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The design of a conceptual segmentation framework for Hilti's supply chain and the impact of forecast consumption logic on system nervousness

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The design of a conceptual segmentation framework for Hilti's supply chain and the impact of forecast consumption logic on system nervousness

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Abstract

Hilti faces high stock levels and unstable production plants. With the large product portfolio Hilti struggles to manage their production and inventory for the entire supply chain efficiently. To make these decisions more manageable a conceptual segmentation method is developed within this master thesis. Additionally, with the use of a case study the performance of several segmentation methods to set service levels was tested under an order line fill rate constraint. It was shown that under such a constraint, segmenting on revenue and order frequency led to to biggest inventory cost reduction, while reaching the same target order line fill rate. Furthermore, this master thesis evaluates the relation between forecast consumption logic and system nervousness. With the use of a case study it was shown that changing the forecast consumption logic can reduce system nervousness. The case study also confirmed the positive relation between fixed planning horizon and stability found in other studies and the relation between forecast accuracy and system nervousness. Lastly, it was shown that Hilti is currently shifting orders month over month due to fluctuating demand, capacity uncertainty, supply uncertainty and production uncertainty.

Management Summary

Companies that have to manage a large product portfolio often struggle to manage their production and inventory for the entire supply chain efficiently (van Kampen et al., 2012). In scientific literature, supply chain segmentation has been suggested to make these decisions more manageable and reduce complexity (Protopappa et al., 2017). Segmentation is the process where SKUs with similar characteristics are grouped together in a segment, and decisions are made per product segment. At Hilti the need for a segmented approach is also observed. The current segmentation guidelines defined by the company are not clear-cut. The guidelines do not always define a single solution per segment and sometimes perceived as in-comprehensive, as guidelines only exist for a limited number of processes. As a consequence, material managers do not always follow the guidelines and do not always know how to manage their inventory efficiently. Especially, managers asked for guidelines in regards to the determination of service levels per segment such that inventory costs could be decreased while the same aggregate customer service could be provided. This led to the following research question:

How should the holistic segmentation concept be designed for Hilti's end-to-end supply chain in order to achieve lower inventory costs and a higher service level?

Before a holistic segmentation concept was defined, a case-study was conducted to find a suitable segmentation method for the determination of stock levels. The case study showed the performance of several segmentation methods in terms of inventory cost under an aggregate order line fill rate constraint. This led to the following conclusions:

- **Order frequency and revenue are recommended to be used as segmentation characteristics** This method led to the best cost improvement, while reaching the same target service. Here priority should be given to SKU's with a high order frequency and a low revenue.
- **Five classes already resulted in significant improvement** Currently Hilti defined 15 class based on order frequency and revenue, based on a two dimensional matrix. In this master thesis, the manageability of 15 classes is questioned. During the case study, these segments where clustered into five groups, and as stated, this led already to a significant cost improvement. Hence, Hilti could reduce complexity, this could be done by compiling the TA classes and CD classes in the TABCD-classification.
- **Making the XYZ-measure a relative measure improves the model since the performance of the model depends on the class sizes**. It was shown that the class sizes of XYZ (order frequency) impact the overall performance of the model. As the size of the markets differ, the amount of SKUs per segment differ per warehouse location. Hence, the thresholds to determine the classes should be relative, such that the number of SKUs per segment is stabilized.

Based on the guidelines proposed in literature, interviews with stakeholders at Hilti and the findings of the case-study a conceptual segmentation method has been defined. As

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an hierarchical process supports a multi-criteria approach while providing understandable guidelines, this method was chosen for the definition of the segmentation concept. the final segmentation criteria for Hilti where recommended: Material status, innovativeness, revenue, order frequency and lead time. The resulting segmentation framework is shown in figure 1.
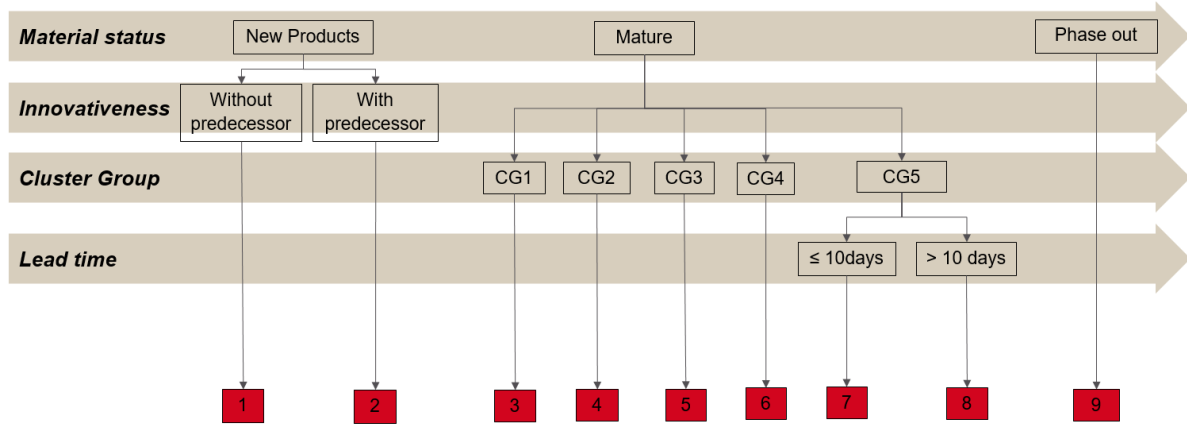

Figure 1: Developed Segmentation framework

Bases on these Segments, inventory management strategies and Forecasting techniques are proposed given in table 1.

Segment	MRP-type	SS	Q	Forecasting strategy
1	MRP-type=X0	SS=SB1	Q=EOQ	Judgmental
2	MRP-type= X0	SS=SB1	Q=EOQ	Statistical with judgmental downward adjustments
3	MRP-type=X0,Y7,Z4 %	SS=SB9 CSL=99.5	Q=EOQ	Statistical
4	MRP-type= X0,Y7,Z4	SS=SB9 CSL=99.5%	Q=EOQ	Statistical
5	MRP-type= X5 or X6	SS= SB9 CSL=98.5%	Q= EOQ	Corporate only
6	MRP-type= X0 or Z0	SS=SB9 CSL=65%	Q=EOQ	Statistical
7	MRP-type= X5 or X6	SS= no	Q= MOQ	Corporate only
8	MRP-type= X5 or X6	SS= SBB	Q= MOQ	Corporate only
9	MRP-type= X5 or X6	SS= SB1	Q= MOQ	rule-based forecasting

Table 1: Proposed segmentation guidelines

It is recommended that Hilti starts further research projects to test and implement the segmentation concept proposed in this master thesis. To fully support material managers in their decisions it is recommended that the developed segmentation method is implemented in a tool that shows the ideal settings and compares this to the current system settings.

The second problem addressed in this master thesis is found in a production planning context, and aims to answer the following research question:

What are the causes of the bow-wave effect within Hilti and can system nervousness be reduced by adjusting the forecast consumption logic in the system

Due to the stochastic nature of production, demand and supply, production plans change constantly over time, leading to frequent replanning and rescheduling activities that negatively influence system performance (Jensen, 1993). This instability in plans, is also called system nervousness or system instability. System nervousness is besides these stochastic characteristics also influenced by the production planning methods and inventory management decisions and is often found in the context of MRP systems. The MRP-logic calculates planned order releases across the supply chain based on forecast and/or demand at the most downstream location. In this master thesis the influence of the integration between forecast and demand on system nervousness is explored. This integration is defined by the forecast consumption logic. Furthermore, currently some of the production plants of Hilti struggle with the changes in planned orders over time. In specific, every month the production plant observes an increase in the orders for the next month that doesn't materialize over time. Within the company this is referred to as the bow-wave effect. Additionally, the causes of the bow-wave effect are explored.

With the use of a case study the forecast consumption logic was examined:
- First it is observed that independent of the frozen horizon length, nervousness could only be reduced when a system enhancement was made. That is, without the inclusion of network demand or keeping unconsumed forecast from the past, nervousness could not be reduced. For the biggest reduction in system nervousness both unconsumed forecast from the past should be kept and network demand should consume the forecast.
- Under daily revisions, the case study showed the biggest reduction, of 24%, in system nervousness when a forward consumption logic was applied. Under these settings, the impact of the length of the consumption horizon on nervousness, cost and fill rate is limited.
- Under a frozen horizon of one week, the nervousness was reduced significantly, by 20%. The effect of forecast consumption logic on system nervousness was small compared to the improvement seen from the implementation of the frozen horizon. Here nervousness could only be reduced when past forecast was kept in the system and network demand was consumed the forecast as well.

Based on these findings, Hilti is recommended to investigate if the cost related to the system enhancements are worth the reduction in system nervousness.

A further analyses into the bow-wave effect was conducted by means of an exploratory research to provide the company with insights in the root-causes of the problem:
- **Flexible production planning system** The bow-wave experienced at Hilti is seen in the assembly to order production lines. By definition assembly to order asks for flexibility from the assemble lines, as the production plan depend on incoming orders and no safety stock is kept within the plant to provide a buffer.
- **over-/under-forecasting** It was observed that the forecast accuracy in SKU level where low and forecasts where systematically under estimating demand during 2018. It remained unclear if forecast updates are really causing the bow-wave as data availability was scarce. However, it is not ruled out that forecasts in the near future are not redundantly adjusted upward. On a global scale it is observed that Hilti does adjust the forecast to the near future over confidently.
- **a mismatch between planned and actual production** A significant amount of

orders was postponed due to production or capacity problems. The postponement of orders can partly explain the bow-wave effect.

- **Lack of understanding of system nervousness** As the production planners are aware of the bow-wave but unaware of the causes, the increase in production orders is not always taken seriously, as they expect the quantities to drop again. This can lead to a vicious circle were production capacity is not increased based on a lack of faith in the production plan, leading again to order postponements and the bow-wave in the next planning cycle. Furthermore, it was observed that the MOs can and do change safety stock settings and forecasts unlimited. These changes in downstream locations influence the production planning and should be limited.

As Hilti has currently no good insight in the amount of system nervousness, it is recommended to first implement a system nervousness measure. This should help to create awareness of the problem and furthermore can show if the current production plans are stable enough or that further actions need to be taken to reduce system nervousness. As capacity planning is a major issue when dealing with system nervousness, both within Hilti and in other companies, a measure is defined within this master thesis that can capture capacity issues. The measure is formulated as follows:

$$I_{line}(k) = \frac{\sum_{t=M_k}^{M_{k-1}+P-1} W_t(t) |\sum_{\forall i} (Q_{i,t}^k - Q_{i,t}^{k-1}) W_i(i)|}{\sum_{t=M_k}^{M_{k-1}+P-1} \sum_{\forall i} Q_{i,t}^{k-1} W_i(i)} \tag{1}$$

where:

i = SKU
k = Planning cycle
t = time period
M_k = Beginning period of planning cycle k
P = Length of Planning horizon
$Q_{i,t}^k$ = Planned order quantity for item i during planning cycle k for period t
$W_i(i)$ = Weight function corresponding to the throughput time of SKU i on the line
$W_t(t)$ = Weight function over time

Further research is necessary to investigate the performance and added value of this system nervousness measure.

At last, it may be concluded that by implementing a good segmentation method and limiting the decision moments to fixed moments in the planning process, system nervousness can be reduced as settings do not consistently change.

Preface

This section is called a preface but given the size of the project and amount of writing that needed to be done it is off-course written last and in a short time-frame.

First of all, I want to thank Hilti for giving me the opportunity to take my first steps in a commercial company. As I started working on the project I realized the difference between what I have learned at the university and real life, as the company environment is much more difficult and comprehensive. I hope that all the efforts that people from Hilti have put into me has payed of at least a bit and that my project and thesis will lead to new developments within Hilti to improve its processes. Given that I was taken on-board to see how processes may be improved I may sound harsh at some places within my thesis about the processes already in place, but this is far from the truth. I think Hilti is a great place to work and that it can out-compete already many other firms when it comes to supply chain management. A special big THANKS off-course to my supervisors within Hilti for all the support. Ralph thank you for all the steering and guidance you provided during the project. Ruediger, thank you for the opportunity of this project and for all the times that you challenged me to improve and provided me with possible directions. Sindri for working with me on bow-wave and eventually system nervousness. You were a big help when it came to content, checking my work that what I wrote down, and teaching me how to make nice presentations. All others of my team and GLMM, for the help and making me feel welcome. Bernd: thanks from your daily desk visitor for all the input you provided me.

Shaunak, it must have been quite a challenge having me as slightly chaotic masters student. I appreciate your patience and steering me in the right directions when I lost track. Tarkan I want to thank you for pushing me and remind me of deadlines, you really woke me up a couple of times which I needed to regain focus. Luc, I was very glad that I could start of my project together with you and I'd like to thank you for all the helpfull and fruitfull discussions.

As I'm finalizing the last parts of this master thesis I realize that I am also finishing an amazing chapter of my life. I want to thank my friends from Eindhoven for the richness of joyful memories you provided me. You made 80 hours per week blocking for exams and deadlines in the library fun. I appreciate that you were able to: deal with my chaotic brain (jumping from idea to idea), offer me support and share summaries and dinner. Special thanks to Laura, for all the help, very much appreciated it and keep in mind that I always try to do the same for you.

And last but definitively not least my family for supporting me both from a distance and on location, and all the unconditional love, patients and evenings of klaverjassen. My brother Hidde for being there when I needed him and my mother for her love and support on structure and content. A special thanks to my father, who travelled all the way to Austria in the final weeks, just to offer me mental support and a lot of take-away delicious dinners. Opoe en Omoe ik hoop binnenkort weer wat meer tijd voor jullie te hebben. Thank you

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List of Abbreviations

APO	Advanced planning and optimization
APS	Advanced planning and schedu;ing
ATO	Assembly- to-order
ATS	Availability to service
BU	Business unit
CG	Cluster Group
CODP	Customer order decoupling point
CoV/CV	Coefficient of Variation
CSL	Cycle service level
CW	Central warehouse
DC	Distribution Center
DFU	Demand forecast unit
EOQ	Economic order quantity
ERP	Enterprise resource planning
FCFS	First come first served
FCL	Forecast consumption logic
FOQ	Fixed order quantities
HAG	Hilti Aktiengesellschaft
HIP	Hilti intergated planning
HNA	Hilti North America
HS/HC	Hilti stores/ hilti center's
INP	Introduction of the New Product
JIT	Just in time
KPI	Key performance indicator
LEC	Logistics region central europe
LRP	Line requirements planning
LW3	Logistics region ..
META	Middle-East and Trans-Atlantic
ML	Montage linien
MM	Material management
MO	Market organisations
MOQ	Minimum order quantity
MPS	Master production schedule
MRP	Material requirements planning
MTO	Make to order
MTS	Make to stock
OFR	Order line fill rate
OQ	Order quantity
PA	Product availability
Pp/ds	Production planning and detailed scheduling

RDC	Regional distribution center
ROP	Reorder point
S&OP	Sales and operations planning
SCV	squared coefficient of variation
SFI	Sales forecast integration
SKU	Stock keeping unit
SS	Safety stock
TM	Transport management
TTM/INP	Time to market/ introduction new product
WH	Warehouse
WM	Warehouse management

1 | Introduction

Based on Champion 2020, Hilti's Global logistics department set visionary goals with three main pillars: improving service levels and customer satisfaction, best-in-class financial performance and flexibility, and "fit to scalability". The distribution network needs to decrease their inventory levels and increase their service levels and the production plants need to be able to deliver what was asked from them without increasing their inventory levels significantly.

However, with the large product portfolio, Hilti struggles to manage their production and inventory for the entire supply chain efficiently. This problem is also found in other companies that have to deal with many Stock Keeping Units (SKUs) (van Kampen et al., 2012). In scientific literature, supply chain segmentation has been suggested to make these decisions more manageable and reduce complexity (Protopappa et al., 2017). Segmentation is the process where SKUs with similar characteristics are grouped together in a segment, and decisions are made per product segment. In this study, it is aimed to develop an holistic segmentation concept for Hilti such that decisions are manageable whilst still offering customers the desired service and reaching best-in-class financial performance. Additionally, this study provides insight in the performance of several segmentation techniques under an order line fill rate (OFR) performance measure, as this measure is comparable to Hilti's own performance measure for service levels.

Furthermore, the flexibility that is asked from the plant is investigated in the context of system nervousness. Currently some of the production plants struggle with the changes in planned orders over time. In specific, every month the production plant observes an increase in the orders for the next month that doesn't materialize over time. In this master thesis the impact of forecast consumption logic on system nervousness will be investigated. Additionally, exploratory research is conducted to conclude on the hypothesized root-causes.

As this master thesis aims to provide insight into two relevant business problems within Hilti, it will be structured into two parts:
Part 1: A conceptual segmentation framework for Hilti's supply chain
Part 2: Evaluation of system nervousness within Hilti and the impact forecast consumption logic on system nervousness

In the remainder of this chapter, Hilti will be introduced with a special attention to supply chain management.

1.1 Company Description

Hilti develops and manufactures products, software, systems and services for construction and energy industries and is operating in more than 120 countries worldwide. By sustainable value creation through leadership and differentiation, Hilti strives to passionately create enthusiastic customers and build a better future. Over the last years Hilti has been growing and exceeded their targets in 2017 with a net sales increase of 11% compared to 2016. This challenges the logistics departments to deliver the products on time to the customer while efficiently managing the supply chain.

1.2 Logistics department set-up

The companies headquarter is located in Schaan, where the organization is divided into four functional units: Corporate Research& technology, Business units (BUs), supply chain, and corporate functions. The eight BUs each manage their own product portfolio. Additionally to these units, marketing and sales are managed by the Market organizations (MOs) located across the world. The global logistics department is the umbrella function within Hilti for all supply chain related topics. Global Logistics (GL) manages three areas, namely Warehouse Management (WM), Transport Management (TM), and Materials Management (MM). Within these areas GL makes strategical decisions such as warehouse placement, provides guidelines and standards for the MOs and BUs, such as how to set safety stock settings for a specific product, tracks the performance of plants and MOs and offers support by specific questions or problems from the BUs and MOs. Hence, GL is accountable, together with the MOs and BUs, for achieving targets with respect to customer satisfaction, service level and inventory level. To confirm with the company's strategy, GL set the following targets: high product availability (more than or equal to 98%) and a reliable order execution (more than or equal to 97.5%) by minimum inventory levels (less than 90 days on hand) against the lowest costs.

In order to create sustainable value creation, GL focuses on three main areas. First, the focus is on offering advanced services. Thereby, Hilti can strengthen its competitive position as a high-quality service provider by offering highly reliable, more advanced and segmented services. Second, Hilti pursues its strong operational foundations by using lean processes, an optimized supply chain network, and a new integrated sales and operations planning. Therefore, Hilti is able to continue providing high quality service levels, reduce inventory, improve productivity, and support global growth.

1.3 Hilti's supply chain

Currently, Hilti has 380 suppliers of raw materials which are supplying the plants. Whereas, 900 suppliers are allied suppliers of finished goods and ship directly to the Hilti AG Warehouses (HAG WHs), central warehouses (CW) or distribution centres (DC). The plants are controlled by the BUs and are dispersed globally. Finished products from the plant are then distributed either to the HAG WHs or to the CWs or DCs. Subsequently the repair centres, Hilti Centres (HCs) and repair vans are resupplied. Although, this structure differs among regions. For instance, in Hilti North America (HNA) products from HAG WHs are consolidated in two national DCs which, subsequently, distribute the products to the other DC's.

Eventually the customer order management is at the HCs, repair centres, and repair vans. Hence, customers can order new products at the HCs or via the internet or can bring their Hilti products to the HCs for repair. However, when a customer has a large order or orders from the internet, then the customer's order will be delivered directly from the CW or DC.

Hence, it can be concluded that Hilti's supply chain is quite complex. Moreover, Hilti's supply chain is quite unique, because Hilti controls almost the entire supply chain from end-to-end (from production to selling to the customer).

1.4 Hilti Integrated Planning (HIP)

To match customers expectations with supply chain and production planning, Hilti is implementing a Sales and Operations Planning framework, i.e., Hilti Integrated Planning (HIP). The goal for implementing HIP is to achieve a higher maturity level in Sales and operations planning (S&OP) and, therefore, achieve better alignment between customer's demand and Hilti's supply chain.

The HIP can be divided into two main processes namely, Sales Planning and Operations/Supply Planning. Each main process consists of sub processes. The first process in Sales Planning is conducted at GL, a statistical forecast is made for the products which have sufficient historical data. Thereafter, the forecast will be reviewed by the MOs, and market intelligence is incorporated. This implies for instance, whether new products will be launched, a new project starts or promotions are expected to increase sales. After the demand review the sales forecasts are integrated with the BUs. In this process, an alignment takes place between marketing & sales and the BUs, which implies that marketing intelligence is managed on product family or item level. The resulting plans are then communicated with the MOs. In the MO, these plans are discussed and then deliberated with different market segments (in Hilti called 'trades') and regions.

Depending on the network set-up and the size of the organization, forecast is either conducted on MO/region level or globally as a corporate forecast when the turnover of the markets is too small. In general, these forecast locations are the most downstream warehouse locations which replenish the HSs and directly deliver to the end customer. An exception here are the regions Middle-East and Trans-Atlantic (META) and HNA. Due to the physical size of these markets additional distribution centres are placed across the country. Here the forecast location delivers to end customers, HSs and downstream warehouses.

With the Sales Planning completed, the Operations Planning starts. First, a capacity preview is done by the plants in order to check if Hilti's plants have enough capacity to satisfy the forecasts. The capacity preview is done for 3 or 4 months ahead and gives insight in the maximum capacity for Hilti's plants. Gaps between available capacity and demand are discussed with the MOs, and it can be decided to increase capacity, postpone orders or anticipate on large expected orders. Thereafter, the master production schedule (MPS) takes place. In this process, the supply plan is disaggregated in weeks instead of months. By dividing the supply plan in weeks, a production schedule is made in such way that set-up times are minimized, and the production pattern is optimized. At last a distribution planning is made to deploy the produced goods to the warehouses and MOs. When the demanded production volume cannot be met, the produced units are fairly shared among the warehouses and MOs.

1.5 System landscape

Hilti uses multiple information systems to execute its S&OP and control process. For daily execution Hilti uses SAP R/3 which is daily updated into their Advanced planning and scheduling (APS) system SAP Advanced planning and optimization (APO). Confirmed orders are referred to as purchase orders in the warehouses and production orders in the plants. In SAP APO Production planning and detailed scheduling (PP/DS) proposed orders are calculated based on the current inventory levels, safety stock, order quantities, actual sales orders and forecasted demand. These proposed orders are called purchase requisitions in the warehouses and planned orders in the plants. APO PP/DS

calculates proposed orders for the coming periods, only the proposed orders within lead time are send to R/3, where material managers can either accept or reject to make it a purchase /production order. The demand forecast, together with the capacity planning is done in a S&OP module offered by a SaaS (software as a service) company called JDA. Demand forecast updates and capacity planning are part of the HIP process which is conducted monthly. The forecast is 18 months ahead. Based on this forecast, a rough-cut capacity plan is made for the next month. The 18 months forecast is also used to make more long-term capacity decisions like number of production lines or employee recruitment.

1.6 Production planning

Recalculation of the net requirements is done daily in the warehouses and weekly for the production lines on HIP. After the recalculation, a detailed production plan is made for the coming three to four months. This production plan is subject to the capacity constraints calculated in JDA. The first week of this production plan is fixed (for plant 6 this is 2 weeks), no changes are made based on changing requirements within this period, this is also called the frozen horizon. Since HIP is still under roll out, the production lines that are not yet on HIP do not follow these guidelines. The assembly lines that are not on HIP in plant 4, are just in time and production plans are made daily. These production plans are made by human planners. When an actual order comes in, this should be produced within 3 or 4 days. Pre-production can be done no more than 3 days in advance, but currently it takes manual effort to ship these pre-produced items earlier to the markets. When the plant has capacity problems, or raw materials are not on-hand, the central planner can contact the market and change the order date. These changes do not influence the Product availability (PA) measure when the central planner agrees upon the postponement.

The production planning does not include safety capacity or safety lead time. However, within the system it is possible to change the utilization of a line. This is normally done within Hilti to account for system change overs. Furthermore, by allocating employees differently, or by overtime, Hilti can manage a certain amount of capacity fluctuations.

Part I

Conceptual segmentation framework

Part I is partly written in collaboration with Luc Sonneville

2 | Introduction

In this chapter the perceived segmentation problem of Hilti in their end-to-end supply chain management is discussed. First, the problem will be introduced and the need for this research is highlighted in section 2.1. Subsequently, the corresponding research questions are defined in section 2.2. The scope of this project is given in section section 2.3. Thereafter, methodology which will be used to answer the research questions is given in section section 2.4. The last section of this chapter outlines the structure of the remainder of the segmentation Project.

2.1 Problem statement

Hilti believes that the current inventory levels among SKUs are not cost effective to reach a certain service level to the customer. The root cause of this problem is found in the missing (segmentation) guidelines, see Figure 2.1.
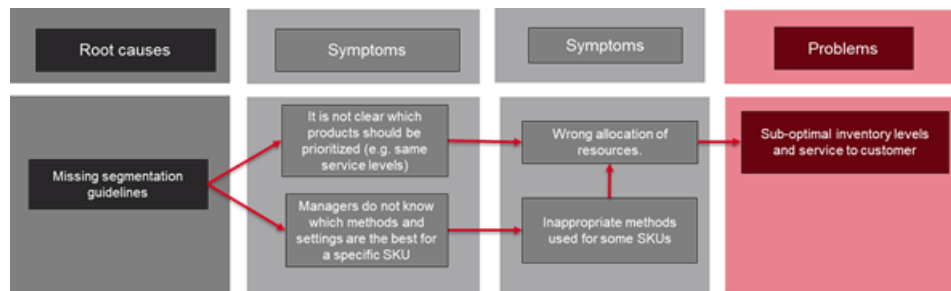
Figure 2.1: Root-cause Segmentation

The problem of the one size fits all policies is twofold. First, one size fit all policies lead to decisions made on inaccurate information and the use of methods that are not suitable for all the SKUs. Second, the missing segmentation guidelines lead to a lack of focus on the products with highest return on investment.

Clearly, not all the products can be treated the same way. Managers within the BUs, MOs and GL are aware of this, and try to optimize their policies for every product. On an individual level, some segmentation guidelines exist in the organization. The forecasts are for example already segmented in terms of demand pattern, where, among others, only products with seasonality are forecasted with the use of holds-winters, which takes seasonality into account. Some HCs have other replenishment policies for core and non-core items with different safety stock settings and even differentiate between consumables, tools and accessories. Although these initiatives may lead to better performance locally, still the missing global overview may lead to poor supply chain integration. In addition, these individually imposed guidelines can be confusing and impede integration when based on the same characteristics. An example of this is seen for the characteristic order frequency, which is used in statistical forecasting, for the service levels and safety stock and for the lot size decisions. In statistical forecasting it is calculated as the % of months there was at least one order line classified into four segments: H,M,L or X. QRS and XYZ both calculate order frequency based on the number of order lines per week, however the cut-off values for the segments is different.

The need to segment based on the importance in terms of sales revenue and order frequency (TABCD-XYZ) is clearly seen within Hilti, since they already segment their SKUs to these criteria. Managers are aware that they should prioritize T items over D, however no guidelines exist to put this to practice. Hence, it is clear that a holistic segmentation concept is missing.

To summarize, the missing holistic segmentation guidelines lead to sub-optimal or even missing guidelines across the organization. This results in sub-optimal SKU management and confusion across the departments. Hence, the need is seen to develop holistic segmentation guidelines. The aim of this project is to make the first step in this development, and is formulated as follows:

> *Develop a holistic segmentation concept on a high level with its advantages and principles*

2.2 Research questions

In order to fulfill the primary goal of this project, the following main research question should be answered:

> *How should the holistic segmentation concept be designed for Hilti's end-to-end supply chain in order to achieve lower inventory costs and a higher service level?*

To answer this research question, the following sub research questions have been formulated:

1. What are the current segmentation concepts in Hilti's end-to-end supply chain?

2. Which current best-practice segmentation concepts or scientific frameworks exist for supply chain segmentation?

3. Which gaps exist between Hilti's current segmentation concepts and the scientific frameworks or best-practice segmentation concepts?

2.3 Project scope

The holistic segmentation concept has a considerable scope whereby the focus will be on the logistics planning and execution. Typically, for analyzing the current situation (AS-IS) the HIP (section 1.4) will be used as a first attempt to discover segmentation concepts within Hilti. Besides the HIP, also other sources within Hilti are used to discover segmentation concepts. Already available guidelines for inventory positioning, lot sizing, material requirements planning, and safety stock calculations within Hilti will be used. Furthermore, segmentation concepts in the end-to-end supply chain will be analyzed such that inter-dependencies among the different locations can be identified.

2.4 Methodology

The first main research question "How should the holistic segmentation concept be designed for Hilti's end-to-end supply chain in order to achieve lower inventory costs and a higher service level" will be answered in three steps. We will start by defining the problem and analyze the current situation in an AS-IS analysis. Afterwards, we will diagnose improvements in the GAP analyses. Finally, we will design a solution in the TO-BE framework. The implementation of the segmentation framework will not be part of this master thesis, however, recommendations will be given to this regard.
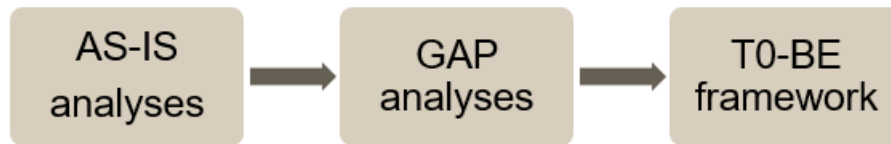
Figure 2.2: Methodology Segmentation

AS-IS analyses

In the as-is analyses an answer will be given to the first sub-question "What are the current segmentation concepts in Hilti's end-to-end supply chain?". In order to answer this question interviews will be conducted with material managers from BU and region and with several team members of the global logistics department responsible for the logistic processes. In addition, documentation of internal processes will be used where available to identify existing guidelines for segmentation within Hilti.

GAP analyses

In the GAP analyses the remaining sub-questions "Which current best-practice segmentation concepts or scientific frameworks exists for supply chain segmentation?" and "Which gaps exists between Hilti's current segmentation concepts and the scientific frameworks or best-practice segmentation concepts?" will be answered. A literature review will be conducted to identify the best segmentation practices. Furthermore, to gain understanding of the idealized situation within Hilti, the interviews conducted will be used as an input.

TO-BE framework

The design of a conceptual segmentation framework should be in line with the idealized design and should be implementable within Hilti. Therefore, the TO-BE framework will be built in an iterative matter, where the conceptual model is improved based on stakeholder feedback. A workshop will be held to gain understanding of the topics that should be considered for the implementation of a segmentation framework.

2.5 Outline Part 1

The remainder of this part is structured as follows: In chapter 3, scientific literature is discussed that could be used by the development of a segmentation method. Subsequently, the current guidelines and principles within Hilti are explored in chapter 4. In chapter 5, a case study is performed to test the performance of several segmentation methods under an OFR constraint. Finally, a conceptual segmentation method for Hilti is developed in chapter 6.

3 | Literature review

Segmentation, also referred to as classification, in operations research is the process of placing SKUs based on their characteristics into segments/groups with as goal to optimize decisions for every segment rather than using a one size fits all concept.

A primary distinction can be made between customer segmentation and product segmentation (Forsting and Alicke, 2017). Where customer or market segmentation focuses on the different service requirements per customer segment and bases their services and supply chain set-up on these requirements. As such customer segmentation brings added value to the customers and can give a competitive advantage. However, to manage the supply chain efficiently, one also needs to consider product characteristics to ensure a good fit(Forsting and Alicke, 2017). Within this master thesis the focus is on product segmentation.

3.1 Segmentation Framework

Two scientific frameworks are found in literature to provide guidance in development of a segmented supply chain: Alicke and Forsting (2017) gives a general holistic approach whereas van Kampen et al. (2012) focuses more on inventory decisions and forecasting. van Kampen et al. (2012) found that the segmentation methods available in literature are formed by the choice of characteristics, the techniques used and the classes finally formalized. where the segmentation method depend on the aim of segmentation and the context, see figure 3.1.
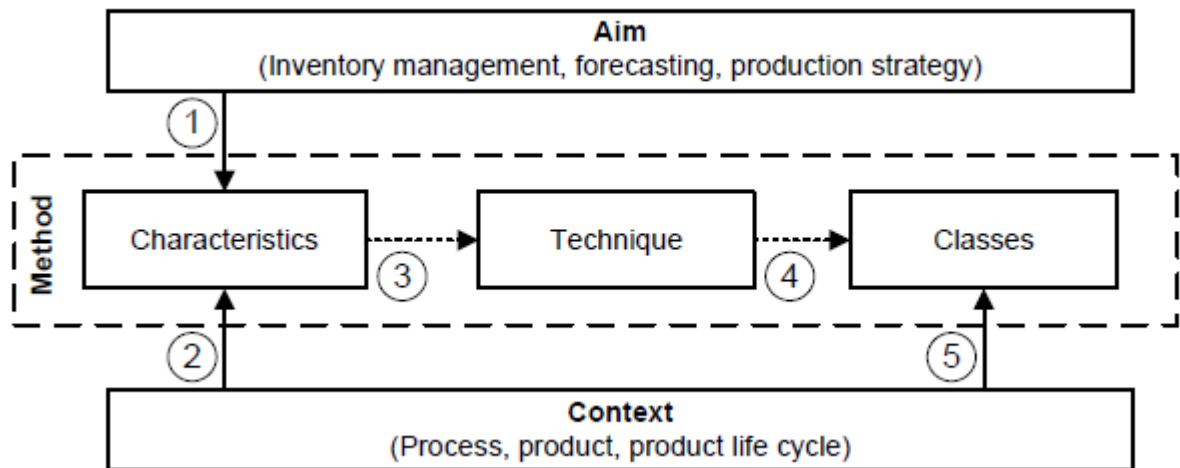
Figure 3.1: Segmentation framework (van Kampen et al., 2012)

3.1.1 Context

As companies differ widely, there is no one size fits all segmentation strategy(Alicke and Forsting, 2017). Hence, before a segmentation strategy can be developed the specific context of the company needs to be understood (van Kampen et al., 2012). van Kampen et al. (2012) defined the context as product specific, production process specific, or product's life cycle specific. in a broad term the context can be defined by for

example the companies industry, and the industry standards which should be considered to decide on customers needs and suitable supply chains(Christopher et al., 2006) and product life cycle, which has a big influence on demand characteristics (Fisher, 1997). To stress the importance of the company context, van Kampen et al. (2012) gives a specific example of a company that sells explosives and as such needs to consider the stock-ability of the products in their segmentation framework. Within Literature there also has been a significant amount of papers focusing on segmentation in the context of spare-parts, where for example criticality is often considered as important characteristic (Bacchetti and Saccani, 2011).

3.1.2 Segmentation Characteristics

In the literature study from van Kampen et al. (2012) the characteristics are distinguished in Volume, Timing, Customer, and Product. The volume characteristic relates to demand volume over a certain period in most literature, however, demand variability – measured in coefficient of variation – is also mentioned in the volume characteristic. Product's unit cost, production lead time and replenishment lead time are examples of Product characteristics whereby the unit cost of the product is most mentioned in literature. For the customer characteristic, the importance of a certain customer is addressed. This is also referred to as the criticality of a product, which is more used in spare parts classification.

3.1.3 Segmentation Techniques

The listed characteristics are subsequently used in a classification technique (**?**; van Kampen et al. (2012)). This technique is either qualitative (judgmental) which is based on judgments from experts or quantitative (statistical). The purpose of the qualitative techniques is to extract knowledge that is often held by managers or other experts. These methods are mostly used to assess the importance of keeping a spare part or normal SKU on stock (Bacchetti et al., 2013). The most popular qualitative techniques are e.g. VED and a (Analytic) Hierarchy Process (AHP). The (Analytic) Hierarchy Process (AHP) is a segmentation technique that combines multi-criteria too and uses paired comparisons in order to make a decision between different options (Saaty, 1990). Flores et al. (1992) showed that the AHP can also be used as a multi-criteria classification method for a more comprehensive ABC classification scheme. The VED classification distinguish in "Vital", "Essential", and "Desirable" items.
The most popular quantitative method is the traditional ABC/Pareto analysis (Bacchetti et al., 2013; van Kampen et al., 2012), where the parameters demand volume times unit price is used. The main advantage of the ABC analysis is its generalizability. However, this segmentation technique is based on two criteria, hence, it is less sophisticated for defining inventory control and forecasting policies.Besides the ABC technique, the Fast-, Slow- and Non-moving (FSN) is a popular segmentation technique as well which segments SKUs based on the order frequency in a defined period (van Kampen et al. (2012); Vrat (2014)).

3.2 Guidelines based on segmentation methods

Following the structure of the framework proposed by van Kampen et al. (2012), several segmentation methods will be discussed in this chapter. In section 4.3.2, the segmented approaches for inventory policies are elaborated. Subsequently, in section

3.2.1, the literature concerning a segmented approach for service levels will be given, followed by a the segmented approaches for forecasting, in section 3.2.2.

3.2.1   Inventory management

A common technique for segmenting products on a strategical level is the ABC analysis or Pareto analysis (van Kampen et al., 2012). In such analyses, the product's unit price is multiplied with the product's demand volume. In case of the ABC analysis, three segments are generated, whereby segment A responsible for 80% of the sales revenue by 20% of the SKUs and, consequently, SKUs in segment C generate the least sales turnover. Furthermore, based on the segments decisions are made on what service to deliver to the customer, which inventory policies to use and where to keep stock in the supply chain.

Inventory policies

To select a suitable inventory policy Ghiani et al. (2004) suggests considering ABC segmentation. Where AB segments should be based on forecasts and frequent monitoring (e.g. by using a continuous review period model for segment A and a fixed review period model for segment B) and segment C should be managed with a two-bin policy. Nahmias proposes the same policies for segment A and B, they however propose to order large lot sizes of C items when they are inexpensive and propose not to keep them on stock when they are expensive but infrequently ordered. Furthermore, Vrat (2014) uses the same segmentation technique and proposes a continuous review period as well for class A items, combined with a fixed order quantity that is based on the economic order quantity (EOQ). This is also proposed in Axsäter (2015). For very high usage value items, Vrat mentions that, despite the high costs, a (s,S)-policy would be beneficial to implement. On the contrary, B-items should be controlled by a simpler inventory policy with a less frequent periodic review and an order-up-to policy. While for C-items one should strive for rule of thumb models (e.g., a two-bin policy). Additionally, Errasti, Chackelson, and Poler (2010) suggest a variable order quantity for stable and normal demand and a fixed order quantity for volatile demand.

Hence, one can conclude that the studies in this section have a similar view with respect to the inventory policy per class. Although, there are differences for how to treat C-items. Ghiani et al. (2004) is clearly opting for a two-bin policy, while Nahmias and Olson (2015) further distinguish between expensive and non-expensive items. At last, Vrat (2014) makes a further differentiation in class A-items, i.e., high value and high usage items should have a continuous review period and an optimized order-up-to level. Hence, it has a slightly different approach compared to the other studies.

Setting service levels

In previous sections service levels as fill rate and cycle service level (CSL) were mentioned. In literature, some segmented approaches are described with regards to setting service level targets for ABC segmentation. Teunter et al. (2010) observed that there are no clear guidelines for setting service level targets per segments. For instance, Armstrong (1985), Stock and Lambert (2001) state that class A items are the most important items and, therefore, should have the highest service level. On contrary, Knod and Schonberger (2001) argue that it is not worth to have stock outs for class C items and therefore, C items should have the highest service level. However, these observations are based on the classical ABC segmentation, where segments are based on annual demand times the price of the SKU. Teunter et al. (2010) state that these different findings are the result of

the lack of the inventory cost perspective. Therefore, Teunter et al. (2010) developed a new criterion to determine segments, such as ABC. Moreover, an overview is given about the class sizes, number of classes, and corresponding service levels. They showed that the new criterion performs significantly better than the classical ABC segmentation. The criterion from Teunter et al. (2010) balances holding and backorder costs, and is denoted for every SKU i as:

$$CSL_i = 1 - \frac{h_i Q_i}{b_i D_i} \tag{3.1}$$

Hence, this criterion means that the CSL is increasing for the criterion $\frac{b_i D_i}{(h_i Q_i)}$ and, therefore, SKUs are ranked in descending order. Furthermore, Teunter et al. (2010) showed that one should define either three or six classes and fix the service level target (either CSL or fill rate) accordingly in a descending order. The class sizes are fixed and are 20%, 30% and 50% for class A, B, and C respectively. In case of six classes the class sizes are 4%, 7%, 10%, 16%, 25%, and 38% for class A until class F respectively. The class sizes and according target service levels are determined by a rule of thumb as observed in Wingerden, Tan, and Van Houtum (2018). Therefore, they propose an algorithm to determine class sizes while considering an aggregate fill rate target for three data sets. Furthermore, four classification methods are considered in the analysis. In general, the segmentation criteria from Teunter et al. (2010) resulted in the lowest costs. Although, van Wingerden et al. (2018) show that only four classes are needed to achieve near-optimal results instead of the six classes proposed by Teunter et al. (2010).

3.2.2 Forecasting decisions

Within literature there are multiple methods used to make sales forecasts. A primary distinction can be made between judgmental and quantitative forecasting methods (Armstrong and Green, 2012).

The first characteristic that needs to be considered when deciding on a forecast method is forecasting ability. The forecasting ability depends on demand characteristics (Armstrong and Green, 2012; Alicke and Forsting, 2017; Boylan et al., 2008) and on the product life cycle (Bacchetti et al., 2013; Armstrong, 1985). In case of new products, one can consider judgmental approaches or when analogies are available use quantitative analogies (Armstrong and Green, 2012). If there is enough data available a quantitative method can be used, where extrapolation is often preferred as quantitative method for demand forecast (Armstrong and Green, 2012). Boylan et al. (2008), created a segmentation framework to select a suitable quantitative demand forecasting method, where four segments (i.e., Erratic, Lumpy, Smooth, and Intermittent) are defined by using the squared coefficient of variation (SCV) and the mean inter-demand interval. For each segment, a forecasting technique is used. For the intermittent and lumpy segments, the Syntetos-Boylan approximation (SBA) and Croston's method is used. For the smooth and erratic segments, simple exponential smoothing (SES) and simple moving average (SMA) are used.

Another aspect that needs to be considered is managers' domain knowledge (Armstrong and Green, 2012; Alicke and Forsting, 2017). Whenever possible, domain knowledge should be incorporated in a quantitative forecasting method(Armstrong, 1985), e.g. incorporate price elasticity knowledge in a causal forecasting model(Tellis, 1988). However, when it is not possible to incorporate the knowledge in a quantitative model, judgmental forecasting techniques can be used in addition to the quantitative methods(Armstrong and Green, 2012). This is for example also seen in the framework of Alicke and Forsting (2017), where promotional information was mentioned as additional to the statistical

forecast method.

4 | Current segmentation concepts

This chapter discusses the current segmentation concepts and methods at Hilti. By elaborating on the current setup, a new conceptual segmentation framework can be developed based on the gaps between the literature and the current situation. First of all, it will be briefly discussed how Hilti differentiated between customers and measures their customer service in section 4.1. In section 4.2, the product segmentation methods that are used at Hilti will be described. At last, it will be discussed how these segmentation methods are used to set guidelines for inventory management, in section 4.3, and to make forecasting decisions, in section 4.4.

4.1 Customer segmentation and customer service

In section 1.3 Hilti's supply chain was discussed. As mentioned there, Hilti has several sales channels. Hilti distinguishes the service levels per sales channel, where a different approach is taken for Hilti stores, Hilti vans and repair centers. Additionally Hilti differentiates between normal customer demand and the project business. Due to the high involvement in project business and the relative large size of orders in the project business Hilti incorporates managerial insights of the running projects in sales forecast and operations planning. The spare-parts within Hilti are managed separately from normal SKUs and it therefore out of scope of this master thesis, a segmented approach for these spare parts is discussed in a previous thesis of (Papadopoulos, 2017). Within the MOs the warehouses aim for an avaiable to service (ATS) service level of 98,7%. A customer order can consist of multiple order lines and every order line consist of one or more pieces from 1 specific SKU. The ATS is calculated as follows:

$$ATS = \frac{\sum_{\forall i} SO_i}{\sum_{\forall i} OL_i} \tag{4.1}$$

where:

i = SKU i
SO_i = The number of order lines directly satisfied from stock for SKU i
OL_i = the number of total order lines for SKU i

4.2 Product Segmentation

Hilti uses several segmentation methods to express the characteristics of their products, in this section these will be discussed.

Sales Revenue
Similar to the classical ABC-analyses or Pareto analyses Hilti clusters their products according to the relevant turn over, An overview of the classes combined with the threshold values is given in Table 4.1. A graphical representation of the TABCD segmentation is given in Appendix A.

Order frequency
The order frequency is classified into three segments based on the order lines in the last 26 weeks. An SKU is high frequent (X) when the order lines are more than 55 in 26

Table 4.1: Overview classes with thresholds TABCD

Class	Relative number of SKUs	Relative number of sales turnover
T	5%	50%
A	15%	30%
B	30%	15%
C	25%	4%
D	25%	1%

weeks. Whereas a medium frequent SKU (Y) has order lines between 55 and 3. At last, a SKU is infrequent (Z) when the order lines are less than or equal to 3.

Product life cycle

Hilti sells products with a long life, that would be clustered as functional items according to Lee (2002). However, as Hilti introduces new (improved) products to the market and old products are deleted from the product portfolio, Hilti defines three product life cycle phases. A newly developed product, known as 'Introduction New Product' (INP) has phase-in status the first 6 months of its life cycle. The Free phase has an undefined duration, this can vary from a couple years to 20 years.Products are clustered as phase-out when they are scraped from the product portfolio. Phase-in items are characterized by high demand and supply uncertainty.

Cluster groups

Within Hilti products are also placed in three cluster groups:Normal(CG1), Variable (CG2), and Sporadic (CG3) items. These groups are based on order frequency, calculated in number of order lines in the past 26 weeks and order variability, measured in the coefficient of variation of an order. The cluster and tresholds values are given in the figure below, see figure 4.1

Figure 4.1: Cluster Groups defined by Hilti

4.3 Inventory management

In order to understand how Hilti manages their inventory, this section will elaborate on inventory positioning, inventory policies, ROP/SS and order quanitites.

4.3.1 Inventory Positioning

Another part where segmentation has a role, is the inventory positioning strategy. Basically, it defines the stocking location in Hilti's supply chain and whether to use a direct shipment (e.g., downstream or upstream) based on some decision criteria. Furthermore, there is a distinction between BU level and MO/Region level. First, the decision on where to stock items in the supply chain is primarily based on the demand cluster group. CG1 and CG2 items, i.e. normal and variable demand items, are stocked in the CWs or regional distribution centres (RDCs) (hence, more downstream). Whereas, sporadic (CG3) items are stored more upstream in a regional consolidation hub or in a HAG WH. The second decision involves whether to ship directly from the plants to MO CWs/RDCs instead of shipping via the HAG WH or a consolidation hub. This decision is first based on the order quantity. If the EOQ is larger than the MDQ of the supplier, then a direct shipment is considered. Thereafter one analyses if there is a direct shipping route to the MO/Region. Otherwise, the product is stocked in a HAG WH or in a regional consolidation hub and from there on shipped to the MO CW. In addition the lead time is considered, such that customers can be delivered on time.

4.3.2 Inventory Policies and stock levels

In Hilti's supply chain inventory policy decisions depends on the location in the supply chain. The main difference is observed between plants and warehouses. Within plants one uses the EKanBan or normal KanBan system where possible. Hence, in this case inventory is continuously reviewed and an order is placed when the inventory falls below the reorder point. Hence it is similar to a (s,S) inventory control policy. Within the warehouses several inventory policies are available. The inventory policies used are reflected in the Material requirements planning (MRP)-types. These can be consumption driven or forecast (with MRP-logic) driven. MRP type X0 and Y0 are based on the MRP-logic and Bill of Material, whereas the other MRP types are demand driven.

First, a MRP-type selection is based on the location in the supply chain. More specifically, there is a differentiation between MOs and Plants/HAG WHs. An overview of the MRP-types is given in Table 4.2. An extensive description can be found in Appendix C.

Table 4.2: Possible MRP types per location

MRP types in MOs	MRP types in plants/HAG WHs
X0	X0
X1, X3	X1, X3
X5, X6	X9
X7	Z0, Z1
Y0, Y5	Z2
X9	Z3, Z4, Z8
	Z5

For the MRP-type selection in Hilti's warehouses, general guidelines are available

as depicted in 4.2. The first step in the decision tree is to evaluate the product life cycle, For a new developed product, known as 'Introduction New Product' (INP), the MRP-type is either X0 or Z0 for the MOs and HAG WHs/Plants respectively. Here the corresponding safety stock (SS) method is SB1, which is based on the average forecasted demand times the number of safety days. The logic behind the use of SB1 is that one can use manual steering for the safety days and be more flexible in the safety stock settings. If the product is in the Free stage of the product life cycle any MRP type according to Table 4.2 is possible and the decision depends on a demand cluster group. In line with the inventory positioning guidelines, sporadic items should not be kept on stock, and should be purchased to order, with an exception of strategic items for which safety stock can be kept. The safety stock is again recommended to be calculated based on the SB1 method. Seasonal products, independent of their cluster group, should also be X0. Here the SS method used is either SB1 or SB5, with no guidelines as to how to choose between these two. If the SKU belongs to cluster group (CG)1 or CG2 a distinction is made in lead time. When it shorter than 14 days, MRP type Y0 or Y5 is selected in combination with safety stock or a reorder point respectively. In both cases safety stock method SBA or SB8 should be used, however, it is not clear which one to select based on certain criteria. This also holds for whether to use a reorder point (ROP) method (i.e., RP1 or RP2). If the lead time is longer, then MRP type X0 or Y0 is selected in combination with safety stock. Again it is not clear which SS method should be used, either SBA or SB8. This option is primarily applicable for MOs outside of Europe (e.g., HNA or META). Phase-out items require manual steering.
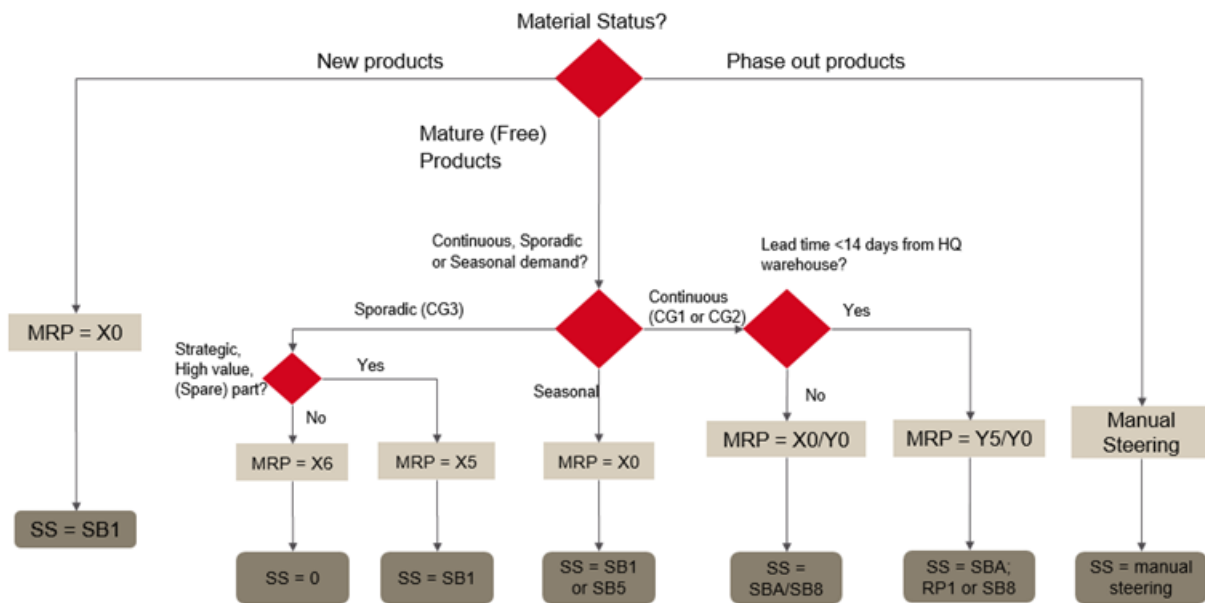
Figure 4.2: Decision tree MRP type and safety stock for MOs

These guidelines do however not cover all the available MRP-types and are not always followed. Furthermore, it is observed that the MRP-type selection is not regularly evaluated.

For the plants and HAG WHs an overview as presented in Figure 4.2 is not available. During interviews with material managers in the plant, it came to light that MRP selection was mainly done for new products, but no clear evaluation moments later on in the product life cycle exist. Within the plant, additionally to the above mentioned

characteristics, set-up times, effort quality tests, flexibility and stock capacity are all important characteristics whilst the material managers decide an appropriate inventory policy. Within the system it is possible to set the cycle service level or safety days, depending on the safety stock method, per TABCD/xyz class, however no guidelines exist as to how these should be set. The need for such guidelines became evident when it was observed that in some markets priority was given to D items when using safety days and T items where given priority when using cycle service levels as input. During the interviews and workshop that was conducted this need was also confirmed by the material managers.

4.3.3 Lot sizing and ROP

Lot size decisions occur in every location in Hilti's supply chain, hence at the plants, the HAG WHs, and CWs. These decisions are made twice a year. First data is extracted, secondly this data is converted into demand and material cluster parameters and thirdly the Lot-size is determined.

For determining the order quantity, the demand cluster groups are used. In principle, one uses the EOQ when dealing with CG1 and CG2 and a minimum order quantity of one for CG3. Furthermore, for cluster groups 1 and 2 the order quantity has a lower bound equal to the demand during lead time and an upper bound of nine times the average weekly demand. The exact calculation is represented in a lot size decision tree found in Appendix D.

4.4 Forecasting

4.4.1 Statistical forecasting

In the HIP structure, the first part where segmentation is used, is during the statistical forecasting. It is important to note that the statistical forecasting is done on Demand Forecasting Unit (DFU) level. That is, downstream in the supply chain and it involves sales data from every MO (Hence, a lower level of SKU). Furthermore, 36 months of history sales data is needed to perform a statistical forecast.

First, a DFU is segmented based on four attributes, that is, Order Frequency, Volatility, Seasonality, and Trend (Figure 9). The order frequency is divided in four categories, i.e., High (H), Medium (M), Low (L), and Rare (X). For instance, a DFU is classified as high if in at least the last 29 months there was an order in every month (or at least 83% of the past 36 months). The second attribute, volatility, is divided in three levels, that is, High (H), Medium (M), and Low (L). In this case the coefficient of variation (CV) determines the thresholds. When the CV is less or equal than 0.5, the DFU has a low volatility. A DFU had medium volatility when the CV is between 0.5 and 1.0. If the CV is higher than 1.0, the volatility is high. For the attributes seasonality and trend, the APO software from SAP decides by autocorrelation whether a DFU is seasonal or has a trend. Hence, it can only be "yes" or "no". Based on this segmentation method a forecast profile is made and one decides on the forecasting method to be used (e.g., exponential smoothing or linear regression). Basically, there are five forecasting profiles. First a DFU can have a constant profile where exponential smoothing is used to forecast. The second profile is seasonal. In this case a DFU has a more volatile demand combined with a medium or high order frequency. In this case, one uses linear regression combined with exponential smoothing or Holt-Winters. Third, a DFU can be classified as a trend

profile. As mentioned before, this is done automatically by APO. The fourth profile is intermittent, which implies that the demand has high volatility and a low or rare order frequency. For such DFUs Croston's forecasting method (Croston, 1972) is used. At last, a new product is considered separately since the low sales history. For such DFUs one uses exponential smoothing with a pre-defined alpha of 0.3.

4.4.2 Judgemental forecasting

Since the statistical forecast does not incorporate market intelligence, the forecast needs to be updated by managerial insights. Hence, a demand review and Sales Forecast Integration (SFI) meetings are needed to adjust the statistical forecast. During these meetings marketing experts and managers, for instance, include information of a new product launch and therefore reduce the forecasted demand from predecessor of the new product. Furthermore, when a new project is initiated, this needs to be incorporated in the forecast as well. Therefore, the forecasted demand is increased for products which are involved in a project. Moreover, the forecasts for new products can be adjusted by market intelligence obtained by customer questionnaires.

4.5 Conclusion/ GAP analyses

In this chapter the current guidelines for inventory management and forecasting at Hilti were discussed. First of all, it was observed that guidelines for inventory management are limited. E.g. Only a segmented framework exists for MO warehouses and even these guidelines are ambiguous and in-comprehensive. Additionally it is observed that Hilti defines cluster groups based on order frequency and order variability but subsequently only differentiates their decisions based on order frequency, since only different policies where used between cluster groups 1 2 and 3, and cluster group 3 is only defined by a low order frequency. Harrison and van Hoek (2008) discuss three strategies for inventory placement in a global supply chain. Products with a high frequent and predictable demand need to be placed downstream in supply chain whereas medium frequent items which are less predictable are stored more upstream in (global) distribution centres (i.e., HAG WH in Hilti's supply chain). The low frequent and unpredictable demand items should be stored in a global distribution centre or have a make to order (MTO) strategy. Hence, one can observe that the inventory positioning strategies of Hilti and Harrison and van Hoek (2008) are quite similar. Furthermore, the placement of the customer order decoupling point (CODP) within Hilti is already investigated by another master thesis (van Wanrooij, 2012), this will be out of scope for this master thesis project.

The operational decision on how the order quantity should be, is clear defined, that is apply EOQ when possible otherwise minimum order quantity (MOQ).Comparing the lot size decisions with the segmentation framework from Bacchetti et al. (2013), and the suggestions proposed by Vrat (2014) and Gelders and van Looy (1978), one can observe a similar decision. Both studies argue that for items with a high demand frequency one should use the EOQ as order quantity.

For phase-out products manual steering is advised with respect to the safety stock method decision. This implies, that material managers need to aim for using the SB1 method. Moreover, manual steering is also proposed for spare parts in the phase out

status in literature (Bacchetti et al., 2013). However, Bacchetti et al. (2013) make a distinction for phase out items with respect to the response lead time to the customers. Only when the replenishment lead time is shorter than the response lead time to the customer an order-up-to level is used based on the average (Poisson distributed) demand. Furthermore, Papadopoulos (2017) investigated in his study that the inventory level of phase out spare parts within Hilti declines exponentially. For this situation, he proposes a (s,S)-policy with a reorder point (s) that is based on the lead time multiplied by the annual demand.

Furthermore, one can observe that there is no connection between the safety stock method selection and the TABCD-XYZ matrix. Although, differentiation is based on demand cluster groups and strategic/high-value parts. Whereas, the term "strategic/high-value parts" remains fuzzy in the classification scheme. Compared to literature a similar approach with respect to the decision-making process for safety stock methods is observed. For instance, in the segmentation framework developed by Bacchetti et al. (2013) safety stock methods are used only for classes with high number of orders and for both low and high demand frequency. Although, for classes in the Introduction Phase and for classes with a low number of orders, no safety stock is used. For the introduction phase, they argue that due to the lack of demand history a safety stock calculation is not applicable. Consequently, a high order-up-to level (based on 6 months average demand) combined with a two weeks review period is used to assure the 95% CSL. Gelders and van Looy (1978) proposed that for all normal-moving and fast-moving items safety stock needs to be used. In both studies, the safety stock includes demand variability and CSL. However, both studies do not consider lead time variability, whereas every safety stock method, proposed for CG1 and CG2 in Figure 11, consider lead time variability. In addition, for seasonal products two safety stock methods are suggested according to Figure 4.2. Whereas, method SB1 does not consider variability, forecast error, and CSL compared to method SB5. The decision between these two methods remains unclear. Furthermore, when it is known one is dealing with seasonal products (based on history sales data), one needs to consider adjusting the safety stock according to the seasonal period as suggested by Herrin (2005).

It is shown that Hilti has already an extensive segmented approach with respect to statistical forecasting that is comparable to the proposed segmented approaches in literature. For instance, Bacchetti et al. (2013) proposes causal forecasting for products that substitute other products in the Phase In period from the product life cycle. Whereas in Hilti one uses market intelligence only for forecasting new product. When enough historical data is available time series forecasting methods are used (e.g., moving average or simple exponential smoothing) for normal or variable demand items with medium or high order frequency Bacchetti et al. (2013); Boylan et al. (2008); Ghiani et al. (2013). These forecasting methods are extended (e.g., Double exponential smoothing) when a trend or seasonal pattern is observed Ghiani et al. (2013) which is observed within Hilti as well. For intermittent or sporadic demand patterns, often Croston's method or Syntetos-Boylan Approximation (SBA) are used (Bacchetti et al. (2013); Boylan et al. (2008)) and Hilti is using th croston's method fore these items. Therefore, it is unnecessary to redesign the segmentation concept within the statistical forecasting process.

5 | SKU segmentation for Service levels

In the previous chapters it was discussed that from a cost perspective it can be beneficial to set service levels for per segment rather than a one size fits all approach. Within Hilti currently the system allows to set standard service levels for TABCD/XYZ -segments. However general guidelines as to how these should be set are still missing. Within Literature, multiple techniques have been discussed that aim to set service levels per product segment, as discussed in section 3.2.1. However, the performance of these measures under an aggregate OFR constraint, which is comparable to the applied ATS service level measure within Hilti, is to the authors knowledge not yet been investigated. Hence, before a general segmentation concept will be described, it will first be analyzed how Hilti may segment on the service levels in this chapter, where the aim is to find the policy that results in the lowest inventory cost while complying with a given aggregate OFR.

This Chapter will start with explaining the Segmentation techniques under consideration in section 5.1. Thereafter the model that can be used to test the performance of the several segmentation methods is described in section 5.2. At last, the performance is evaluated based on a case study in section 5.3.

5.1 Segmentation Techniques

Selection of characteristics

Under an OFR constraint, products with higher order frequency contribute more to the overall OLFR compared to items with a low order frequency. The use of order frequency as segmentation characteristic is already found useful, both for the choice of inventory policies (Gelders and van Looy, 1978; Vrat, 2014; Bacchetti et al., 2013; van Kampen et al., 2012) and for selecting suitable forecasting techniques (Armstrong and Green, 2012; Boylan et al., 2008). Under an OLFR, it is expected in this master thesis that order frequency can also be used to set service levels per segment. Subsequently, van Wanrooij (2012) suggests segmenting on order variability since Hilti is dealing with high variable demand which can make the stock points uncontrollable. Order variability is also used in other studies to determine replenishment strategies and or forecasting techniques (Errasti et al., 2010; Reiner and Trcka, 2004). However, a segmented approach for setting target service levels per class is not discussed in both papers. We expect that segmenting on variability is useful, because products that have a higher variability need to be stocked more to reach the same OFR. Hence, the expectation is that segmenting on order variability will reduce the total inventory cost.

Hence, order frequency and variability will be used in this master thesis as segmentation criteria. Additionally, the performance of a classical abc-classification method based on sales revenue, the technique proposed by Teunter will be tested and two two-dimensional approaches where order frequency is combined with order variability and where order frequency is combined with revenue will be considered. Here the last approach is especially interesting for Hilti, since currently their information system gives the possibility to define service levels per TABCD/XYZ.

Defining class sizes

The next decisions is to define the number of classes. Teunter et al. (2010); van Wingerden et al. (2018) showed that increasing the number of classes increases the performance. However, simultaneously, the complexity of the model increases when more classes are used, which makes it less manageable(van Wingerden et al., 2018). van Wingerden et al. (2018) also showed that increasing the number of classes further then three classes leads to a more limited performance improvement as from two to three classes. Silver et al. (1998) mentioned that the increase in complexity is more severe when using more than six classes. Hence is was chosen to stay within these boundaries of number of classes. In order to make the analyses suitable for Hilti, it was chosen to cluster the one dimensional criteria in three groups, with five groups as exception for revenue, since Hilti currently defines this in 5 classes. For manageability, The two-dimensional models are limited to 5 classes by clustering the segments. A further explanation of the determination of class sizes can be found in appendix H.

5.1.1   Considered Segmentation methods

The resulting segmentation methods under consideration will be discussed below.

Order frequency

Order frequency is measured in the number of order lines per SKU over 12 months. The classes for the order frequency are denoted as XYZ (similar to the current situation within Hilti). However, during a workshop within Hilti it turns out that the current fixed class sizes are not feasible for every region. The current absolute threshold values are not suitable for some markets due to a lower order frequency in general. Therefore, a relative approach is used to classify the order frequency, as can be seen in table 5.1

Classes	Threshold values
X	80% of total orders
Y	19% of total orders
Z	1% of total

Table 5.1: Threshold values for order frequency

Variability

Variability is measured as the coefficient of variation of the weekly demand per SKU. The threshold values for order variability (divided in three classes as well) are determined based on the gradient of the order variability in the sample data Appendix H.

Table 5.2: Threshold values for Variability

Classes	Threshold values
U	CoV<1
V	$1 \leq$ CoV<2
W	CoV ≥ 2

Revenue

The TABCD analysis (Demand * Unit Price) is considered since this segmentation technique is used in the TABCD-XYZ analysis within Hilti. This technique is selected in order to determine if the current segmentation TABCD-XYZ analysis can be simplified to just the TABCD analysis. The threshold values for the classes are defined as described in Table 5.3.

Table 5.3: Threshold values for Revenue

Classes	Threshold values
T	50%
A	30%
B	15%
C	4%
D	1%

Demand/ (holding cost * order quantity)

Teunter's criterion is considered since Teunter et al. (2010) showed that inventory costs can be reduced significantly. Although, in Hilti's situation the Teunter's criterion needs to be adjusted. Teunter's cost criterion is based on the criterion $(b_i D_i)/(h_i Q_i)$. Since Hilti has not defined a back-order cost and no different criticality measures are known for the products we assume that back-order costs are linear to price, $b_i = b*\text{price}_i$, due to the lost revenue when a back-order results in lost sales. Holding cost per product are also linear to the price, $h_i = h*\text{price}_i$. Hence, Teunter's criterion can be rewritten for Hilti as D_i/Q_i . According to Teunter et al. (2010) applying six classes leads to better results compared to three classes. However, three classes are used in order to see first how beneficial the simplified version of Teunter's cost criterion is. The classes and corresponding threshold values are given in table 5.4.

Table 5.4: Threshold values for Teunter's criterion

Classes	Threshold values
A	20% of SKUs
B	30% of SKUs
C	50% of SKUs

Order frequency and revenue

For this segmentation technique, the same class sizes are used for the TABCD classification as described in section above. As the TABCD-XYZ method results in 15 classes, these where clustered again. The resulting cluster groups are graphically depicted in figure 5.1.

Order frequency and Order Variability

To determine the segments based on order frequency and order variability, a two-dimensional matrix is used. The threshold values for order frequency are similar to the threshold values in the TABCD-XYZ analysis. The threshold values are summarized in Figure 5.2.

Figure 5.1: Segments based on Order Frequency and Revenue

Figure 5.2: Segments bases on Order Frequency and Order Variability

5.2 Experimental Design

The performance of the several segmentation methods will be tested in a a case study of a single echelon inventory system. It is assumed that the inventory system is controlled with a (R,s,nQ)-policy with a review period of R=1. This assumption was made since it closely resembles the current inventory control policies within Hilti, where the system reviews the order quantities with a daily review period, a fixed lot size and a predefined safety stock. Furthermore, incoming orders are treated first come first served (FCFS), partial order fulfillment is not allowed and unsatisfied demand is back-ordered. The lead time of the replenishment orders are randomly generated from a normal distribution, based on the known average lead time and variation of the lead time. Furthermore the model uses known lot sizes.

The performance of this model will be evaluated by the inventory costs while achieving an aggregated order line fill rate adopted from Larsen and Thorstenson (2014). Based on the segmentation method defined in section 5.1, K classes are defined. Let $K = \{1, \ldots, |K|\}$ denote the set of classes such that class $k \in K = \{1, \ldots, |K|\}$ and the classes are ordered with decreasing priority, so $k = 1$ is the class with the highest priority. As it is mathematically difficult to set safety stock based on an OFR constrained, it is chosen to specify the cycle service level per class α_k to determine the safety stock. This also supports the implementation of the model, as SAP can calculate safety stock based on a target cycle service level but not on a target OFR.

Let $\alpha = \{\alpha_1, \ldots, \alpha_{|K|}\}$ denote the set of specified cycle service levels per segment, where $\alpha_i \geq \alpha_{i+1}$. Then the total inventory cost under the given cycle service levels is denoted as C(α) and the aggregate OFR as OFR(α). Each SKU i is allocated to one of the segments, where k_i denotes the segment in which SKU $i \in I = \{1, \ldots, |I|\}$ belongs. Then objective function is to minimize the cost C(α) constrained to an aggregate target OFR^0:

$$minimize C(\alpha) \tag{5.1}$$

s.j.

$$OFR(\alpha) \geq OFR^o \tag{5.2}$$

where:

$$\alpha_i = \alpha_k \forall i, k_i \in k \quad and \quad \alpha_k = (0,1) \forall k \in K \tag{5.3}$$

The total cost C(α) can be denoted as the sum of all inventory cost for each SKU i based on the service level for SKU i.

$$C(\alpha) = \sum_{i \in I} C_i(\alpha_i) \tag{5.4}$$

The inventory cost per item is denoted as the on-hand inventory for each SKU i in time period $T = 0, \ldots, |T|$ and is dependent on the price of the SKU i times the interest rate of the holding cost h.

$$C_i(\alpha_i) = p_i * h * \sum_{t=0}^{T} IOH_i^t \quad \forall \quad i \in I \tag{5.5}$$

For calculating the OFR(α) we denote n as the total set of order lines during the period under consideration $n = \{1, \ldots, N\}$ where order line $n = 1$ is the first order line and n+1 is the next order line that arrives. Furthermore, let N_i be the set of order lines for SKU i during the period under consideration and $s_i \subseteq N_i$ be the subset of of incoming orders that could be satisfied from stock. Then the aggregate OFR of all items can be calculated by dividing the total number of elements in s_i (denoted by the cardinality notation $|s_i|$) by the total number of elements in N_i:

$$OFR(\alpha) = \left(\frac{\sum_{i \in I} |s_i|}{\sum_{i \in I} |N_i|} \right) \tag{5.6}$$

In order to solve the model, a recursive formula is applied. The analyses is done in Matlab. Based on given demand, order quantities and starting inventories the model first calculates the order line fill rate per item for a specified range of cycle service levels. As the lead time was randomly generated this was done 500 times and to determine the average. Subsequently the model searches for the optimal combination of cycle service levels per segment that result in the lowest cost, under several OFR^0.

5.3 Case study

5.3.1 Experimental set-up

To compare the performance of the proposed segmentation models a case study is conducted. The case study includes 600 items, of which 500 are to solve the objective function recursively and the other 100 are used as a test set, where the optimal service levels from the other data set are implemented. For all segmentation methods, several values for α_k where tested where ({0, 0.5, .55, .6, .65, .7, .75, .8, .85, .86, .87, .88, .89, .90, .91, .92, .93 .94 .95 .955 .96 .965 .97 .975 .98 .985 .99 .995}) under the constraint $\alpha_k \geq \alpha_{k+1}$.

For the case study one year of demand history data (i.e., year 2017) is used from a CW in Germany, since this warehouse covers the most important regions for Hilti. The analysis is conducted for 500 randomly picked SKUs from the CW Germany. From this sample size five SKUs were omitted, because of no demand information during this year. Hence, 495 items SKUs remain. The selection was made from SKUs that are in the life cycle free and since another approach is recommended for spare parts these were also excluded from the selection. In reality, the segments based on historical data can differ from the actual segment, since the purpose of the case study is to demonstrate the impact on service levels and costs. An overview of the selected SKUs can be found in Appendix G. The data is retrieved from the enterprise resource planning (ERP) system SAP. No information was found that represented the real customer sales orders, hence instead the delivery lines, the orders that where actually shipped out to the customer, where used. Customer sales orders and delivery orders can differ when there was not enough stock on hand, but since Hilti has a high customer performance target we expect this difference to be minimal.

5.3.2 Results

This section discusses the results obtained from the scientific design. First the results from the case study based on the 495 items are presented. Secondly, we validate the results by using another randomly selected data set of 100 items. Ultimately, the results of the sensitivity analysis are discussed from the best performing segmentation technique. In order to have a fair comparison, the current situation for the 495 items is considered in the case study (presented as the single dot inFigure 5.3. In the current situation, the safety stocks where set according to the system. Resulting from the case study the current situation achieved an OFR of 89% with 63 kCHF inventory costs. As depicted in Figure 5.3, the current situation performs far from optimal whereby even an unsegmented (where all SKUs have equal service level settings) approach performs better. The TABCD-XYZ approach with relative order frequency thresholds and a higher service level for the C and D classes has the best performance with the lowest inventory cost from an aggregated service level of 85% and on-wards. Compared to the current situation it achieves a cost reduction of 28%. Hence, as discussed in Teunter et al. (2010) and in Vrat (2014) the addition of the Order Frequency may prove to be useful in selecting the right inventory control policy. However, the case study shows that the Order Frequency is useful for target service level setting per segment as well and reducing inventory costs.

Observe that the TABCD segmentation technique (i.e., solely based on demand value) has a similar performance compared to the Order Frequency/Order Variability technique. This is because in the TABCD segmentation the C and D items have a higher service level than T and A items. Consequently, resulting in lower inventory costs.
A remarkable result is that Teunter's cost criterion is performing worse than other segmentation techniques. A possible explanation is the simplification. Due this simplification the cost aspect is omitted from the equation. However, this is not validated.
Furthermore, the case study gives no results for target service levels above 97%. When achieving an aggregate performance of 97% the algorithm selects already a 99.5% service level for some classes (see Appendix V for an overview of the service level settings per segment). A possible explanation is standard normal distribution assumption of the safety factor. An overview of the exact service level setting per class and corresponding inventory costs can be found in Appendix **??**
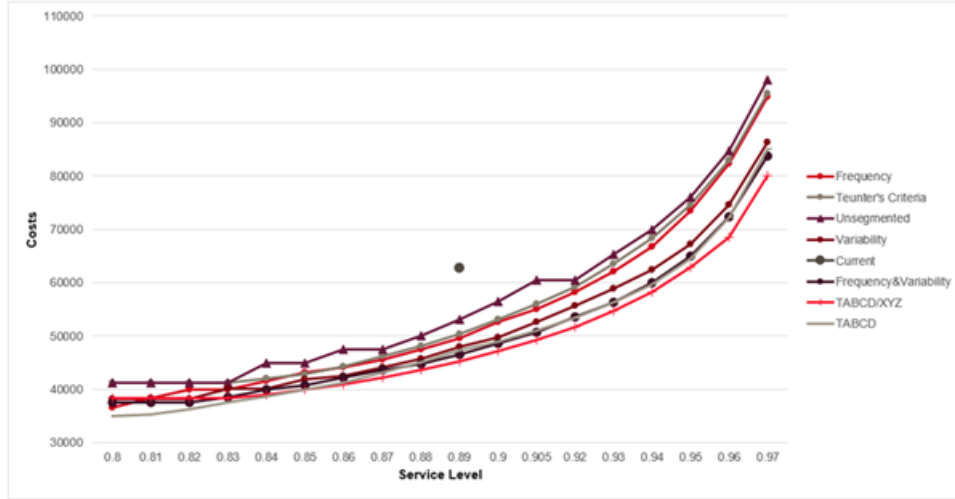
Figure 5.3: Results from case study

In the validation run, the current situation achieves a target of 91% (Figure 5.4). For this dataset, the unsegmented approach as well as the Teunter's cost criterion performs worse than the current situation. The worse performance of the unsegmented approach is straightforward because slow-moving-items have same service levels as fast-moving items, resulting in high inventory costs and the risk of obsolescence. The best performing segmentation technique is still the TABCD-XYZ approach as depicted in Figure 5.4. Furthermore, there is no significant difference in the performance of other models. One can still observe that the Order Frequency/Order Variability and the TABCD approach are still performing well with a minor difference of 4.6% and 6.2% respectively at a target service level of 97% compared to the TABCD-XYZ approach.
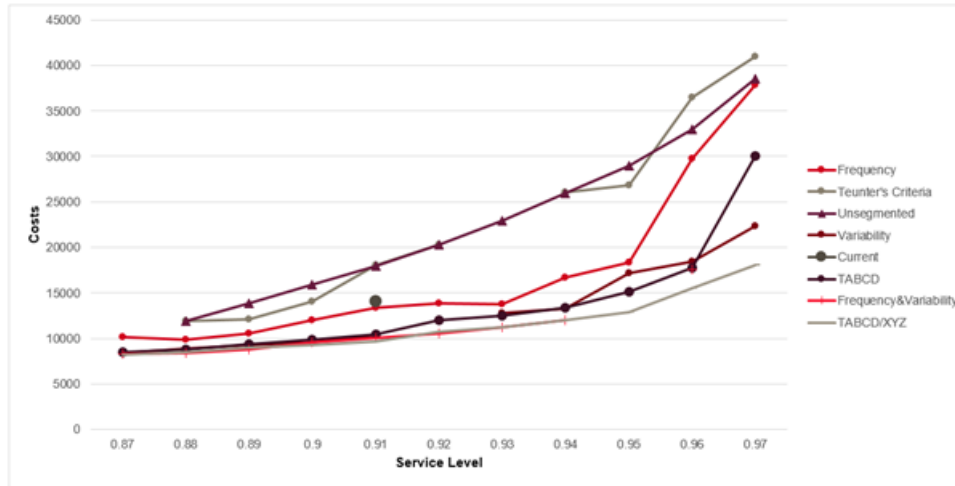
Figure 5.4: Results from case studywith 98 SKUs

We can conclude that in a quantitative segmentation technique order frequency is an important criterion to segment on. It performs well with the TABCD segmentation. Hence, this is a confirmation of the system approach (Sherbrooke, 1986) where SKUs with a high price should have a lower service level target compared to SKUs with a low price. Moreover, this also confirms the idea of Teunter's cost criterion Teunter et al. (2010);van Wingerden et al. (2018)), although the segmentation technique based on Teunter's cost
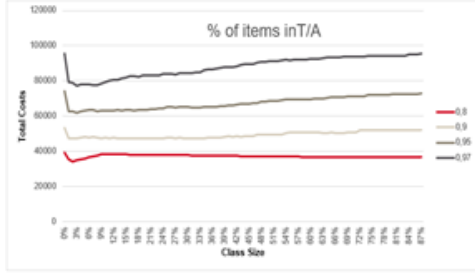
Figure 5.5: Sensitivity analysis class size T/A items
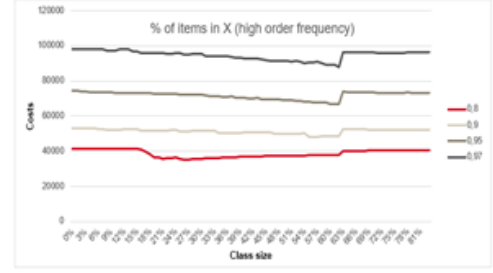
Figure 5.6: Sensitivity analysis class size X items

criterion performs worse in the case study.

5.3.3 Sensitivity analysis class sizes

Since the class sizes do have a significant impact on the performance of a segmentation technique (van Wingerden et al., 2018), a sensitivity analysis is performed on the class sizes of the TABCD-XYZ approach. Especially for the classes (in this case CG5) where the decision is made to keep the items not on stock due to the slow-moving demand and high valued items. The class size needs to be such that an aggregate service level will be met with the lowest costs.

For the TABCD-XYZ segmentation technique the class size is dependent on the numbers of SKUs in the T and A class (Demand value), and dependent on the number of products in the X class (Order frequency). The size of the T and A class is of importance due to high valued items. If this class is too small, it means that the most expensive items are in the other classes with higher service level targets, and consequently, higher inventory costs. If this class is too large, fast-moving items with a relatively lower value will have a lower service level, which results in not achieving the aggregated target service level. According to the results (Figure 5.5) one can observe that the inventory costs are high when the T/A class is too small. For an aggregate service level target of 97% the T/A class should consist of maximum 9% of the total amount of SKUs. Similarly, the same reasoning holds for the size of class X (i.e., fast-moving SKUs). If class X is too large, it means that it is more likely that slow- or non-moving items are then classified as fast-moving as well. Consequently, this results in high service levels for slow-moving or non-moving items, which implies high inventory costs. On the contrary, when the size of class X is too small, it results in items that are classified as slow-moving or non-moving with lower corresponding service levels. Hence, it is most likely that the aggregate target service level is not achieved. With regards to the class size of the X items one can observe similar results for an aggregate service level of 95% and 97% (Figure 5.6). In these cases, the class size should be around 63%. When the aggregate target service level is lower, the class size of X items can be smaller since fast-moving items contribute more to the aggregate target service level (10) and, consequently, the target service level is reached earlier.

6 | Conceptual design of segmentation concept

In the previous chapters it was shown that clear segmentation guidelines are missing within Hilti while a segmented approach can reduce inventory costs and optimize service levels. In this chapter a conceptual segmentation framework is designed for Hilti. This chapter discusses first the variables and parameters on which the segmentation concept is based on. Subsequently, these variables and parameters are used by a classification technique, as discussed in van Kampen et al. (2012), such that the segments and their boundaries are defined, and SKUs are allocated to these boundaries. Thereafter, for each segment guidelines are presented with regards to tactical decisions (e.g., inventory control policies and service level definition) and operational decisions (e.g., SFI meetings and forecasting).

6.1 Segmentation design

In the previous section we showed which quantitative segmentation technique achieves the best performance by setting service levels per class in order to achieve an aggregate target service level. However, the holistic approach with regards to e.g. products in the phase-in and phase-out life cycle are neglected. Therefore, the hierarchical process approach (Bacchetti et al. (2013); Papadopoulos (2017)) is used. By using the hierarchical process nine classes are obtained. How these classes are obtained, and which guidelines are best used for each class is discussed in this section. The segmentation concept is based on the following criteria:

– Material Status
– Innovativeness
– Cluster group derived from TABCD-XYZ
– Lead time

The segmentation concept based on these criteria is depicted in Figure 6.1. Furthermore, the reasoning behind each criterion is described below.

Material Status

The first segmentation criterion is the Material Status. According to literature (Persson and Saccani (2009); Rink and Swan (1979)) one differentiates between four categories in the product life cycle (i.e., Introduction phase, Growth phase, Mature Phase, Decline Phase), whereas Hilti uses three categories. As observed in Bacchetti et al. (2013), three categories for the product life cycle are fine as well. Hence, we propose to use three classes as currently used within Hilti. The main reason is that from an inventory management perspective there is no difference between the Mature Phase and the Growth Phase. Only from a forecasting perspective one should be careful with selecting the correct forecasting policy. Since in the Growth Phase a company might experience an exponential increase in demand (Rink and Swan, 1979). Hence, the (double) exponential smoothing forecasting strategy might be the most suitable for this life cycle phase since it put more emphasis on the latest history, which makes it more useful for forecasting the increasing trend (Armstrong and Green, 2012).

Further segmentation is considered for the Introduction phase of the product life cycle, that is, Innovativeness. It distinguishes between products with a predecessor and without a predecessor. For the Mature Phase a differentiation is made in the cluster groups derived from the TABCD-XYZ analysis. Nevertheless, for determining the cluster groups at least six months of sales history data is needed. There is no further distinction for Phaseout items since this requires more judgmental coordination in general (see section 6.2).

Innovativeness

With regards to Innovativeness, a distinction is made between items with a predecessor and without a predecessor. The reason behind this distinction is that a new product with a predecessor can use data from its predecessor in the past. This data can be useful to successfully introduce the new product based on causal relationships from its predecessor, which is also observed in Bacchetti et al. (2013). Whereas, for items without a predecessor a more judgmental approach from the marketing department is needed for introducing the product into the market.

Cluster Groups

The results of the case study from chapter chapter 5 shows that the TABCD-XYZ (a 5 by 3 matrix) divided in five cluster groups results in the best performance regarding inventory costs. As earlier mentioned the CGs were defined for avoiding long calculation times in the case study and for manageability. CG1 consists of the fast-moving and relatively cheap items. Hence, keeping this SKUs on stock would not results in high inventory costs. Similarly, for CG2, these items are relatively cheap as well, and it contains fast-moving items and slower-moving items (i.e., class Y). CG3 contains slow-moving items only, though relatively cheap. The case study showed that this CG should have a higher service level than CG4 which contains of relatively expensive though fast-moving items only. Hence, items from CG3 should always be stocked in a warehouse. Furthermore, items in CG3 are more difficult to forecast because of the slow-moving demand. One should pay attention to CG4, since these items are expensive (i.e., the T and A class) though fast-moving. Hence, over stocking these items will negatively impact the inventory costs. More care should be taken for CG5 since this CG contains expensive and slow-moving items only. Hence these items are difficult to forecast and keeping safety stock for these items would result in too high inventory costs and on the long term the risk of obsolescence arises.

Lead time

In the case study the policy for CG5 is to keep no safety stock in all cases. However, according to internal safety stock documentation and the study from Papadopoulos (2017) Hilti would need to keep safety stock for items with a lead time of more than 10 working days (Papadopoulos, 2017). This will be further investigated refer to MT Luc. In the next section we propose guidelines per segment with regards to MRP-type selection, safety stock, order quantity and forecasting strategy.
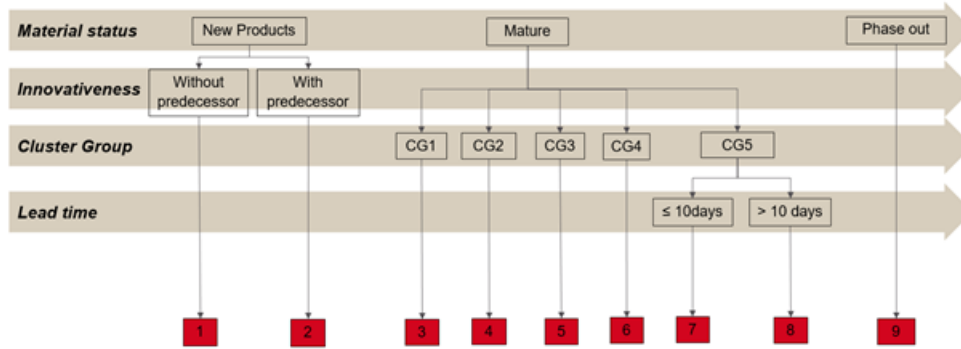
Figure 6.1: Proposed Conceptual segmentation framework for Hilti

6.2 Guidelines for each segment

This section elaborates on the guidelines for each segment. For each segment guidelines are given with regards to which forecasting and MRP-type to use. In the case study a (R,s,nQ)-inventory control policy was used due to modelling purposes. However, within Hilti the MRP logic in SAP is used instead of the classical inventory control policies from Silver et al. (1998), which is also a misconception in the study of Papadopoulos (2017). Therefore, we suggest per segment a MRP-type. Furthermore, almost for every segment the EOQ is used as order quantity since Axsater (2015) argues that an order-up-to level in practice is approximately equal to n times the EOQ. Since practical implication is more important for this section, we use this approximation.

Segment 1 - New products without predecessor

- Forecasting policy: Judgmental forecast.
  Due to the lack of data judgmental forecasting is required. The judgmental forecasting is best performed by the BU material managers in alignment with the marketing department.

- MRP-type: X0 with SS=SB1 method and Q=EOQ.
  New products, excluding specials, need to be stocked close to the customer to encourage sales. The focus for new products should be to get the sales up. Less important are the inventory costs. With regards to the parameters of the SS method (i.e., the safety days), the lead time is suggested as the number of safety days. A service level as safety factor is not applicable in this case

. Segment 2 – New Products with predecessor

- Forecasting policy: Statistical forecasting with judgmental downward adjustments
  These products will cannibalize the sales of its predecessors. In the start of the Introduction of the New Product (INP) process the supply chain pipeline is filled with the INP products and the phase-out products are cleaned from stock. The statistical forecasting would ideally be based on data from its predecessor before the INP process starts, since predecessor sales start declining when the INP process starts. Furthermore, statistical forecasting should include a factor to reflect sales increase due to renewal. In general, product renewal increases product sales (Cucculelli et al., 2016). It is therefore recommended that Hilti investigates the impact of product renewal on its sales. Judgmental downward adjustments need to be performed when inventory levels of the predecessor are still high.

- MRP-type: X0 with SS=SB1 and Q=EOQ.
  Due to the lack of data of lead time variability, the use of safety stock method SB1 is proposed whereby the safety days must be equal to the lead time. Furthermore, the safety stock is ideally kept close to the customer (hence, downstream in the supply chain) in order to achieve a high service level. The order quantity Q is better based on the EOQ while considering the average demand from the causal forecast from its predecessor.

Segment 3 – Mature products, CG1

- Forecasting policy: According to statistical forecasting segmentation
  Products in this segment show a stable high frequent demand, which makes statistical forecasting suitable. The forecasting policy is selected according to the segmentation concept for forecasting presented in section subsection 4.4.1. However, caution must be taken with items which are in the Growing phase (see section 6.1). Therefore, double exponential smoothing would need to be used in order to consider the upward sales trend from the most recent sales period(s).

- MRP-type: X0, Y7, Z4 with SS=SB9 and target service level of 99.5% and Q=EOQ
  For CG1 MRP-type X0, Y7 or Z4 should be used. CG1 consist of fast-moving items, hence a consumption driven MRP-type (i.e., Y7) is more suitable since it also forces to use a ROP for determining when to place an order. The difference between X0 or Y7 is on which level the forecast takes place. Typically for smaller markets the forecast is made on an aggregated level (i.e., HQ level), whereas for larger markets the forecast is made on MO-level. The MRP-type Z4 is only used for plants and HQ warehouses. During this phase there is enough data available to consider safety stock method SB9. Whereby the safety factor k should be based on a 99.5% service level according to the results in chapter chapter 5.

Segment 4 – Mature products, CG2

- Forecasting policy: According to statistical forecasting segmentation
  This CG contains fast-moving and slower-moving items; hence forecasting is possible. Although, the statistical forecasting team selects the correct method and parameterization of the variables.

- MRP-type: X0, Y7, Z4 with SS=SB9 and target service level of 99.5% with Q=EOQ.
  Similar to CG2, one should use the MRP-type X0, Y7, or Z4, depending on the location in the supply chain. Since the items in this CG are (relatively) fast-moving and (relatively) cheap, a consumption driven MRP type should be used. Regarding the safety stock, a safety factor based on a 99.5% service level is used since this was the outcome of the case study when the aggregated target service level is 97%.

Segment 5 – Mature Products, CG3

- Forecasting policy: Corporate forecast only.
  Since this CG contains only of slow-, or non-moving items a statistical forecast is not necessary. Hence, a corporate forecast is sufficient, this also complies with the MRP-type.

- MRP-type: X5 or X6 with SS=SB9 and target service level of 98.5% with Q=EOQ. Due to the sporadic demand the MRP-type X5 or X6 is the most suitable since these items are generally purchase to order items. The case study showed that the safety factor for the SS-method should be 98.5% in order to achieve an aggregated target service level of 97%. However, since the items in this CG are slow-moving, another safety stock method might be more suitable.

. Segment 6 – Mature products, CG4

- Forecasting policy: According to statistical forecasting segmentation
  SKUs in CG4 are generally expensive and fast-moving, therefore forecasting is applicable and important as well. Especially for this CG one should strive for an accurate forecast, because in case of over forecasting the inventory holding costs increase significantly.

- MRP-type: X0 or Z0 with SS=SB9 and target service level of 65% with Q=EOQ
  The MRP-type needs to be forecast driven with high accuracy, since consumption driven might result in high inventory cost due to the high value SKUs. Therefore, MRP-type X0 for the MOs and MRP-type Z0 for the plants and HQ warehouses are appropriate. The case study showed that for this CG a service level is appropriate for achieving an aggregated target service level of 97%. The reason for such a low safety factor in the safety stock calculation is for preventing high inventory costs.

Segment 7 – Mature products with short lead time ($\leq$ 10 days), CG5

- Forecasting policy: Corporate forecast only.
  Since this CG contains only of slow-, or non-moving items a statistical forecast is not necessary. Hence, a corporate forecast is sufficient, this also complies with the MRP-type.

- MRP-type: X5 or X6 with no SS and Q=MOQ
  Because of the sporadic demand, the MRP-types X5 or X6 are used. The case study showed that, in order to reduce inventory costs, no safety stock is needed. Hence, safety stock should be considered for one location upstream in the supply chain. With regards, to the order quantity Q, the minimal order quantity would need to be used in order to reduce obsolescence risks.

Segment 8 – Mature products with long lead time ($>$ 10 days), CG5

- Forecasting policy: Corporate forecast only.
  Since this CG contains only of slow-, or non-moving items a statistical forecast is not necessary. Hence, a corporate forecast is sufficient, this also complies with the MRP-type.

- MRP-type: X5 or X6 with SS=SBB and Q=MOQ
  Similar to segment 7, the MRP-type X5 or X6 should be used for this segment. In order to comply with the current guidelines for safety stock and inventory positioning, a small amount of safety stock should be considered for long lead time markets. Hence, the SS method SBB is appropriate for this case.

Segment 9 – Phase-out items

- Forecasting policy: rule-based forecasting
  With rule-based forecasting managerial information can be included that is necessary to predict the decrease in demand during phase-out.

- MRP-type: X5 or X6 with SS=SB1 and Q=MOQ
  A phase-out product is sold to get rid of inventory of the product in the pipeline. Because of the rule-based forecasting an MRP-type should be selected were planning is allowed, therefore X5 or X6 need to be used. Normally, phase-out products have a decreasing demand pattern. Especially when the product has a successor Hilti has to a certain extend influence on the decrease in sales. Within the INP process the introduction to the market is done step-wise in multiple waves. The products are first introduced to the stable markets, every three months the product is introduced to other markets. Total inventory in the location is ideally limited to the expected demand until the new product will be sold. To overcome obsolescence the order quantity should be minimized. Furthermore, the safety stock requires manual steering. Therefore, the SB1 method is preferred whereas the safety days are determined based on the rule-based forecasting. Since the duration of the phase-out period for a non-spare part is not as long for spare-parts (Papadopoulos, 2017), no service level target is required.

Part II

System nervousness

7 | Introduction

7.1 Problem statement

Hilti plants experience a problem with changing production plans over time. In specific, the production plants that assemble tools, e.g. plants 4 and 88, observed that production quantities are recurrently increased one month in advance and again decreased as the schedule is rolled out. This obviously disrupts capacity planning and the faith of Hilti personnel in the production planning. Subsequently, these problems can possibly propagate through the supply chain where it can lead to increases in inventory levels and decreased service levels. At Hilti, these recurrent production planning adjustments are called the bow-wave effect. In the literature, the instability of plans both in MRP and MPS is referred to as system nervousness (Andersen et al., 2014). Therefore, the bow-wave effect is a specific case of system nervousness. This thesis defines the following definition of the bow-wave effect:

The bow-wave effect is a phenomenon where the production orders for the upcoming period increase and then again decrease as the schedule is rolled out

The existence of the bow-wave in plant 4 is graphically shown in figure 7.1, The figure shows the total order volume planned in a specific month on the horizontal axis for the deadline month in the title. The quantities reflect the total quantities per month, including planned orders, open orders and finished orders. The figure shows that the planned volumes have a wave as time approaches the deadline. The figure clearly shows the impact of the bow-wave effect in the first 7 months of 2018. In August the bow-wave effect seems to have disappeared.
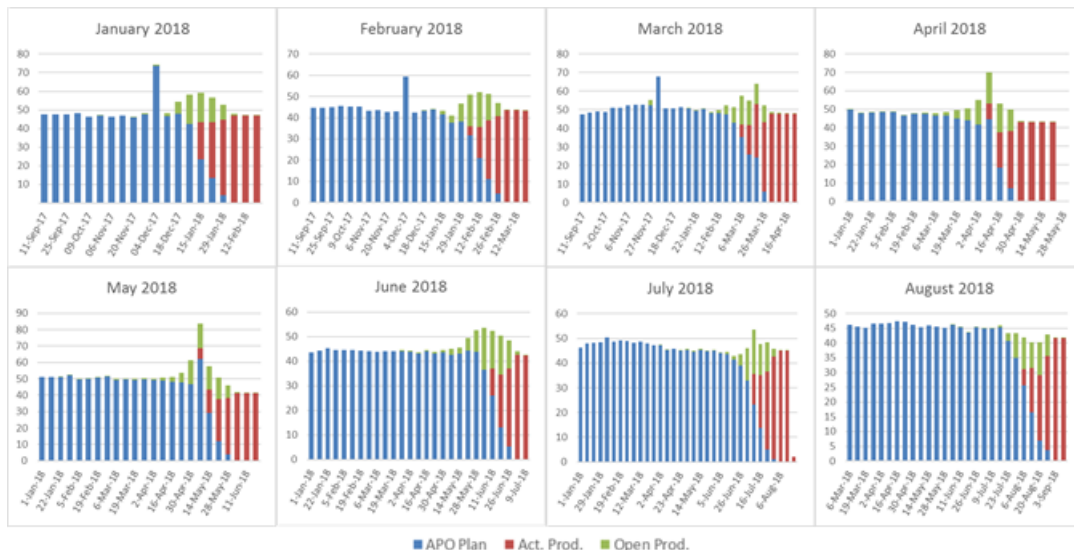
Figure 7.1: Production orders plant 4, x1000

Hilti has identified three root-causes of the bow-wave effect:
- over-/under-forecasting

- a mismatch between planned and actual production
- sub-optimal forecast consumption logic

Although all three of these root-causes demand thorough investigation, Hilti was initially interested in the sub-optimal forecast consumption logic. The impact of forecast consumption on the bow wave effect will therefore be further investigated in this master thesis. The remaining identified root-causes will not be the primal subject of this thesis, but their existence at Hilti and their impact are explored to provide the company with more insight in the problem.

7.2 Forecast consumption logic context

Forecast consumption logic is a setting within the MRP system used at Hilti. In this section

7.2.1 MRP systems

With the introduction of MRP, material planning shifted from the use of manual reorder points to a system based upon multi-level bill of material processing (Mabert, 2006). The MRP-logic calculates the planned order releases at the most downstream location based on forecast and/or demand and uses this information to calculate the planned order releases more upstream in the supply chain. The planning functionalities of MRP-1 are summarized by Wiers and de Kok (2018) as follows:

1. Material explosion. The logic uses the Bill of Materials to calculate the demand of components based on the demand for the final end-item. Where the Bill of Materials specifies all the components that are needed for an end-item.

2. Lead time off-setting. A fixed lead time to form an item from its components is taken to determine production dates of items based upon an assumption that will make it possible to have the final item on time.

MRP gives the quantities ideally needed, however it ignores feasibility constraints as material availability and finite capacity (Wiers and de Kok, 2018). Furthermore, the fixed lead times are often not a good offset of reality. Lead times are subject to uncertainty due to the stochastic nature of the production process. They furthermore depend on system load and available capacity(Nieuwenhuyse et al., 2010). Today, additional to the MRP-1 modules, APS modules are offered by major ERP providers (Wiers and de Kok, 2018), like the APO module offered by SAP (Vecchietti and Vidoni, 2015).
In accordance with the definition of Wiers and de Kok (2018) APS differ from standard MRP solutions by their ability to cope with time, resource and material constraints. However, many definitions for APS exist in literature that differ in both their modules and solutions and the systems available on the market do not always fulfill a common description (Vecchietti and Vidoni, 2015). This makes it hard to compare the system in use at Hilti relative to those published in literature.

7.2.2 Rolling horizon planning concept

An MPS is often based on demand forecast and includes a high level production plan of end items during a given time interval (Tang and Grubbström, 2000). Production plans, and in particular MPS, are often made under rolling planning horizons (Vargas and Metters, 2011). Under a rolling planning horizon, a production planning schedule is

made every planning cycle. The system iteratively solves stationary production planning problems where updates are made every re-planning period. The production plan is made for a fixed planning horizon. Each planning period, the production plan of the nearest future, the frozen horizon, is fixed. The length of the frozen horizon is either defined by a fixed time (time-based) or a fixed number of orders (order-based) (Sahin et al., 2013). The remainder of the planning horizon, the free interval can still be changed.

Although MRP is mostly used in relation to production plants upstream of the MPS, the MRP-logic is also often used to calculate the planned order releases of finished goods based on downstream purchase orders (Donselaar et al., 2000). This is also seen within Hilti, where the MRP-logic is applied for many items in the forecast location.

7.2.3 Forecast consumption logic

As described above, the MRP-logic calculates orders based on actual demand and/or forecast. On the forecast location, actual incoming demand and forecast are integrated together to planned demand. With the forecast consumption logic it can be defined how incoming demand is integrated in the forecast. Currently at Hilti, when actual orders come in, the order amount is subtracted from that day's forecast, where the forecast can be zero at the lowest. As described above, HNA and META forecast the direct sales to customers and the so-called network demand, the demand from the DC's that are replenished. However, this network demand is not subtracted from the forecast. Additionally, corporate forecasts are completely overridden by actual demand, so when actual demand comes in, the forecasted demand is set to zero for that day.

7.3 Hypotheses

In an MRP driven system, warehouses place orders based on the expected total demand during lead time. The total expected demand consists of the demand forecast and the actual orders. As actual orders come into the system, they are currently subtracted from the forecast on that day. This is the current forecast consumption logic. Consumption of multiple days of forecast may also be considered as a forecast consumption logic setting. With the current consumption logic at Hilti, every deviation in demand from forecast leads directly to a change in net requirements. Within literature a well known risk-pooling strategy is demand aggregation(Tabar et al., 2012). This strategy may be used to make more reliable forecasts. In this case the variability of the aggregated demand, e.g. total monthly demand, is lower than the variability of the original data, e.g. daily demand (Tabar et al., 2012). Following the same principle, it is expected that increasing the forecast consumption horizon reduces variability as the relation between the demand and the forecast is evaluated on a higher aggregation level. The system does not immediately react to daily deviations since less emphasizes is put on the daily expected total demand and more emphasis is put on the aggregated expected total demand during the forecast consumption horizon.

Example

Consider the following example of forecast and demand in a warehouse, where the warehouse has to order from the plant with a lead time of 4 days and no lot size restrictions:

Before any demand data is known, the planned order are 10 pieces a day. During

---

PERIOD	1	2	3	4	5	6	7
INITIAL FORECAST	10	10	10	10	10	10	10
START INVENTORY POSITION	30						
PLANNED ORDERS	(40-30=)10	10	10	10			
Safety Stock = 0	Lot size = 1	Lead time= 4					

Figure 7.2: Example: Original planned orders

the week every day orders can come in, in our example only 1 order comes in on day 1. Under the current consumption logic the net requirements change as follows as the week progresses, see figure 7.3.

PERIOD 1	INCOMING DEMAND	40						
	RENEWED FORECAST	0	10	10	10	10	10	10
	START INVENTORY POSITION	30						
	PLANNED ORDERS	40+30-30 = 40	10	10	10			
PERIOD 2	INCOMING DEMAND		0					
	RENEWED FORECAST		0	10	10	10	10	10
	START INVENTORY POSITION	30+40-40=>	30					
	PLANNED ORDERS		0+30-30 = 0	10	10			
PERIOD 3	INCOMING DEMAND			0				
	RENEWED FORECAST			0	10	10	10	10
	START INVENTORY POSITION		30+0=>	30				
	PLANNED ORDERS			0+30-30 = 0	10			
PERIOD 4	INCOMING DEMAND				0			
	RENEWED FORECAST				0	10	10	10
	START INVENTORY POSITION			30+0=>	30			
	PLANNED ORDERS				0+30-30 = 0			
	Safety Stock = 0	Lot size = 1	Lead time= 4					
	CHANGE IN PLANNED ORDERS	**+30**	**-10**	**-10**	**-10**			

Figure 7.3: Example: Planned orders under Roll-out without forecast consumption

In this example the 40 pieces customer order in the beginning of the week leads directly to an increase in the order that is placed to the plant, being 30 more. As the week progresses and no additional orders come in, every day the warehouses adjust their planned orders by the unmet forecast of 10 pieces a day. Clearly there is system nervousness in this plan. Now consider the same forecast and demand data, but this time with a forecast consumption logic where the demand consumes multiple days of the forecast:

PERIOD 1	INCOMING DEMAND	40						
	RENEWED FORECAST	0	0	0	0	10	10	10
	START INVENTORY POSITION	30						
	PLANNED ORDERS	40+0-30 = 10	10	10	10			
PERIOD 2	INCOMING DEMAND		0					
	RENEWED FORECAST		0	0	0	10	10	10
	START INVENTORY POSITION	30+10-40=>	0					
	PLANNED ORDERS		0+10-0 = 10	0	0			
PERIOD 3	INCOMING DEMAND			0				
	RENEWED FORECAST			0	0	10	10	10
	START INVENTORY POSITION		0+10=>	10				
	PLANNED ORDERS			0+20-10 = 10	0			
PERIOD 4	INCOMING DEMAND				0			
	RENEWED FORECAST				0	10	10	10
	START INVENTORY POSITION			10+10=>	20			
	PLANNED ORDERS				0+30-20 = 10			
	Safety Stock = 0	Lot size = 1	Lead time= 4					
	CHANGE IN PLANNED ORDERS	**0**	**0**	**0**	**0**	**0**		

Figure 7.4: Example: Planned orders under Roll-out with forecast consumption

The warehouse places orders based on the total demand during lead time and as the entire order is subtracted from the forecast, the planned order on day 1 does not change. Since no further orders come in during the week the planned orders also do not change during the week. In this example, no system nervousness is observed.

7.4   Research questions

Given that the bow-wave effect is a specific case of the concept system nervousness, the goal of the research described in this thesis is to reduce the bow-wave effect at Hilti and to provide valuable insights by investigating system nervousness in general. Due to the considerable size of the problem, the focus will be on one of the identified potential root-causes being the sub-optimal forecast consumption logic. It was decided to focus on forecast consumption logic since Hilti indicated that they had special interest in this topic. Additionally, by means of an exploratory analysis and a literature review into system nervousness this investigation aims to shed light on the root-causes in order to provide Hilti with possible directions for further research. Based on these objectives, the research question is formulated as follows:

> ***What are the causes of the bow-wave effect within Hilti and can system nervousness be reduced by adjusting the forecast consumption logic in the system***

To answer the main research question, the following five sub-questions are defined:
1. What are the factors causing system nervousness according to literature?
2. Which factors are causing system nervousness and bow-wave specifically within Hilti?
3. What is the most suitable way to quantify system nervousness?
4. Does demand uncertainty mediate the effect of forecast consumption logic on system nervousness and inventory levels in the supply chain?
5. What is the effect of forecast consumption logic on system nervousness and inventory levels in the supply chain?

7.5   Scope

A detailed analyses will be conducted based on forecast, sales and production data to answer the research question. The locations under consideration will be plant 4 and the regions HNA and LEC (central Europe). With these locations, both short and long supply lead time to the markets and a 2- and 3-tiers network are included.

7.6   Methodology

This research is based on the empirical cycle of van Aken and Berendsand will follow the methodology as depicted in Figure 7.5.

The empirical cycle is used for explanatory research, where an observation is seen for a specific relation(van Aken and Berends). Within this master thesis this concerns the relation between forecast consumption logic and system nervousness. Subsequently, the observation is translated into hypotheses about a general relation in an induction phase. How the hypotheses and heuristics developed during the induction phase will be validated, is explained in the deduction phase. Here, the methodology of Mitroff et al. (1974) will be used. The aim of the deductive phase is to create a scientific model which can be used to prove the relations between: forecast consumption logic and system nervousness/ bow-wave effect. First, during conceptualization the problem and the relevant system environment are given. Secondly, the scientific model is developed, which is the quantitative model that is used to validate hypotheses and heuristics. The next phase in this thesis is
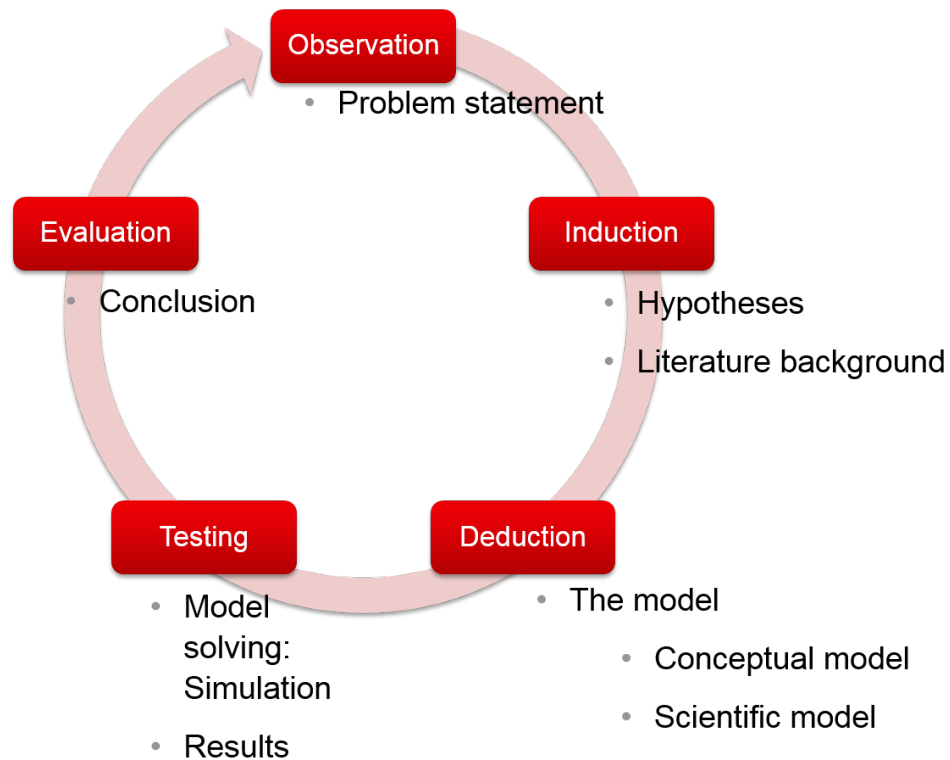
Figure 7.5: Methodology part 2

the test phase or model solving phase consisting of a case study that will be conducted with the use of Matlab. The case study will quantify the hypothesized relations, which in this case are the effects of forecast consumption logic on system nervousness. The thesis ends with an evaluation of the results of the model. Whether these results can be generalized and consequently the scientific value of this research will be discussed based on the conceptual model.

7.7 Thesis part outline

The remainder of this thesis is structured as follows: In Chapter 8,, a literature review is performed which provides the current understanding regarding system nervousness. In Chapter 9, the model which will be used to test the relation between forecast consumption logic and system nervousness, is given. In chapter 10, a case study will be conducted to give insight in the effect of Forecast consumption logic on system nervousness. Chapter 11 explores the existence and the effect of the other two root-causes on the bow-wave effect within Hilti as a start to further research.

8 | Literature background

In this chapter an overview is given of system nervousness and the bow-wave effect based on literature. First, the definition of system nervousness is defined in section 8.1 to ensure a common understanding of the concept. Thereafter, a distinction is made between factors that drive system nervousness and factors that influence system nervousness. Driving factors are in general hard to control by companies themselves and discussed in section 8.2. Influencing factors, discussed in section 8.3, are under control of a company and can be used to hedge against nervousness. The conclusions of these influencing factors including their impact are summarized in Table 8.1. The literature background ends with several available measures of system nervousness in section 8.4. With these measures, a suitable measure for the relation between forecast consumption logic and system nervousness can later be selected.

8.1 Nervousness definition

Today, production systems are expected to be flexible to reduce inventory costs and at the same time be able to react to demand changes (Bregni et al., 2013). Based on forecasts and with the use of rolling horizon planning, companies try to anticipate on the demand during coming periods. However, due to the stochastic nature of production, demand and supply production plans change constantly over time. This frequent replanning and rescheduling negatively influences system performance (Jensen, 1993). This instability in plans, is also called system nervousness or system instability. Other authors have defined system nervousness more specifically to either horizontal propagation in the supply chain, which is also referred to as the bullwhip effect, or vertically through planning hierarchies and through product structure levels(Andersen et al., 2014). Further differentiation's in nervousness can be found in section 8.4 where the system nervousness measures are explained.

System nervousness results in costs related to handling and implementing replanning and rescheduling messages, a complicated planning process and above all problems with capacity planning (Jensen, 1993). Other pitfalls of system nervousness are the general loss of confidence in planning (Inderfurth and de Kok, 1997) and increased inventory buffers (Andersen et al., 2014). These negative consequences of system nervousness are hard to translate to costs of lost profit (Inderfurth and de Kok, 1997) and hence are often evaluated as separate criterion in literature, see section 8.4.

In practice implementation of a rolling planning horizon is often found in MRP-systems, hence system nervousness literature is mainly in the context of MRP systems and MPS. Other investigation directions include line requirements planning, supply chain planning and planning hierarchy(Andersen et al., 2014).

8.2 Driving factors of system nervousness

When looking at the causes of system nervousness within literature a significant part is focused on demand characteristics(van Donselaar and Gubbels, 2002). The stochastic nature of demand causes expected demand to differ from actual demand and hence leads to system nervousness when production plans are flexible and react to demand (Demirel et al., 2018). In other words, the forecast error drives system nervousness. However,

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although majority of research conducted in the field of system nervousness is focused on demand uncertainty the same holds for production, capacity and supply uncertainty: when the planned productions orders cannot be produced in earlier cycles this will change the planned orders in the next production cycle(Pujawan, 2004).

A quasi optimal control rule based system performs optimally in a deterministic environment. Hence, when the production and demand characteristics become more stochastic the added value of quasi-optimal planning and control rules decreases. (van Donselaar and Gubbels, 2002). This phenomenon will be discussed in more detail for MRP systems, which is such a quasi-optimal control-rule and consequently received much criticism on its performance related to system stability.

Furthermore, since system nervousness is likely to ramify throughout the system (Inderfurth and de Kok, 1997), the number of item-levels itself and the complexity of the production process will influence system nervousness (Kaipia, 1997). The same holds true for the number of interrelations in planning systems and the delay of information between locations (Kaipia, 1997). To overcome information loss in the supply chain that may lead to increased system nervousness, information both upstream and downstream needs to be synchronized and plans should be stabilized (Kaipia, 1997).

8.3   Influencing factors of system nervousness

The drivers of system nervousness, as explained in the previous section, are in general hard to control for (Andersen et al., 2014). However, production planning decisions and inventory control decisions have a moderating effect between these drivers and system nervousness. Hence, companies can protect against system nervousness by making smart production planning and inventory decisions. In this sections these moderating effects will be discussed in more detail.

Under a rolling horizon planning, the length of the frozen horizon and the re-planning frequency directly influence system nervousness since it influences how the plan will react to external changes. Freezing the horizon limits the number of reruns and hence gives more stability in the production plan (Sridharan, 1990; Sahin et al., 2008). This also holds true for the re-planning frequency, a lower re-planning frequency leads to less system nervousness (Sahin et al., 2008) . Hence, increasing the frozen horizon or decreasing the re-planning frequency dampens system nervousness. Furthermore, the frozen horizon can best be managed by a order-based method. This may be done by e.g. taking a fixed number of orders instead of a fixed time of the frozen horizon. (Sahin et al., 2013). Zhao and Lee (1993) have stated that the choice of the frozen horizon length and re-planning frequency are a trade-of between costs, service levels and system nervousness. Although increasing the length of the frozen horizon decreases system nervousness, it also negatively affects service levels and costs under stochastic demand conditions (Zhao and Lee, 1993) . Increasing the planning horizon also increases system nervousness under stochastic demand conditions (Zhao and Lee, 1993). Less frequent re-planning seems to improve both service levels and schedule stability as well as reducing total system cost (Zhao and Lee, 1993) .

As described by Inderfurth and de Kok (1997) "the application of rolling horizons in inventory management is often found when inventory control rules are integrated in production planning where safety stocks and lot-sizing techniques are used to create medium-term sequence of production and ordering decisions for a certain number of planning periods". Inventory control rules and control parameters should be considered

when nervousness plays a role (Heisig and Fleischmann, 2001).

MRP systems have gained significant amount of criticism in literature (Inderfurth, 2009), with one of its major drawbacks nervousness (D'avino et al., 2013) . As mentioned above, MRP assumes deterministic demand and lead times and does not consider any capacity or supply constraints. Hence, rescheduling is necessary to come with a feasible solution that reacts on the stochastic behavior which can lead to instability. Based on this knowledge several authors have tried to improve the MRP logic itself to reduce system nervousness. D'avino et al. (2013) proposed an iterative solution where the MRP logic is first applied under a L4L policy. Subsequently a simulation is run that takes into account the capacity constraints and finally the simulation outputs are used to determine the orders using pre-defined lot-sizes.van Donselaar and Gubbels (2002) compared the MRP logic with line requirements planning (LRP), which differs from the MRP logic since it directly uses demand from final customers to determine the item demand in each level in the supply chain rather than calculating the demand backwards trough the supply chain (van Donselaar and Gubbels, 2002). LRP performed better in terms of costs, but no conclusions were drawn about the impact on system nervousness.
Research in the area of production and capacity uncertainty in relation to system nervousness is limited. Suggested methods to incorporate these uncertainties in the production plan are the use of safety lead time or safety capacity (Buzacott and Shanthikumar, 1994; van Kampen et al., 2012). Safety lead time is the overestimation of the average production time and/or transport time. Preparing capacity for more demand that is expected is called safety capacity.

One of the earliest and most investigated research directions in system nervousness was the relation with lot-sizes. If fixed lot sizes are used in production this leads to less nervousness in comparison to period lot-sizes(van Donselaar and Gubbels, 2002). van Donselaar and Gubbels (2002) explained the robustness of the fixed order quanitities (FOQs) model as follows: " the reason that less nervousness is reached with lot-sizes with FOQs is that there is a 'built-in robustness' in these FOQs. With FOQ more products are ordered so demand change has to be a lot bigger, before orders will be rescheduled". Comparable findings were found in inventory policies, where (s,nQ)-policies showed lower instability than (s,S)-policies (Inderfurth and de Kok, 1997). Although it should be noticed that for multi-level systems, a lot-for-lot order size for scheduling dependent items reduces overall system nervousness (Sahin et al., 2013).
Several authors have argued that the re-order point, or safety stock, does not influence system nervousness in production planning (Heisig and Fleischmann, 2001; Inderfurth and de Kok, 1997). However, holding safety stock is a common method to hedge for quantity uncertainties (Inderfurth, 2009). The economic benefit of safety stock is found with infrequent rescheduling in combination with safety stock (Sahin et al., 2013). Here, infrequent rescheduling reduces system nervousness, whereas the same service level can be reached due to safety stock. Hence, even though safety stock does not change the net requirements in the system, it does give the production more tolerance to react on demand changes.

To conclude, it is important that companies are aware that inventory decisions and production planning decisions influence the amount of system nervousness. When applying changes, like a new segmentation approach companies may consider the trade-off

between costs, service level and stability. Table 8.1 gives an overview of the several factors that impact system nervousness.

Table 8.1: factors that impact system nervousness

System nervousness drivers	↑ Demand uncertainty	↑
	↑ Forecast error	↑
	↑ Capacity uncertainty	↑
	↑ Production uncertainty	↑
	↑ Supply uncertainty	↑
Production planning decisions	↑ Planning horizon	↓
	↓ Replanning frequency	↓
	↑ Frozen horizon	↓
	Order-based frozen horizon method	↓
	Capacity based planning	↓
	Safety capacity	↓
	Safety lead time	↓
Inventory management decisions	↑ Safety stock	↓
	Fixed production lot sizes	↓
	↑ Network cooperation	↓
	↑Human interference	↑

8.4 Measuring system nervousness

Since system nervousness is investigated in multiple contexts there are also different ways that system nervousness is measured in literature. Blackburn et al. (1986) were one of the first to define a measure for system nervousness. They recorded the total unplanned and changed orders placed in period one of the planning horizon as compared to the previous planning cycle. Despite the simplicity of this measure, it has been used in several studies to show system nervousness In this section, the focus is on articles that have (in)stability measures as main investigation topic;(Kabak and Ornek, 2009; Jensen, 1993; Sridharan et al., 1988; Kimms, 1998; Tunc et al., 2013)

8.4.1 The first metric: single-item single-level quantity approach

Sridharan et al. (1988) argued that the metric proposed by Blackburn et al. (1986) was not adequate, since it does not consider the entire planning horizon and depends strongly on the planning horizon length. Furthermore, when the entire planning horizon is considered one should consider the relative impact of system nervousness over the planning horizon. The metric they proposed overcomes these problems and is known in literature as the SBU metric. By taking the weighted average over the schedule changes of the planning horizon, the SBU puts more emphasizes on nervousness close to the current period (Sridharan et al., 1988). Furthermore, the SBU method takes the absolute values of order deviations between two successive time periods into account to incorporate both up and downward adjustments. The SBU method is mathematically formulated as follows:

$$I = \frac{1}{S} \left(\sum_{\forall k > 1} \sum_{t=M_k}^{M_k-1+N-1} |Q_t^k - Q_t^{k-1}|(1-\alpha)\alpha^{t-M_k} \right) \tag{8.1}$$

Where:

t = time period

Q_{tk} = scheduled order quantity for period t during planning cycle k

M_k = beginning period of planning cycle k

N = planning-horizon length

α = weight parameter $(0 < \alpha < 1)$ S = total number of orders over all planning cycles

R = average period requirements T = natural cycle $\left(\frac{eoq}{R}\right)$

8.4.2 Set-up oriented vs quantity oriented approach

A distinction can be made between set-up oriented and quantity oriented nervousness measures. This distinction was first made by Jensen (1993) inspired by the well-known α and β service levels. He stated that these measures should be used complementary to one another. The importance of both measures depends on the production characteristics and its set-up. When set-up times are long or set-up costs are high companies might be more interested in set-up oriented nervousness. Whereas, if the number of set-ups is relatively stable, or set-up times are negligible a quantity oriented measure might give more insights in the performance of the system.

8.4.3 Multi item quantity-oriented approach

Kimms (1998) adds to the quantity-oriented stability measure literature by defining a measure that weights not only over time but also over items. Hereby enabling to compare total system instability while the impact of several items can still be considered. Moreover, Kimms (1998) proposes two measures, one that looks at the average instability over the planning horizon and a second that looks at the maximum instability over the planning time horizon. Furthermore, it is stressed that an instability measure should be solved in combination with the cost objective functions. Kimms (1998) recommends adding a maximum allowed instability to the optimization production schedule module.

8.4.4 Multi-item Multi-level approach: planned vs. open orders

Kabak and Ornek (2009) defined 4 multi-item multi-level criteria that could be combined to one weighted criterion. The four criteria consist of : 1. Quantity oriented POR instability 2. Quantity oriented SR instability 3. Set-up oriented expedited released POR instability 4. Setup-oriented SR instability. Hereby several weighting factors are included per criterion. One major difference between this measure and earlier proposed measures is that two of the measures proposed are looking at scheduled receipts/open orders. Reshuffling of open orders may increase costs and/or impact lower tiers (Kabak and Ornek, 2009). Furthermore, several weighting factors are included to reflect the seriousness of a change, both for item-level and position in planning horizon. The impact of rescheduling open orders is measured as a function of the change in cumulative lead-time and is higher for expedited items as for postponed items.

8.5 Reflection on nervousness measures

This section will reflect on the applicability of the nervousness measures proposed in section 8.4 for Hilti and a new system nervousness measure will be proposed based on the recognized shortcomings of the measures from Literature.

Kabak and Ornek (2009) developed the most extensive system nervousness metric in which several factors can be taken into account. This metric was proposed as a way

to compare several production systems and could additionally be used as a warning tool that tracks the performance of the current production system. Within this master thesis the need for such a tool within Hilti is recognized. First of all, at Hilti multiple projects are started related to system nervousness: bow-wave and now subsequent to that net requirements change. Consequently, there is currently no tool in place to measure nervousness adequately. Additionally, the implementation of HIP is expected to influence system nervousness and hence it would be beneficial to track its performance. When Hilti wants to build such a tool this requires first of all a link to the system in a way that order data can be extracted. Furthermore when implementing such a system the definition of the weighting factors need to be determined. For Hilti stability is especially important in terms of capacity, such that the planned capacity suits the actual needed capacity.

A shortcoming of the proposed measures is their inability to capture capacity planning issues. None of these measures are able to signal time capacity problems per production line since downward and upward deviations among items do not level each other out. As capacity planning is a major issue when dealing with system nervousness, both within Hilti and in other companies, a new measure is suggested in this master thesis that aims to reflect the severity of nervousness for capacity problems on a weighted line level. This measure differs from other measures in three ways. First of all, the measure looks at the relative change in net requirements as compared to the previous period. In this way, the measure directly shows the impact on the shop floor. Secondly, the weighted factor per item is based on the throughput time of that item on the line, such that the measure shows how the required capacity changes. Thirdly, the measure aggregates on items per production line, the absolute value is taken from the total deviations per period. In comparison to previous measures that take the absolute deviation per item before aggregating, this measure reflects the net changes per line per period rather than the overall item level nervousness. The measure is formulated as follows:

$$
I_{line}(k) = \frac{\sum_{t=M_k}^{M_{k-1}+P-1} W_t(t) \left| \sum_{\forall i} (Q_{i,t}^k - Q_{i,t}^{k-1}) W_i(i) \right|}{\sum_{t=M_k}^{M_{k-1}+P-1} \sum_{\forall i} Q_{i,t}^{k-1} W_i(i)}
\tag{8.2}
$$

where:

i	= SKU
k	= Planning cycle
t	= time period
M_k	= Beginning period of planning cycle k
P	= Length of Planning horizon
$Q_{i,t}^k$	= Planned order quantity for item i during planning cycle k for period t
$W_i(i)$	= Weight function corresponding to the throughput time of SKU i on the line
$W_t(t)$	= Weight function over time

The weighting factor over time, $W_t(t)$, may differ based on companies preferences, how this is defined in previous research can be found in appendix **??**.

9 | Experimental design

To the author's knowledge, the relation between forecast consumption logic and system nervousness has not been investigated before. In this chapter an evaluation model is developed that can be used to investigate the relation between forecast consumption logic and system nervousness. First, the decision parameters that define the forecast consumption logic are given in section 9.1. Second, the experiments that will be used to test the performance of the several forecast consumption logics will be formulated in the model description(section 9.2). This section includes the relevant variables, the scope of the problem, the interaction between variables and the assumptions that where made. Third, the performance measures that are used to interpreted the outcomes are formulated in section 9.3. The mathematical formulation of the experimental design can be found in Appendix J.

9.1   Forecast consumption logics

In section 7.3 it was hypothesized that the forecast consumption logic should be extended to multiple days to reduce nervousness. In this section, the decision parameters that define the exact forecast consumption logic are introduced.

The first decision parameter is whether the orders should consume forecasts in subsequent periods (forward consumption policy), in preceding periods (backward consumption policy) or both (Forward-Backward policy). Note that backward consumption is only possible when orders are known in advance.

The second decision variable is the length of the consumption horizon (denoted by c_h). As the consumption horizon increases more emphasizes is put on the forecast and less on the actual demand. This makes the system less reactive to demand changes. How this influences the outgoing orders to the plant also depends on the lead time as orders are placed based on the expected demand during lead time. This can be demonstrated by a simple example: for a given product the daily forecast is 20, incoming orders are consumed forward and today an order comes in for 200 pieces. With a lead time of 10 days, there is no change in observed net requirements during lead time and no additional orders are placed. With a lead time of 2 days however, the increase in net requirements over these two days is 160, which might result in an additional order to the plant.

The third decisions variable is how the forecast horizon is fixed. Here two options are explored: fix the number of days forecast should be consumed (c_Δ=days) and fix the forecast horizon on the number of weeks forecast should be consumed(c_Δ=Weeks) . Since the forecasts are originally made for weeks, a potential benefit is expected from using a forecast consumption logic that consumes on weekly buckets.

The fourth decision variable is the allocation of consumption. When the consumption horizon is determined, it must be chosen which days in the forecast horizon will be consumed. It was chosen to consume the days closest to the incoming order date.
The forecast consumption logic aims to reduce the nervousness when demand is higher

---

	Week	1					2					3					4				
		Mo	Tue	Wed	Thur	Fr	Mo	Tue	Wed	Thur	Fr	Mo	Tue	Wed	Thur	Fr	Mo	Tue	Wed	Thur	Fr
	Forecast	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20
	Order							200													
Forward	5 days	20	20	20	20	20	20							20	20	20	20	20	20	20	20
	1 week	20	20	20	20	20	20					20	20	20	20	20	20	20	20	20	20
Backward	5 days	20							20	20	20	20	20	20	20	20	20	20	20	20	20
	1 week	20	20	20	20	20			20	20	20	20	20	20	20	20	20	20	20	20	20
Forward Backward	5 days	20												20	20	20	20	20	20	20	20
	1 week	20	20	20	20	20						20	20	20	20	20	20	20	20	20	20

Figure 9.1: Example of forecast consumption logics

than expected. However, also when demand is lower than expected, the forecast consumption logic can be used to stabilize net requirements by keeping unconsumed forecasts in the system. The number of days the forecast is kept in the system is set equally to the chosen consumption horizon. Currently, keeping the unconsumed forecasts is not supported by the systems at Hilti. Therefore, the fifth decision variable concerns the consumption when demand is lower than forecasted. Both situations, where past forecast is kept in the system ($\delta_{fcstkept}$ = Yes) and where past forecast is deleted ($\delta_{fcstkept}$ = No), are investigated.

The last decision variable is the inclusion of network demand. Currently at Hilti, only direct customer orders are consumed, and lower tier orders are not. As the forecast is based on both direct customer orders and lower tiers orders, it seems logical to expect that network demand is included in the consumption logic. As this is currently not the case at Hilti both situations, where network demand is included in consumption (δ_{nd}=yes) and where network demand is not included in the consumption (δ_{nd}=no), are evaluated.

9.2 The model

To capture the effect of forecast consumption logic on system nervousness the model aims to resemble the current used MRP logic within Hilti. Due to time limitations it was chosen to focus on a single echelon model, in which the forecast location is examined. By measuring the satisfied orders from lower tiers and the nervousness in planned receipts to the plant, the effect of the forecast consumption logic on the entire network is approximated. A rolling planning horizon is used, similar to the system at Hilti: every day the expected net requirements for the coming 4-months are re-calculated, which is based on the (updated) demand and forecast and the inventory levels. Unsatisfied demand in case of shortages are back-ordered. Furthermore, it is assumed that incoming orders are treated FCFS, and that there is no supply uncertainty (deterministic lead times and ample capacity at the plant). The input parameters are visualized in 9.1.

General Variables	Demand
Order Quantities	Daily Demand Forecast
Lead times	Daily replenishment orders
Cost parameters	Daily customer orders
Safety Stocks	

Table 9.1: Input parameters and variables quantitative model

9.3 Performance measures

To be able to compare the influence of several forecast consumption logics, three key performance indicators (KPIs) are defined. First of all a measure is introduced that captures system nervousness. Additionally, The performance to the customers and lower tiers needs to be monitored and the stock levels in the warehouse should be captured. The notation that is used in this section is defined in table 9.2.

Table 9.2: definition of variables

Variable/ Parameter	Definition
i	SKU
k	Planning cycle
t	period for which the plan is made, in this case equal to k
T	Frozen horizon length
m_k	Start of planning cycle k
p_i	price of SKU i
SR_i^k	Scheduled Receipts for SKU i scheduled at planning cycle k
$PO_{i,t}^k$	Planned Orders for SKU i , planned in period k for period t
$D_{i,t}$	Total demand for SKU i for period t
$IOH_{i,t}$	inventory on hand at t

System nervousness measure

As the focus is on the nervousness that comes from the forecast consumption logic in the warehouses, we cannot measure the impact on planned order releases and scheduled receipts within the plant but focus solely on the outgoing scheduled receipts from the warehouses. Hence, the nervousness measure will be a simplified measure of the measure proposed earlier. The measure will compare the actual scheduled receipts to the planned orders the previous day, and is mathematically defined by:

$$Nervousness = \frac{\sum_{\forall i} \sum_{\forall k} \sum_{t=M_k}^{m_k+T} |SR_i^k - PO_{i,t}^{k-1}|}{\sum_{\forall i} \sum_{\forall k} \sum_{t=M_k}^{m_k+T} D_{i,t}} \tag{9.1}$$

Fill-rate

To track the service level offered to lower tiers and customers the aggregate fill rate will be measured, which is calculated as follows:

$$Fillrate = \frac{\sum_{\forall i} \sum_{\forall t} min\left(D_{i,t}, IOH_{i,t}\right)}{\sum_{\forall i} \sum_{\forall t} D_{i,t}} \tag{9.2}$$

Average inventory cost

The expected inventory cost is the expected cost incurred due to holding inventory in a certain time period. This is calculated based on the expected on hand inventory and product holding cost. The product holding cost are equal to product price times .12, as is standard formulation within Hilti.

$$IneventoryCost = \sum_{\forall i} \sum_{\forall t} p_i IOH_{i,t} \tag{9.3}$$

10 | Case Study

10.1 Experimental Setup

To compare the performance of different forecast consumption logic's a case study is conducted on data of 51 SKUs within Hilti from June 2017 to July 2018. In the previous chapter six decision parameters are identified that together form the forecast consumption logic. In total 112 different policies(see table 10.1) are evaluated in MATLAB, as described in the experimental design.

Table 10.1: Case study decision variables

Decision Variable	Values
Policy	[Backward, Forward, Backward Forward]
δ_{nd}	[Yes, No]
$\delta_{fcstkept}$	[Yes, No]
c_Δ	[weeks, days]
c_h	[0,1,5,10,15,20] for c_Δ=days
	[5,10,15,20] for c_Δ=weeks

Based on Hilti's recommendation it was chosen to focus on the regions HNA and LEC, as these regions make up for a large part of Hilti's profit and reflect both short and long lead times in a 2- and 3-tiers network. There are 5 RDC's in LEC and 2 in HNA. The warehouses under consideration in E3 deliver both to the end-customers and Hilti stores. HNA additionally delivers to downstream distribution centres, the so called network demand. The choice of SKU's was based on several criteria. First of all, products were chosen that where produced in plant 4, such that a possible relation with the bow-wave could be investigated. Secondly, the production lines under consideration should not have too many phase-in and phase-out items, and the items should be forecast driven, make to order. Together with the material manager from plant 4 based on these criteria, production lines montage linien (ML) ML05, ML53, ML45,ML34 where selected. This resulted in 51 SKU's that where forecast driven during June 2017 to July 2018. The necessary input parameters for the model where retrieved from Hilti's database, below it will be discussed how these parameters where retrieved and how these could deviate from the real parameters. An overview of the input data is given in Appendix K

Actual demand

Actual demand can be divided into replenishment orders and customer orders. Customer order can be known in advance, hence we collected both the date the order was created and the date the order should be delivered. From the replenishment orders we have extracted the delivery dates. We argue that replenishment orders are not known in advance, since locations downstream of the forecast location work with simple reorder methods such as base-stock and min-max criteria. Emergency shipments to other warehouses and returns are excluded from the model.

Demand forecast

At Hilti the forecasts can be changed everyday, however these changes are not stored in

the system. From the past only three snap-shots are available of the forecast: the last updated forecast(lag 0), a forecast made 2 months in advance (lag -2) and a forecast made 4 months in advance (lag -4). Hence, in the simulation we will include a forecast horizon of 4 months. Starting with the lag -4, at the beginning of month 3 the forecast will be changed to lag -2 and at the beginning of month 4 this will be changed to lag 0. Furthermore, the forecasts are made on a weekly basis in JDA, within APO these weekly forecasts are allocated to days. The allocation rule allocates as much as possible equally over the week days. When the forecast is not a multiple of five, the remaining forecast is allocated as follows:

If 1 pcs → Friday
If 2 pcs → Friday and Wednesday
If 3 pcs → Friday, Thursday and Tuesday
If 4 pcs → Tuesday to Friday

Inventory management and general variables
Safety stock, order quantity, lead times and product costs are assumed to be constant over time and are set equal to the current settings in SAP.

10.2 Results

In this section, the results of the experiment as described above will be discussed. In figures 10.1,10.2,10.3,10.4,10.5,10.6,10.7,10.8, these decision variables where plotted on the x-axis. The bars reflect the policies in which replenishment orders are consumed (δ_{nd} = 'Yes') or not (δ_{nd} = 'No') and whetor not unconsumed forecast from the past is kept (respectively, $\delta_{fcstkept}$='Yes' or $\delta_{fcstkept}$='No').

Initially the performance of the several forecast consumption logics (FCLs) was compared in the situation where MO's can place order daily, which is the real situation for the production lines that are not yet on HIP. Subsequently, it is tested how these FCLs would perform when production plants freeze the production for one week on Monday, which reflects upon the HIP process, with weekly order commitment.

10.2.1 Without HIP (daily fluctuations)

Effect of FCL on Nervousness
From figure10.1 it can be observed that without the inclusion of network demand and/ or keeping unconsumed forecast there is no FCL that reduces system nervousness as compared to the current approach. The inclusion of network demand in the forecast consumption logic immediately improves the nervousness, with an 8% reduction. However, when a longer forecast consumption horizon is taken, the inclusion of network demand only harms system nervousness when past unconsumed forecast is not kept. When past unconsumed forecast can be kept in the system, nervousness is decreased when a forward weekly consumption policy is applied.
Fill rate vs costs FCL
In figure 10.2 the Fill rates and cost for the several FCLs are shown. The most outstanding results are those when unconsumed past forecast is kept in the system and network demand is not consumed. This can be explained by the fact that the amount of forecast that is kept is high, since network demand does not consume the forecast. Hence
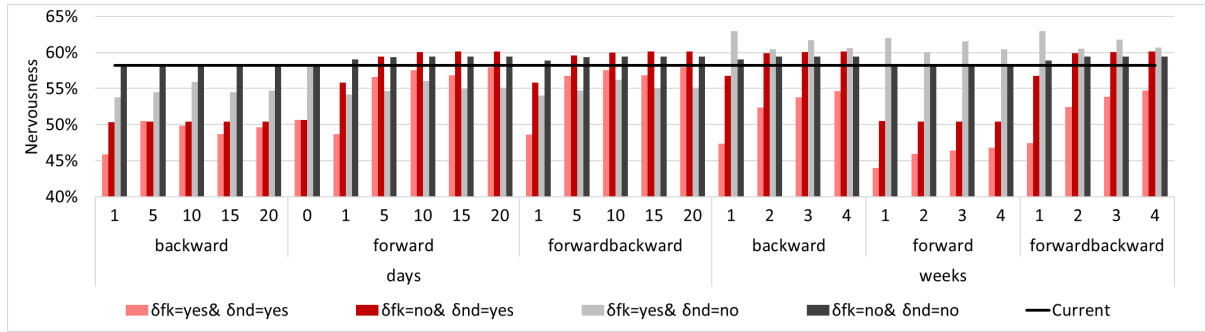
Figure 10.1: Nervousness against FCL's (non-HIP)

inventory levels are high and both Fill rate and cost increase. Another interesting finding is that the weekly forward policy, where unconsumed forecast is kept in the system and network demand consumes the forecast, did not significantly change the fill rate and cost compared to the current situation. Overall there was no logic that improved both Fill rate and costs, in Appendix L the Fill rates and Costs are plotted.
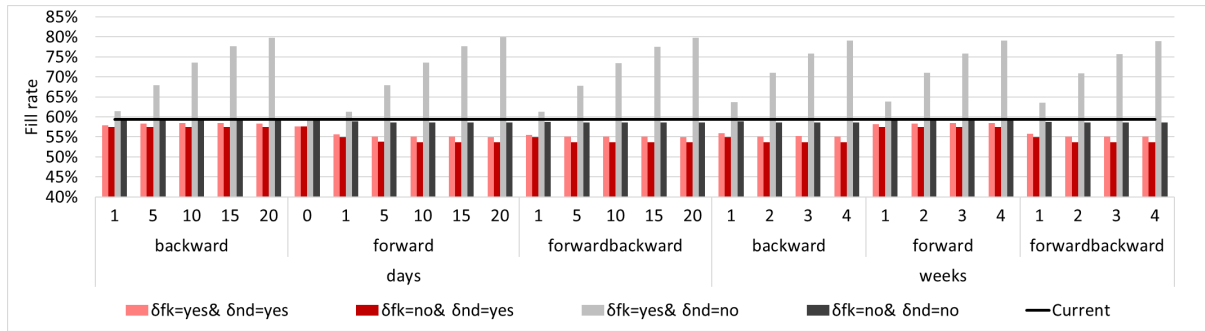
Figure 10.2: Fill rate against FCL's

Figure 10.3: Cost against FCL's
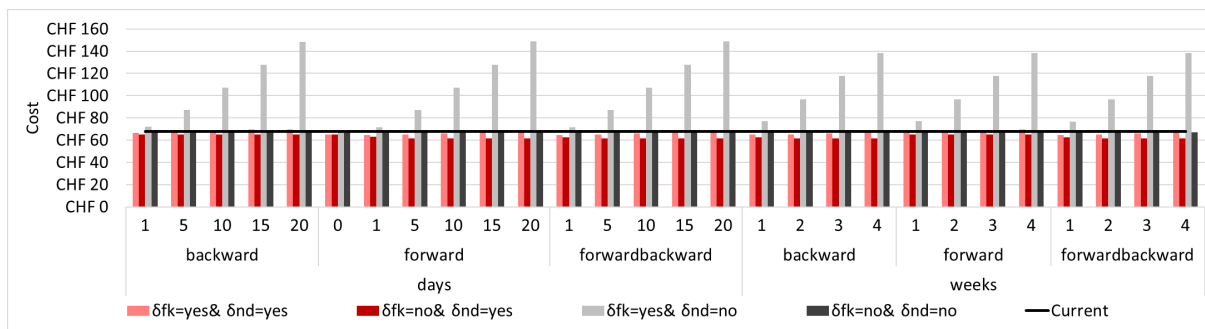
Difference between product segments

Until now, the results have been discussed based on the average nervousness among all products. Additionally, the nervousness among items is tested. To do so, the items are clustered based on three different criteria:

1. Lead time (>week= High, ≤week=Low)
2. weekly CoV (>1,33= high, < 1,33 & ≥ 0,75=medium, < 0.75 =low van Wanrooij (2012))

3. Forecast Accuracy

The results per cluster showed a significant difference. To be able to graphically show the results, it was chosen to focus here on the output of the logics where replenishments consumed demand and past unconsumed forecast was kept. The biggest difference was observed when segmented on Forecast accuracy, see Figure 10.4b. Products with a high forecast accuracy experienced around 30% less nervousness as compared to products with a low forecast accuracy. However, it can also be observed that the performance of the several forecast consumption logics does not depend on the forecast accuracy. The same holds true for the CV, see Figure 10.4a. The products with a high CV resulted in 25% higher nervousness as compared to the products with a low CV. When comparing FCLs, the same trend is observed for products with different CV's. Lastly, it was observed that products with a long lead time resulted in 10% less nervousness as compared to products with a short lead time, see figure 10.4c. Again, no difference was found in the effect of FCLs between a long lead time and a short lead time.
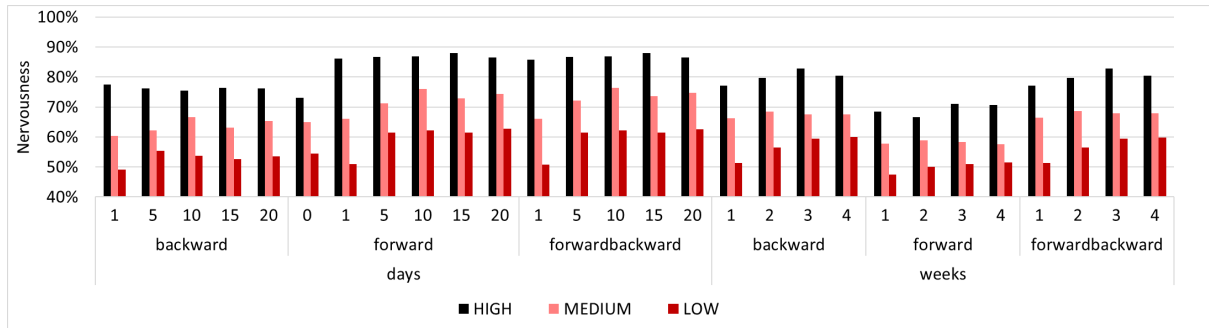
(a) CV
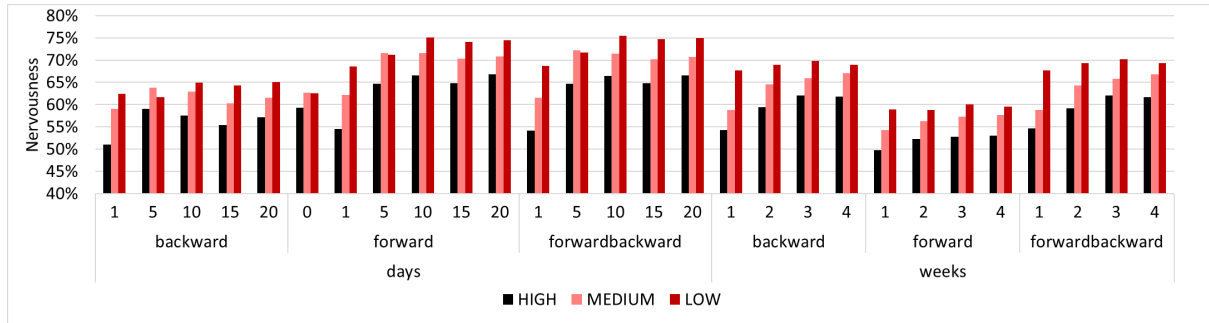
(b) FA
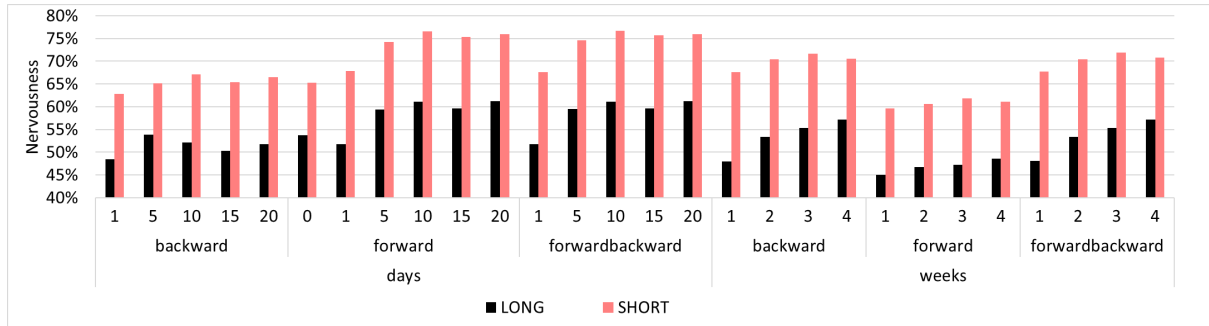
(c) LT

Figure 10.4: Nervousness per segment non-hip

10.2.2 With HIP

With the implementation of HIP, the production plants fix the produced quantities on Monday for the rest of the week. Hence, we also looked at the nervousness under such order commitment.

Effect of forecast consumption logic on nervousness

Figure 27 shows the nervousness among the different FCL's when the production plant fixes the production quantities every Monday. The most outstanding result is that the order commitment itself reduced system nervousness by 26%, which is more than could be reached by applying a different FCL alone. Further, it is observed that the inclusion of network demand no longer has a major effect on system nervousness when unconsumed forecast is not kept. The inclusion of both past unconsumed forecast and consuming replenishment orders did lead to a decrease in nervousness among most of the FCLs, with as exception those with a small consumption horizon.
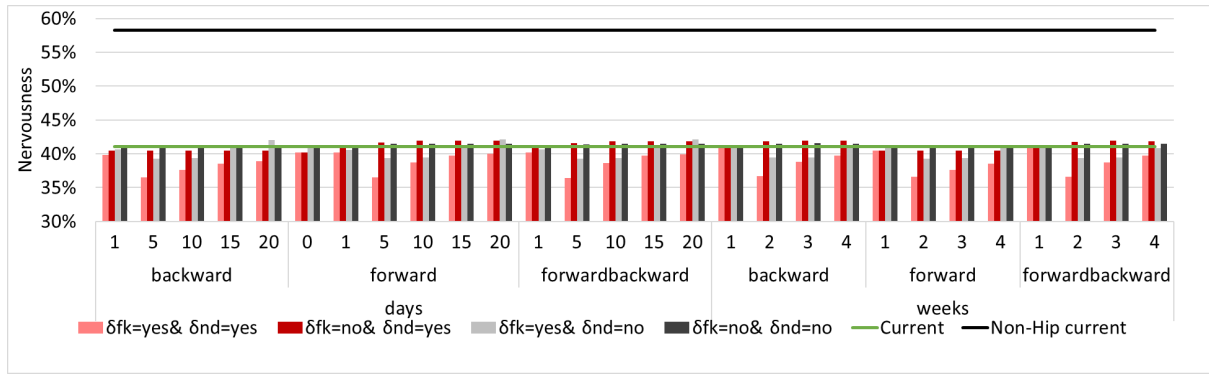
Figure 10.5: Nervousness against FCL's (HIP)

Relation between Forecast consumption logic and Fill rate/ cost

First of all, it can be observed that the implementation of HIP reduces also the fill rate and costs, see figures 10.6 and 10.7. Also the inclusion of network demand resulted in both a fill rate and cost reduction. Keeping past unconsumed forecasts improved the fill rate and increased the costs, especially when replenishment's did not consume the forecast.

Figure 10.6: Fill rate against FCL's
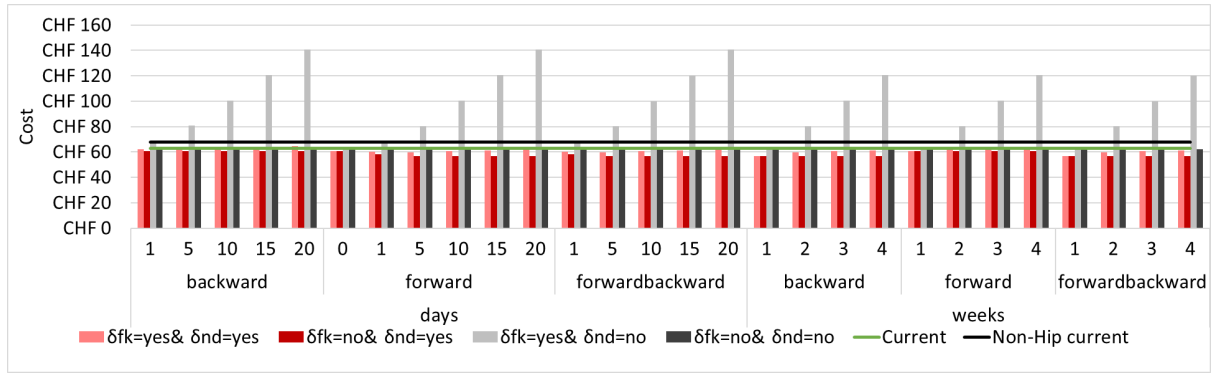
Figure 10.7: Cost against FCL's

Nervousness for different product segments

At a first glance figure 10.8 shows comparable results to the situation without HIP. Products with a high FA, low CV and long lead time showed less nervousness as compared to the products with a low FA, high CV and short lead time respectively. However, when taking a closer look at the FA, this relation looks less stable among different FCLs. Here the nervousness observed for products with a high FA fluctuates up and down when increasing the consumption horizon. The products with medium or low FA, show a concave pattern when looking at the length of the forecast consumption horizon length. This property is not seen for the products with a high FA, which makes it more difficult to draw conclusions with respect to the optimal FCL.
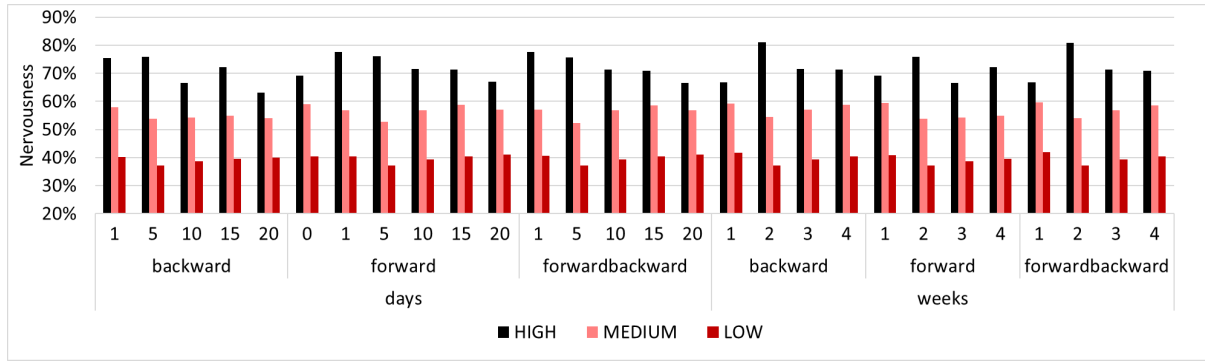
(a) CV
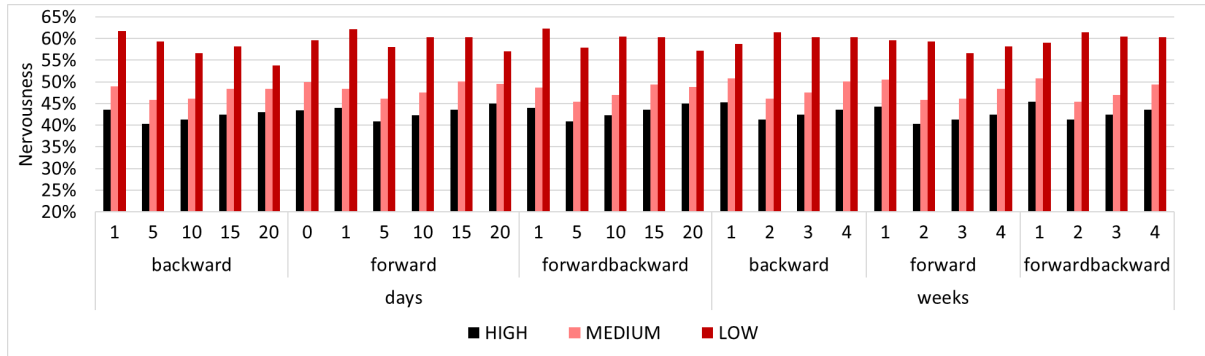
(b) FA

(c) LT

Figure 10.8: Nervousness per segment HIP

10.3 Conclusion

In this chapter the current consumption logic within Hilti is challenged by means of a case study. It was found that the Forecast consumption logic that is chosen in the MRP system does influence system nervousness, costs and fill rates. In this case study, the best policy in terms of reducing nervousness was a forward weekly consumption logic where replenishment orders consume the forecast and past unconsumed forecast was kept during the week. This policy did however slightly decrease the fill rate, but the costs where comparable to the cost of the current logic.

The introduction of HIP, where the MO's commit to the orders every Monday, did decrease system nervousness significantly. Furthermore, the costs and fill rate showed a decrease from non-HIP to HIP.

The impact of the forecast consumption logic on system nervousness was small compared

to the improvement that is reached by the introduction of HIP. Again a weekly forward policy in which past unconsumed forecast was kept and replenishment orders were also consumed, performed best in terms of stability. Here a two- or three-week forward consumption logic did not seem to harm the fill rate significantly, nor did it increase the costs. Furthermore, it was observed that the SKU's with a high CV of low FA showed much higher nervousness, which was expected as explained in the literature review. However, the effect of several FCLs on system nervousness showed the same pattern for products within the different segments, with an exception of products with a high FA under HIP. Hence, based on this analysis, the need for a segmented approach for FCL is not seen.

11 | Remaining Root-causes: exploratory research

As identified in the problem statement, three possible root-causes to the bow-wave effect have been identified by Hilti:

- Over-/under-forecasting
- A mismatch between planned and actual production
- A sub-optimal forecast consumption logic

The developed model has proven the small impact of a sub-optimal forecast consumption logic on the bow-wave effect or in general on system nervousness. Therefore, the interest in the other two root-causes needs to be further explored as more likely causes of system nervousness. With the aid of interviews and data evaluation the impact of over-/under- forecasting and a mismatch between planned and actual production is evaluated as a start to further research in 11.1and 11.2 respectively. Section 11.3 concludes on important findings of the causes of the bow-wave effect.

11.1 Over-/under-forecasting

Over-/under-forecasting is the first root-cause Hilti identified for the Bow-wave.In chapter 8 it was concluded that forecast inaccuracy is in general a driver of system nervousness. As can be seen in figure Figure 11.1, the monthly forecast accuracy on SKU level in region LEC, the region with the highest forecast accuracy, is on average between 12%-60%. Moreover, as the frozen planning horizon is shorter than 1 month, the forecast accuracy during this period will be even lower. This indicates that Hilti has to deal with a significant amount of demand uncertainty.

Forecast Accuracy lag 4		Year ▼	Month ▼						
		⊟2018							
Logistics Hub ▼	Deman ▼	1	2	3	4	5	6	7	8
⊟LEC	MAT	53.5 %	54.5 %	58.7 %	62.4 %	51.8 %	60.9 %	60.7 %	58.5 %
	MBE	41.9 %	46.1 %	45.4 %	44.9 %	46.9 %	49.8 %	21.2 %	45.4 %
	MCH	57.6 %	60.3 %	58.7 %	57.9 %	54.9 %	56.4 %	55.6 %	57.1 %
	MCZ	49.9 %	51.2 %	52.4 %	48.1 %	54.6 %	50.5 %	52.2 %	51.6 %
	MDE	56.7 %	56.2 %	59.2 %	59.8 %	47.8 %	57.4 %	60.1 %	62.6 %
	MNL	50.3 %	44.6 %	46.2 %	45.6 %	37.7 %	41.9 %	39.3 %	26.2 %
	MPL	55.6 %	49.4 %	56.2 %	59.2 %	51.5 %	54.9 %	54.7 %	52.7 %
	MSI	25.6 %	12.3 %	16.9 %	28.6 %	34.7 %	23.5 %	26.5 %	22.7 %

Figure 11.1: Forecast accuracy lag 4 LEC

Sahin et al. (2013) noted that currently no research has been conducted regarding forecast updating in relation with rolling horizon planning. Although the exact relation between forecast updates and planning instability has yet to be investigated, changing forecasts within the planning horizon does influence the production plan. On a global level it is observed that Hilti's short term forecasting are over-forecasting demand en their long term forecasts are underestimating demand, see figure 11.2a. This can lead to a bow-wave, as the planned orders for the next month will increase as the forecast

increases and during the month the number of orders will decrease when the real demand turned out to be lower than the latest forecast. One explanation of the increased forecast close to the current period could be that the judgmental forecast update, which is in general done for periods close to the current period, are over-estimating demand. Judgmental forecasts are more often over-estimating demand in general (Armstrong and Green, 2012). However, while taking a closer look at the forecast of plant 4, it turned out that the consensus forecast for plant 4 was underestimating demand, see Figure 11.2b.

(a) Global forecast accuracy

(b) Forecast versus demand plant 4
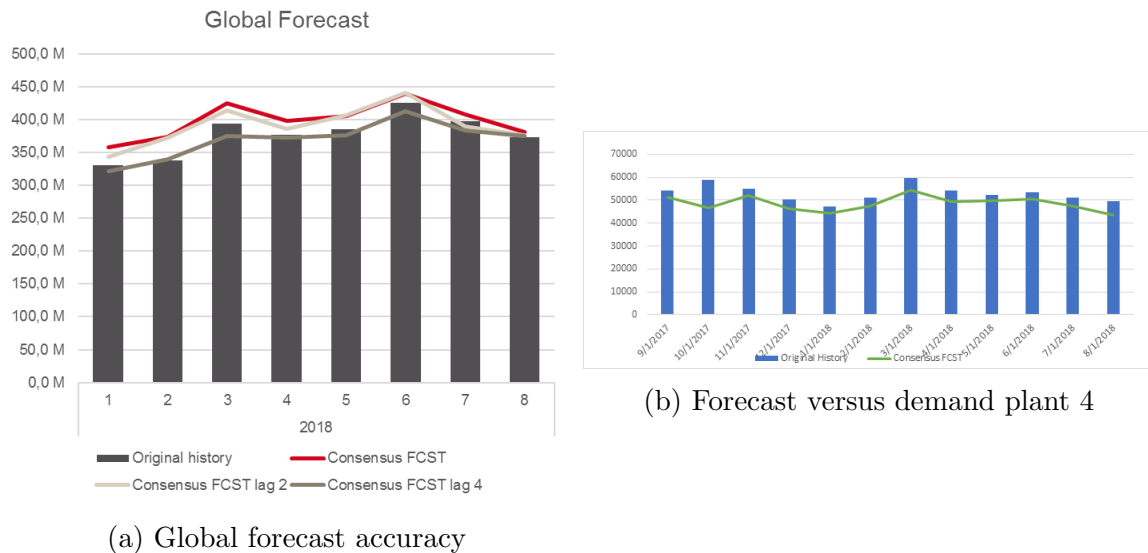
Figure 11.2: Forecast vs real demand

As the forecast can change daily, the consensus forecasts are not enough to provide clear insight into the forecast updates. However, the daily or weekly forecast updates are normally not kept in the system. The only available weekly forecast updates are from ML05, ML09, ML45 from May to July. This data is depicted in figure Figure 11.3. Here it looks like the forecast 1 month in advance is increased, corresponding to the timing of the observed bow-wave. However, due to the limited data it is hard to draw general conclusions.
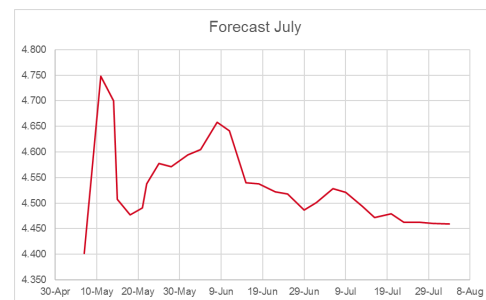
Figure 11.3: Forecast for July over time for ML05, ML09, ML45

Lastly, it is observed that the forecasts for new products are more often adjusted in the last minute. New products are harder to forecast, introduction to the market can be postponed and supply issues occur more often than for normal products. Production line ML09 is currently dealing with phase-in and phase-out items, where the introduction to the market was postponed, within the bow-wave tool it was observed that this line showed a strong bow-wave.

11.2 A mismatch between planned and actual production

Capacity, production and supply uncertainty can cause order postponements, which lead to system nervousness, as discussed in chapter 8. Plant 4 tracks their order postponements in an excel file, this file will be used to explore capacity, supply and production uncertainty. Table 11.1 shows the total postponed order quantities during the first 7 months of 2018. The rows show the month in which the orders were originally planned and columns show the month in which they were eventually produced. As can be seen production quantities are postponed over months. The quantities postponed are lower than the total quantities in the wave, as observed in 7.1, e.g. in January the bow-wave was around 10000 pieces, and here we see that only 1900 pieces where postponed. Hence, order postponement partly explains the bow-wave effect.

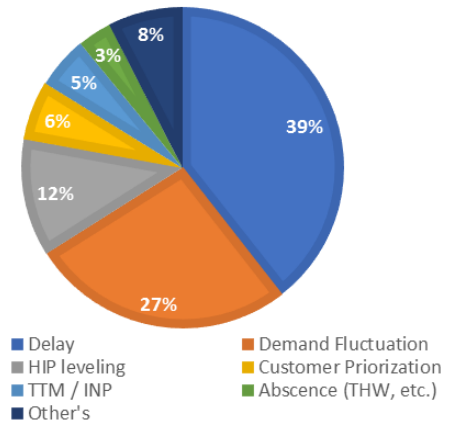|	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Jan	89	19	1						
Feb		33	11						
Mar			35	13					
Apr				42	19	1			
May					60	19			
Jun						41	14		
Jul							37	8	
Aug								26	3
Sep									28

Table 11.1: Quantities moved between months in hundreds

Figure 11.4: Reason for postponement

A further analysis was necessary to see what caused the order postponements. In Figure 11.4, the reasons for postponement are graphically depicted. 39% of the orders where postponed due to a delay in production, production uncertainty. Another 39% percent of postponed orders resulted from demand fluctuations and HIP levelling, i.e. demand uncertainty. HIP levelling is the capacity based planning, meaning that the total orders in a period could not be produced with the given capacity. The same holds for forecast fluctuations, which means that in the just-in-time (JIT) process the total amount of incoming orders exceeded the capacity. Customer prioritization means that the production was focused on a big order for a market, for example due to extra demand during promotions and events. When new products are developed and test cases have to be made, these are prioritized above other orders, this is called Time to market/ introduction new product (TTM/INP). Absence is another source of capacity uncertainty. Other reasons for postponement include maintenance, supply issues, human mistakes, quality issues and system errors.

In addition, the plant confirmed that already postponed orders are given less priority to ensure that the other orders are not delayed. Sometimes postponed orders are shifted further then subsequent orders for the same location. It is often uncertain whether these postponed orders are still required. An extreme example encountered was an order that was postponed eight times, with more than 3 months delay.

11.3 Concluding

In this chapter the underlying root-causes of the bow-wave effect where explored further. The analysis showed that for plant 4 the overall forecast is underestimating demand and forecasts fluctuate over weeks. Additionally, a significant amount of orders was postponed during the first half of 2018. The current available forecast data is not enough to draw hard conclusions on the relation between forecast updates and the bow-wave effect. What can be concluded is that the forecasts do fluctuate over time and that on a global level the forecasts to the near future are over-estimating demand. Furthermore, the mismatch between planned and actual production was confirmed, where it was observed that production quantities where shifted over months. Two main reasons were found for the postponement of orders that accounted for 78% of all postponed orders: production uncertainty(delay) and demand uncertainty(demand fluctuations and HIP leveling).

In chapter 8 , it was discussed that a trade-off must be made between stability (reducing system nervousness), service level and cost (keeping safety stock). When production lines are subject to more uncertainty, one needs more flexibility in the production process or keep more stock to be able to satisfy demand on time. The number of postponed orders indicate that the stock and/or capacity buffers within the plant are not always sufficient to produce the orders on time in case of @@increased@@ demand, @@ reduced@@ capacity and production uncertainties. However, as the production plants deliver to the markets, and not directly to customers, the impact on customer service level depends also on the safety stock that is kept in the MO. Hence, the back orders in the plant don't necessarily result in a bad customer service. Keeping in mind the trade-of between stability, service levels and cost, the stability reached by the implementation of HIP can lead to a decrease in service levels when the MO's do not adjust their inventory policies taking into account the weekly order commitment.

INP's and phase-outs are product segments that phase more uncertainty, one should be aware of this when making any production or inventory decisions to either deal or hedge nervousness.

Furthermore, MO's should be aware of the impact of changing orders on the plant. With the HIP S&OP, safety stock and forecast changes would preferably only happen once a month, however forecasts seem to change every week and safety stock changes were observed up to 5 times a month. Safety stock changes, along with changes in forecasts are to be restricted to a minimum.

During the analyses it was also observed that some orders are repeatedly moved forward to hit the service target. One order that was postponed eight times was 95 pieces. Due to the large order size, this would take 3 days on the production line to finish this order. When the line would start working on this order all other incoming orders would not have been satisfied. Hence, to reach the performance target this order was postponed repeatedly. By allowing partial deliveries or defining a maximum order quantity this problem could be improved. To overcome this problem Hilti may implement a partial fulfillment policy or implement a maximum order quantity.

12 | Conclusions and recommendations

This master thesis aims to develop a conceptual segmentation framework for Hilti's supply chain, provide insight into system nervousness within Hilti and to shed light on the relation between Forecast consumption logic and system nervousness.

To conclude on these topics this chapter firstly summarizes the answers to the research questions in section 12.1. Based on the findings in this master thesis, recommendations will be provided for Hilti in section 12.2. In section 12.3 the limitations of this master thesis are discussed. Finally, it will be described how the knowledge gained during this master thesis adds to scientific literature and which future research directions are seen, in section 12.4.

12.1 Conclusions

How should the holistic segmentation concept be designed for Hilti's end-to-end supply chain in order to achieve lower inventory costs and a higher service level?

In this master thesis the framework of van Kampen et al. (2012) was used to design a segmentation concept for Hilti. According to this framework, first the aim of the segmentation concept and the context must be clear before the characteristics on which segmentation are based can be chosen.

Current segmentation concepts and gaps

First, the current segmentation concepts where investigated, as described in chapter 4, which led to the following main conclusions:

- **Current guidelines seem ambiguous and in-comprehensive** General segmentation guidelines in terms of inventory control and forecasting techniques exist only for a limited number of processes within Hilti. At the warehouses guidelines exist to determine MRP types, safety stock methods and forecasting techniques. However, the established guidelines are sometimes ambiguous and given that they are not always followed in-comprehensive. For example, the safety stock guidelines suggested multiple suitable methods to deal with one specific product segment and the guidelines within the production plants are missing.
- **Missing Guidelines to determine Safety stock levels** Within the system, material managers are able to define a given cycle service level or days of coverage per TABCD/XYZ segment used to calculate the safety stock. However, there are currently no guidelines that explain which segments should be prioritized or for that matter, what the ideal settings would be.
- **No support for SKU evaluation** MRP types, safety stock methods and service level, need revisions over time since SKUs may change from segment. Currently there is no tool available that supports managers with this evaluation. Consequently it is expected that not all SKUs are revised on time as there are to many SKUs to evaluate manually on a regular basis.

Determining service levels per product segment

As guidelines to determine safety stock levels were missing, it was deemed necessary to further investigate this before defining a holistic segmentation concept. Several authors have investigated this problem and proposed characteristics, techniques and class sizes to come up with a solution to this problem under a target fill rate constraint or cycle service level constraint(Teunter et al., 2010; Armstrong, 1985; van Wingerden et al., 2018; Knod and Schonenberger, 2001). In this master thesis, additional criteria were introduced and tested in a case study comparing it's performance in terms of cost to the earlier proposed techniques under an OFR constraint. This led to the following conclusions:

- **Use order frequency and revenue as segmentation characteristics** This method led to the best cost improvement, while reaching the same target service. Here priority should be given to SKUs with a high order frequency and a low revenue.

- **Five classes already resulted in significant improvement** Currently Hilti defined 15 classes based on order frequency and revenue, based on a two dimensional matrix. In this master thesis, the manageability of 15 classes is questioned. During the case study, these segments where clustered into five groups, and as stated, this led already to a significant cost improvement. Hence, Hilti could reduce complexity, this may be done by compiling the TA classes and CD classes in the TABCD-classification.

- **The performance of the model may improve by making the XYZ-measure a relative measure as the performance of the model depends on the class sizes**. It was shown that the class sizes of XYZ (order frequency) impact the overall performance of the model. As the size of the markets differ, the amount of SKUs per segment differ per warehouse location. Hence, the thresholds to determine the classes would need to be relative, such that the number of SKUs per segment is stabilized.

Final segmentation concept

Hence, after the case study the final segmentation criteria for Hilti where recommended: Material status, degree of innovation, revenue, order frequency and lead time. The most suitable segmentation technique for inventory management and forecast decisions with multi-criteria was found to be the hierarchical process of Bacchetti et al. (2013) on which the final segmentation model was designed. This resulted in nine segments for which guidelines where discussed.

Part 2

The second main research questions was formulated as follows:

> ***What are the causes of the bow-wave effect within Hilti and can system nervousness be reduced by adjusting the forecast consumption logic in the system***

To answer this research question, we will conclude on the sub questions formulated in chapter 7.4.

What are the factors causing system nervousness according to literature? In chapter 8, system nervousness was described from a scientific point of view. The main

driver of system nervousness was found to be uncertainty, originating from demand, supply and/or production. The impact of uncertainty on system stability or system nervousness depends on the production and inventory decisions made. Companies can create more stability in their production planning by for example, prolonging the frozen horizon, use buffers in terms of lead time or safety stock, fix production quantities per planning cycle for end-item levels and use a lot-for-lot approach for upstream items.

What is the most suitable way to quantify system nervousness?

In section 8.4 system nervousness measures were proposed specifically for Hilti, where a new system nervousness measure was introduced to reflect nervousness in terms of capacity.

What is the effect of forecast consumption logic on system nervousness and inventory levels in the supply chain?

In order to gain insight into the relation between system nervousness and forecast consumption logic a case study was performed. A relation was found between forecast consumption logic and system nervousness.

First it is observed that for both non-HIP and HIP, nervousness could only be reduced when a system enhancement is made. That is, without the inclusion of network demand or keeping unconsumed forecast from the past, nervousness could not be reduced. For the biggest reduction in system nervousness both unconsumed forecast from the past should be kept and network demand should consume the forecast.

For non-hip, the case study showed the biggest reduction, 24%, in system nervousness when a forward consumption logic was applied, where network demand consumed the forecast and unconsumed forecast of the past was kept in the system. Under these settings, the impact of the length of the consumption horizon on nervousness, cost and fill rate is limited.

With the implementation of HIP, under a frozen horizon of one week, the nervousness was reduced significantly, by 20%. The effect of forecast consumption logic on system nervousness was small compared to the improvement seen from the implementation of HIP. Here nervousness could only be reduced when past forecast was kept in the system and network demand consumed the forecast as well.

Does demand uncertainty mediate the effect of forecast consumption logic on system nervousness and inventory levels in the supply chain?

By segmenting based on FA and CV, the mediating effect of demand uncertainty on the relation between forecast consumption logic and system nervousness was explored. This resulted in a similar optimal policy for all segments, which shows that no segmented approach based on FA or CV is needed for the forecast consumption logic. Additionally, this exploratory analyses did confirm the relation between demand uncertainty and nervousness, as segments with a higher CV and segments with a lower FA showed less nervousness.

Which factors are causing system nervousness and bow-wave specifically within Hilti?

The bow-wave experienced at Hilti is seen in the assembly to order (ATO) production lines. By definition ATO asks for flexibility from the assemble lines, as the production plan depends on incoming orders and no safety stock is kept within the plant to provide

a buffer. In chapter 11, Hilti's system set-up in the context of system nervousness was evaluated and a further analyses in the root-causes of the bow-wave was conducted. Here it was observed that the forecast accuracy at SKU level where low and forecasts where systematically under estimating demand during 2018. It remained unclear if forecast updates are really causing the bow-wave as data availability was scarce. However, it is not ruled out that forecasts in the near future are not redundantly adjusted upward. On a global scale it is observed that Hilti does adjust the forecast to the near future higher than demand requires. Furthermore, a significant amount of orders was postponed due to production or capacity problems. The postponement of orders can partly explain the bow-wave effect. Moreover, as the production planners are aware of the bow-wave but unaware of the causes, the increase in production orders is not always taken seriously, as they expect the quantities to drop again. This can lead to a vicious circle where production capacity is not increased based on a lack of faith in the production plan, leading again to order postponements and the bow-wave in the next planning cycle. Furthermore, it was observed that Hilti currently does not measure system nervousness

12.2 Recommendations for Hilti

Based on the findings of this master thesis, we provide Hilti with the following recommendations:

- **Define a final segmentation method** During this master thesis, a conceptual segmentation design has been developed that may provide Hilti with a good starting point for a holistic segmentation concept. This segmentation method needs to be tested however before it can be implemented.

- **Reconsider the amount of segments** In chapter 4 it was shown that the cluster groups defined by Hilti were based on order frequency and order variability, and three cluster were defined. However, subsequent guidelines did only differentiate for one cluster group, which was only defined by a different order frequency. This unnecessary complexity can cause confusion. Furthermore, the TABCD-XYZ classification results in 15 classes, which is difficult to manage and during the case study it was shown that 5 classes already performed well.

- **Change the order frequency clusters to relative thresholds based on total orders on a specific location** Based on the case study results, it is recommended to change the calculation of the XYZ (order frequency) by using relative thresholds, such that it is relevant for both small and large MO's.

- **Implement a tool that shows the correct settings for each SKU based on the segmentation guidelines** During the evaluation of the current segmentation techniques it was found that there are currently no fixed moments to evaluate MRP-type selection, safety stock method selection and the safety stock input parameters nor is there a tool available that provides managers with insights into which SKUs demand revision. Although providing segmentation guidelines is the first step, we argue that this next step may support managers in their decisions and make the evaluation of decisions more manageable. Such a tool would preferably show managers on a regular basis, e.g. every half a year, which SKUs do not follow the guidelines and therefore require revision.

- **Investigate the associated cost from system enhancement for forecast consumption logic** Since the current system within Hilti may be enhanced to include past forecast and network demand in the forecast consumption logic, further

research is necessary to see if the benefits from this change, in terms of system nervousness reduction, outweigh the costs associated with this enhancement.

- **Implement a system nervousness measure** As Kimms 1998 already indicated, the optimization of the supply chain is always a trade-off between service levels, costs and stability. This trade-off should also be made for Hilti. Before this trade-off can be made, stability of the current production set-up offers would need to be investigated. In order to get this insight Hilti can implement system nervousness measures, where the system nervousness measure introduced in this master thesis can be used as a starting point.
- **Create awareness/ limit the decision moments** As the implementation of a segmentation concept would lead to more structured decisions, this may positively influence the stability of incoming orders in the plant.
- **Challenge order method** During this master thesis is was also observed that the forecast accuracy on SKU level was low, which made the order methods based on MRP logic questionable. As Hilti owes the entire distribution channel, it is possible to look into other order methods/ demand signalling procedures, by for example using point of sales data to determine production quantities. (**?**)Jin et al. , 2015). (related to LRP in nervousness literature)

12.3 Limitations

The research conducted in this master thesis is subject to a couple of limitations that influence the whether the findings can be generalized.

The first limitation is the choice to use case studies. For both the segmentation concept as well as the forecast consumption logic, the results might have been specific for the used data. Different outcomes might have been observed in cases where demand patterns follow a different distribution. During the segmentation case study a test data set was used which aimed to overcome the problem of over-fitting. For the forecast consumption logic only one data set was tested. In particular, it was noticed that the forecast of the data set was under-estimating demand during the year. This might have resulted in worse performance of a longer consumption horizon.

The second limitation is the choice of fixed class sizes in the analyses of a segmentation method to determine the service levels. The class sizes are known to influence the performance and since two methods under consideration had 5 classes and the others 3 classes this might have caused (part of) the better performance of the 5 class segmentation methods compared to the other methods. Furthermore, as the number of classes was limited to five, we might have missed potential benefits.

The third limitation is the lack of testing of the conceptual segmentation framework. During this master thesis a conceptual segmentation method was designed, however it has not yet been investigated if this method would perform well in practice. During the workshop the stakeholders where positive about the conceptual framework. However, the final guidelines would still need to be tested.

The fifth limitation is the assumption of fixed safety stocks and other settings in the

forecast consumption logic case study. The results showed a low fill rate, which might have been caused by the choice of this fixed safety stock level.

The sixth limitation is the simplification of Teunter's criteria used in the segmentation case study, which might not reflect the real performance of this measure.

The seventh limitation is the lack of validation of the newly proposed system nervousness measure.

12.4 Scientific Contribution and Future Research

This thesis contributes to scientific literature by examining an optimal segmentation concept under an order line fill rate constrained. By using a case study it was shown that the inclusion of order frequency as segmentation criteria in combination with revenue led to the lowest cost whilst reaching a fixed order line fill rate. Furthermore the relation between forecast consumption logic and system nervousness was explored. In a case study it was proven that forecast consumption logic does influence system nervousness. Thereby, a new system nervousness measure was introduced that is expected to better capture capacity fluctuations.

During this project we have identified a couple of gaps within Scientific literature which demand further investigation.

- **Design heuristics to determine optimal stock levels per product segment under an order line fill rate** Within this master thesis the performance of several segmentation methods under an order line fill rate have been investigated. However, no general heuristic is proposed that can be used to determine service levels per segment. Hence, this still remains open for investigation.
- **Investigate the performance of a capacity based system nervousness measure** In this master thesis, a new system nervousness measure was introduced that is expected to better capture capacity fluctuations. It is suggested to further investigate the performance of this measure.
- **Investigate the trade-off between cost, flexibility and system nervousness** The trade-off between cost, flexibility and system nervousness remains unclear, as already stated by Kabak and Ornek (2009). Several authors aimed to provide measures that deal with this trade-off. Kimms (1998) proposed to add the nervousness as a constraint to original planning program. However, this does not consider the trade-off with other decision parameters like replenishment policies and CODP.
- **Investigate system nervousness originating downstream from the end-item level** Most literature concerning system nervousness focuses on the decisions made within the production plants. However, in a collaborative supply chain or in an integrated supply chain such as the supply chain of Hilti, more information is available. Interesting research directions could be to investigate other demand signalling processes or look at the relation between system nervousness and inventory management decisions downstream of the MPS.

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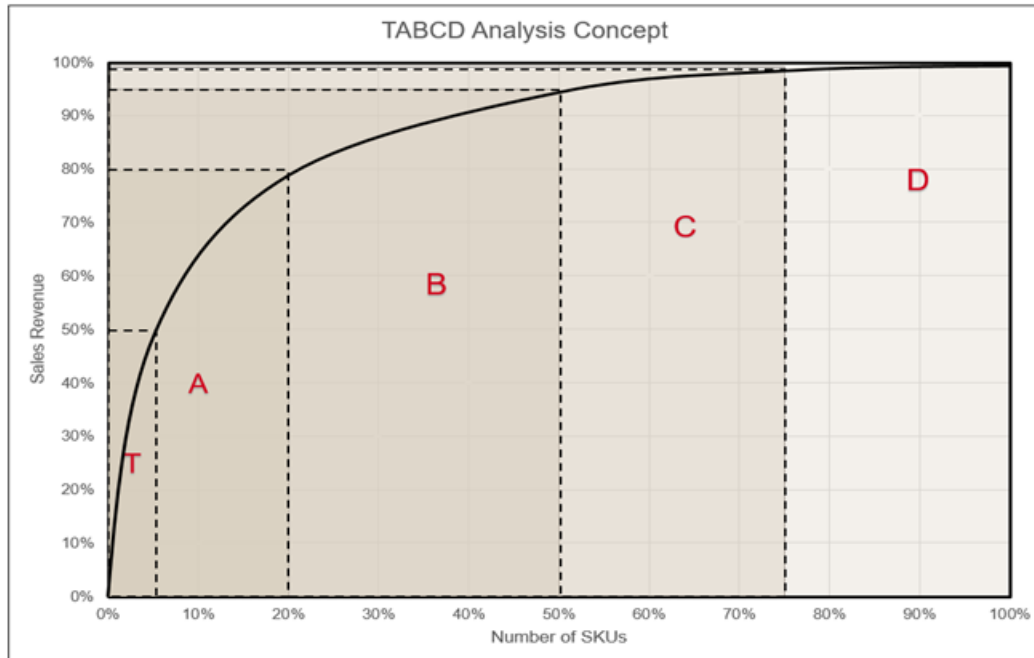
A | The concept of TABCD analyses

Figure A.1: The concept of TABCD analysis

B | Demand cluster groups

Several segmentation methods (see section 4.2) within Hilti uses demand and cluster groups. Therefore, it is important to elaborate more on these cluster groups. These cluster groups are originated from two variables, i.e., Order Frequency and Order Quantity Variability. The order quantity variability is measured in the coefficient of variation (CoV). It is a ratio of the standard deviation of the orders to the mean of the orders. Furthermore, the variability is divided into three groups (i.e., U, V and W) as depicted in Figure 28. On the other hand, the order frequency is based on the number of movement documents (i.e., the number of order lines) in the last 26 weeks. Similar to the order variability, the order frequency is divided into three groups (i.e., Q, R, and S) of which the threshold values between the different groups is given in Figure 28.

Note that this results in a 3x3 matrix and that the demand is clustered in Normal (CG1), Variable (CG2), and Sporadic (CG3) demand. These cluster groups are used in decision models for the MRP-type selection in the MO's, for whether to use the EOQ and which safety stock method to use. Note as well that the differentiation is primarily driven by the order frequency. In fact, as described in the section 4.2 one can conclude that in practice there is no difference between CG1 and CG2.

Figure B.1: Demand cluster groups within Hilti

C | Overview of available MRP types at Hilti

| MRP type	Description	Used for
ND	No active planning and forecasts used. Safety stock is possible, but not mandatory	Obsolete items, terms into phase out, Items without any replenishment function, Indirect items
X0	Planning through APO. Mostly used in MO's, SS calculation takes place into APO	Standard calculated items in the several MO's
X1	Planning through APO - SS calc. in R/3 - Purchase to Order (production takes place when there is a demand).	Purchase to Order items, **Not** planned special or make to order items
X3	Planning through APO without any transmission to R/3 - Special Items	Planned special items and MTO items
X5, X6, X7, Y0, Y5	Only used in MO's – Forecast via corporate Forecast – adjustments taken over through the HQ Material management.	Sporadic items, Phase out, No forecast driven items on MO side.
X7	Consumption driven requirements planning with reorder point in R/3 and fill up to defined maximum stock level (Min/Max).Forecast is used only for demand review and capacity planning. The maximum stock level is based on the capacity in the plant or it is a rounding value from the EOQ calculation.	Products with short lead time. High volume products
X9	MRP-type used in MO's and plants where a subcontractor is needed. Items are sent to the subcontractor for assembling or packing. Thereafter, the items are sent back to the plant or warehouse.	Items that needs to be assembled or packed at a subcontractor.
Z0	Standard definition for HQ and Plant items where the SS calculation or settings takes place in APO and overwrites the Safety Stock method in R/3.	In-house produced items Purchased items
Z1	Similar to MRP-type Z0, however, the safety stock is calculated or determined in R/3 and cannot be overwritten by APO.	In-house produced items Purchased items
Z2	Only used in HQ WH and plants. Z2 items are only produced with an existing customer order. A customer order is done in R/3 and generates automatically a production order. Forecasting is only used for demand review and capacity planning. There is no safety stock.	MTO/PTO items.
Z3	Only used in HQ WH and plants. Consumption driven requirements planning with reorder point in R/3 and fill up to defined maximum stock level (Min/Max). Forecast is used only for demand review and capacity planning. The maximum stock level is based on the capacity in the plant or it is a rounding value from the EOQ calculation.	In-house items and purchased items, Products with continuous demand during replenishment time Product with short lead-time (<6 days), **Not** used for phase-out items
Z4	Similar to MRP-type Z3, however, there is no maximum stock level.	In-house items and external purchased items, Items with short lead times (<6 days), For some phase-out items
Z5	Only used in Plant 4. Kanban items. Consumption driven requirements planning via annual order level. The article is planned in APO. The in R/3 created order is not transmitted to APO. Articles are via Kanban either manual (Kanban cards) or E-Kanban.	Purchased items in plant 4, C-part (e.g., screws, labels or card boxes) Products with short lead time (<6 days), Products from regional suppliers with the possibility to order and deliver in a regular base., **Not** for phase-out items
Z8	Similar to MRP-type Z4, however, a reorder point or safety stock is not needed. Hence, the safety stock or reorder point can be set to 0.	In-house items and purchased items, Assemblies (e.g., engines, impact testers etc), Allowed for manufacturing plants and for replenishment items.

D | Decision tree lot sizes
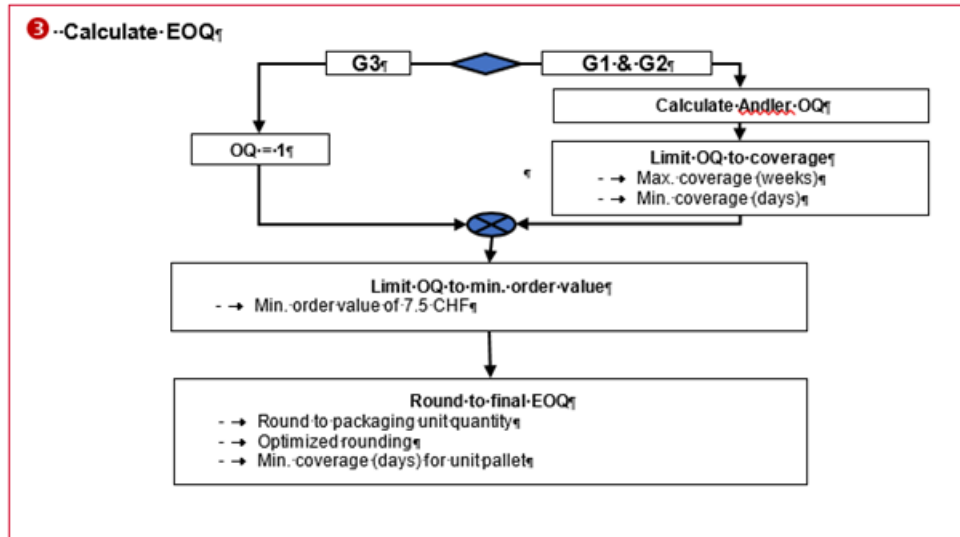
Figure D.1: Decision tree EOQ

E | Comparison fill rate, cycle service level and OFR

The order line fill rate (OFR) seems to be a more realistic case for measuring the performance in Hilti's situation. To see what the OFR exactly is and how it behaves compared to the cycle service level (CSL) and fill rate, a small example is given in Table 14. For simplicity in this example, it assumed that the average order size is equal to the demand divided by the number of lines.

Inventory	Demand	# of Order lines	CSL	Fill rate	OFR
100	20	2	100%	100%	100%
80	40	4	100%	100%	100%
40	60	4	0%	66.6%	50%

F | Safety stock method used within Hilti

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. $$SS = \frac{Orig. Hist. (x\ months)}{Frequency(x\ months)}$$

Figure F.1: Safety stock method used within Hilti

G | Case study Segmentation data set

In order to get more insight in the randomly selected data, the distribution of TABCD-items and XYZ-items is given in the figures below. It seems that a relatively small amount are T- and A-items. Furthermore, 50% of the items are fast-movers (X-items). In addition, more than 80% are make to stock (MTS) items (MRP-type X0), whereas the remaining items are PTO items (MRP-type X5 or X6). The dataset contains 495 SKUs.
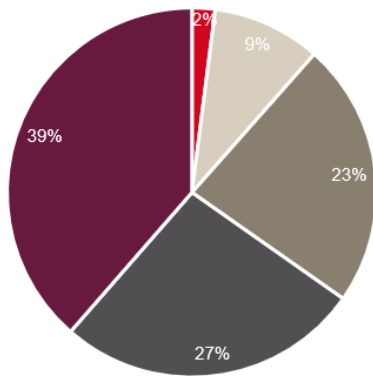
(a) Distributiopn of TABCD items
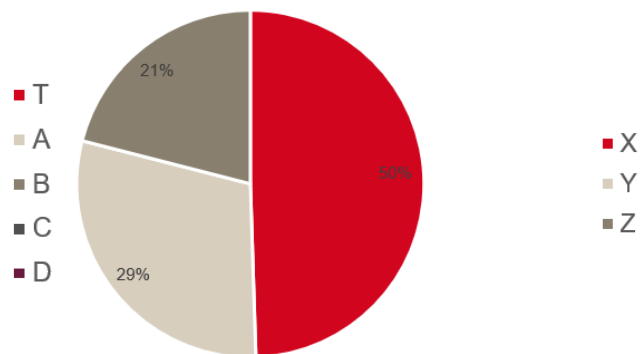
(b) Distributiopn of XYZ items

(c) Distributiopn of MRP types

(d) Price vs demand

(a) Service level per item TABCD in data set   (b) Service level per item XYZ in data set

H | Choice of treshold values for Segments in case study

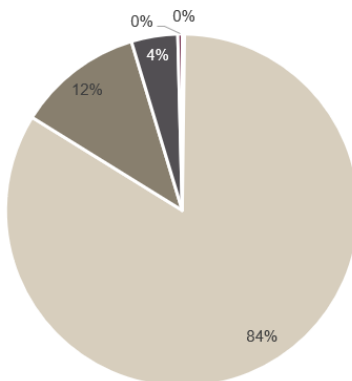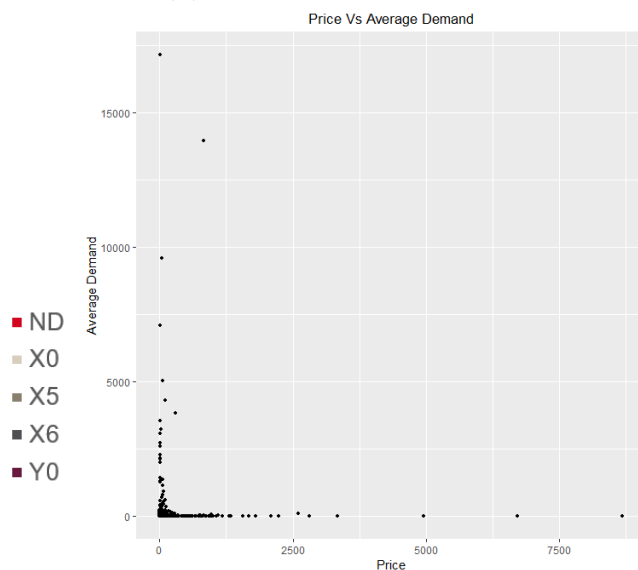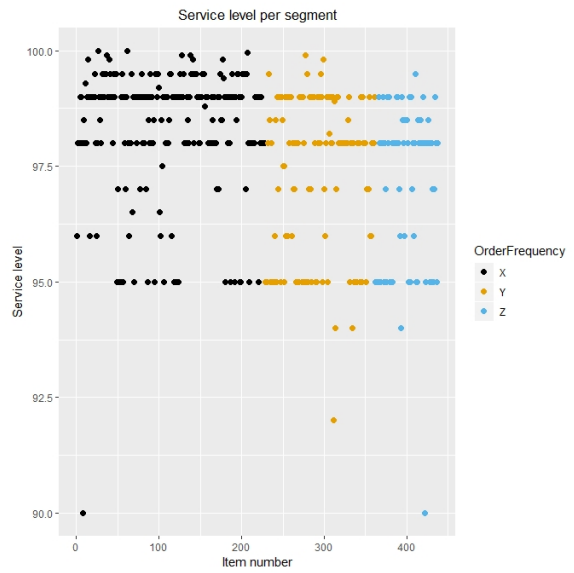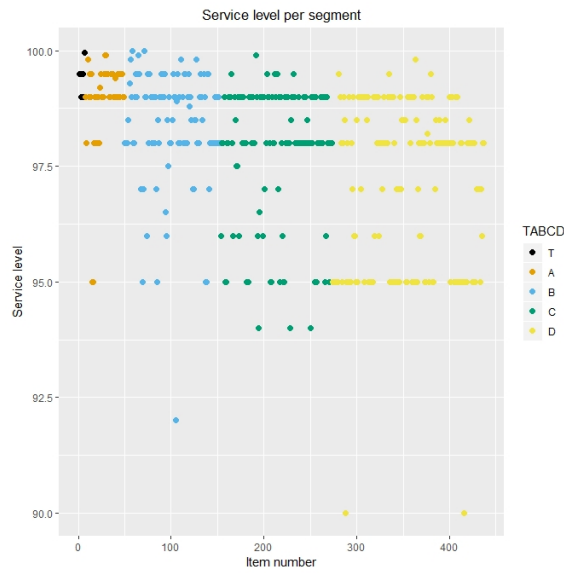Figure 29 gives the cumulative distribution function of the TABCD segmentation technique. Although less extreme then for Hilti's overall portfolio, it is observed that a small amount of product contributes to a large amount in revenue. Hilti currently divides its items into five clusters. In these 100 products the cut-off between T and A items seems unnecessary. From the relatively constant slope of the first 20 products it can be concluded that these products have approximately the same contribution to the total revenue and segmenting should not be necessary. During the simulation, these five segments where preserved.

Figure 30 shows the cumulative distribution function of Teunter's Criterion. The first 18 products have a high D/Q value, that contribute together for 95% of the sum of D/Q values. Thereafter an offset is seen in the curve and after a total of 38 products the curve barely increases any further. The threshold values for the simulation of Teunter's segmentation criteria where based on this graph and set to 95% and 99%. In comparison to the previous criteria order frequency is more spread out over the 100 items. The slope of the graph is slowly decreasing without any outstanding bending points. It was chosen to classify slow movers as the slow-moving items that contributed together only for 1% of the total orders placed. This is in line with the current cluster group cut-off since these where products with less than 24 orders per year. However, the current cluster groups are currently defining fast movers as products with more than 60 order lines per year, in our simulation this was only a very small part of the products. If we would preserve this cut-off value 65% of the products would have been classified as fast movers. Hence, we have chosen for a different cut-off, on 80% of total orders. Although the current simulation only looked at 100 items, the overall high number of order lines asks for further investigation into the correct cut-off values. From the 100 selected items RDC Oberhausen 13 items have a purchase to order policy and only 2 of the items are not kept on stock. The proposed threshold values by van Wanrooij (2012) for order variability are 0.75 and 1.33 would mean that almost 60% of the products are highly variable, see Figure 32. The threshold values of 1 and 2 where chosen instead. Further research should be conducted to determine the right cut-off values for Hilti.
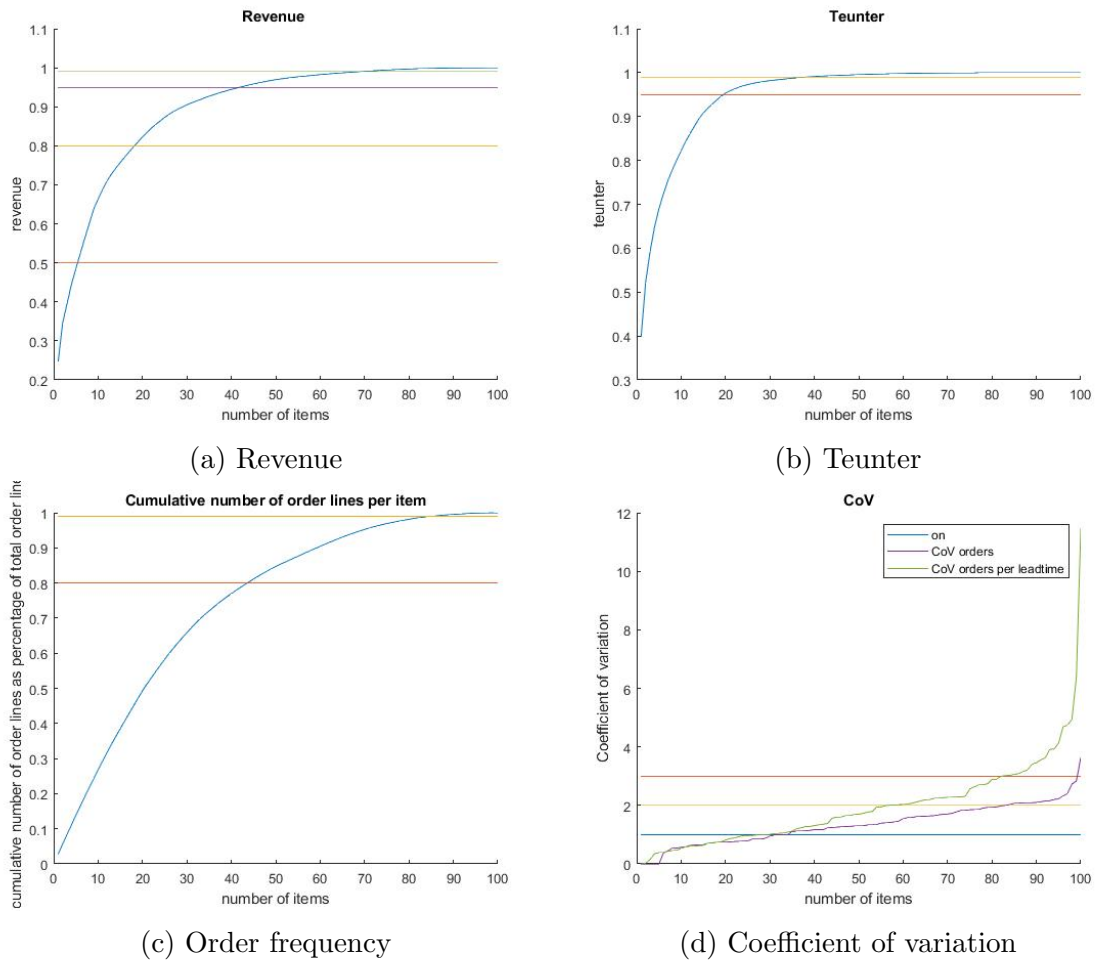
(a) Revenue

(b) Teunter

(c) Order frequency

(d) Coefficient of variation

Figure H.1: Cumulative distribution functions

I | Service level settings per segmentation technique

Target service level	TABCD – XYZ		TABCD		Frequency – Variability		Frequency		Variability		Teunter's cost criterion	
	Class/CG	Service Level setting	Class/CG	Service Level setting	Class/CG	Service Level setting	Class/CG	Service Level setting	Class/CG	Service Level setting	Class/CG	Service Level setting
85%	CG1	80%	T	n.a.	CG1	60%	Q	55%	U	60%	A	60%
	CG2	55%	A	60%	CG2	50%	R	50%	V	50%	B	55%
	CG3	50%	B	60%	CG3	50%	S	50%	W	n.a.	C	50%
	CG4	n.a.	C	75%	CG4	50%						
	CG5	n.a.	D	94%	CG5	n.a.						
90%	CG1	93%	T	50%	CG1	80%	Q	75%	Q	80%	A	80%
	CG2	80%	A	65%	CG2	65%	R	60%	R	75%	B	70%
	CG3	60%	B	70%	CG3	50%	S	50%	S	n.a.	C	65%
	CG4	50%	C	85%	CG4	50%						
	CG5	n.a.	D	97%	CG5	n.a.						
95%	CG1	99%	T	55%	CG1	96%	Q	95.5%	Q	95%	A	96.5%
	CG2	96.5%	A	91%	CG2	93%	R	80%	R	92%	B	95.5%
	CG3	87%	B	96%	CG3	75%	S	80%	S	60%	C	89%
	CG4	55%	C	99%	CG4	70%						
	CG5	n.a.	D	99%	CG5	n.a.						
97%	CG1	99.5%	T	80%	CG1	99%	Q	99%	Q	99.5%	A	99.5%
	CG2	99.5%	A	99.5%	CG2	99%	R	98%	R	99.5%	B	99.5%
	CG3	98.5%	B	99.5%	CG3	99%	S	87%	S	65%	C	98%
	CG4	65%	C	99.5%	CG4	99%						
	CG5	n.a.	D	99.5%	CG5	50%						

Figure I.1: Service level settings per segmentation technique

J | Scientific model part 2

The scientific model explains the mathematical formulation that is used to validate the effect of forecast consumption logic on system nervousness, inventory cost and service level. In section J.1, equations are formalized that should resemble the MRP logic used within Hilti. The adjustment of the forecasts, based on the forecast consumption logic, are explained in J.1.1. The notation that will be used in this master thesis, can be found in Table J.1.

Table J.1: definition of variables

Variable/ Parameter	Definition
t	Time period
k	Planning cycle
P	Planning Horizon length
T	Fixed horizon length
M_k	Beginning period of planning cycle k
i	SKU
LT_i	Lead time for SKU i
$PO_{t,i}^k$	Planned order quantity for SKU i for period t during planning cycle k
$SO_{t,i}$	Scheduled order quantity for SKU i at period t
$D_{t,i}^k$	Direct customer demand for SKU i at time k for period t
$R_{t,i}$	Replenishment demand for SKU i at period t
$IP_{t,i}^k$	Inventory position expected in at period t during planning cycle k
$IN_{t,i}$	Net inventory at period t
$IOH_{t,i}$	Inventory on hand at period t
$BO_{t,i}$	Back orders for item i at location j during period t
$F_{t,i}^{k-\Delta}$	Forecast for SKU i during planning cycle k for period t before consumption takes place
$F_{t,i}^k$	Forecast for SKU i during planning cycle k for period t after consumption
δ_{nd}	Boolean, consume network demand yes or no
$\delta_{fcstkept}$	Boolean past forecast is kept yes or no
c_h^B	Backward consumption horizon in days
c_h^F	Forward consumption horizon in days
c_Δ	Δ = {weekly, daily}, weekly or daily consumption policy
KF_k	Number of days unconsumed forecast is kept in the system
δ_f	Shows if Demand is consumed forward $\delta_f = 1$ if Forward or backward Forward policy is applied, else $\delta_f = 0$
δ_b	Shows if Demand is consumed forward $\delta_f = 1$ if Backward or backward Forward policy is applied, else $\delta_b = 0$
H_t^F	The number of days consumed forward in period t
H_t^B	The number of days consumed backward in period t

J.1 MRP/system logic

In order to solve the model, a recursive formula is applied over every planning cycle k, given the initial state of the system(k=1).

$\forall\ k \in K$ and $t:\ M_k \leq t < M_k + T$:

$$IP_{t,i}^k = IOH_i^{k-1} - BO_i^{k-1} - \Sigma_{x=t}^{t+LT}[\Sigma_{y=0}^K D_{x,i}^y + F_{x,i}^k] + \Sigma_{x=t-LT}^t SR_i^x \tag{J.1}$$

$$IP_{t,i}^k = IP_{t-1,i}^k + PO_{t-1,i}^k - F_{t+LT,i}^k - \Sigma_{y=0}^K D_{t,i}^y \qquad \forall\ k \in K, \forall t \in T, t > k \tag{J.2}$$

$$PO_{t,i}^k = \begin{cases} 0 & if\ IP_{t,i}^k \geq SS_i \\ n * OQ_i & if\ IP_{t,i}^k < SS_i \end{cases} \quad, \qquad where\quad n = \left\lceil \frac{SS_i - IP_{t,i}^k}{OQ_i} \right\rceil \tag{J.3}$$

$$SR_i^k = PO_{t=k,i}^k \tag{J.4}$$

$$IN_i^k = IN_i^{k-1} + SR_i^{k-LT_i} - \Sigma_{y=0}^{k-1} D_{t=k,i}^y - R_i^{k-1} \tag{J.5}$$

$$IOH_i^k = \left[IN_i^k \right]^+ \tag{J.6}$$

BO_i^t, denotes the total open ordered quantities that still should be satisfied from stock at time

$$BO_i^k = \left[IN_i^k \right]^- \tag{J.7}$$

J.1.1 Forecast update

Subject to the chosen forecast consumption logic, H_t^F is defined as the number of days forecast is consumed forward for time period t and H_t^B as the number of days forecast is consumed backward for time period t. H_t^F and H_t^B are defined as functions dependent on the chosen forecast consumption logic, reflected in the several decision variables and are given by:

$$H_t^F (c_h, c_\Delta, \delta_f) = \begin{cases} \delta_f (c_h + ((t-1)mod5) - 1) & if\ c_\Delta = weekly \\ \delta_f (c_h) & if\ c_\Delta = daily \end{cases} \tag{J.8}$$

$$H_t^B (c_h, c_\Delta, \delta_b) = \begin{cases} \delta_b (c_h - ((t-1)mod5) - 1) & if\ c_\Delta = weekly \\ \delta_b (c_h \qquad\qquad) if\ c_\Delta = daily \end{cases} \tag{J.9}$$

Let $F_{t,i}^{k-\Delta}$ denote the initial forecasted quantity during planning cycle k for time period t, before demand is consumed and $F_{t,i}^k$ the forecasted quantity during planning cycle k for time period t, after demand is consumed. Then, during each planning cycle k, the forecast consumption logic is applied to retrieve $F_{t,i}^k$ for every $t \geq k$.

At the start of each planning cycle, first the uncomsumed forecast from the past if shifted:

---

1. Set $KF_k = max(CF_t, CB_t)$

   Set $F_{t,i}^k = F_{t,i}^{k-\Delta} + \delta_{Fkept}\left(\Sigma_{x=1}^{KF_k} F_{t-x,i}^{k-\Delta} - D_{t-x,i}^k - \delta_{nd}R_i^{k-x}\right)^+, \quad for \quad t = k$

Let $C_{t,i}^k$ be the total demand for period t in planning cycle k for sku i.

   The total demand that can be consumed for period t in planning cycle k, is subsequently set for every $t \geq k$:

2. Set $C_{t,i}^k = \Sigma_{x=1}^k D_{x,i}^k + \delta_{nd}R_i^k$

   Set $x = 0$

Then total demand that can be consumed for period t in planning cycle k, is subtracted from the forecast by iterating through the forecast in the forecast horizon:

3. While: $C_{t,i}^k > 0$ & $\Sigma_{y=t-C_b,i}^{t+C_f} F_{y,i}^k > 0$:

   (a) If $x < H_t^F$:
   $$F_{t+x}^k = \left(F_{t+x,i}^k - C_{t,i}^k\right)^+$$
   $$C_{t,i}^k = \left(C_{t,i}^k - F_{t+x,i}^k\right)^+$$

   (b) If $x < H_t^B$:
   $$F_{t-x,i}^k = \left(F_{t-x,i}^k - C_{t,i}^k\right)^+$$
   $$C_{t,i}^k = \left(C_{t,i}^k - F_{t-x,i}^k\right)^+$$

   (c) $x = x + 1$

K | Input parameter description FCL

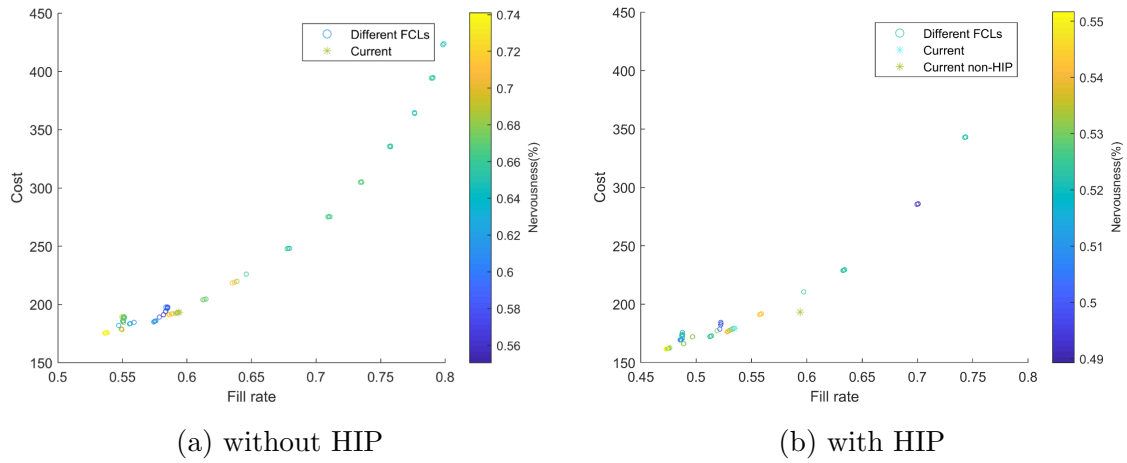| line	Material	Plant	SS	OQ	LT	price per piece	Forecast Accuracy (weekly)	Forecast Error (yearly)
ML05	428938	2100	9	10	5	1549	0,31	-0,40
	428939	8110	6	10	5	483	0,36	-0,28
		8150	40	20	5	483	0,24	-0,33
		8180	15	20	5	483	0,51	-0,07
	428940	8110	19	20	5	837	0,39	-0,49
		8130	17	20	6	837	0,51	-0,28
	428944	6000	29	9	47	494	0,46	-0,35
		6004	49	18	38	494	0,39	-0,26
		6815	51	10	27	476	0,40	-0,27
ML34	2105319	8110	5	8	2	1254	0,32	-0,51
		8130	4	4	3	1254	0,18	-0,33
		8150	9	12	2	1254	0,49	-0,53
		8180	3	12	2	1254	0,18	-0,22
	2112351	6000	25	9	43	896	0,52	-0,17
		6004	32	9	34	896	0,54	-0,33
		6815	7	6	23	864	0,11	-0,30
	2124832	8150	3	4	2	1245	0,08	-0,36
		8180	1	4	2	1245	0,01	-0,31
	2124834	2100	2	4	2	2231	0,05	-0,53
	2124835	2100	1	4	2	1744	0,01	-0,90
	2124840	6000	30	9	43	891	0,46	-0,34
		6004	46	9	34	891	0,45	-0,23
ML45	2101332	2100	3	5	2	750	0,12	-0,27
		8110	10	10	2	472	0,43	-0,38
		8130	9	10	3	472	0,53	-0,31
		8150	28	10	2	472	0,18	-0,18
		8180	8	10	2	472	0,55	-0,21
	2101333	8110	2	8	2	453	0,11	-0,23
		8130	2	4	3	453	0,03	-0,43
		8150	2	4	2	453	0,10	-0,55
	2101336	6000	30	20	43	428	0,36	-0,28
		6004	50	20	34	428	0,30	-0,29
		6815	8	4	23	413	0,27	-0,42
	2161469	2100	3	10	2	704	0,03	0,17
		8110	15	10	2	501	0,22	-0,43
		8130	3	10	3	501	0,12	-0,38
		8150	54	10	2	501	0,12	-0,47
		8180	13	10	2	501	0,30	-0,36
	2161625	6000	100	20	43	398	0,16	-0,19
		6004	100	20	34	398	0,14	-0,06
ML53	2126350	8110	7	20	5	628	0,47	-0,28
		8130	17	20	6	628	0,56	-0,38
		8150	56	20	5	628	0,10	-0,27
		8180	26	20	5	628	0,23	-0,34
	2127969	6000	162	18	47	385	0,15	-0,23
		6004	143	18	38	385	0,11	-0,15
		6815	21	18	27	372	0,30	-0,34
	2128233	2100	11	10	5	1209	0,50	-0,23
	2135439	8110	25	10	5	627	0,40	-0,33
	2146841	8150	12	1	5	273	0,16	-0,23
	2191485	8110	9	20	2	276	0,07	-0,66

L | Fill rate vs cost in case study FCL

(a) without HIP

(b) with HIP

Figure L.1: Fill rate vs cost