristic. The results will be discussed in the next chapter. Finally the design of the supply chain collaboration model is given where a central independent entity is suggested that collects and analyses the data and distributes to the links within the supply chain would replenish according in a base stock manner. Next, the quantitative results will be given.

6. Results

Using the heuristics from previous chapter, the insight into the decision-making and collaboration possibilities will be given in this chapter. Chapter 6.1 will give the results and unveils the optimal base stock level needed for the different kind of data, when the base stock policy is applied. Chapter 6.2 takes into account the order quantity restriction when full pallet layers or full pallets are taken as a restriction. In chapter 6.3 we will compare the optimal base stock levels with the current stock levels and see the impact. Chapter 6.4 we will explain the influences of these results on production and finally, in chapter 6.5, the costs of the multi echelon system are explained.

6.1. Optimal base stock level

The parameters from Mars and Jumbo are used as follows. As explained in chapter 4, the average and standard deviation are derived from the demand and applied to the heuristics assuming a Normal distribution.

Table 9 Input parameters for cases

Product A	μ	σ	β	L_2 (weeks)	L_1 (weeks)	h_2 (€/case)	h_1 (€/case)	Cases/ pallet	b (€/case)
Product A.1									
b) Delivery Mars	45.16	35.35	0.98	1.432	0.200	0.01059	0.00141	100	0.588
c) Retailers orders	46.71	10.23	0.98	1.432	0.200	0.01059	0.00141	100	0.588
d) POS	37.08	8.04	0.98	1.432	0.200	0.01059	0.00141	100	0.588
Product A.2									
b) Delivery Mars	55.11	45.25	0.98	1.436	0.200	0.02648	0.00353	40	1.470
c) Retailers orders	67.66	26.51	0.98	1.436	0.200	0.02648	0.00353	40	1.470
d) POS	57.60	12.47	0.98	1.436	0.200	0.02648	0.00353	40	1.470
Product A.3									
b) Delivery Mars	5.55	4.17	0.98	0.929	0.200	0.02353	0.00313	45	1.307
c) Retailers orders	6.29	3.15	0.98	0.929	0.200	0.02353	0.00313	45	1.307
d) POS	5.87	2.87	0.98	0.929	0.200	0.02353	0.00313	45	1.307

Table 9 depicts the input parameters assuming a Normal distribution (this will be discussed more extensively in the sensitivity analysis in chapter 7). The value of the local holding cost at stock point 1 is unknown, which is the Jumbo warehouse. Assuming the local holding cost at a downstream location is higher than the upstream location, the value of €1.20 per pallet per week is taken for stock point 1. For stock point 2, the value of €1.059 is the local holding cost per pallet per week. At the sensitivity analysis (chapter 7), the influence of variation on the holding cost at Jumbo warehouse will be regarded. The numbers of the holding cost in Table 9 depicts the echelon pallet holding cost divided by the pallet size, thus the echelon holding costs for one case. The pallet sizes are respectively 100, 40, and 45 cases per pallet. Moreover, the service level is the fill rate required at the downstream location. As a producer's aim is to have its products available for the consumer whenever there is a need for its products, the emphasis is laid on serving the end consumer. Having an excellent service level at the end of the chain mean that this will illustrate product availability and contribute to the awareness of the brands and products.

Using the calculations resulted in the approximation of the optimal base stock levels for both warehouses.

Table 10 **Approximate base stock levels**

Product A	s_2^{α}	s_1^{α}
Product A.1		
Delivery Mars	222.3	80.5
Retailers orders	200.1	68.9
POS	158.8	54.7
Product A.2		
Delivery Mars	275.1	99.9
Retailers orders	299.2	104.1
POS	247.1	85.0
Product A.3		
Delivery Mars	21.2	9.8
Retailers orders	22.3	10.0
POS	20.7	9.3

From Table 10 it is again clear that whenever the type of data is located closer to the end consumer, the lower the base stock level needs to be in order to obtain the same service level.

The amount of cases needed to hold in stock at stock point 2 is considerably higher than the amount at stock point 1. This is explained by the flexibility that the system provides. This flexibility is due to the lead-time. It takes longer to produce certain products to stock, thus to replenish stock point 2 than it would be needed to transport the stock to stock point 1. This requires stock point 1 to cover the uncertainty in lead-time.

These results are the preferred optimal results using the multi echelon base stock policy assuming centralized control. As optimizing locally is likely to result in suboptimality, the model assumes centralized control. However, the current collaboration between Jumbo and Mars requires Jumbo to order in batch order sizes such as a full pallet or pallet layer. From a theoretical perspective, this will lead to suboptimality. In the next paragraph, this restriction will be considered quantitatively.

6.2. Base stock level with quantity restriction

So far, the base stock policy is a policy that can be seen as a (S-1, S)-policy. As soon as there is demand (thus as 1 case is demanded), one orders up to base stock level S directly placed. When the restriction of an order quantity Q holds, one can view the individual orders in aggregate. Thus considering these demand in multiples of Q. This means that the policy can be seen as (S-Q, S)-policy. When 1Q in stock decreases, an order is placed to replenish this amount up to S. As an example, if the size of Q is 30 cases and the first 4 orders are 8, 6, 12, and 10 cases. After the time needed for the first 4 orders, the order quantity of Q=30 is accumulated. The remaining demand of 6 is taken into consideration for the next Q demand. This results into new demand distributions. Considering these distributions given in Appendix XI, one can use the same heuristics based on Normal distributed demand.

Table 11 **Input parameters for pallet layers**

Product A	μ	σ	β	L_2 (weeks)	L_1 (weeks)	h_2 (€/case)	h_1 (€/case)	layers/ pallet	b (€/case)
Product A.1									
Delivery Mars	3.23	2.57	0.98	1.4318	0.2000	0.1059	0.0141	10	5.88
Retailers orders	3.34	0.82	0.98	1.4318	0.2000	0.1059	0.0141	10	5.88
POS	2.68	0.75	0.98	1.4318	0.2000	0.1059	0.0141	10	5.88
Product A.2									
Delivery Mars	6.91	5.70	0.98	1.4356	0.2000	0.2118	0.0282	5	11.76
Retailers orders	8.48	3.35	0.98	1.4356	0.2000	0.2118	0.0282	5	11.76
POS	7.31	1.59	0.98	1.4356	0.2000	0.2118	0.0282	5	11.76
Product A.3									
Delivery Mars	0.63	0.60	0.98	0.9291	0.2000	0.2118	0.0282	5	11.76
Retailers orders	0.72	0.60	0.98	0.9291	0.2000	0.2118	0.0282	5	11.76
POS	0.69	0.61	0.98	0.9291	0.2000	0.2118	0.0282	5	11.76

Given the restrictions of ordering full pallet layers at Mars, the parameters are given in Table 11 where the values of the averages and standard deviation are in multiples of pallet layers (Q).

After calculation, the results are found in Table 12. Rounding the numbers up to entire pallet layers and transforming it back to cases results in the following number of cases.

Table 12 **Base stock levels with Q restriction in layers and cases**

Product A	s_2^α (layers)	s_1^α (layers)	s_2^α (cases)	s_1^α (cases)
Product A.1				
Delivery Mars	16.229	5.862	238	84
Retailers orders	14.574	5.012	210	84
POS	11.752	4.051	168	70
Product A.2				
Delivery Mars	35.104	12.702	288	104
Retailers orders	38.103	13.221	312	112
POS	31.836	10.916	256	88
Product A.3				
Delivery Mars	2.637	1.228	27	18
Retailers orders	2.892	1.332	27	18
POS	2.821	1.305	27	18

Considering the results from Table 12 one can see that the required amount of base stock is slightly higher in this situation for both stock points. Given room for this restriction means building up higher inventories. One should weigh this decision against the possible reduction in handling cost as ordering in batches require less handling compared to ordering individual cases.

6.3. Comparison with current situation

The obtained results can now be compared with the current inventory levels in order to see the effect of the multi echelon policy for Mars and Jumbo.

The required current Kanban sizes (with accounted percentage for Jumbo) from Mars and the average inventory levels from Jumbo are acquired and listed in Table 13.

Table 13 Comparison base stock levels

Product A	s_2^{α} (without Q)	s_1^{α} (without Q)	s_2^{α} (with Q)	s_1^{α} (with Q)	Kanban size Mars	Inventory Jumbo
Product A.1					110	144
Delivery Mars	222.3	80.5	238	84		
Retailers orders	200.1	68.9	210	84		
POS	158.8	54.7	168	70		
Product A.2					204	169
Delivery Mars	275.1	99.9	288	104		
Retailers orders	299.2	104.1	312	112		
POS	247.1	85.0	256	88		
Product A.3					14	79
Delivery Mars	21.2	9.8	27	18		
Retailers orders	22.3	10.0	27	18		
POS	20.7	9.3	27	18		

The required Kanban size is taken, as this value should be similar to the base stock value having the same principle. Because Jumbo does not work with this same pull method, the average inventory is taken.

It is noticeable that the current Kanban size, thus the required inventory from the pull project, is lower than any calculated optimal base stocks but the required inventory for Jumbo is much lower than the current inventory at Jumbo. After deeper investigation, the explanation is found in the way that the current maximum demand is established with respect to the Kanban calculations.

As explained in chapter 6 the maximum demand used to calculate the needed Kanbans is constituted, after data cleaning, as the average plus one standard deviation. Then, this value is multiplied with a certain safety factor ranging from 0.2 to 0.3. This safety factor is used to buffer uncertainties such as late signal to the warehouse, scrap during physical distribution, impact of quality incidents, and MFI deviation, thus the exceptional incidents. Moreover, this safety factor is also independent of the demand variation.

However, using the heuristic, under the assumption of Normal distribution, would require a higher multiple of the standard deviation in order to obtain the service level of 0.98. Moreover, since the calculations are focused on supply chain optimization instead of local optimization, it is explainable the base stock would be higher for certain stage of the supply chain.

Now, taking a look into the total needed stock across the supply chain the following values arise.

Table 14 Improvement percentages

Product A	s_{total} (without Q)	% Improvement	s_{total} (with Q)	% Improvement	s_{total} actual
Product A.1					254
Delivery Mars	302.8	-19%	322	-27%	
Retailers orders	269.0	-6%	294	-16%	
POS	213.5	16%	238	6%	
Product A.2					373
Delivery Mars	375.0	-1%	392	-5%	
Retailers orders	403.3	-8%	424	-14%	
POS	332.1	11%	344	8%	
Product A.3					93
Delivery Mars	31.0	67%	45	52%	
Retailers orders	32.3	65%	45	52%	
POS	30.1	68%	45	52%	

Table 14 depicts the sum of both stock points in the situation with and without the restriction of Q and the sum of the actual values. This time it is clear that using POS data results in the highest overall improvement of the inventory level throughout the supply chain.

The actual values of the total safety stock appear to be quite low compared to the required values from the heuristics. This is partly due to improvement initiatives already implemented from the pull project. However, more improvements are possible from a supply chain perspective with the use of POS data.

To see whether the obtained results show improvement from the situation before pull, the obtained result is also compared to the needed stock cover during the push operations. As the calculated base stock level is an order up to level, just as this is the case for the Kanban system, the numbers should be compared to the replenishment maximum during push replenishment. The numbers are depicted in Table 15 and these values are taken as the part accounted for Jumbo on the national level.

Table 15 Comparison base stock, pull, and push

Product A	s_2^{α} (without Q)	S_2 Kanban	S_2 Push
Product A.1		110	271.31
Delivery Mars	222.3		
Retailers orders	200.1		
POS	158.8		
Product A.2		204	261.25
Delivery Mars	275.1		
Retailers orders	299.2		
POS	247.1		
Product A.3		14	27.80
Delivery Mars	21.2		
Retailers orders	22.3		
POS	20.7		

As mentioned earlier the required number of cases to be held as base stock is higher than the current Kanban levels accounted for Jumbo. However, this base stock level is a level that secures performance at the next link of the supply chain. Compared to the original (push) situation the required base stock is lower and at its lowest when POS data is used. This confirms the preference for a pull replenishment policy. In order to implement this strategy, Kanban type of information is needed to ensure that a certain work in process is being kept.

6.4. Influence on production

The obtained results and possibility of improvement in stock level has influence on decisions of stock control and planning. The influence on production is yet to be discussed.

Reconsider chapter 5.2 and 6.4. In these parts the influence of lead-time is discussed in qualitative aspects and respectively the quantitative aspects. These aspects do influence production whenever the reduced or increased amount to be made is sufficiently large that extra production run needs to be started or skipped. According to the production planning department, the minimum amount to start a production run is 200 cases of products as it should be worth planning the delivery of packaging material and set ups. Although this is not a strict rule, there are little exceptions. As the products allocated to Jumbo is a small part of the production on national level, at the moment there is less need for drastic changes in production. However, when this research is extended to include a bigger amount of Mars' Dutch sales, there might be sufficiently large reductions that a certain production run will become unnecessary. Moreover, the manufacturing frequency index might need to be reconsidered when other data is used. The current MFI resulted in 10 percent emergency runs that are actually undesirable.

The statement that reducing the lead time from Mars warehouse to retailer's warehouse leads to bigger reductions than from factory to Mars warehouse implies more focus on order picking and delivery to Mars' customers. In case more time is needed within the supply chain (although it is undesirable as it reduces ones reactiveness), it is less harmful, with respect to the needed base stock, to increase the lead time from factory to Mars warehouse than from Mars warehouse to the customer's warehouse. In this way more slack can be build with regards to production planning and even the manufacturing frequency index.

6.5. Costs

The costs of maintaining the suggested base stock policy are derived from the formulae in chapter 5.4. Under the optimal base stock levels, the following costs are derived.

Table 16 Base stock policy costs

Product A	C2 (€/week)	C1 (€/week)
Product A.1		
Delivery Mars	42.11	14.97
Retailers orders	35.40	12.58
POS	28.95	10.29
Product A.2		
Delivery Mars	171.02	60.76
Retailers orders	145.56	51.69
POS	117.08	41.57
Product A.3		
Delivery Mars	11.17	4.77
Retailers orders	9.87	4.22
POS	9.13	3.90

Table 16 shows the costs under the optimal base stock policy. Given that the lowest stock level is required at POS level to obtain the same fill rate, it is natural that the costs are the lowest with the use of POS data. It is however important to note that the optimal base stock levels are derived from cost minimization and an artificial substitute for the back order cost is assumed given a certain case fill.

6.6. Summary

In summary, this chapter provided insight to the quantitative aspects of the multi echelon base stock policy. The optimal base stock level is calculated. Although the base stock policy requires more stock at the Mars warehouse (from a supply chain wide perspective) than the current pull project; it is still an improvement compared to the original push situation. The stock level for the total supply chain is reduced from 11% to even 68% using POS data. For the Jumbo warehouse, large reductions are obtained when complying with the base stock policy. The order quantity restriction is shown to increase the needed base stock level and a trade-off should be made to weigh the benefits. It is interesting to see this analysis for other products outside of the pull control and for other retailers. This will be discussed in the next chapter.

7. Sensitivity/scenario analysis

The calculations within this report are done under several assumptions in order to be able to use the given models and heuristics. However, one should check the assumption and conduct a sensitivity analysis in order to see how the results could vary. In chapter 7.1 the influence of lead-time is discussed. In chapter 7.2 the variability of the holding cost at Jumbo is analysed. Next, the distribution of the different demand is considered in chapter 7.3.

7.1. Influence of lead time

Because of the transparency of the heuristics, it is possible see the influence of the lead-time on the supply chain base stock levels. The set up is to alter L_1 as well as L_2 with the same amount of time to see which lead-time is more influential and where focus should be laid in order to gain most improvements.

Consider the following adjustments to the calculations made in chapter 8.1 where L_2 is the lead time from factory to Mars and L_1 is the lead time from Mars to Jumbo warehouse (see Figure 10 for illustration of the echelon system):

1. Increase L_1 with 12 hours and L_2 stays the same
2. Increase L_2 with 12 hours and L_1 stays the same
3. Reduce L_1 with 12 hours and L_2 stays the same
4. Reduce L_2 with 12 hours and L_1 stays the same

Thus, the total lead-time is either incremented with 12 hours (1, 2) or reduced with 12 hours (3, 4).

Table 17 Different influences of lead times

	1		2		3		4	
	s_2^α	s_1^α	s_2^α	s_1^α	s_2^α	s_1^α	s_2^α	s_1^α
Product A.1								
Delivery Mars	228.7	95.5	228.7	80.5	215.7	63.1	215.7	80.5
Retailers orders	206.1	82.1	206.1	68.9	194.0	53.8	194.0	68.9
POS	163.6	65.2	163.6	54.7	154.0	42.7	154.0	54.7
Product A.2								
Delivery Mars	283.0	118.5	283.0	99.9	267.1	78.4	267.1	99.9
Retailers orders	308.1	123.9	308.1	104.1	290.2	81.3	290.2	104.1
POS	254.5	101.2	254.5	85.0	239.6	66.3	239.6	85.0
Product A.3								
Delivery Mars	22.1	11.6	22.1	9.8	20.4	7.7	20.4	9.8
Retailers orders	23.2	11.9	23.2	10.0	21.3	7.8	21.3	10.0
POS	21.6	11.1	21.6	9.3	19.9	7.3	19.9	9.3

Table 17 illustrates that in terms of increasing the lead time, the option of increasing L_2 result in lower overall base stock levels compared to increasing L_1. In terms of reducing the lead-time, the reduction of L_1 leads to lower overall base stock level compared to reducing L_2.

To put this in graphical terms the following pattern in effect (Figure 13) is present in all products and data levels. Thus one example is shown below.

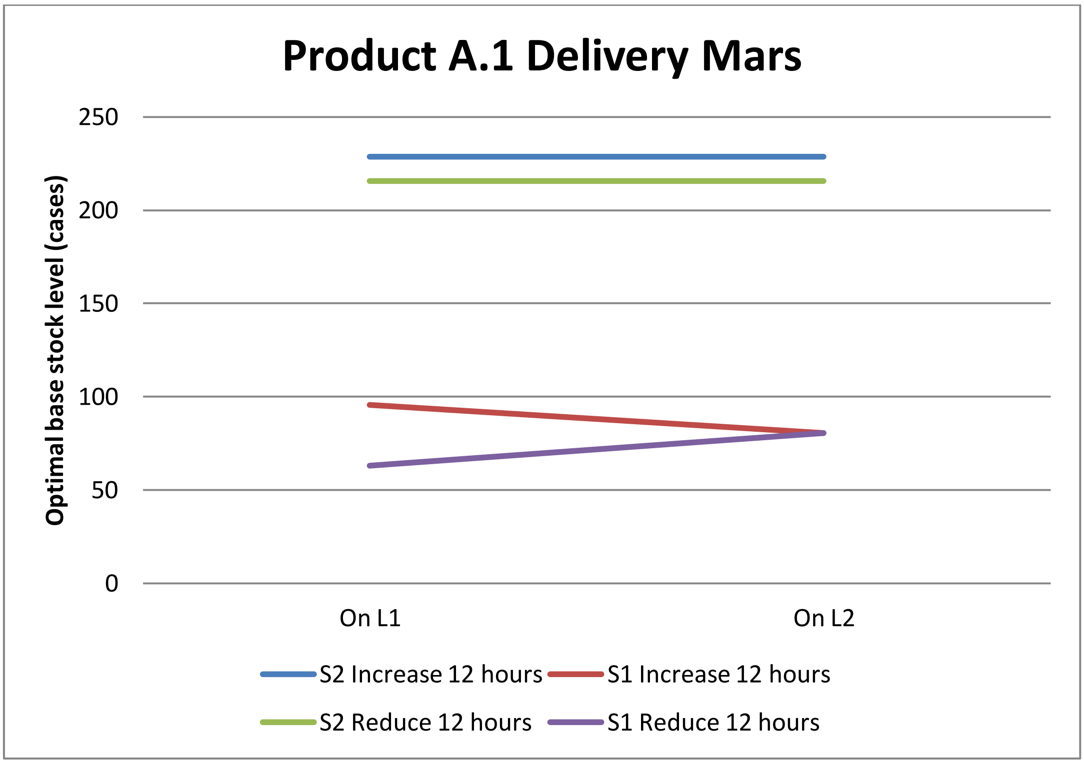


Figure 13 **Influence of lead-time increment and reduction**

It is visible in Figure 13 that for S2, the optimal base stock level is constant. For S1 however, reducing 12 hours on L1 leads to the lowest base stock level needed. Thus when decisions are made with regards to lead-time; it is more advantageous to shorten the lead-time from Mars warehouse to the retailer's warehouse rather at vice versa. This leads to overall bigger reductions in the base stock level throughout the supply chain.

7.2. Holding Costs Jumbo

As explained in chapter 6.1 the holding cost at the Jumbo warehouse is unknown and for the calculations in chapter 6 the value of €1.20 is assumed. To see the influence of the holding cost at the Jumbo warehouse on the calculations of the optimal base stock levels, the value of this holding cost is varied.

The holding cost for the Mars warehouse is €1.059 per pallet per week. Assuming that the holding cost at locations more downstream (closer to the customer) is more expensive than its previous location, the holding cost of Jumbo warehouse will be varied between €1.06 and €1.50.

The exact values of the analysis can be found in Appendix XII. Appendix XII also include the graphical representation of the variation in holding cost.

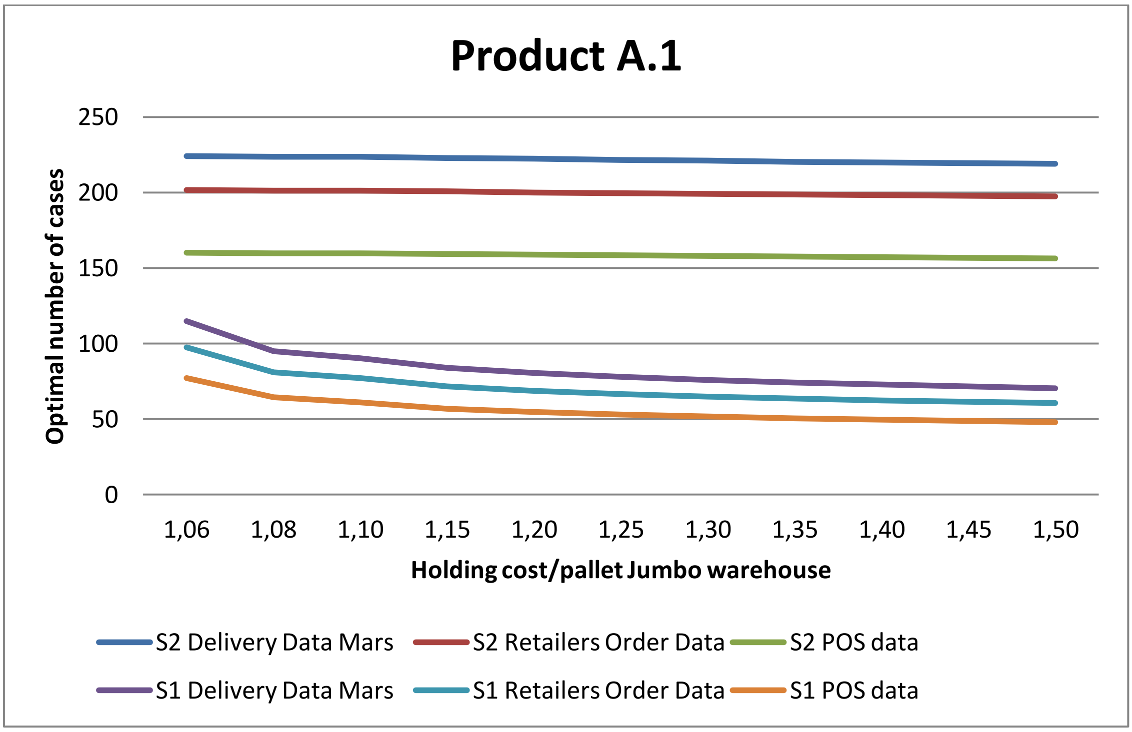


Figure 14 **Influence of holding cost for Product A.1**

Figure 14 shows the influence of the holding cost for the Product A.1. The other products are shown in Appendix XII and all show the same pattern. One can see that for the holding cost at the Jumbo warehouse, it require higher number of base stock when the holding cost approaches the holding cost at Mars warehouse. However, when the holding cost at the Jumbo warehouse start to increase, it does not affect the optimal base stock level much. This effect is also visible for the other products.

7.3. Demand distribution

Within this report all distribution of the different demands are assumed to be normally distributed. This is due to several reasons that are mentioned in chapter 6.4

Many researches include the Poisson distribution, as this is fairly easily computable. However, this distribution assumes a large standard deviation, as this should be the same as the mean (thus the coefficient of variation is above 1). This distribution is not applicable when one needs to examine the influence of the variance in demand.

In this research the normal distribution is assumed as the sigma is in most cases are sufficiently smaller than the mean (the coefficient of variation is smaller than 0.5). However, there are some cases where the coefficient of variation is above 0.5. In this case the research by van Houtum (2007) is applicable. Moreover, the chi squared fit of the demand distributions given in Appendix X mostly complies with the normal distribution as well as the exponential and gamma distribution. Thus another method using these distributions is researched in order to see whether big differences occur.

The Erlang distribution consists of k independent amounts that are each exponentially distributed with parameter λ. In the case with k=1, the distribution is simplified to the exponential distribution. The Gamma distribution is related to the Erlang distribution, as the shape parameter k is an integer with the Erlang distribution. In the Gamma distribution, this parameter is not restricted to the integers.

Using the heuristics of van Houtum (2007) the objective is to minimize the average costs of the multi echelon base stock policy.

$$G(y_1, y_2) = h_2(y_2 - (l_2 + 1)\mu) + h_1(y_1 - EB_1 - (l_1 + 1)\mu) + (p + h_1 + h_2)EB_0$$

Where

$$B_1 = \left(D_{t_0,t_0+l_2-1} - (y_2 - y_1)\right)^+$$

$$B_0 = \left(B_1 + D_{t_0+l_2,t_0+l_2+l_1} - y_1\right)^+$$

The optimal base stock level S_1 follows from the Newsboy equation and has to be turned such that

$$P\left\{B_0^{(1)} = 0\right\} = \frac{p + h_2}{p + h_1 + h_2} = P\{D_{t_0+l_2,t_0+l_2+l_1} \leq S_1\}$$

Through bisection search this value can be approached. This is done by determining the first two moments of $D_{t_0+l_2,t_0+l_2+l_1}$ with mean $(l_1 + 1)\mu$ and standard deviation $\sqrt{(l_1 + 1)}\ \sigma$.

The distribution of $D_{t_0+l_2,t_0+l_2+l_1}$ can then be fitted. An Erlang (k-1, k) distribution can be used if the coefficient of variation is at most equal to 1, otherwise either a Hyperexponential or an Erlang (1, k) distribution should be used.

Once S_1 is determined, S_1 is fixed and is not being changed anymore. The next step is to find an optimal value for S_2. S_2 has to be turned such that $P\{B_0 = 0\} = \frac{p}{p+h_1+h_2}$ and may also be determined by bisection.

When $S_2 \geq S_1$ the probability $P\{B_0 = 0\}$ may be approximated as follows. The first two moments D_{t_0,t_0+l_2-1} with mean $l_2\mu$ and standard deviation $\sqrt{l_2}\ \sigma$ needs to be determined. Then, a distribution on D_{t_0,t_0+l_2-1} needs to be fitted. Again, when the coefficient of variation is at most or equal to 1, the Erlang (k-1, k) distribution can be used.

Next, the first two moments of B_1 need to be determined. Where $B_1 = \left(D_{t_0,t_0+l_2-1} - (y_2 - y_1)\right)^+$. The first two moments of $B_1 + D_{t_0+l_2,t_0+l_2+l_1}$ with mean $EB_1 + (l_1 + 1)\mu$ and the standard deviation $\sqrt{Var(B_1) + (l_1 + 1)\sigma^2}$ needs to be determined next.

A distribution on $B_1 + D_{t_0+l_2,t_0+l_2+l_1}$ will be fitted and finally $P\{B_0 = 0\} = P\{B_1 + D_{t_0+l_2,t_0+l_2+l_1} \leq S_1\}$ can then be determined by means of bisection.

When $S_2 < S_1$, the shortcut can be taken by using the property that then B_0 reduces to $B_0 = \left(D_{t_0,t_0+l_2+l_1} - S_2\right)^+$.

The distribution function of the Erlangs (k-1, k) distribution is given by

$$E_{k-1,k}(x) = q\left(1 - \sum_{j=0}^{k-2} \frac{(\lambda x)^j}{j!} e^{-\lambda x}\right) + (1-q)\left(1 - \sum_{j=0}^{k-1} \frac{(\lambda x)^j}{j!} e^{-\lambda x}\right), \qquad x \geq 0$$

This heuristics under Erlang (k-1, k) distribution can then be implemented using the data that is also used for the calculations under the Normal distribution. This results in the following values.

Table 18 Comparison base stock levels under different demand distributions

Product A	S2 Erlang	S1 Erlang	S2 Normal	S1 Normal	% change S2	% change S1	% change total
Product A.1							
Delivery Mars	278.8	226.0	222.3	80.5	20%	64%	40%
Retailer orders	158.9	93.0	200.1	68.9	-26%	26%	-7%
POS	126.2	73.4	158.8	54.7	-26%	25%	-7%
Product A.2							
Delivery Mars	365.5	287.0	275.1	99.9	25%	65%	43%
Retailer orders	282.3	187.0	299.2	104.1	-6%	44%	14%
POS	195.9	114.0	247.1	85.0	-26%	25%	-7%
Product A.3							
Delivery Mars	28.3	26.4	21.2	9.8	25%	63%	43%
Retailer orders	24.9	20.9	22.3	10.0	11%	52%	29%
POS	23	16.9	20.7	9.3	10%	45%	25%

Table 18 shows the sensitivity analysis of the different distributions. It is visible that quite big changes are present at both stock levels separate. However, the change in total stock level is small when data is used with lower values of standard deviation. The percentage change becomes larger when larger standard deviations in demand are present. With the Erlang distribution it noticeable that the required base stock level for stock point 1 is higher than in the Normal distribution. It appears that when the standard deviation is larger (thus the coefficient of variance is above 0.5) the Normal distribution might be less accurate as the percentage change is higher compared to the Erlang distribution. Nevertheless, when variance is low, the two distributions results in similar base stock levels for the total amount of stock needed throughout the supply chain.

7.4. Summary

In this chapter the influence on lead-time is discussed. It is shown that the biggest reduction in base stock is obtained when lead-time reduction can be obtained from the Mars warehouse to the customer warehouse. Next, the assumption of the holding cost for Jumbo warehouse and the demand distribution for base stock computation are relaxed. It is shown that variation in the holding cost for Jumbo has little to no effect on the required base stock level. However, larger differences appear when comparing the assumption of Normal distribution with Erlang distribution. When the base stock levels are considered throughout the supply chain, it is noticed that the data with lower standard deviation exert less difference between the two distributions.

8. Extensions

The collaboration between Mars and Jumbo can be viewed beyond the Product A products, thus the products that are not within the pull project. Moreover, collaboration with Mars' other customers is also possible. The possible improvements can be calculated to see its impact. In chapter 8.1 the extension to other products is discussed. In chapter 8.2 the extension with other customers is explained.

8.1. Other products (in push situation)

Because the Product A products are enrolled into the pull project, it is interesting to see what the effects are when the base stock policy is applied to products in a push system. As mentioned before, the focus on freshness of the product is important within Mars. This is why a Product B product is chosen to be analysed.

After the initial analysis of the percentage of the national share per product that is accounted for Jumbo, the Product B appears to have the greatest share of 10.07 percent of the total sales in the Dutch market for this product. Thus this product will be analyzed as a test case.

For the base stock calculations, the same information as for the Product A products is obtained. The different data levels (POS, retailer's orders, delivery Mars and forecast Mars accounted for Jumbo) are gathered again except this time for the Product B. The graphical representation of the data can be found in Appendix XIII. Again we see that the effect of noise in the data is bigger when data is measured deeper within the supply chain up to the delivery data from Mars.

Next, the data will be cleaned by means Winsorization. The averages and standard deviation is then derived and used as input for the base stock calculations. The lead-times at Mars are given by the supply chain planner. Under the collaboration between Mars and Jumbo, the same parameters hold for Jumbo. The parameter that changes is the lead-time from the Mars factory to the Dutch warehouse.

The replenishment lead-time constitutes of the following variables:

$$T_{L,i} = MFI_i + P_i + T_f + MH_r$$

The Manufacturing Frequency Index is on average 1 week. The production time depends on the size of the batch production (with average of 500 cases in 6 hours) and the standard operating capacity of 83.3 cases per hour plus the set up time of 45 minutes. The transportation time to the Dutch warehouse is two days as this product is produced in the German factory in Viersen. However, the transportation time is within the 72 hours of micro hold and will thus be subtracted from the micro hold time, thus leaving the last variable the remaining micro hold time.

Table 19 Base stock level for Product B

Product B	S_{2a} (cases)	S_{1a} (cases)	Current S_{2a}	Current S_{1a}	Total base stock	Total current stock
Delivery Mars	319.6	113.9	279	179	433.5	458
Retailer Orders	439.0	149.5			588.5	
POS	373.0	127.1			500.1	

The current maximum stock cover for the Product B at the Mars warehouse is 279 cases (10.07 percent of the national stock of 2766 cases) and for Jumbo warehouse 179 cases as the current measured stock (Table 19). Reduction is noticeable at the Jumbo warehouse. Surprisingly the needed base stock level for the Mars warehouse is larger than it currents stock levels.

The inconsistency with previous results is partly due to the input parameters given in Table 20.

Table 20 Input parameters Product B

Product B	μ	σ	β	L_2 (weeks)	L_1 (weeks)	h_2 (€/case)	h_1 (€/case)	Cases/ pallet	b (€/case)
Product B									
Delivery Mars	64.25	47.54	0.98	1.4509	0.2000	0.01375	0.00183	77	0.764
Retailers orders	100.18	21.35	0.98	1.4509	0.2000	0.01375	0.00183	77	0.764
POS	85.11	18.25	0.98	1.4509	0.2000	0.01375	0.00183	77	0.764

As can be seen in Table 20 the average demand is quite different for the data in the different levels. However, the pattern for the standard deviation is still the same as the standard deviation becomes smaller moving to the POS data. A look into the case fill might explain the differences in average demand. Unfortunately, case fill information from the retailer orders is only available for 3 periods (of 4 weeks per period). During these periods the case fill has predominantly been 100%. However, there was one occurrence of a case fill of 80.95%.

From Table 19, the use of delivery data from Mars results in the lowest needed base stock level. However, as the use of delivery data does not reflect the actual demand, one can suppose that out of stock may have occurred seeing that the retailers and end consumers have ordered a sufficiently larger amount.

8.2. Other customers

Considering the extension of data sharing onto other customers, the multi echelon serial system transforms into a distribution system. When more customers can be taken into consideration, one can benefit from risk pooling.

Consider that each retailer has uncorrelated normally distributed demand with mean μ_i and standard deviation σ_i . The replenishment lead times for all these retailers are the same and all the retailers guarantee the same service level. Eppen (1979) compared two operational modes of the J-retailer system: decentralized mode and centralized mode. The completely decentralized system is a system in which a separate inventory is kept to satisfy the demand at each source of demand. The completely centralized system is a system in which all demands are satisfied from one central warehouse.

In the decentralized mode, each retailer orders independently to minimize its cost. The total demand during lead-time to the manufacturer can then be viewed as $L * \sum_{i=1}^{J} D_i$ and the standard deviation as $\sqrt{L} * \sum_{i=1}^{J} \sigma_i$.

In the centralized mode, all the retailers are considered as a whole so as to minimize the total expected cost of the entire system. Since in the centralized mode all the retailers are grouped, and the demand at each retailer follows a normal distribution $N \sim (\mu_i, \sigma_i^2)$, the total demand during lead time to the manufacturer will be $L * \sum_{i=1}^{J} D_i$ as well. However, the standard deviation is then considered to be $\sqrt{L} * \sqrt{\sum_{i=1}^{J} \sigma_i^2}$.

This indicates the pooling of risks. For example if 100 retailers are considered, each retailer has uncorrelated normal distributed demand with identical mean μ and standard deviation σ. The standard deviation in the decentralized situation would be $\sqrt{L} * 100\sigma$ and in the centralized situation it would be $\sqrt{L} * 10\sigma$.

To consider this advantage in terms of a distribution system one can approach the system with the decomposition and aggregation heuristic. First the system can be decomposed into J serial systems (Figure 15).

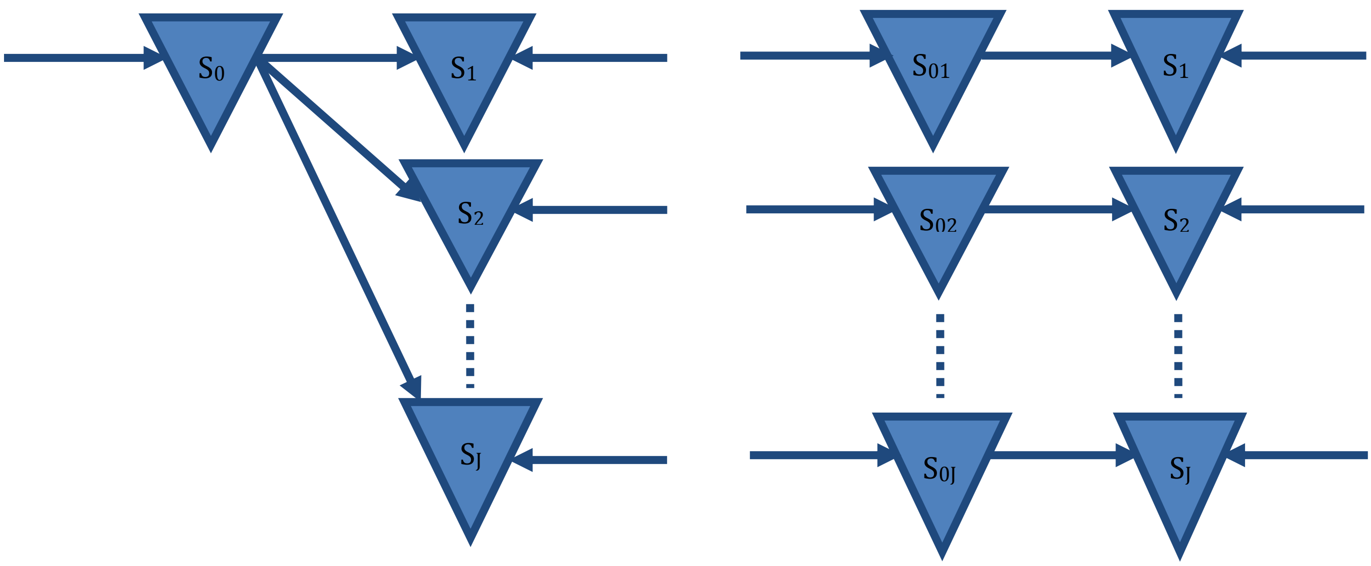


Figure 15 Decomposition of the distribution system into serial systems

Then the optimal base stock levels can be solved according to the serial systems heuristic. After the serial system optimization, the values of the retailers' base stock levels need to be fixed.

With the values of base stock levels for the retailers fixed, one can search for the optimal base stock level for the manufacturer using aggregation benefiting the advantage of risk pooling. The aggregation can then be considered as a serial system with the sum of the retailers' demand as the downstream echelon.

Due to the absence of POS data from other customers, the quantitative analysis cannot be made for this part of the extension at the moment. However, the effects could be significant and the current research can be used by means to persuade other retailers to share their data.

8.3. Summary

After the analysis on the Product B it appears that for this particular product, the delivery data from Mars results in the lowest needed base stock levels with a total base stock level of 433.5 cases compared to 458 from the current total needed stock. However, the data of delivery from Mars shows substantial smaller averages than the retailer order and POS data, suggesting out of stock may have occurred. The reduction in variability in demand while moving to the use of POS data is still present. With the addition of other customers the needed base stock could be lowered as variability could be pooled. To check whether the assumptions made during the calculations are justified, sensitivity analysis needs to be conducted. This will be explained in the next chapter.

9. Conclusion and recommendations

In this chapter a conclusion and recommendations for Mars Nederland B.V. will be given. Not all subjects are covered and these will be discussed in the recommendations for future research. The conclusion will be given in chapter 9.1. Next the recommendation for Mars is given in chapter 9.2 and finally the recommendation for future research in chapter 9.3.

9.1. Conclusion

The aim of this research was to look into the possibilities of supply chain cooperation between Mars and its customers extending the pull project currently implemented for line X at Mars. As former pull practices are implemented for the automotive and process industry, research should be conducted for the Fast Moving Consumer Goods industry with regards to pull principle of replenishment. The project definition is set as follows:

> *'Design a collaboration model for Fast Moving Consumer Goods companies to control information sharing onto the involvement of customers in order to optimize stock levels and replenishment time.'*

Part of this collaboration model turned out to have the form of a serial multi echelon base stock control model that is in line with the pull principle. As replenishment only takes place when demand has occurred, the number of work in process is secured to a fixed maximum. Additionally a fixed value of order up to level secures the stock cover during replenishment time in order to service the customers at the next step of the supply chain but more importantly, the end consumers. A central and independent entity or system is suggested to collect and analyse the data from different links of the supply chain. The information should then be transferred to every link in the supply chain and replenishment should then be based on the pull principle. The project had several research questions.

'What kind of information exchange model is needed in order to design the framework of the new collaboration?'
The condition to obtain the collaboration is a central EDI system is required in order to transfer demand data in a timely fashion such that replenishments can be reactive to the given input. This implies that the links in the supply chain should be able to have trust in each other in order to share information and replenish only what is necessary.

'Which aggregation level of shared demand data is needed to have more accuracy to control the supply chain?'
From the results of the base stock control heuristics it is visible that the closer to the end consumer the demand data is measured, the less variation the data exerts. Thus using POS data leads to the lowest level of stock needed as opposed to using the delivery data from Mars.

'What will be the total replenishment lead-time in the new collaboration, specifically from the Mars factory to the Dutch warehouse and from the Mars warehouse to the Jumbo warehouse?'
The replenishment time will not be affected by the replenishment system of the base stock policy. However, effects of changes in lead-time for both the Mars factory to the Mars warehouse and Mars warehouse to Jumbo warehouse is considered. More reductions can be obtained when initiatives are taken in order to shorten the lead-time from the Mars warehouse to the customer's (Jumbo) warehouse.

'What are the possibilities to focus on other chocolates?'
The quantitative analysis of multi echelon base stock can be made for every other product at Mars. However, because of the current pull project initiated for the Product A products on line X, this line is already able to respond to demand in a Kanban replenishment manner. Other lines are not yet able to be this reactive and therefore require larger replenishment times and thus will not reflect the benefits of the pull replenishment. Nevertheless, POS data can still be shared to eliminate the Bullwhip effect throughout the chain.

'How can the collaboration with Jumbo be generalized in order to be applicable for other collaborations?'
As the obtained improvements in stock reduction is only considered for one retailer the effects for the production planning is small. Once more retailers are involved, the data will cover a larger part of the Dutch market. In this way bigger effects can be obtained that might affect the production more. In order to generalize the applicability of the collaboration with Jumbo, more retailers have to be involved. This transforms the current serial multi echelon system into a distribution multi echelon system by means of the decomposition aggregation heuristics.

9.2.Recommendations for Mars Nederland B.V.

Central data sharing system
The influence of using POS data is described in this research. In order to implement this data for real time reactiveness from the links within the supply chain, a central data sharing system is required where a central planner knows information for entire system. Thus, the view is not on each company separately. Instead, the supply chain is seen as a one single organization.

POS data of products with best before date implemented
As freshness is an important factory within the company one should be able to research the freshness of the products the moment they are sold to the end customer (as the item is being scanned). This will provide a measurable factor on freshness and freshness improvements.

Lead time reduction by reducing micro hold time
When considering the lead-time from the Mars factory to the Mars warehouse it is noticeable that the micro hold time of three days is often experienced as a bottleneck. Reductions in production are minimal when compared to the fixed micro hold. Further research should be conducted on microbiological testing in order to improve this fixed waiting time.

Reconsider full pallet full truck agreement
From the collaboration between Mars and Jumbo the agreement is made to deliver within 24 hours when full pallets and full trucks are ordered. Although this agreement frees handling this should be reconsidered. When the restriction to order in full pallets and trucks is set, it distorts the ordering behaviour and the demand information. This reasoning is also against the principle of pull or base stock replenishment and will result in higher stock levels. Thus therefore the trade off should be made to consider less handling cost and shorter lead-time against information distortion and higher stock levels.

Case packs sizes in order to reduce the stock cover at the supermarket
The stock cover from the Mars warehouse to the end consumer is large due to the case sizes of the different products. The Dutch market is small relative to other countries. This is noticed considering the amount of a product that is sold at a random supermarket. For the Product A products, an average of 4 to 5 consumer units is sold per week per supermarket for a certain product. Thus a case of 22 consumer units of a product is kept at a supermarket implies that this would be on shelf (or at least within the supermarket) for 4 to 6 weeks. Reconsidering the size of these case packs could already improve the freshness of the product at the moment of sale.

9.3. Future research

Extending this research for more Mars customers
Due to the absence of POS data from other customers, the quantitative analysis cannot be made for the extension at the moment. However, the effects could be significant and the current research can be used by means to persuade other retailers to share their data. The effect would be larger when bigger part of the sales (and thus uncertainty) is accounted for.

Substitution and cannibalism
Research into substitution behaviour (in case of out of stocks) of the chocolate products is also needed as this directly influences the nature of the POS data. Moreover, when comparable other products are in promotion, it might cannibalize the sales of Mars' products. This should also be researched.

Demand data instead of delivery data Mars

This research is conducted using three types of data; POS, retailer orders, and the delivery data from Mars. The first two types of data are the direct demand from the next link in the supply chain. However, Mars is currently using its delivery data in order to forecast and replenish. This data does not completely reflect the actual demand as out of stock also occurs. Therefore it is interesting to research the nature of the out of stocks and document the order data as well as the delivery data.

Effects and forecasting of promotions, listings, and delistings using POS

In the current pull project the volatility translator is used to take into account the peaks in demand in order to start stock building. The volatility translator uses current forecasting from Mars to generate the peaks. However, when POS is available one can research the direct effects of these promotions and use this information to have a more accurate stock building level.

Supply chain profit and risk sharing

When close collaboration takes place between the supplier and the retailer, risk can be pooled in order to obtain the most efficient supply chain. Subsequently, it is interesting to find out how this risk can be allocated to the different links in the supply chain. Through a game theory perspective, one can research how the amounts of risk can be determined and allocated with regards to its benefits.

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Websites:

http://www.mars.com Last visited 16-07-2012

Appendix I List of Mars brands

The list of Mars brands per business segment:

Chocolate	Petcare	Wrigley
M&M's	Pedigree	5Gum
Snickers	Royal Canin	Extra
Dove	Whiskas	Orbit
Mars	Banfield	Doublemint
Twix	Cesar	Skittles
3 Musketeers	Nutro	Eclipse
Bounty	Greenies	Airwaves
Maltesers	The Goodlife Recipe	Starburst
Celebrations	Temptations	Lifesavers
Balisto	Sheba	Freedent
Combos	Crave	Juicy Fruit
Revels	Kitekat	Excel
Kudos	Frolic	Hubba Bubba
Tracker	Chappi	Witer Fresh
Goodness Knows	Winergy	Altoids
Pure Dark	Trill	Sugus
Milky Way	Waltham	Boomer
Galaxy	Aquarian	Pim Pom
My M&M's	Catsan	P.K. chewing gum
Marathon		Solano
American Heritage Chocolate		Big Red
Amicelli		Kenman
		Lockets
		Lucas Tunes
		Spearmint
		Rondo

Food	Drinks	Symbioscience
Uncle Ben's	Alterra	Cocoa Via
Dolmio	Bright Tea co.	Wisdom Panel
Masterfoods	Klix	Seramis
Suzi Wan	Flavia	
Royco	Dove hot chocolate	
Ebly		
Seeds of Change		
Raris		
Kan Tong		

Chocolate ice cream products are produced under a few of the chocolate brands.

Appendix II Production lines Mars Veghel

Due to confidentiality, this appendix is removed.

Appendix III Pull control systems

Within this section an overview is given for the different kinds of pull control mechanisms. A pull control mechanism in a multi-stage system is a mechanism that coordinates the release of parts into each stage of the system with the arrival of customer demands for final products. In part i the base stock system is explained. Then, in part ii the Kanban system is explained. Part iii illustrates the Generalized Kanban system and iv the Extended Kanban system. Next, the hybrid Kanban system is explained in part v.

i. Base Stock system

The purpose of the Base Stock policy is to satisfy demands to its maximum level. When a demand arrives in the system, an entity is simultaneously transferred to each stage of the manufacturing process (Duri, Frein, & Mascolo, 2000). The philosophy of the Base Stock system is the following. When a customer demand arrives to the system, it is immediately transmitted to every stage in the system, authorizing it to immediately start working on a new part, which it pulls from the output buffer of its upstream stage.

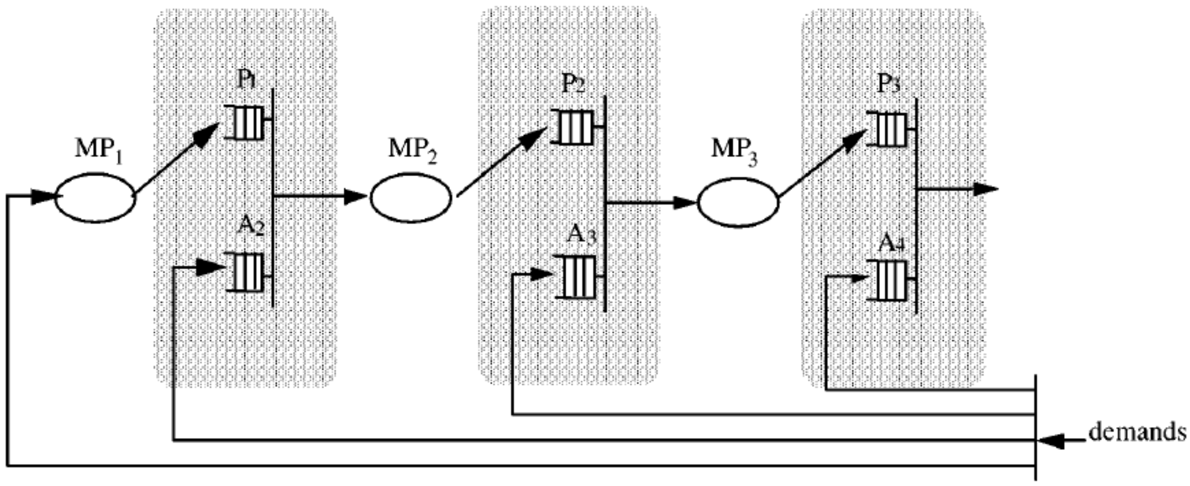


Figure 16 Base Stock system

As seen on Figure 16 the manufacturing process is represented by MPi and the link between stages is modelled by a synchronization station at the output of each stage. The synchronization station is made up of two queues, one containing the finished parts of the stage (P_i) and the other containing demands for the products from the next stage (A_{i+1}).

Echelon Base Stock

The echelon stock of a certain echelon j (in a general multi-echelon system) is the number of units in the system that are at, or have passed through, echelon j but have not yet been specifically committed to outside customer (Clark & Scarf, 1960).

Within an echelon Base Stock the decisions for any particular stocking point are based on its stock position and its direct demand process. Considering a general (s, S) system; the order-up-to level S, also called the Base Stock level, is determined by:

$$S = s + Q$$

Where:

S = Base Stock level

s = Safety stock

Q = Order quantity

In terms of physical operation, the echelon inventory position at each level is monitored according to the following relation:

$$Echelon\ inventory\ position = (echelon\ stock) + \ (on\ order)$$

The 'on order' term refers to an order placed by an echelon on the next higher echelon.

The echelon inventory position is reviewed after each transaction or on a periodic basis. Whenever the inventory falls below the reorder point s, enough is ordered from the preceding echelon to raise the position to the Base Stock level S (Silver, Pyke, & Peterson, 1998).

ii. Kanban system

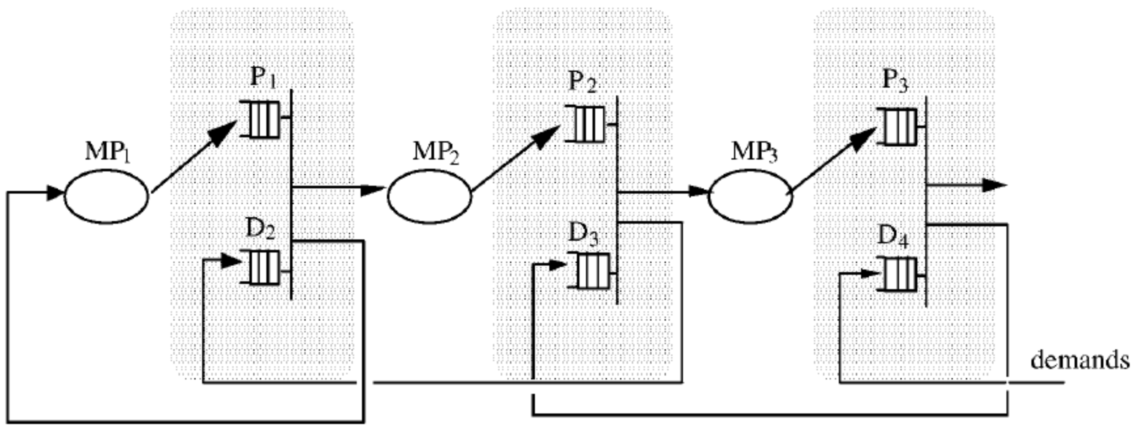


Figure 17 **Kanban system**

The most popular control system is the Kanban control system (Figure 17) Kanban means card in Japanese and refers to the mechanism whereby a production authorization card is attached onto a part authorizing its release into a stage. The philosophy of Kanban is that a customer demand is transmitted upstream of the system from stage i only when a finished part is released downstream of stage i. The Kanban control system provides tighter coordination between stages than the Base Stock system (Liberopoulos & Dallery, 2000).

CONWIP control system

The CONWIP is a pull control mechanism that holds the following principle. As soon as a finished product leaves the system, a new part enters the system to begin its processing. It is noticeable that a CONWIP control system is equivalent to a single-stage Kanban control system that uses Kanban control to release parts into and out of that system.

iii. Generalized Kanban system

The generalized Kanban control system was proposed as a general approach to pull production control incorporating the Kanban and the Base Stock systems. The difference between the Kanban control system (KCS) and the generalized Kanban control system (GKCS) is in the way information is transferred: in a GKCS the transfer of a finished part from a given stage to the next one and the transfer of demands to the input of this stage may be done independently of one another, whereas in a KCS they are done simultaneously (Duri, Frein, & Mascolo, 2000).

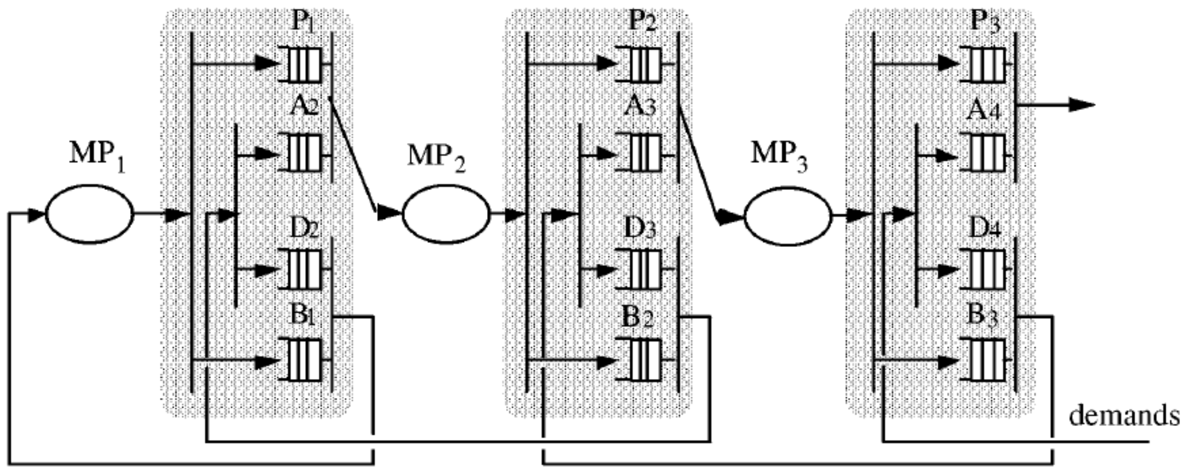


Figure 18 **Generalized Kanban system**

The GKCS (Figure 18) can be viewed as an extension of the KCS by noting that queue Pi in the KCS is split into two queues, namely Pi and Bi, in the GKCS, and queue Di+1 in the KCS is split into two queues, namely Di+1 and Ai+1, in the GKCS. Entities in queue Pi represent the inventory of finished parts of stage i. Entities in queue Ai+1 are stage (i+1) Kanbans and represent authorizations to transfer stage i finished parts to stage i+1. Entities in queue Di+1 represent demands from stage i+1 for production of new parts by stage i. Entities in queue Bi are stage i Kanbans and represent authorizations to transfer stage (i+1) demands to stage i (Frein, Di Mascolo, & Dallery, 1995).

iv. Extended Kanban system

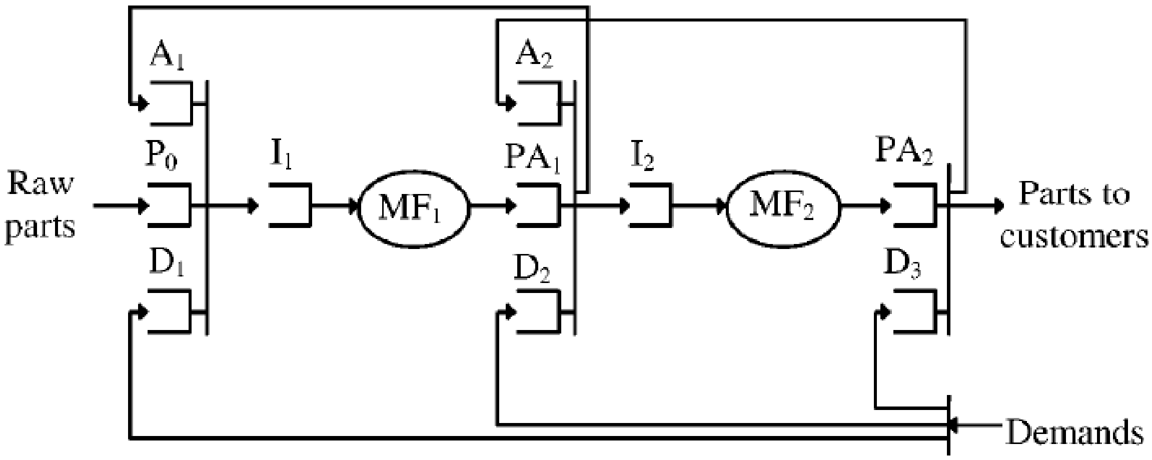


Figure 19 Extended Kanban system

The Extended Kanban control system (Figure 19) was proposed as a general approach to pull production control combining the Base Stock and Kanban control systems. Like the Generalized Kanban system, the Extended Kanban control system depends on two parameters per stage; the number of Kanbans and the base stock of parts in inventory.

When a customer demand arrives to the system, it is immediately broadcast to every stage in the system, as is the case in the Base Stock system. However, unlike the Base Stock system, a part is actually authorized to be released from one stage to the downstream stage only if one of a finite number of production authorizations of Kanbans associated with that stage is available, as is the case in the Kanban system.

v. Hybrid Kanban system

The hybrid Kanban system is not a true pull strategy. It relies on forecasting for high-volume, stable products, and build low-volume products to order (Holweg & Pil, 2001). Thus this combines the with the pull strategy. The hybrid control strategy can be classified into two categories: vertically integrated hybrid systems or horizontally integrated hybrid systems. Vertically integrated hybrid systems consist of two levels, usually an upper level push-type production ordering system and a lower level pull-type production ordering system. Horizontally integrated hybrid systems consist of one level where some production stages are controlled by push-type control and other stages by a pull-type control (Geraghty & Heavey, 2004).

Appendix IV List of resources

During the execution of this project many people within both Mars and Jumbo have contributed to this report with their knowledge and information. During the initiation phase of the project, the following interviews were taken in order to form a research proposal.

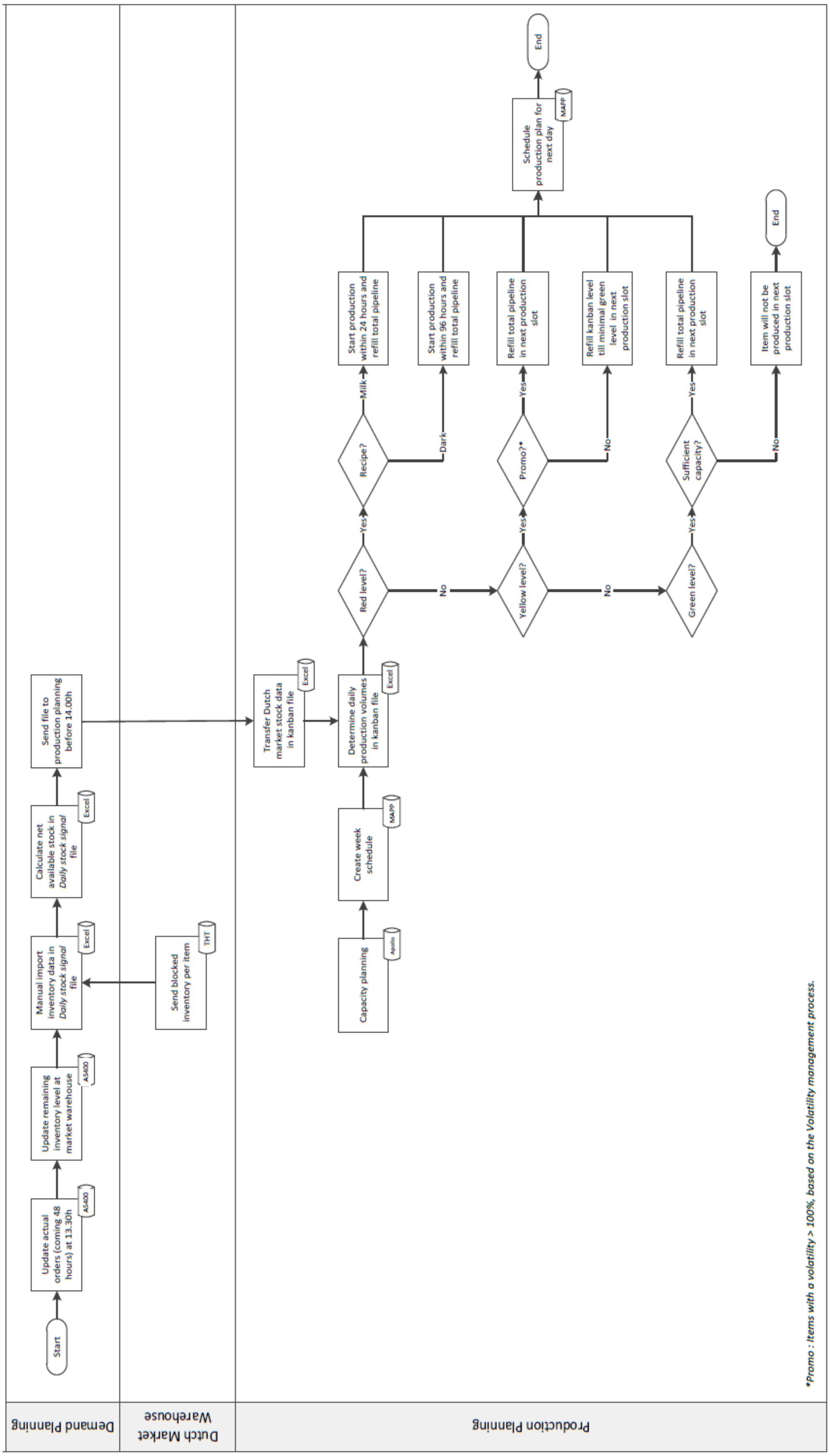
Date	Person	Function
09-02-2012	Daniel Morgan	Senior Demand & Availability Planner Confectionary
09-02-2012	Houkje Zwinkels-Janssen	Lean Implementation Manager
10-02-2012	Frans van den Boomen	Value Chain Manager
15-02-2012	Dirk van den Hoogen	Production Planner
	Mieke Derkx	Supply Chain Planning Supervisor
17-02-2012	David van Hommel	Scheduler
	Luc Janssen	Central Industrial Engineer
21-02-2012	Suzanne Pegge	Manager Outbound Logistics
	Marleen van Vilsteren	Customer Logistic Coordinator

After the introductory interviews, more in-depth meetings have taken place during the project with the following list of people.

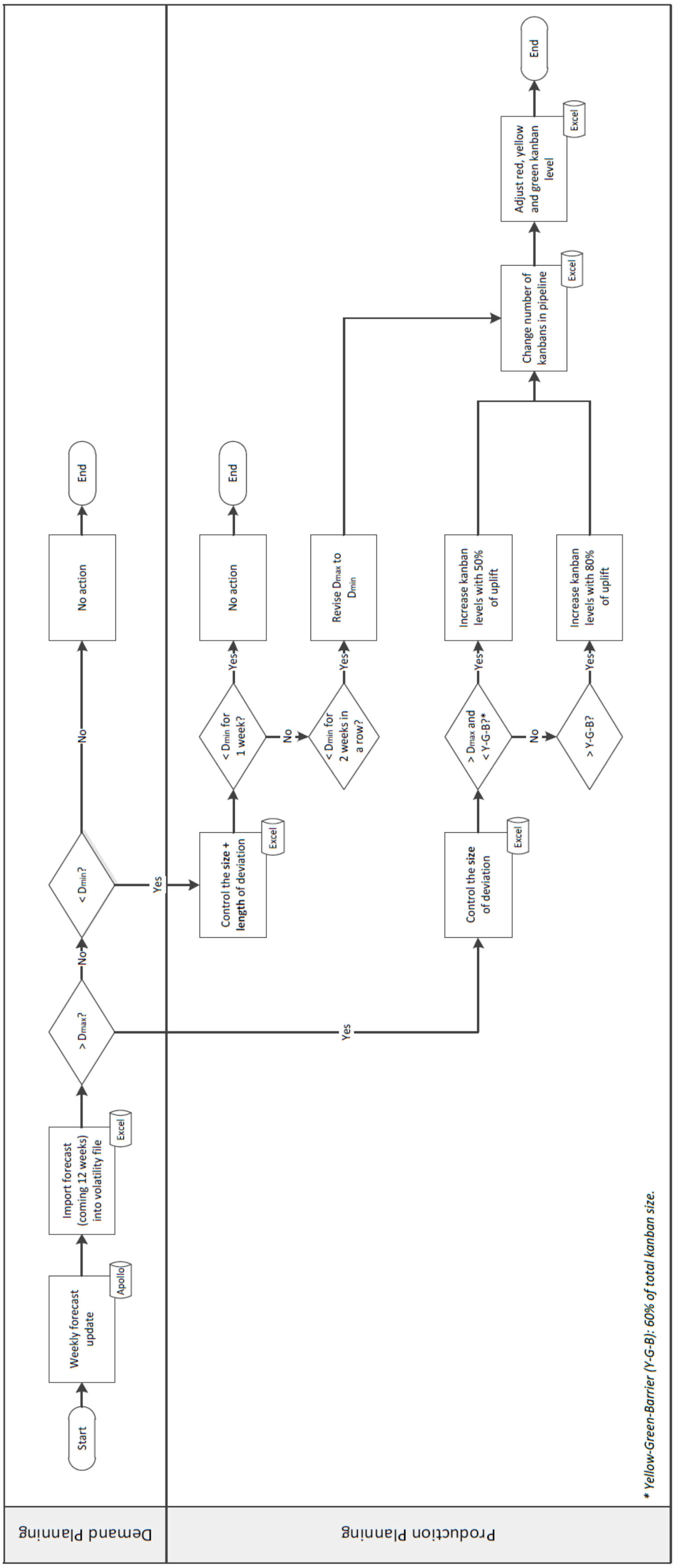
Person	Function
Daniel Morgan	Senior Demand & Availability Planner Confectionary
Houkje Zwinkels-Janssen	Lean Implementation Manager
Frans van den Boomen	Value Chain Manager
Marleen van Vilsteren	Customer Logistic Coordinator
Natasha Vriens	Demand & Inbound Logistics Manager
Chris van Bavel	Replenisher CM Jumbo
Martijn Lekkerkerker	Supply Chain Operator DKW Jumbo (Project team Mars Jumbo)
Lieke van Amelsfort	Senior Demand & Availability Planner Petcare (Project team Mars Jumbo)
André Vriens	Consultant Eye On (Project team Mars Jumbo)
Niek van de Crommert	Consultant Eye On (Project team Mars Jumbo)

Next to the meetings documentation in the form of Excel files and PowerPoint presentations about the pull project were made available. Moreover, from the supply chain collaboration with Jumbo, the data of Jumbo was made available through a file sharing site. Furthermore, a web seminar is followed at Mars academy about the usefulness of POS data.

Appendix V Daily pull planning process

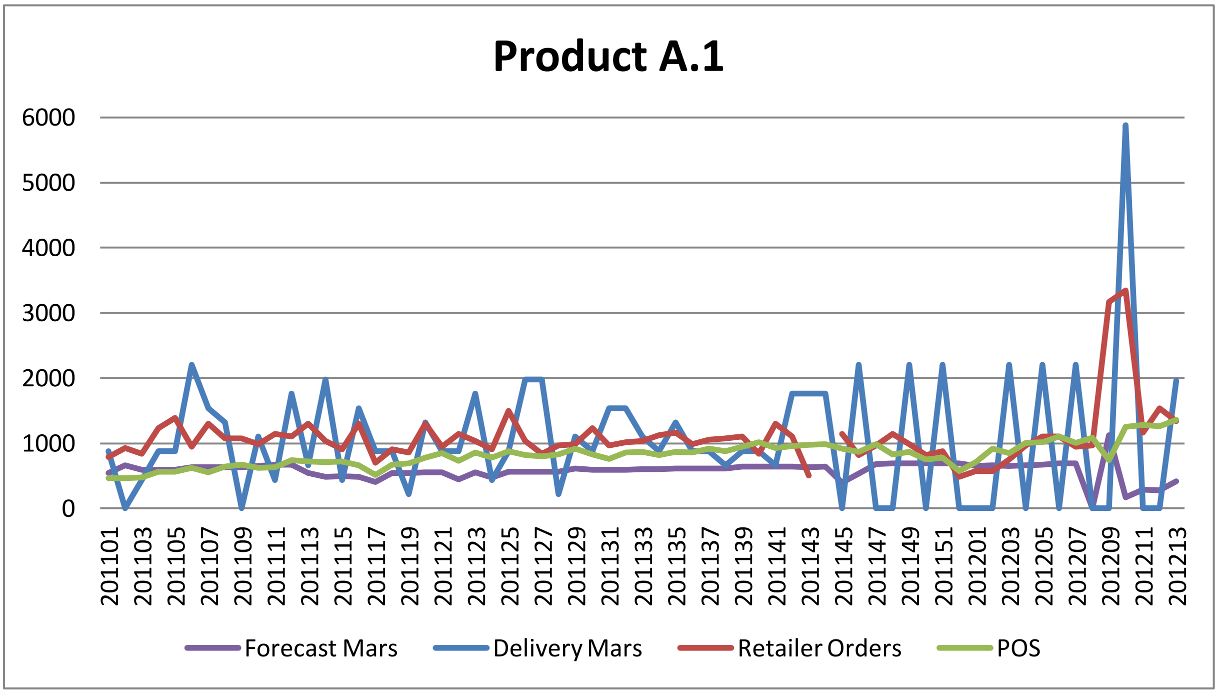


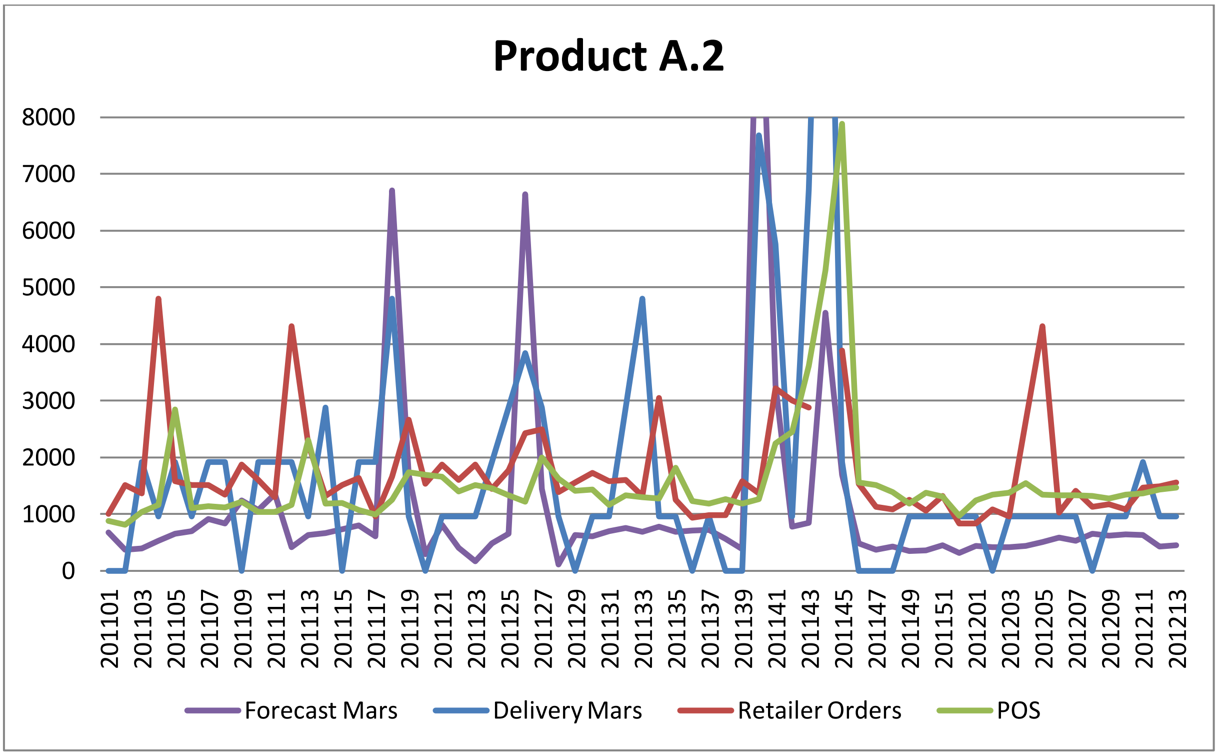
Appendix VI Weekly volatility management process

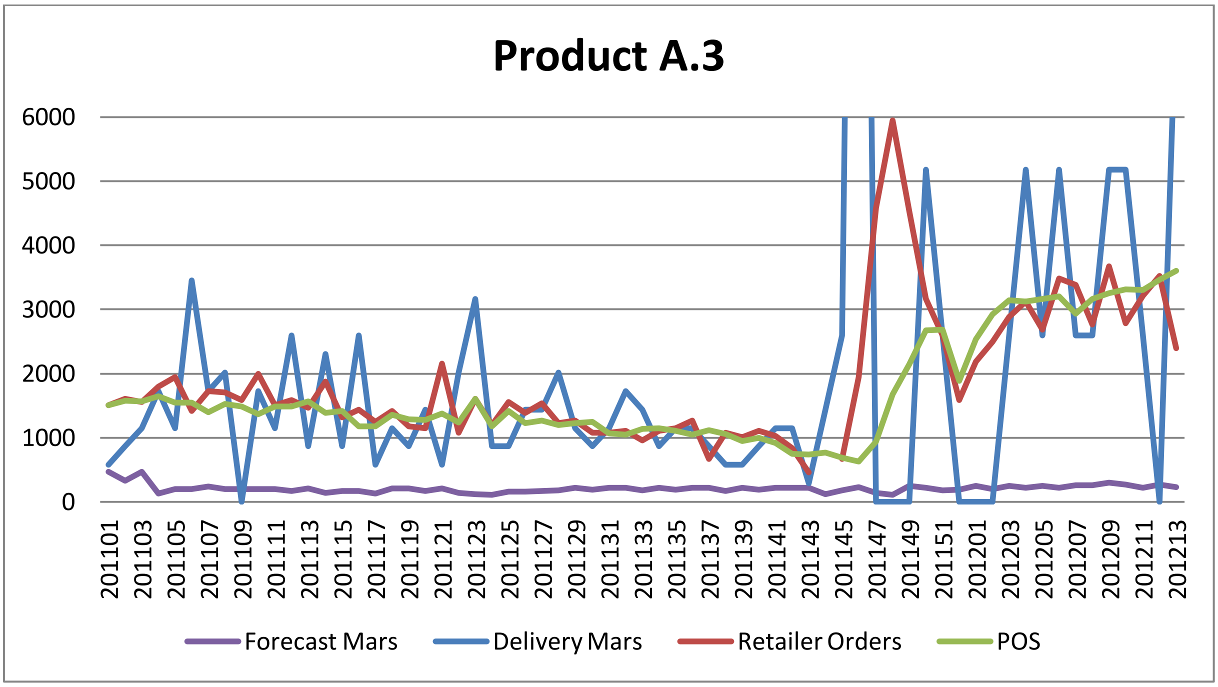


Appendix VII Demand Product A products at Jumbo

Vertical axis in consumer units.

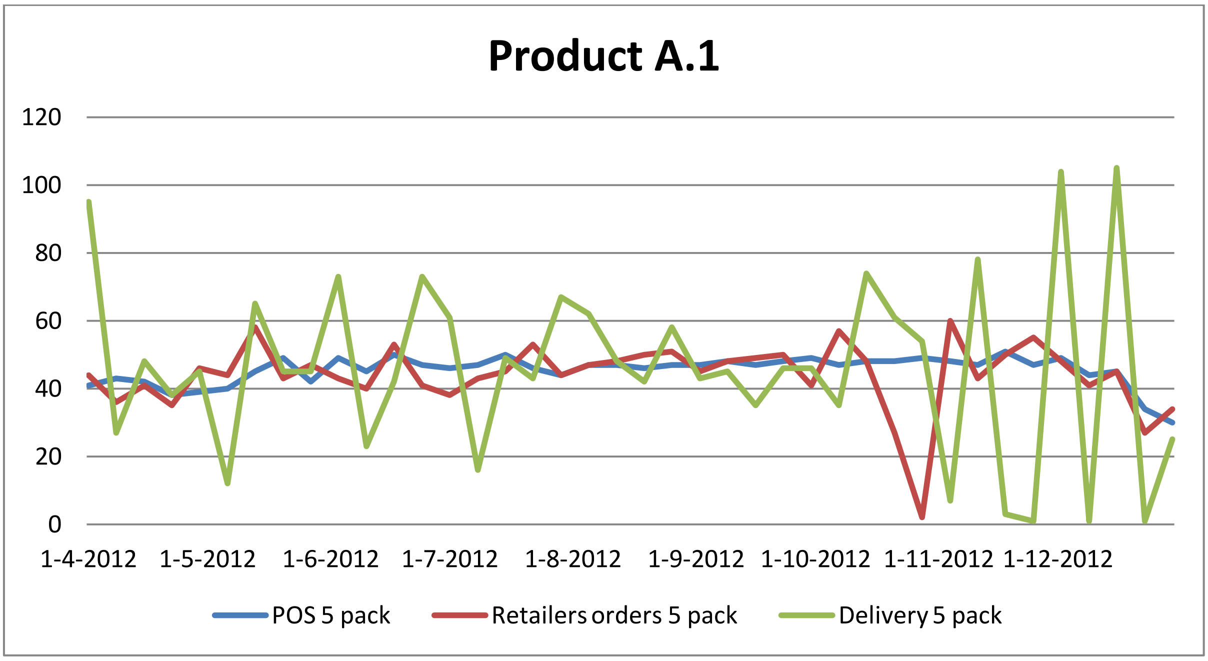


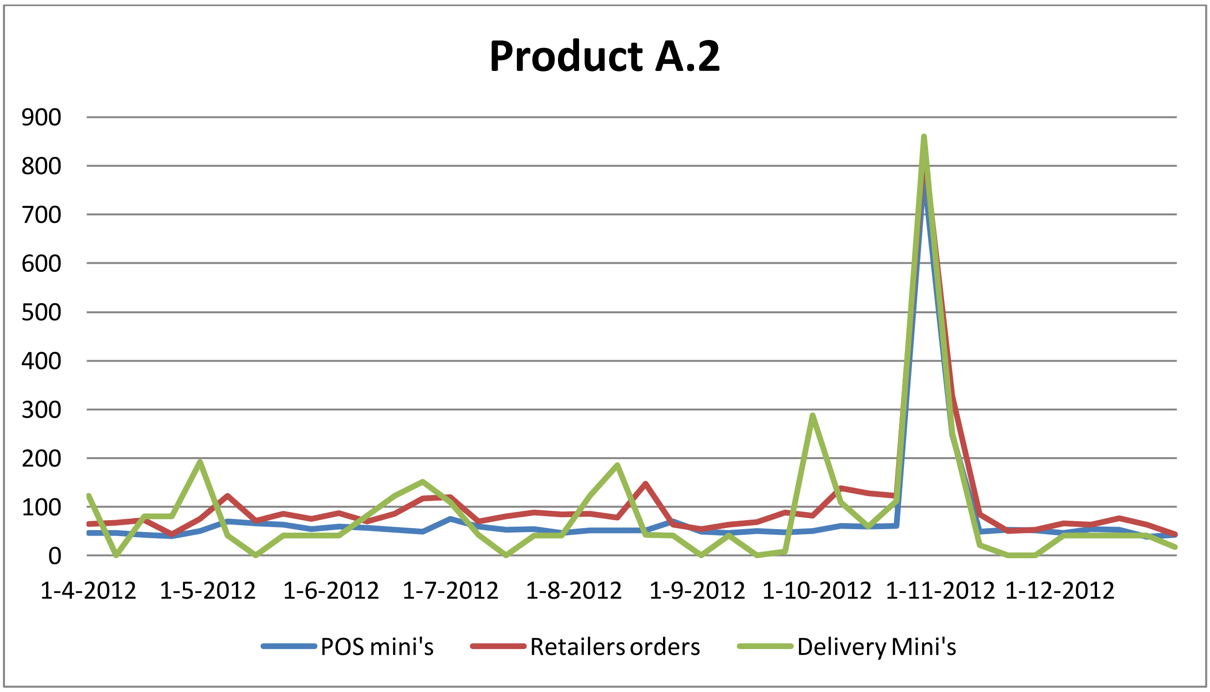



Product A.3
6000
5000
4000
3000
2000
1000
0
201101
201103
201105
201107
201109
201111
201113
201115
201117
201119
201121
201123
201125
201127
201129
201131
201133
201135
201137
201139
201141
201143
201145
201147
201149
201151
201201
201203
201205
201207
201209
201211
201213
Forecast Mars
Delivery Mars
Retailer Orders
POS

Appendix VIII Forecasting Apollo using retailer orders & POS data

Vertical axis in consumer units.





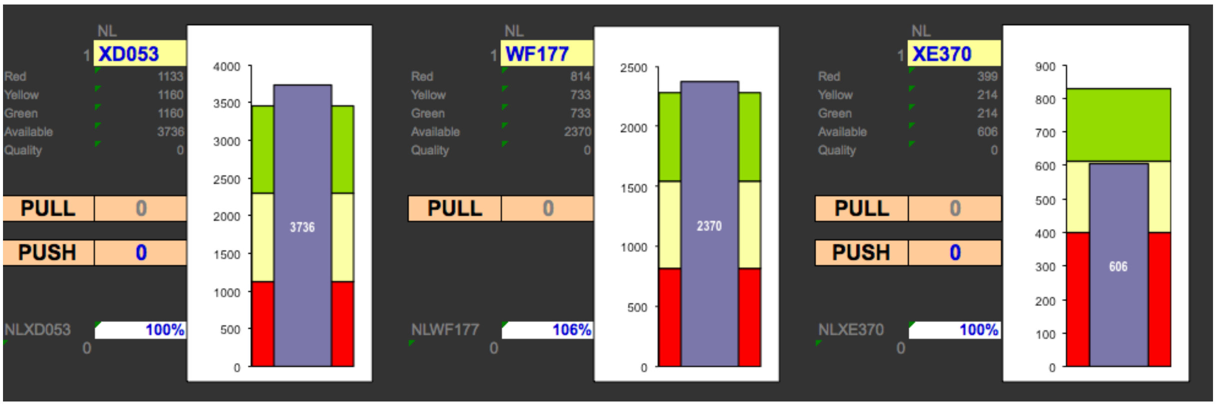

Product A.3
50
45
40
35
30
25
20
15
10
5
0
1-4-2012
1-5-2012
1-6-2012
1-7-2012
1-8-2012
1-9-2012
1-10-2012
1-11-2012
1-12-2012
POS single
Retailers orders single
Delivery single

Appendix IX Kanban calculations & electronic representation

Kanban file

Quantity Unit	Ware-house	% Jumbo of national	Dmax: Total (Cases/wk)	Replenishment Time: Tr — MFI (Hours)	prod	SOC (Cases)	Prod. Time (Hours)	Emergency Start Time (Hours)	Tr: Factory to DD-whs (Hours)	Micro Hold (Hours)	Remaining Micro Hold (Hours)	Emergency (Hours)	weeks	Total loop (Hours)	weeks
[redacted]			A	B		C	a=A/C	D	F	G	b=G-(E+F)	c=D+a+E		f=d+e	
	NL-1	11,585%	529	168	1	110	4,8	24,0	13,0	72	59	101	0,600	244,81	1,4572
	NL-1	7,432%	1593	168	1	101	15,8	24,0	13,0	72	59	112	0,665	255,79	1,5226
	NL-1	1,621%	707	84	0,5	131	5,4	24,0	13,0	72	59	101	0,603	161,39	0,9606

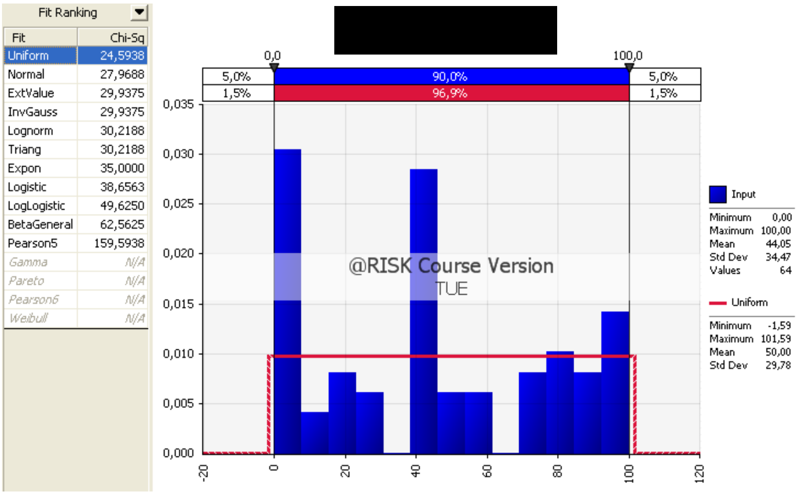
Quantity Unit	Kanbans (cases) without Sf (cases)	Safety Factor: Safety Factor	Compensation factor	Total Safety factor	Kanban Calculation: Kanban Unit (Cases/Palle)	Kanbans	Kanbans in cases	Warehouse Supermarket for Direct delivery: Hub Super Market Stock — Total	Red	Yellow	Green	Warehouse Supermarket
[redacted]	A*f	H	J	g=1+H+J	L	h = (A*(f / 24 / 7)*g)	L x h					
	771	30%	0%	130%	100	10,02	1002	1002,11	317,43	342,34	342,34	
	2425	20%	0%	120%	40	72,76	2911	2910,55	1060,03	925,26	925,26	
	679	30%	0%	130%	45	19,62	883	882,92	426,67	228,13	228,13	



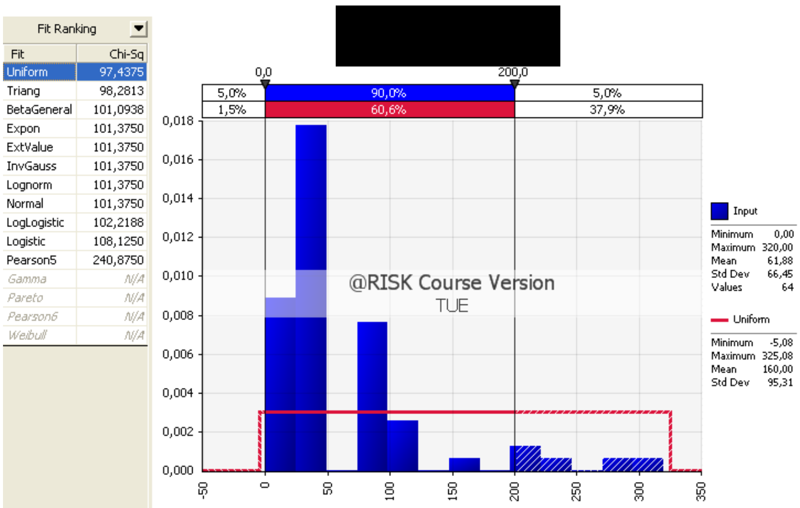
When demand falls in the yellow region, the required amount to reach the green region needs to be produced by the next production run. When demand falls in the red region, thus exceeding the yellow green barrier, the required amount needs to be replenished within the next 24 hours. The required amount is the amount needed to have the stock level on the highest level of the green region. However, it must not surpass the green area (unless a batch of products needs to be finished). These data will be sent to the production department on a daily basis. It should be noted that most changeover to other products of Line X is for different packaging. When set up in different recipe (from milk chocolate to dark chocolate or vice versa) is required, the 24 hour replenishment cannot be met due to longer set up time.

Appendix X Demand distribution fitting using @Risk

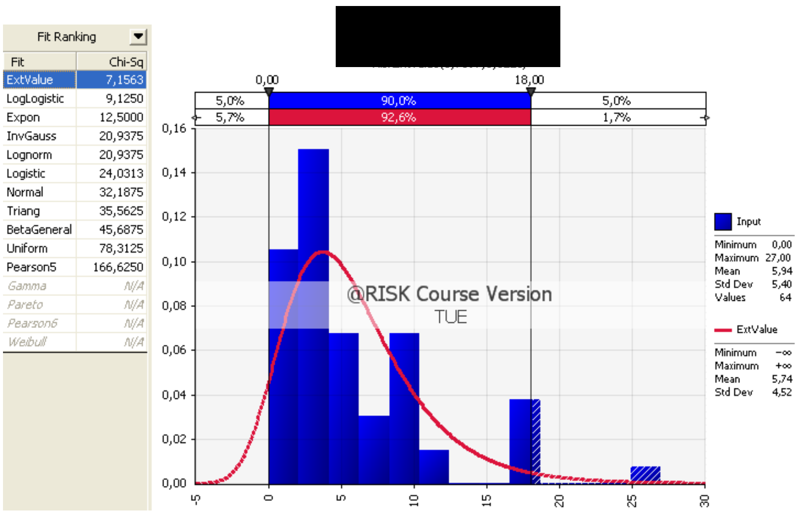
Delivery data Product A.1



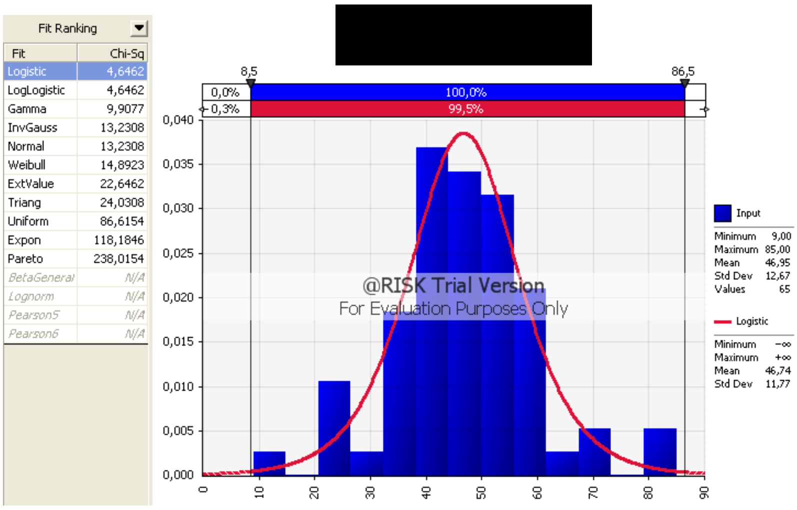
Delivery data Product A.2



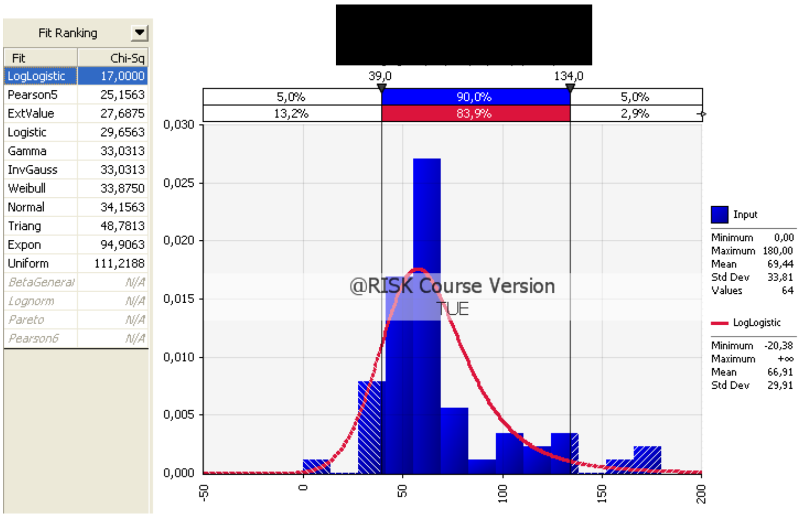
Delivery data Product A.3



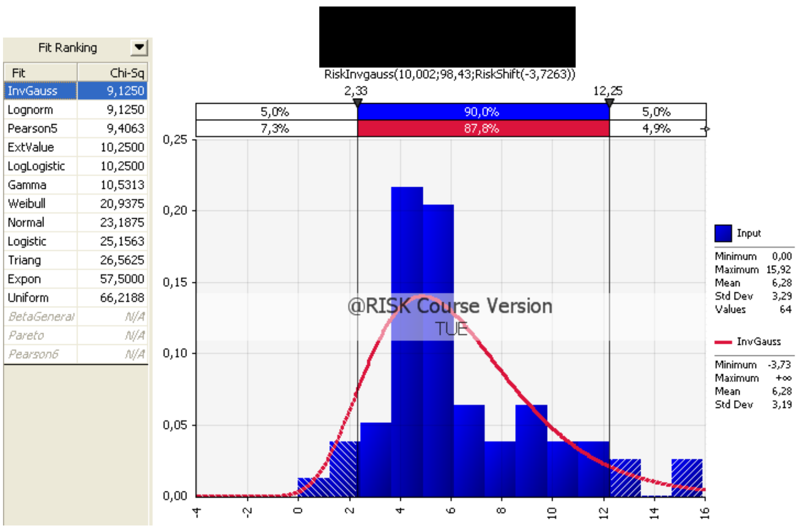
Retailer orders data Product A.1



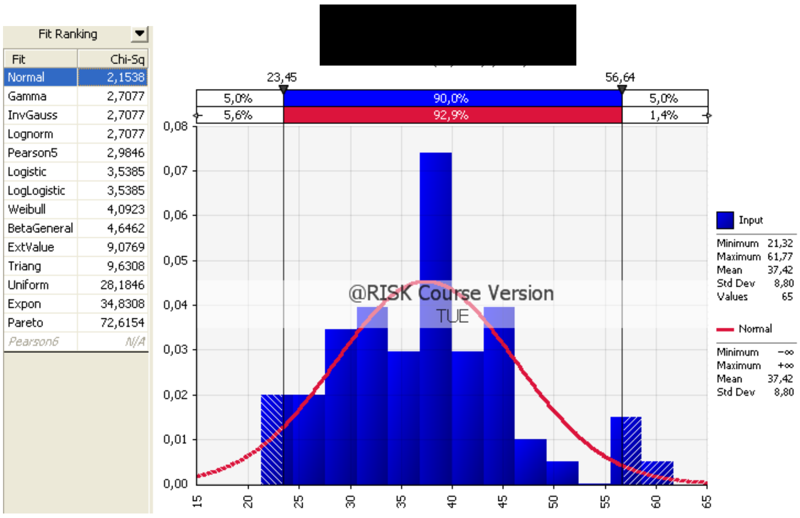
Retailer orders data Product A.2



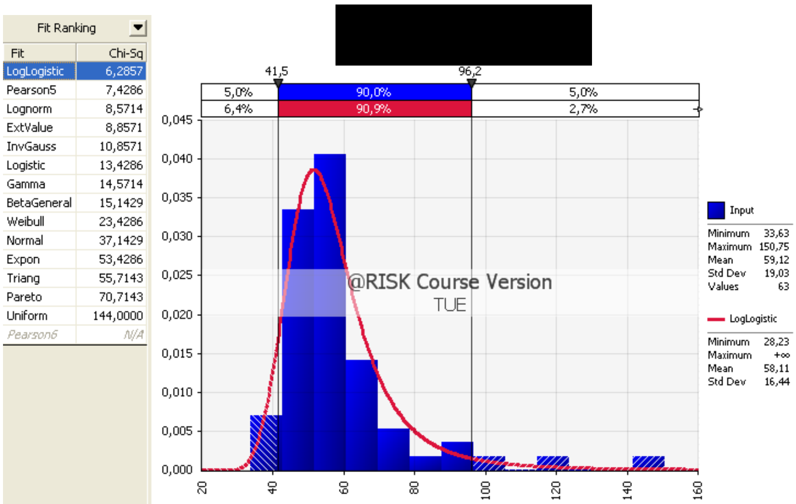
Retailer orders data Product A.3



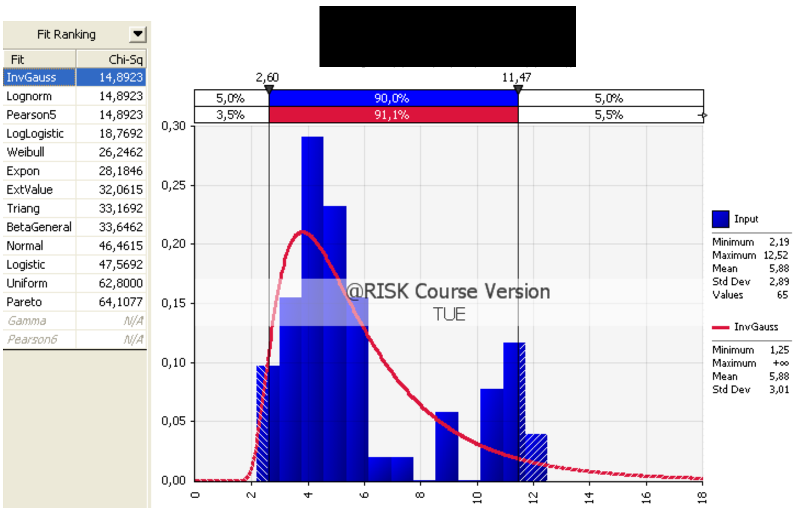
POS data product A.1



POS data Product A.2

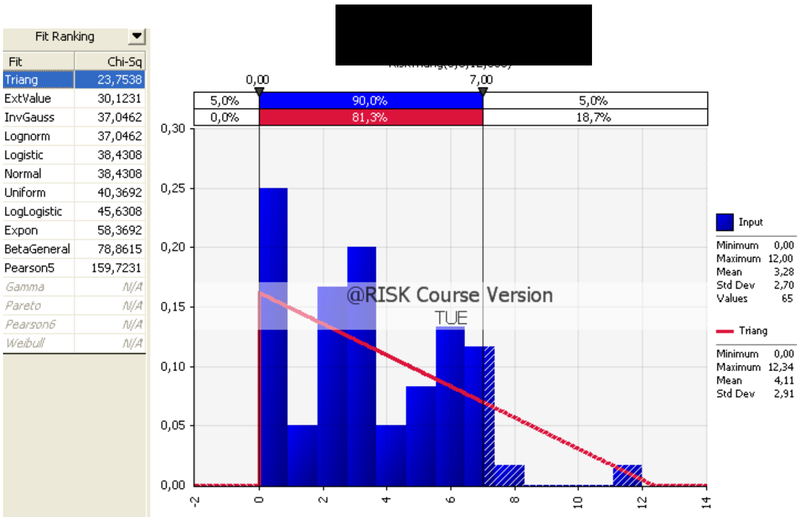


POS data Product A.3

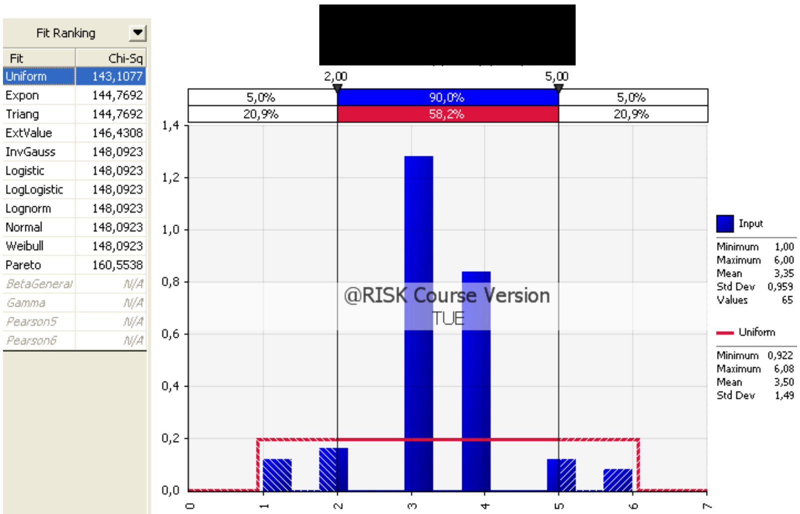


Appendix XI Demand distribution fitting using @Risk with Q

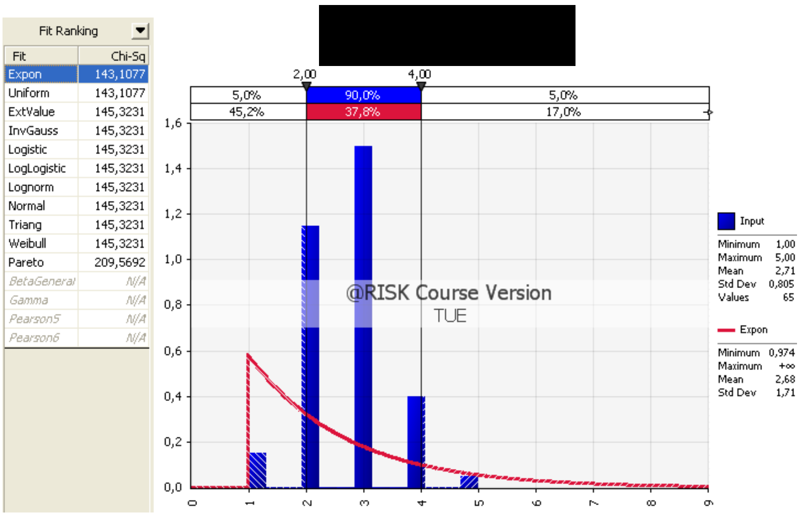
Delivery data product A.1 in pallet layers



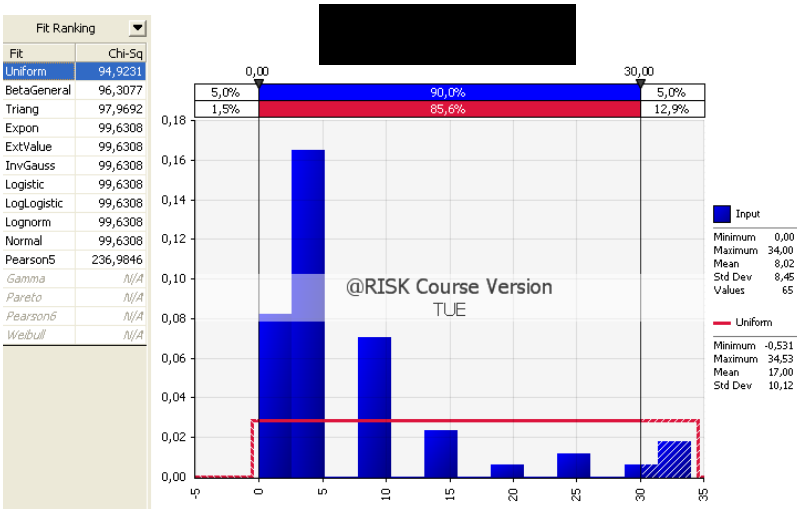
Retailers orders data product A.1 in pallet layers



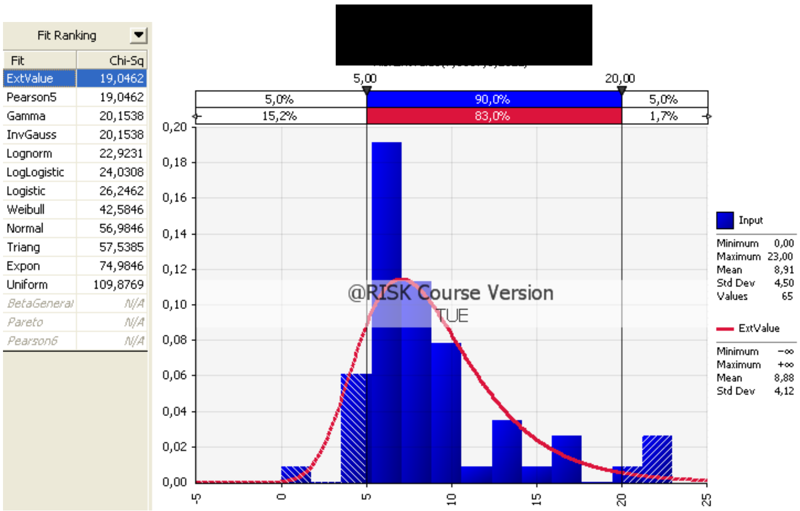
POS data product A.1 in pallet layers



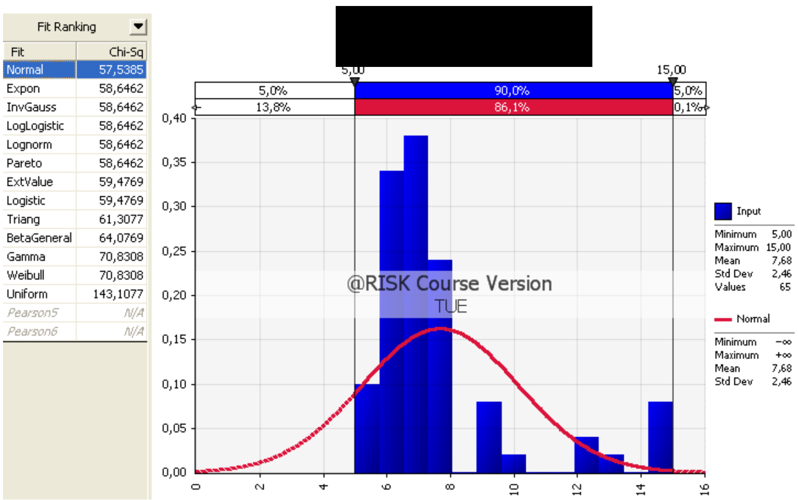
Delivery data Product A.2 in pallet layers



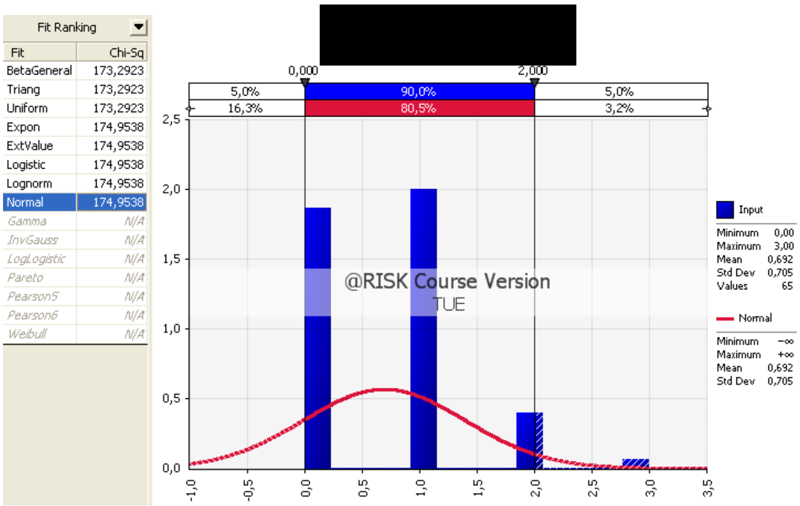
Retailer orders data Product A.2 in pallet layers



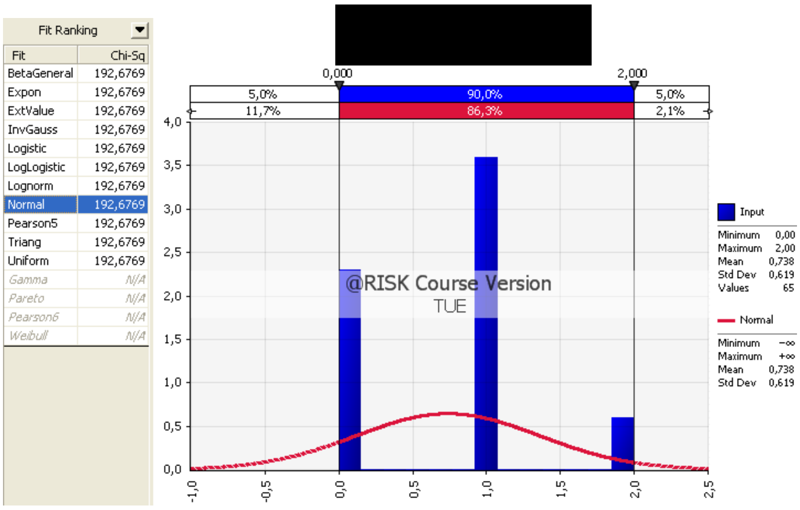
POS data Product A.2 in pallet layers



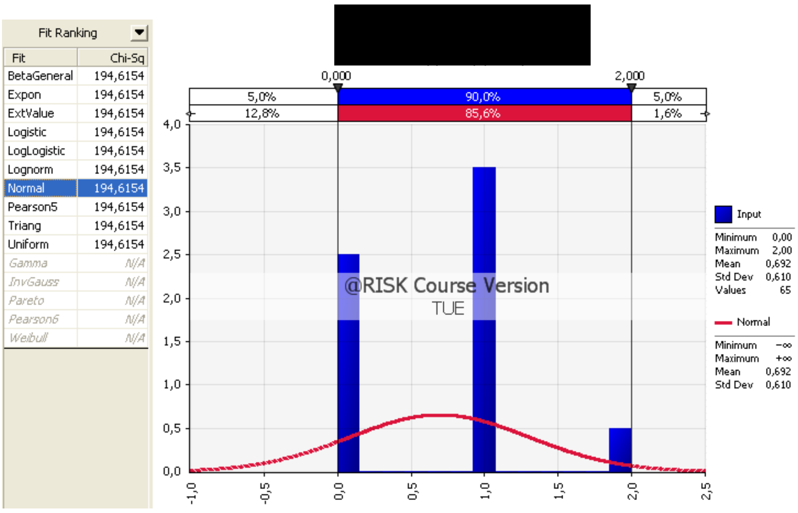
Delivery data Product A.3 in pallet layers



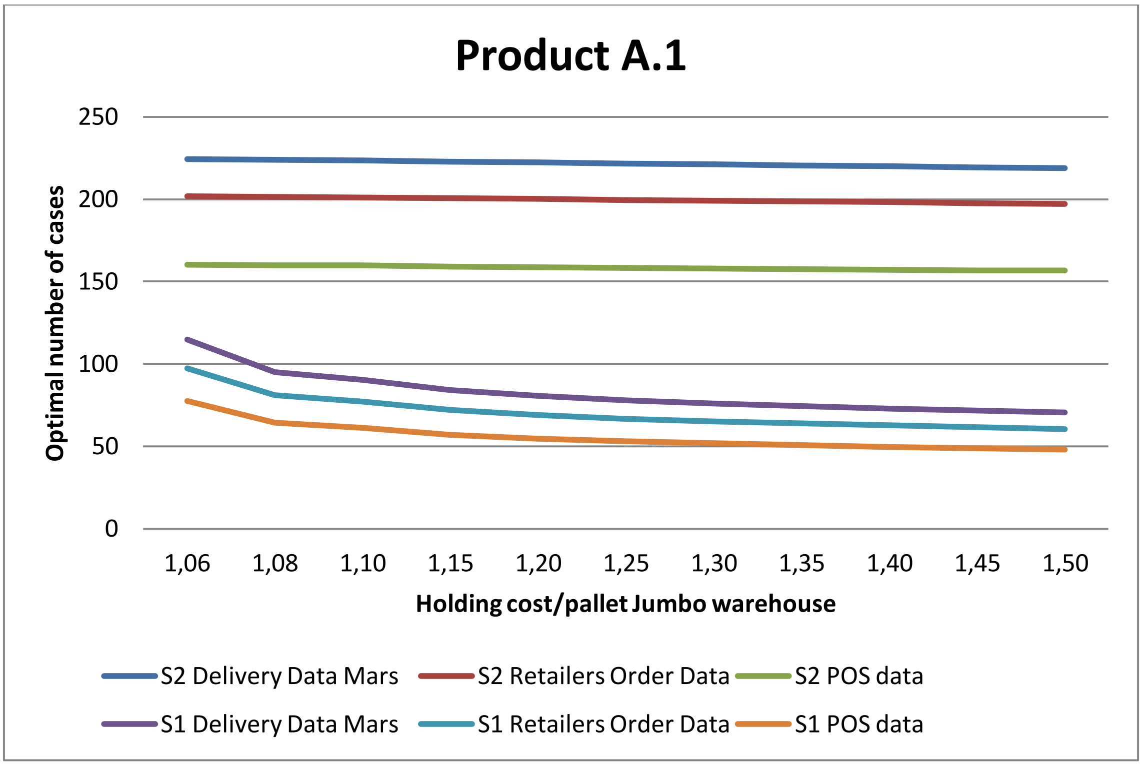
Retailer orders data Product A.3 in pallet layers

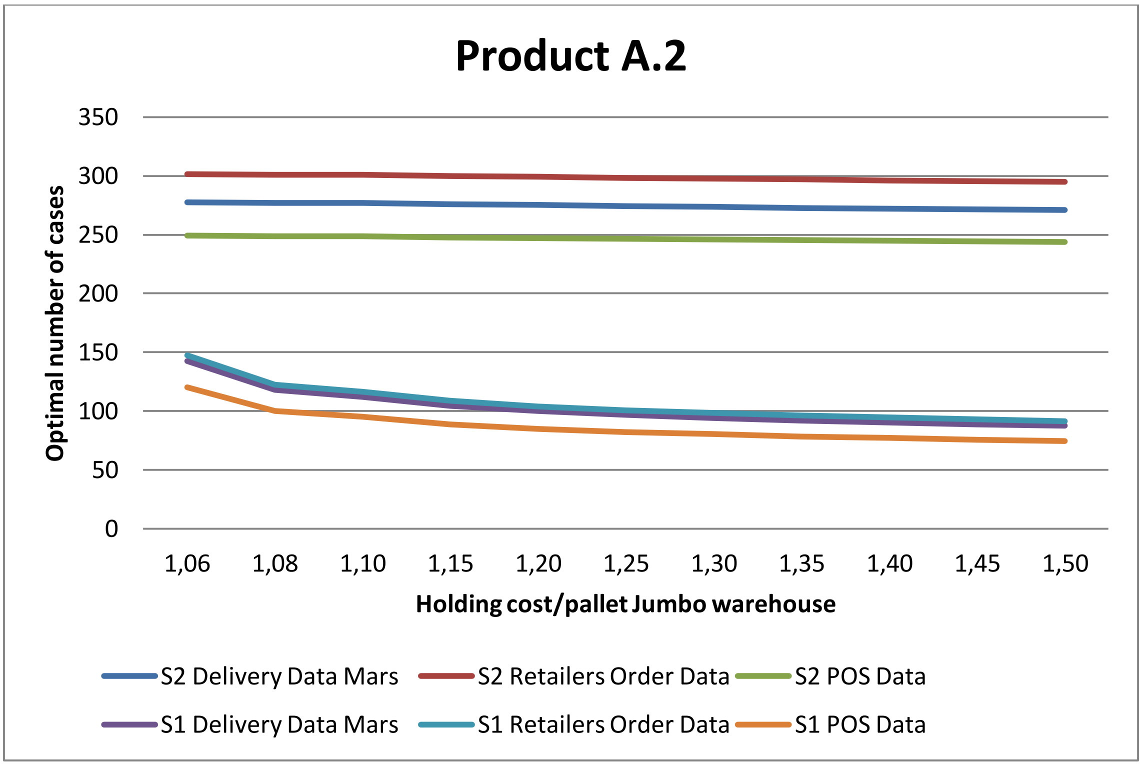


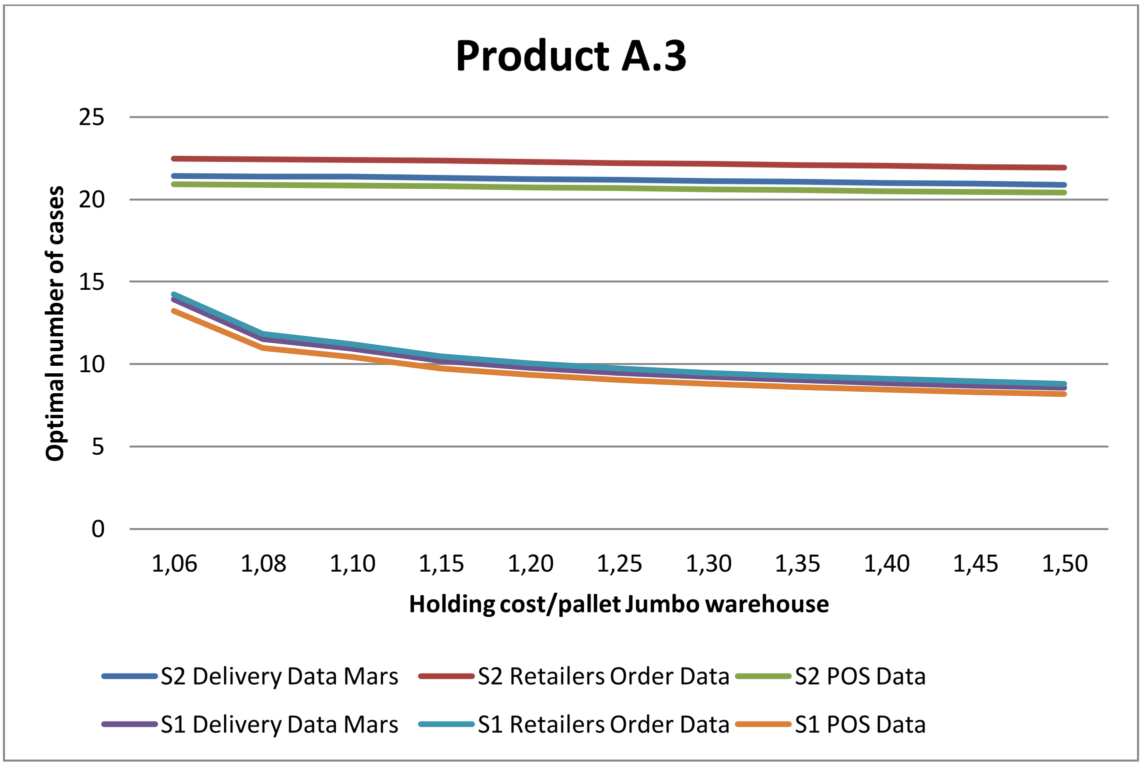
POS data Product A.3 in pallet layers



Appendix XII Sensitivity holding cost assumption







S2 h1 (€)	1.06	1.08	1.10	1.15	1.20	1.25	1.30	1.35	1.40	1.45	1.50
product A.1											
Delivery Mars	224.1	223.8	223.6	222.9	222.3	221.6	221.0	220.5	219.9	219.4	218.8
Retailer orders	201.6	201.4	201.2	200.6	200.1	199.6	199.1	198.6	198.1	197.7	197.2
POS	160.0	159.9	159.7	159.2	158.8	158.4	158.0	157.6	157.3	156.9	156.6
Product A.2											
Delivery Mars	277.4	277.0	276.7	275.9	275.1	274.3	273.6	272.9	272.2	271.5	270.8
Retailer orders	301.5	301.2	300.8	300.0	299.2	298.4	297.6	296.9	296.2	295.5	294.8
POS	249.0	248.7	248.4	247.8	247.1	246.5	245.9	245.3	244.7	244.1	243.6
Product A.3											
Delivery Mars	21.4	21.4	21.4	21.3	21.2	21.2	21.1	21.1	21.0	20.9	20.9
Retailer orders	22.5	22.4	22.4	22.3	22.3	22.2	22.1	22.1	22.0	22.0	21.9
POS	20.9	20.9	20.8	20.8	20.7	20.7	20.6	20.6	20.5	20.5	20.4

S1 h1 (€)	1.06	1.08	1.10	1.15	1.20	1.25	1.30	1.35	1.40	1.45	1.50
product A.1											
Delivery Mars	114.7	95.1	90.2	84.1	80.5	78.0	76.0	74.3	72.9	71.6	70.5
Retailer orders	97.5	81.1	77.0	71.9	68.9	66.8	65.1	63.8	62.6	61.5	60.6
POS	77.3	64.4	61.1	57.1	54.7	53.0	51.7	50.6	49.7	48.8	48.1
Product A.2											
Delivery Mars	142.4	118.0	112.0	104.3	99.9	96.7	94.2	92.2	90.4	88.8	87.5
Retailer orders	147.5	122.6	116.4	108.6	104.1	100.9	98.3	96.2	94.4	92.9	91.4
POS	120.1	100.0	95.0	88.6	85.0	82.4	80.3	78.6	77.1	75.9	74.7
Product A.3											
Delivery Mars	13.9	11.5	10.9	10.2	9.8	9.5	9.2	9.0	8.8	8.7	8.6
Retailer orders	14.2	11.8	11.2	10.5	10.0	9.7	9.5	9.3	9.1	8.9	8.8
POS	13.2	11.0	10.4	9.7	9.3	9.0	8.8	8.6	8.5	8.3	8.2

Appendix XIII Demand Product B

The vertical axis is in consumer units allocated for Jumbo.