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Quantifying the benefits of multi-echelon inventory control
a case study in the multi-echelon distribution network of Hilti AG

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Quantifying the benefits of multi-echelon inventory control

A case study in the multi-echelon distribution network of Hilti AG

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Master of Science
in Operations Management and Logistics

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Abstract

Increased data availability and advanced technologies challenge companies to raise their supply chain processes to a higher level. From an inventory optimization perspective, multi-echelon inventory control may be applied to reduce inventory costs, enhance customer service levels and decrease misalignment across the supply chain. However, changing to such an inventory control policy is challenging and requires a thorough analysis of the potential benefits. This report provides insights into the potential of multi-echelon inventory control under different supply chain characteristic settings.

First, a simulation model is proposed to study the effect of different inventory control policies on product availability and inventory costs in a forecast-driven supply chain. This simulation model is used to compare different safety stock setting procedures, based on decentralized and centralized inventory control policies. Secondly, a detailed comparison is performed to study for which type of items a centralized control policy is most important. The results prove that the potential highly depends on the supply chain characteristics. Based on the findings, companies are recommended to consider multi-echelon inventory control, especially if their product portfolio consists of 'high-potential' items.

Management summary

Problem description

This research is conducted at Hilti AG, a company that is developing, manufacturing and directly selling leading-edge technology for the professional construction industry. Currently, Hilti's inventory control strategy is based on decentralized control. The locations within the supply chain network operate independently with the aim to offer a high service level to their direct successors against lowest inventory costs. From a holistic point of view, this might not be the most cost-efficient solution. Therefore, this master thesis is initiated to research the potential benefits of a centralized inventory control policy. Although the literature stream on centralized inventory control is broad and results are promising, reported practical applications are scarce. Most probably, the high complexity of the analysis of multi-echelon systems and the required organizational commitment across the supply chain prevent real-world implementations. Furthermore, comparison studies are limited and the gap between local and centralized inventory control requires further research attention. It is hypothesized that the potential of centralized inventory control depends on combinations of supply chain characteristics. Hence, empirical evidence that shows the benefits of centralized inventory control under different supply chain settings can support decision-making; for which items is the potential of centralized inventory control most promising? Consequently, the main research question is formulated as follows:

Under which supply chain characteristics does a centralized inventory control policy outperform a local inventory control policy the most?

The following five supply chain characteristics are considered:

1. Customer demand
2. The variability of the customer demand
3. The lead-time to the most upstream location in the distribution network
4. The variability of the lead-time to the most upstream location
5. Holding costs

Research design

To answer the research question, a simulation model is designed in which three-echelon distribution networks can be modelled. The simulation is based on a forecast-driven supply chain, where demand forecasts are propagated to upstream locations and dependent demand is planned by a time-phased approach. Furthermore, unsatisfied demand is backordered and locations are replenished in batches.

Four different safety stock setting procedures are considered:

1. ***Historical safety stock values as set by Hilti***
2. ***Safety stock values based on single-echelon, decentralized inventory control***
3. ***Safety stock values based on multi-echelon, centralized inventory control***
4. ***Safety stock values based on single-echelon inventory control with an adapted upstream service level***

Results case study

A case study has been performed to compare the difference in inventory investment between the different control policies. 26 articles were studied, randomly selected without restrictions on the number of locations or echelons. Overall, the multi-echelon centralized control policy outperforms local policies. However, the benefits depend largely on the supply chain characteristic settings. In Table 1, the yearly savings in inventory holding costs are presented (ranked from highest to lowest) under different combinations of the studied variables (bench mark single-echelon inventory control).

Table 1 Yearly savings from moving from Single-Echelon to Multi-Echelon inventory control

Savings	Demand	Lead-Time	CoV Demand	CoV Lead-time	Holding costs
4645	H	H	L	L	H
1109	H	L	L	L	L
494	H	H	L	H	H
486	H	L	L	H	H
369	H	H	L	H	L
333	L	H	H	H	H
191	L	H	H	H	L
186	H	H	L	L	L
166	H	H	L	L	L
163	L	H	H	H	L
142	L	L	H	H	H
79	L	L	L	H	H
71	H	H	H	H	L
64	L	L	H	H	H
63	L	H	L	L	H
61	L	H	H	L	L
59	L	H	H	L	H
46	L	L	H	L	H
38	H	L	L	L	H
32	L	L	H	L	H
22	L	L	L	H	L
17	L	H	L	L	L
10	L	L	L	H	L
-2	L	L	H	H	L
-4	L	L	H	L	L
-18	H	L	L	H	L

Although the savings of the centralized control policy show deviations across the three decentralized inventory control policies differ, general findings hold under all settings:

- The benefits of centralized control are expected to be high when the demand rate, the lead-time to the first location in the distribution system and the holding costs are high.
- The potential savings for low demand, low cost items are expected to be quite low, especially when the central warehouse is resupplied within a short time frame.
- For items with a high demand rate and a high lead-time to the first location in the distribution network, the centralized control policy shows substantial savings even though holding costs and variability in supply and demand are low.

Sensitivity analysis is performed to study the effect of i) the forecast and ii) the internal lead-times. The general findings remain consistent. Hence, the benefits of centralized inventory control appear to be dependent on the supply chain characteristics settings. Based on the same line of reasoning, numerical results show that the impact of lowering or increasing service level targets is different under different scenario settings.

Conclusions and recommendations

Most importantly, the potential of centralized safety stock setting across Hilti's distribution network is quantified. The results can be used to make valid choices whether changing to a centralized inventory control policy is worthwhile. From an information system perspective, the only required change are the safety stock parameter settings. However, two other important organization challenges have to be overcome. Change management is needed to prevent reluctancy across supply chain partners and the performance measurement policies within the supply chain have to be aligned with the centralized policy. After the decision is made to pilot a multi-echelon controlled safety stock setting, the items for the pilot have to be carefully picked. Based on this report, starting with high demand, high cost items with a long lead-time to the upstream warehouse can be a good starting point.

Limitation and future research

The main limitation is that the case study is performed for a small set of articles under predefined parameter settings (e.g. batch sizes, amount of locations, demand per location etc.). Although the results cannot be generalized due to the small subset, the findings are expected to hold when more items are studied. Furthermore, focus has been placed on centralized control of safety stock parameters. Thus, the full potential of centralized inventory control has not been explored. However, safety stock parameter setting can serve as a first step towards a practical implementation of centralized inventory control policies, making the study very relevant from a practitioner's point of view. Several directions for future research are identified. The research findings can be strengthened by a larger case study with more test instances. By extending the scope of the research, statistical analysis can be applied to quantify how combinations of different variables affect the cost gap between multi-echelon and single-echelon inventory control. Optimally, a prediction model can be formulated such that companies have a first, quantitative based idea about the potentials for their products. Other future research directions can be extensions to other systems structures and the inclusion of warehouse capacity restrictions.

Preface

Beek en Donk, September 2019

This thesis marks not only the final step towards my master's degree, but also marks the end of my time as a student. After five years, I can proudly say it has been a wonderful journey with many cheerful and educational moments. All of this would not have been possible without the support of others.

First of all, I would like to thank my first supervisor Zümbül Atan. I highly appreciate your guidance throughout my master's. From the start of our collaboration onwards, you managed to let me develop my skills and emphasized I should strive for a 'challenging project'. I can assure you this project fulfilled your requirement. Even more important, you are a fantastic mentor and your continuous confidence encouraged me to pursue my ideas. Additionally, I would like to thank my second supervisor Ton de Kok. Your knowledge and enthusiasm in the field are admirable and inspiring. I highly value the time and interest you devoted to this project. Our discussions definitely improved the insights I gained and always let me think about the project in a different way.

This master thesis would not have been established without the support of Hilti. I would like to express my gratitude to Roeland Baaijens and Ruediger Kuebler for granting me the opportunity to conduct my project within GLMP. Moreover, I owe a sincere thank you to my company supervisor Federico Scotti-di-Uccio for supporting me with insights, evaluating my work and helping me with the presentation of results. The great discussions we had about the practical relevance of the topic served as an important motivator for the content of this report. GLMP-team, thanks for making me feel welcome and supporting me with the input I needed.

Next, I am extremely grateful to my friends from TU/e with whom I shared great moments, but also many hours working together. I truly believe that our team dynamics and motivated mindsets resulted in valuable learning moments. A special thanks to Stan. During all those years, we have spent a lot of time together on projects, studying for exams and travelling to university. I could not imagine a more trustworthy and better colleague. Another big thanks to Jordy for always ending up with great discussions during projects, dealing with our diverse working styles, visiting me during my exchange semester and reviewing my report.

Finally, I have to express my deepest gratitude to my family and friends. I realize how lucky I am to have you in my life. A special thanks to those who took the effort to visit me during my graduation project; I really enjoyed those weekends and you ensured I was not thinking about my thesis for a moment. Last, but foremost, I want to thank my parents Rini and Evelyn for supporting me to realize my ambitions and letting me explore the world. Whether it means moving to Mexico or Austria, you always stand me by in all possible ways. I am very grateful to have you in my life.

Lisa van Lierop

If you can't explain it simply, you don't understand it well enough
-Albert Einstein

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List of abbreviations

BU	Business Unit
CoV	Coefficient of Variation
CW	Central Warehouse
DC	Distribution Center
HAG WH	Headquarter Warehouse
HIP	Hilti Integrated Planning
ME	Multi-Echelon
MEIM	Multi-Echelon Inventory Management
MM	Materials Management
MO	Market Organization
MRP	Material Requirement Planning
NDC	National Distribution Center
PP	Production Plant
RDC	Regional Distribution Center
SE	Single-Echelon
SS	Safety Stock

1. Introduction

The aim of this chapter is to provide an overview of the problem context and introduce the problem description. To start, the fundamentals and the structure of the company are addressed. Moreover, a high-level overview of Hilti´s supply chain is provided. The problem and the research questions are introduced in the second section. Sequentially, the project scope is defined.

1.1 Hilti fundamentals

1.1.1 Company introduction

In 1941 two brothers, Martin and Eugene Hilti, founded a five-man manufacturing workshop in their garage. Their company gradually expanded and is now worldwide known as Hilti AG (hereafter called Hilti). Hilti's main business is developing, manufacturing and directly selling leading-edge technology for the professional construction industry. They employ more than 27000 people in order to reach their corporate goal: 'passionately create enthusiastic customers and build a better future'.

With their headquarter located in Schaan, Liechtenstein, Hilti operates in more than 120 countries worldwide. Although the company is globally dispersed, half of total net sales are generated in Europe (Eastern Europe excluded). North-America is the second largest region in terms of sales. Figure 1 shows the distribution of net sales over the regions in 2018 and 2013.

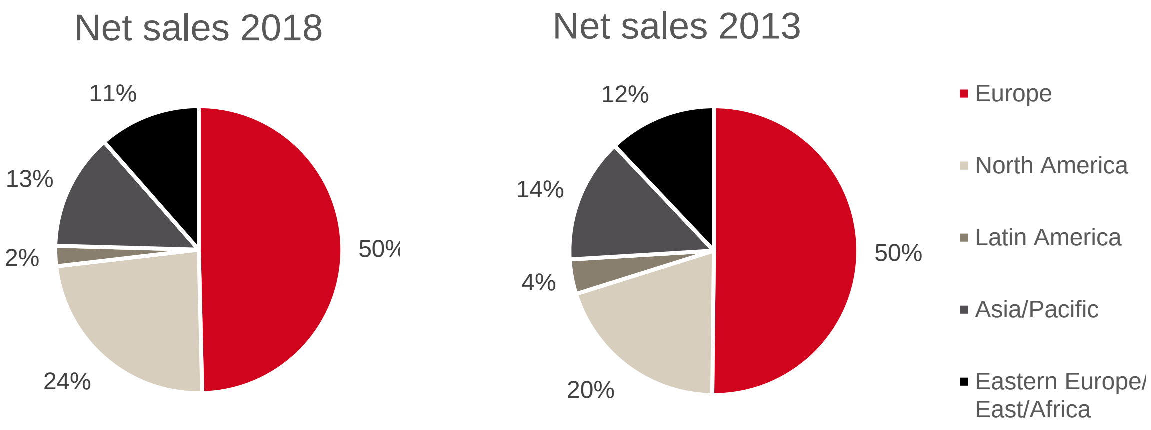


Figure 1 Net sales per region in 2018 and 2013

Hilti´s product portfolio consists of two main business areas: electric tools & accessories and fastening & protection. Within those areas, products are classified into business units. Furthermore, Hilti owns 8 production plants (PPs) located around the world. Next to a division in business units, Hilti also distinguish between 9 different market regions. Regions are further split into multiple market organizations (MOs), where an MO oftentimes represents one country.

1.1.2 Global Logistics

This master thesis is conducted at the Global Logistics department of Hilti, located in Nendeln, Liechtenstein. The Global Logistics department is responsible for the design of global logistic processes and closely collaborates with PPs, BUs and markets in order to improve logistics on a global and regional level. Global Logistics is divided into four functional areas: warehouse management, materials management, transport management and service management.

This project belongs to the Materials Management (MM) focus area of Global Logistic. An important concept within MM is the Hilti Integrated Planning (HIP), introduced in 2013. The aim of the HIP is to improve customer satisfaction, reduce inventory and improve productivity by facilitating an integrated sales & operations planning.

The main objectives of the HIP concept are the following:

- Implement an integrated planning process from customer to supplier
- ‘One number´ principle to steer the value chain
- Synchronized planning calendars and workflow
- Central coordination for all levels of planning
- Improve core processes like Forecasting, Production & Distribution Planning, Fulfillment

Based on the HIP concept, monthly and weekly workflows are designed to support S&OP planning. The monthly workflow, for example, defines when sales history data is collected and analyzed, when the statistical forecast is made, when safety stocks and Min/Max values can be re-calculated and adapted, when the monthly production and capacity planning is prepared and when the distribution planning is made.

1.1.3 Hilti´s supply chain

In Figure 2, a high-level overview of Hilti´s supply chain network is visualized.

Hilti has around 380 suppliers who supply raw material to Hilti´s production plants. In those plants, production and assembly takes place. Afterwards, the finished goods are distributed. They are either shipped to the headquarter warehouses (HAG WHs) or directly to the regional markets. There are two types of regional warehouses: central warehouses (CWs) and regional distribution centers (RDCs). In terms of ‘the supply chain stage’, CWs and RDCs are positioned at the same place: after the HAG WH. The only difference between a CW and an RDC is that a CW serves one MO whereas an RDC serves multiple MOs.

Next to in-house production, Hilti sources many products at allied suppliers. Those products do not require any product modification by Hilti. The finished goods are shipped directly from the supplier to the HAG WHs, MO CWs or RDCs.

In the regions, CWs and RDCs supply Hilti stores, repair centers and vans. Moreover, customers can directly go to CWs or RDCs to buy their products or they can decide to order their products (online) to receive them on location.

It has to be mentioned that there are some exceptions to the general supply chain network. In North-America, for example, there is an additional chain between the HAG WHs and the CWs/RDCs: two national distribution centers (NDCs).

Overall, there are different ways how customer orders are fulfilled, and finished goods are supplied. Uniquely, Hilti only makes use of direct selling to supply its customers. Although this leads to a large supply network from manufacturing up to retailing, it also provides Hilti with a high level of control over its end-to-end supply chain processes.

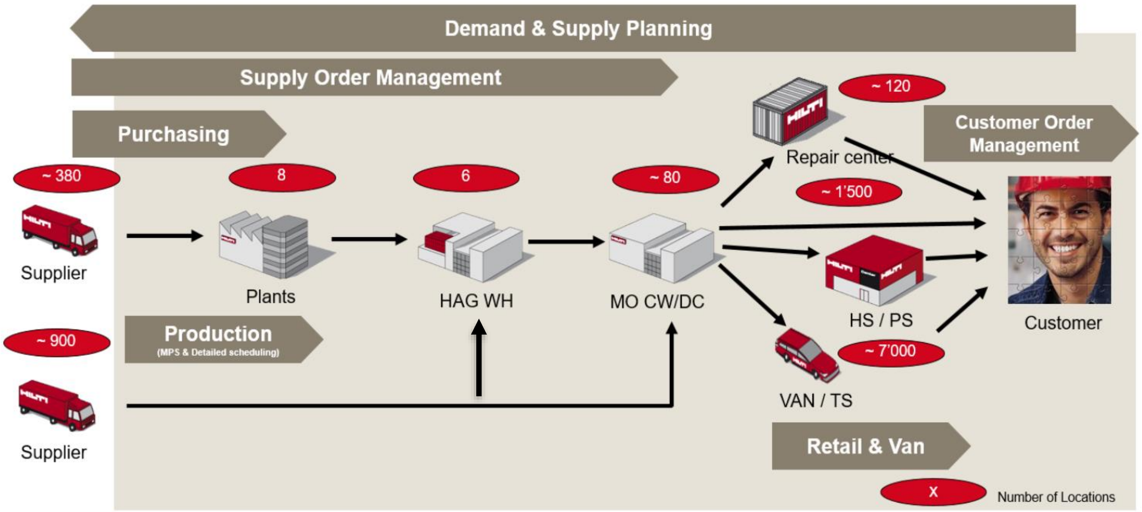


Figure 2 A high level overview of Hilti's supply chain

1.2 Problem definition

1.2.1 Research motivation based on literature

Stank, Autry, Daugherty and Closs (2015) evaluated the progress of ten supply chain management megatrends defined in 2000. Additionally, the authors introduced five new megatrends. Based on these trends, Speranza (2018) derived three major directions for supply chain research: a systemic, a collaborative and a dynamic direction. The systemic direction suggests to model and optimize a broader part of the supply chain jointly in order to improve supply chain solutions. Managing inventory from end-to-end instead of controlling inventory separately for each supply chain stage is a good example of such a jointly optimized solution. Mainly due to advancement in technological solutions, it is not surprising that the interest in multi-echelon inventory control and optimization has increased over the years.

According to literature, multi-echelon inventory control is very promising and can lead to impressive cost savings. Farasyn, Humair, Kahn, Neale, Rosen, Ruark and Willems (2011), for example, reported a 7% inventory reduction realized by multi-echelon inventory optimization at P&G (multi-echelon was implemented for 30% of their business). On the other hand, De Kok, Grob, Laumanns, Minner, Rambau and Schade (2018) performed a literature study and concluded that not even 5% of 394 classified papers discuss a real-world application of a multi-echelon inventory control model. In industry, multi-echelon inventory systems are still often controlled as a network of single-echelon inventory systems due to simplicity of managerial authority, organizational control and performance monitoring (Hausman and Erkip, 1994). Other researchers highlight the difficulties of centralized control: it is a technical challenge to obtain and process all data centrally (Andersson and Marklund, 2000) and completely centralized policies are difficult to derive (Axsäter, 2015). The inevitable question for companies is *if* and *when* it is worthwhile to change to a centralized multi-echelon inventory policy.

To the best of the author´s knowledge, no framework has been developed in scientific literature to compare the cost gap between a centralized inventory control approach with a decentralized local control approach under different supply chain characteristic settings. However, some researchers compared a centralized inventory policy with a decentralized one and investigated the effect of certain supply chain characteristics. The interaction of different supply chain characteristics is an interesting contribution to the research field.

1.2.2 Research motivation based on company needs

Local vs. centralized inventory control

Up to this moment, every stage in Hilti´s internal supply chain controls and manages its own inventory. Performance targets are measured location wise and every stage tries to achieve high performance on its own KPI targets. Thus, the different internal echelons operate in silos (decentralized inventory control). Controlling inventory from end-to-end could lead to lower stock on hand and higher customer service levels. On the other hand, changing to a centralized multi-echelon policy is a technical and organizational challenge for which a large amount of organizational commitment is required. Therefore, an extensive analysis of the potential benefits is needed to compare the performance of local inventory control with the performance of centralized inventory control.

Lack of global policy deployment

Global Logistics supports Materials Managers in Plants, BUs and MOs with guidelines regarding inventory management and control. However, the final responsibility and decision of e.g. choosing a MRP type or safety stock method lays at the Materials Manager in charge of the item-location SKU. An example of this is safety stock setting. Currently, 6 different safety stock methods can be chosen in the system (see Table 2 in section 1.5). Following the guidelines, there are cases where more than one option is recommended. Secondly, the Materials Manager is free to deviate from the guidelines, can choose another method and can adapt the input parameters (e.g. service level target, safety days). Thus, there is no global holistic work stream in place. A centralized multi-echelon inventory replenishment policy would eliminate local decision-making. At the same time, the advantages of local control would disappear. A detailed comparison of centralized vs. decentralized inventory control under different supply chain settings could show *if* and *when* decentralized control makes sense.

No holistic service level segmentation strategy

As will be explained in section 1.5, for some safety stock methods a target service level input needs to be provided by Materials Managers. Although in some regions and BUs local guidelines exist to support service level target setting, a differentiated global strategy is missing. There is no holistic procedure to define which service level should be assigned to which items. This might lead to sub-optimal processes, e.g. the same end-customer service levels might be reached with lower stock values and costs.

High inventory levels

In the last couple of years, the total days on hand inventory at Hilti always exceeded 100. Hilti´s objective is to reduce inventory on hand to 90 days. Thus, the current inventory levels are too high compared to the global target. Although this does not necessarily imply that there is an excessive amount of stock, Global Logistics strongly believes there is a potential to reduce inventory levels whilst maintaining a high service level. The resulting question is to which amount a centralized inventory policy can help to realize this reduction potential.

Concluding, one of the strategic objectives of HIP is a centralized planning concept. Thus, a centralized inventory policy is in line with future company directions. Furthermore, a large part of the supply chain is under Hilti´s own control, facilitating the possibility to manage supply chain processes from end-to-end. Therefore, Hilti would like to gain more insights into the potential benefits of a centralized multi-echelon inventory approach.

1.2.3 Research objectives and research questions

Based on the problem description, the main research question is defined:

Under which supply chain characteristics does a multi-echelon inventory policy outperform a local inventory policy the most?

In order to answer the main research question, the following sub questions will be answered:

1. *How does Hilti currently replenish, control and position finished goods inventory in its distribution network?*
2. *What type of inventory management policies exist for inventory replenishment and allocation in distribution networks? What are the advantages and disadvantages of those policies?*
3. *What is the performance of centralized inventory control compared to the performance of decentralized inventory control?*
4. *How do different product/supply chain characteristics affect the performance of a centralized multi-echelon approach compared to a locally managed approach?*
5. *Can a service level differentiation strategy help to improve inventory performance?*

1.3 Project scope

1.3.1 The supply chain scope

As described in section 1.1.3, the supply chain network of Hilti consists of multiple echelons. The most upstream echelon consists of external suppliers who supply raw material and components to Hilti´s PPs. Moreover, external, allied suppliers supply finished goods to Hilti´s distribution network. These external suppliers are not in scope of this project as their inventory is not under control of Hilti. The next echelon consists of internal production plants. Here, stock consists of raw material, components and finished goods inventory (after assembly/production). As the focus of this research is on the finished goods distribution, the inventory at the plants is out of scope.

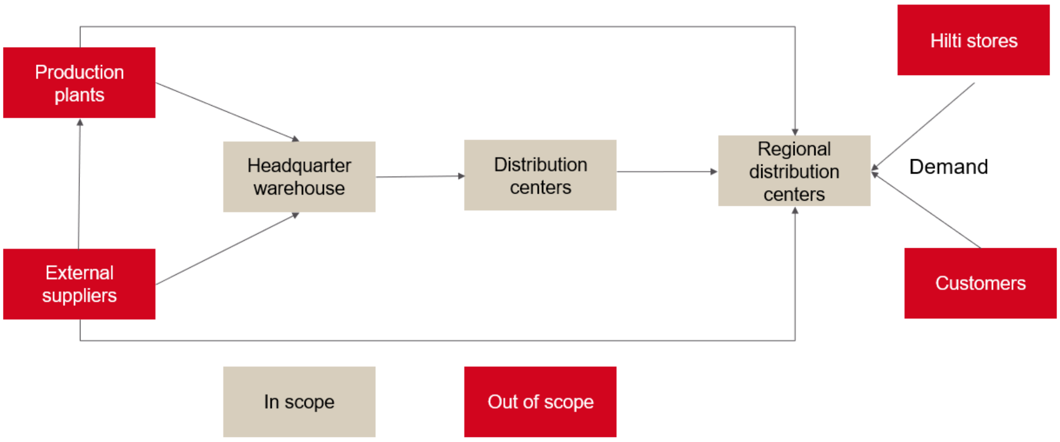


Figure 3 Supply chain scope

To support the decision to focus on the finished goods distribution network (and not on the production/assembly network), the distribution of stock value over the plants, headquarter warehouses and the MO CWs/RDCs regions is graphically illustrated in Figure 4. As can be observed, 50% of total stock is located downstream in the regions. Thus, by focusing on finished goods inventory more than 75% of total stock value will be covered.

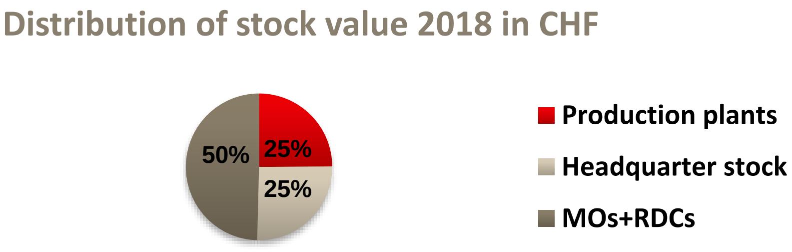


Figure 4 Distribution of stock value across the supply chain

Next, the definition of `customer´ needs to be addressed. Final customers can obtain their products directly at CWs/RDCs, they can order via the internet, they can go to Hilti stores or a Hilti van comes by and sells directly to the customer. Only a small part of total sales is generated by Hilti stores (around 20%). Most sales are generated in MO CWs/RDCs. Therefore, the aggregated demand of Hilti stores, vans, direct customer demand at CWs/RDCs and online sales will be considered as `customer demand´.

Thus, this project focuses on the distribution network of Hilti´s internal supply chain from finished goods at the headquarters up to the distribution centers in the regions.

1.3.2 The SKU scope

This research deals with different product/supply chain characteristics and how these characteristics affect inventory control performance. Therefore, the items for the case study should be selected carefully in order to ensure a high variability across the selected items on the studied supply chain characteristics. A representative sample has to be chosen to mimic the supply chain.

Based on these requirements, SKUs from BU 9 will be used for the case study. The product portfolio of BU 9 consists of in-house produced items (produced in Europe and Asia) and sourced finished goods from allied suppliers. Thus, the lead-time range is large. As the product portfolio consist of thousands of items, diversity in demand is also guaranteed. Additionally, BU 9 holds more than 1/3 of total stock value. Thus, inventory reduction potential in this BU is of high interest.

1.3.3 The market scope

If one wants to apply a multi-echelon approach, the complete aggregated demand arriving at the upstream location needs to be considered. Concretely, all regions which are supplied from the same headquarter warehouse need to be in scope. Thus, we cannot limit ourselves to certain markets. Moreover, by taking all regions into account, a full and complete representation of Hilti´s distribution network can be analyzed.

1.4 Methodology

The research methodology chosen to conduct this project is based on a method designed by Van Aken, Van Der Bij and Berends (2012), following the design science research paradigm. Their proposed method is the so-called problem solving cycle, shown in Figure 5. Although their methodology consists of five steps, this project will go through the first three steps of the cycle.

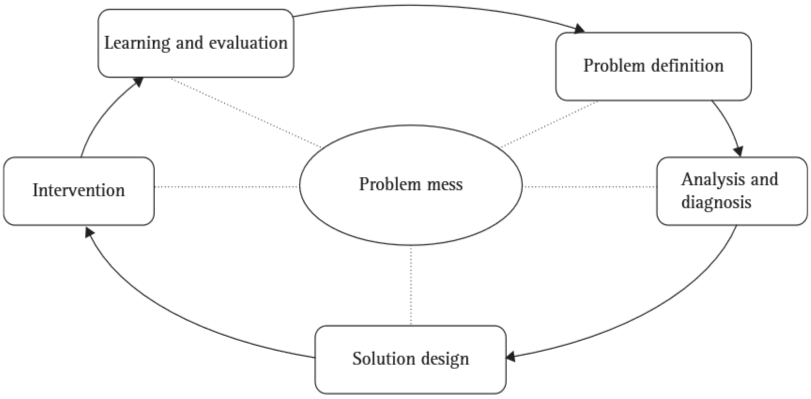
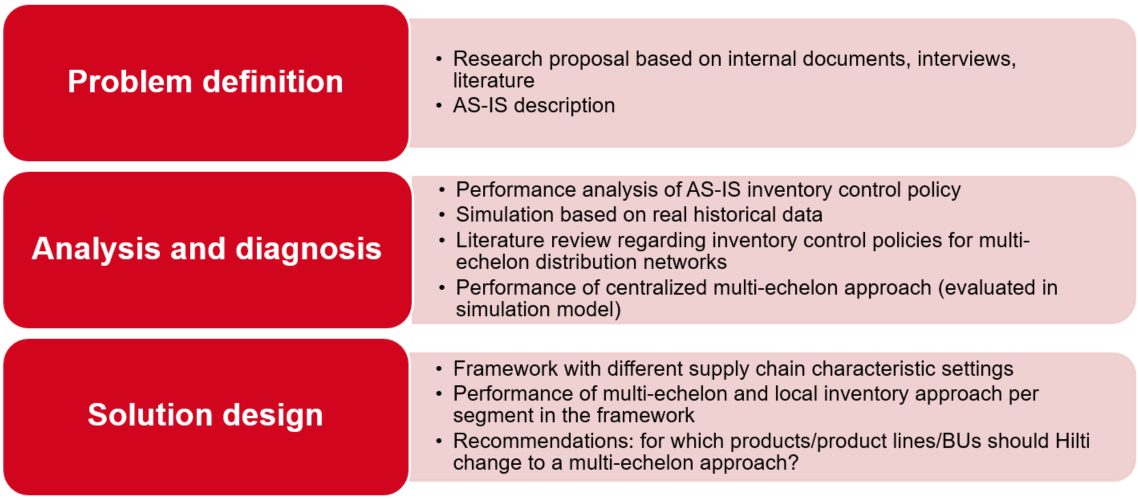


Figure 5 Problem solving cycle (Van Aken et al. 2012)

The problem is defined in the previous sections. Next, the current inventory replenishment process will be addressed. Meanwhile, a scientific literature review is conducted to present an overview of inventory management policies applicable to the replenishment and allocation of inventory in multi-echelon distribution systems. Furthermore, comparison studies that address the gap between decentralized and centralized inventory control are discussed.

A new simulation model will be developed based on the company's current replenishment process combined with alternative inventory control approaches addressed in the analysis section. A case study will be performed based on real historical data.

Based on the previous two steps, a solution design will be developed. A framework will be designed to compare the performance of a centralized multi-echelon and a decentralized local inventory policy under different product/supply chain settings. Additionally, the effect of service level targets on inventory investment will be addressed. Figure 6 summarizes the research methodology and deliverables.



Problem definition

- Research proposal based on internal documents, interviews, literature
- AS-IS description

Analysis and diagnosis

- Performance analysis of AS-IS inventory control policy
- Simulation based on real historical data
- Literature review regarding inventory control policies for multi-echelon distribution networks
- Performance of centralized multi-echelon approach (evaluated in simulation model)

Solution design

- Framework with different supply chain characteristic settings
- Performance of multi-echelon and local inventory approach per segment in the framework
- Recommendations: for which products/product lines/BUs should Hilti change to a multi-echelon approach?

Figure 6 Summary of research methodology and deliverables

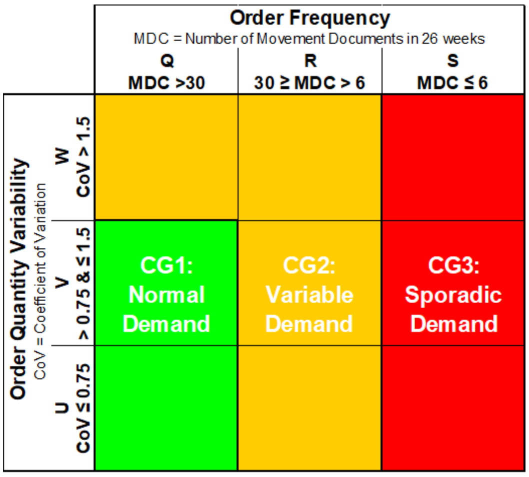
1.5 AS-IS Inventory control strategy

In this section, the replenishment processes in Hilti´s distribution network are described. Note that the replenishment process of raw material and components at the production plants is not described here, as the focus of the project is on finished goods.

1.5.1 Inventory positioning

The inventory positioning strategy within Hilti defines at which locations stock for an item is kept and whether items are shipped directly from suppliers/plants to MO CWs/RDCs or are consolidated in upstream locations.

The decision where to hold items on stock primarily depends on demand characteristics. Demand (on item-location level) is clustered based on order frequency and order quantity variability. Those two dimensions form the matrix as illustrated in Figure 7. Order frequency measures the number of movement documents of an item in the past 6 months. Order quantity variability is measured as the coefficient of variation of the demand (ratio between the standard deviation and average). Based on the position in the matrix, demand is either classified as normal (CG1), variable (CG2) or sporadic (CG3). Note that the same item number can be clustered differently for each location in the network (i.e. an item can be sporadic in a MO CW, but variable in a HAG WH). Demand clustering of items is done twice a year to ensure regularly updated values.



Order Frequency
MDC = Number of Movement Documents in 26 weeks

Order Quantity Variability CoV = Coefficient of Variation	**Q** **MDC >30**	**R** **30 ≥ MDC > 6**	**S** **MDC ≤ 6**
W **CoV > 1.5**	🟨	🟨	🟥
V **> 0.75 & ≤ 1.5**	🟩 **CG1: Normal Demand**	🟨 **CG2: Variable Demand**	🟥 **CG3: Sporadic Demand**
U **CoV ≤ 0.75**	🟩	🟨	🟥

Figure 7 Demand clustering

Hilti strives to hold normal and variable demand (CG1 & CG2 in the market organization) as well as country specific items on stock in the MO CWs/RDCs. Sporadic demand items (CG3 from a MO CW/RDC perspective) are stocked more upstream in the distribution network (i.e. in HAG WH for Europe, in NDC for North-America). Hilti has decided that the HAG WHs also serve as an upstream location for global slow movers: items with ≤ 6 movements in the past 6 months from the headquarters warehouses perspective (global sporadic demand CG3).

To balance holding and ordering costs, Hilti replenishes downstream locations in lot sizes instead of replenishing one-for-one. Those lot sizes are primarily based on the EOQ formula and adapted based on packaging quantities and min-max values.

Apart from deciding where to stock which items and in which quantities inventory is replenished, inventory positioning also refers to the choice of direct vs. consolidated shipments from PPs and suppliers to MO CWs/RDCs.

If the EOQ is higher or equal than the minimum delivery quantity (MDQ) of the supplier/production plant and a direct shipment route from the supplier/production plant to the MO CW/RDC exists, a direct shipment is possible and recommended by Global Logistics. If those conditions are not fulfilled, shipments are consolidated at upstream locations (e.g. HAG WH for Europa, HNA for North-America) from where consolidated shipments are sent to the MO CW/RDC.

1.5.2 Replenishment logic

The replenishment logic within Hilti is based on MRP logic. Demand forecasts are propogated across the supply chain and replenishment decisions are taken based on a time-phased approach.

At the HAG WH and MO CWs/RDCs, orders are triggered whenever there exists a net requirement above 0. Orders are either manually or automatically released. Net requirements are computed with the following formula:

$$Net\ requirements\ at\ period\ t = forecasted\ demand\ up\ to\ period\ (t+L) + safety\ stock - inventory\ position\ at\ period\ t$$

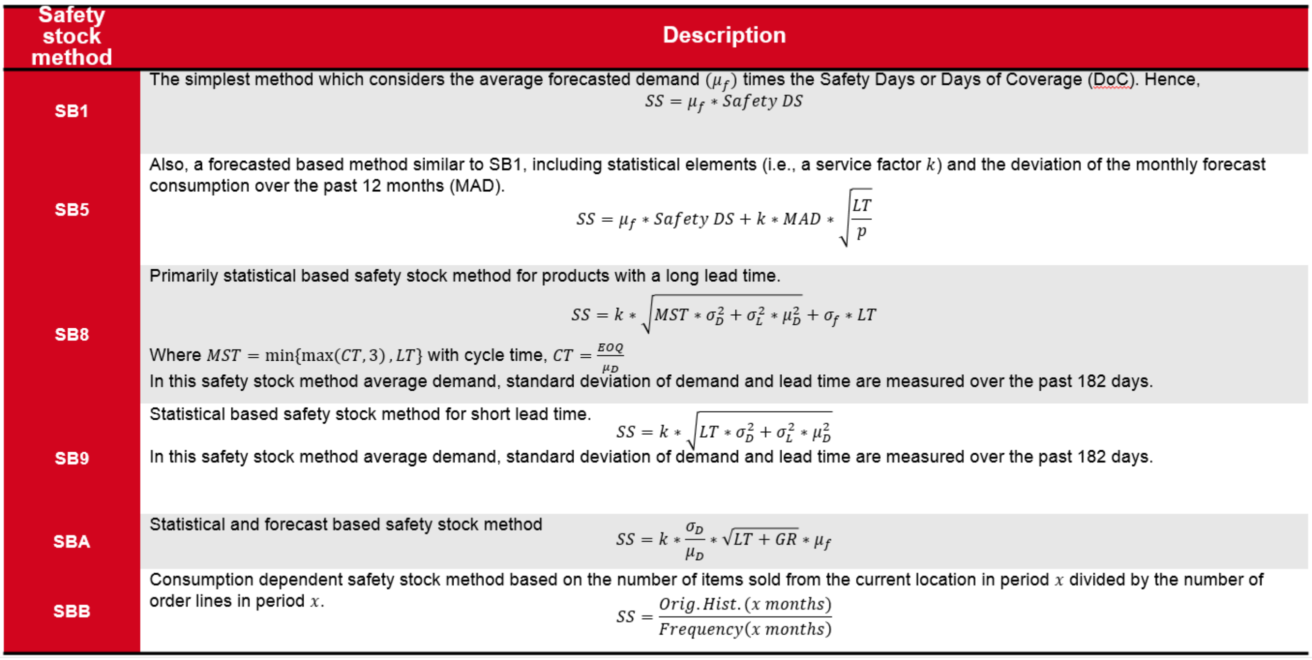
Note that L denotes the replenishment lead-time. The net requirements for an item-location combination are rounded up to an integer number of the predefined batch size for the SKU. A more detailed description on of the computation of net requirements follows in section 3.2.5.

Hilti has implemented various safety stock (SS) methods throughout the years. Among the different variants, a purely forecasted SS, purely statistical SS and combinations of statistical and forecast-based SS methods exist. A detailed description of the implemented methods can be found in Table 2 (Sonneville, 2018). For some SS methods, a service level target input from the Materials Manager is required which is transformed and captured in a service factor.

Allocation of stock in case of shortages

In case of a stock shortage, the responsible Materials Manager will decide which downstream location receives which amount of stock. Hilti strives to apply fair share logic in case of shortages. However, Materials Managers also take other factors into account when deciding which downstream stages to prioritize (e.g. customer back-orders).

Table 2 Safety stock methods currently in use (Sonneville, 2018)



Safety stock method	**Description**
SB1	The simplest method which considers the average forecasted demand (μ_f) times the Safety Days or Days of Coverage (DoC). Hence, $SS = \mu_f * Safety\ DS$
SB5	Also, a forecasted based method similar to SB1, including statistical elements (i.e., a service factor k) and the deviation of the monthly forecast consumption over the past 12 months (MAD). $SS = \mu_f * Safety\ DS + k * MAD * \sqrt{\frac{LT}{p}}$
SB8	Primarily statistical based safety stock method for products with a long lead time. $SS = k * \sqrt{MST * \sigma_D^2 + \sigma_L^2 * \mu_D^2} + \sigma_f * LT$ Where $MST = \min\{\max(CT, 3), LT\}$ with cycle time, $CT = \frac{EOQ}{\mu_D}$ In this safety stock method average demand, standard deviation of demand and lead time are measured over the past 182 days.
SB9	Statistical based safety stock method for short lead time. $SS = k * \sqrt{LT * \sigma_D^2 + \sigma_L^2 * \mu_D^2}$ In this safety stock method average demand, standard deviation of demand and lead time are measured over the past 182 days.
SBA	Statistical and forecast based safety stock method $SS = k * \frac{\sigma_D}{\mu_D} * \sqrt{LT + GR} * \mu_f$
SBB	Consumption dependent safety stock method based on the number of items sold from the current location in period x divided by the number of order lines in period x. $SS = \frac{Orig.Hist.(x\ months)}{Frequency(x\ months)}$

1.5.3 Materials Management (MM)

Safety stock settings, service level settings, order replenishment, MRP-Type selection and allocation planning all belong to the responsibilities of MM. The MM function is divided over the plants, BUs and regions, where Materials Managers are in charge of those tasks. Materials Managers in the plants are responsible for the supply of raw material and components to the plant. The replenishment of the headquarter warehouses falls under the responsibility of the Materials Managers at the headquarters. In the headquarters, the MM function is divided over the different BUs. Moreover, BU Materials Managers also manage the replenishment of finished goods from allied suppliers to the headquarter warehouses. Regional Materials Managers are responsible for the replenishment of the stock points in the regional MO CWs/RDCs.

Guidelines

The Global Logistics department provides Materials Managers of PPs, HAG WHs and MO CWs/RDCs with guidelines regarding MRP type selection and safety stock setting. An example of such a guideline is shown in Figure 8 (Sonneville, 2018). This process flow serves as an advice for safety stock and MRP-type setting for MO Materials Managers. Such process flows also exist for BU and Plant Materials Managers. Note that these guidelines serve as a recommendation and Materials Managers are free to deviate from the guideline. The final execution and responsibility of safety stock levels, service level setting, MRP type selection and allocation is given to the Materials Manager in charge of the item-location.

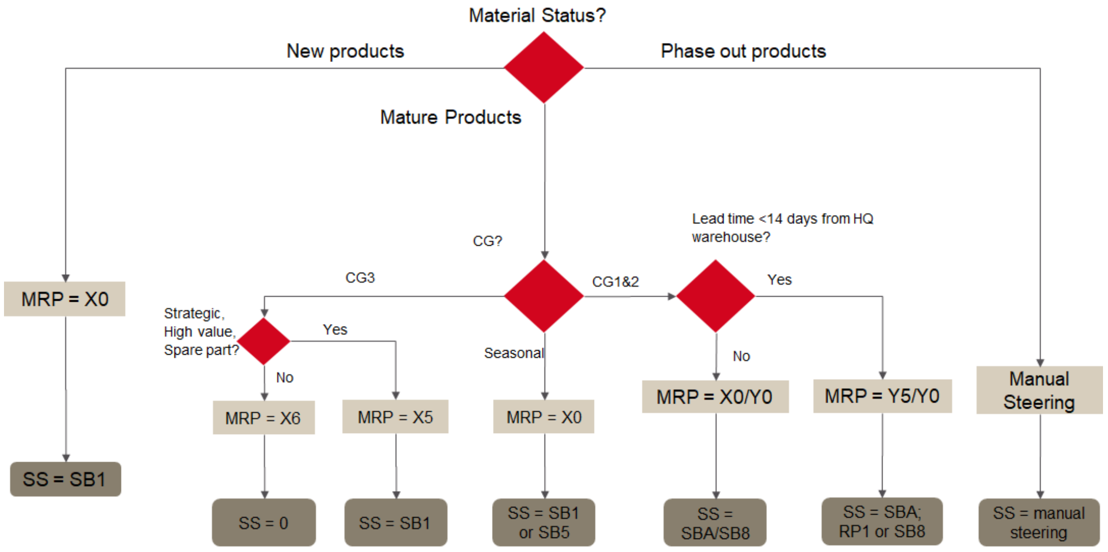


Figure 8 Guidelines for MRP type and safety stock settings

1.5.4 Performance Indicators

Table 3 summarizes the Global Logistics key performance indicators (KPIs) with their strategic target. The ATS and CPOi KPI represent the service to the customer. To ensure service and costs are balanced, the ICL and cost productivity KPI form the operational counterpart.

Table 3 Global Logistics KPIs

KPI	Description	Target
ATS **Availability to Standard**	**Percentage of order lines that are available on the same day as ordered.**	**98.0%**
CPOi **Customer Perfect Order internal**	**Percentage of customer orders that is issued to the customer on time**	**98.5%**
ICL	**The days on hand inventory compared to consumption**	**90 days**
Cost productivity	**Sales growth minus cost growth**	**3%**

The ATS measures the percentage of order lines that are available on the same day as ordered. The CPOi measures the percentage of customer orders that is issued to the customer on time. The ICL compares the inventory on hand with the consumed inventory according to the following Expression:

$$ICL(Month\ x-1) = \frac{Average\ inventory\ value\ month\ x-1}{Cumulated\ logistics\ consumption\ value\ over\ the\ last\ 6\ months/6} * 30$$

Lastly, the cost productivity compares the growth in sales with the growth in logistic costs. As the master thesis focusses on inventory replenishment, ICL and ATS are of special interest.

2. Literature review

In this chapter, relevant literature for the purpose of this thesis is discussed. First, a distribution inventory control classification is presented. Secondly, different ways of multi-echelon inventory control are shortly addressed and their applicability to this case study is reviewed. Thirdly, the interaction between forecasting and inventory control in multi-echelon systems is addressed. Lastly, comparison findings based on decentralized and centralized inventory control are presented.

2.1 Distribution control

De Leeuw (1996) defines distribution control as `*All activities taking place to co-ordinate the place and timing of demand over a finite horizon with the supply of products and capacities, in such a way that the objectives of the distribution process are met, given the characteristics of the product and the requirements of the market.*' Several techniques have been developed to accomplish this. However, the appropriateness of those techniques depends on the characteristics of the company environment. Therefore, De Leeuw, Van Donselaar and De Kok (1998) introduced a classification of four distribution control decisions that have to be considered when selecting a distribution control technique. Below, these distribution control decisions are explained.

1. *The type of reorder planning*

Reorder planning involves the planning of both independent and dependent demand. Independent demand refers to the demand of the final customer whereas dependent demand consists of the net requirements from downstream locations (successors). For independent demand planning, demand can be forecasted with or without a demand pattern. Dependent demand can be handled by a time phased or a non-time phased planning technique. The time phased approach aims to ensure stock is available just before a downstream location will place an order. Non-time phased planning, on the other hand, replenishes up to a predefined target inventory level.

2. *Status information*

For the replenishment of goods in distribution networks, information about demand and stock levels is required. Replenishment decisions can be based on either local or integral information. When using local (installation) information, solely the inventory of the location itself and the direct demand faced by the location is considered. A more holistic approach requires integral (echelon) information; inventory information of the entire distribution network and demand information purely based on the independent customer demand. In Figure 9, the difference between local and integral status information is illustrated for a 2-echelon distribution network.

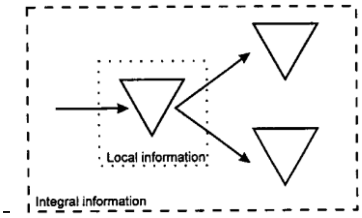


Figure 9 Local vs. integral information

3. Central stock

In a distribution network, stock can be hold centrally at an upstream location, locally at downstream distribution centres or both up- and downstream. Those stock holding decisions affect the way inventory has to be managed in the network (e.g. if no stock is kept upstream, this upstream location acts like a cross-docking point rather than a warehouse).

4. Co-ordination of the allocation process

The allocation of stock in distribution networks can be performed locally or centrally. Under a local allocation co-ordination policy, local distribution centers independently order goods at their supplier (predecessor). Thus, all locations make their own decisions regarding when and how much to order. Another possibility is to implement a central allocation co-ordination policy. In that case, a central department decides when and which amount of goods to ship to downstream locations (successors).

Hilti's distribution control can be classified according to the four decisions presented above.

1. The type of reorder planning

Within Hilti, independent demand is classified as seasonal, trend-based or stationary. In this master thesis, stationary independent demand is studied. Dependent demand is handled by a time-phased approach, supported by MRP logic.

2. Status information:

Within Hilti, forecasts are shared across the echelons. Moreover, replenishment decisions are based on net requirements of downstream locations. Thereby, demand and inventory information of downstream locations is indirectly used for replenishment decisions. However, safety stock calculations are solely based on local information.

3. Central stock

The decision where to hold stock depends on the inventory positioning strategy as applied by Hilti nowadays (section 1.5.1). However, this master thesis focusses on articles that are hold both up- and downstream.

4. Co-ordination of the allocation processes

Currently, the different locations within Hilti's supply chain network act independently in terms of order releases. However, in case of supply shortages, upstream locations decide which locations receive which amount of available supply. Thus, the allocation process is primarily locally co-ordinated with some features of centralized control.

2.2 Multi-echelon inventory control

In this section, multiple directions for multi-echelon control are discussed. The applicability to the problem in this study is also addressed.

2.2.1 Base-stock policies

Clark and Scarf (1960) are usually considered to be the founders of the literature stream on multi-echelon inventory management (MEIM) and base-stock policies. Base-stock policies usually assume periodic-review, full-backordering and order-up-to-*S* policies. Optimal echelon base-stock levels are derived based on newsboy equations and decomposition of the supply chain networks (see for explanation of echelon policies section 2.4.2). Clark and Scarf (1960) proved the optimality of base-stock policies in serial system under a finite planning horizon. They extended their model to distribution systems by making use of the balance assumption; after allocation, successors are assumed to be in their optimal states given the available stock at the predecessor location (De Kok, 2018).

Eppen and Schrage (1981) applied the model of Clark and Scarf (1960) in a distribution system with identical retailers and normally distributed demand. In their model, the upstream location is not allowed to hold stock. Later, extensions to distribution systems with non-identical retailers and stock-holding central warehouses were proposed based on the approach of Clark and Scarf (1960).

2.2.2 METRIC approach

The basic METRIC model, first proposed by Sherbrooke (1968), is based on a continuous review, one-for-one replenishment policy with a Poisson demand distribution. Demand that can not be directly met from stock is backordered. METRIC approaches start with the derivation of the average delay at the most upstream location (warehouse). By assuming that the warehouse fulfills retailers' orders based on a first-come, first-served (FCFS) allocation procedure, the average delay to the retailers is set equal to the average delay at the warehouse. This result is used to approximate the lead-time from the warehouse to the retailers. Although this lead-time is stochastic in reality, the METRIC approach replaces the lead-time to the retailers with a constant value that consists of the transportation time plus the average delay at the warehouse.

Deuermeyer and Schwarz (1981) propose a MEIM method based on the METRIC approach for distribution systems with identical retailers that order in batches. Hence, they extend the original METRIC model from a one-for-one replenishment policy to a batch ordering policy. First, the mean and the variance of the demand over the lead-time at the warehouse is approximated. Sequentially, a normal distribution is fitted to these parameters after which the average delay to the warehouse is estimated. Similar to Sherbrooke (1968), the resulting average delay at the warehouse is added to the transportation time to the retailers to represent the lead-time from the warehouse to the retailers. Later, Svoronos and Zipkin (1988) extended the approach of Deuermeyer and Schwarz (1981) by estimating the variance of the delay to the warehouse next to the average delay to the warehouse. Consequently, the demand over the lead-time at the retailers follows a negative binomial distribution.

METRIC approaches prove to be simple and computationally efficient. A drawback of the METRIC approach is that analysis becomes more complicated when non-identical, batch-ordering retailers are considered (in that case, the average delay to the retailers differs for the different retailers).

2.2.3 Disaggregation of backorders approach

Within the disaggregation model, the total backorders from an upstream location are disaggregated over the successor locations (Axsäter, 2003). When the demand follows a Poisson distribution and a one-for-one replenishment policy is applicable, an exact binomial disaggregation can be derived. However, when successors order in batches, the complexity of the disaggregation procedure increase significantly. Chen and Zhen (1997) present an exact procedure for an (*R,Q*) echelon policy with Poisson demand that can also be applied to a non-identical retailer setting.

2.2.4 The follow-unit approach

The follow-unit approach is based on a recursive procedure where each supply chain unit is followed through the system. The flow-unit approach can be extended to batch size policies by setting a batch equal to a package of units. An exact analysis when demand follows a Poisson distribution and retailers order in batches is performed by Forsberg (1997). Axsäter (2000) and Axsäter (1997) propose exact analyses for installation and echelon policies respectively under compound Poisson demand. Flow-unit approaches may be feasible for distribution systems with low demand and small batch sizes. However, for larger systems the computational complexity grows rapidly (Axsäter, 2003).

2.2.5 Guaranteed-service and stochastic-service models

Another stream of MEIM literature focusses mainly on the optimization of safety stocks in multi-echelon networks. Historically, two different MEIM approaches have emerged to optimize safety stocks in multi-echelon networks: the guaranteed-service models (GSM) and the stochastic-service models (SSM). The main underlying assumption of GSM is that each stage promises a delivery time to its downstream stages that can always be satisfied (Graves and Willems, 2003). On the other hand, SSM assume that the delivery time between locations depends on the material availability at the supplier stage resulting in varying delivery times (Graves and Willems, 2003). GSM and SSM models appear to be most often used in software tools. Hence, the practical relevance of these approaches is high.

2.2.6 Synchronized base-stock policy

The synchronized base-stock (SBS) policy is primarily based on the original base-stock model by Clark and Scarf (1960). For divergent systems, Diks and De Kok (1999) propose a linear allocation procedure and an algorithm to compute echelon base-stock levels based on Newsvendor equations. Based on these results, the synchronized base-stock policy for divergent systems is derived (De Kok, 2018). The SBS-policy differs from a pure base-stock policy as it only allows material-feasible order releases. For more details about the synchronized base-stock policy for assembly and general structures, the papers of De Kok and Fransoo (2003) and De Kok (2018) can be consulted. The most important underlying assumption is the balance assumption. Generally, the SBS-policy is not cost-optimal because inventory is allocated before stock is physically available. Thus, the allocation decision could have been delayed to the moment stock is physically available.

Based on numerical studies, De Kok (2018) states that the cost performance under the balance assumption is close to the analytical lower bound when i) the end-item coefficient of variation of demand is below 1 and ii) end-item mean demands are similar.

2.2.7 Other methods

Besides the methodologies discussed above, other heuristics, approximations and simulation-optimization approaches have been proposed in literature. Examples can be found in Rong, Atan and Snyder (2017) who propose two heuristics for locally controlled, distribution systems with stochastic demand and in Noordhoek, Dullaert, Lai and de Leeuw (2018) who propose a simulation-optimization model.

2.3 Forecast-driven multi-echelon supply chains

The majority of the literature dealing with MEIM does not address the interaction of forecasting and inventory control. However, in practice the mean and variance of customer demand is not known upfront and even for stationary demand, replenishment decisions are often based on forecasts.

In De Kok, Janssen, Van Doremalen, Van Wachem, Clerkx and Peeters (2005), the implementation of an advanced planning and scheduling system to support collaborative planning between Philips Semiconductors and Philips Optical Storage is discussed. Based on stochastic multi-echelon inventory control, a model is developed to reduce the bullwhip effect in the supply chain. The model is based on forecasted demand, where demand realizations are assumed to be equal to the forecasts. The implementation led to considerable savings in inventory investment.

Another model that incorporates forecasts in inventory control is proposed by De Kok (2012). In this paper, a two-echelon distribution system is considered where demand is forecasted based on simple exponential smoothing. Dynamic periodic review order-up-to policies are derived based on updated forecasts.

Boulaksil (2016) suggests a simulation approach in which mathematical models are solved under a rolling horizon setting. Customer demand is modeled based on the Martingale Model of Forecast Evolution. The proposed model can be used to optimize safety stock placements in supply chains.

2.4 Trade-offs when managing multi-echelon systems

2.4.1 Multi-echelon vs. single-echelon policies

Mathematically, multi-echelon policies always outperform single-echelon policies. However, this holds only if all relevant system information is available centrally and all managerial concerns are incorporated in the objective function (Hausman & Erkip, 1994). In real-life supply chains, inventory control is usually decentralized where each supply chain stage independently manages inventory and is responsible for its performance. This simplifies managerial authority, performance monitoring and organizational control (Hausman and Erkip, 1994). Thus, the potential benefits of multi-echelon policies should be evaluated to make a trade-off between better inventory performance on the one hand and easier managerial/organizational processes on the other.

Muckstadt and Thomas (1980) studied a two-echelon system with one central distribution center and multiple warehouses. They compared a multi-echelon with a single-echelon approach for low demand, high cost items. For those type of items, an (*s-1,s*) ordering policy and Poisson demand distribution is often appropriate and therefore assumed by the researchers. According to Muckstadt and Thomas (1980), changing to a multi-echelon approach can lead to inventory investment savings, especially when the number of low demand items is large. Low demand, high cost items are typically encountered in spare-parts supply chains (Axsäter, 2003). However, in many other supply chains the majority of items face a low demand rate as well.

Another study that compares single-echelon with multi-echelon control for low demand, high cost items is performed by Hausman and Erkip (1994). Similar to Muckstadt and Thomas (1980), a two-echelon divergent structure with one central depot and multiple warehouses facing demand based on a Poisson distribution is considered. The performance of the multi-echelon approach proposed by Muckstadt and Thomas (1980) is compared with the performance of an improved single-echelon inventory model. The purpose of their study is to quantify the level of sub optimization when a multi-echelon system is controlled by multiple single-echelon systems for low demand, high cost items. Applying their improved single-echelon policy led to a 3 to 5% increase in inventory investment compared to the multi-echelon approach. The remaining open question is whether the outperformance of the multi-echelon policy is large enough to change to this more advanced inventory control technique.

2.4.2 Installation vs. echelon reorder points

As mentioned in section 2.1, replenishment decisions in multi-echelon networks can be based on local or global information. Oftentimes, MEIM literature distinguish between installation and echelon inventory positions. While the installation policies only require information about the stock level of the location itself and its directly observed demand, the echelon policies require global information about the stock levels of the location and all its downstream stages (including the inventory in transit). Moreover, echelon policies require information about the end customer demand while installation policies only look into the directly observed demand for each stage. Figure 10 illustrates the composition of echelon inventory stock and echelon inventory positions.

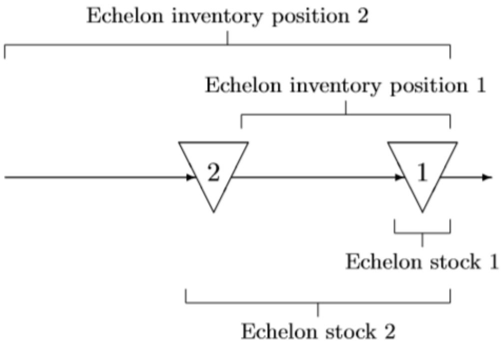


Figure 10 Echelon stock and echelon inventory position (Van Houtum, 2006)

Axsäter (2015) states that a major advantage of installation stock reorder point policies is that they are easy to implement, because they only need local information about inventory positions after setting the control parameters. However, the supply chain information is delayed. Echelon stock reorder point policies do not have this restriction; system wide information is immediately available in the entire network. In terms of modeling, the major difficulties for installation policies are the determination of the demand process at upstream stages and the determination of the delay time characteristics (Diks and De Kok (1996)). For echelon stock policies, the biggest challenges are related to the imbalance problem and the analysis of divergent systems with lot sizing.

Axsäter and Rosling (1993) proved that echelon stock (*R,Q*) policies perform better than installation stock (*R,Q*) policies for serial and assembly systems. However, this finding does not hold for distribution systems. Therefore, a follow-up study has been performed by Axsäter and Juntti (1997) to compare the installation and echelon stock policy for an (*R,Q*) distribution system. Findings revealed that the performance depends on the length of the lead-time to the warehouse. Concretely, the installation policy outperforms when the lead-time to the warehouse is short. A longer lead-time to the warehouse results in the outperformance of the echelon policy over the installation policy. This is in line with the findings of Chen (1988) who showed that the value of information increases in the lead-time for serial systems.

2.4.3 Centralized vs. decentralized inventory control

As the concept centralized/decentralized inventory control is often ambiguously used, in this master thesis the definitions of Duan and Liao (2012) are followed. Hence,

Decentralized control refers to supply chains where each player independently makes replenishment decisions with the aim to minimize its own inventory costs without considering the total system costs. Under a **centralized control** policy, decisions are made with the objective to minimize the total inventory costs of the supply chain network. If decisions about the allocation and replenishment policies for the complete supply chain are made by one central authority, this is denoted by the term ‘completely centralized inventory control’.

Andersson and Marklund (2000) discuss the difficulties that arise when a company moves from a decentralized control policy to a centralized inventory control policy. They argue that data collection and processing needs to be centralized (the technical challenge), leading to additional costs (Axsäter, 2015). Moreover, ‘completely centralized policies are difficult to derive’ (Axsäter, 2015). If the general structure of an organization is decentralized, it will be an organizational challenge to centrally control inventory. Coordinating inventory centrally will be even a bigger challenge if the supply chain locations belong to independent companies. According to Lee and Whang (1999), decentralization of decisions can not be avoided in large organizations as the person on the spot has the knowledge of his surroundings. However, the potential misalignment between the agents in the supply chain can be a problem. They point out that to overcome misalignment and still manage a supply chain decentral, corporate rules can be introduced. As the supply chain in this study does belong to the same firm, no further attention is paid to the introduction of corporate rules for supply chain alignment.

Due to the complexity of centralized control policies, Andersson and Marklund (2000) propose a heuristic to manage inventories decentral in a two-echelon multi-echelon distribution network with non-identical retailers and continuous (*R,Q*) installation policies. The results of their heuristic show that a decentralized approach of optimizing inventory in a multi-echelon distribution network is close to the centralized multi-echelon inventory policy. Concluding, it might sometimes be better to control different supply chain stages independently instead of having one central authority who is responsible for the entire inventory replenishment and allocation process.

Based on the same line of reasoning, Axsäter (2015) emphasizes that local control rules might be a good substitute of completely centralized policies under normal circumstances. This holds especially for distribution systems as locations are usually spread across the globe and replenishment decisions are made by independent organizational units. As an alternative they suggest multi-level methods; in those models, local decision rules are coordinated to obtain satisfactory coordinating control of the system as a whole.

Several studies comment on the performance differences of centralized and decentralized inventory control. Abdul-Jalbar, Gutiérrez, Puerto and Sicilia (2003) studied a one warehouse, multiple retailers distribution system and compared a decentralized algorithm with a centralized procedure. By comparing the two approaches for a different number of retailers, they found that the centralized approach performs better when the number of retailers is low. However, when the number of retailers expands, the decentralized approach performs better. Their results are restricted to the assumption of a constant, known demand rate at the retailers and no lead-time between locations. Those assumptions are not reflecting the demand and supply processes of most real-life supply chains. Hence, the question arises whether the same findings hold under stochastic demand and supply. Whereas the former study assumes a constant demand rate, the effect of different demand patterns on the performance of centralized vs. decentralized control is studied by Duan and Liao (2012). They consider two-echelon capacitated distribution system with one distributor and multiple retailers who order based on a periodic review (*s,S*) replenishment policy. Customer demand at the retailers is deterministic and demand that cannot be immediately satisfied from stock is lost. The optimization framework consists of a hybrid meta-heuristic optimization algorithm combined with a supply chain inventory simulation model. Duan et al. (2012) observed that the unit system cost savings of adopting a centralized control approach differs for different demand patterns. They conclude that the savings for patterns such as Lumpy, Exponential, Gamma and Laplace are higher than for regular demand patterns like Constant and Cyclic. Moreover, they argue that the demand volume will also be of importance as for demand patterns with relatively insignificant savings per unit system cost, savings can be substantial if the demand volume is large.

Rached, Bahroun and Campagne (2016) compare five different scenarios; decentralized control without information sharing (1), decentralized control with information sharing about demand (2), decentralized control with information sharing about lead-time (3), decentralized control with information sharing about demand and lead-time (4) and centralized control (5). The relative cost difference between scenario 5 and 1 is substantial (approximately 36%). Interestingly, the cost difference between scenario 4 and 5 is lower than 2.5%. An increased standard deviation of the demand even resulted in a relative cost difference lower than 0.5%. Thus, sharing of information can substantially improve performance while centralized control only slightly contributes to supply chain improvement.

Based on the discussed comparison findings, the following hypotheses are defined:

Demand: The percentual difference between the inventory holding costs of multi-echelon vs. single-echelon inventory policies is expected to be higher for low demand items based on the statement made by Muckstadt and Thomas (1980). For two items with an equal percentual difference between the costs of multi-echelon vs. single-echelon control, the item with the higher demand rate has a higher positive influence on revenue (Duan and Liao, 2012).

Demand variability: If the variability in customer demand is higher, the percentual benefits of a centralized inventory control policy are expected to increase. It is argued that centralized policies better make use of information of the complete supply network and consequently, reduce the bull-whip effect. For stable demand patterns the bull-whip effect is usually lower than for unstable demand patterns. The findings of Duan and Liao (2012) support this hypothesis for distribution systems. However, Chen (1988) concludes the opposite holds true for serial inventory systems.

Lead-time*:* If the lead-time to the first location in the distribution system is longer, the benefits of a centralized inventory control approach are expected be higher. This hypothesis is based on the findings of Moinzadeh (2002) for decentralized vs. centralized control, Gallego et al. (2007) for completely centralized control vs. centralized control and Axsäter and Juntti (1997) for installation vs. echelon reorder points. Although these papers did not compare multi-echelon with single-echelon control, the results are expected to be similar for the comparison of multi-echelon and single-echelon inventory control.

Lead-time variability: Although no literature is presented that discusses the effect of lead-time variability on the performance of difference inventory control policies, higher lead-time variability is expected to result in higher percentual differences between centralized multi-echelon and single-echelon inventory control policies. Atan and Snyder (2012) studied the effect of supply disruptions on optimal base-stock policies. Their paper can be consulted for the effects of disrupted supply on optimal base-stock levels.

3. Conceptual model

This chapter starts with commenting on the choices that have been made before developing the model. Thereafter, the proposed simulation model is presented. The input for the simulation is addressed in section 3.3. The chapter is closed by commenting on the different safety stock setting procedures that are considered.

3.1 Analyzing choices

Harrison, Lee and Neale (2004) discuss the main challenges that arise when analyzing multi-echelon inventory systems. Among others, one has to make choices regarding the scope of the problem, the level of detail, the definition of data, the determination of the objective function and the way the system is controlled. Below, those factors will be explained as the conceptual model is based on these decisions.

Problem scope: The scope of the supply chain network under consideration should be large enough to create significant improvement potential. However, the analysis and implementation should remain feasible. Hence, the scope of the problem has to be set wisely. This project will focus on the ***distribution network*** of Hilti's supply chain.

Granularity: The level of detail, for which the analysis will be performed, needs to be predefined. Hilti stores will be out of scope as most sales are generated in the MO CWs/DCs and stock in Hilti stores is usually uncontrollable (Van Wanrooij, 2012). However, replenishment orders of Hilti stores affect the inventory levels of successor locations. Thus, Hilti stores are considered to be a customer such that their demand is included in the demand processes.

Data definition: Before collecting the data, the stakeholders should clarify what data they exactly want to incorporate in the model to prevent misunderstanding/misalignment of input data. In section 3.3, the input data for the simulation model is extensively described.

Objective function determination: Prior to the implementation of an inventory control system, the objective function has to be clearly defined. Usually, the objective of inventory control systems is to minimize costs under a service level target or to maximize profit. Thus, the way of performance measurement and the desired targets have to be determined upfront. The objective of the inventory control policies in this research is to minimize investment in inventory while customers should still be served with a fill rate of 98%.

Centralized versus decentralized control: Before starting a MEIM project, the way the network will be controlled has to be defined. Multi-echelon inventory systems can be controlled by independent supply chain stages that optimize their own local objectives (decentralized control) or by a central decision maker that optimizes the supply chain network as a whole (centralized control). Oftentimes a pure centralized control policy is not feasible. However, some characteristics of centralized control policies can be implemented in decentralized systems by making use of information sharing and supply chain collaboration. In section 2.4.3, centralized versus decentralized control is extensively discussed.

In this research, we research the impact of centrally 'optimizing' safety stock parameters. The software tool ChainScope, developed by De Kok, is used for the analysis under centralized inventory control. The tool is based on the Synchronized Base Stock (SBS) policy, introduced in section 2.3.6.

3.2 Simulation model design

In this section, the simulation model is introduced. First, the underlying assumptions are defined. Next, the parameter setting of the simulation study is clarified.

3.2.1 Assumptions

1. Demand that can not be directly met from stock is backordered
2. Partial deliveries between locations within the distribution network are not allowed
3. Partial deliveries to customers are allowed
4. Transshipments do not occur
5. There are no warehouse capacity restrictions
6. Replenishment order quantities are integer multiples of a given batch size (unique per item-location)
7. Demand is stationary

Case-study assumptions

- The lead-times between location within the distribution network are deterministic, unique per item-location
- The lead-time to the most upstream location of the distribution network is stochastic (based on a gamma distribution)
- Customer demand is stochastic (based on a gamma distribution)
- Demand forecasts are propagated through the system
- Every working day, each location can generate a replenishment order (review period 1 day)
- In case of supply shortages, available stock is allocated according to the following procedure:
    1. Customer backorders are fulfilled
    2. Backorders from downstream locations are fulfilled according to FCFS logic.
    3. Incoming direct customer demand is fulfilled
    4. Incoming replenishment orders are fulfilled

The simulation is performed per item and based on the following order of events.

1. Replenishments arrive
2. Orders are released
3. Demand is fulfilled (if possible)
4. Performance measures are updated

3.2.2 Simulation parameters

Welch's method, described in Law and Kelton (2000), is used to determine the warm-up period of the simulation. In Appendix A, the method is explained and the results are visualized. Thus, the warm-up period is set to 180 periods after which the simulation runs for 370 periods. 10 model replications are performed. 95% confidence intervals are computed on item-level based on the output of the 10 simulation runs and the expression below:

$$\left[\bar{X} - t_{n-1,1-\propto/2}\sqrt{\frac{S^2}{n}}, \bar{X} + t_{n-1,1-\propto/2}\sqrt{\frac{S^2}{n}}\right]$$

$\bar{X}$ denotes the sample mean, S^2 the sample variance, $n = 10$ and $t_{n-1,1-\propto/2}$ is equal to 2.232 for a 95% confidence interval with 9 degrees of freedom.

3.2.3 Simulation variables

In this section, the sets and the variables of the simulation model are defined.

Sets

ε^h	location in the highest echelon of the distribution network
J	all locations in the distribution network
K	all items
P^J	predecessor ('supplier') of location J
S^J	successors ('customers') of location J
T	all periods

Variables

$AI_{k,j}(t)$	average inventory of item k measured over period $[1, t]$ at location j
$AI_k(t)$	average inventory of item k measured over period $[1, t]$ over all locations
$B_{k,j}(t)$	customer backorders of item k at the end of period t at location j
$CD_{k,j}(t)$	customer demand of item k during period t at location j
$DB_{k,j}(t)$	replenishment order quantity of item k of location j at the end of period t that is not available at j's supplier
$F_{k,j}(t)$	forecasted demand of item k for period t at location j
$FBO_{k,j}(t)$	fulfilled backorder quantity of item k during period t to location j

$FR_{k,j}(t)$	customer fill rate of item k measured over period $[1,t]$ at location j
$FR_k(t)$	customer fill rate of item k measured over period $[1,t]$
$I_{k,j}(t)$	physical on $-$ hand inventory of item k at the end of period t at location j
$IFR_{k,j}(t)$	internal fill rate of item k measured over period $[1,t]$ at location j
$IFR_k(t)$	internal fill rate of item k measured over period $[1,t]$
$IN_{k,j}(t)$	net inventory of item k at the end of period t at location j
$IOQ_{k,j}(t)$	delivered replenishment order quantity of item k at the beginning of period t at location j
$IP_{k,j}(t)$	inventory position of item k at the end of period t at location j
$IT_{k,j}(t)$	inventory in transit of item k at the end of period t to location j
$LT_{k,j}(t)$	lead time to location j at period t for item k
$NR_{k,j}(t)$	net requirements of location j at the beginnning of period t for item k
$OQ_{k,j}(t)$	quantity ordered by location j at the beginning of period t for item k
$Q_{k,j}$	batch size for replenishment orders to location j for item k
$RLT_{k,j}$	replenishment lead time to location j for item k
$SNR_{k,j}(t)$	scheduled net requirements of item k at location j at the beginning of period t as observed by j's predecessor
$SOQ_{k,j}(t)$	scheduled order quantity of item k at location j at the beginning of period t as observed by j′s predecessor
$ss_{k,j}$	safety stock of item k at location j
$TB_{k,j}(t)$	total customer backorders upto period t of item k at location j
$TD_{k,j}(t)$	total customer demand upto period t of item k at location j
$TDB_{k,j}(t)$	total backorders from successors$'$ upto period t of item k at location j
$TR_{k,j}(t)$	total dependent demand upto period t of item k at location j

3.2.4 Simulation model

The set-up of the simulation model is explained based on the order of events.

1. <u>Arrival of replenishment orders and backorder fulfillment</u>

Each morning, every location processes its incoming goods. The delivered replenishment order quantity at the beginning of period t is derived from earlier generated replenishment orders that will arrive at the beginning of period t ***(see Expression 1 and 18)***.

The net inventory and physical on-hand inventory are raised by the delivered replenishment order quantity (***Expression 1 and 2***) whilst the inventory in transit is updated by subtracting the delivered replenishment order quantity (***Expression 3***). Hence, the inventory position remains unchanged (***Expression 4***).

$$IN_{k,j}(t) = IN_{k,j}(t-1) + IOQ_j(t) \qquad \forall j \epsilon J, k \epsilon K \qquad (1)$$
$$I_{k,j}(t) = I_{k,j}(t-1) + IOQ_{k,j}(t) \qquad \forall j \epsilon J, k \epsilon K \qquad (2)$$
$$IT_{k,j}(t) = IT_{k,j}(t-1) - IOQ_{k,j}(t) \qquad \forall j \epsilon J, k \epsilon K \qquad (3)$$
$$IP_{k,j}(t) = IP_{k,j}(t-1) \qquad \forall j \epsilon J, k \epsilon K \qquad (4)$$

In case there are customer backorders, the available on-hand inventory is used to fulfill as many customer backorders as possible ***(Expression 5)***. The satisfied customer backorders are subtracted from the on-hand inventory level ***(Expression 6)***.

$$B_{k,j}(t) = \left[B_{k,j}(t-1) - I_{k,j}(t)\right]^+ \qquad \forall j \epsilon J, k \epsilon K \qquad (5)$$
$$I_{k,j}(t) = \left[I_{k,j}(t) - B_{k,j}(t-1)\right]^+ \qquad \forall j \epsilon J, k \epsilon K \qquad (6)$$

In case there are backorders from successor locations, the available on-hand inventory is used to fulfill as many backorders as possible according to FCFS-logic. Every time a backorder is fulfilled, the on-hand inventory of the supplier location needs to be updated before moving on to the next possible fulfillment. This procedure is illustrated below.

Procedure for backorder fulfillment of backorders from successors

1. Check whether there is available on-hand inventory at location j and positive backorders from successors
$$I_{k,j}(t) > 0 \wedge \sum_{m \in S^j} DB_{k,m}(s) > 0 \qquad \forall s \epsilon T, k \epsilon K$$
If yes, go to Step 2 *If no, STOP*

2. Fulfill oldest backorder from successors ($DB_{k,m}(s)$) <u>if</u> the on-hand inventory of location j can cover the size of this backorder
$$I_{k,j}(t) \geq DB_{k,m}(s)$$
If yes, proceed to step 3 *If not, STOP*

3. Update available on-hand inventory at location j: $I_{k,j}(t) = I_{k,j}(t) - DB_{k,m}(s)$, update the fulfilled backorder quantity $FBO_{k,m}(t) = FBO_{k,m}(t) + DB_{k,m}(s)$ and set backorder $DB_{k,m}(s)$ to 0: $DB_{k,m}(s) = 0$

As soon as an outstanding order from a successor can be cleared, the order is sent to the successor. The moment the successor receives the order can then be expressed by adding the replenishment lead-time to the moment the outstanding order is sent out. Thus, in case backorders from successor locations are fulfilled, the arrival moment of the replenishment order is determined by ***Expression 7.***

$$IOQ_{k,j}\left(t + RLT_{k,j}\right) = FBO_{k,j}(t) \qquad \forall j \epsilon J, k \epsilon K \qquad (7)$$

2. Check inventory position and place replenishment orders if needed

Every location checks whether there is a need to place an order at their predecessor location.

Forecasts propagate through the system. To mimic this behavior, scheduled order quantities of downstream locations are incorporated in the net requirement calculations of upstream locations. Before presenting the Expressions, an example will illustrate the logic behind the Expressions.

Example

Consider the three-echelon distribution network as presented below.

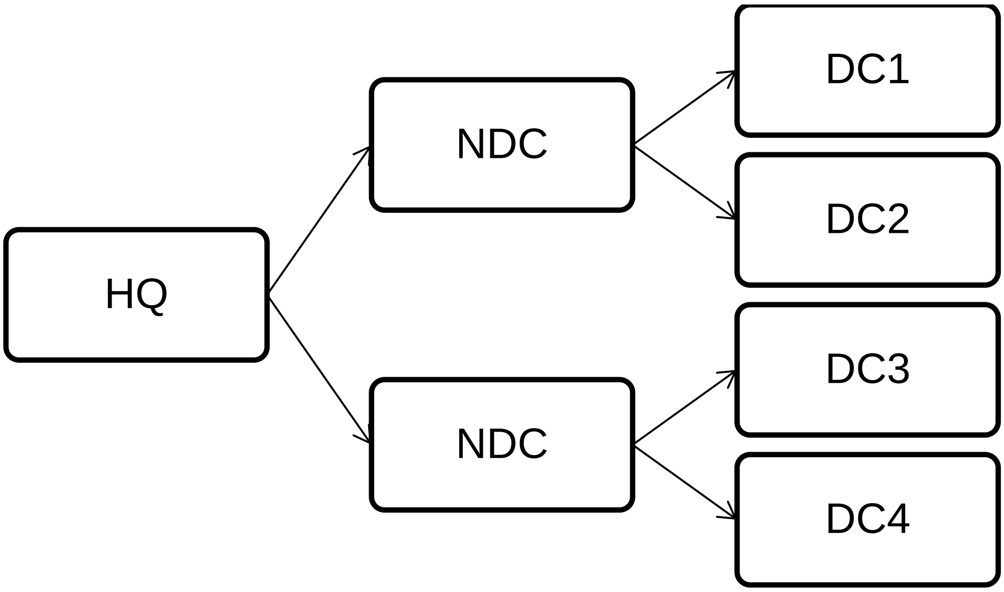


Figure 11 Example three-echelon distribution network

Assume that customer demand only occurs at the DCs. The forecasted customer demand from the DCs propagates through the network. Hence, the inventory position at the NDC should cover the forecasted orders from the DCs during the replenishment lead-time of the NDC (+ the safety stock of the NDC). The inventory position at the HQ should cover the forecasted orders from the NDCs during the replenishment lead-time of the HQ (+ the safety stock of the HQ).

To accurately replicate the forecast propagation, the scheduled net requirements are computed for every location from the perspective of its predecessor. This results in ***Expression 8.***

$$SNR_{k,j}(t) = \left\lceil \sum_{s=t}^{t+RLT_{k,P^j}+RLT_{k,j}} F_{k,j}(s) + ss_{k,j} - IP_{k,j}(t) + \sum_{m \epsilon S^j} \max\left(0, \left\lceil \frac{\sum_{s=t}^{t+RLT_{k,P^j}+RLT_{k,j}+RLT_{k,m}} F_{k,m}(s) + ss_{k,m} - IP_{k,m}(t)}{Q_{k,m}} \right\rceil * Q_{k,m}\right) \right\rceil^{+} \quad \forall j \epsilon J, k \epsilon K \quad (8)$$

Note that ***Expression 8*** works for multi-echelon distribution networks with a maximum of three echelons (in this case study we never exceed 3-echelons). However, the expression could be extended to simulate distribution network with more than 3 echelons under a *(R,s,nQ)*-policy in an MRP environment.

After the scheduled net requirements are derived, the resulting value is rounded up to an integer number of the corresponding batch size (***Expression 9***).

$$SOQ_{k,j}(t) = \left\lceil \frac{SNR_{k,j}(t)}{Q_{k,j}} \right\rceil * Q_{k,j} \qquad \forall j \epsilon J, k \epsilon K \qquad (9)$$

The above calculations (***Expression 8 and 9***) are solely needed as input for the net requirements calculations. Replenishment orders are triggered when the current inventory position is not sufficient to cover the forecasted demand during the replenishment lead-time (customer demand and dependent demand) and the safety stock; thus, when the net requirements (***Expression 10***) exceed 0. Note that the forecasted demand from successors is represented in ***Expression 10*** by the scheduled order quantities from successors. As batch sizes need to be respected, the net requirements are rounded up to the smallest number of batch sizes required to reach a positive inventory position (***Expression 11***).

$$NR_{k,j}(t) = \left\lceil \sum_{s=t}^{t+RLT_{k,j}} F_j(s) + ss_{k,j} - IP_{k,j}(t) + \sum_{m \epsilon S^j} SOQ_{k,m}(t) \right\rceil^{+} \qquad \forall j \epsilon J, k \epsilon K \qquad (10)$$

$$OQ_{k,j}(t) = \left\lceil \frac{NR_{k,j}(t)}{Q_{k,j}} \right\rceil * Q_{k,j} \qquad \forall j \epsilon J, k \epsilon K \qquad (11)$$

3. Processing customer and dependent demand

Customer demand arrives based on a gamma distribution ***(Expression 12)*** and is rounded to an integer value.

$$CD_{k,j}(t) \sim \left[Gamma\left(\beta_{k,j}, \alpha_{k,j}\right),\right] \; where \; \alpha_{k,j} = \frac{\mu_{k,j}^2}{\sigma_{k,j}^2} \; and \; \beta_{k,j} = \frac{\sigma_{k,j}^2}{\mu_{k,j}} \qquad \forall j \epsilon J, k \epsilon K \qquad (12)$$

The customer demand that can be directly met from stock is fulfilled. The inventory on hand is updated ***(Expression 13)***. If the available stock is lower than the total customer demand, the customer demand that can not be fulfilled immediately is backordered ***(Expression 14)***. The backorder level is updated ***(Expression 15)***.

$$I_{k,j}(t) = \left[I_{k,j}(t) - CD_{k,j}(t)\right]^{+} \qquad \forall j \epsilon J, k \epsilon K \qquad (13)$$

$$CB_{k,j}(t) = \left[CD_{k,j}(t) - I_{k,j}(t)\right]^{+} \qquad \forall j \epsilon J, k \epsilon K \qquad (14)$$

$$B_{k,j}(t) = B_{k,j}(t) + CB_{k,j}(t) \qquad \forall j \epsilon J, k \epsilon K \qquad (15)$$

Now, the replenishment orders have to be processed. Locations in the highest echelon of the distribution system, receive their orders after a gamma-distributed lead-time ***(Expression 16 & 17)***.

$$LT_{k,j}(t) \sim \left[Gamma\left(\beta_{k,j}, \alpha_{k,j}\right)\right], where\ \alpha_{k,j} = \frac{\mu_{k,j}^2}{\sigma_{k,j}^2}\ and\ \beta_{k,j} = \frac{\sigma_{k,j}^2}{\mu_{k,j}} \qquad \forall j \epsilon \varepsilon^h, k \epsilon K \qquad (16)$$

$$IOQ_{k,j}\left(t + LT_{k,j}(t)\right) = OQ_{k,j}(t) \qquad \forall j \epsilon \varepsilon^h, k \epsilon K \qquad (17)$$

For all other locations, it is checked whether the replenishment order can be fulfilled from the on-hand stock at its predecessor. If this is the case, the replenishment order arrives after the planned replenishment lead-time ***(Expression 18)*** and the on-hand stock of the supplier is updated ***(Expression 19)***. If the predecessor does not have enough stock, the replenishment order is recorded as a backorder ***(Expression 20)***. Note that Expression 18, 19 and 20 occur immediately after each other before the next location is considered.

$$\forall j \epsilon J \backslash \varepsilon^h, i \epsilon P^j, k \epsilon K$$

$$\begin{cases} IOQ_{k,j}\left(t + RLT_{k,j}\right) = IOQ_{k,j}\left(t + RLT_j\right) + OQ_{k,j}(t) & if\ I_{k,i}(t) - OQ_{k,j}(t) \geq 0 \qquad (18) \\ I_{k,i}(t) = I_{k,i}(t) - OQ_{k,j}(t) & if\ I_{k,i}(t) - OQ_{k,j}(t) \geq 0 \qquad (19) \\ DB_{k,j}(t) = OQ_{k,j}(t) & if\ I_{k,i}(t) - OQ_{k,j}(t) < 0 \qquad (20) \end{cases}$$

Now that all events have occurred, the net-inventory, inventory position and inventory in transit are updated ***(Expression 21, 22 and 23)***.

$$IN_{k,j}(t) = IN_{k,j}(t) - CD_{k,j}(t) - \sum_{m \epsilon S^j} OQ_{k,m}(t) \qquad \forall j \epsilon J, k \epsilon K \qquad (21)$$

$$IP_{k,j}(t) = IP_{k,j}(t) - CD_{k,j}(t) - \sum_{m \epsilon S^j} OQ_{k,m}(t) + OQ_{k,j}(t) \qquad \forall j \epsilon J, k \epsilon K \qquad (22)$$

$$IT_{k,j}(t) = IT_{k,j}(t) + OQ_{k,j}(t) \qquad \forall j \epsilon J, k \epsilon K \qquad (23)$$

4. Update performance indicators

The relevant output of the simulation model is the obtained service level and the average on-hand inventory required to reach this service level. Service is measured by the fill rate. Hence, the first performance indicator that is derived from the simulation results is the customer fill rate (*the fraction of customer demand directly available from stock*).

The total amount of customer backorders and customer demand up to period t is updated in ***Expression 24*** and ***Expression 25*** respectively. With this information, the customer fill rate is computed per location (***Expression 26***) and over the entire network (***Expression 27).***

$$TB_{k,j}(t) = TB_{k,j}(t-1) + CB_{k,j}(t) \qquad \forall j \epsilon J, k \epsilon K \qquad (24)$$

$$TD_{k,j}(t) = TD_{k,j}(t-1) + CD_{k,j}(t) \qquad \forall j \epsilon J, k \epsilon K \qquad (25)$$

$$FR_{k,j}(t) = \left(1 - \frac{TB_{k,j}(t)}{TD_{k,j}(t)}\right) * 100\% \qquad \forall j\epsilon J, k\epsilon K \tag{26}$$

$$FR_{k}(t) = \left(1 - \frac{\sum_{j=1}^{J} TB_{k,j}(t)}{\sum_{j=1}^{J} TD_{k,j}(t)}\right) * 100\% \qquad \forall k\epsilon K \tag{27}$$

Although the product availability as observed by customers is the most important service performance indicator, the internal service levels (*fraction of dependent demand directly available from stock*) are also derived to gain insights into the product availability of predecessors as observed by successors. The total amount of backorders and dependent demand up to period t is updated in ***Expression 28*** and ***Expression 29*** respectively. With this information, the internal fill rate is computed per location (***Expression 30***) and over the entire network (***Expression 31).***

$$TDB_{k,j}(t) = TDB_{k,j}(t-1) + \sum_{m\in S^j} DB_{k,m}(t) \qquad \forall j\epsilon J, k\epsilon K \tag{28}$$

$$TR_{k,j}(t) = TR_{k,j}(t-1) + \sum_{m\in S^j} OQ_{k,m}(t) \qquad \forall j\epsilon J, k\epsilon K \tag{29}$$

$$IFR_{k,j}(t) = (1 - \frac{TDB_{kj}(t)}{TR_{k,j}(t)}) * 100\% \qquad \forall j\epsilon J, k\epsilon K \tag{30}$$

$$IFR_{k}(t) = (1 - \frac{\sum_{j=1}^{J} TDB_{k,j}(t)}{\sum_{j=1}^{J} TR_{k,j}(t)}) * 100\% \qquad \forall\ k\epsilon K \tag{31}$$

Lastly, the average stock on-hand is derived per location (***Expression 32***) and over the entire network (***Expression 33***). With this average stock on-hand values, the holding costs can be computed.

$$AI_{k,j}(t) = \frac{\sum_{k=1}^{t} I_{k,j}(k)}{t} \qquad \forall j\epsilon J, k\epsilon K \tag{32}$$

$$AI_{k}(t) = \frac{\sum_{j=1}^{J} AI_{k,j}(k)}{t} \qquad \forall\ k\epsilon K \tag{33}$$

3.3 Simulation model input

In this section, the input parameters that are used in the simulation model are shortly described.

Lot sizes

The main purpose of lot sizes is to balance handling, holding and transportation costs. As it is not preferred to order one-for-one (which could lead to substantial cost increases), downstream location should order in integer numbers of the lot size. Those values are retrieved from the BI system and not changed during the simulation study.

Planned lead-times

The replenishment lead-times are derived based on the planned delivery time and the goods receipt time as available in the information system. With these replenishment lead-times, the MRP system computes the net requirements.

The planned delivery time ($PDT_{j,k}$) within Hilti is defined in calendar days, the goods receipt time ($GR_{j,k}$) in working days. As both values need to be combined into one single number, the replenishment lead-time ($RLT_{j,k}$) is transferred to working days according to the following expression:

$$RLT_{j,k} = \left\lceil \frac{PDT_{j,k}}{7} * 5 \right\rceil + GR_{j,k}$$

Demand

For the replenishment of orders within Hilti, it is important to distinguish between customer demand and independent demand (orders from successors). However, the total demand faced by upstream location is an aggregation of both demand sources. Transactional replenishment data of 2018 is collected to derive demand parameters (average and standard deviation per item per location). Demand parameters are expressed in working days.

Forecasted demand

The recorded monthly historical forecasts are converted to daily forecasts. As stationary demand is assumed, the daily forecasts are computed by dividing the total forecast quantity for the year 2018 by 260 working days.

Lead-time to first location in the distribution network

The average and standard deviation of the lead-time to the first location in the distribution network (HAG WHs) are derived from historical replenishment data collected in the BI system. The parameters are computed in working days.

Target service level

As stated earlier in section 1.5.4, Hilti measures service based on the ATS. Hence, both the fill rate and ready rate are not one-to-one comparable to the ATS service levels. However, the fill rate seems to be most relevant and accurate for this study. Hilti strives for a very high service level (98%) to its customers. For the matter of this thesis, service levels are measured by the fill rate.

3.4 Additional input parameters for ChainScope modeling

The important parameters that serve as an input for the ChainScope optimization are shortly described.

Service levels

The target fill-rates are set to 98% for every article and every location where demand occurs.

Yield

The yield is set to 1 as in a distribution system no changes in the structure of the item (material itself) occur. Furthermore, it is assumed that damage or product loss does not occur.

Added value

The added value for the most upstream location is equal to the COGS. Within the distribution network, the value-adding activity between location consists of transportation costs. The transportation costs are relatively low and set to 1 cost unit for all items and locations (except for the most upstream locations). The results are not expected to be affected by this, especially as locations should be threated homogenously.

Other parameters

- The expected demand and the standard deviation of the demand per item and location are set equal to the demand parameters used for the simulation
- The expected lead-time to the first location in the distribution network is based on the average lead-time observed from the data. The expected lead-times between locations within the distribution network are set equal to the replenishment lead-times defined earlier (ChainScope already incorporates material availability in the optimization model. Hence, only the time needed for the actual transformation process is required).
- Review period is set to 1 for all items and all locations

3.5 Safety stock setting procedures

3.5.1 Hilti´s method

For the analysis of the AS-IS situation, the historical safety stock values are retrieved from the BI system. Although different safety stock computation methods are used by Hilti, we strive to stay as close as possible to the current inventory policy to be consistent with the current inventory strategy. The safety stock values vary each month (section 1.5). Hence, rounded (upwards) averages of the safety stocks of 2018 are used for the simulation of the current situation.

3.5.2 Single-echelon control

In order to compare the multi-echelon controlled inventory policy with the single-echelon controlled inventory, safety stocks are computed based on the following expression:

$$ss = k * \sqrt{\sigma_D^2 * \mu_L + \sigma_{LT}^2 * \mu_D^2 + Var(U)}$$

where μ_L is the average lead-time, μ_D the average demand, σ_D the standard deviation of the demand observed by the location and σ_{LT} the standard deviation of the replenishment lead-time. The undershoot can be computed with $E(U) = \frac{(a+1)}{2\lambda}$ and $E(U^2) = \frac{(a+1)(a+2)}{3\lambda^2}$, where $a = \frac{E^2[\mu_D]}{\sigma^2(\sigma_D)}$ and $\lambda = \frac{a}{E[\mu_D]}$. Thereafter, the variance of the undershoot is determined with $Var(U) = E(U^2) - E(U)^2$.

k is the safety factor depending on the target service level. The relevant service level for this thesis is the fill rate. Hence, the standard loss function needs to be applied. The standard loss function is represented by the following equation:

$$G(k_\beta) = \frac{(1-\beta)Q}{\sigma\sqrt{L}}$$

where β is the target fill rate, Q the order quantity and $\sigma\sqrt{L}$ the variance of the demand during the lead-time ($\sqrt{\sigma_D^2 * \mu_L + \sigma_{LT}^2 * \mu_D^2 + Var(U)}$).

As demand is assumed to be Gamma distributed, the standard loss function is combined with a Gamma inversion algorithm proposed by De Kok and Verrijdt (1995) to determine the value of the service factor k.

For all locations within the distribution network the target fill rates are set to 98%. With this high upstream service-level at the first echelon, the standard deviation of the replenishment lead-time from the first echelon onwards is considered to be negligible and set to 0. Safety stocks are rounded up to an integer number.

3.5.3 Single-echelon control with updated upstream service level

In most cases, replacing a simple inventory control system with an advanced multi-echelon inventory system is quite challenging. Therefore, Axsäter (2003) suggests to analyze a small set of items based on multi-echelon inventory control after which the service levels in the existing system can be adapted according to the multi-echelon control analysis. In the same paper, the researcher states that optimal solutions usually result in warehouse fill rates slightly above 50%. Based on these statements, an adapted single-echelon controlled policy will be included in the comparison study. The upstream target fill rate will be set to 60% while the target fill rates at the downstream locations remain 98%. However, under this procedure, the lead-times to successors of the upstream location are expected to be more unstable (less risk pooling upstream). Hence, the lead-time parameters of downstream locations have to be adapted accordingly. To accomplish this, the following procedure is applied.

1. Adapt safety stock of most upstream location according to new target fill rate of 60%
2. Run simulation with run length 550 days, warm-up period 180 days and 10 replications
3. Compute average and standard deviation of replenishment lead-times to successors
4. Adapt safety stock of successors with updated lead-time parameters and target fill rate of 98%
5. Run simulation with run length 550 days, warm-up period 180 days and 10 replications

3.5.4 Multi-echelon control

For the simulation of multi-echelon controlled inventory management, the safety stock values as optimized by ChainScope are rounded up and implemented in the simulation model.

3.6 Output of the simulation model

Average inventory on-hand (physical stock)

To compare the costs of the decentralized inventory control approach with the centralized optimized approach, the average on-hand inventory values will be recorded. Despite the stock on hand at the distribution centers, the inventory in the pipeline is also available in the network. Thus, the total network inventory consists of the stock levels at the locations plus the inventory in transit in the network. Note that both inventory types will also be measured separately. We expect that the inventory in transit will not be affected by the control type. However, the inventory on stock at the locations will be largely affected by the inventory control approach.

The average inventory on-hand will be used to compute the average holding costs in the system. The actual holding costs are rescaled in this report to maintain data confidential.

Service level

The obtained fill rates are recorded per item and location to see whether the target service levels are reached.

3.7 Validation and verification

The simulation needs to be validated to ensure the model adequately represents the real process. The underlying logic of the simulation model has been validated during an extensive discussion with a team member of the GLMP department. Additionally, data has been validated by randomly comparing the parameters reported in the BI tool and the APO tool. Another validation is performed by comparing output values of the simulation with the output of the ChainScope tool.

The model is verified by scenario analysis. The demand and the lead-time are independently changed to extreme low and extreme high values.

When no demand occurs, inventory levels are expected to remain stable. On the other hand, extreme demand will lead to 0 stock and high backorders. When lead-times are set to 0, orders are immediately processed and delivered. Hence, a perfect service can be provided to customers (fill rate 100%). Under high lead-times, replenishments will never arrive with 0 stock and high backorders as a result. The results of the simulation resembled the expected outcomes.

4. Case study

In this chapter, the safety stock setting control policies are compared for multiple items flowing through Hilti's distribution network. In Figure 12, an example of a possible distribution supply chain network within Hilti is illustrated. Note that the distribution network structure is not identical for the different items.

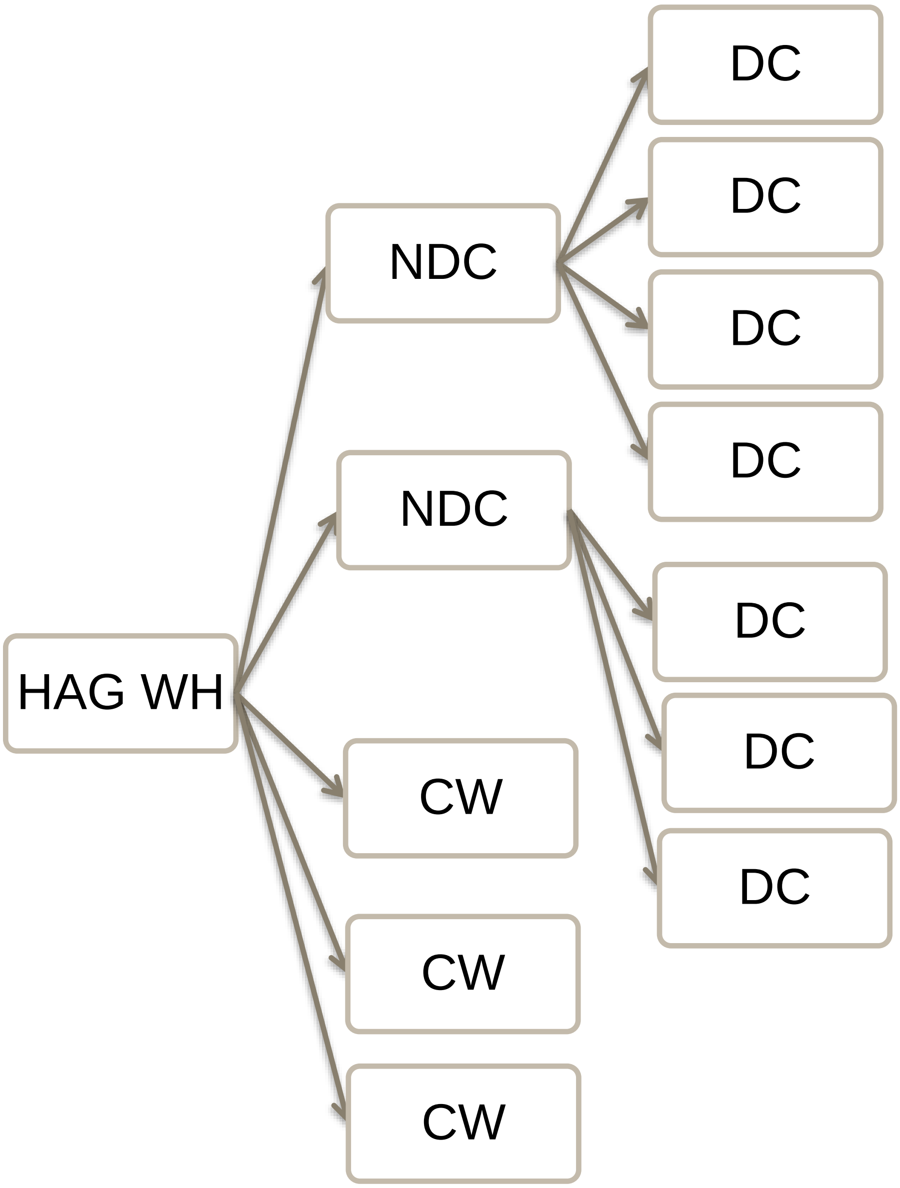


Figure 12 Example distribution network structure

4.1 Case study set-up

The case study should cover a very diverse subset of articles. Although 32 scenarios are theoretically possible (Appendix B), the analyses concentrate on 21 different scenarios. The scenarios that are excluded from the case study, are not encountered regularly in Hilti's supply chain. An example is scenario 31, which represents an item with a low lead-time, a low demand rate and low variability in supply and demand. Usually, low demand, low lead-times items go hand in hand with higher variability.

The articles to include in the case study meet the following requirements:

i. The article flows via the headquarter warehouse to the regions
ii. The article is sold throughout the complete year (no phase-in or phase-out)
iii. The article is not a spare part

No restrictions have been placed on the number of locations nor the amount of echelons (2 or 3) within the distribution networks of the different articles.

26 articles are included in the case study. Besides articles for the different scenarios, 5 additional items are randomly chosen to see whether findings remain consistent when equal scenarios are compared.

The considered supply chain characteristics of the items can be found in Appendix C. To classify items as 'high' or 'low', threshold values are defined based on data observations.

- An average daily demand lower than 3 is low
- An average lead-time lower than 20 is low
- A daily demand variability lower than 2.0 is low
- A lead-time variability lower than 0.3 is low
- Holding costs lower than X are low

Denote that variability is measured by the coefficient of variation. Although a demand variability of 2.0 might seem high at first sight, 1) variability over the lead-time is usually lower and 2) Hilti's product portfolio consists of many high variable items in general. Holding costs are rescaled in this report to maintain the data confidential.

In Appendix D, the items are classified based on the five characteristics and the corresponding scenario is indicated.

Note that SE 98% refers to the single-echelon controlled safety stock setting procedure and ME 98% denotes the multi-echelon controlled safety stock setting procedure. The adapted single-echelon controlled safety stock setting procedure is denoted by `SE downstream 98%, upstream 60%'. Hilti's current safety stock setting procedure is denoted by current'.

4.2 Case study results

Before moving to the results of the case study, the forecasted daily demand is plotted against the actual average daily demand as this information is important for further analysis (Figure 13).

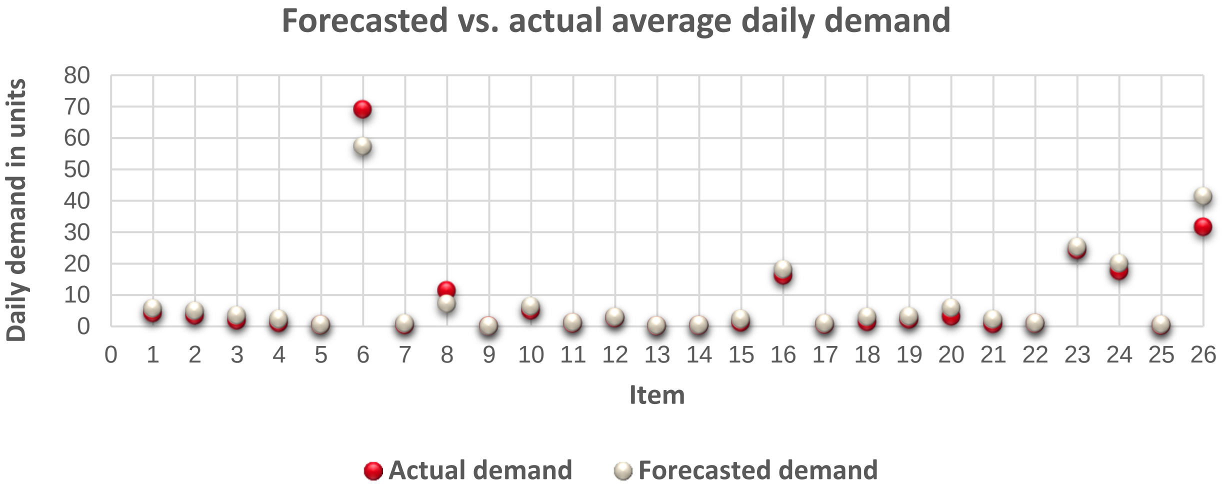


Figure 13 Forecasted vs. actual average daily demand

4.2.1 Service levels

In Figure 14, the resulting fill rates on item-level are illustrated. In most cases, the differences in fill rates between the policies do not differ largely. However, item 6, 8 and 11 require further explanation. The low service performance of item 6 and 8 can be explained by a large under-forecast of the average daily demand (see Figure 13). Interestingly, the adapted single-echelon policy with a low upstream service level still results in a high service level performance for these items. These results can be explained by the fact that 1) higher safety stocks are kept downstream compared to the normal single-echelon policy and 2) more safety stock is allocated to the upstream location compared to the multi-echelon policy.

Item 11 is the item with the highest lead-time variability (*CoV* 0.9). The majority of multi-echelon literature does assume that the lead-time to the first location within a network is deterministic. Hence, the lower service level under the ME policy can be explained by the fact that ChainScope does not allow for lead-time variability into the first echelon of the distribution network. To prevent an underperforming service level when the lead-time variability is high, additional safety stock could be held upstream. However, the required additional safety stock to respond to uncertain lead-times from external suppliers should be investigated further.

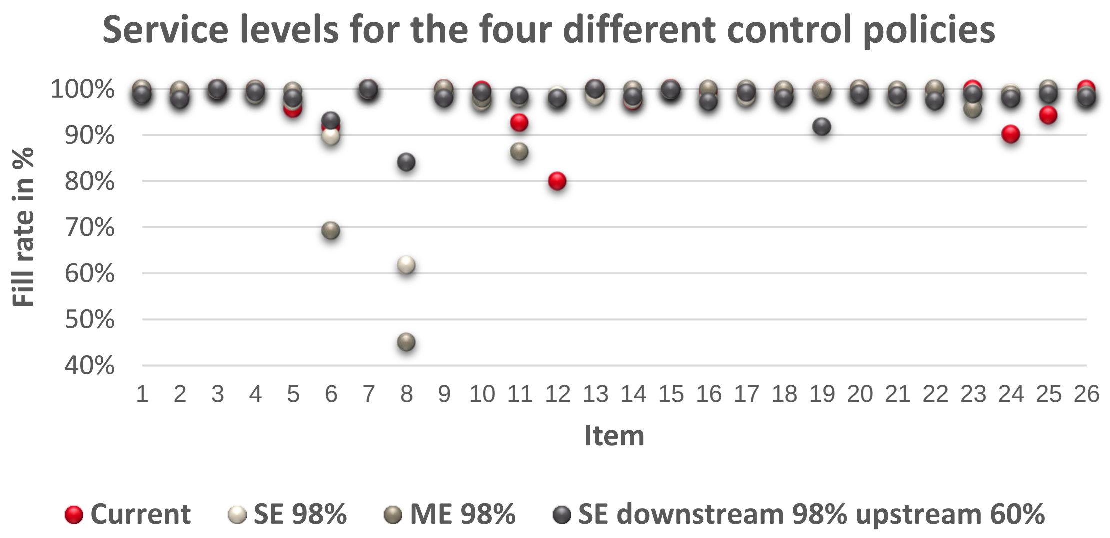


Figure 14 Fill rates under different inventory control policies

4.2.2 Inventory on-hand

In Figure 15, the average inventory on-hand is graphically presented under the four policies. For detailed simulation results and confidence intervals per item and control policy, the reader is referred to Appendix E, F and G for the single-echelon, the multi-echelon and the adapted single-echelon policy respectively.

The multi-echelon policy outperforms the local policies in almost all instances. Three articles showed better performance under single-echelon inventory control (item 5, 16 and 25). Item 5 and 25 both have a low average daily demand and an extremely high demand variability (*CoV* 4.0 and 4.5). The high variance of the demand combined with the low demand rate seem to be well-handled by single-echelon control. It could also be argued that the high coefficient of variation causes a higher deviation from the analytical lower bound under the balance assumption for the multi-echelon control setting (De Kok, 2018).

Item 16 represents a high demand, low cost item with a low lead-time, high lead-time variability and low demand variability. A low lead-time combined with low demand variability decreases the up- and downstream safety stock while high lead-time variability and high demand increases the upstream safety stock under single-echelon control. However, a higher *CoV* for a low lead-time causes less additional safety stock then a high *CoV* for a high lead-time (standard deviation higher). Hence, a possible explanation of the outperformance of the single-echelon inventory control policy is that single-echelon theory can handle high, stable demand under low, very unstable lead-times quite good.

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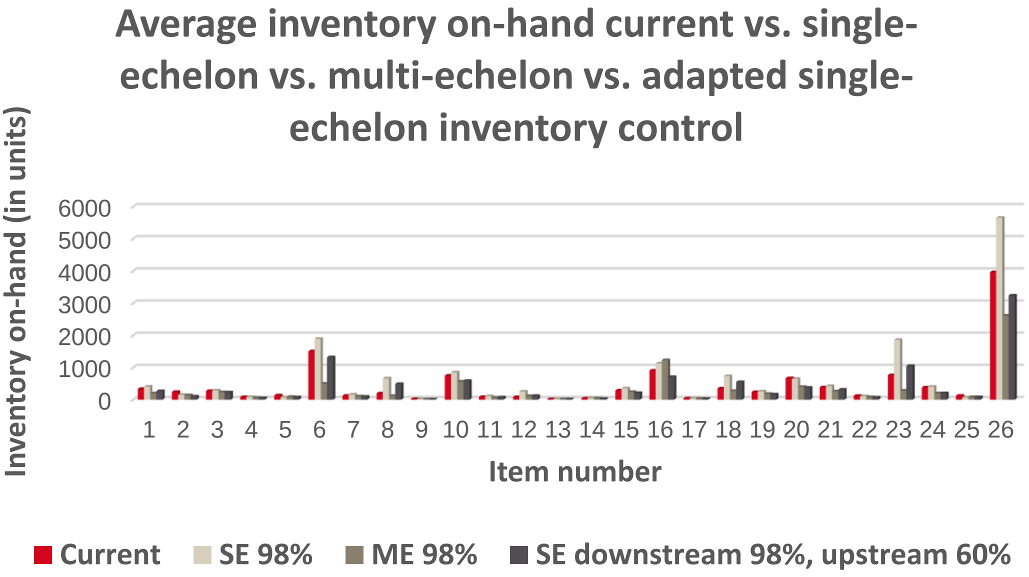

Figure 15 Average inventory on-hand under the different inventory control policies

In Figure 16, the percentual difference between the average inventory on-hand for the multi-echelon vs. the single-echelon safety stock procedure is plotted against the daily demand (per working day). The same figures are drawn for the difference between the average inventory on-hand plotted against the lead-time to the HAG WH in working days, the variability in demand and the variability in the lead-time to the HAG WH (Figure 17, 18 and 19 respectively). At first sight, the percentual difference in inventory on-hand does not seem to depend on one characteristic only; for none of the studied characteristics the percentual inventory reduction/increase shows a clear pattern based on the magnitude of the characteristic. Thus, the underlying hypothesis of this research proves to be relevant; the reduction in inventory on-hand is expected to depend on combinations of supply chain characteristics. To investigate whether the difference in inventory on-hand between SE and ME control can be estimated with a regression model, a regression analysis is performed on the dataset. The dependent variable is denoted by the difference in inventory on-hand while the independent variables are the demand, the lead-time, demand variability (*CoV*) and lead-time variability (*CoV*). The demand and the lead-time both gave significant results (demand $p<0.01$, lead-time $p<0.05$). However, the variability in both demand and lead-time were not found to be significant. Hence, a regression model is fitted with only the demand and the lead-time as independent variables. The output indicates that the regression is statistically significant ($p<0.01$) with an R^2 value of 0.614. Hence, 61.4% of the total variation in the difference in inventory on-hand between SE and ME can be explained by the demand and lead-time. The corresponding regression equation is:

$$-240.596 + (31.493 * demand) + (9.118 * lead\ times)$$

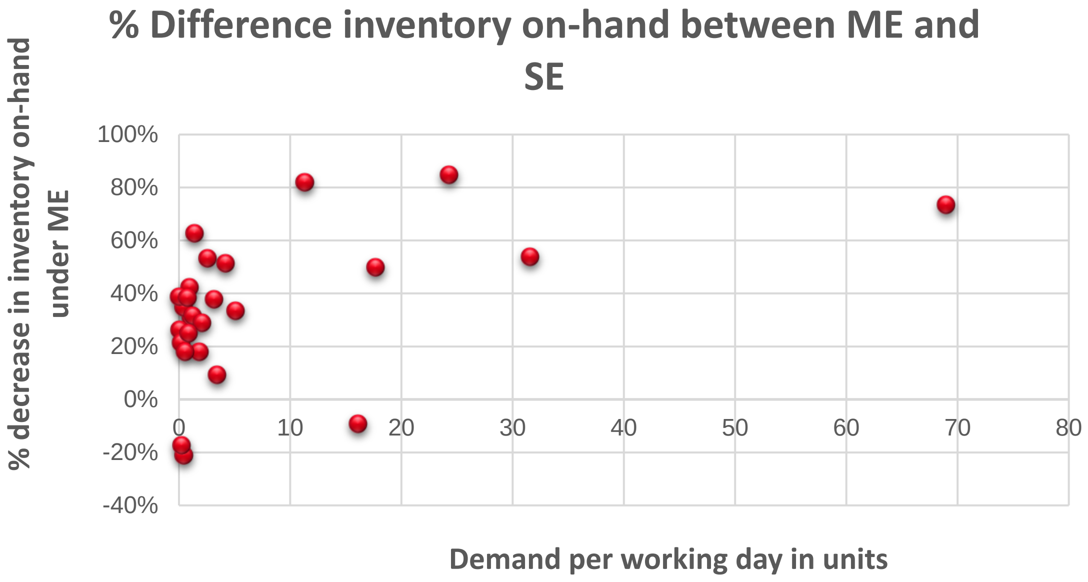

Figure 16 Difference inventory on-hand between ME and SE plotted against demand

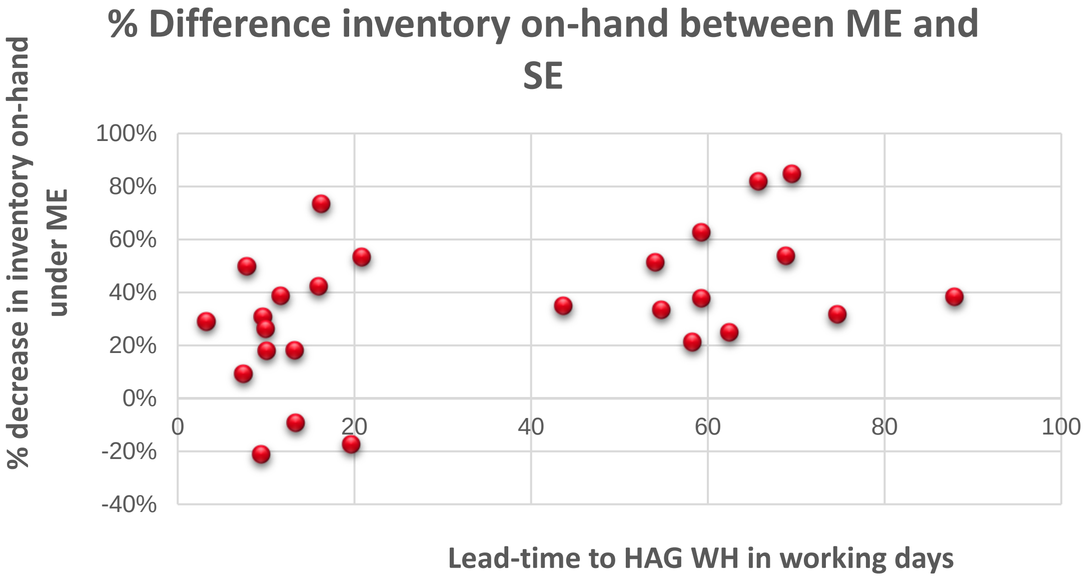

Figure 17 Difference inventory on-hand between ME and SE plotted against lead-time

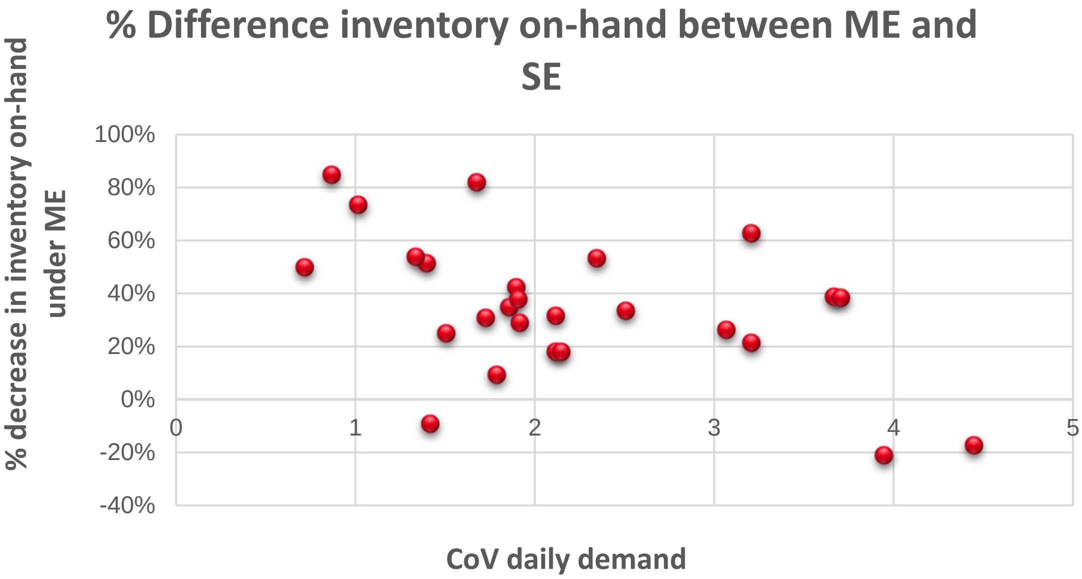

Figure 18 Difference inventory on-hand between ME and SE plotted against demand variability

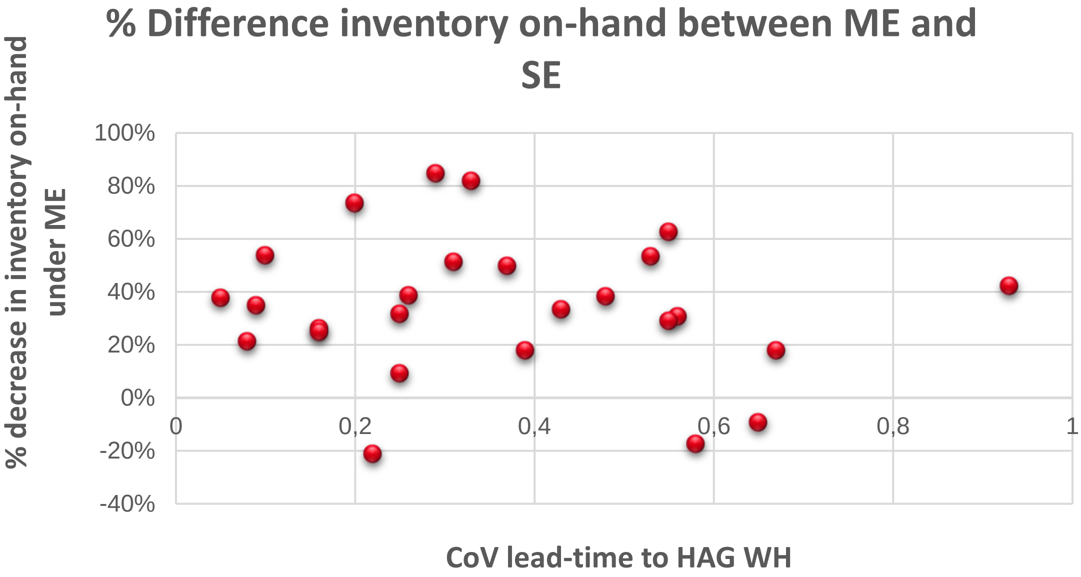

Figure 19 Difference inventory on-hand between ME and SE plotted against lead-time variability

4.2.3 Cost gap

The differences in yearly holding costs between the multi-echelon and single-echelon policies are ranked from high to low in Table 4. It can be observed that the monetary benefits of multi-echelon inventory control highly vary. The same comparison has been made for the holding costs between the current policy compared to the multi-echelon control policy (Appendix H) and the adapted single-echelon control policy and the multi-echelon control policy (Appendix I). While for most instances, the current policy outperforms the 'general' single-echelon policy, the opposite holds when the upstream service level of the single-echelon policy is adapted. For 16 items, the adapted single-echelon policy requires less investment in inventory on-hand compared to the centralized multi-echelon policy. However, the performance of the adapted single-echelon policy is lacking behind the performance of the multi-echelon policy for the most promising scenarios. It is argued that the approximation of a 60% upstream service level is a too rough guess and better estimates can lead to more satisfactory results for these items. Overall, the adapted single-echelon policy leads to significant savings compared to the general single-echelon policy. Hence, adapting upstream service level targets according to multi-echelon control analysis can be very interesting and practically relevant.

Table 4 Yearly savings obtained by changing from SE to ME

Savings	Demand	Lead-Time	CoV Demand	CoV Lead-time	Holding costs	Scenario
4645	H	H	L	L	H	7
1109	H	L	L	L	L	16
494	H	H	L	H	H	5
486	H	L	L	H	H	13
369	H	H	L	H	L	6
333	L	H	H	H	H	17
191	L	H	H	H	L	18
186	H	H	L	L	L	8
166	H	H	L	L	L	8
163	L	H	H	H	L	18
142	L	L	H	H	H	25
79	L	L	L	H	H	29
71	H	H	H	H	L	2
64	L	L	H	H	H	25
63	L	H	L	L	H	23
61	L	H	H	L	L	20
59	L	H	H	L	H	19
46	L	L	H	L	H	27

38	H	L	L	L	H	15
32	L	L	H	L	H	27
22	L	L	L	H	L	30
17	L	H	L	L	L	24
10	L	L	L	H	L	30
-2	L	L	H	H	L	26
-4	L	L	H	L	L	28
-18	H	L	L	H	L	14

For some scenarios, the decentralized policies rank the savings from centralized control differently. In Table 5, the ranking of scenarios is compared under the three decentralized policies.

High potential items

Scenario 7 resulted in the highest savings obtained by centralized control. The findings hold for all comparison studies. Thus, this high demand, high lead-time and high cost item is considered to be of special importance when high savings have to be gained quickly. Remarkably, the savings for scenario 5 are lower. Scenario 5 experiences a high lead-time variability while the other characteristics are identical to the classified characteristics of scenario 7. Although lead-time variability is hypothesized to have a positive effect on the potential benefits of centralized control, this is not observed when we compare scenario 5 and 7. Looking at the top-5 ranked scenarios, scenario 16 is the remaining item ranked in the top 5 of all decentralized policies. However, this scenario can not be classified as high potential as the service level under the centralized control policy is highly underperforming due to the underestimated forecast that has been mentioned earlier (item 6). Note that this item represents a high demand, low cost item with ‘stable’ demand and supply. Hence, it would be counterintuitive to estimate the possible benefits as ‘high’ (low variability usually results in significant safety stock reductions under single-echelon control).

Low potential items

The monetary benefits of centralized control for low demand, low cost items fall in the lower segments of the potential savings ranking under all decentralized policies. One exemption is scenario 18 where high variability in supply and demand and a high lead-time come along with low cost, low demand items. This supports the statement made in Duan and Liao (2012); the benefits for low demand, low cost items are higher under more unstable demand. Hence, if a company’s product portfolio consists of very diverse items, it might not be worthwhile to change to more advanced centralized inventory control policies for low demand, low cost items. The adapted single-echelon policy performs very well for this type of items and may be a good substitute of a centralized multi-echelon policy. However, if the product portfolio mainly consists of low demand, low cost items, relative small savings on item-level can lead to substantial cost savings in total.

Table 5 Scenarios ranked based on saving potential compared to ME policy

Rank	**SE 98%**	**Current**	**SE 60% upstream**
1	7	7	7
2	16	16	16
3	5	13	6
4	13	5	5
5	6	15	17
6	17	17	18b
7	18a	8a	8b
8	8a	25a	18a
9	8b	23	2
10	18b	8b	30a
11	25a	29	13
12	29	6	26
13	2	2	24
14	25b	25b	28
15	23	27a	30b
16	20	18b	27b
17	19	20	20
18	27b	30b	8a
19	15	27b	25a
20	27a	28	29
21	30b	26	27a
22	24	24	23
23	30a	30a	25b
24	26	19	19
25	28	18a	14
26	14	14	15

4.3 Sensitivity analysis

4.3.1 Forecasts

In the previous section, a forecast-driven supply chain is considered. However, the forecast performance (accuracy, bias) may influence the supply chain performance. This section discusses whether the conclusions drawn in section 4.2 are still valid when the forecasted daily demand is set equal to the actual average daily demand (denoted by 'perfect' forecast).

First of all, the statement made in section 4.2.1 appears to be validated; the low service levels for items 6 and 8 are not observed under the 'perfect forecast' scenario. For some items, the service levels under SE are better, for other items the service levels under ME are better. However, for most instances the obtained service levels are close to each other. Moreover, random variations around the actual targets are assumed to cancel out after aggregation.

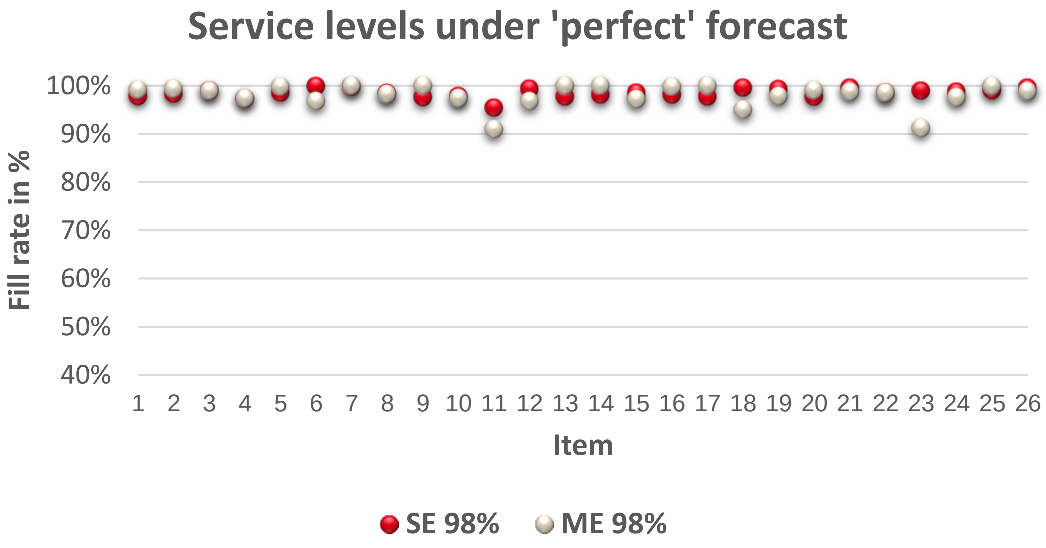

Figure 20 Service levels under 'perfect' forecast scenario

Concerning the cost gap between centralized and decentralized control, the savings from moving from a single-echelon to the multi-echelon safety stock procedure can be observed in Table 6. It is expected that the main findings remain consistent as the safety stock values are exactly the same as in the previous section. This statement appears to be correct; most items remain at their position in the ranking scheme. Some items slightly changed position, but the savings for those items are close to each other. Hence, it can be stated that the potential of centralized inventory control is not affected by the forecast accuracy.

Similar as in the previous section, Scenario 7 and 5 are items that are classified to be of high potential for centralized inventory control. All scenarios where high demand and high lead-time are considered suggest promising savings. A very notable finding is the high performance for item 6 (scenario 16). As discussed earlier, it is counterintuitive to expect high savings for items with stable demand and supply patterns. In section 4.2.1, the under-forecast resulted in an underperforming service level under centralized control. However, when forecasts would be equal to the average demand, the savings for item 6 are still ranked second while the service level remains high. It is argued that a large demand rate can offset variability in terms of centralized inventory control potential (in line with findings discussed by Duan and Liao (2012)). Again, the savings for most of the scenarios with low demand, low cost items fall under the lower savings segments. A last comment will be made on the ‘double’ scenarios. In Table 6, the items that fall under the same supply chain characteristic settings often show comparable savings potential.

Table 6 Yearly savings obtained from moving from SE to ME under perfect forecasted demand

Savings	Demand	Lead-Time	CoV Demand	CoV Lead-time	Holding costs	Scenario
4637	H	H	L	L	H	7
1141	H	L	L	L	L	16
497	H	H	L	H	H	5
466	H	L	L	H	H	13
409	H	H	L	H	L	6
350	L	H	H	H	H	17
199	L	H	H	H	L	18
188	H	H	L	L	L	8
163	H	H	L	L	L	8
162	L	H	H	H	L	18
154	L	L	H	H	H	25
77	L	L	L	H	H	29
70	L	H	L	L	H	23
69	H	H	H	H	L	2
66	L	L	H	H	H	25
62	L	H	H	L	L	20
59	H	L	L	L	H	15
57	L	H	H	L	H	19
48	L	L	H	L	H	27
32	L	L	H	L	H	27
18	L	L	L	H	L	30
17	L	H	L	L	L	24
8	L	L	L	H	L	30
-2	L	L	H	H	L	26
-3	L	L	H	L	L	28
-16	H	L	L	H	L	14

4.3.2 Internal supply chain structure

To study whether the internal supply chain structure affects the results, the cost gap between the centralized and the decentralized policy is studied under a predefined supply chain structure.

For both the single-echelon and the multi-echelon policy, the internal lead-times (which differ in reality between locations for the same item) are set to 3 days. Hereafter, the simulation study is performed and the savings are recorded. Table 7 shows the resulting savings. Although the magnitude of savings is different (as expected due to changing lead-times), the ranking of high-potential vs. low-potential scenarios appears to be quite stable. The 12 highest ranked items and the 6 lowest ranked items are exactly ranked at the same positions. Thus, general findings remain consistent.

Table 7 Yearly savings obtained from moving from SE to ME for predefined supply chain structure

Savings	Demand	Lead-Time	CoV Demand	CoV Lead-time	Holding costs	Scenario
4653	H	H	L	L	H	7
679	H	L	L	L	L	16
486	H	H	L	H	H	5
477	H	L	L	H	H	13
330	H	H	L	H	L	6
284	L	H	H	H	H	17
197	L	H	H	H	L	18
180	H	H	L	L	L	8
150	H	H	L	L	L	8
149	L	H	H	H	L	18
95	L	L	H	H	H	25
79	L	L	L	H	H	29
73	L	H	L	L	H	23
67	L	L	H	H	H	25
59	H	H	H	H	L	2
59	L	H	H	L	H	19
55	L	H	H	L	L	20
49	L	L	H	L	H	27
31	L	L	H	L	H	27
20	H	L	L	L	H	15
19	L	L	L	H	L	30
17	L	H	L	L	L	24
9	L	L	L	H	L	30
-1	L	L	H	H	L	26
-4	L	L	H	L	L	28
-25	H	L	L	H	L	14

4.3 Service level differentiation

In this section, service level differentiation is shortly addressed. The costs differences between service level targets are based on the increased/decreased inventory on-hand investment. The simulation is performed under centralized inventory control (safety stocks derived from ChainScope tool). The analysis focusses on the additional/reduced investment in inventory on-hand.

In Table 8, the reduction in inventory on-hand investment when a 95% target fill rate is applied can be found. Under scenario 14, 25 and 7 the savings are highest. Another observation is that the savings for low cost, low demand items are low for most instances.

Note that the savings for some items are relatively low compared to other items. Hence, service level differentiation can help to create a more cost-efficient supply chain. However, the strategical importance of items should also be considered. An example would be scenario 14 that represent a high, stable demand and low cost item. For such items, a company usually strives to always offer a high service level to customers.

Table 8 Yearly savings obtained by reducing target fill rate to 95%

Savings	Demand	Lead-Time	CoV Demand	CoV Lead-time	Holding costs	Scenario
100	H	H	L	H	L	14
64	L	L	H	H	H	25
59	H	H	L	L	H	7
42	L	H	H	H	H	17
39	H	L	L	L	L	16
33	L	L	H	H	H	25
31	H	H	L	H	L	6
27	L	H	H	H	L	18
25	L	H	H	L	H	19
20	H	L	L	L	H	15
12	L	H	L	L	H	23
11	L	L	H	L	H	27
10	H	H	L	H	H	5
9	L	L	L	H	H	29
9	H	H	H	H	L	2
8	L	H	H	L	L	20
6	L	L	H	L	H	27
5	H	H	L	L	L	8
5	H	H	L	L	L	8
3	L	L	L	H	L	30

2	L	H	H	H	L	18
1	L	L	H	L	L	28
0	L	H	L	L	L	24
0	L	L	H	H	L	26
-2	L	L	L	H	L	30
-6	H	L	L	H	H	13

In Table 9, the additional investment in inventory when changing from a 98% to a 99% target fill rate can be observed. Compared to the difference in stock investment between a 95% and 98% fill rate, the additional investment from changing from a 98% to a 99% service level is usually higher than the investment needed to change from 95% to 98%.

Table 9 Additional yearly investment for fill rate increase to 99%

Additional investment	Demand	Lead-Time	CoV Demand	CoV Lead-time	Holding costs	Scenario
153	H	L	L	L	H	15
105	H	L	L	L	L	16
86	H	H	L	H	L	14
70	L	H	H	H	L	18
69	H	H	L	L	H	7
65	H	L	L	H	H	13
35	L	L	H	H	H	25
34	L	L	H	H	H	25
31	H	H	L	H	H	5
19	L	H	H	L	H	19
18	H	H	L	H	L	6
17	L	H	H	H	H	17
15	H	H	H	H	L	2
11	L	L	L	H	H	29
10	L	L	H	L	H	27
9	H	H	L	L	L	8
7	H	H	L	L	L	8
7	L	H	H	L	L	20
6	L	L	L	H	L	30
6	L	H	H	H	L	18
5	L	L	H	L	H	27

5	L	L	H	L	L	28
4	L	L	L	H	L	30
1	L	H	L	L	L	24
1	L	L	H	H	L	26
-4	L	H	L	L	H	23

5. Conclusions

5.1 Answering the research questions

In this chapter, the sub research questions are answered based on the project findings.

Subquestion 1 *How does Hilti currently replenish, control and position finished goods inventory in its distribution network?*

Nowadays, Hilti's replenishment policy is based on MRP logic. Customer demand is forecasted and dependent demand is handled by a time-phased approach. Furthermore, parameter setting is performed locally, leading to decentralized inventory control. In section 1.5, the current inventory control strategy is explained in detail.

Subquestion 2 *What type of inventory management policies exist for inventory replenishment and allocation in distribution networks? What are the advantages and disadvantages of those policies?*

Based on the literature research, multiple directions of inventory control in multi-echelon distribution networks are addressed. The applicability of the policies is discussed in section 2.2. Generally, centralized control policies that can deal with non-identical retailers under batch-ordering policies (Hilti's context) are scarce. Optimal solutions to this case do not exist yet and are not expected to be found. Hence, relying on near-optimal policies is a good alternative.

Subquestion 3 *What is the performance of the centralized inventory control compared to the performance of the decentralized inventory control?*

The centralized multi-echelon safety stock setting procedure outperforms the single-echelon decentralized control in most instances. Some exceptions exist which are described in section 4.2. An adapted decentralized control policy with an upstream target fill rate of 60% leads to significant reductions in inventory investment compared to the general single-echelon policy. However, the multi-echelon centralized control policy outperforms the adapted single-echelon control policy for the items with most inventory investment reduction potential.

Subquestion 4 *How do different product/supply chain characteristics settings affect the performance of a centralized multi-echelon approach compared to a locally managed approach?*

The most important finding is that the monetary savings of the more advanced centralized multi-echelon policy differs largely under the different characteristic settings. This proves the relevance of this study. The benefits of centralized control are expected to be largest for high demand, high cost and high lead-time items. Another interesting observation is that the benefits for low demand, low cost items are relatively low.

Subquestion 5 *Can a service level differentiation strategy help to improve inventory performance?*

Changing to a higher service level target, requires additional inventory investment. In section 4.3, we commented on the extra investment needed under different supply chain settings. Hence, service level differentiation can make a supply chain more cost efficient. However, the strategical relevance of the items should always be kept in mind.

5.2 Contributions to literature

First, this study contributes to literature by comparing multi-echelon and single-echelon controlled safety stock settings in a forecast-driven, MRP-planned supply chain. Most literature on multi-echelon inventory control does not address the effect of forecasts on inventory performance. In practice, stationary demand is oftentimes forecasted as customer demand is unknown upfront. Hence, this study is very relevant for companies operating under a forecast-driven, MRP-planned supply chain.

Secondly, a simulation model is proposed that can be used to model the effects of safety stocks on inventory performance for 3-echelon distribution networks. Extension to more echelons only requires a slight adaption of the model. Most existing reported simulation models are limited to 2-echelons.

Thirdly, the output safety stock values of the ChainScope tool are used in an independent simulation model. The empirical findings support the validity of the tool.

Fourth, the effect of service level target settings on different type of items is addressed. Although research streams on cost optimized multi-echelon systems exist, this analysis can support companies differentiating items on service levels while still using service-constrained inventory techniques. Additionally, the results stress out the importance of considering combinations of supply chain characteristics on the potential of inventory savings.

The literature on the benefits of more advanced inventory control techniques is scarce. However, this type of literature is highly relevant for practitioners. To the authors' knowledge, this is the first attempt to quantify the benefits of multi-echelon inventory control under 5 combined supply chain characteristic settings. Thus, a gap in literature is opened and is considered to be worthwhile for further exploration.

5.3 Company recommendations

Most importantly, the potential of centralized safety stock setting across Hilti's distribution network is quantified. The results can be used to make valid choices whether changing to a centralized inventory control policy is worthwhile. From an information system perspective, the only required change are safety stock parameter settings. However, two other important organizational challenges have to be overcome.

First of all, change management is needed to prevent reluctancy of the new way of working. Most probably, local Materials Managers will feel out of control when safety stocks are optimized centrally. It is of uttermost importance to ensure the concept is shared, discussed and verified before implementation can take place. The results of this study can be used to enhance the credibility of the concept internally within the company.

Another fear local managers may have, is the effect on their performance measurement. Thus, performance measurement has to be adapted to the new way of managing inventory. Service levels at upstream locations will decrease; hence, the product availability performance at the HAG WH will decrease. Alignment on new targets can resolve this problem. Potential ideas are shared performance targets across the multi-echelon distribution network (based on customer service levels) or adapted local performance measures based on the fill rates proposed by the centralized inventory control policy.

After the decision is made to pilot a multi-echelon controlled safety stock setting, the items for the pilot have to be carefully picked. Based on this report, starting with high demand, high cost items with a long lead-time to the most upstream warehouse is expected to lead to substantial savings.

Adapted decentralized control, based on upstream target service setting, is an interesting direction for further exploration. A pilot implementation could show whether adapted service level targets lead to substantial inventory reductions.

6. Limitations and future research

6.1 Limitations

The main limitation is that the case study is performed for a small set of articles under predefined parameter settings (e.g. batch sizes, amount of locations, demand per location etc.). Hence, the results of the analyses may depend on the specific characteristics of the items. Although the results cannot be generalized due to the small case study, the general conclusions are strongly believed to remain consistent. The threshold values that are identified for the classification of the items may be questioned. However, most likely the behavior of comparison studies will act similar as long as threshold values are based on data observations. Future research could extend the findings in this report by conducting the comparison study for scenarios derived by generalized parameter setting.

In this study, focus has been placed on centralized control of safety stock parameters. Thus, the full potential of centralized inventory control has not been explored. However, safety stock parameter setting can serve as a first step towards a practical implementation of centralized inventory control policies, making the study very relevant from a practitioner view.

The underlying assumption for the allocation of stock under shortages is based on FCFS-logic. This is not the optimal solution. E.g. if the available inventory on-hand is not enough to cover the oldest backorder, the simulation does not check whether another backorder can be fulfilled from the available stock on-hand. More advanced allocation algorithms might positively affect the service performance. The research of Verburg (2015) could be consulted and his findings could be incorporated in the simulation model.

Adapted decentralized control could reduce the gap between centralized and decentralized control. In this thesis, an oversimplified adapted decentralized control policy has been investigated. Although the results were not as promising as expected, the thesis did not further investigate how the performance could be improved by a more quantitative, extensively research based approach.

6.2 Future research

Several directions for future research can be identified.

The research findings can be strengthened by a larger case study with more test instances. By extending the scope of the research, statistical analysis can be applied to quantify how combinations of different variables affect the cost gap between multi-echelon and single-echelon inventory control. Optimally, a prediction model can be formulated such that companies have a first, quantitative based idea about the potentials for their products.

Extending the research to assembly and general multi-echelon systems would be a valuable contribution from both an academical and a business perspective. The cost gap between multi-echelon and single-echelon inventory control is expected to increase when a larger part of the total supply chain is in scope.

The usual outcome of multi-echelon inventory control suggests high stock levels downstream whilst reducing the stock levels upstream. These increased stock levels at downstream locations will results in a higher capacity utilization of local warehouses. In this study, no warehouse capacity restrictions were considered. Future research could investigate how warehouse capacity restrictions affect the differences between the performance of multi-echelon and single-echelon control.

In this thesis, attention has been paid on the potential savings/required investment in inventory when service level targets are increased/lowered. This study mainly provided insights into the differences in investment under different supply chain settings. Thus, no service level differentiation optimization has been performed. However, such an optimization would be a valuable direction for further exploration.

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Appendix A Warm-up period

The warm-up period of the simulation is defined by using Welch's method.

To define the warm-up period, 10 replications (n) with a run length of 550 (m) days are simulated. The daily on-hand inventory is recorded for all replications (Y_{nm}). Next, the averages of the daily on-hand inventory over the 10 replications are derived:

$$\bar{Y}_i = \sum_{j=1}^{n} \frac{Y_{ji}}{n} \qquad for\ i = 1, 2, 3 \dots\dots m$$

w is a positive integer that should satisfy $w \leq \frac{m}{4}$. Hence. w is set to 130. Hereafter, the moving averages $\bar{Y}_i(w)$ are defined based on the expressions below:

$$\bar{Y}_i(w) = \frac{\sum_{s=-w}^{w} \bar{Y}_{i+s}}{2w+1} \qquad for\ i = w+1, w+2, w+3 \dots .m-w$$

$$\bar{Y}_i(w) = \frac{\sum_{s=-(i-1)}^{i-1} \bar{Y}_{i+s}}{2i-1} \qquad for\ i = 1, 2, 3 \dots\dots w$$

Finally, the values of $\bar{Y}_i(w)$ are plotted for $i = 1,\ 2, \dots..m-w$ (Figure 21). Based on the obtained figure, we can set the warm-up period to L which is the value after which $\bar{Y}_i(w)$ appears to be converged.

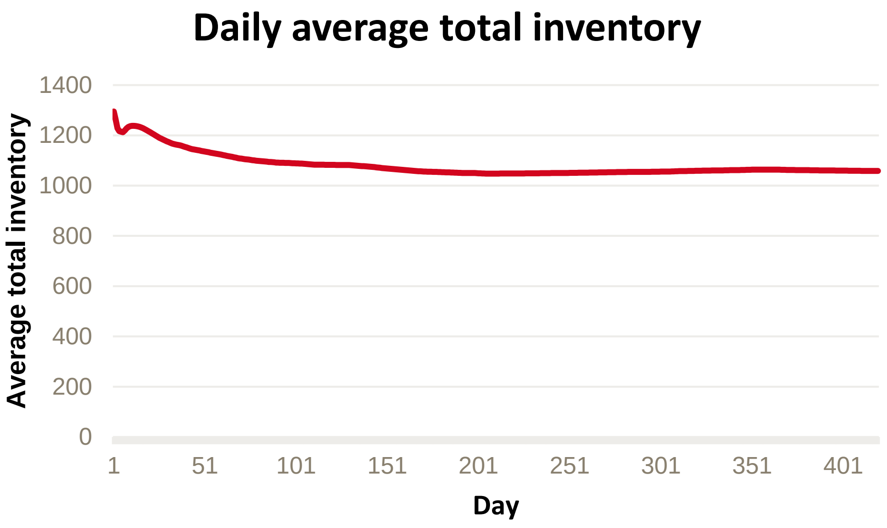

Figure 21 Graph to determine warm-up period

Appendix B Possible supply chain characteristic combinations

Table 10 Possible supply chain characteristic scenarios

Scenario	Demand	Lead-time	Demand variability	Lead-time variability	Holding costs
1	H	H	H	H	H
2	H	H	H	H	L
3	H	H	H	L	H
4	H	H	H	L	L
5	H	H	L	H	H
6	H	H	L	H	L
7	H	H	L	L	H
8	H	H	L	L	L
9	H	L	H	H	H
10	H	L	H	H	L
11	H	L	H	L	H
12	H	L	H	L	L
13	H	L	L	H	H
14	H	L	L	H	L
15	H	L	L	L	H
16	H	L	L	L	L
17	L	H	H	H	H
18	L	H	H	H	L
19	L	H	H	L	H
20	L	H	H	L	L
21	L	H	L	H	H
22	L	H	L	H	L
23	L	H	L	L	H
24	L	H	L	L	L
25	L	L	H	H	H
26	L	L	H	H	L
27	L	L	H	L	H
28	L	L	H	L	L
29	L	L	L	H	H
30	L	L	L	H	L
31	L	L	L	L	H
32	L	L	L	L	L

Appendix C Supply chain characteristics of case study items

Table 11 Supply chain characteristics of case study items

Item	Demand	Lead-time	CoV Demand	CoV Lead-time	Holding costs
1	4.2	54.1	1.4	0.3	2.4
2	3.5	7.5	1.8	0.2	2.7
3	1.9	13.3	2.1	0.7	2.8
4	1.1	9.7	1.7	0.6	2.9
5	0.5	9.5	4.0	0.2	0.3
6	69.0	16.3	1.0	0.2	0.8
7	0.5	43.7	1.9	0.1	0.3
8	11.4	65.8	1.7	0.3	0.7
9	0.1	10.0	3.1	0.2	6.1
10	5.1	54.8	2.5	0.4	0.3
11	1.0	16.0	1.9	0.9	0.2
12	2.6	20.9	2.4	0.5	1.4
13	0.1	11.7	3.7	0.3	4.8
14	0.2	58.3	3.2	0.1	5.2
15	1.2	74.7	2.1	0.3	0.6
16	16.1	13.4	1.4	0.7	0.2
17	0.6	10.1	2.1	0.4	8.5
18	1.5	59.3	3.2	0.6	0.4
19	2.1	3.3	1.9	0.5	0.3
20	3.2	59.3	1.9	0.0	0.8
21	0.8	88.0	3.7	0.5	2.1
22	0.9	62.5	1.5	0.2	2.3
23	24.3	69.6	0.9	0.3	3.0
24	17.7	7.9	0.7	0.4	2.4
25	0.3	19.7	4.5	0.6	0.2
26	31.6	68.9	1.3	0.1	0.1

Appendix D Classification of articles based on scenarios

Table 12 Classification of case study items

Item	Demand	Lead-time	CoV Demand	CoV Lead-time	Holding costs	Scenario
1	H	H	L	H	H	5
2	H	L	L	L	H	15
3	L	L	H	H	H	25
4	L	L	L	H	H	29
5	L	L	H	L	L	28
6	H	L	L	L	L	16
7	L	H	L	L	L	24
8	H	H	L	H	L	6
9	L	L	H	L	H	27
10	H	H	H	H	L	2
11	L	L	L	H	L	30
12	L	H	H	H	L	18
13	L	L	H	L	H	27
14	L	H	H	L	H	19
15	L	H	H	L	L	20
16	H	L	L	H	L	14
17	L	L	H	H	H	25
18	L	H	H	H	L	18
19	L	L	L	H	L	30
20	H	H	L	L	L	8
21	L	H	H	H	H	17
22	L	H	L	L	H	23
23	H	H	L	L	H	7
24	H	L	L	H	H	13
25	L	L	H	H	L	26
26	H	H	L	L	L	8

Appendix E Simulation results average inventory on-hand under SE 98%

Table 13 Simulation results average inventory on-hand under SE control

Item	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8	Run 9	Run 10	Confidence interval	Average
1	400.8	413.8	417.3	402.0	406.5	402.2	419.6	413.0	414.8	394.4	**[402.5,414.4]**	**408.4**
2	158.9	155.4	151.2	151.8	155.4	160.0	160.2	152.3	158.1	152.0	**[153.1,158]**	**155.5**
3	287.7	288.0	286.8	277.2	300.0	301.8	300.9	296.0	273.0	274.6	**[281.1,296]**	**288.6**
4	94.3	86.1	87.8	88.4	89.2	91.9	87.9	90.5	74.5	93.3	**[84.6,92.1]**	**88.4**
5	83.4	81.6	69.0	79.5	70.0	75.5	66.6	69.4	75.0	78.2	**[70.9,78.8]**	**74.8**
6	1980.5	1943.3	2013.9	2007.3	1956.8	1798.7	1825.9	1800.6	1814.6	1774.0	**[1825.9,1957.2]**	**1891.6**
7	165.3	156.9	171.2	161.3	159.6	160.4	157.9	154.4	159.7	165.6	**[157.9,164.6]**	**161.2**
8	722.1	703.4	706.6	617.8	634.0	649.2	673.9	633.0	650.7	655.5	**[640.6,688.7]**	**664.6**
9	20.2	21.1	16.8	20.0	21.0	19.7	20.2	20.1	19.1	19.9	**[19,20.6]**	**19.8**
10	915.2	837.9	881.4	905.4	783.3	873.0	805.3	800.4	927.1	791.6	**[814.7,889.4]**	**852.1**
11	128.5	103.1	125.8	114.7	124.8	124.8	124.8	59.3	117.4	135.0	**[101.1,130.5]**	**115.8**
12	267.4	258.7	256.3	239.0	256.7	238.5	256.3	268.9	247.8	251.4	**[247.1,261.1]**	**254.1**
13	24.5	25.8	24.9	25.0	25.6	26.6	24.0	25.5	22.8	27.0	**[24.3,26]**	**25.2**
14	55.8	55.7	50.1	51.8	50.6	58.1	49.3	50.4	52.2	54.6	**[50.8,54.9]**	**52.9**
15	357.7	349.4	357.1	349.1	359.0	368.1	336.0	348.4	368.3	372.1	**[349,364.1]**	**356.5**
16	1151.0	1090.8	1157.1	1138.0	1132.5	1084.0	1135.0	1103.8	1134.3	1157.1	**[1110.3,1146.4]**	**1128.4**
17	41.2	42.7	43.5	43.6	42.6	42.5	42.2	40.1	41.5	41.8	**[41.4,42.9]**	**42.2**
18	732.9	753.5	716.6	722.0	730.1	714.7	743.4	727.7	742.0	746.9	**[724,741.9]**	**733.0**
19	265.5	262.0	267.9	254.2	262.8	249.5	272.6	258.2	216.9	274.8	**[247.2,269.7]**	**258.4**
20	658.7	603.5	648.4	650.0	673.9	667.8	661.3	641.2	635.6	625.7	**[632.3,661]**	**646.6**
21	413.9	441.1	412.9	418.4	444.0	429.3	426.1	438.4	410.2	429.0	**[418,434.6]**	**426.3**
22	109.1	114.7	110.6	110.8	101.2	110.1	122.3	117.6	109.9	106.3	**[107.3,115.2]**	**111.3**
23	1954.8	1854.3	1914.8	1762.5	1889.5	1924.0	1844.1	1818.4	1814.4	1841.3	**[1822.1,1901.6]**	**1861.8**
24	390.9	407.1	406.8	426.7	402.5	402.8	393.7	409.2	413.1	410.7	**[399.5,413.2]**	**406.3**
25	63.6	62.5	72.4	74.1	76.1	71.5	70.1	73.4	65.0	85.7	**[66.8,76.1]**	**71.4**
26	5754.9	5541.0	5568.8	5656.6	5770.2	5731.5	5528.6	5677.9	5665.4	5659.0	**[5597.2,5713.6]**	**5655.4**

Appendix F Simulation results average inventory on-hand under ME 98%

Table 14 Simulation results average inventory on-hand under ME control

Item	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8	Run 9	Run 10	Confidence interval	Average
1	191.7	203.5	213.7	192.4	194.2	193.2	205.9	205.9	199.0	189.7	**[193.2,204.6]**	**198.9**
2	143.4	137.6	142.4	140.8	140.3	146.3	146.1	136.7	139.3	139.7	**[138.9,143.6]**	**141.3**
3	235.0	235.7	237.5	219.9	244.4	240.9	232.4	240.4	234.4	247.6	**[231.4,242.3]**	**236.8**
4	65.5	59.1	60.8	61.4	62.2	64.8	61.0	63.5	47.5	66.3	**[57.4,65]**	**61.2**
5	99.3	96.9	85.0	95.5	86.0	91.5	82.6	85.3	90.9	93.7	**[86.6,94.8]**	**90.7**
6	582.1	553.8	593.1	579.2	540.4	443.8	454.1	430.5	433.5	415.8	**[450.5,554.7]**	**502.6**
7	109.3	100.9	115.2	105.3	103.6	104.4	101.4	98.4	103.7	109.6	**[101.6,108.7]**	**105.2**
8	157.2	142.0	153.7	101.8	119.7	113.5	110.0	96.7	110.0	104.1	**[105.1,136.6]**	**120.9**
9	14.1	14.3	16.2	14.7	15.0	14.0	13.8	15.6	13.9	14.5	**[14.1,15.2]**	**14.6**
10	538.5	555.8	601.7	625.5	536.6	552.0	539.1	613.8	581.3	535.9	**[543.2,592.8]**	**568.0**
11	88.2	19.5	84.2	75.5	77.9	34.8	90.4	90.2	25.0	83.7	**[46.5,87.4]**	**66.9**
12	129.6	108.0	131.3	113.8	126.9	102.2	124.5	113.3	131.3	106.9	**[110.8,126.8]**	**118.8**
13	13.8	17.9	12.9	14.4	15.0	16.4	14.5	16.5	18.3	14.8	**[14.2,16.7]**	**15.4**
14	41.6	41.1	41.7	38.9	41.4	42.3	42.7	40.1	44.2	42.7	**[40.6,42.7]**	**41.7**
15	249.7	233.5	267.6	250.7	238.8	237.4	241.6	236.2	247.0	237.2	**[236.7,251.3]**	**244.0**
16	1238.7	1241.4	1188.0	1231.5	1184.6	1243.0	1267.0	1202.9	1277.9	1255.6	**[1210.2,1255.9]**	**1233.1**
17	33.1	34.8	34.7	34.5	35.6	35.6	34.7	34.5	34.8	34.2	**[34.2,35.1]**	**34.7**
18	298.4	275.4	273.1	265.4	284.1	273.3	270.2	267.9	278.4	255.3	**[265.9,282.4]**	**274.2**
19	189.2	175.9	204.6	179.6	198.7	191.2	206.8	178.2	191.5	121.9	**[166.5,201.1]**	**183.8**
20	393.2	383.3	372.2	415.4	403.5	427.5	429.7	412.4	393.0	395.6	**[389.2,415.9]**	**402.6**
21	275.4	244.3	263.2	286.1	277.5	262.9	260.5	248.0	258.4	259.7	**[254.3,272.9]**	**263.6**
22	80.0	83.8	78.9	81.7	82.6	78.1	88.0	93.5	91.2	78.3	**[79.7,87.6]**	**83.6**
23	200.6	236.0	327.7	305.1	314.6	352.2	282.9	237.1	303.9	282.6	**[250.7,317.8]**	**284.3**
24	204.5	199.5	207.8	215.9	206.1	193.3	201.8	206.7	213.5	194.3	**[199.1,209.6]**	**204.3**
25	91.7	80.2	85.8	78.0	98.1	87.3	73.8	81.0	88.2	74.3	**[78.3,89.4]**	**83.8**
26	2655.3	2594.1	2390.4	2456.7	2836.2	2757.0	2539.0	2672.8	2553.2	2718.9	**[2519,2715.8]**	**2617.4**

Appendix G Simulation results average inventory on-hand under adapted SE (60% upstream, 98% downstream)

Table 15 Simulation results average inventory on-hand under adapted SE control

Item	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8	Run 9	Run 10	Confidence interval	Average
1	260.8	277.2	263.9	285.3	259.7	292.7	263.0	249.1	283.1	265.6	**[260.2,279.9]**	**270.1**
2	95.8	103.0	106.9	104.7	105.0	105.1	105.3	103.3	106.9	107.7	**[101.9,106.8]**	**104.4**
3	223.8	227.4	229.5	227.0	214.8	234.8	232.6	247.0	233.5	224.1	**[223.4,235.5]**	**229.4**
4	52.7	50.4	53.3	51.6	55.0	55.6	52.5	47.9	53.0	49.5	**[50.5,53.9]**	**52.2**
5	76.5	77.0	75.4	77.4	66.1	72.9	83.4	70.4	80.8	73.5	**[71.8,78.9]**	**75.3**
6	1468.0	1343.0	1355.3	1413.2	1247.0	1312.0	1266.1	1326.3	1277.9	1190.9	**[1262,1378]**	**1320.0**
7	100.6	91.5	88.1	90.7	100.4	93.5	97.9	94.3	97.0	94.8	**[91.9,97.8]**	**94.9**
8	504.4	412.0	566.8	525.2	556.7	522.6	423.6	463.2	497.8	442.8	**[452.8,530.2]**	**491.5**
9	8.8	9.8	8.9	8.6	12.0	9.9	11.0	9.2	9.2	11.6	**[9,10.8]**	**9.9**
10	608.1	519.1	559.6	666.7	528.3	604.9	615.0	571.1	648.1	566.8	**[554.2,623.4]**	**588.8**
11	80.8	68.6	70.6	69.1	75.6	71.6	77.1	73.1	79.7	69.9	**[70.4,76.8]**	**73.6**
12	137.6	126.6	123.1	107.3	123.6	122.2	117.6	117.6	121.5	135.0	**[117,129.4]**	**123.2**
13	12.7	12.8	11.8	11.5	12.8	14.3	10.7	12.7	9.7	14.7	**[11.3,13.5]**	**12.4**
14	28.8	33.0	32.9	27.3	27.4	28.6	28.5	31.3	29.8	31.1	**[28.4,31.4]**	**29.9**
15	217.2	221.7	214.4	198.6	218.2	212.8	205.5	199.7	223.1	194.4	**[203.2,217.9]**	**210.6**
16	696.7	693.4	729.3	674.4	739.6	698.8	754.7	731.2	701.9	653.1	**[685,729.7]**	**707.3**
17	29.7	29.1	28.4	30.4	30.9	28.4	29.7	30.9	27.1	27.5	**[28.3,30.2]**	**29.2**
18	569.0	534.4	564.2	557.7	545.8	538.4	566.6	542.2	547.6	546.4	**[542.5,560]**	**551.2**
19	171.8	176.6	173.8	171.7	157.3	156.5	163.6	171.5	163.0	166.9	**[162.3,172.2]**	**167.3**
20	359.9	394.1	352.8	372.0	373.9	368.4	395.8	388.2	370.3	391.2	**[366,387.3]**	**376.7**
21	319.4	325.6	271.0	326.8	310.9	332.0	315.4	296.0	319.1	336.1	**[301.5,329]**	**315.2**
22	64.8	69.7	66.1	69.3	72.7	57.5	61.3	68.4	82.1	85.5	**[63.6,75.9]**	**69.8**
23	1069.6	1037.7	1087.5	1006.3	1031.8	1066.2	1070.3	1044.0	1004.8	1091.4	**[1028.8,1073.1]**	**1051.0**
24	205.6	200.1	210.3	192.2	212.7	197.3	203.2	208.0	201.0	210.4	**[199.4,208.7]**	**204.1**
25	85.7	81.3	76.9	73.7	71.7	76.9	85.3	81.8	78.3	81.0	**[75.9,82.6]**	**79.3**
26	3274.7	3247.9	3146.9	3218.7	3186.1	3253.7	3315.0	3188.5	3291.2	3295.3	**[3202.3,3281.3]**	**3241.8**

Appendix H Savings obtained compared to current situation

Table 16 Potential yearly savings obtained by moving from current to ME control

Savings	Demand	Lead-Time	CoV Demand	CoV Lead-time	Holding costs	Scenario
1410	H	H	L	L	H	7
801	H	L	L	L	L	16
429	H	L	L	H	H	13
325	H	H	L	H	H	5
280	H	L	L	L	H	15
252	L	H	H	H	H	17
203	H	H	L	L	L	8
103	L	L	H	H	H	25
88	L	H	L	L	H	23
74	H	H	L	L	L	8
62	L	L	L	H	H	29
53	H	H	L	H	L	6
46	H	H	H	H	L	2
40	L	L	H	H	H	25
32	L	L	H	L	H	27
27	L	H	H	H	L	18
25	L	H	H	L	L	20
17	L	L	L	H	L	30
14	L	L	H	L	H	27
12	L	L	H	L	L	28
7	L	L	H	H	L	26
7	L	H	L	L	L	24
4	L	L	L	H	L	30
-9	L	H	H	L	H	19
-49	L	H	H	H	L	18
-57	H	L	L	H	L	14

Appendix I Savings obtained compared to adapted single-echelon

Table 17 Potential yearly savings obtained by moving from current to adapted SE control

Savings	Demand	Lead-Time	CoV Demand	CoV Lead-time	Holding costs	Scenario
2258	H	H	L	L	H	7
653	H	L	L	L	L	16
252	H	H	L	H	L	6
168	H	H	L	H	H	5
106	L	H	H	H	H	17
98	L	H	H	H	L	18
34	H	H	L	L	L	8
6	L	H	H	H	L	18
5	H	H	H	H	L	2
1	L	L	L	H	L	30
-1	H	L	L	H	H	13
-1	L	L	H	H	L	26
-3	L	H	L	L	L	24
-4	L	L	H	L	L	28
-5	L	L	L	H	L	30
-15	L	L	H	L	H	27
-18	L	H	H	L	L	20
-20	H	H	L	L	L	8
-20	L	L	H	H	H	25
-26	L	L	L	H	H	29
-29	L	L	H	L	H	27
-32	L	H	L	L	H	23
-46	L	L	H	H	H	25
-62	L	H	H	L	H	19
-92	H	L	L	H	L	14
-99	H	L	L	L	H	15