A step forward optimizing inventory management

Using a probabilistic discrete-event simulation model to improve service levels and minimize the finished product inventory levels for the Baby care supply chain at P&G

JMR Vrouenraets

Master thesis – April 2013

Information	Master thesis - System Engineering, Policy Analysis and Management Jeroen Marc Roger Vrouenraets – 1264761 26 April 2013
Graduation committee	
Chairman:	Prof. dr. ir. A. Verbraeck
First supervisor:	Dr. M.E. Warnier
Second supervisor:	Dr. J.Rezaei
External supervisor:	Ir. Y. Vergouwen
Academic information	Delft University of Technology Faculty of Technology, Policy and Management
External sponsor	Procter and Gamble - SNO

Preface

This thesis is the final result of the research performed for the Baby care supply chain at P&G and it is the capstone for my master System Engineering, Policy Analysis and Management (SEPAM) at Delft University of Technology. Procter and Gamble has sponsored this research and gave me the opportunity to conduct this academic research.

As a SEPAM student I'm challenged to explore new complex matter and apply learned concepts and methodologies to understand the key dynamics in complex systems. The moment I started looking for a graduation assignment, I wanted to challenge myself one more time and prove to myself that I could apply these learning's during my time in Delft to a, for me, whole new field of science: supply chain management. With lots of literature on inventory management and a company which finds itself at the top of the world regarding supply chain management, the first challenge already was to define a research question both beneficial for science as for P&G.

After having spent some time on familiarizing me with the literature on supply chain management and related subjects, it became clear that most of the literature lacked practical applicability. Therefore creating a simulation model for inventory management seemed a step forward optimizing inventory management. To model this complex system, clear communication was essential. In order to do so, I designed a small framework. It helped me structure my own findings of the system analysis and to be sound in the communication with experts at P&G. After the comprehensive analysis phase, the modeling phase entailed new challenges: my limited experience with Visual Basics brought along repetitive errors and unexpected behavior. The interesting results and curious colleagues at P&G kept me motivated until the conclusions.

In hindsight, it has been a raging storm in which multiple times new system elements dawned upon me and increased the complexity. The road to get to the conclusions was paved with some tricky stones but supported by many I I`m now can say that I`m very satisfied with this final thesis, the simulation model and the related conclusions. Therefore my appreciation first of all goes out to my graduation committee who guided me through the complexities of inventory management using their academic and practical insights. During my time at P&G, many helped me not only to understand the processes at P&G and moreover helped me having a good time. In particular I want to thank Mattias and Ergin who helped me structure my thoughts and connected me with other experts. Furthermore I want to thank my roommates for pulling me through this last part of my study, my parents for supporting me my full academic career and Almira for always making me smile.

Jeroen

April, 2013

Executive summary

Supply chain management focuses on the optimization of inventory, supply chain capabilities and customer demand in order to achieve targeted service levels. Inventory is kept, amongst others to cover demand in case of unexpected variation in lead time and demand in order to achieve target service levels.

At Procter and Gamble, currently multiple analytical inventory models are used which suggest target inventory settings. These inventory settings are the core of every inventory management strategy but are not fully relied on due to the perceived black box effects of these settings on the inventory performance. Currently, most s.k.u. are sufficiently achieving the target service levels however, these targets are accompanied with high inventory levels and corresponding costs.

Given the fact that P&G`s Baby care category was chosen as case study, the main research question central in this research was;

How can the targeted service levels in the P&G distribution centre in Rumst be realized for s.k.u. of the Baby care category using the right inventory management strategy and how can a dynamic inventory model improve the inventory levels in Rumst?

By answering the individual sub questions stated below, the main question could be answered:

1) What processes are involved for inventory management?
2) How should an inventory simulation model be developed?
3) How can the inventory management be improved using an inventory simulation model?

A comprehensive literature and desk research on supply chain elements, inventory management and the role of analytical inventory models was performed. The system analysis of the Baby care supply chain added valuable insights on practical dynamics in the supply chain. Design cycles were used to develop an inventory simulation model to perform Monte Carlo analysis with. By performing several tests, insights were gained on how a practical applicable simulation model can improve inventory management.

Results

Based on the literature study, a framework to assess inventory management is created which defines inventory management as an iterative process of planning the work and working the plan, with the aim of optimizing the target performance measures. Each pillar is driven by different elements (figure I).

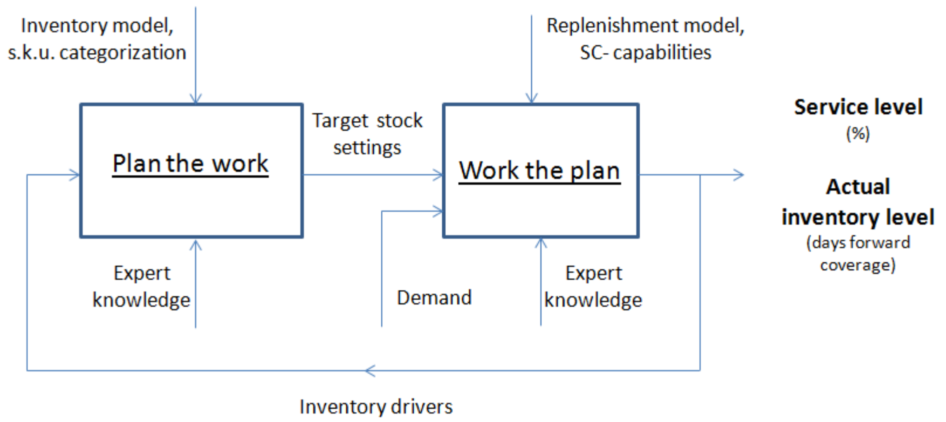


Figure I: Framework for analyzing inventory management

The findings on inventory management using the framework are used for the conceptualization of the simulation model. For the design approach of the simulation model three viewpoints have been combined: The simulation method of Banks (1999), the META model (Herder & Stikkelman, 2004) and the spiral model (Boehm, 1988). This combination of these methods has given a structured approach for the design of a practical applicable simulation model (Figure II).

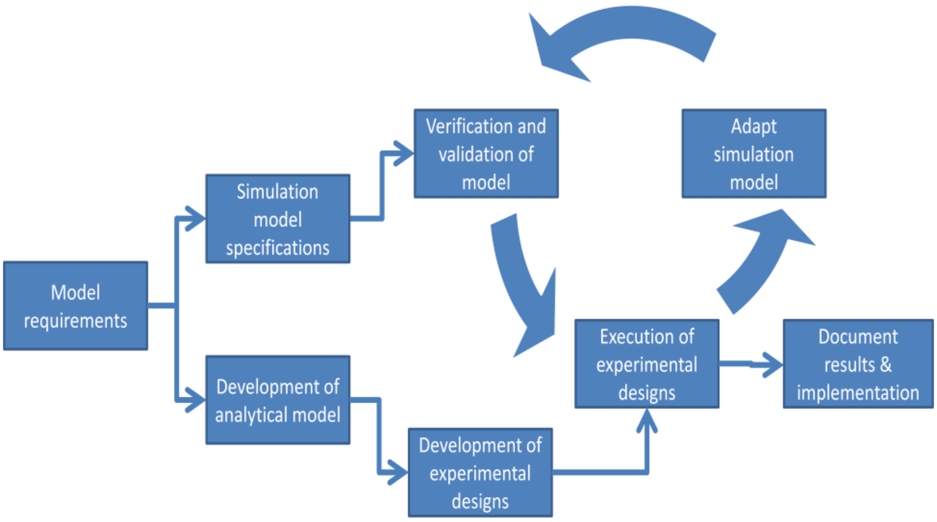


Figure II: Design framework for inventory simulation model

For the resulting simulation model three objectives are defined in line with the main research question:

1- Create insights on the dynamic behavior of performance measures by creating scoring ranges with the use of different inventory safety setting strategies
2- Quantify current inventory performance
3- Test the practical applicability of an analytical inventory model to achieve target case fill rate of 99% and minimize inventory levels

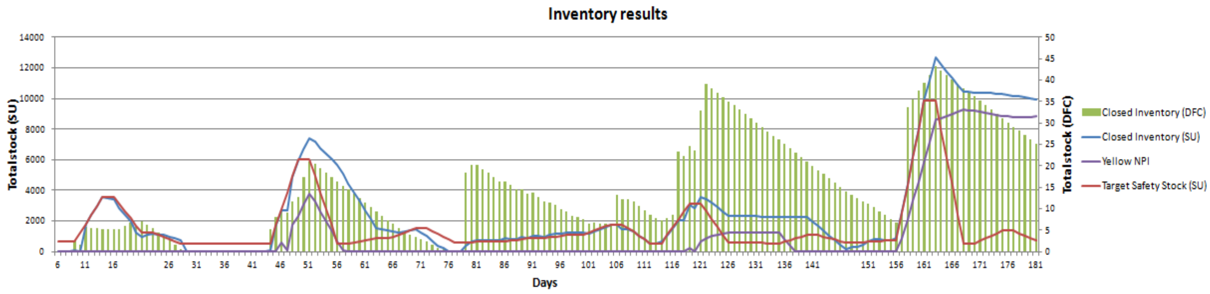
To achieve these objectives, several scenarios were developed: Four s.k.u. classes were defined based on average daily demand and the size of the fore cast error. Next, three scenarios were designed for the use of different types of safety settings:

(1) Reflection of current situation with a combination of both fixed safety stock and dynamic safety time.
(2) The use of only dynamic safety time
(3) The use of only fixed safety stock

Developed insights on dynamics of performances measures

Compared with the use of safety time, a fixed safety stock setting is a robust approach for covering for errors during the replenishment lead time. Extreme low values for CFR scores or high values for total inventory are not as common as with the use of safety time. Moreover, according to the simulation study the average performance of both the CFR and inventory level improve, compared with the use of safety time.

The simulation results moreover show that in many cases yellow NPI (excessive but still workable inventory) is created. In reality, yellow NPI is often seen as undesirable and therefore it`s used as trigger to intervene in planned replenishments. However, this simulation model shows that depending on the s.k.u. characteristics, yellow NPI is expected.



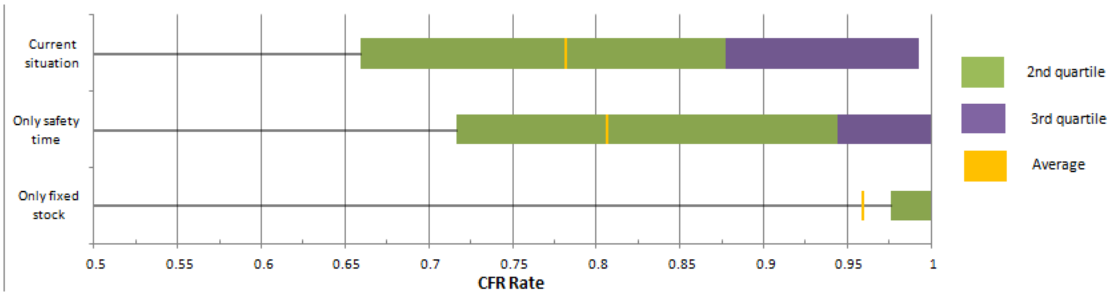
Graph I: Inventory dynamics for s.k.u. with the use of fixed safety stock and dynamic safety time

Graph I shows the results of the inventory dynamics for which a combination of fixed safety stock and dynamic safety time was used. This is used in reality and can result in extreme inventory levels.

Quantification of current inventory performance

In the current situation, the Baby care category uses a strategy in which the use of fixed safety stock and dynamic safety time is combined. The results of this currently applied scenario are compared with scenarios where only either type of safety setting is used.

The simulation showed that for the four analyzed s.k.u., in case only fixed safety stock settings are used, the average inventory can be reduced with an average of 20%. Generalizing for the whole baby care category by taking into account the volume shares of each s.k.u. class, the inventory reduction is estimated on 1%. Moreover, the weighted CFR can on average be improved with 2 percent points.



Graph II: Risk profiles for s.k.u. 81324782 for three different scenarios

Graph II compares the risk profiles for inventory performance on CFR for a selected s.k.u. for three different scenarios.

Practical applicability of analytical inventory models

The verified and validated simulation model is used to analyze the suggested safety stock settings for the analytical model that has been developed based on Silver et all (1998). The suggested safety stock settings by this analytical model to obtain a CFR score of 99%, do not deviate significantly in most of the tested scenarios. This means that the particular developed analytical model is practical applicable for inventory management.

Recommendations for P&G

The recommendations which can be made for P&G in particular are described according to the pillars defined in figure I and used throughout the thesis: 'Plan the work' and 'Work the plan'. For each pillar, recommendations are given to improve the supply chain performance.

Plan the work

Based on the theoretical analysis, a first conclusion is drawn: The structure of the inventory model currently used at P&G deviates from the suggested model by theory in two ways.

- The coefficient of variance (COV) of the forecast error is constrained with a maximum error of 100%. P&G deliberately designed the model this way because it has the opinion that COV_{FE} above the max should not be covered by excessive safety stock levels, but by improving forecasts instead. However, while often no improvement is made (e.g. because a s.k.u. is not part of a focus category), the product will be at high risk a substantial part of the time. To improve the service levels, this upper level should be removed from the model.
- One assumption made for the development of the model is that the standard deviation of the estimated errors is the square root of the summation of squared standard deviations of errors in the supply chain (forecast errors, productions errors and transportation time errors). However, literature describes a different, equation which, although equally easy to use, reflects reality more accurate. This rather small adaption could be made to the analytical model.

Secondly, the inventory model at P&G produces two suggested safety stock settings, in safety time (days) and safety stock (SU). During the inventory parameter review, experts are ought to combine both suggestions into an agreed setting. Although expert knowledge is valuable to include information on difficult products (like difficult to forecast promotions), the essence of using a theoretical optimal setting is lost. Simulations show that the solution in most cases is to let go of safety time and use 100% safety stock instead.

Thirdly, the communication on the analytical model has some challenges. Most users don`t have the need to understand the exact calculation, but knowledge on important drivers is required and should be easy available and understood. One example is the use of coefficients of variance. Although the COV are integrated in a mathematically correct way, the model itself and the data source for many input parameters of the model (IDF) show the 'standard deviation'.

Fourthly, to set the glide-path-targets, currently estimates are used to calculate the total expected inventory for the segment. This estimate can be used to monitor the actual value and size of the inventory against to see deviations between product categories, distribution centers or markets. However, when it is used as signal to trigger intervention of production, a more accurate way of setting the target is needed. A first step can be made by not including safety time (which needs an uncertain forecast of demand to calculate the expected stock level) will make the glide-path target more accurate.

Work the plan

The recommendation regarding the execution of the plan, concerns the use of the glide-path target as trigger to lower inventory production. The simulation model showed that s.k.u. independent of its safety setting strategy, naturally creates some yellow NPI. The moment a s.k.u. has more inventory than planned (for which yellow NPI is a good indicator), the glide-path target triggers an intervention. An intervention can be postponing or cancelling non-critical replenishments (P&G considers non-critical those replenishments that would be used mostly to get inventory levels up again to the safety target). The effect is that these (non-critical) healthy s.k.u. get a CFR risk. According to P&G these risk are mitigated by micro-managing possible issues.

With regard to the use of the glide-path institution itself: First, the intervention can be triggered by a healthy s.k.u. which sometimes happens to create some yellow NPI. Second, if it would concern excessive amounts of inventory (of an unhealthy s.k.u.), the intervention by postponing replenishments of other s.k.u. won`t solve the problem: the excessive inventory remains, only on paper the average segment inventory looks better. Thirdly, it only creates more problems by intervening on other healthy s.k.u. and putting those at CFR risk.

The objective of the glide-path is to monitor and manage the maximum inventory levels. For monitoring purposes, this works fine: the target can be used to review performance across categories and across distribution centers (DC). However, the use of the glide-path target to manage the maximum inventory levels is wrong: Preventing high inventory levels means among others the prevention of yellow NPI. Currently, the glide-path target doesn`t prevent this, but mitigates the overall inventory levels by slowing down the creation of inventory for a whole segment. However, to really achieve the intended objective, the focus should be on the sources that drive the overshoot of inventory creation, like over-forecasting of demand. Therefore, already other performance measures like SP1 and SP3 are used. Concluding, the glide-path target should not be used as an intervention measure because the way it is triggered and is performed are not in line with its objective.

Blank intentially

[redacted]

After having changed the perception on the safety settings, a pilot phase should be used to test the use of safety stock for a select group of products. It doesn`t matter of which classification this model is: high or low volume, high or low COV_{FE}. However, the effects are most clear when a s.k.u. with a high COV_{FE} is used. Therefore also the cap on the COVFE in the inventory should be removed in order to get optimal safety stock suggestion.

For this group of s.k.u., only safety stock should be used as suggested by the analytical inventory model without any expert intervention. Also, for this group of products, it should become clear that these s.k.u. should not be affected by interventions triggered by the glide-path target. This would darken the performance. Once the performance is improved, the safety settings can be applied to a larger group of s.k.u.

Recommendations for future research

The focus in this thesis is on finding the optimal safety setting strategy, achieving a target CFR rate with as little inventory as possible. Based on literature, the lot for lot replenishment strategy is selected and implemented in the simulation model. This strategy results in the lowest average inventory but it does not look at lowest average costs. Other replenishment strategies however do include the cost for every replenishment and stock holding costs. Examples are the economic order quantity and the Silver-Meal heuristic. Because the objective of this thesis was to achieve target service levels while minimizing the inventory levels (and not inventory costs), no other replenishment strategies were chosen. However, in the developed simulation model, other types of strategies can be implemented easily. Due to the use of Excel, the model can be used widely.

During the course of the research and especially during the interviews taken, it became clear that there is a lot of misunderstanding on the effects of different safety settings on inventory performance. The developed simulation model can help educate involved parties by visually showing these dynamics and their effects. A step further could be to implement the simulation model into a serious game. This would make it possible to let the planners experience the effects of their choices on inventory performance without affecting the actual performance.

Table of contents

Table of figures

Table of definitions

CFR	Case fill rate, CFR = $1 - \frac{\text{Mean demand not fulfilled in period}}{\text{mean demand per period}}$
DC	Distribution centre
GBU	Global business unit
IM	Inventory model
IP	Inventory parameter
Inventory position	$\text{Inventory position} = \text{on hand} + \text{on order} - \text{back orders}$ (Silver, Pyke, & Peterson, 1998).
MC	Monte Carlo
MDO	Market Development organization
Net stock	The net stock equals the on-hand stock minus backorders. If the backorders exceed the on-hand stock, this amount can become negative (Silver, Pyke, & Peterson, 1998).
On-hand stock	On-hand stock are all the products that are physically in the distribution centre, therefore this level can never be negative. This amount is relevant to determine the ability to satisfy customer demand right from the shelf (Silver, Pyke, & Peterson, 1998).
S.k.u.	Stock keeping unit
SU	Statistical Unit, equals the yearly consumption of an average American family

Part I: Introduction

Part I describes the context of this thesis and the research framework. The first chapter introduces selected general elements of a supply chain. Also, the company where the research is conducted, Procter and Gamble, is described.

In the second chapter the research approach is defined, introducing the used research framework and corresponding research questions. After elaborating on the methods used for answering the research questions, the further outline of the report is given.

1. Background

The first chapter will describe the context of the research problem and the company at which the research is conducted: Procter and Gamble (P&G). First, supply chain concepts will be introduced stating both important supply chain elements and the goal of a supply chain. In paragraph 1.2 a brief history of the company and its corporate structure is described. Then, the research problem and the practical challenges will be introduced, the research objective will be stated and the relevance of this research will be illustrated. Thereafter the scope will be elaborated on. The final paragraph shows an overview of the thesis.

1.1 Introduction of supply chain concepts

In order to understand supply chain dynamics and inventory management, several aspects are introduced. First concepts of a supply chain will be described by introducing definitions and identifying involved parties. Next, the role of the producing organization will be explained and the reasons for having inventory will be elaborated on.

1.1.1 Overview of a supply chain

In literature many definitions are used to define a supply chain e.g. La Londe and Masters (1994). From an analytical point of view Davis (1993) suggests that a supply chain is a network of processing cells with characteristics of supply, transformation and demand. However, the author of this thesis considers the definition proposed by Mentzer et al the most representative and holistic one, combining multiple definitions of predecessors. According to Mentzer, a supply chain is,

'a set of three or more entities directly involved in the upstream and downstream flows of products, services, finances and/or information from a source to a customer' (Mentzer, et al., 2001).

Figure 1-1 shows an overview of a direct supply chain, meaning that only suppliers, the manufacturing company and the customer are involved. Mentzer et al (2001) define two more complex types of supply chains: (1) the extended supply chain and (2) the ultimate supply chain. Both include additional parties in the supply chain. However it is not necessary to elaborate hereon because the focus of this thesis will be on the inventory within the manufacturing organization itself.

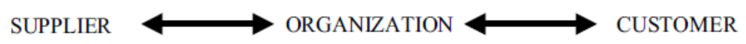


Figure 1-1: Representation of a direct supply chain, (Mentzer, et al., 2001)

The previously stated definition of a supply chain means that a supply chain can exist whether or not it is properly managed. Here is where the distinction is made between a *supply chain* and *supply chain management.* The latter is the effort to properly manage the flow of the material, information and money. The alignment of these elements is the core of supply chain management as has been acknowledged by multiple authors (Croxton, García-Dastugue, Lambert, & Rogers, 2001) (La Londe & Masters, 1994) (Houlihan, 1988).

1.1.2 Functional elements in the supply chain

Van Goor et al (1990) define two tasks that are performed by the manufacturing organization in a supply chain: (1) Production planning and (2) inventory management.

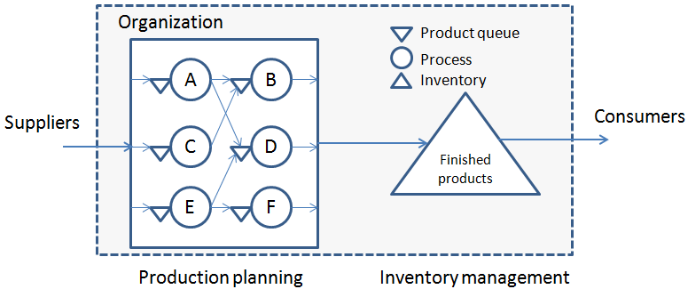


Figure 1-2: Representation of organizational elements in a supply chain, adapted from van Goor, Kruijtzer & Esmeijer (1990)

Production planning coordinates the flows of information and material on each site or department (Stadtler, 2005). It is used as guidance for the actual processes of converting (raw) materials, received by one or more suppliers, into half-fabricates or finished products. Inventory management throughout the supply chain is aimed at improving the service for customers while keeping a minimum amount of inventory. This is done by optimizing the inventory size based on optimal production settings and by anticipating on deviations in all the parts of the supply chain (Lee & Billington, 1992). Using an inventory model the right inventory levels can be targeted.

1.1.3 Goal & performance measures for supply chain management

Goal of a supply chain

The alignment of supply chain processes should in the end achieve the overall goal. This goal in the overall supply chain is to *(1) maximize the rate at which the system generates money through sales, while (2) minimizing the money that the system has invested in purchasing things that it intends to sell and (3) minimize the money that is spend in order to turn inventory into throughput* (Goldratt & Cox, 2004). This goal entails three parts: (1) maximize throughput, (2) minimize inventory and (3) minimum operational expenses.

Performance measures are used to test a supply chain regarding these goals: On the one hand to describe the current situation and on the other hand to set performance goals. By setting targets on these measures, it is possible to study the progress in reaching the goals.

These measures can be covered by a set of indicators, which represent relevant criteria in a clearly defined way (Stadtler, 2005). For proper supply chain management it is important to define the performance indicators covering the shared goals of all the entities in the supply chain. When choosing indicators just focusing on specific parts of the supply chain, it can result in local optima instead of improving the overall goals.

Some important notion on performance indicators should be considered. Because supply chains often spans over multiple companies (Figure 1-1), it is important to exactly align on the respective indicators` definition. The same goes for the data used for these indicators. These should be retrieved consistently across the supply chain.

Due to unique characteristics in every supply chain, it is impossible to identify one comprehensive list of measures for proper supply chain management. However for introduction purposes, a set of *key* performance measures and indicators is discussed: Service level and inventory (Stadtler, 2005).

Service level

Service level can be measured in several ways but in general it means getting the right product in time to the customer (Lee & Billington, 1992). Schneider (1981) introduces three types of distinction for the service level: *α-, β- and ϒ- service level*.

The first measure is event-oriented reflecting the probability that an order can be fully fulfilled from inventory. The β- service level is quantity oriented and focuses on the portion of the incoming orders that can be fulfilled with inventory (Equation 1). The ϒ-service level not only considers the size of the backorders but also the waiting time on these backorders. The performance measure is also used at Procter and Gamble. Internally it is defined as the *Case Fill Rate (CFR).* A CFR of 99% means that on average P&G directly wants to deliver 99 cases out of the 100 that are ordered.

$$\boldsymbol{\beta - \text{service level} = 1 - \frac{\text{Mean demand not fulfilled in period}}{\text{mean demand per period}}} \qquad \text{Equation 1}$$

Inventory

One clear indicator of the inventory performance is the *stock on hand*. This can be expressed in several different units like dollars, statistical units and days forwards coverage (chapter 3.4 elaborates on these units of measure). For better comparison also the relative measure of *inventory turnover* rate is used. This measure indicates how much inventory value is kept relative to the value of the sales made in a certain period (Equation 2).

$$\textbf{Inventory turnover} = \frac{\textbf{Annual sales}}{\textbf{Average inventory}} \qquad \text{Equation 2}$$

Van Goor et al (1989) summarize advantages and disadvantages for keeping inventory, shown in Figure 1-3. In line with the definition of Goldratt and Cox, it makes clear that too much inventory cost money. Healthy inventory levels secure high service levels with a minimum of inventory.

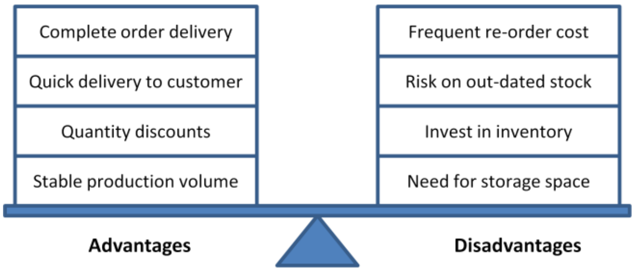


Figure 1-3: Conflicting interests considering the maintenance of inventory, adapted from van Goor et al (1989)

1.2 Introduction of P&G

This paragraph will introduce the brief history of P&G and elaborate on its corporate structure. Also, the departments involved in the supply chains of P&G will be discussed.

1.2.1 History

Procter & Gamble was founded in 1837 in Cincinnati by William Procter, a candle maker from England, and James Gamble, a soap maker from Ireland. These two Europeans emigrated to America and created what is now one of the world's leading manufacturers of consumer goods. The first big brand of P&G was Ivory, a 2-in-1 soap, introduced in 1879. With this soap one could take a bath as well as wash your clothes.

The products sold by P&G are labeled as fast moving consumer goods (FMCG). These types of product are being sold with high frequency for a relative low price. Although margins on a product are small, the large quantities that are being sold make producers continuously fight for market shares. The FMCG is becoming increasingly competitive and therefore companies need to keep improving their services to compete with other FMCG suppliers. Procter & Gamble (P&G) is one of the internationally top FMCG companies with a worldwide net sale of 83 billion US dollar (P&G, 2012).

1.2.2 Corporate structure

In the P&G corporate organizational structure, three global business units (GBU) work on the strategic leadership for a production unit: 'Beauty & Grooming', 'Household care' and 'Health & Well-being'. Every unit produces multiple product categories which are listed in **Error! Reference source not found.**.

The day-to-day management responsibilities for these products are centralized in regional markets. In the Western-European (WE) unit, one of the markets is the Benelux (BNL) in which the Market Development Organization (MDO) is selling and distributing the GBU products (Figure 1-4) (P&G, 2011).

Figure 1-4 Overview of the GBU – MDO structure at P&G

A graphical overview of how these departments operate in the supply chain is given in Figure 1-5. The GBU`s are responsible for the production at the plants and have a shared responsibility for the inventory management at the distribution centers (DC). MDO also have a shared responsibility for the allocation of products over the DC`s and are responsible for the communication with customers regarding marketing, sales and distribution.

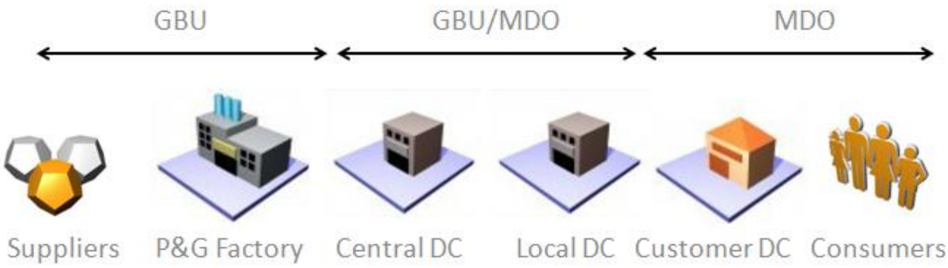


Figure 1-5 Roles of GBU and MDO in a P&G supply chain

1.2.3 Product supply organization

Product supply (PS) organization focuses on having the right amount of products, on the right time, on the right place for the right price (P&G, 2011). Five disciplines can be distinguished Manufacturing, Engineering, Quality assurance, Purchase and Supply Network Operations. The matrix in Figure 1-6 shows how these functions are managed by the GBU and MDO.

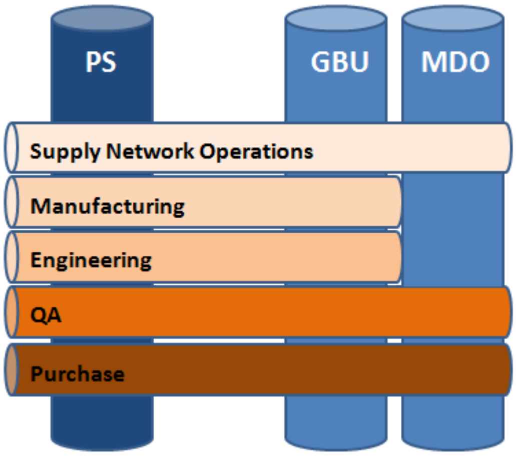


Figure 1-6 Product supply matrix structure adapted from (P&G, 2011)

Blank intentionally

1.3 Research challenge & objective

Currently at P&G two performance measures of the supply chain are of particular interest: The service level and the inventory size.

During the past 2 years the focus on cash and profitability within P&G has significantly increased, driven by increased commodity costs and decreased operating margins. In order to improve the operating margin, P&G (GBU) has reduced the inventory targets expressed in the amount of days on hand. Next to this, the BNL SNO organization has set a target to become the undisputed number one supplier in Benelux. An important measure contributing to this qualification is the service level.

CFR-targets

In order to become the number 1 preferred supplier, the BNL MDO has set the CFR targets of 99%. Table 1-1 shows that for several product segments, these targets are not achieved yet nor is a stable score achieved. This is the reason to analyze the way inventory at P&G is managed, understanding that: keeping inventory is needed to absorb deviations in up- and downstream processes, in order to achieve a steady CFR on target.

Blank intentially

Table 1-1: Case fill rate (SU) for 3 product segments, (P&G, 2012)

Inventory targets

Besides the need to improve the service levels, inventory level targets are sharpened. This has resulted in reduced inventory levels. Table 1-2 shows how the observed safety stock is below the target safety stock setting, putting the CFR at risk.

Blank intentially

Table 1-2: Difference between target and observed safety stock for 4 product categories, period Dec 11 – Dec 12 (P&G, 2012)

Both the insufficient scores on the service level and the deviation from the inventory targets raise questions on what elements in the current approach for inventory management are performing insufficiently.

To classify the P&G inventory model several methods are used like the one proposed by Min et al (2002) which suggests the models is hybrid while it takes into account both real-world uncertainties and random elements such as stochastic elements and targeted service levels. Naresh & Rivera (2011) categorize this type of model as hybrid because it involves discrete decisions (start of production) and continuous variables (like demand forecast). A final approach is used by Sarimveis et al (2008) who distinguish static and dynamic models. Pointing out the fact that static models are based on average performance.

Although P&G models use quarterly reviews to update the IP and some of the outputs are used for 'dynamic' safety stock settings, the models itself can be classified as static. Considering dynamic characteristics in supply chains like lead-time delays, forecast errors and market volatility, these static models using inputs computed a priori, are not sufficient to qualify as a dynamic model (Sarimveis, Panagiotis, Tarantilis, & Kiranoudis, 2008).

Considering the current challenges at P&G the research objective therefore is twofold:

Research objectives:

Research objectives

1.) to make possible recommendations to the Supply Network Operations of P&G in the Benelux, regarding how to improve the inventory management
2.) To explore the potential contribution of using simulation to improve the used static inventory model.

The main research question that should be answered in order to reach this objective is;

How can the targeted service levels in the P&G distribution centre in Rumst be realized for s.k.u. of the Baby care category using the right inventory management strategy and how can a dynamic inventory model improve the inventory levels in Rumst?

1.4 Relevance

The aim of the research is to both contribute to science as well as help P&G`s inventory management by answering the performed research questions. Both aspects are now explained.

1.4.1 Academic relevance

Supply chain management is a widely discussed subject in literature. A particular branch, inventory management, has received much attention in the past decades, producing many methods of securely planning inventory processes and optimally executing the plans. However, not all elements are discussed to the full extent leaving opportunities for the misuse of concepts. The challenge is to create a simulation model which can be used to create insights on the behavior of certain inventory elements and use this model to test specific inventory theories.

First, although dynamic programming is viewed as an increasingly valued framework for analyzing optimal control problems, it has mainly been limited at proving theories instead of implementing models in practice for real-world validation (Sarimveis, Panagiotis, Tarantilis, & Kiranoudis, 2008). It often concerns the deterministic nature of parameters, e.g. the exclusion of forecast errors, the stationary character of demand (Zizka, 2005) or only analyze the effects over a short period (Garcia & Saliby, 2002). Hereby should be included that although literature is mentioning dynamic inventory programming, these academic models often don`t fit that well in an industrial world (Farasyn, Perkoz, & van de Velde, 2008). Therefore, the first contribution to science this research aims for is to test the performance of theoretical analytical inventory models in a realistic simulation model. In order to do so a probabilistic simulation model is developed, which is practical applicable, and is used to perform Monte Carlo analysis with.

A second point of scientific interest is the use of Monte Carlo simulation. Recent studies have been using Monte Carlo simulation for inventory management problems (Cáceres-Cruz, Grasman, Bektas, & Faulin, 2012) (Jaio & Du, 2010). However little effort has been spent in using Monte Carlo simulation specifically to explore the risks involved in the analytical model for determining optimal safety stock levels.

The last point of academic relevance is the acquired insight in the guidance of the use of either safety stock or safety time. At the core of inventory management are the analytical inventory models with which the optimal safety settings are calculated (safety stock and safety time). However, little attention is given to the distinction between these two safety setting strategies, and not at all to quantifying the differences. By using the Monte Carlo simulation model, this thesis provides examples to clarify the different effects of these strategies with respect to performance.

1.4.2 Practical relevance

This research study has the potential added value for SNO BNL as well. First of all, in the current situation the international supply chain at P&G has become complex and difficult to manage. This research uses one of the supply chains at P&G as a case study. A system analysis is performed on this supply chain. Relevant differences with literature are flagged, discussed and opportunities for improvement proposed.

Secondly, the design of a simulation model improves inventory management at P&G in different ways. Currently, the analytical inventory model used for calculating the optimal safety settings is perceived as being a black box. This means that although clear mathematical equations are used in the model itself, the optimal use of its output (the suggested inventory settings) and the effects on performance are unknown to the user. Now this results in the arbitrarily use of either safety time or safety stock settings. The simulation model has the ability to show the dynamic effects of different inventory strategies on the performance measures used in the supply chain. This will support decision making in the supply chain.

2. Research framework

Ostrom (2008) defined the hierarchy between three levels of analysis: frameworks, theories and models. She stated that frameworks help to identify general concepts including important elements and constraints for understanding the problem. Theories are a level lower and are used to focus on the key parts of a framework and make certain assumptions to analyze the problem. Finally models fill in a selected group of parameters which result in a set of outcomes. This chapter will start by introducing the research framework, which will be the start to select applicable theories and models.

2.1 Introduction

For a structured approach a research framework is designed based on Verschuren & Doorewaard (2010) and using the defined research objective. The framework (Figure 2-1) shows an overview of 4 stages which result in recommendations for P&G`s inventory management. The stages now will be elaborated on.

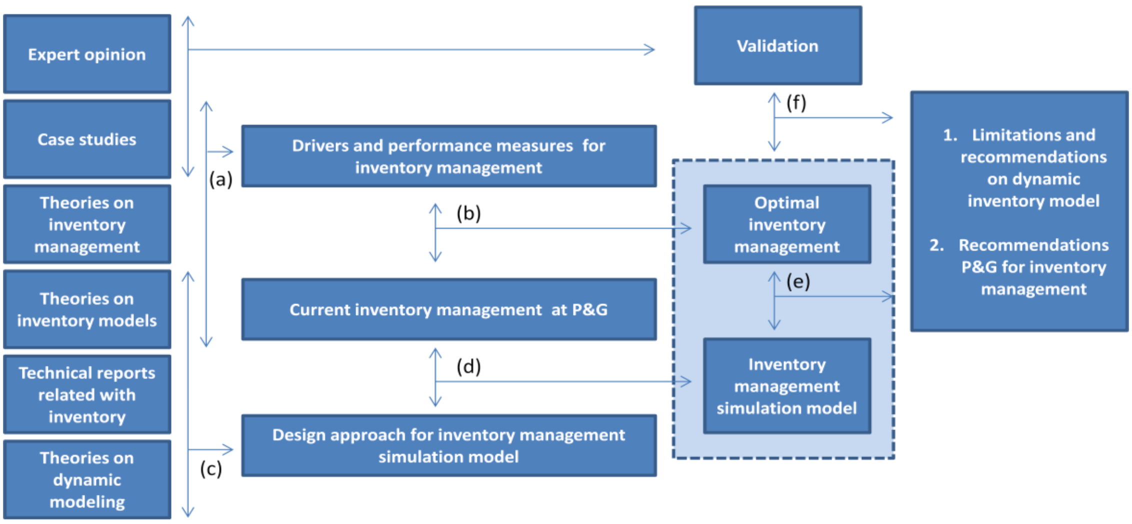


Figure 2-1: Framework for research approach

a) Select key drivers and performance measures for inventory management

In order to understand the purpose of inventory management, first theoretical drivers of inventory will be gathered. This includes the analysis of the currently used analytical inventory model. Also, measures will be selected to rate the performance of inventory management practices.

b) Perform case study to analyze current inventory management for a product category at P&G

Using the developed framework in phase a), a cross reference study will be performed amongst relevant western European DC`s at P&G to acquire real-world data on performance indicators and corresponding drivers. First the data on the theoretical performance measures will be gathered for multiple categories at P&G. Next, based on this review, one product category will be selected to perform a detailed system analysis on. The results of the system analysis among else are to define strategies currently used for inventory management.

c) Set up approach for developing an inventory management simulation model

A design approach for the simulation model is developed using literature on inventory modeling, simulation and general modeling methods. Theories on commonly used analytical methods for inventory management are used to develop tests with. Technical reports are used to acquire data for creating realistic scenario`s.

d) Design inventory simulation model and validation tests

The design approach and the system analysis of the current situation are used to develop an inventory management simulation model. Purpose of this model is to validate the static results returned by the analytical inventory model and test different inventory strategies.

e) Analyze inventory management strategies using the simulation model

The performance of strategies identified with the system analysis are tested using the simulation model. Results are recommendations for inventory management at P&G and the added value of using a simulation model for inventory management.

f) Validate new inventory management practices

The results of the simulation model are validated with expert opinion. Limitations of the simulation model are identified and recommendations for future research and implementation are defined.

2.2 Selection of focus category

To achieve the research objective within the given timeframe, the project is delineated. In order to both deliver a thesis which is valuable for Procter & Gamble as for science, a case study is performed on a valuable and representative product category at P&G.

An extensive analysis of the inventory performance for different product categories at the distribution centre in Rumst is performed in order to select a representative product category (**Error! Reference source not ound.**). A valuable category is defined as one of which inventory management is not performed optimally and results into unhealthy inventory levels. Such a category could be improved using the results of this thesis.

The results of the analysis show that the Baby care category both has a relative low average inventory level and also low service levels. However, it is difficult to select Baby care based only on these top line analysis. Therefore, the results are discussed with experts to select a product category to perform the case study on (Sabbe & van der Oost, 2013). However, the discussion reinforced the choice for the Baby care category.

The Baby care product category is selected based on the following considerations:

- The analysis shows that Baby care in Rumst has relative low inventory levels but underperforms on the target service levels. This triggers the question how inventory is managed.
- For the Baby care category, a lot and easy accessible knowledge is available.
- The Baby care category is one of the largest value categories with respect to the BNL market and therefore benefits a lot from optimal inventory management.
- The Baby care category is one of the most mature categories at P&G which suggest a solid supply chain should be in place which isn`t affected by many coincidences.

The selection of the baby care category results in several delineation choices. E.g. the Baby care category uses a r,s,S-ordering system. Although other ordering systems are discussed during the literature review, the focus during the development of the simulation model is on this type of model due to the selection of the Baby care category. Other, delineations based on the choice of the Baby care category are discussed in chapter 6 and 7.

After performing the analyses on the Baby care case study, the results are discussed in order to draw general conclusions. This discussion results in conclusions which are applicable to other categories within P&G and to other supply chains in general.

2.3 Research questions

As stated earlier, the main research question to be answered in this research project is:

How can the targeted service levels in the P&G distribution centre in Rumst be realized for s.k.u. of the Baby care category using the right inventory management strategy and how can a dynamic inventory model improve the inventory levels in Rumst?

By answering the individual sub questions stated below, the main question should be answered.

1) **What processes are involved for inventory management?**
2) **How should an inventory simulation model be developed?**
3) **How can the inventory management be improved using an inventory simulation model?**

After answering these sub questions the following questions can be answered regarding the use of a dynamic inventory model.

1) **What recommendations can be given to SNO BNL to improve its inventory management?**
2) **What recommendations can be given for the use of the inventory simulation model?**

2.4 Research methods

This section elaborates on the methods for acquiring knowledge to answer the research questions. First a *literature study* is performed to gain insights in supply chain concepts and inventory management. Using *desk research*, these concepts are compared in order to define performance measures and drivers for this research. Further literature study is used to develop a model design approach.

By means of *interviews* and *brainstorm sessions*, additional model requirements are gathered. During the model design approach, desk research is conducted to acquire input for the model. Interviews are used to validate the model and further literature study is used for developing tests for the simulation model.

2.5 Outline of report

The report consists of several parts. First, an introduction is given into the subject and to define the academic and practical relevance of the research. In this first part, a research objective with adherent research questions are defined. The following parts are used to answer these questions.

In the second part results of a supply chain analysis are presented. First, a literature study on supply chain and inventory management is elaborated on. This results in performance drivers and measures for inventory. Next A system analysis on the Baby care supply chain is performed to identify deviations from supply chain best practices as described in literature.

The third part discusses the development of both the analytical model and the simulation model for inventory management. After defining the right modeling approach, several modeling cycles are discussed which result in testing the analytical model and identifying the impact on the defined performance measures.

The final part discusses the results from the simulation and draw conclusions. Furthermore, limitations of the simulation model and opportunities for further research are elaborated on. Figure 2-2 shows a visual representation of the thesis outline.

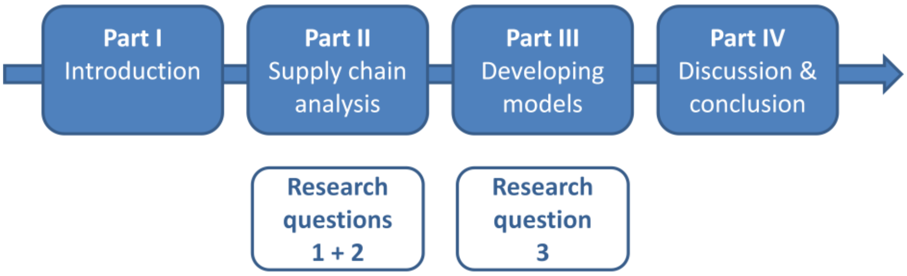


Figure 2-2: Structure of this thesis

Part II

Supply chain analysis

In this part, first the analysis of literature on supply chain management and inventory management are described. Next, methods to determine the optimal inventory safety settings are introduced. The last chapter in this part performs a system analysis at the selected Baby care category at P&G. The findings are used to conceptualize a simulation model in part III.

3. Supply chain management

In order to analyze the theoretical drivers and performance of a supply chain, a framework (similar to the one used by Haans (2001) and adapted by Snauwaert (2012)) is used, which suggests a relation between inventory drivers and the overall objective, a high service level. All concepts as shown in Figure 3-1 are discussed in this chapter.

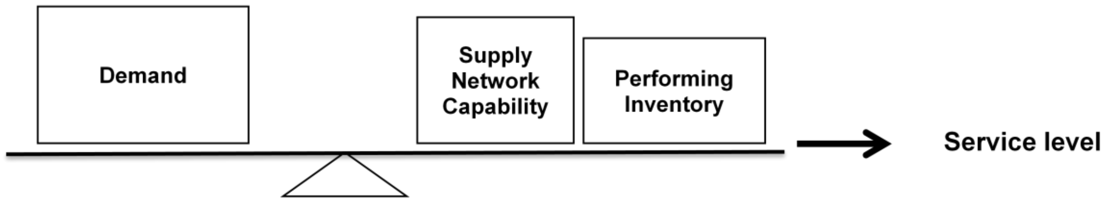


Figure 3-1 Supply chain drivers, adapted from Snauwaert (2012)

3.1 The performance measure: service level

The ultimate performance measure for the whole supply chain is the service level of the customer. This is measured by comparing the daily requested volumes with the daily shipped volumes. For this, it is important to understand how service is defined. An overview of frequently used service measures is given in Table 3-1.

Performance measure	Definition
α - service level (P1: cycle service level)	Probability of no stock out during the replenishment lead time
β – service level (P2: fill rate)	Fraction of demand to be directly satisfied from shelf
ϒ-service level (P3: Ready rate)	Fraction of the time which the net stock is positive
Service as measured by customer (SAMBC)	Availability level according customer

Table 3-1 Definitions of service level, (Schneider H. , 1981)

Case fill rate (%)

The service level can be calculated on different levels (case, product-line and order level). At P&G the β – service level (P2) is the key performance measure for the service level on case level. The *case fill rate* (CFR) is calculated as shown in equation 3 and reflects the fraction of demand that can be satisfied directly from shelf.

$$CFR\ (\%) = \frac{Q_{shipped}}{Q} * 100\%$$

equation 3

CFR = Case fill rate (%), fraction of requested volume satisfied directly from shelf

$Q_{shipped}$ = Volume directly shipped from shelf (cases)

Q = Requested volume (cases)

What the target service level is, is a strategic decision. Van Goor et al (1989) describe that the optimal service level is a tradeoff between the cost of inventory and the cost of not selling products to the customer.

3.2 1st performance driver: demand of finished products

Whenever it is known what type of product the customer is looking for, there often is uncertainty on the *size of the demand*. In order to predict the size of the expected demand, different forecast methods are used (Appendix B). To measure the performance of the forecast, several measures of demand forecasting are used which are discussed in this section.

First a distinction needs to be made between dependent and independent demand. As is explained in chapter 4.3, dependent demand are the orders from an echelon directly downstream in the supply chain whereas independent demand is coming from the final customer of a finished product for which a forecast of demand is used. Forecast of demand therefore only is necessary for the *uncertain* independent demand.

3.2.1 Performance measures for demand forecast

Forecast of demand

The aim of any forecast technique is to predict the future demand as accurate as possible, resulting in a minimal difference between forecast of demand and the actual daily demand (Table 3-2). A mathematical model is used as a base which is able to extrapolate historical data (statistical forecast). If needed, business intelligence (based on human input) on future promotions and new product launches can be added. The amounts that are forecasted are used for several reasons (van Goor, van Amstel, & van Amstel, 1989);

1) planning the right allocation of inventory over the distribution centre's
2) planning the right replenishment orders
3) identify the need for additional production capacity
4) business development projections

Demand measure	Description
Forecast of daily demand (SU)	The amount of products that is predicted to be needed to satisfy demand. E.g. business intelligence and statistical is used for forecasting right amounts.
Daily demand (SU)	Actual daily demand averaged over review period. This amount is actually being shipped to customer

Table 3-2: measures to track size of the demand

Forecast error

However, it is certain that the forecast is not correct. To measure the size of this error, the forecast error is used. This output is used for two reasons:

1) The forecast error should be used as feedback on the subjective human input
2) The forecast error is used for setting the inventory settings

The forecast of demand of finished products, is the quantity which is expected to be needed in order to meet demand. To measure this accuracy compared with the actual demand, the forecast error is used. As will be discussed in chapter 5 in more detail, uncertainty of this forecast error is essential for the calculation of the necessary safety stock, which is used to cover for the *uncertainty in demand* during the replenishment lead time. To do so, the variation of the errors of forecast of total demand over a period of the replenishment lead time is measured and expressed as a standard deviation.

In literature, several types of forecast error calculations are given of which the most relevant for inventory management are listed in Table 3-3 (Everette & Gardner, 1990) (Hyndman & Koehler, 2006) (Vergouwen, 2012).

	Forecast measure	Description	Calculation
MAPE	Mean Absolute Percentage Error (MAPE)	Absolute forecast error relative to demand	$MAPE = \frac{\sum_{t=1}^{max}(\lvert forecast_t - demand_t \rvert)}{\sum_{t=1}^{max}(actuals_t)}$ Equation 4
BIAS	Bias	Consistent over- or under forecasting of demand	$Forecast\ bias = \frac{\sum_{t=1}^{max}(forecast_t - Actual_t)}{\sum_{t=1}^{max}(forecast_t)}$ Equation 5
σ_{FE}	Standard deviation of the forecast error	Variation of the errors of forecast of total demand over the lead time	$\sigma_{FE} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n}}$ Equation 6

Table 3-3 Overview of forecast measures

3.3 2nd performance driver: supply chain capability

Both the duration and the variation in the duration matter. If the lead time is long, it is relatively hard to produce more products should the demand rapidly increase. Also, variations (delays) in supply lead time can result in not meeting the demand and thus lower service levels (Stadtler, 2005). Both elements can be coped with by keeping relatively more inventory.

The supply network capability is expressed in terms of the time it takes from the moment an order for an item is placed and when it is actually available for satisfying customers demand at a distribution centre, also known as the replenishment lead time (Liao & Shyu, 1991). This lead time can be split into two components of production and transportation, as shown in equation 7 (Farasyn, Perkoz, & van de Velde, Spreadsheet models for inventory target setting at Procter & Gamble, 2008).

$RLT = PRT + EFT$ **equation 7**	RLT = Replenishment lead time, time (working days) between initial order and product availability at distribution centre. PRT = Plant reaction time, time (working days) after ordering until the actual production can start EFT = Emergency frozen time, time (working days) after the actual production until a product is delivered at the final distribution centre

3.3.1 Plant reaction time

The plant reaction time is the time (in working days) required to restore a normal inventory position. This are the working days that elapse between the identification of the production need and the actual production.

Potential delays are,

- Scheduling time
- Lead time until next planning cycle (e.g. planning is done every Monday and a request for production is identified on a Tuesday).
- Supply lead time for material that not is kept in stock (this can be the case for special materials which are too expensive to keep in stock).

3.3.2 Emergency frozen time

The emergency frozen time is the time between production and availability of the finished product, ready to be picked up at the storage location. If shipment of a finished product to a storage location is only possible after quality control (QC), the EFT can be calculated using Equation 8. If authorization is given to ship ahead of the final quality release (shipment under quarantine) Equation 9 can be used.

$EFT = QC + ETT$ Equation 8	QC = Quality control. Time (working days) between production and quality release ETT = Emergency transit time. Minimum lead time (working days) in case of availability risk, using an confirmed shipment route
$EFT = MAX(QC, ETT)$ Equation 9	QC = Quality control. Time (working days) between production and quality release ETT = Emergency transit time. Minimum lead time (working days) in case of availability risk, using an confirmed shipment route

3.3.3 Concluding remarks on the replenishment lead time

Figure 3-2 summarizes the total replenishment lead time. When determining the values for the lead times, the following notions should be considered.

Safety stock is required for emergencies (when demand is greater than the forecast or when supply is unreliable). Therefore, it is essential the forecast as realistic as possible. On the one hand it is important not to be too optimistic: Defining too short plant reaction times result in low safety stock settings which then forces to produce with the specified short lead time. On the other hand, being over conservative, results in too much inventory.

While the emergency transit lead time is taken into account for setting the safety stock, the emergency route should be proven and agreed on (the organization has to be willing to pay for the extra costs).

In Figure 3-2 the order pick phase is shown for clarification reasons: The order pick time shouldn`t be included for calculating the RLT: The order pick time increases the lead time for the orders from customers and therefore this customer should take into account this lead time by taking it into account when deciding on its safety stock levels in the customer`s storage location.

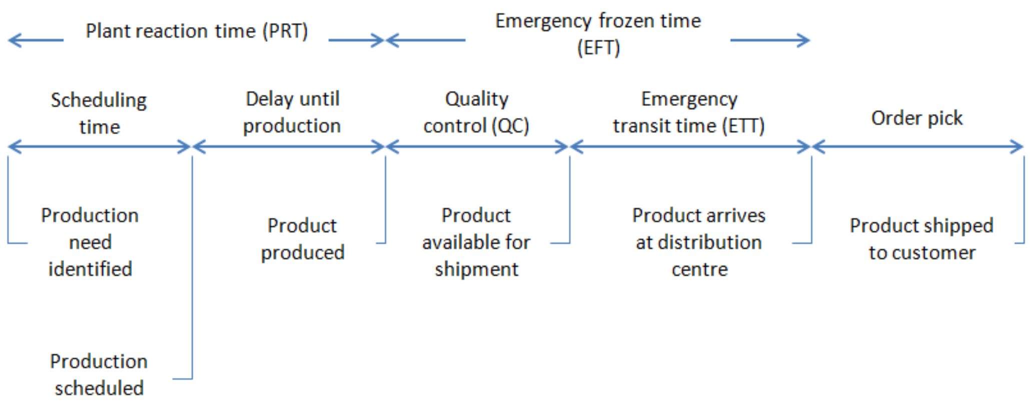


Figure 3-2: Overview of the replenishment lead time components

3.4 3rd performance driver: inventory

Finished product inventory is kept to cope with uncertainties in the lead time and demand, benefit from economies of scale during production and to comply with technical constraints (van Goor, Kruijtzer, & Esmeijer, 1990). Both the quantity and quality of inventory are important. If not the *right products* are stored at the *right moment* (e.g. products out of date) the case fill rate will be affected.

Inventory can be defined as 'all the money that the system has invested in purchasing things which it intends to sell' (Goldratt & Cox, 2004). Aligned with this definition, inventory can be found from the beginning of the supply chain (as raw materials), until the end when a product is delivered to the customer (as finished product).

3.4.1 Inventory in the supply chain

In the supply chain, three types of inventory are categorized: (1) Work-in-progress (WIP), (2) pipeline inventory and (3) finished inventory. Figure 3-3 shows the two organizational elements in the supply chain (just like Figure 1-2), but now shows the different locations of the inventory types in the supply chain.

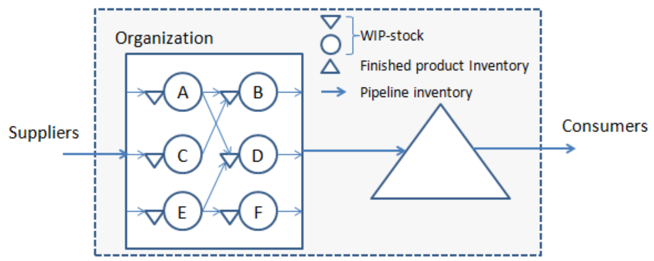


Figure 3-3: Different types of inventory in an organization

Depending on the type of business that is analyzed, the primary need of controlling inventory is focused on either one of the above discussed categories (Silver & Peterson, 1985). At P&G, finished inventory is of most interest (Table 3-4).

Industry type	WIP	Pipeline	Finished products
Capital goods	16	60	24
Garment industry	60	36	4
Consumer goods	12	60	28
P&G worldwide	*9*	*24*	*67*

Table 3-4 Inventory distribution (%) in different U.S. industries and P&G in percent of total inventory investment, adapted from Silver & Peterson (1985) and (P&Ga, 2010)

Goor et al (1990), Silver & Peterson (1985) and Stadtler (2005) use a number of more specific concepts of which the *cycle stock* and *safety stock*, being the most actionable, are introduced here. Other concepts can be found in **Error! Reference source not found.**.

Cycle stock

Cycle stock is the result of producing products in batches instead of one at a time. Three reasons can be identified. The first reason is to achieve economies of scale by dividing the high set-up costs over a large batch size. The second reason is to satisfy technological constraints due to for example tank size. The third reason is to achieve quantity discount in purchasing resources or transportation of goods.

Safety stock

Safety stock is a part of the inventory that is held in excess of expected demand due to variable demand rate and/or lead time (Stevenson, 2005). Customers, manufacturers and suppliers all have own causes (e.g. machinery mall function, forecast errors on demand) for deviating from their expected performance (Figure 3-4). The *observed* safety stock is defined as the average level of net stock just before a new replenishment arrives. This amount can differ from the *necessary* safety stock which can be calculated as is explained in chapter 5.

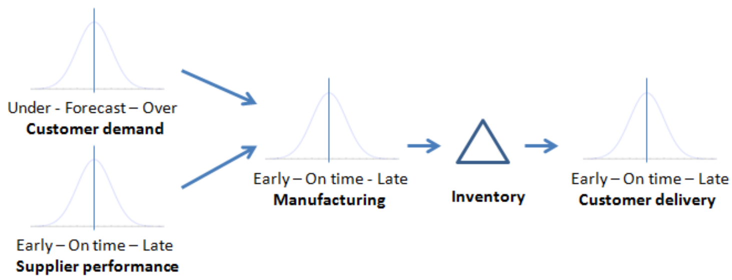


Figure 3-4: Uncertainty in the supply chain, adapted from Davis (1993)

3.4.2 (Un)productive inventory

Procter and Gamble uses an extra categorization of *performing* and *unproductive* inventory to identify excessive inventory which should be taken care of. The total size of the inventory remains the same, only a distinction is made to signal inventory that is not used or tends to lose value in the near future. This part of the inventory is called unproductive inventory (UPI) and consists of four different categories: red, orange, yellow (R-O-Y) inventory (together called non-performing inventory, NPI) and dead stock. All the on-hand stock minus the un-performing inventory is called performing inventory.

3.4.3 Inventory lifecycle

Depending on the stage of the product lifecycle, different inventory elements (e.g. cycle stock, safety stock) need more management attention. Although this research only focuses on s.k.u. in the mature part of the lifecycle, to be complete here other elements are discussed briefly.

Figure 3-5 gives an overview of the inventory elements during a product lifecycle (growth, maturity and decline). The inventory growth phase start when the first production is started until these quantities are being shipped to the customer. In this phase, anticipation stock (2) is kept to cover for the hard to predict demand.

During the mature period of the product, just before the inventory hits the safety stock it is replenished (5).

The decline phase starts as soon as the production of the product is terminated until the last order has been fulfilled (Pourakbar, van der Laan, & Dekker, 2011). In this phase inventory management focuses on having enough inventory to deliver to demand, but few enough so no NPI (6) is left.

In Figure 3-5 the inventory position and inventory on hand are depicted as if demand and production are constant. In reality this is not the case.

Products in different stages of the lifecycle have the need for different managerial approaches. However, due to the large impact on inventory of s.k.u. during the mature phase of the lifecycle, only this phase is considered.

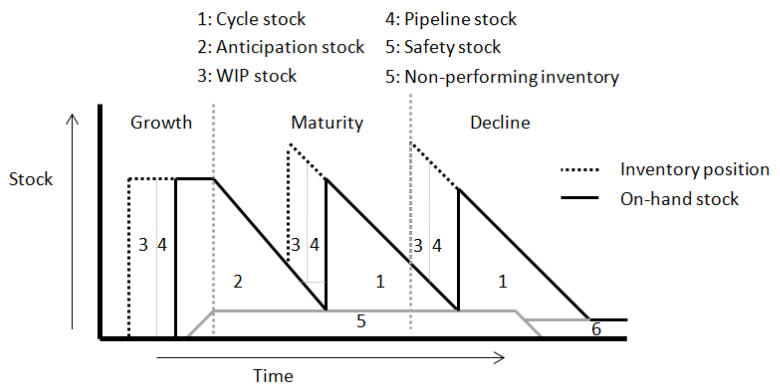


Figure 3-5: Overview of the different inventory types and components adapted from de Kok, Fortuin & van Donselaar (2012)

3.4.4 Units of measure

There are multiple units of measure are used to express the size and performance of inventory (Table 3-5). These units of measures both have advantages and disadvantages which are discussed now.

Measure	Short description	Used to
Base unit of measure (BuoM)	Way of expressing the physical size of a product type (cases, pallets)	Get impression of physical size of the inventory
Statistical unit (SU)	1 SU equals the average one year usage of a product by a common American family	Get impression of the size of inventory relative to usage
Product Value ($)	Unit value when sold to customer	Identify high value products
Days forward coverage (DFC)	Number of days that can be covered with the current stock compared with the current expected demand	Get impression of relative size of inventory compared with other products and markets

Table 3-5 Different units of measure for inventory

Although it always depends on market and supply chain conditions what a healthy amount of inventory is, a study on inventory across different markets like fast moving groceries and non foods, showed that on average inventory levels range between 8 and 25 days forward coverage (van Goor, Kruijtzer, & Esmeijer, 1990).

Multiple costs factors can be described relating to inventory management which are elaborated on in **Error! eference source not found.**. These factors consist of the unit value (v), the carrying charge (r), (hence, storage costs (C_s) = *vr*) and the ordering costs (C_o).

3.4.5 Inventory aggregation levels

Decisions on inventory management in the end have to be made on the level of an individual product. This is
s.k.u. called a stock keeping unit (s.k.u.) which is defined as an item of stock that is completely specified as to function, style, size, color and location (Silver & Peterson, Decision systems for inventory management and production planning, 1985).

Category Besides the s.k.u. an important aggregation levels is the product category. At this level, the aggregation is based on similarities in product purpose and strategic alignment. This creates manageable groups. Depending on the importance of a category, a demand planner is assigned one or more categories to manage. Most of the time, a plant is dedicated to a certain category as well. The strategic leadership for a sector is performed by a GBU as explained in chapter 1. Other levels of aggregation can be found in **Error! Reference source not ound.**.

3.4.6 Concluding remarks on the inventory analysis

This paragraph introduced the most important inventory categories in a supply chain (WIP, pipeline and finished product inventory). Thereafter the most important elements of the finished product inventory were elaborated on. This resulted in a distinction between performing and non-performing inventory. During the mature phase of a product life cycle, the main focus of inventory models is on the performing inventory by calculating and managing the right amounts of safety and cycle stock.

The most important cost variables for inventory management are introduced: the unit value (v), the carrying charge (r), (hence, storage costs (C_s) = *vr*) and the ordering costs (C_o).

Finally, commonly used units of measures were introduced such as the 'base unit of measure', 'statistical unit' and 'days forward coverage'. In order to analyze the inventory within P&G, the aggregation method for s.k.u. at P&G is explained.

3.5 Findings of the supply chain analysis

The most important performance measure in a supply chain is the service level. In this thesis the P2-service level is used which is expressed as the amount of products that can be delivered to the customer directly from shelf, which is known as case fill rate (CFR).

Three performance drivers are identified: 1) demand of finished products, 2) supply chain capabilities and 3) inventory.

Forecast of demand of finished products are made among else to support accurate replenishments of distribution centers (short term) and need for additional production capacity (long term). The inaccuracy of this forecast is used to give feedback on the forecaster. Variation of the errors of the forecast of total demand over the lead time is used to plan the safety stock with.

In order to measure the supply chain capabilities the lead time can be measured. This is the amount of time it takes to produce and deliver finished products to the customer. Longer lead times make supply chain inflexible because changing demand during the lead time can`t be anticipated on. Hence, the lead time is an important driver for inventory and CFR.

Finished product inventory is kept to achieve economies of scale, comply with technical constraints and to cover for uncertainties in the supply chain discussed above. Although inventory helps to improve the case fill rate, stocks need to be minimized to save costs. Extreme levels of inventory are defined as non-performing inventory (NPI). Due to size and manageability, safety stock and cycle stock are the most important categories of finished product inventory. Several stages of the product lifecycle need different inventory management approaches. This thesis focuses on the mature stage of the lifecycle.

4. Inventory management

Inventory among else is used as buffer to cover for demand due to several types of uncertainty and to benefit from economic production characteristics. However, keeping inventory costs money. In the best case scenario, just enough inventory is kept to achieve the target performance with.

Inventory management focuses on this objective and is discussed in this chapter. In order to explore different elements of inventory management in a structured way and prevent confusion, first a framework is discussed.

4.1 Introduction on the inventory management framework

Silver and Peterson (1985) and van Goor et al (1990) indicate that for the design of inventory management systems, answers should be found for the following questions:

1) What s.k.u. should the control system be focused on? *(4.2.1)*
2) What form should the inventory system take? *(4.2.2)*
3) What cost or service objective should be set? *(4.2.2)*
4) When should the replenishment order be placed? *(4.3)*
5) What should the quantity of the replenishment be? *(4.3)*

A framework is created which identifies two pillars of inventory management: 'Plan the work' and 'work the plan'. These pillars are based on the questions posted above and the process analysis performed during the case study (chapter 6.1). It structures inventory management into two phases as shown in Figure 4-1. Questions 1 up to and including 3 regard the 'Plan the work' pillar, questions 5 and 6 regard 'Work the plan'.

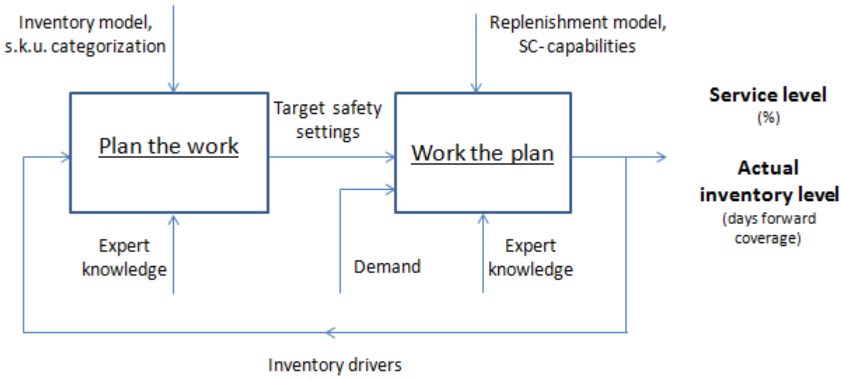


Figure 4-1: Framework for analyzing inventory management

This framework is used to easily communicate and discuss relevant elements of inventory management. The remaining part of this chapter discusses the two pillars in this framework.

4.2 Plan the work: setting targets

Planning the work is defined by the answers on the following questions:

1) What s.k.u. should the control system be focused on?
2) What form should the inventory system take?
3) What cost or service objective should be set?

4.2.1 S.k.u. classification

Depending on the size of a company, the number of s.k.u. can exceed 100.000. Due to time and cost constraints, it is not possible to retrieve detailed information for every s.k.u. to accurately manage the inventory with. Therefore s.k.u. are categorized to efficiently and effectively manage inventory. Based on the s.k.u. classification, the detailed planning is just used for the important s.k.u. The less important s.k.u. are managed using less complex and more generic inventory management rules.

Table 4-1 shows the considerations of the reviewed methods for s.k.u. classification. This review is elaborated on in **Error! Reference source not found.**. The Simple Pareto Analysis categorizes products using the Pareto rinciple (the 80 -20 rule) but has the disadvantage of creating uni-directional categories. The joint criteria matrix overcomes issues with uni-directionality but creates an impractical amount of categories. The method proposed by van Goor et al (1990) overcomes both problems but doesn`t clearly define what thresholds to use.

Therefore the author suggests to combine the focus groups by van Goor et al and the joint criteria matrix by Flores and Whybark. This results in a multi criteria matrix in which per parameter, two groups are created based on the Pareto principle. The author calls this Joint Focus Matrix as it combines only four practical focus groups. In chapter 7 this matrix is used to categorize the s.k.u. within Baby care.

The benefit of using this matrix which isn`t defined in literature, is that creates a manageable number of categories but still uses the power of the Pareto as decision rule.

Method	Advantage	Disadvantage
Simple Pareto Analysis creates 3 categories using Pareto on one parameter **(Berniker & McNabb, 2005)**	- Efficient categorization of products (Wendell, 1987)	- Uni-directional (increasing inventory can also reduce stock out cost) -
Joint criteria matrix creates 9 categories using Pareto on two parameters **(Flores & Whybark, 1986)**	- Efficient categorization of products, using Pareto - No uni-directionality and one-dimensionality	- 9 categories are often impractical to manage - One-dimensional, high volume & low value products are managed same way as high-value & low volume products
Focus groups creates four categories using Pareto on two parameters **(van Goor, Kruijtzer, & Esmeijer, 1990)**	- Efficient categorization of products - No uni-directionality and one-dimensionality - Manageable amount of categories	- No method for the cut-off point is defined between the groups
Joint Focus Matrix	- Combines the joint criteria matrix and the focus groups	

Table 4-1: Consideration of three commonly used s.k.u. classification methods and a new proposed method

4.2.2 Inventory settings

Four types of order replenishment systems (see paragraph 4.3) can be selected based on strategic considerations to determine both the right moment and the right amount of products to replenish the DC with (van Goor, van Amstel, & van Amstel, 1989). The key settings which have to be determined independent of the selected system used are:

- The target safety setting strategy.
- The optimal replenishment quantity.

Target safety setting strategies

Different methods such as an analytical model or simulation (discussed in chapter 5) can be used to retrieve the right safety stock settings. The output of such inventory models, are a *proposed* target safety stock setting.

In the safety settings strategy in essence two types can be distinguished, being (1*) fixed safety stock* (in SU) or a (2) *safety time* (in days) (Rosen, 2009). The relation between these 2 variables is shown in Equation 10. A fixed target safety stock is a predetermined buffer which doesn`t change over time. Safety time creates a time buffer by replenishing inventory requirements certain days before the actual need. To predict the demand for this period, the forecast is used.

$$SS(days) = \frac{SS\ (SU)}{\mu_{demand}}$$

Equation 10

SS	= suggested fixed safety stock (SU) according to inventory model
SS	= Dynamic safety stock setting (days)
μ_{demand}	= Historical average daily demand (SU/day)

Optimal lot size strategies

A lot size strategy determines what amounts of products should be replenished each time. The use of a particular lot sizing strategy affects the target safety stock settings to some extent (chapter 5), but moreover affects the size and cost for inventory in two ways:

1) The number of orders made effects the total order costs
2) The size of the orders, effects the total average inventory and thus the costs for the total average inventory.

The economic order quantity (EOQ), always should provide the least expensive result. However, it uses assumptions which often do not hold in reality, e.g. the assumption of constant demand. Moreover, there are occasion in which deviation from EOQ is justified such as the need to replenish a minimum order quantities (MOQ). Because this research focuses on achieving the target CFR while minimizing the total average inventory, no attention is given to the inventory cost on which many lot sizing strategies are focused. Thus, the lot-for-lot strategy is selected because it results in the lowest average inventory (Reid & Sanders, 2013).

Lot sizing strategy	Concept	Advantages / disadvantages
EOQ	Determines the economical order quantity given a set of deterministic conditions (static)	+ minimizes costs and inventory size - Assumes deterministic demand & lead time
Silver-Meal Heuristic	Focus on minimizing the cost of operations	- no focus on inventory size in particular + low costs
Lot for lot	Replenish exactly what is needed (dynamic)	+ minimizes total average inventory - high cost for ordering

Table 4-2: Lot sizing strategies

4.2.3 Rightness values

The values that are being used for calculating the target inventory settings should reflect reality. There are two reasons why the used values can differ from what it should be: Firstly, strategic behavior can make stakeholders manipulate values to their favor (Ten Heuvelhof & De Bruijn, 2012). E.g. having high stock settings is beneficial for most stakeholders while it increases the chance on a high CFR. Thus, it makes sense to opt for higher values when calculating the target inventory settings.

Secondly, to set the right target inventory settings, a feedback loop is needed, to adapt the inventory settings to the current situation. The settings should be used for a longer period of time in which no significant structural changes take place. During such a period, inventory is affected by stochastic behavior of both demand and supply lead times. Hence it is possible that certain periods can pass without even the safety stock being touched (creating dead stock) but also periods with a lot of safety stock being used. When this happens without large structural changes in the supply chain (extra trade lanes, production facilities, hard changes), there is *no need* for adjusting the parameters. (Rosen, Dr. Ir., 2013).

4.3 Work the plan: the replenishment system

After having determined the right settings during the planning phase, now the replenishment processes can be executed. The types of system that can be used for replenishment are grouped using two dimensions: Information and control.

Global information implies that the decision maker has an overview of all data regarding demand, costs and inventory status of all locations in the system. Centralized control means that one decision maker makes central decisions on which locations needs the inventory the most. Table 4-3 gives an overview of possible replenishment systems for each combination.

Control Information	Centralized	Decentralized
Global	-Vendor managed inventory (VMI) -Distribution Requirements Planning (DRP-I)	-DRP-I - Base stock replenishment systems
Local	*Doesn`t make sense*	Base stock replenishment systems

Table 4-3: Information and control, adapted from Silver et al (1998)

P&G has global SC data available which gives the opportunity to select one of the global replenishment systems shown in Table 4-3. VMI expands the manufacturers` control over in supply chain by including the control over the customers` warehouse. Currently, this type of system is in use for some of the large customers of P&G. However, for the most part DRP-I is used (also for the Baby care category).

One important difference between the use of DRP-I and the base stock replenishment systems is that the latter are static over time: the main focus is on when to replenish a DC instead of when the inventory is needed at the DC. In order to clarify this and other differences between the dynamic DRP-I and the static base stock replenishments systems, both are now discussed and compared.

4.3.1 Base stock replenishment systems

Table 4-4 gives an overview of the four possible base stock replenishment systems (Silver & Peterson, 1985) (van Goor, Kruijtzer, & Esmeijer, 1990). The systems are elaborated on in **Error! Reference source not ound.**.

Moment of ordering	Order quantity independent of inventory on moment of ordering	Order quantity dependent of inventory on moment of ordering
Continuous ordering (dynamic)	(s, Q)	(s, S)
Periodical ordering (Static)	(R, Q)	(R, S)

Table 4-4 Overview of four possible ordering systems (s = order point, R = review period, Q =order quantity and S= order-up-to-S), adapted from van Goor et all (1990).

The base stock replenishment system is defined by its re-order point and the order quantity. Equation **11** shows how the re-order point is determined for base stock replenishment systems. The order quantity is determined by one of the heuristics discussed in paragraph 4.2.

$s = SS + \mu_D L$	s	= re-order point (SU)
Equation 11	SS	= safety setting (SU)
	μ_D	= Historically average daily demand (SU/day)
	L	= Lead time (Day)

The elements of equation 11 are determined during 'plan the work'. This results in a fixed re-order point which automatically triggers a new replenishment whether this is functional or not. E.g. when the actual demand is lower than the historical average daily demand, it is not necessary to trigger a replenishment.

4.3.2 Distribution requirements planning (DRP-I)

DRP-I

In essence, DRP-I determines the time-phased requirements for replenishments at the distribution centers. In order to do so, it uses data on the forecast of demand.

Given the lead time, the safety stock parameters and an order quantity (based on one of the heuristics of chapter 4.2), a DRP system analyzes the current inventory level. Rather than using a fixed order-point system, each DC uses a master schedule.

This a projected replenishment pattern to satisfy the net requirements (Table 4-5). This schedule reflects the evolution of inventory over time by using the forecasted demand over the lead time. Only when the inventory is expected to drop below the safety setting, a replenishment is triggered. This results in a dynamic re-order point (van Goor, van Amstel, & van Amstel, 1989).

Lead time: 2 periods
Safety stock: 400 units
Order quantity: 550

Time Period	0	1	2	3	4	5	6	7	8
1. Projected gross requirements		200	180	210	190	200	210	170	230
2. Projected net inventory at end of period	900	700	520	860	670	470	810	640	410
3. Planned order receipts		0	0	550	0	0	550	0	0
4. Planned order releases		550	0	0	550	0	0	0	0

Table 4-5: Distribution requirements plan Master schedule

4.3.3 Advantages of DRP-I compared with base stock replenishment systems

In essence both with DRP-I and the classical systems, a replenishment is triggered by the inventory dropping below a re-order point (either static or dynamic). Also, for all systems the replenishment quantity can be determined using a heuristic as explained in paragraph 4.2.2.

Although DRP-I has a lot of similarities with the base stock ordering system, Van Goor et al (1989) summarize three key differences which support the choice for DRP-I. Base stock replenishment systems;

1. do not anticipate on fluctuation in demand,
2. use average demand and do not consider irregular demand patterns,
3. determine when the DC needs the replenishment instead of using a fixed re-order point

The last two differences should be evidently after reading the previous sections. However, the first difference needs more explanation.

Multi-echelon

To understand the first difference, one should understand the dynamics of demand in multi-echelons which are apparent in each supply chain (Figure 4-2). Van Goor et al (1989) indicate that a distinction is needed between dependent and independent demand. *Dependent demand* is the demand from an echelon directly downstream in the supply chain or is calculated using independent demand whereas *independent demand* is coming from the final customer of a finished product for which a forecast of demand is needed.

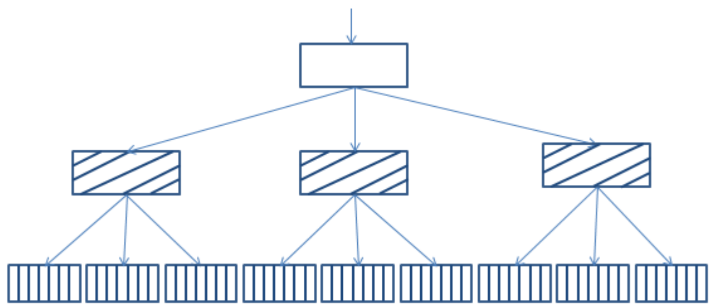


Figure 4-2: Multi-echelon inventory system

Bullwhip effect

Base stock replenishment systems focus on the replenishment of echelons independent from the flow of the inventory levels at other echelons and assume that an independent demand between different echelons in the supply chain. A slight change in independent demand often is seen as a changing market. Silver et al (1998) discuss that this increase of demand variability moving up the supply chain results in increased inventories up in the supply chain. Graphically, this amplification looks like the cracking of a whip for which the motion near the handle is amplified towards the end of the whip. DRP-I systems use demand between different echelons in the supply chain as dependent demand to minimize the bull whip effect.

4.4 Findings for inventory management

In this chapter an inventory management framework is introduced to communicate different elements for inventory management in a comprehensive and structured way. The framework consists of a 'Plan the work' pillar and a 'Work the plan' pillar.

Plan the work

In order to properly plan the work for hundreds of s.k.u., first a classification is needed to categorize s.k.u. (e.g. based on volume, value or volatility). For important s.k.u. more detailed data should be used to optimally plan the inventory settings to get high performance on these s.k.u.

Inventory management strategy

Before executing the replenishment procedures, two inventory settings have to be determined, the target safety setting and a lot size strategy. Firstly, based on the performance drivers described in paragraph 3.2-3.4, target safety settings are calculated. Different methods such as analytical models and simulation are possible. Different safety setting strategies are available like dynamic safety time (targets replenishments days before the actual need) or a fixed safety stock (SU). Secondly, a lot sizing strategy has to be determined. The combination of inventory settings for a certain product categorization will be referred to as inventory management strategy in the remainder of this thesis.

Work the plan

After having selected the target safety stock setting, a replenishment system should aim at getting the actual inventory levels as close to the targeted inventory levels as possible. DRP-I determines the time-phased requirements for replenishments at the distribution centers. In order to do so, it only uses independent demand.

5. Methods for finding the optimal inventory level

Literature clearly makes a distinction between analytical and simulation models (Haugh, 2004) (Shanthikumar & Sargent, 1983):

Analytical methods

- The *analytical model* is a set of multiple equations that characterize a system. Its solution usually uses either an analytical equation or a numerical algorithm to obtain a desired result (point-estimate). This often requires less work than creating a simulation model, however the analytical model doesn`t suffice for complex problems.

Simulation

- A *simulation model* is a dynamic model of a system that performs the operating behavior and contains its functional relationships. From a certain starting situation a model simulates the evolution of the system which is able to create more realistic results compared with analytical models.

Although simulation models deliver more realistic results than analytical models do, costs for developing and using the simulation in general are higher.

Paragraph 5.1 elaborates on the analytical approach which is currently used at P&G. Paragraph 5.2 discusses the possibilities when using simulation methods and elaborates on Monte Carlo simulation in particular.

5.1 Analytical method

Target safety stock

Safety stock is a part of the inventory that is held in excess of expected demand due to variable demand rate and/or lead time (Stevenson, 2005). Silver et al (1998) derived Equation 12 up and until Equation 15 which underpin the analytical method to obtain the target safety stock for finished products.

$\boldsymbol{SS = k_\beta \sigma_{EE}}$ Equation 12	SS = safety stock (SU), expected net stock immediately before the arrival of a replenishment order $\boldsymbol{k_\beta}$ = safety factor for P_2-service level (fill rate) $\boldsymbol{\sigma_{EE}}$ = Standard deviation of the estimated error (SU) during the replenishment lead time

Where

$\boldsymbol{\sigma_{EE} = \sqrt{\mu_L \sigma_D^2 + {\mu_D}^2 \sigma_L^2}}$ Equation 13	$\boldsymbol{\sigma_{EE}}$ = Standard deviation of the estimated error (SU) during the replenishment lead time L = Lead time with expected average $\boldsymbol{\mu_L}$ and variance $\boldsymbol{\sigma_L^2}$ D = Demand with expected average $\boldsymbol{\mu_D}$ and variance $\boldsymbol{\sigma_D^2}$

Risk factor

The k-factor represents the number of standard deviations of the estimated errors that needs to be kept to achieve a target service level (CFR). Using Equation 14 and Equation 15, the value for k_β can be retrieved.

$\boldsymbol{G(k_\beta) = \frac{Q}{\sigma_{EE}}(1-\beta)}$ Equation 14	$\boldsymbol{\beta}$ = P_2, target service level (%) $\boldsymbol{\sigma_{EE}}$ = Standard deviation of the estimated error (SU) during the replenishment lead time Q = Average order quantity per cycle (SU) $\boldsymbol{G(k_\beta)}$= Tabulated function of the standard normal distribution
$\boldsymbol{G(k_\beta) = n(k_\beta) - kN(-k_\beta)}$ Equation 15	$G(k_\beta)$= Tabulated function of the standard normal distribution $n(k_\beta)$ = Standard normal distribution $N(k_\beta)$ = Cumulative standard normal distribution

The result of the model is a safety stock setting which can be expressed as safety stock (a fixed amount) or safety time (expressed in days). Using safety time with value *x* targets a replenishment to be delivered at a DC, x days before the replenishment is actually needed.

Whybark and Williams (1976) pose that uncertainty in timing of demands should be dealt with using safety time, whereas uncertainty in quantity should be dealt with using safety stock. However, other literature like Buzacott and Shanthikumar (1994) argue that in general a fixed target safety stock setting is preferred over target time.

5.2 Opportunities of the use of Monte Carlo analysis

5.2.1 The use of a simulation model

Simulation models mimic the operating behavior of a system. To understand the most important behavior and to create a simulation model often is more time consuming (and expensive) than the use of an analytical model. However, for complex problems often an analytical solution doesn`t suffice to describe the system and solve the problem with (Verbraeck & Valentin, 2006).

Furthermore, simulation has the opportunity to create insights on performance of the system in certain scenarios which are too risky or expensive to test in the real system (Van der Aalst). For P&G it is not acceptable to find the right inventory settings by trial and error. Although it currently uses an analytical model, there hasn`t been a quantitative way to validate the model (Farasyn, 2012).

Also, currently it is not clear for planners at P&G how the chosen safety settings affect the inventory performance (Alves, 2013): The dynamics of the real inventory system are perceived as a black box. Because the effects of choosing between safety stock and safety time on the inventory performance are not clear, it is hard for the users to make well-founded decisions. As stated by Aguilar et al (1999), for such cases simulation is an effective tool to communicate process analysis results and can improve process performance.

5.2.2 The use of Monte Carlo analysis

Monte Carlo

Monte Carlo (MC) analysis is a computerized mathematical technique that produces a sequence of numbers from certain random variables that accord with a certain probability density function, and use these as an input variable sequence to perform experiments with and solve complex problems (Jaio & Du, 2010).

Monte Carlo is based on two mathematical theorems: the law of large numbers and the central limit theorem. Not only can MC simulation, considering the first theorem, show an *estimate of the expected result (*which also is done by an analytical model), it also returns an *estimate of the uncertainty in this estimate* (Dunn & Shultis, 2011). These characteristics make MC useful to account for risk in quantitative analysis and decision making (Palisade, 2013).

Recent studies have been using Monte Carlo simulation for inventory management problems (Cáceres-Cruz, Grasman, Bektas, & Faulin, 2012) (Jaio & Du, 2010). However little effort has been spent in using Monte Carlo simulation specifically to explore the risks involved in the analytical model for determining optimal safety stock levels.

5.3 Findings on methods for finding optimal inventory

Analytical models are relative cheap to develop but produce less realistic results. Simulation models require more effort to simulate complex functional relationships but have distinct benefits like the opportunity to test scenario`s and communicating the effect of decisions. In particular, Monte Carlo analysis is used to simulate a sequence of numbers based on realistic probability density functions to perform experiments with. The combination of both methods can simulate realistic behavior of performance measures based on certain scenarios. Moreover, the simulation model can be used to add value on the estimates of the uncertainty of the optimal inventory settings made by analytical models.

6. System analyses of the Baby care category

The TIP-framework as proposed by Koppenjan and Groenenwegen (2005) is used to analyze current inventory management at P&G for the Baby care category which results in the requirements for the simulation model. This framework is used as a structured guidance to map key elements in a supply chain. The TIP-framework is chosen while it fits the complex nature of a supply chain both from a technological and process perspective.

First the structure of processes (P) is mapped, after which the technical (T) aspects are discussed in paragraph 6.2. In paragraph 6.3 the institutional analysis (I) is performed after which conclusions on the current situation are drawn.

6.1 Process analysis

The inventory management processes are analyzed based on the categorization made in chapter 5, 'Plan the work' and 'Work the plan'.

Blank intentionally

different types of business intelligence) (Vergouwen, 2012).

Blank intentially

6.2 Technical analysis

First the adaption of the analytical model by P&G is elaborated on. Next, a classification of the s.k.u. in the Baby care category is suggested after which some technical elements of the supply chain are discussed.

6.2.1 Deviation of literature for the analytical model

At P&G different analytical models (Table 6-1) are developed for calculating the optimal inventory settings. The decision for a model depends on the inventory type and the supply chain structure. For the calculation of target safety settings for finished products at a local DC (like Rumst DC) both the FIM and XIM model can be used. However, because most supply chains at P&G use the model at a central point to calculate target settings for a whole supply chain (thus, multiple DC and inventory at the plant itself), the XIM model is used.

Blank intentially

COV_{EE}

Blank intentially

not found..

Blank intentially

Blank intentially

Glide-path target

The institutional analysis resulted in a list of commonly known performance measures in a supply chain. One

Blank intentially

Part III:

Inventory simulation model

In this part the development of the simulation model is described. Next, scenarios with different safety settings are introduced to be tested with the simulation model. Hereafter, the simulation experiments are performed and the findings are introduced.

7. Inventory management simulation model

This chapter elaborates on the design process and the resulting simulation model for testing inventory management strategies with. First the design approach is introduced, after which the consecutive steps are discussed. The chapter finishes with the simulation model that can be used for experiments.

7.1 Design approach

For the design approach of the simulation model three viewpoints have been combined. First, the simulation method of Banks (1999) is used for general modeling methods. Secondly, the META model (Herder & Stikkelman, 2004) is used. It is a design framework which considers design as "selecting an instance in the design space that meets the objectives and constraints". The model starts with defining the model requirements and the possible solution space to answer to these objectives with.

Last, the spiral model (Boehm, 1988) is used for the approach. The spiral model consists of several iterative stages in which the model is designed, tested and adapted resulting in a robust model design. This approach is visually shown in Figure 7-1 and is used an outline for the following two chapters.

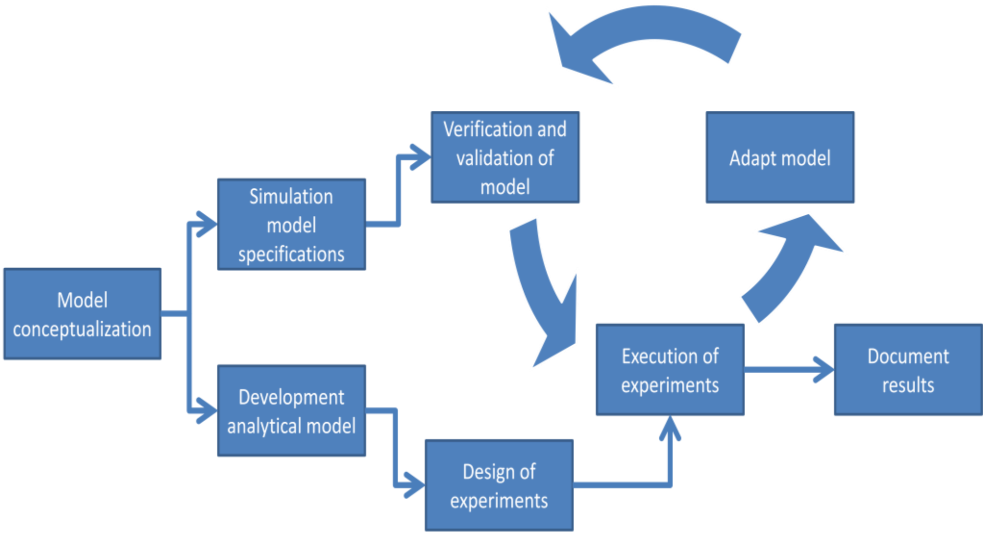


Figure 7-1: Design framework for an inventory management simulation model

7.2 Model conceptualization

The definition of the model conceptualization consists of three parts. First, the definition of the objectives of the model. Secondly the demarcation of the model and finally the conceptualization of the model. The model objectives and its boundaries need to be clearly defined. Focusing on the model objectives, the demarcation is discussed. The demarcation is used to reduce the complexity of the reality although but still be able to use the model for relevant analyses. The result is a conceptual model which shows all the relevant factors and processes to characterize the system with.

7.2.1 Model objectives

The previous chapters have described inventory management according to literature and the applied case at P&G. It was defined that during the 'Plan the work' phase, the safety settings are selected which are the core of the 'Plan the work' phase. Moreover, the processes during the 'Work the plan' phase were defined. Together, both phases result in the performance of inventory.

Insight in the dynamics that lead to the current performance of inventory at the Baby care category is can lead to conclusions on the quality of certain inventory management strategies. However, currently there is no appropriate method to assess the performance of different strategies.

Therefore, the three-folded objective to be achieved with the simulation model is defined as follows:

1- Create insights on the dynamics of performance measures with the use of different inventory management strategies.
2- Quantify current inventory performance
3- Test the practical applicability of an analytical inventory model to achieve target case fill rate of 99% and minimize inventory levels

Inventory performance

Regarding inventory performance, the scorecard analysis showed that that there are multiple measures for performance of inventory in a supply chain. Given the results of the analysis a selection is made. First of all the focus is on the case fill rate (%) which is the overarching goal in the supply chain. The P2-service level is used because this is the same measure as used at P&G. Next, the average inventory is used. Not only to gain insights on the dynamics of inventory but also because inventory is an important indicator for costs. Finally, yellow NPI is included to get a sense of extreme inventory levels.

7.2.2 Demarcation of reality

The simulation model can`t and should not entail all details of reality. Putting too much exact details into a model results in over fitting. Over fitted models are good to show the behavior of the system in the past but won`t reflect the systems behavior looked for (Silver N. , 2012). The demarcation is shown in Table 7-1.

Demarcation	Explanation
Production time errors are excluded from the model	The COV_{PE} are zero for almost all s.k.u. in the Baby care category (P&G, 2012).
Demand is known one day in advance	Most of the time exact demand is known one or two days in advance (Alves, DRP planning at P&G, 2013). While influence on the safety stock is expected to be small (while all s.k.u. have a lead times of at least two days), this assumption makes the model less complex.
The simulation model is designed on s.k.u. level	In order to compare the analytical model with the simulation model, focus should be on the same aggregation level.
Lot for lot strategy is used	Baby care uses a lot for lot strategy to replenish its DC with. Therefore this strategy is used for replenishments. This strategy is in line with achieving the project objective of minimizing total inventory (and not inventory costs).
No costs are included	In line the project objective only the size of inventory is considered. Any inventory costs (e.g. re-order costs or storage costs) are excluded from the model.
Seasonal and other long term trends do not influence demand	Long term trends could increase the average demand over time. However, for simplification reasons it is left out of the model.
The human intervention is not adopted in the model.	In reality not all suggested replenishments are (fully) actually executed. However, the dynamics of these interventions cannot be modeled and thus are left out.
Model includes single product, single DC and single plant	To accurately analyze the dynamics of different safety setting strategies, the SC is reduced to its minimum.
Inventory is modeled at one echelon only	In reality, some inventory is kept at the plant. However this research focuses on a single echelon inventory for which this buffer at the plant only would increase the capacity to the DC.
The glide-path review is left out of the simulation	In reality, the glide-path makes DRP planners lower production at the end of each month due to high stocks. However, because the glide-path focuses on

	segment level, in is no use to incorporate the effect on s.k.u. level.
No distinction is made between orders from the distributors	The average demand is important for the model, however, to whom the products are shipped is not.
Only mature stage of the lifecycle is modeled	Phase in and phase out of products involve detailed information and interaction of planners. As explained, this is not included in the model.
Daily demand doesn`t vary during the week	Although in reality demand varies during the week, in the simulation this variation is not included.
Only yellow NPI is included	While only the mature part of the lifecycle is taken into account, no red or orange NPI is created. Yellow NPI is measured using the following rule: Yellow NPI is all the stock above 135% of cycle stock and safety stock.
Smallest time step is one day	Because the inventory management processes occur on a daily basis, the smallest time step is one day. This also defines that a discrete model is developed.
Minimum delay is one day	Although in reality deliveries can be delayed by hours, in the simulation model, the smallest time step is one day. Therefore, the minimum delay is one day.

Table 7-1: Demarcation of the system for the use of the simulation model

7.2.3 Conceptual model

After defining the objectives of the simulation model and demarcating the system, now a conceptual model is defined. Based on the performed process analysis, a functional model is made of the inventory replenishment system. Figure 7-2 shows the steps that the simulation model should incorporate in order to resemble the processes to achieve the model objectives with.

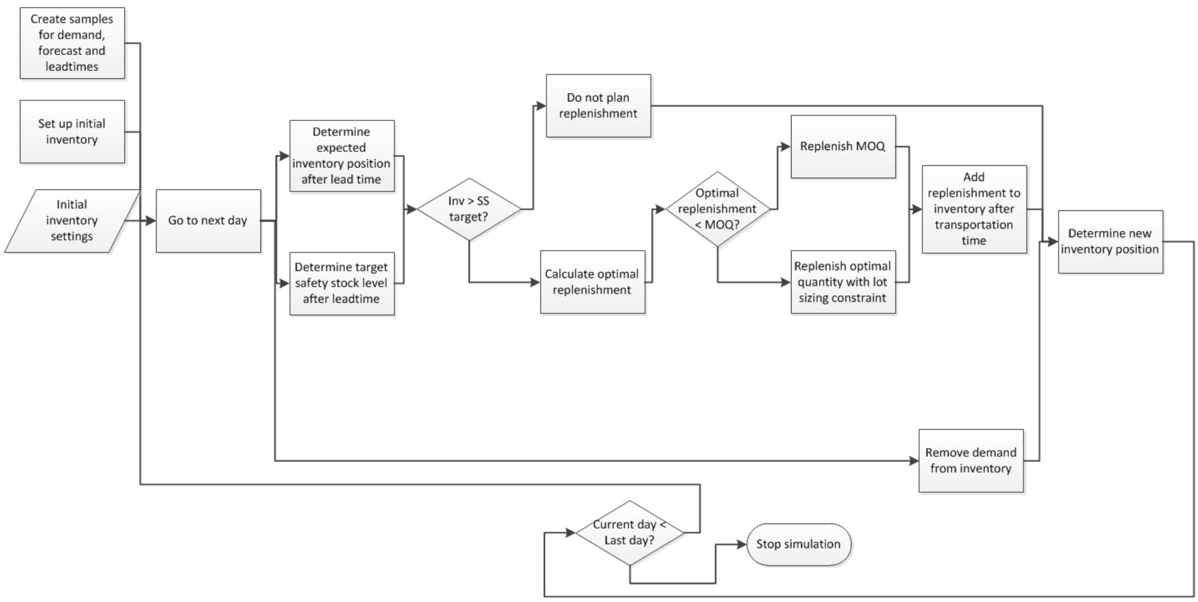


Figure 7-2: Conceptual model of inventory management with a lot for lot strategy

7.3 Simulation model specifications

In order to develop a, model based on the model requirements defined in the previous section, the following steps are performed. First, a simulation environment is selected in which the model is built. Next, data analysis is performed to select the input variables which are used in the model. Thirdly the choice for distributions is discussed. Finally, a part of the coded simulation model is elaborated on.

7.3.1 Simulation archetype

In order to select the right properties for the simulation environment first the model archetype has to be identified. It considerations are shown in Table 7-2.

	Static vs. dynamic	Discrete vs. continuous	Deterministic vs. stochastic
Inventory simulation model	Dynamic	Discrete	Stochastic

Table 7-2: Simulation archetype

The first consideration is whether the model resembles a state on a certain point in time (static) or evolves over time. The evolution of inventory over time is seen as a dynamic process. An example of a static model is the description of a molecule.

The second consideration regards how the model evolves over time. Continuous means that at every point in time the state of the system can change. In this case, the model changes in discrete time steps: The need for a replenishment is reviewed daily.

Finally, the model is classified as either deterministic or stochastic. Models that do not contain any random (stochastic) components are defined as deterministic. For a stochastic element there is no clear relationship between time and the value of the element. This applies to some of the elements of inventory management, such as the average daily demand. It`s only possible to use a probability distribution to represent the parameter. This also means that the output of stochastic models has to be interpreted as being an estimate of the true characteristic of the system.

Discrete event simulation

Kelton and Law (2000) define a model with above discussed characteristics as a discrete-event simulation model.

7.3.2 Simulation environment

Discrete-event simulation in essence could be solved by hand calculations but the size and complexity make the need for computer power necessary. Several simulation packages are available with specific (dis-)advantages depending on the type of model that is designed.

In order to select an appropriate simulation environment, a set of functional requirements is defined based on the model objectives.

- The environment should cope with the model archetype requirements
- Monte Carlo analysis is needed to analyze the risk profile of safety setting strategies
- It would be an opportunity to use the simulation model for additional purposes and other supply chains

Because of the distinct (daily) time steps identified in the inventory management system, the discrete event approach is selected. Available software packages are MS Excel and Arena.

For Monte Carlo simulation many distributions need to be drawn and easily be implemented as input variables for each iteration of a simulation run. Several software packages are available such as Cristal Ball and @risk. Both packages are add-ins for Excel. Also, iterations can be simulated using the visual basic (VBA) extension in MS Excel.

A combination of MS Excel (for the sampling) and Arena (for the discrete event modeling) could be used but the importing of sample data into Arena is expected to take relatively a lot of time. Therefore, only Excel is used. Excel has standard functionalities to create simple equations to simulate most of the simple system processes and create useful (graphical) results. For the more complex discrete events, visual basics is used. The use of Excel also has the benefit of being relatively inexpensive and used by many companies which makes the model widely usable.

7.3.3 Data analysis

The input parameters are listed in Table 7-3 and the output measures in Table 7-4. The data for all input parameters is stored in two central data systems; (1) IDF Inventory master (P&G, 2012) and the (2) IDF Lane master (P&G, 2013). The Inventory master extracts data from concerning demand and forecasting data. The Inventory master extracts information on lead time elements which are set up manually for each transportation lane of each s.k.u. in the Lane master.

Input parameter	Unit of measure
Demand & forecast	
Weekly COV_{FE}	%
Forecast Bias	%
Average daily demand	SU
Number of shipping days per week	Days
Distribution of weekly demand per day	%
DRP Planning	
Average lead time	Days
COV_{TTE}	%
Production capacity plant	SU/day
Safety stock setting	SU
Safety time setting	Days
Minimum order quantity	SU

Table 7-3: Input parameters for the inventory management simulation model

Output measures	Unit
Performance measures	
Case fill rate	%
Average inventory	SU
Average safety stock level	SU and Days
Average NPI	SU
Other output measures	
Bias	%
COV_{FE}	%
Forecast	SU
Demand	SU

Table 7-4: Output measures of the inventory management simulation model

Validation of these data sets resulted in deviations from reality, such as lead times of two instead of three days and different MOQ (Alves, 2013). Although the deviations are apparent, it can be coped with by using the same input values for both the simulation model and the analytical model for validation. When analyzing the simulation results, the notion for these deviations should be taken into account.

7.3.4 Selecting probability distributions

An important part of the specification of the model, is the selection of the right distributions to draw the samples from both for the average weekly demand and the forecast error. Law (2011) describes a proper method in order to do so, first estimating the distribution and right parameters and secondly testing the goodness of fit.

Several distributions were considered to sample the demand from. One of the main considerations is the fact that demand cannot be negative which excludes the normal distribution. The demand should have a certain average demand and often has a long tail near the end which resembles very large orders. A triangular distribution is considered but the need for a maximum and minimum value is impractical from a data collection point of view.

For a set of demand data (n=76) for a particular s.k.u. the goodness of fit is tested using the Anderson-Darling test. This test is good for testing distributions with a long tail (Anderson, 2011) and shows that the gamma distribution is a good fit (**Error! Reference source not found.**). Hence, the gamma distribution can be used or the simulation of demand.

For the distribution of the forecast error Silver et al (1998) provide multiple arguments why a normal distribution suffices. However, Silver notes that one should always use a plot to verify.

7.3.5 Example of model logic

Here a part of the model logic for simulating forecast of demand and the actual demand is described **Error! eference source not found.** elaborates on all elements of the simulation model.

Because of the need to control the forecast error, the forecast is calculated using the sampled demand and the COV_{FE}. At the start of each iteration, for each day two random seeds are drawn. The random seed for the demand is used in an inversed gamma distribution, combined with the calculated α and β which are based on the average weekly demand and the weekly COV_{FE}. The result is sampled weekly demand which is evenly distributed over the seven days.

The second range of samples is used for the calculation of the forecast. One sample is used as input parameter for an inverse standard normal distribution and is multiplied with the weekly COV_{FE}. This is the relative forecast error and thus is used, in combination with the bias, to calculate the actual forecast with. The forecast error is the difference between the daily demand and forecast (Figure 7-3).

		Mon	Tue	Wed	Thu	Fri	Sat	Sun	Mon
Random seed demand		0.43	0.51	0.79	0.35	0.68	0.12	0.86	0.66
Daily demand (SU)		471.39	471.39	471.39	471.39	471.39	471.39	471.39	255.75
Weekly demand (SU)								**3299.75**	
Random seed forecast		0.57	0.14	0.96	0.06	0.47	0.48	0.57	0.91
weekly forecast error factor		0.23	0.23	0.23	0.23	0.23	0.23	**0.23**	2.21
forecast (SU)		375.00	375.00	375.00	375.00	375.00	375.00	375.00	0.00
Forecast error		-96.39	-96.39	-96.39	-96.39	-96.39	-96.39	-96.39	-255.7

Figure 7-3: Screenshot of the simulation model, focus on demand and forecast calculations

7.4 Verification and validation of model

Before the model can be used to perform tests with, first assessments are performed for the (1) verification and (2) validation of the model. The first assessment verifies that the conceptual model is coded in the right way, whereas the second assessment assesses if the model behavior resembles reality sufficiently (Verbraeck & Valentin, 2006). Part of the validation is to perform a sensitivity analysis.

7.4.1 Verification

The verification ensures that the conceptual model is translated using the right coding into a computerized model. Table 7-5 gives an overview of the used verification methods.

Verification method	Approved?
Conceptual model and model input is properly implemented on the computer	
- Structured walk-through	Approved
- Extreme values	Approved
Simulation language is properly used	
- Use of VBA debugger tool	Approved

Table 7-5: Verification methods

First a structural walkthrough of the simulation model is performed (**Error! Reference source not found.**) hich focuses on the right use of formulas and the exact resemblance with the conceptual model. This walkthrough shows that the model constructions are accurate.

Secondly, extreme values are used to test the boundaries of the model (no forecast error, COV_{FE} of 150%, an average daily demand of 1 SU, a production capacity of 10 SU/day and a COV_{TTE} of 100%). Except for the COV_{TTE}, all elements showed expected behavior. The identified problem for the COV_{TTE} was adapted and verified again.

Finally, the VBA debugger is used during the development of the model in order to assure that coding in VBA done correctly. **Error! Reference source not found.** describes the verification and the adjustments made to he model in detail.

7.4.2 Validation

After having concluded that the model is correctly programmed, the model is compared with reality. The validation is carried out in order to determine if the model resembles reality to sufficient extent. Table 7-6 gives an overview of the used validation methods. No sensitivity analysis is performed to validate the model because this is the essence of the MC analysis.

Validation method	Approved?
Expert validation	Approved
Quantitative validation	-

Table 7-6: Validation methods

Expert validation

For the first assessment to validate the simulation model, interviews are conducted with three experts in different field of expertise (demand planning, inventory control and DRP planning) were interviewed to verify the correct behavior of the model (Sarikaya, 2013) (van der Oost, 2013) (Alves, 2013). Each expert is asked to check the dynamics by looking at the specific parts of the model and the output graphs. All acknowledged the validity of the model. Alves recognized the fact that no inventory is simulated at the plant location. The effects of this choice (as described in the discussion in chapter 9) were discussed and it was agreed that this doesn`t affect the validity of the model related to its objective. Moreover, the expert validated the behavior of the model and agreed on the validity.

Quanti-tative validation

Quantitative validation is used to show resemblance of the simulation with reality in terms of output results. In this case, proving significant similarities between the inventory evolution in the simulation model and reality, has no value: In reality a lot of noise (Silver N. , 2012) is apparent besides the key dynamics (such as the interfering of replenishments due to the glide-path target). Having (statistical) similar results as reality means the model is over fitted and describes noise instead of key dynamics. Hence, no statistical test is performed on the inventory evolution.

7.5 Development of analytical model

Both the simulation model and the analytical model produce an optimal inventory setting which minimizes the inventory and achieves a target CFR. In order to use to analyze the similarities and differences between the outputs of the models, the analytical model is developed using literature and the XIM model of P&G.

In chapter 6 the differences between literature and the XIM model developed at P&G are discussed. The differences are discussed and decisions to adapt the model are here proposed.

7.5.1 Use of coefficient of variance instead of standard deviation

P&G uses the coefficient of variance as a normalized unit of dispersion instead of the standard deviation to track deviation over time. If the COV is calculated correctly (using Equation 18), the safety stock won`t differ compared with the use of the standard deviation. Because of the fact the data sets at P&G are measuring the COV instead of the standard deviation, the use of the COV is selected and if necessary, equations are adapted. Necessary changes are made to calculate the value of the k-factor and of the σ_{EE}.

7.5.2 Different approach for $\boldsymbol{\sigma_{EE}}$

In the XIM model, developed at P&G, Equation 17 is used which is a simplification to calculate σ_{EE} with. Multiple sources in literature suggest however the use of Equation 21 (de Kok, Fortuin, & van Donselaar, 2012) (Silver, Pyke, & Peterson, 1998) and therefore is selected. **Error! Reference source not found.** describes hich equations are used to re-write the equation into equation 22. Using the new equation, data on the COV can be used to calculate the optimal safety stock settings with.

$\boldsymbol{\sigma_{EE} = \sqrt{\mu_L \sigma_D^2 + \mu_D{}^2 \sigma_L^2}}$ Equation 21	$\boldsymbol{\sigma_{EE}}$	= Standard deviation of the estimated error (SU) during the replenishment lead time
	L	= Lead time with expected average $\boldsymbol{\mu_L}$ and variance $\boldsymbol{\sigma_L^2}$
	D	= Demand with expected average $\boldsymbol{\mu_D}$ and variance $\boldsymbol{\sigma_D^2}$
$\boldsymbol{\sigma_{EE} = \sqrt{L(COV_{FEFB}\sqrt{FB} * \sqrt{L} * \mu_D)^2 + \mu_D{}^2 * (COV_{TTE} * TT)^2}}$ Equation 22	FEFB	=Forecast error over the measures forecast bucket
	FB	= Forecast bucket
	TT	= Transportation lead time

7.5.3 Use of maximum for the coefficient of variation of the forecast error

At P&G a maximum cap is used for the COV of the forecast error. This cap is not implemented in the new analytical model. Values above this maximum urge the need for safety stock and therefore should not be capped.

7.6 Concluding remarks

In this chapter the process of developing the simulation model is described. After defining the objective of the simulation model and demarcating the system, a conceptual model is created. To further specify the discrete-event model, first MS Excel is chosen as the simulation environment. Using selected parameters and distributions, the simulation model is programmed. After an iterative process of verification and validation, it is concluded that the simulation model can be used to simulate the inventory performance given the selected demarcation.

It should be noted that this simulation model is not intended to exactly predict inventory performance. Instead it will provide an indication of the dynamics.

8. Simulation & results

This chapter continues with the approach defined in the previous chapter but focuses on the execution of simulation experiments and the results. First, the experiments are designed after which the experiments are executed using the simulation model. The changes needed after the validation, verification and testing phase are also discussed. Finally the results of the experiments are presented.

8.1 Design of experiments

The objective simulation model is used to (1) create insights on behavior of inventory performance using different types of stock settings and create insight in performance ranges and (2) find the optimal safety settings to achieve the target CFR rate (chapter 7). Now, for each objective the experimental designs are defined. Because the simulation model is designed on s.k.u.-level, each experiment is performed for each s.k.u. category.

Figure 8-1 gives a graphical representation of how the experimental designs result in insights on inventory performance and thus the optimal safety setting strategy. The following sections describe the s.k.u. characteristics and safety setting strategies that are used in the experiments.

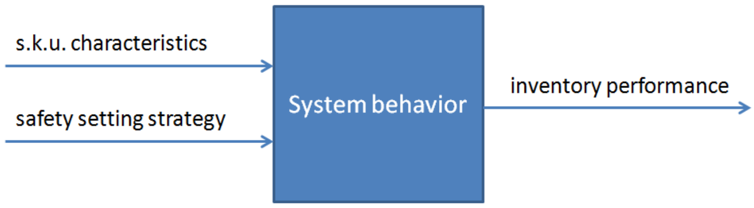


Figure 8-1: Use of experiments to gain insights on inventory performance

8.1.1 S.k.u. characteristics

In order to simulate the scenario which reflects the currently used safety settings (the current situation at P&G), also actual data on the s.k.u. characteristics need to be used. This makes it impossible to create virtual s.k.u. with zero, low and high COV_{FE}. Instead, a s.k.u. classification is used to analyze the effects on four types of s.k.u.

The parameters used for the categorization are: (1) COV_{FE} and (2) shipment volume. These criteria are used to create a joint focus matrix (chapter 4). The threshold for both criteria is defined in consultation with a demand planner expert (Sarikaya, 2013) and the Pareto rule. The result corresponds roughly to a Pareto distributed classification (Table 8-1). For clarification purposes each category is named as a class.

The benefit of using this method over other classification methods is that it creates a manageable number of categories and uses the power of the Pareto as decision rule. The classification at P&G lacked Pareto distribution which suggests that the thresholds aren`t optimal to create high and low impact categories.

Number of s.k.u. in each category		**Coefficient of variation of the forecast error**	
		>100%	<100%
Average daily demand	> 100 SU/day	2 (class I)	7 (class II)
	< 100 SU/day	75 (class III)	14 (class IV)

Table 8-1: Joint focus matrix for the s.k.u. classification at P&G for simulation analysis

Table 8-2 shows the summary of the s.k.u. characteristics and safety setting strategy corresponding with the s.k.u. classification. Notable is the little change in safety time between the categories, although the difference between the average COV_{FE} is large. These settings are used to simulate the current situation for four types of s.k.u.

ST = safety time (days) Coefficient of variation of the forecast error

Blank intentially

Table 8-2: Current values for the agreed safety stock and safety time in the Baby care category (P&G, 2012)

To generalize the impact of the findings for the whole Baby care category, the values found for each classification are weighted using the volume size. Thus, the results of a class I s.k.u., is weighted with the volume of 166 SU.

8.1.2 Scenario 1- 3: Different safety setting

Above, four s.k.u. categories are created to perform experiments with. To gain insight on the impact of different safety setting strategies, three scenarios are created. Each scenario uses a different safety setting strategy. Scenario 1 resembles the current situation in which a combination of fixed safety stock and dynamic safety time is used based on the P&G inventory model. Scenarios 2 and 3, either only use fixed safety stock or dynamic safety time.

	Stock settings suggestions by analytical model of P&G
Combination of fixed stock and safety time in DFC	Scenario 1
Safety time (days)	Scenario 2
Fixed safety stock (SU)	Scenario 3

Table 8-3: Scenario design to create insights on inventory behavior with

The safety settings agreed on for the current situation (scenario 1) are directly retrieved from the IDF system (P&G, 2012), which stores the actual inventory settings. The IDF system also shows the analytically found safety stock (in SU) and the safety time (in days) which are used for scenario 2 and 3. Thus, in scenario 2 and 3 the safety setting resembles an optimal setting according to the analytical model developed by P&G. In scenario 1, the output of the analytical model is only used as suggestion but is overruled by expert knowledge.

8.1.3 Scenario 4: Find the optimal safety setting

A fourth scenario is used to test the validity of the developed analytical model. In order to do so, the optimal value for the fixed safety stock is calculated using a binary search algorithm (**Error! Reference source not ound.**) keeping the samples for the demand, forecast error and lead time errors constant. The result is a range of optimal stock settings (to the nearest SU) for a certain s.k.u.

The range of safety stock settings should not deviate significantly from the suggested inventory setting found with the analytical model. A one sample T test is used to prove the hypothesis that there is no deviation between the range of safety stock settings calculated with the simulation model and the safety stock settings as suggested by the analytical model.

An overview of all experiments is shown in Table 8-4. Each scenario is performed for each of the four s.k.u. categories.

S.k.u. category 1/2/3/4	**Stock settings suggestions by analytical model of P&G**	**Optimize stock settings for target CFR using simulation model**
Combination of fixed stock and safety time in DFC	Scenario 1	
Safety time (days)	Scenario 2	
Fixed safety stock (SU)	Scenario 3	Scenario 4

Table 8-4: Overview of experiments: for each s.k.u. category, 4 scenarios are tested.

8.2 Execution of experiments

In order to execute the experimental designs on the verified and validated model, the following sections discuss the simulation set up.

8.2.1 Model set up

One simulation run simulates 25 weeks (194 days). In such a period, important model behavior occurs without increasing the total simulation time too much.

Some models have a warm-up period before it resembles accurate data: e.g. the phase in which people are entering into a shop which is not useful when the objective is to analyze queuing at the cash register. Such a warm-up period should be excluded from the analyzed data. In case of the simulation model, the inventory needs to reach a stable level before the data can be used for analysis.

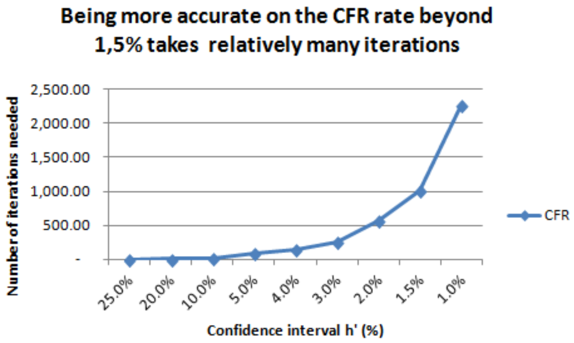
To reduce the warm-up period, an initial inventory level is set-up based on the average demand and the safety stock settings. This results in a starting inventory which is close to the target inventory level and thus diminishes the effects of a possible start-up period. Using graphical output on the inventory level, a start-up period of four days is selected. Hence, the values for the first four days are not included in further analysis.

8.2.1 Number of Monte Carlo iterations

Next to the model set-up for a single iteration, the number of Monte Carlo iterations is determined. For the first three scenarios an initial 100 iterations are executed. Using equations Equation 23 up till Equation 27, for each performance measure, the 95% confidence interval is calculated (Verbraeck & Valentin, 2006). Using Equation 28 the total number of replications is retrieved to obtain the desired confidence ($h^{'}$) for each performance measure.

$\mu = [\bar{x} - h, \bar{x} + h]$	Equation 23
$\bar{x} = \sum_j \frac{x_j}{n}$	Equation 24
$\sigma^2(x) = \sum_j \frac{(x_i - \bar{x})^2}{n-1}$	Equation 25
$\sigma^2(\bar{x}) = \frac{\sigma^2(x)}{n}$	Equation 26
$h = t_{n-1,1-\frac{\alpha}{2}} \sigma(\bar{x})$	Equation 27
$n' = \left\lceil n \left(\frac{h}{h'}\right)^2 \right\rceil$	Equation 28

The desired confidence range is decided on (1) based on discussion on what accuracy is needed for each performance measure to be useful (Sarikaya, 2013) and (2) based on plots of the behavior of the confidence interval (Graph 8-1) to set limits to the number of iterations. As the graph shows, being more accurate beyond 1,5% takes relatively many extra iterations. Table 8-5 shows the results for these calculations for the class I.



Graph 8-1: Dynamics of confidence interval for the CFR

The number of iterations is driven by the degree of variation in the measures. Notable is the fact that scenarios in which (a large part) of the safety stock setting is based on days forward coverage, the variation in performance parameters increases.

Number of iterations needed	Average inventory (confidence interval = 250 SU)	Average safety stock (confidence interval = 25 SU)	CFR (confidence interval = 0,016)	Yellow NPI (confidence interval = 250 SU)
Scenario 1	999	885	831	750
Scenario 2	1151	1182*	876	617
Scenario 3	54	156	1	26
Scenario 4	120	133	54	50

Table 8-5: Number of iterations needed for confidence interval. *confidence interval lowered to 60 due to extreme number of iterations needed

8.3 Adapt simulation model

Iteratively changes have been made to the simulation model after verification, validation and testing. The most important changes are listed in Table 8-6.

What kind of adaptation	For what reason
Adaptation of the target stock calculation	Due to specification error, target was calculated in wrong way
Adaption of the MOQ	Due to specification error, MOQ was calculated in cases instead of SU
Addition of row for delayed replenishments	Either the delayed replenishment or the planned replenishment of that day could be replenished. By adding an extra row, both quantities can be added.
In scenario 4 the found optimal safety stock settings deviated significantly from the suggestions from the analytical model	The analytical model is using the COV_{FE} on a weekly basis instead of a daily basis

Table 8-6: important improvements to simulation model after verification, validation and testing

8.4 Results

The presentation of the results consists of (1) the dynamics of the inventory during a single simulation run and (2) the results of the Monte Carlo analysis. For scenario 1, 2 and 3, the performance behavior during single iteration is analyzed. Next, for all four scenarios, the results of the Monte Carlo analysis are presented.

8.4.1 Performance behavior during one iteration

For the performance behavior during a single iteration, the focus is on s.k.u. with a high COV_{FE} and a large volume size. The used s.k.u. has a COV_{FE} is 137% and the average daily demand is 213,79 SU. For this s.k.u. category the dynamics of inventory during one iteration is discussed. The dynamics for the other s.k.u. classifications are discussed in **Error! Reference source not found.**.

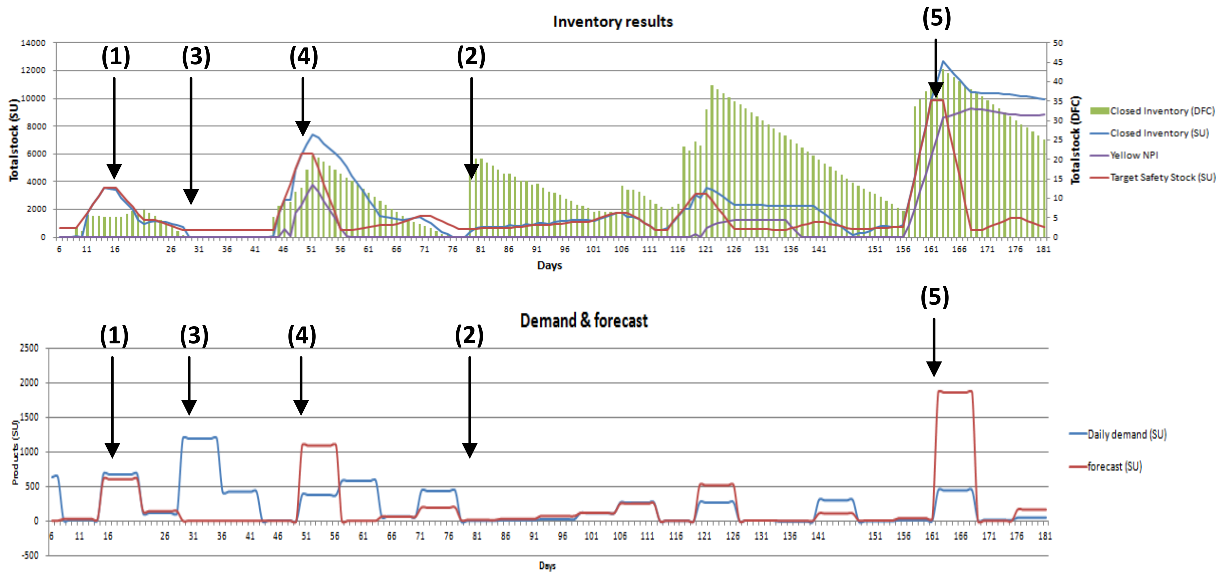
To analyze the differences in behavior of inventory, plots are created for the several parameters over time: (1) the closed inventory position in SU, (2) the target safety stock, (3) yellow NPI and (4) the total inventory in days. Observations for scenario 1, 2 and 3 are discussed using the same initial conditions (exact same demand, forecast errors and lead time errors).

Scenario 1: current situation with use of both safety stock and safety time

Scenario 1 uses a safety setting strategy which combines the use of fixed safety stock and dynamic safety time. Based on the s.k.u. characteristics, experts have selected a safety stock setting of 561 SU and a safety time of 5 days.

After a single iteration, four interesting dynamics in inventory evolution are visible which result from the use of safety time (Graph 8-2). The first, two dynamics (1) and (2) show the benefits of safety time but (3) and (4) show two important negative side effects of the use of safety time.

(1) The first peak in the target safety stock (1) is exactly matched mainly because of the good forecasting. The inventory goes up to match the demand and after the peak in demand, it lowers again.
(2) Half way the simulation (2), the target safety stock is very low due to the low forecast. This time, no under forecast has happened so the inventory in SU can be lower than the scenario if only safety stock would have been used (scenario 3).
(3) The second peak in the target safety stock (3) is driven by actual demand and is totally missed in the forecast: the forecast was wrong and the demand was now known only one day in advance, too late to plan a new replenishment for. Now, the little safety stock that was left can`t help to cover a lot of missed shipments.
(4) Around day 50 (4), the first *over* forecast is a fact. Here, too much stock is replenished immediately resulting in yellow NPI (the purple peak). Moreover, the total stock expressed in days rises because the large amounts of stock (in SU), don`t have any expected demand (forecast) soon. Near the end of the run (5), again an over forecast results in major amount of yellow NPI.



Graph 8-2: Scenario 1: Inventory results for current scenario (above) & demand and forecast results (below)

Scenario 2: use of safety time only

In the second scenario, only safety time is used. This means that when no demand is forecasted, the target safety stock goes to zero. Also, peaks in forecast of demand result in a higher target safety stock. On the other hand, no fixed buffer is in place to save unforeseen demand.

Graph 8-3 shows the results for the iteration with the use of safety time only. The difference in the safety settings are as follows: the safety time increases from 5 days to 13,69 days and the safety stock decreases from 561 SU to 0 SU. An important remark is that for this simulation, all other settings are the same as in the above discussed run, including the forecast of demand and actual demand (Graph 8-2).

(1) One can see that the dynamics remain more or less the same. The peaks hitting earlier, take longer and are more extreme.

> Finding 1: Use of safety time results in extreme inventory dynamics

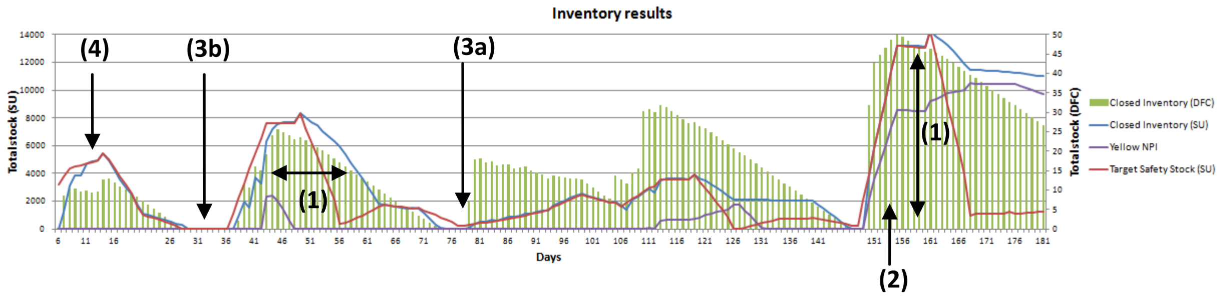
(2) The creation of yellow NPI also increases more rapidly when only safety time is used. E.g. due to the last extreme over forecast, a lot of yellow NPI is created. The duration of the yellow NPI wave is larger because it is replenished already a few days earlier compared with the previous scenario. The peak of yellow NPI is higher because the target safety setting goes up as it 'looks' further in the future.

The creation of extra yellow NPI is not only inconvenient for this particular s.k.u. However as has been concluded, the creation of yellow NPI is a good indicator for the product segment to go above the glide-path target. This means that replenishments for other s.k.u. are intervened to get near the glide-path target again. These peaks are inconvenient for this particular s.k.u., but hurts double while due to glide-path targets, production for other healthy s.k.u. is lowered.

(3) One of the assumed benefits of safety time is that it should lower inventory in case no demand is expected. On the one hand, this is true. With low forecast of demand, the target safety setting gets near 0 which saves inventory costs (3a). However, at this point the difference between forecast and actual demand is rather low. Point (3b) gives an example where no demand is forecasted which takes the inventory to 0, but unfortunately gets surprised by a peak in demand (3, in Graph 8-2). Now, no stock can satisfy the unexpected demand during the lead time: *and this is exactly the type of demand safety stock should be used for.* Demand hurts the most, when it is least expected. And that is why there should be safety stock, which now is not the case.

> Finding 2: Use of safety time for s.k.u. with (high) COV_{FE} exposes CFR to risk during periods with low forecast of demand

(4) An example of where the safety time does prove its benefits is the moment when the forecast of demand is accurate (1 in Graph 8-2). The first weeks (4) the inventory goes up and down with the accurate safety setting which provides safety.



Graph 8-3: Scenario 2: Inventory results using safety time only and the same conditions as scenario 1

Scenario 3: use of safety stock only

In this scenario, only safety stock is used. This means that independent from the forecast, a fixed amount of safety stock should be kept at the DC. Again, the same initial model conditions are used including the forecast of demand and the actual demand (Graph 8-2).

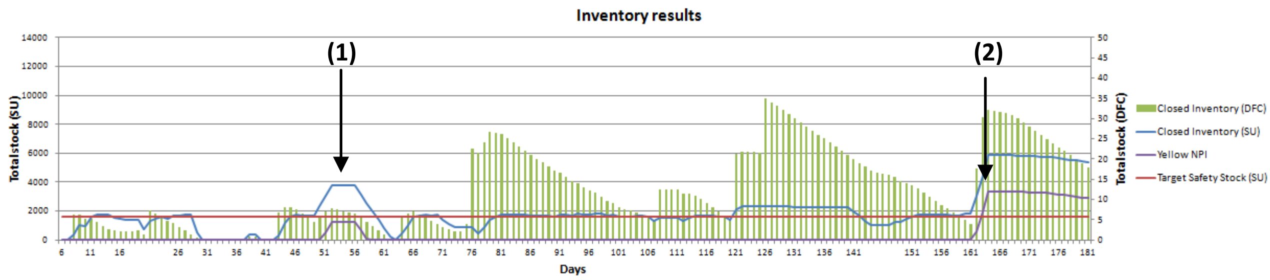
(1) Compared with both of the previous graphs of the inventory results, it immediately becomes clear the inventory with the use of safety stock is more stable: Peaks are less extreme and only need a shorter time to restore around the inventory target.

Finding 3: Safety stock results in a more stable inventory pattern

(2) With the use of fixed safety stock, also there is creation of some yellow NPI. The largest peak happens near (2), driven by the over forecast of demand. Given the fact that in all three scenarios, an over forecast of demand leads to yellow NPI, means that yellow NPI can`t be prevented with high COV_{FE}.

Again, based on the dynamics of yellow NPI, a remark can be made regarding the glide-path. Given the fact that s.k.u. with a high s.k.u. are likely to create yellow NPI and the fact that yellow NPI is a good indicator for not achieving the glide-path target, it is likely that normal replenishments for healthy s.k.u. in the product segment are adapted to get the total segment at the glide-path target again.

Finding 4: A high COV_{FE} is a key driver of yellow NPI



Graph 8-4: Scenario 3: Inventory results using fixed safety stock only and the same conditions as scenario 1

For the three discussed scenarios, the results on performance measures and the initial safety setting strategy are depicted in Table 8-7. It shows that the use of fixed safety stock results in the best CFR result and the lowest average inventory.

(Performance) measures	Scenario 1	Scenario 2	Scenario 3
CFR (%)	63,4	34,7	20,5
Average inventory (SU)	1991	4044	2803
Average yellow NPI (SU)	387	1782	1329
Initial safety stock setting (SU)	2915	0	561
Initial safety time setting (days)	0	13,69	5

Table 8-7: Performance measures for three scenarios under same initial conditions

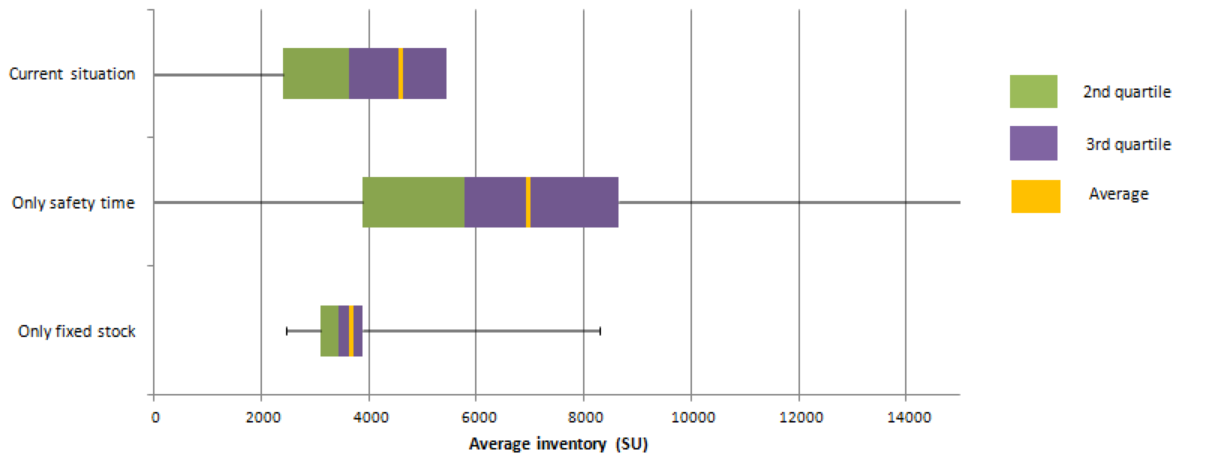
Although these results give an indication of the performance of the use of each safety setting, this is only a single simulation run. The input parameters reflect one possible state of the system regarding the used probability distribution function for some of the input parameters. In order to get an estimate of the true characteristic of the system, the next section discusses the Monte Carlo results.

8.4.2 Monte Carlo simulation results

This section presents the results of the Monte Carlo simulation. For each scenario around 1000 runs (exact numbers are presented in paragraph 8.2.1) are simulated to get an estimate on performance of the inventory given the scenario settings. The results for three performance measures and related safety settings are discussed: (1) the average inventory level, (2) the case fill rate and (3) the average yellow NPI. Again a s.k.u. is used with high demand volume and a high COV_{FE}. Results of other s.k.u. can be found in **Error! Reference ource not found.**.

Average total inventory results

The results of the Monte Carlo simulation are shown represented in the whisker-tail plots (Graph 8-5). The 2nd and 3rd quartiles reflect the range of 50% of the results. The larger this range is, the more insecure the performance of a safety strategy is. The golden bar shows the average inventory level. This inventory is expected in reality when one of the strategies is used. The grey bars extending the 50%-range.



Graph 8-5: Average inventory for s.k.u. with high volume and high COV_{FE}

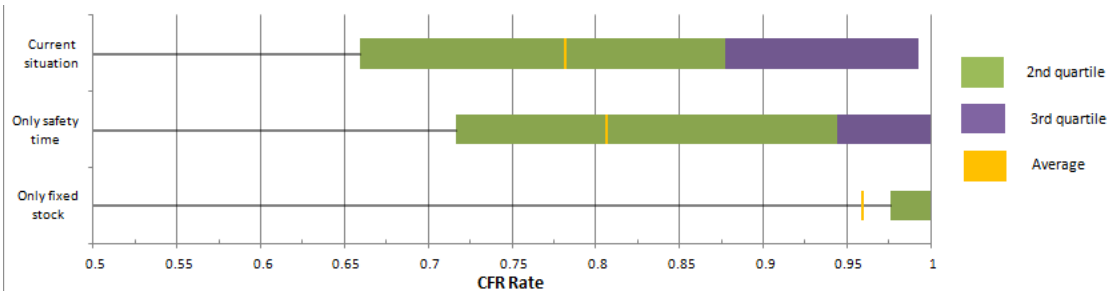
First the average inventory levels are discussed. The plot shows that the use of only fixed safety stock results in the lowest average inventory (3640 SU). When only safety time is used, the expected average inventory is almost twice as high (6929 SU).

Next, the ranges of the plots make clear that when safety stock is used, the expected performance can be predicted with more accuracy. As concluded above, the expected average inventory is the lowest when using only fixed safety stock. However, the 2nd quartile of the current scenario, shows that the current situation has a high chance to have lower inventories compared with the used of only fixed safety stock.

Finding 5: The use of only a fixed safety stock setting results in the lowest average inventory

Case fill rate results

The same whisker-tail plot is created for the results of the CFR (Graph 8-6).



Graph 8-6: Ranges of CFR rate for s.k.u. with high volume and high COV_{FE}

First, the average CFR is discussed. The use of only fixed stock results in the highest expected CFR of 95,8%. For this scenario, the fixed safety stock setting is calculated using an analytical model in which the target case fill rate is 99%. The deviation can be explained by outliers and the effect of the so-called undershoot phenomenon: The analytical model assumes that replenishments are planned exactly on the moment that the inventory reaches the re-order point. However, in reality due to the irregular size of orders, the inventory can undershoot the re-order point. Therefore, the re-order point is a little lower than optimal, resulting in CFR of 95,8%.

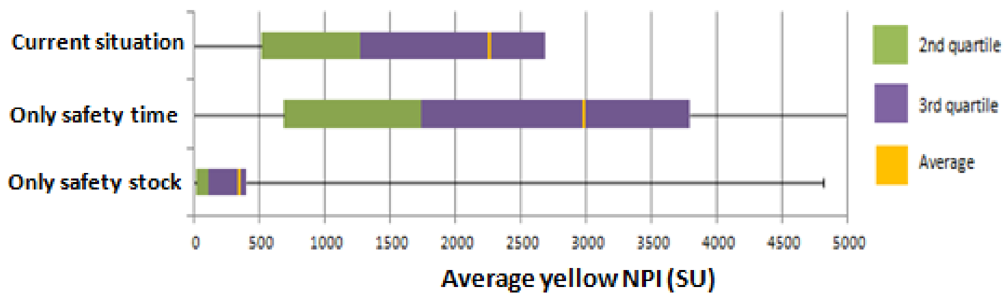
The expected CFR in the other scenarios lies around the 80%. This already gives an indication why the current performance is lacking behind: the 'plan the work' results in the wrong safety setting strategy. The reason that in reality the CFR is higher than 80% is that inventory planners recover a lot of demand by manually intervening in the replenishment process.

The last notion is on the range of the CFR performance. For the current situation and the scenario with the use of only safety time, the ranges of the 2nd and 3rd quartile are very broad. This means that it is likely that for these settings, over the course of time not only a lot of high CFR scores are achieved, but also a lot of very low scores. This is insecurity is unwanted.

> Finding 6: An only fixed safety stock setting results in the highest and accurate case fill rate

Average yellow NPI results

The last performance measure is the yellow NPI, which here is discussed using a whisker-tail plot (Graph 8-7).



Graph 8-7: Ranges of average yellow NPI for s.k.u. with high volume and high COV_{FE}

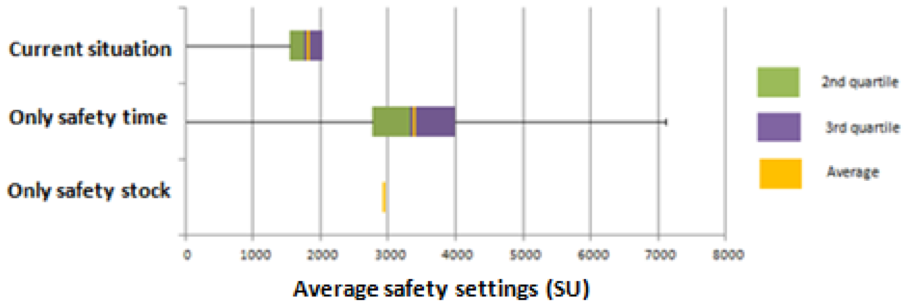
Remarkable is the fact that according to the simulation model, regardless of the safety setting used, yellow NPI is expected. This has impact on the use of the glide-path target. Given the fact that s.k.u. with a (high) COV_{FE} are likely to create yellow NPI and the fact that yellow NPI is a good indicator for not achieving the glide-path target, it is likely that normal replenishments for healthy s.k.u. are delayed or cancelled to get the total segment at the glide-path target again.

Secondly, the use of safety time increases the chance of extreme values. This can be seen in Graph 8-7 by the large 2nd and 3rd quartiles.

Finding 7: Yellow NPI is expected by s.k.u. with a high COV_{FE}

Ranges for optimal safety stock

To review the used safety setting strategies, also the box-and-whisker graphs are plotted for the used safety stock targets.



Graph 8-8: Ranges of average safety settings (SU) for s.k.u. with high volume and high COV_{FE}

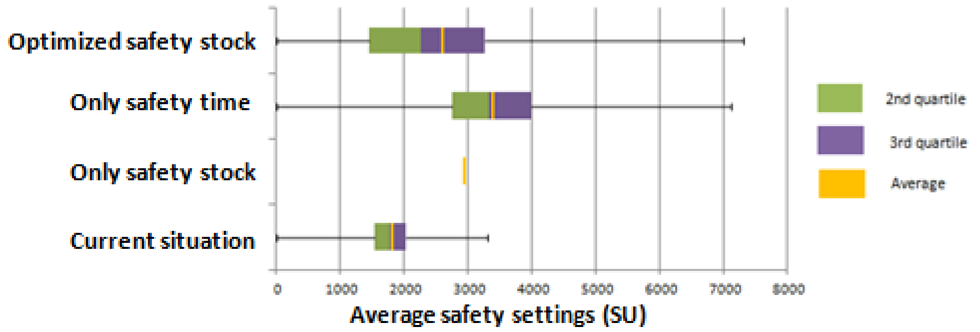
For the fixed safety stock strategy, this setting is the same for all simulation runs (2925 SU). However, when safety time is used, the target safety stock (in SU) depends on the forecasted demand. Because these forecast changes for every simulation, it results in a range of target safety stock settings.

Although the safety stock settings between the scenario with only safety time and only safety stock differ only a bit, the effects on the performance measure is are eminent. Regarding the current situation, it is clear that the setting is below the analytical optimal.

Based on this graph in combination with the results of the other previous discussed graphs on average inventory, it can be concluded that a higher safety stock setting, does *not* necessarily lead to higher average inventory.

Optimizing for 99% CFR target

The previous discussed scenarios (scenario 1 and 2) used safety settings calculated by the P&G analytical model and the current situation in which experts have decided on the combination between both. Now, the simulation model is used to calculate the optimal safety stock. This is done using a binary search algorithm as explained in paragraph 8.1.3.



Graph 8-9: Ranges of average safety stock settings (SU) for s.k.u. with high volume and high COV_{FE}

The whisker-tail plot (Graph 8-9) shows the previously discussed safety stock settings but now also includes the optimal safety stock settings to achieve 99% CFR with. The range of appropriate safety stock setting is large and slightly smaller than what the analytical model of P&G suggests.

The range of optimal safety stock settings is compared with the suggestions of the analytical model based on literature (developed in chapter 7), using a one sample T tests (**Error! Reference source not found.**). For the .k.u. with high volume and high COV_{FE}, it can be concluded that there is no statistical difference between the optimal safety stock setting by the analytical model and the simulation model.

Finding 8: The analytical model of Silver et al produces the same safety stock settings as the simulation model

Part IV: Discussion & conclusions

The last part discusses the results of the different scenarios to get towards the conclusions for the case study category. These conclusions are discussed to conclude to which extent it can be generalized for other categories within P&G and other supply chains outside of P&G. The conclusion are reflected with literature and used to define an implementation strategy for P&G. After answering all the research questions, the last chapter reflect on the performed research.

9. Discussion of results

In the previous chapter the simulation model is used to quantify the performance of several safety stock strategies for different product categories. Before elaborating on the conclusions, first the results are discussed in more detail. First, the impact of modeling choices on the validity of the results is discussed in paragraph 9.1. In paragraph 9.2 the possibilities are discussed to generalize the results found in the Baby care case study to other product categories within P&G and other supply chains. Paragraph 9.3 discusses the confrontation of the results with literature. Paragraph 9.4 concludes the discussion section by elaborating on recommendations for implementing steps for improvement.

9.1 Impact of modeling choices

The choice for a discrete event simulation model on which a Monte Carlo analysis is performed, is described in chapter 7. The impact of this choice compared with other modeling types is discussed in paragraph 9.1.1. The demarcation reduced the complexity of reality and resulted in a model with only the most relevant factors and processes to characterize the inventory system with. To be able to draw conclusions on the results which are valid for use in reality, the impact of the scoping choices are discussed in paragraph 9.1.2.

9.1.1 Impact of design choices

Two structural decisions were made before developing the simulation model. The first decision was (1) to develop a discrete event simulation model and secondly (2) to develop a single plant, single DC and single product model. The impacts of these decisions are now discussed.

(1) The decision to develop a discrete event simulation model is driven by the interest to quantify the risks of certain inventory management strategies using Monte Carlo analysis. This risk analysis cannot be performed with the analytical model that solves for only 1 optimal solution. Instead, the whole inventory system had to be modeled. The choice for a discrete event simulation model seemed right because it characterizes the daily sequences of events that occur in reality. Moreover, inventory itself is discrete of its nature. A top down approach was used to identify the key processes that characterize the system.

    In literature System dynamics is mentioned as possibility to simulate the dynamics of inventory with. System dynamics often is preferred for processes where feedback significantly affects behavior. Because this is not the case regarding the scope of the research, discrete-event simulation is a solid choice. However, to focus more on the dynamics of feedback loops for inventory management, system dynamics could be considered.

    Also the use of an agent based model is considered: The use of this type of model could focus more on the rules and institutions regarding inventory management. Such a model simulates the actions and interactions of autonomous agents. In order to do so, a bottom up approach should be used to identify all the rules that involved parties use for its processes. Next, these rules can be applied to the agents in the model to see what effect this interactions have on the inventory. However, this would focus more on the rules and institution regarding inventory management instead of the performance of inventory. And given the fact that, as is discussed in the next section, some institutions are not designed optimally, a study using agent based model could result in valuable new insights.

(2) A single plant, single DC and single product scenario differs from reality, where a plant serves multiples products to multiple DCs. This reduction affects on the inventory *at the plant* but has only little affect on the inventory at the DC.

- If more plants would have been modeled, the same demand would have been delivered from the plant which wouldn`t have resulted in any additional useful insights regarding the objectives. As explained in the next section, extreme peaks in demand are either rare or should be solved by improving the C:D ratio.

- If more DCs would have been modeled (and thus increasing the overall demand), it is likely that the plant capacity should be bigger to cover the demand and the DC of interest probably would have a slightly higher safety stock due to larger uncertainty in the supply chain. However, the dynamics of the inventory would remain the same.
- If multiple products were simulated at the same time, the plant needs to keep an inventory as well in order to cover for a period in which other products are produced. Again, this would merely affect the inventory at the plant. The safety stock at the DC is likely to increase a little due to higher uncertainties in the supply chain but the effects of certain dynamics, such as the safety setting strategy, on performance measures remain the same.

9.1.2 Impact of scoping choices

Two processes are excluded from the scope for the simulation model being (1) the use of inventory at the plant and (2) production time errors.

(1) In reality, inventory is kept at the plant for the same technical, financial and safety reasons as for a DC. Most important however, is the fact a plant needs to switch between production of different products. In case product X can`t be produced due to other production runs, products can be shipped using the inventory of X at the plant. This is especially the case when a plant produces 100 types of products for multiple DC. This research focused on a scenario with 1 plant, 1 DC and 1 product type. In this scenario, there is only use for inventory at the plant if the demand from the DC pattern shows extreme peaks (and not in case of long term production issues). In such case there are two options: (1) the extreme demand is an outlier, in which case it is not important to satisfy the demand using inventory at the plant. (2) the extreme demand is structural. Having too few capacity at the plant indicates that the Capacity: Demand ratio is below its target. Here, changes in production capacity or safety settings should be made instead of the use of temporarily capabilities. This is outside the scope of this model. The exclusion of inventory if other cases then the case of a single plant, single DC and single product scenario does, not affect the results. Moreover, this exclusion is approved during the expert validation.

(2) In reality production time errors occur due to e.g. malfunctions at the plant. This can lower the capacity of the plant and thus its replenishment capabilities. However, as shown in chapter 5, only the largest type of error (often the forecast error) significantly impacts the safety stock level. Therefore, to reduce complexity this process is left out of the model. Now, the model shows slightly better results than reality in case production time errors occur. However, all the s.k.u. that are used for the simulation had a COV of the production time error of 0% according to its data source (P&G, 2012). The impact of the exclusion of this process on the results is minor: For s.k.u. with production time errors the model shows negligible better results.

Furthermore, human interaction is left out of the model. First, (1) the exclusion of expert knowledge to decide on the right safety settings is discussed. Next, (2) the effects of human interventions on replenishments due to the glide-path target are discussed.

(1) The effects of the expert deliberation regarding the combination of the safety settings are excluded from the model. However, the resulting settings for a s.k.u. (which are the historical used settings) are used and combined with other corresponding input parameters of that s.k.u. This incorporates the expert deliberation to the maximum extend. The effects on the results are therefore slim.

(2) The glide-path target sets a cap on the total inventory a product segment (which consists of multiple products) can have. At the end of each month, the inventory should be at or under this target. In the Baby care category, in the course of the month, the SIP planner reviews the inventory levels and flags segments

which are over the glide-path target. This means that one or more s.k.u. have too much inventory. While it is hard to sell the products quicker, it is possible to not replenish other s.k.u. in this segment to not further tense the glide-path target. In order to do so experts consider the risks of not replenishing certain s.k.u. and decide on actions accordingly. There are two reasons why this human intervention is not included in the model:

- The model only simulates 1 model and thus makes it impossible to include the glide-path effects.
- If multiple products are simulated, it is impossible to simulate all the decision criteria on which experts decide to intervene, let alone to calculate the right actual intervention.

The results show that for some s.k.u. (e.g. s.k.u. with a low average daily demand), yellow NPI is created no matter what safety setting type is used. Yellow NPI is a good indicator for being above the glide-path target and thus would have triggered human intervention in reality. However, the question is whether this intervention is a good thing to do (why intervene when the results are according to plan?).

Currently, the goal of the glide-path target is to reduce yellow NPI. First of all, to use the glide-path target as a trigger, the value should be determined accurately instead of using rough estimates based on the whole segment. Secondly, when it triggers an intervention, it results in intervening replenishments for *healthy* s.k.u. and thus does not reduce yellow NPI. Therefore, the target should be to *prevent* the creation of yellow NPI.

Because yellow NPI is created by different sources and different departments (e.g. over forecasts or over production), the target shouldn`t be focused only on the SIP (who now can solve problems created by others) but on all creators of NPI. E.g. for a market planner, there already is a target (MAPE) that focuses on the prevention of NPI by over forecasting.

The conclusion is that the glide-path target is a wrong incentive to lower the total stock by decreasing healthy inventory. The glide-path should still be used to monitor inventory and compare it performance with other supply chains, but not be used as trigger to intervene. The effect of not using the glide-path as trigger to intervene is the increase of average inventory. But this is an increase of healthy performing inventory.

9.1.3 Model additions

The current simulation model comprehends the most important features to test and simulate scenarios in a actual environment. However, the model is limited by some design choices made to fit the Baby care category. Some suggestions now are discussed which can be added to the simulation model to increase the applicability.

1. Add option for different ordering strategies
2. Add option for different lot sizing strategies
3. Add costs to the model

(1) The Baby care category uses a r,s,S replenishment system. Once every day, the inventory level is checked and if the inventory is expected to fall below the target level *s,* a replenishment is triggered to get the inventory back to level *S.* However, in many smaller supply chains it can be expected that replenishment is triggered on a weekly basis and every time consists of the same order quantity: an r,Q ordering system. The simulation model can be adapted for this by adding a conditional value which allows replenishments only to happen when a review is performed. The size of the target replenishment than also should be adapted.

(2) A part from the target replenishment size (which is defined by the used ordering system), the lot size strategy can affect the size of the inventory as well. Because the objective in this research was to minimize inventory levels and not the related cost, the inventory minimizing heuristic of lot for lot was used. However, when an analysis is focused on the quantification of cost, other heuristics are likely to be used such as the

economic order quantity. These heuristics can be implemented in the simulation model by changing the target inventory levels.

Other replenishment heuristics do not affect the moment of replenishment but only the quantity. This means that it can be expected that the dynamics regarding the use of safety time and safety stock remain the same, only the resulting size of the inventory can deviate.

(3) The current simulation model has focused on the objective to minimize inventory while achieving the target service levels. However, no inventory costs were included. It is useful when exploring for optimal inventory strategies to take costs for placing orders and keeping inventory, into account. As explained at the previous note, it is likely that other replenishment heuristics need to be implemented in the model. Moreover, different cost elements (e.g. ordering cost and stock keeping cost) have to be added to the model and accounted for during a simulation.

9.2 Applicability of the Baby care results

First, the findings of chapter 8 are discussed to draw conclusions for the inventory management of Baby care. Next, the generalization of the results to other categories within P&G and other supply chains are discussed.

9.2.1 Conclusions 1: Fixed stock should be used to achieve CFR targets and minimize inventory levels

In order to simulate the scenario which reflects the current safety settings (the current situation at P&G), also actual s.k.u. characteristics need to be used. This makes it impossible to create virtual s.k.u. with zero, low and high COV_{FE}. Instead, a s.k.u. classification was used to analyze the effects on four types of s.k.u. (Table 9-1).

	High COV_{FE} (group A)	Low COV_{FE} (group B)
High average demand (Group 1)	Class I	Class II
Low average demand (Group 2)	Class III	Class IV

Table 9-1: Recap of s.k.u. classification

Table 9-2 compares the ranking of the average CFR score for each class for the safety settings scenarios. It clearly shows that in case of s.k.u. with a high COV_{FE} (Class I and III), a fixed safety stock setting results in the best CFR score. This also counts for class II s.k.u. Only, for the class IV s.k.u. the current situation slightly outperforms the fixed stock strategy. This can be explained by the unnecessary amounts of inventory kept in the current situation (next section).

Not only does the use of fixed safety stock out-perform other strategies on the average CFR score, it also makes the scoring range more narrow (not shown in table below). This means that less (extreme) outliers are expected when fixed safety stock is used (findings 1 and 3).

The most important conclusion that can be drawn from Table 9-2 is that in order to optimize average CFR, fixed safety stock always outperforms safety time (Findings 2 and 6). A weighted (based on average daily demand) average CFR improvement of 2 percent points.

Av
Sc
co
Sc
Sc

Blank intentially

Table 9-2: Ranking of scenarios on the average CFR score per s.k.u. class

Table 9-3 compares the ranking of the average inventory levels for each class for the safety setting scenarios. Also for the inventory, three of these s.k.u. classes benefit most from a fixed stock setting. Only in class III, the current scenario outperforms fixed safety stock. This can be explained by the extreme low average CFR score that is achieved in this scenario (previous section), i.e. there is too few inventory in the current scenario.

Not only does the use of fixed safety stock out-perform other strategies on the average inventory level, it also makes the inventory range more narrow (not shown in table below). This means that less (extreme) outliers are expected when fixed safety stock is used (Findings 1 & 3).

Most important conclusion that can be drawn from Table 9-3 is that in order to optimize average inventory, fixed safety stock always outperforms safety time (Findings 2 and 7).

Blank intentially

Table 9-3: Ranking of scenarios on the average inventory level per s.k.u. class

For all classes it is important to value a high CFR versus low inventory in order to find the optimal balance. As described in chapter 3, there are methods to express inventory in terms of money. However, it is hard to do the same with the service level. Schneider (2009) suggests that an increase of the on shelf availability with 3%, increases the turnover with 1.3% given a scenario at a different FMCG company. Unfortunately, this research does not focus on the value of CFR at a DC. Using Table 9-3 it can be concluded that on average the use of fixed safety stock only will lead to a 20% decrease in inventory. Generalizing for the whole baby care category by taking into account the volume shares of each s.k.u. class, the inventory reduction is estimated on 1%.

Concluding, at P&G management has set the target to have a CFR of 99%. Therefore, an increase in inventory is approved as long as it improves the CFR score. Considering the discussed simulation results, using a fixed safety stock improves the CFR towards the target in all cases. Moreover, inventory levels are reduced.

9.2.2 Conclusions 2: Yellow NPI can occur at healthy s.k.u. inventories

Finding 4 and 7 regard the creation of yellow NPI and show that forecast errors are a key driver in the creation of yellow NPI: No matter what safety setting strategy is chosen, the moment the forecast is over the actual demand, yellow NPI is created. This in an important conclusion regarding the classification of 'healthy' inventories: inventories with yellow NPI still can be healthy.

9.2.3 Conclusions 3: The glide-path target hurts inventory performance

The fact that yellow NPI is expected for a lot of s.k.u. at P&G (considering the high COV_{FE} of many products), asks for a discussion on the glide-path institution. The concern does not regard the monitoring purpose of the glide-path target but the intervention purpose: If the inventory glide-path is projected to be off-track, for which yellow NPI is a good indicator, an intervention is planned by postponing or cancelling non-critical replenishments for other s.k.u. in the product segment.

Among else, non-critical replenishments are at P&G those replenishments that take the inventory level up to the target safety setting (Hadikbarkoczy, 2013). According to literature and performed analyses, these types of replenishment can be regarded as the opposite of being non-critical. As acknowledged by planners at P&G, such interventions can lead to exposure of CFR but these risks often can be mitigated by micro-management.

Now, given the fact that healthy s.k.u. are likely to have yellow NPI. And given the fact that yellow NPI is a cause to intervene in replenishment for other healthy s.k.u., it can be concluded that the current usage of the glide-path target puts CFR of healthy s.k.u. at risk. On the one hand, this is due to the trigger itself: yellow NPI is regarded as being wrong while it is not. On the other hand, the intervention hurts the replenishment of healthy s.k.u., which it shouldn`t.

9.2.4 Conclusions 4: The analytical model by Silver is practical applicable

Scenario 4 is designed to calculate the safety stock settings according to the simulation model and compare this range of suggested settings by the point estimated made by the developed analytical model based on Silver et al (1998). Using a one sample T test, it is shown that the results of both models do not significantly differ. Given the fact that the simulation model is a valid representation of reality, it can be concluded that the analytical model of Silver is practical applicable for inventory management purposes.

9.2.5 Generalization of findings for other categories within P&G

Blank intentially

Hadikbarkoczy, 2012).

	Safety setting strategy	Replenishment strategy	Use of glide-path target

Blank intentially

Table

Overa

used for replenishing the inventory, the simulation model should be adapted to analyze the new effects.

9.2.6 Generalization of results for other supply chains

In the previous section, the results for the Baby care category are generalized to be applicable for other categories at P&G as well. Here, the generalization of the results for supply chains outside P&G is discussed. The same three elements are discussed: s.k.u. characteristics, the use of the glide-path target and supply chain characteristics.

As for the s.k.u. characteristics the reasoning is the same as in the previous section: Although exact characteristics will differ, the resulting dynamics of the model and the results will remain the same. Considering only the s.k.u. characteristics, this means that the conclusion on the dynamics of inventory performance using different safety settings is applicable for other supply chains outside P&G as well.

As shortly discussed above, supply chains which use an DRP-1 (r,s,S) system, the results hold. Such a system often is used for inventory management at large distribution centers such as those at P&G. Smaller inventories such as for a clothing shop, often rely on periodical review systems. If other systems are used, the dynamics will differ from the results shown for the Baby care category. For these systems, the simulation model needs to be adapted and tested again.

For other supply chains which use a (similar target to the) glide path target to cap the maximum inventory, the following reasoning applies: Considering that the simulation model can be applied to other r,s,S supply chains, it is likely that also in other supply chains yellow NPI is created by healthy s.k.u. Hence, the conclusions for the glide-path target also hold for other supply chains.

9.3 Confrontation with literature

Literature on supply chains and inventory management discuss many elements to be analyzed and decisions for design. In order to analyze the current situation at P&G, a framework was created which defined the two main stages for inventory management: Plan the work and work the plan. First, the use of the framework is discussed considering existing literature. Next, the simulation model is confronted with the analytical model. Paragraph 9.3.3 discusses the confrontation between the results and applicable theory.

9.3.1 Review: Plan the work, work the plan

Because inventory management is a complex matter, the confrontation of literature with the case study needed a clear and crisp structure. In literature different inventory management concepts are discussed but none could easily be used for communication purposes. The widely applied Supply Chain Operations Reference (SCOR) model (Supply Chain Council, 2012) was considered but did not had enough focus on inventory management in particular.

Therefore, a conceptual model of what inventory management entails, was designed based on 'Plan the work' and 'Work the plan'. It proved useful for communication during interviews and other case study analyses. Therefore this framework was adopted and used to structure the outline of this thesis as well. Next to the fact that the framework is useful for communication purposes, it also outlines which elements one should consider when designing a supply chain. Although the power of this framework is the clear overview, it lacks the identification of institutions. Further research which focuses more on the use of institutions within supply chains, could use the framework to start their analysis with and add institutional elements.

9.3.2 Confrontation analytical model and simulation model

The structural differences between analytical and simulation models are discussed in chapter 5. Here only the added value and negative points of simulation for inventory management are discussed.

It is clear that both types of models used in this thesis are white box models, as all relations are clearly defined using mathematical equations (and probabilistic values in case of the simulation model). However, the involved parties perceive the behavior of inventory performance in reality as a black box: it is not understood how the chosen settings affect the inventory performance. Here is where the simulation clearly distinguishes itself from the analytical model by showing these dynamics graphically.

Moreover, looking at the structure of both models, it is easier to explain what is being done in parts of the simulation model (because it represents real-world elements) instead of the parameters used in the analytical model.

The combination of a discrete-event model with Monte Carlo simulation resulted in risk profiles for the chosen safety settings. Probably because both methods are often used separately, little has been written on the combination of both let alone the results for inventory management.

However, using the binary search algorithm to find the optimal safety setting according to the simulation model takes a lot of time. Therefore, in order to calculate the optimal safety stock settings, the analytical model is preferred to calculate settings for hundreds of s.k.u. The following should be taken into account: Many analytical models are available and all make different assumptions. The results of the simulation model doesn`t differ significantly with the analytical model discussed by Silver et all (1998) although, different inventory performance is expected when other analytical models are used. However, the dynamics shown by the simulation model remain the same.

9.3.3 Confrontation results and theory on safety time

Apart from the simulation model, one other inventory management concept which is underexposed in literature is the use of safety time. Literature which discuss inventory models often present ways to calculate safety stock and mention that the use of safety time also is possible. However, no discussion is presented on possible advantages and disadvantages.

The case study showed that this in practice leads to the perceived advantages of safety time: high inventory when needed and no stock when no demand is forecasted. However, the negative dynamics are unknown or ignored. The simulation model now is used to set clear guidelines for the effects of the use of safety time.

9.4 Implementation strategy

In order to implement the findings into the current inventory management, a solid implementation strategy is needed. First, the challenges are identified which should be tackled using the learning's of this thesis. Here after an implementation approach is discussed.

9.4.1 Challenges in current situation

In the current situation several challenges are identified. First of all there is the perception on the inventory settings: it is assumed by many that safety time has many advantages and safety stock results in a lot of dead stock. These are half-truths and undermine optimal inventory performance. Therefore first the perception on these settings needs to be changed.

The second challenge is that in the core of the inventory model, a cap is used for the COV_{FE} which limits the power of the suggested safety settings.

Next, people are likely to be risk averse and don`t want to initiate any changes. So, once the perception on the safety settings is changed, they need results to proof higher management that the changes are useful.

A last challenge considers the glide-path target. This measure is used by upper management to control inventory targets. Improving results are needed to proof the benefit of not using the glide-path target to prevent interventions on healthy s.k.u.

9.4.2 Approach to implement improvements

These challenges aren`t solved by implementing fixed safety stock overnight. First the perception on the use of only safety stock needs to be changed. This can be done by using the simulation model to show the effects on the dynamics of inventory performance. By using realistic parameters corresponding with a specific category, the simulation model can reflect familiar scenarios for the involved planners. The objective of this phase should be to educate the planner on the impact of *all* effects of different safety settings.

After having changed the perception on the safety settings, a pilot phase should be used to test the use of safety stock for a select group of products. It doesn`t matter of which classification this model is: high or low volume, high or low COV_{FE}. However, the effects are most clear when a s.k.u. with a high COV_{FE} is used. Therefore also the cap on the COVFE in the inventory should be removed in order to get optimal safety stock suggestion.

For this group of s.k.u., only safety stock should be used as suggested by the analytical inventory model without any expert intervention. Also, for this group of products, it should become clear that these s.k.u. should not be affected by interventions triggered by the glide-path target. This would darken the performance. Once the performance is improved, the safety settings can be applied to a larger group of s.k.u.

While applying the safety settings to the whole product category, also the glide-path target needs to be re-evaluated. As discussed, it pretends to prevent excessive inventory but instead it reduces healthy inventory. If the objective is to prevent the creation of yellow NPI, one should tighten other targets which drive inventory such as their forecast error (SP1 and SP3). If the objective is to cross reference inventories across categories and markets, it should not be used to trigger interventions.

10. Recap, conclusions & recommendations

With the results obtained from the simulation model, the main research question posted at the beginning of this thesis could be answered. Before doing so, a recap towards the answers is described.

Supply chain management focuses on the optimization of inventory, supply chain capabilities and customer demand in order to achieve targeted service levels. Inventory is kept, amongst others to cover demand in case of unexpected variation in lead time (supply chain capabilities) and demand (forecast errors) in order to achieve target service levels.

At Procter and Gamble, currently multiple analytical inventory models are used which suggest target inventory settings. These inventory settings are the core of every inventory management strategy but are not fully relied on due to the perceived black box effects of these settings on the inventory performance. Currently, s.k.u. are sufficiently achieving the target service levels, but it is accompanied with high inventory levels and according costs.

A comprehensive analysis of the supply chain elements, inventory management and the role of analytical inventory models is performed. The results are used to develop an inventory simulation model which is considered the next step towards well founded inventory management decisions. Given the fact that P&G`s Baby care category was chosen as case study, the main research question central in this research was;

How can the targeted service levels in the P&G distribution centre in Rumst be realized for s.k.u. of the Baby care category using the right inventory management strategy and how can a dynamic inventory model improve the inventory levels in Rumst?

By answering the individual sub questions stated below, the main question could be answered.

1) **What processes are involved for inventory management?**
2) **How should an inventory simulation model be developed?**
3) **How can the inventory management be improved using an inventory simulation model?**

10.1 What processes are involved for inventory management?

Based on a literature study, a framework to assess inventory management is created which defines inventory management as an iterative process of planning the work and working the plan, with the aim of optimizing the target performance measures. Each pillar is driven by different elements (Figure 10-1).

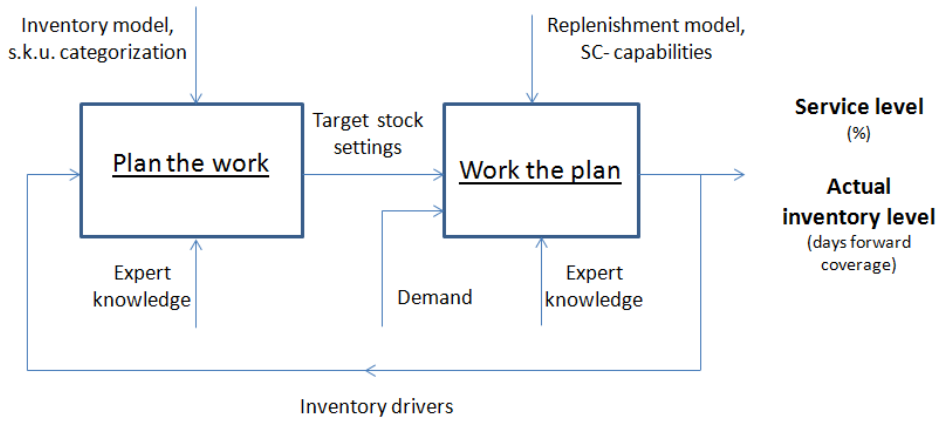


Figure 10-1: Framework for analyzing inventory management

Plan the work

In order to properly plan the work for hundreds of s.k.u., first a classification is needed to categorize s.k.u. according to importance. For the important s.k.u. (e.g. based on volume, value and/or demand volatility) more detailed information should be used to accurately deliver inventory settings which fit the particular circumstances of this s.k.u. in order to achieve high performance with.

A second part of planning the work is deciding on the value for the inventory safety settings First, based on the performance drivers (inventory, demand, target service level and supply chain capabilities) target safety stock settings are calculated which is able to cover for uncertainties of supply chain elements during the replenishment lead time. In order to do so, analytical models are used which return an optimal value for the safety stock. Experts need to decide whether to use dynamic safety time (in days, which targets replenishments days before the actual need), a fixed safety stock (SU) or a combination which then is used as the target safety stock level.

Last, a lot sizing strategy has to be determined which affects the size of a replenishment. The lot sizing strategy doesn`t affect the safety stock levels. However, because different strategies differ in number of replenishments and size of replenishments, it does affect inventory costs via the ordering and stock keeping cost. The selected inventory settings and lot sizing strategy together are called inventory strategy. For the selected Baby care category, lot sizing strategy is the so called ‘lot for lot’ strategy which minimizes the average total inventory but not necessarily minimizes the inventory cost.

Work the plan

After having selected the inventory strategy, a replenishment system should aim at getting the actual inventory levels as close to the targeted inventory levels as possible. DRP-I determines the time-phased requirements for replenishments at the distribution centers. In order to do so, it only uses depended.

10.2 How was the inventory simulation model developed?

For the design approach of the simulation model three viewpoints have been combined. First, the simulation method of Banks (1999) for the general modeling methods.

Secondly, the META model (Herder & Stikkelman, 2004) is used. It is a design framework which considers design as "selecting an instance in the design space that meets the objectives and constraints". The model starts with defining the model requirements and the possible solution space to answer to these requirements with.

Last, the spiral model (Boehm, 1988) is used for the approach. The spiral model consists of several iterative stages in which the model is designed, tested and adapted resulting in a robust model design. The resulting design framework is shown in Figure 10-2.

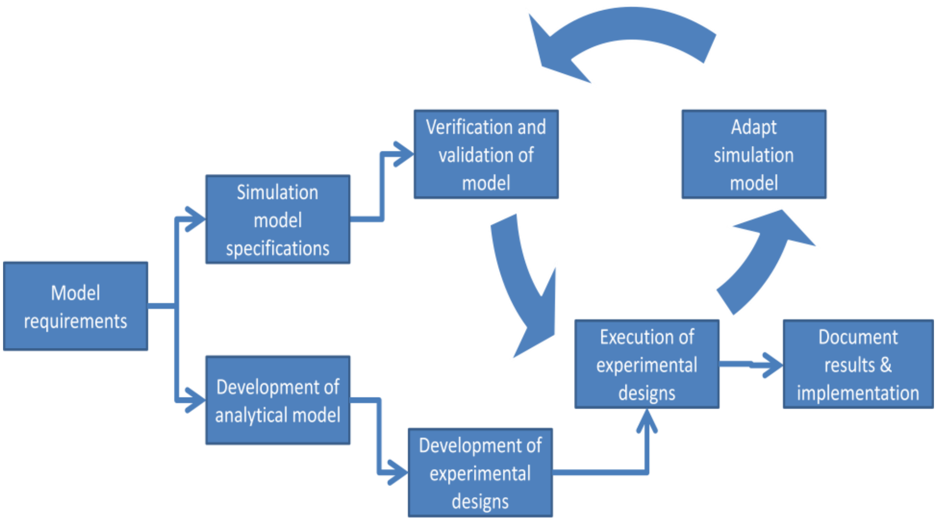


Figure 10-2: Design framework for inventory simulation model

Monte Carlo simulation in particular is selected due to the combination and effects of two mathematical theorems: the law of large numbers and the central limit theorem. Not only can MC simulation, considering the first theorem, show an *estimate of the expected result* (which also is done by an analytical model), it also returns an *estimate of the uncertainty in this estimate*. This makes Monte Carlo an interesting simulation approach to create insights on the dynamics of performance measures.

10.3 How can the inventory management be improved using an inventory simulation model?

The conclusions on how inventory management can be improved using the inventory simulation model are elaborated on using the simulation objectives as pillars. The objective to be achieved with the simulation model, echoes the research objectives set at the introduction of this research:

1- Create insights on the dynamics of performance measures with the use of different inventory management strategies.
2- Quantify current inventory performance
3- Test the practical applicability of an analytical inventory model to achieve target case fill rate of 99% and minimize inventory levels

10.3.1 Create insights on dynamics of performances measures

In this thesis the effects of different types of safety stock settings are discussed and tested using a simulation model. The simulation model has shown the effects of the use safety time and safety stock:

Safety time The use of safety time has positive effects when (1) the forecast is accurate. Inventory benefits from accurate low forecasts, which results into a decrease of the total inventory whereas high CFR score are obtained in case of accurate forecasted peaks in demand.

However, the negative effects of safety time perhaps are bigger than currently known at P&G. On the one hand, when over forecast are made, the dynamics of safety time enlarges the creation of excessive inventory. On the other hand, when the forecast of demand is too low, there is not enough safety stock to cover for the forecast error. This leads to the reasoning why P&G inventory is now at its most vulnerable: Demand hurts the most, when it is least expected. And that is exactly when (and why) there should be safety stock. This is not the case with the use of safety time.

Safety stock Safety stock is a robust approach for covering for errors during the replenishment lead time. Extreme low values for CFR scores or high values for total inventory, are not as common as with the use of safety time. Moreover, according to the simulation study the average scores for both CFR and inventory are better than when safety time is used.

Yellow NPI The simulation results moreover show that in many cases yellow NPI is created. In the reality, yellow NPI is often thought of as wrong and thus is used as trigger to intervene. However, this simulation model shows that for some s.k.u. categories, yellow NPI is expected.

10.3.1 Quantification of current inventory performance

In the current situation, the Baby care category uses a strategy in which the use of fixed safety stock and dynamic safety time is combined. The results of this actual scenario are compared with scenarios where only either type of safety setting is used.

The simulation showed that for the four analyzed s.k.u., in case only fixed safety stock settings are used, the average inventory can be reduced with an average of 20%. Generalizing for the whole baby care category by taking into account the volume shares of each s.k.u. class, the inventory reduction is estimated on 1%. Moreover, the weighted CFR can on average be improved with 2 percent points.

10.3.2 Optimize inventory strategy

The verified and validated simulation model is used to analyze the suggested safety stock settings for the analytical model that has been developed based on Silver et all (1998). The suggested safety stock settings by this analytical model to obtain a CFR score of 99%, do not deviate significantly in most of the tested scenarios. This means that the developed analytical model is practical applicable for inventory management.

The analytical model developed at P&G deviates from the analytical model suggested by literature. Although deviations between the suggested settings are small, the key issue is the fact that the analytical at P&G proposes both safety stock and safety time. This leaves experts (with different scorecards) to decide on the right balance between safety stock and safety time. Although the analytical model consists of clear mathematical equations, currently the effects on inventory performance by of choosing a safety setting strategy are perceived as a black box. Evidently, this now has resulted in experts preferring safety days and arbitrarily adding some safety stock, not being aware of the negative side effects mentioned above.

The use of the simulation model (in comparison with an analytical model) shows the dynamics which are a consequence of choosing either type of setting which result in (1) different average scores on the performance measures and (2) different ranges of uncertainty around these averages. Educating the involved parties about these consequences is required to make sound considerations before selecting safety stock settings.

10.4 Recommendations for future research

In this thesis an inventory management simulation model is developed using literature and a case study at Procter and Gamble. The simulation model is valid given a set of boundaries which are reflected on in the discussion (chapter 9). The focus in this thesis is on finding the optimal safety setting strategy, achieving a target CFR rate with as little average total inventory as possible.

Based on literature, the lot for lot replenishment strategy is selected and implemented in the simulation model. This strategy results in the lowest average inventory but it does not look at lowest average costs. Other replenishment strategies however do include the cost for every replenishment and stock holding costs. Examples are the economic order quantity and the Silver-Meal heuristic. Because the objective of this thesis was to achieve target service levels while minimizing the inventory levels (and not inventory costs), no other replenishment strategies were chosen. However, in the developed simulation model, other types of strategies can be implemented easily. Due to the use of Excel, the model can be used widely.

During the course of the research and especially during the interviews taken, it became clear that there is a lot of misunderstanding on the effects of different safety settings on inventory performance. The developed simulation model can help educate involved parties by visually showing these dynamics and their effects. A step further could be to implement the simulation model into a serious game. This would make it possible to let the planners experience the effects of their choices on inventory performance without hurting the actual performance.

10.5 Recommendations for P&G

The recommendations which can be made for P&G in particular, are described according to the pillars used

thro

the s

Blank intentially

Base

used

Seco

safet

an a

diffic

that

Third

unde

and

mathematically correct way, the model itself and the data source for many input parameters of the model (IDF) show the 'standard deviation'.

Blank intentially

Fourt
for th
devia
trigge
inclu
make

1

The r
to lo
strate
yello
postp
woul
critic
issue

On th
some
an u
probl
it onl

The
purp
Howe
inven
preve
segm
overs
meas
meas

11. Reflection

This last chapter reflects on several elements of this research project. Five different aspects are reflected on in the following order: The academic relevance, the practical relevance, the results of this thesis, the methods and approach used and finally the process in general.

11.1 Academic relevance

Supply chain management is a widely discussed subject in literature. A particular topic, inventory management, has received much attention in the past decades, producing many methods for securely planning inventory processes and optimally executing the plans. However, not all elements are discussed to the full extent leaving risk open for the misuse of concepts.

First, based on current literature, in this thesis a comprehensive discrete event model is developed which is used for Monte Carlo analysis. Although the use of discrete simulation models is common in supply chain literature, many models involve constraining elements which make applicability for actual situations limited. It often concerns the deterministic nature of parameters, e.g. the exclusion of forecast errors, the stationary character of demand (Zizka, 2005) or only analyze the effects over a short period of time (Garcia & Saliby, 2002).

The developed dynamic inventory model is one of the few to simulate the inventory behavior using predominantly stochastic input parameters for a daily reviewed inventory and a lot for lot replenishment strategy (s,S model). Moreover, due to the use of an easy to understand modeling langue (MS Excel), it has opportunities to implement different replenishment systems as well. The model is used to validate the practical applicability of analytical models.

The second point of relevance is the use of the simulation model to analyze the effects of different inventory strategies in practice to create risk profiles. The results show that depending on the safety setting used, CFR performance and inventory performance can be predicted with more or less accuracy.

The last point of relevance is the guidance of the use of either safety stock or safety time. At the core of inventory management are the analytical inventory models to calculate the optimal safety settings with (safety stock and safety time). However, little attention is given to the distinction between both safety setting strategies, let alone ways to quantify the differences. This thesis has used simulation to provide examples to clarify and quantify the different effects of these strategies.

11.2 Practical application

The practical added value consists of two parts. Firstly, the insights in the dynamics of different safety setting strategies support the inventory parameters reviews at P&G. In the past, experts used their experience to balance the use of safety time and safety stock, not knowing the impact of each setting on both CFR and inventory. The results of this study show how the dynamics of different safety strategies impact the inventory and the service level. Although expert review remains valuable, this thesis makes the need for consideration between safety days and safety stock, obsolete.

Secondly, in the past, the analytical model provided two point estimates. On the one hand this provides clear handhelds for experts when they select the appropriate safety setting. On the other hand, it does not tell anything on the risk profile of this decision. However, the use of Monte Carlo analysis on the simulation model shows which are the risks involved using certain safety setting strategies.

Finally, in order to educate stakeholders on among else above findings, the simulation model can be used to show the dynamics resulting from the used safety setting strategy. Currently, the effects on inventory performance by choosing a safety setting strategy is perceived as a black box. Using the results of a single simulation run, the behavior of inventory over time can be analyzed. These graphics help understand both positive and negative consequences of safety setting strategies.

11.3 The results

The results of this research project are two-fold; first, the simulation model and second this thesis.

Past experiences have proven that simulation models both can add a lot of value to a research but also a lot of pain in the process towards the results. During the development of this simulation model the admonition is "The more complex you make the model the worse the results get". Especially after reading Silver (2012) on the negative effects of too much complexity and the power of simple models, I`m convinced that the final simulation model is both a comprehensive and useful simulation model to mimic real inventory dynamics with.

This thesis is the breech on the work performed and describes the design of the inventory simulation model leading to both practical and scientific relevant conclusions. In order to describe a complex problem like this clear and crisp, a lot of attention was given to the writing in this report. First, the division of the thesis into several parts enables the reader to select relevant parts. Secondly, defining the 'Plan the work' and 'Work the plan' pillars proved to be useful in communication during the performance of the case study. Therefore these pillars are used in the structure of this report as much as possible as well. Finally, the author aimed at using accessible language and concepts throughout the report.

11.4 The methods and approach

This research started with the objective to identify unhealthy inventory at P&G. Soon it became clear that there is no easy definition on what a healthy inventory is. Therefore first a comprehensive literature review was conducted on supply chain management and inventory management in particular.

Hereafter, the literature was applied on several inventories at Procter & Gamble which made clear two things. (1) Even within one company, knowledge on and strategies for inventory management differ. (2) Literature sets no guidelines for the differences between safety setting strategies and is lacking models to accurately test these strategies with practical applicability. Here the academic challenge took shape.

Although literature gave a solid start by identifying inventory elements, performance drivers and ordering systems, it lacked realistic simulation models to test inventory strategies with. Most simulation models used for inventory simulation and discussed in literature involve constraining elements which make the applicability in practice limited. Therefore a model design approach was developed that would secure the practical applicability of the results of the model. Central part of this approach is the use of the TIP-framework. The author values the power of this framework to map key elements across three pillars to get a comprehensive system understanding. Secondly, the use of the META-model creates a structured way from initial objectives towards the simulation model. Finally, the elements from the spiral model proved its value during the modeling phase. Many design iterations were made based on expert interviews and reviews. The combination of a system approach and a structured modeling framework has supported the development of a practical applicable simulation model.

Besides performing a literature review and desk research to create an understanding of all system elements, several other methods proved to be valuable as well. P&G is one of the world`s leading FMCG companies with numerous benefits but also some pitfalls when performing a case study. First of all, an overload of data is available at P&G. Therefore it is important to develop a focused approach in order to prevent drowning in irrelevant datasets. Discussions on the right scope of the project helped to overcome this pitfall. Secondly, obtaining tacit knowledge from colleagues throughout the supply chain, helped creating an understanding of the P&G processes and the differences with literature. Because not everyone was aware of the challenges this research was focusing on nor was familiar with all technical details, clear communication (e.g. the use of the plan the work, and work the plan – pillars) was essential. After the first results became clear, colleagues became enthusiastic about the possibilities of the model and the use of the results. P&G was a great environment to perform this research at and learned me a lot more than only the results delivered within this thesis.

11.5 Process steps taken

During the period that I`ve been working on this graduation thesis, I`ve learned a lot both on an academic and personal level. First of all, a research project in a supply chain is not quite the subject that I have been studying over the past years at Delft University of Technology. Over the past years my focus has been on the Energy domain and to some extent the fields of modeling, simulation and gaming. The reason that I looked for a supply chain subject is that I wanted to pull myself out of my comfort zone and proof that with the lessons I`ve learned I could handle challenges in other knowledge fields. Moreover, I believe that discussion with other fields of expertise prevents you from getting stuck with possible conventional ways of thinking. It is important to keep asking yourself always "why are we doing this and why are we doing it in this way?" (whether you are an expert or an outsider). Discussing such a question helps identifying the real challenges as well as the real solutions. At the beginning of this research I sometimes assumed that founded literature would have all the answers needed. However, as this thesis describes, this was not always the case which forced me to combine methods and create new types of models.

During my academic career I`ve been learning different types of modeling approaches. For discrete event simulation models I`ve been using Arena software in the past. One of the values of the use of Arena, is the possibility to animate the system process. For this case however, instead of the processes, the output measures were more important to animate which made the use of Arena less applicable. Moreover, to make the model useful for Procter and Gamble, the software package used should be available at the company, which made MS Excel a good fit. These reasons triggered me to develop the simulation model entirely in MS Excel. Although I already had some basic Excel skills, the use of Visual Basics for Applications was new to me. With help of different Excel fora and the debugging function I mastered the skills needed for the simulation model. In hindsight, I`m glad that I taught myself this modeling language because it opens up new possibilities when working with MS Excel.

A last learning worth mentioning concerns the struggle between doing academic research and the need to support practical processes at the same time. At times either aspect had the need for more attention. Overall I have tried to focus on the usability of the simulation model. In this way I could use the model to analyze the use of different safety setting strategies to support literature with, but also use the simulation to improve practice at P&G. This struggle is hard, especially for graduating students with relative little experience with company processes. However, iteratively combining literature and knowledge from a case study not only speeds up the learning curve but also shows that the perceived distance between both worlds isn`t as big as some think. Moreover, the useful results of this thesis have motivated me throughout the process.

12. Bibliography

Aguilar, M., Pater, A. J., & Rautert, T. (1999). Business Process Simulation: A fundamental step supporting process centered management. *Proceedings of the 31st conference on Winter simulation: Simulation---a bridge to the future - Volume 2* (pp. 1383 - 1392). Amsterdam: Andersen Consulting.

Alves, E. (2013, January 25). DRP planning at P&G. (J. Vrouenraets, Interviewer)

Alves, E. (2013, March 18). Validation of simulation model. (V. Jeroen, Interviewer)

Anderson, T. (2011). Anderson-Darling Tests of Goodness-of-Fit. *International Encyclopedia of Statistical Science, Springer* , p. 1-7.

Banks, J. (1999). Introduction to simulation. *Simulation Conference Proceedings, 1999 Winter - Vol 1* (pp. 7 -13). Atlanta, USA: AutoS.

Berniker, E., & McNabb, D. E. (2005). Applying Matrixed Pareto Analysis with activity based costing for operations and cost management. *Journal of Business & Management;Jan2005, Vol. 11 Issue 1* , 73-88.

Bland, J., & Altman, D. (1995). Multiple significance tests: the Bonferroni method. *BMJ: British Medical Journal 310 (6973)* , p. 170.

Boehm, B. W. (1988, May). A spiral model of software development and enhancement. *Computer Vol 21, Issue 5* , pp. 61-72.

Buzacott, J., & Shanthikumar, J. (1994, December). Safety Stock versus safety time in MRP Controlled Production systems. *Management Science Vol 40* , pp. 1678 - 1689.

Cáceres-Cruz, J., Grasman, S. E., Bektas, T., & Faulin, J. (2012). Combining Monte Carlo Simulation with heuristics for solving the inventory routing problem with stochastic demands. *Winter Simulation Conference* (p. p. 274). Barcelona: Open University of Catalonia.

Calvert, S. C., & Taale, H. (2012). Verschuiving naar Probabilistische Modellering is geen keuze. *Colloquium Vervoersplanologisch speurwerk* (p. 13). Amsterdam: TU Delft.

Croxton, K. L., García-Dastugue, S. J., Lambert, D. M., & Rogers, D. S. (2001). The Supply Chain Management Processes. *The International Journal of Logistics Management, Vol 12, Number 2* , p. 13-35.

Davis, T. (1993). Effective supply chain management. *Sloan Management Review* , p. 35-46.

de Kok, A., Fortuin, L., & van Donselaar, K. (2012). *Analysis of stock control models for one location with one product.* Eindhoven: Technische Universiteit Eindhoven.

Dunn, W. L., & Shultis, K. J. (2011). *Exploring Monte Carlo Methods.* Elsevier science.

Everette, S., & Gardner, J. (1990). Evaluating forecast performance in an inventory control system. *Management science 36(4)* , p. 490-499.

Farasyn, I. (2012, October 2). (J. Vrouenraets, Interviewer)

Farasyn, I. (2012, 10 02). Inventory models at P&G. (J. Vrouenraets, Interviewer)

Farasyn, I., Perkoz, K., & van de Velde, W. (2008, July - August). Spreadsheet models for inventory target setting at Procter & Gamble. *Interfaces* , pp. p. 241 - 250.

Flores, B. E., & Whybark, D. C. (1986). Multiple Criteria ABC Analysis. *International Journal of Operations & Production Management 6(3)* , p. 38-46.

Garcia, E. S., & Saliby, E. (2002). A simulation model to validate and evaluate the adeaquacy of an analytical expression for proper safety stock sizing. *Proceedings of the 2002 Winter Simulation Conference Vol 2* (pp. p. 1282 -1288). Rio de Janeiro: IEEE.

Goldratt, E. M., & Cox, J. (2004). *The Goal: A process of ongoing improvement.* North River Press.

Haans, M. (2001). *Consolidations in logistics.* Eindhoven.

Haugh, M. (2004, September). Overview of Monte Carlo Simulation, Probability Review and Introduction to Matlab. New York, USA.

Herder, P. M., & Stikkelman, R. M. (2004). Methanol-based industrial cluster design: A study of design options and the design process. *Industrial & engineering chemistry research 43(14)* , pp. p. 3879 - 3885.

Houlihan, J. B. (1988). International Supply Chains: A New Approach. *Management Decision 26(3)* , p. 13-19.

Hyndman, R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy. *Internatuional Journal of Forecasting 22(4)* , p. 679-688.

Jaio, S., & Du, S. (2010). Modeling for Random Inventory System Based on Monte Carlo Theory and Its Simulation. *Third International Symposium on Information Science and Engineering* (pp. 296 - 399). IEEE.

Kelton, W., & Law, A. (2000). *Simulation modeling and analysis.* Boston: McGraw Hill.

Koppenjan, J., & Groenewegen, J. (2005). Institutional design for complex technological systems. *International Journal of Technology, Policy and Management 5(3)* , p. 240-257.

Koray Perkoz, M. (2004). *Manual for the Standard Finished Products Inventory Model FIM_04.* Brussels: P&G.

La Londe, B. J., & Masters, J. M. (1994). Emerging Logistics Strategies: Blueprints for the next century. *International Journal of Physical Distribution and Logistics Management 24(7)* , p. 35-47.

Law, A. M. (2011). How to select simulation input probability distributions. *Proceedings of the Winter Simulation Conference* (pp. p. 1389 - 1402). Tucson: Winter Simulation Conference.

Lee, H. L., & Billington, C. (1992). Managing supply chain inventory: Pitfalls and opportunities. *Sloan management review 33(3)* , p. 65-73.

Lee, H. L., & Billington, C. (1992). Managing supply chain inventory: Pitfalls and opportunities. *Sloan management review 33(3)* , p. 65-73.

Liao, C.-J., & Shyu, C.-H. (1991). An Analytical determination of Lead Time with Normal Demand. *International Journal of Operations & Production Management 11(9)* , p. 72-78.

Mentzer, J. T., DeWitt, W., Keebler, J. S., Min, S., Nix, N. W., Smith, C. D., et al. (2001). Defining supply chain management. *Journal of business logistics 22(2)* , p. 1-25.

Min, H., & Zhou, G. (2002). Supply chain modeling: past, present and future. *Computers & Industrial Engineering 43(1)* , p. 231 - 249.

Nandola, N., & Rivera, D. (2011). Hybrid Model Predictive Control Applied to production inventory systems. *18th IFAC World Congress 18(1)*, (pp. p. 7328 - 7333). Milan.

Ostrom, E. (2008). Doing Institutional Analysis Digging Deeper than markets and hierarchies. *Handbook of New Institutional Economics* , p. 819 -848.

P&G. (2012). *Annual Report 2012.* The Procter and Gamble Company.

P&G. (2013, 02 11). *CBA`s / Best in class.* Retrieved 02 11, 2013, from Teamspace.pg.com: http://teamspace.pg.com/sites/bfferp/CBA/Shared%20Documents/Forms/SIPCBA.aspx

P&G. (2012, 10 05). Daily Control Chart (site based). Rotterdam, The Netherlands.

P&G. (2013, January 16). *IDF Lane master*. Retrieved January 16, 2013, from Intelligent Daily Forecast system: http://bdc-intra627.internal.pg.com/Citrix/MetaFrame/auth/login.aspx

P&G. (2012, December 04). *Intelligent Dailty Forecast system.* Retrieved December 04, 2012, from Intelligent Dailty Forecast system: http://bdc-intra627.internal.pg.com/Citrix/MetaFrame/auth/login.aspx

P&G. (2011). *Market Planning On-boarding Training Program.* The Procter & Gamble company.

P&G. (2012, 10 04). SourceOne Analyzer - CFR WE Cube. Rotterdam, The Netherlands.

P&G. (2011, June 3). The eight habirts - WEMDO Superior Demand Planning Issue 3 jun 11. Brussels, Belgium.

P&G. (2012, 12 2). The Six habits - WEMDO superior Supply Planning. Brussels, Belgium.

P&Ga. (2010). Inventory training 101 v 12-2010. Rotterdam, The Netherlands.

P&Gc. (2012c, October 03). Standard ad-hoc report. Rotterdam.

Palisade. (2013, February 07). *About Monte Carlo Simulation.* Retrieved February 07, 2013, from www.palisade.com: http://www.palisade.com/downloads/factsfax/WhatIsMonteCarloSimulation.pdf

Pourakbar, M., van der Laan, E., & Dekker, R. (2011). End-of-Life Inventory Problem with Phase-out Returns. *Econometric Institute Report* , p.1-30.

Reid, D. R., & Sanders, N. R. (2013). *Operations Management.* Singapore: John Wiley & Sons.

Rosen, O. (2013, January 29). Dr. Ir. (J. Vrouenraets, Interviewer)

Rosen, O. (2008). *Forecast error calculation for safety stock target setting.* Cincinatti: P&G.

Rosen, O. (2009). *Proper use of Safety stock and safety time.* Cincinatti: P&G.

Rusin, D. (2013, february 22). BPE - responsibility split clarification. (J. Vrouenraets, Interviewer)

Sabbe, M., & van der Oost, M. (2013, 01 09). Selection of product category for case study. (J. Vrouenraets, Interviewer)

Sarikaya, E. (2013, January 21). Ir. (J. Vrouenraets, Interviewer)

Sarimveis, H., Panagiotis, P., Tarantilis, C. D., & Kiranoudis, C. T. (2008). Dynamic modeling and control of supply chain systems: a review. *Computers & Operations research 35(11)* , p. 3530-3561.

Schneider, H. (1981). Effect of service-levels on order-points or order-levels in inventory models. *International Journal of Production Research* , 615-631.

Schneider, M. (2009). *Out of stock! Out of business?* Twente: Twente University.

Shanthikumar, J., & Sargent, R. (1983, November-December). A Unifying view of Hybrid Simulation / Analytic Models and modeling. *Operations Research 31(6)* , pp. p. 1030 - 1052.

Silver, E. A., & Peterson, R. (1985). *Decision systems for inventory management and production planning.* New York: John Wiley & Sons Inc.

Silver, E. A., Pyke, D. F., & Peterson, R. (1998). *Inventory management and production planning and scheduling.* New York: John Wiley & Sons.

Silver, N. (2012). *Signal and the noise.* New York: The Penguin Press.

Snauwaert, D. (2012, September 07). Inventory workshop. Brussels, Belgium.

Stadtler, H. (2005). Supply chain management and advanced planning––basics, overview and challenges. *European Journal of Operational Research 163(3)* , p. 575–588.

Stevenson, W. J. (2005). *Operations Management.* The McGraw-Hill Companies Inc.

Ten Heuvelhof, E., & De Bruijn, H. (2012). *Management in Networks: on multi-actor decision making.* Routledge.

van Amstel, G. (2013, March 7). Code list NL. Rotterdam, Zuid-Holland, The Netherlands.

Van der Aalst, W. *Handboek simulatie.* Eindhoven: Faculteit Wiskunde en Informatica Technische Universiteit Eindhoven.

van der Oost, M. (2013, March 26). Validation of the simulation model. (V. Jeroen, Interviewer)

van Goor, A., Kruijtzer, A., & Esmeijer, G. (1990). *Goederenstroombesturing, voorraadbeheer en materials handling 1(3).* Leiden/Antwerpen: Stenfert Kroese Uitgevers.

van Goor, A., van Amstel, M. P., & van Amstel, W. P. (1989). *Fysieke distributie: denken in toegevoegde waarde 1(2).* Leiden/Antwerpen: Stenfert Kroese Uitgevers.

Verbraeck, A., & Valentin, E. (2006). Discrete modellen Deel II Distcrete simulatie. *Discrete modellen Deel II Distcrete simulatie* . Delft, Zuid-Holland, Nederland: Faculteit Techniek, Bestuur en Management.

Vergouwen, Y. (2012, 09 10). Ir. (J. Vrouenraets, Interviewer)

Verschuren, P., & Doorewaard, H. (2010). *Designing a research project.* The Hague: Eleven International Publishing.

Wendell, W. (1987). Inventory information. In J. H. Green, *Production and inventory control* (pp. 12.1-12.5). New York: McGraw-Hill.

Whybark, D., & Williams, J. (1976). Materials Requirement Planning under uncertainty. *Decision Science 7(4)* , pp. p. 595-606.

Zizka, M. (2005). The analytic approach vs. the simulation approach to determining safety stock. *Problems & Perspectives in Management (3)* , p. 119 - 128.

Table of Contents