MASTER THESIS

A first step towards fully automated spare parts planning systems

An empirical study on ordering behaviour

F. Geertjes (s0166995)
Industrial Engineering and Management
3rd of April 2014

Public version

Supervisors University of Twente
Dr. A. al Hanbali
Dr. M.C. van der Heijden

Supervisor Gordian
S.P.J. Wouters MSc

UNIVERSITY OF TWENTE.

Gordian
Logistic Experts

Management Summary

This research is conducted at Gordian Logistics Experts in the field of spare parts planning. In particular, we focus on the process of replenishing spare parts inventories and we study the ordering decisions made by planners.

Research motivation
Gordian has a spare parts planning tool (SPPT) for spare parts planning and control. This tool focuses on the optimisation of tactical parameter setting (forecasting and inventory control) in order to find the right balance between material availability and costs. However, Gordian observed that many purchase requisitions generated by the SPPT were modified or rejected by planners. Consequently, the benefits of the optimised system are squandered. At this moment, Gordian does not know how many purchase requisitions are modified by planners and what the underlying reasons are for these modifications. Therefore, Gordian would like to have more insight into these issues. The main goal of this assignment is to gain insight into spare parts planning decisions and the root causes of adapting or rejecting generated purchase requisitions by planners.

Research design
First, we study the factors causing interventions in spare parts planning. We use scientific literature and interviews with planners in order to list these factors. Secondly, we define key performance indicators to assess the quality of planning decisions. Thirdly, we analyse the current situation at three companies: RET (arranges the public transport of Rotterdam), the Royal Netherlands Navy and IBM. We briefly describe the companies' characteristics, the planning systems they use and the ordering process of planners.

Next, we analyse ordering decisions to determine the key factors and we estimate the impact of intervening. Once the root causes of intervening are known, we provide areas for improvement and we provide a priority list of key factors that should be addressed. The actual implementation of these improvements is out of scope of this research.

Results and conclusions
Based on an extensive literature review and interviews with planners, we find 31 potential factors causing interventions in spare parts planning. In addition, we categorise these factors according to five different processes concerning spare part planning and control, in order to allocate the factors to concrete process owners.

Based on the empirical data, about 75% of the purchase requisitions are modified at RET and at the Navy whereas just 5% (rough estimation) of the purchase requisitions are overruled at IBM. This outcome suggests that planners have more confidence in the requisitions of IBM's planning system (Servigistics) and/or Servigistics proposes better order recommendations.

At RET, we find seven key factors causing interventions and these factors represent 85,1% of the interventions that occur. RET's planners intervene mainly because they face phase-in (29%) and phase-out (12%) issues regarding a part. Moreover, planners tend to increase the proposed order quantity when the value of a part is low (19%).
At the Navy, we also find seven key factors that represent 71,5% of the interventions that occur. Three main reasons to intervene at the Navy are: 1. Round order quantities (29%) to "nice looking" numbers such as tens or hundreds 2. Anticipate on a peak in the demand (16%) and 3. Increase order quantities because the value of a part is low (8%).
At IBM, we identify four key factors causing interventions. Planners tend to decrease the proposed order quantity when the value of a part is high. Furthermore, planners also anticipate on a peak in the demand and they correct the system because of complicated substitution-relationships. However, the results of IBM are less robust since the data sample is small (86 ordering decisions are analysed).

Overall, a main finding is that lots of interventions took place in the low price segment (unit price of part < 25 Euro) at RET and at the Navy. Remarkable is the fact that planners mostly decreased and rejected the proposed order quantity. Especially this segment has little influence on the capital employed and more influence on the realised fill rate. Another important finding is that the majority of interventions can be considered as a human factor. In this case, the interventions can not be related to data issues or model issues.

Next, we analyse the key factors individually. For each key factor we determine the estimated impact of intervening and the effort required to tackle the factor. We list the main factors in the table below which requires low effort to tackle the factor. We briefly describe the issue, possible solutions and the potential reduction of interventions.

Factor	Description of issue	Possible solutions	Max. gain
Low unit value (RET)	Proposed order quantity of SAP is not related to the price of a part	Balance ordering and holding costs by means of EOQ-model or set minimum order value	19%
MOQ (RET)	MOQ is missing in system	Add MOQ-values into the system	11%
Rounded quantities (Navy)	Planners round quantities to tens or hundreds	Add MOD-values for cheap spare parts	29%
Peak in demand (Navy)	Planners intervene after a peak demand occurred	Implement an automated outlier filter	16%
Low unit value (Navy)	Service level settings in "C1 quadrant" are too low	Increase service levels in "C1 quadrant"	8%

Overview of key factors that requires low effort to improve.

For the assessment of ordering decisions, we use the fill rate, the holding costs and ordering costs as KPIs. Unfortunately, the assessment of ordering decisions is not straight forward and the exact impact of intervening can only be measured after a long period of time. Therefore, we provide methods to estimate the theoretical fill rate and the expected logistics costs at the moment of intervening.

Recommendations and further research

First, we recommend to modify the planning systems in such a way that interventions and reason for interventions are stored. In this way, the effectiveness of the implemented improvements can be determined and ordering decisions can easier be monitored in the future. Secondly, we recommend the companies to provide solutions for the following key factors to reduce the fraction of interventions:

- **RET:** Tackle the factors *low unit value* and *MOQ* as described in the table above (a potential reduction of 30% of interventions can be realised).
- **Navy:** Tackle the factors *rounded quantities, peak in demand* and *low unit value* as described in the table above. In this manner, potential reduction 53% of interventions can be realised.
- **IBM:** Since the expected reduction of interventions will be small (acceptance rate is already about 95% at this moment), further research is needed to determine if it is efficient to tackle the key factors.

As majority of interventions are related to the human factor, we suggest to develop a feedback mechanism to learn from own past decisions. Secondly, a limitation of this study is that we were not able to determine the actual impact of interventions. Therefore, our second suggestion for further research is to study the exact impact of intervening.

Preface

This report is the final result of my master thesis conducted at Gordian Logistic Experts in the partial fulfilment of the requirements for an MSc degree in Production and Logistic Management.

During my master courses I really enjoyed the course "Reliability Engineering and Maintenance Management" and for this reason I searched for a graduation project in the field of spare parts management. Gordian is a well-known company specialised in the niche market "service logistics" and I was very glad that Gordian offered me the opportunity to do an internship at this company. Gordian introduced me into the world of spare parts and during my internship I went to a number of companies to perform my research, including a small trip to Budapest. Afterwards, it has been an enriching experience which contributed extensively to my personal and professional development.

This thesis would not have been possible without the help of others, who deserve acknowledgement for their support. First of all, I would like to thank my first supervisor of the University of Twente, Ahmad al Hanbali, for his guidance and for sharing his vision over the past seven months. His interest and involvement in my project enabled me to achieve these results. Moreover, I sincerely appreciate his flexibility and cooperation in making appointments and providing feedback. Furthermore, I would like to thank my second supervisor from the University of Twente, Matthieu van der Heijden, for his valuable insights and critical feedback on my thesis.

Next, I would very much like to thank my company supervisor, Stijn Wouters, for his inspiring support and constructive approach that greatly dedicated to the results of this research. His profound business knowledge combined with an endless drive for improvement truly helped me to deliver a research with practical relevance. I would also like to thank Maarten Driessen for sharing his knowledge and visions on the topics related to my research, especially his expertise in inventory models and planning systems. Furthermore, I would like to thank the partners of Gordian, Jan Willem Rustenburg and Jürgen Donders, for giving me this opportunity and their support during my project.

Finally, I would like to thank my family and friends for their support and interest during my graduation time. In particular, I would like to thank my parents for their unconditional support throughout my years in college.

Frank Geertjes

Utrecht, April 2014

Table of contents

1 Introduction

This report is written to complete the Master of Industrial Engineering and Management at the University of Twente. The main goal of this assignment is to gain insight into spare parts planning decisions and the root causes of adapting or rejecting generated purchase requisitions by planners. In this introduction we provide some background information about Gordian and after that we introduce the topic of the assignment.

1.1 Gordian Logistics Experts

Gordian is a logistics management consultancy and deployment agency, specialised in service logistics and supply chain management (Gordian, 2013). The company is founded in 2005 and is located in Utrecht, the Netherlands. Service logistics focuses on after-sales business. Maintenance organisations want to guarantee a certain up-time for an asset and an important factor is the availability of the right spare parts at the right place and at the right time. Otherwise the down time of an asset could result in (i) lost revenues, (ii) customer dissatisfaction or (iii) public safety hazard (e.g. power plants) (Driessen et al., 2013). Another important characteristic of service logistics is the fact that optimising spare parts planning mainly rewards for high-value capital assets such as air planes, trains, large ships, and expensive production machines. For these high-value capital assets financial risks are high.

The main activities of Gordian are consulting and spare parts planning on a tactical level (called Planning Services). The tactical planning of spare parts focuses on parameter settings in forecasting and inventory control. The Planning Service activities consist of managing the top-100 spare part items for a client for example. Here, top-100 spare parts items are the most critical, expensive and slow moving spare parts.

Gordian observed that well educated employees with expertise in logistics are rare (on HBO-level), nevertheless there is much to gain in the tactical planning of spare parts. For this reason, companies outsource their tactical spare parts planning and Gordian assists companies regarding spare parts planning issues. For the Planning Services, Gordian developed a tool for spare parts planning and control. Currently, several companies like the Royal Netherlands Navy, NedTrain (SCO dep.) and Alstom use the spare parts planning tool (SPPT) of Gordian.

1.2 Spare parts planning

The key in spare parts planning is finding the right balance between performance and costs. Usually, companies would like to increase their service level – the availability of spare parts – and to decrease their inventory level. Driessen et al. (2012) developed a framework for spare parts planning and control in which he indicates eight different processes in the spare parts supply chain. Four of these processes and corresponding planning decisions play a crucial role for the auto-order assessment, namely:

- Assortment management (i.e., define spare parts assortment)
- Demand forecasting (i.e., classify parts, characterise demand process and generate forecasts)
- Inventory control (i.e., determine stocking strategy and replenishment policy)
- Deployment (i.e., define preconditions ordering process and manage procurements)

In this research we study the ordering decisions made by planners, related to the deployment process. The purpose is measuring and improving the quality of planning decisions. Secondly, an underlying purpose of Gordian is improving the auto-order assessment and this will be a central theme in this graduation project.

1.3 Auto-Order Assessment

At this moment, most software packages determine purchase requisitions per item, still the planner has to review these requisitions and next he or she places the purchase order manually. Some other planning systems like Servigistics contain functionality for automatic ordering. However, this function is on item level; per item the planner can enable or disable this option. When you enable this function the purchase requisitions are automatically processed as purchase orders and these orders are sent directly to the supplier.

Gordian proposes an automatic order assessment where items are classified based on price, demand frequency, demand patterns and lead times. The idea is that certain purchase requisitions could be processed automatically - as group, not on item level - when these requisitions meet the criteria of the auto order assessment (decision rules). For example, an item is worth less than hundred Euros, the demand is stable and the delivery times are reliable, in this case the purchase requisition of this item could be processed automatically.

This year Gordian starts with the project “auto-order-assessment”; they implemented decision rules in their SPPT for the acceptance of auto-orders. During a pilot at the Royal Netherlands Navy, decision rules are implemented for fast and medium movers and for items with low and medium prices. Gordian categorised spare parts based on price and demand frequency as shown in Figure 1.1. In the short term, Gordian would like to extend the decision rules for the remaining parts of the assortment.

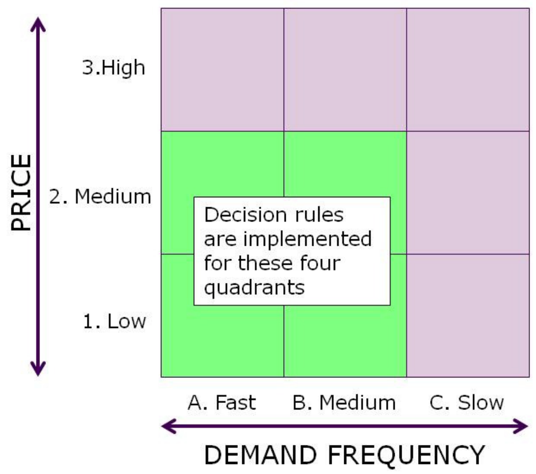


Figure 1.1 Assortment groups currently used at Gordian.

The results of the first pilot at the Navy are positive; Gordian indicates that 25-35% of the purchase requisitions in quadrants A1, A2, B1 and B2 can be processed automatically based on their criteria (decision rules). However, this means that still 65-75% of the orders should be reviewed manually by the planner. Another remarkable outcome of the first pilot is that purchase requisitions – which are indicated as requisitions that could be automated - were adapted or rejected by planners.

Before Gordian continues with improving the auto-order assessment, they would like to have insight in how planners take planning decisions and the root causes of adapting or rejecting generated purchase requisitions by planners. At this moment, Gordian does not know how many purchase requisitions were modified, if planners increase/decrease quantities, if the modifications are systematically or randomly and what the impact is of these actions. When Gordian has more insight into these topics, they can incorporate these results in the design of a robust auto-order assessment system.

2 Research design

In this chapter, we describe the research motivation, research questions, research scope, research methods to provide answers to the research questions, deliverables, research interests and the thesis outline.

2.1 Research motivation

As mentioned before, Gordian has a spare parts planning tool (SPPT) and recently they started with the project "auto order assessment". The purpose of this project is to implement decision rules for the acceptance of auto-orders for spare parts. Auto-orders means that purchase requisitions are processed automatically, without verification by planners or a third party. By means of auto ordering the amount of mistakes reduces and the process becomes less time consuming. As a result, planners can attune their efforts to those assortments (expensive and slow moving) that need human interpretation the most. Figure 2.1 shows a simple overview of the replenishment process of the SPPT.

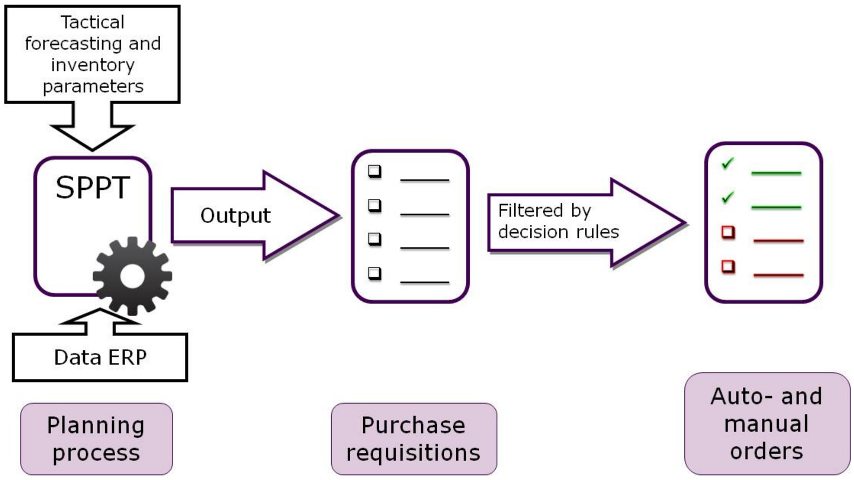


Figure 2.1 Simple overview of replenishment process of SPPT.

Decision rules for auto-order assessment are implemented for the quadrants A1, A2, B1 and B2, see Figure 1.1. Gordian use as rule of thumb the 50^{th} and 80^{th} percentile for the thresholds regarding the frequency and price. Consequently, 50 percent of all spare parts are classified as cheap spare parts, 30 percent are medium spare parts and the last 20 percent are expensive spare parts.

After the first pilot, Gordian faced a few issues regarding the auto order assessment. First, it turns out that 65-75% of the orders are still handled manually, these orders did not meet the implemented decision rules for auto ordering. Secondly, the pilot shows that many purchase requisitions were adapted or rejected by planners. Gordian would like to have more insight into both issues, especially the root causes of adapting or rejecting generated purchase requisitions by planners. In advance, Gordian expects that the "human factor" is a major issue. However, we have to research these issues to find explanatory factors.

Gordian argues that these planning issues, revealed by the pilot, were consistent with reviews at a number of companies using advanced planning software as such as Servigistics, MCA solutions and Xelus. These companies also observed that planners make lots of manual modifications in their purchase requisitions. Therefore, Gordian would like to have insight in the processes of spare parts planning systems in general and we will also research other spare parts planning systems like Servigistics.

Concerning the planning process, we need to study what the main drivers are for ordering decisions of planners (e.g. price, ordering costs, variability of demand, lead time). In which situations do planners adapt or reject purchase requisitions? In case the planner modifies a purchase requisition; was the planner right, was the tool right or were they both right (e.g. tool and planner have different incentives/objective functions; tool minimise costs and planner maximise availability)? In other words, we need a planning decision benchmark in order to judge the planning decisions of the tool and the planner. To research these topics we formulate the following research goal:

Research Goal: *To gain insight into the processes of spare parts planning and the root causes of adapting or rejecting generated purchase requisitions by planners, in order to improve the planning and replenishment decisions of spare parts.*

Note: For the remainder of this thesis, if planners overrule a generated purchase requisition we call that an intervention.

2.2 Research questions

In order to structure this research, we formulate four research questions. These questions represent the phases of the research and the chapters of this report. The research goal will be achieved by answering the **main research question**, which is:

What are the root causes of adapting or rejecting generated purchase requisitions by planners and how can spare parts planning decisions be modified in order to improve the quality of planning and replenishment decisions?

We formulate four sub questions in order to answer the main research question. First, we briefly describe the characterisation of spare parts. Next, we focus on spare parts planning systems, however, since there is less literature available on this topic we research planning systems in general and use expert opinions. Using both sources, we define factors which influence planning decisions. In particular, the factors which influence deployment decisions, this is the process of replenishing spare parts inventories (Driessen et al., 2013). Finally, we provide an overview of relevant factors for planning decisions in spare parts planning (sub question 1).

Secondly, we need to define metrics (or performance indicators) to assess the quality of planning decisions. We define metrics in order to determine the impact of interventions empirically (difficult and should be measured over a long period) and we define metrics in order to estimate the impact of interventions at the moment of intervening using theoretical models (sub question 2).

Thirdly, we analyse the current situation at three companies: RET, the Royal Netherlands Navy and IBM. We briefly describe the companies' characteristics and the spare part planning systems used in this empirical research. Next, we want to know how planners currently take decisions. Which factors play an important role in planning decisions? We want to know in which cases planners adapt or reject the generated purchase requisitions and/or in which situation (sub question 3). Finally, we determine the impact of interventions.

Next, we evaluate the results of our analysis. Once the root causes of interventions by planners are known, we provide areas for improvement and we make a priority list of recommendations (sub question 4). The actual implementation of these improvements is outside the boundaries of this research. Finally, we draw conclusions and suggest topics for further research.

Overview of sub questions:

1. What are the factors that influence planning decisions?
   a. What is the characterisation of spare parts?
   b. Which factors influence the planning decisions in general?
   c. Which factors are relevant for planning decisions in spare parts planning?
2. How can we assess interventions by planners?
   a. How can we measure the impact of interventions by planners?
   b. How can we estimate the impact of interventions by planners?
3. What are the root causes of interventions?
   a. What are the main characteristics of the companies used in this empirical research?
   b. Which spare parts planning systems are used at the companies?
   c. How do planners take ordering decisions?
   d. Which factors play an important role in interventions?
   e. What is the impact of interventions?
4. How can we improve the quality of planning decisions?
   a. Which improvement areas can be identified according to the results of the empirical data analysis?
   b. Outline recommendations for the short term and for the long term

2.3 Research scope

The time frame for the research is 5 months, which is the general guideline for the length of a master thesis. The following aspects are incorporated into this research:

- We research purchase requisitions and planning decisions of planners at an operational level. Planning decisions on a tactical level are given, e.g. parameter settings in forecasting procedures and inventory control.
- There are three types of decisions that could result in poor performance: 1. Not intervening when it is necessary 2. Intervening when it is unnecessary 3. Intervening when it is necessary, but in the wrong way. We consider the last two types of decisions, when intervening. The first type of decision is outside the scope, see Figure 2.2.
- We consider only the purchase requisitions that are generated by the planning system. Orders that are placed without any trigger of the system (e.g. planned maintenance work) are out of the scope.
- The efficiency of decision making, in terms of time, are outside the scope. E.g. whether a planner spends 5 minutes to review a purchase requisition or 60 minutes. We focus on the impact of the decision, measured in availability of parts and costs.
- Repairable spare parts are outside the scope, we only consider consumables. The replenishment process mainly contains consumables, purchase orders for repairable units are rare and furthermore repairable spare parts have more complicated characteristics.
- For data analysis we use a representative sample of spare parts (not all SKUs).
- Psychological (cognitive) factors are mentioned but not researched in-depth, we focus on operations management factors (e.g. demand, supply, spare parts characteristics) in order to explain ordering behaviour.

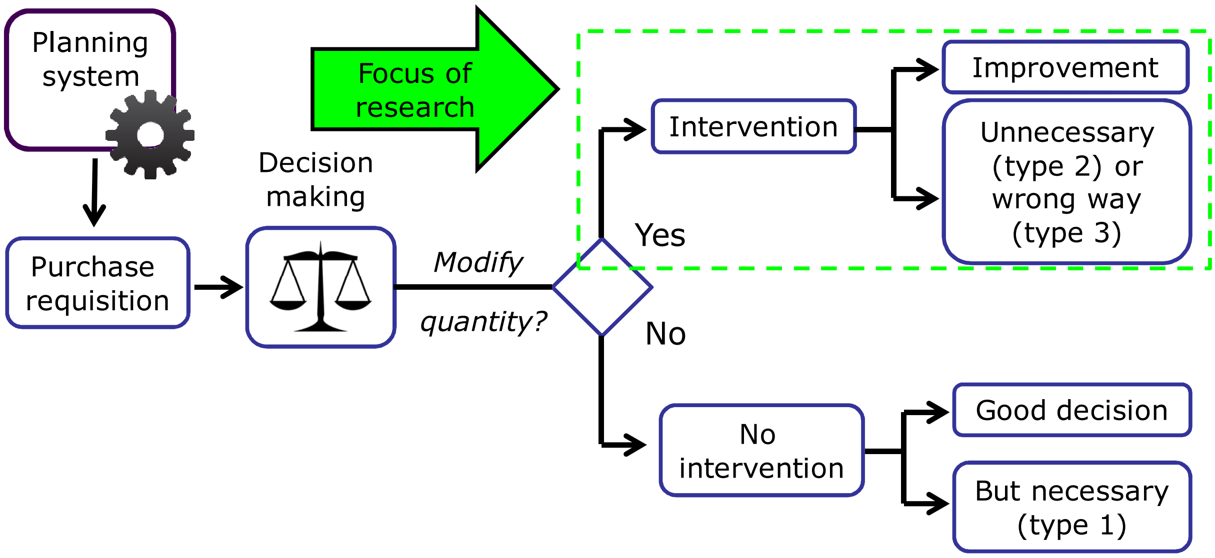


Figure 2.2 Decision-making process.

2.4 Research methodology

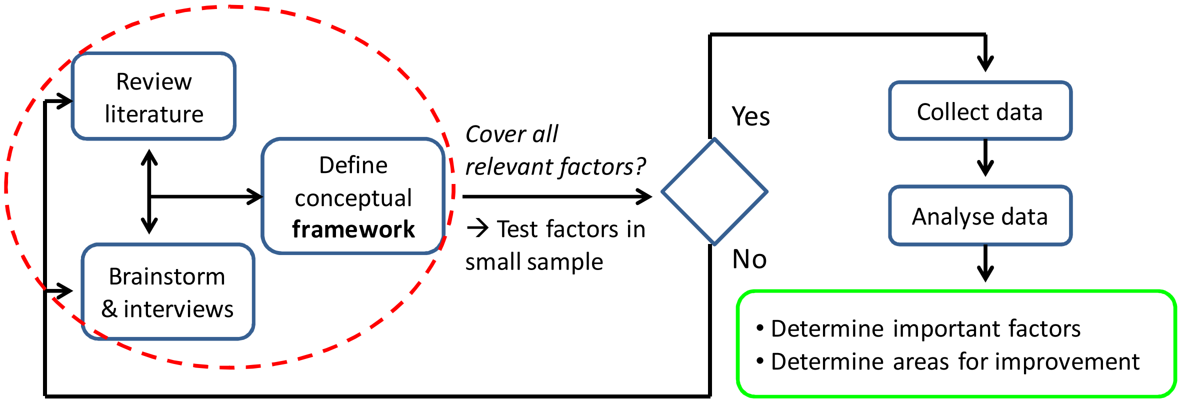
In order to answer the sub questions, we use a combination of literature review, data review, interviews, expert opinions, and brainstorming sessions. The data sources consist of scientific literature, Gordian (employees), RET (employees and databases), Royal Netherlands Navy (employees and databases) and IBM (employees and databases). Table 2.1 presents an overview of the research subjects, their corresponding research methods and data sources.

	Subject	Methodology	Data sources
1.	Collecting factors that influence planning decisions	Literature review Expert opinions Interviews	Scientific literature Gordian (employees) RET, IBM, Navy (employees)
2.	Defining metrics for planning decisions	Literature review Expert opinions	Scientific literature Gordian (employees)
3.	Analysing root causes of interventions	Interviews Data review Expert opinions	RET, IBM, Navy (employees) RET, IBM, Navy (databases) Gordian (employees)
4.	Presenting results and improvements	Brainstorm	Gordian (employees)

Table 2.1: Overview of research questions, corresponding methods and data sources.

This research is an empirical research to get insight into the spare parts planning process and the ordering decisions of planners. The main aim of the first part of the research is explanatory and we will use the data of three different companies. The data of these three companies will provide possibly relevant factors and root causes of interventions; this type of empirical research is called case study design (De Vaus, 2010). The second part of the research is about determining the impact of intervening and providing areas of improvement according to the results of the analysis.

Regarding the data analysis, first we have to determine the factors that influence ordering decisions (e.g. phase-out of an asset). Secondly, we will conduct a data analysis to find evidence for factors that influence interventions in practice. Next, we will determine which factors are most important and we estimate the impact of these interventions. Figure 2.4 presents an approach for the data analysis.



2.3: Plan of approach for data analysis.

2.5 Deliverables

This section outlines the deliverables of this research. Some of these deliverables aim to increase the understanding of the spare parts planning process, whereas others are results of the empirical research. The actual deliverables are listed below.

- Overview of factors that influence planning decisions in spare parts planning.
- Root causes (key factors) of interventions.
- The estimated impact of interventions.
- Areas of improvements based on the results.

2.6 Research interest

This research provides Gordian insight into planning decisions and interventions of planners. This report will outline the root causes of intervening at the participating companies and the report will indicate areas for improvement. When we are able to increase the quality of planning decisions, the planning and replenishment process becomes less time consuming and planners can attune their efforts to those assortments (expensive and slow moving) that need human interpretation and intervention the most.

In addition, this research will contribute to an innovative project of DINALOG called the Ultimate Spare Parts Planning (USP - work package one). This thesis will outline starting points for further research.

2.7 Thesis Outline

In the remaining chapters of this thesis we provide answers to the research questions as defined in section 2.2. First, in chapter 3, we discuss factors that influence planning decisions and we select relevant factors that influence ordering decisions in spare parts planning. Secondly, we discuss methods to assess ordering decisions in chapter 4. Next, in chapter 5, we briefly describe the case studies and we analyse the collected data. Moreover, we select the key factors for intervening and we estimate the impact of intervening. In chapter 6 we define areas for improvement and we provide a priority list of recommendations. Finally, chapter 7 provides the main conclusions of this research and suggestions for further research.

3 Literature review

In this chapter we conduct an extensive literature review in order to find relevant factors for planning decisions in spare parts management. First, we briefly describe the characterisation of spare parts in section 3.1. Secondly, in section 3.2 we research planning systems in general, in order to find factors which influence planning decisions. In particular, we search for factors which influence deployment process. Finally, in section 3.3 we provide an overview of relevant factors used in our research (research question 1).

3.1 Characterisation of spare parts

In this section, we provide an answer to sub question 1.a: *What are the characteristics of spare parts*? As a starting point, the research paper by Driessen et al. (2013) is used, which reviews spare parts management literature and these authors provide a framework for spare parts planning and control. In subsection 3.1.1 we briefly discuss the characteristics of spare parts and in subsection 3.1.2 we describe the decision-making in spare parts management. Furthermore, we reviewed two state-of-the-art review papers concerning spare part management (Guide & Srivastava, 1997; Kennedy et al., 2002).

3.1.1 Spare parts

The spare parts industry is about high-value capital assets, e.g. air planes, trains, large ships and expensive production machines. For these high-value capital assets, the financial risks are high if an asset is not available to provide their services or to manufacture their products. Therefore, maintenance organisations want to guarantee a certain up-time for an asset and an important component is the availability of the right spare parts at the right place and at the right time. Otherwise the down time of an asset could result in (i) lost revenues, (ii) customer dissatisfaction or (iii) public safety hazard (e.g. power plants) (Driessen et al., 2013).

Within spare parts inventories, there are two types of spare parts (Driessen et al., 2013):

1. Repairable spare parts: parts that are repaired rather than procured, i.e. parts that are technically and economically repairable. After repair the part becomes ready-for-use again.
2. Non-repairable spare parts or consumables: parts which are scrapped after replacement.

As stated in section 2.3 (Research scope), this research focus on consumables.

Spare parts inventory differ from other common inventories in several ways (Kennedy et al., 2002). First, the function of spare parts inventories is to assist the maintenance staff in keeping equipment in operation condition. Spare parts are not intermediate or final products to be sold to a customer. Spare parts inventory are held as protection against prolonged equipment downtime. There is no alternative use for it, except to sit in inventory as insurance cost against downtime. Consequently, obsolescence is a problem for those parts which are rarely needed. Secondly, the policies that govern spare parts inventories are different from those which govern WIP and final product inventories. WIP and final product inventories can be increased or decreased by changing production rates and schedules and improving quality. In contrast, spare parts inventory levels are largely a function of how equipment is used and how it is maintained. Thirdly, spare parts inventories are more complex than common inventories due to their lumpy demand patterns (Bachetti & Saccani, 2012). An item is said to have an erratic demand pattern if the variability is large relative to the mean (Silver et al., 1998). When time between demand moments is very long, then demand is said to be intermittent (Driessen et al., 2013). When intermittence is combined with an erratic pattern, demand is said to be lumpy. Moreover the demand process we discuss in the next subsection.

3.1.2 Spare parts decisions

As argued by Bachetti & Saccani (2012), several aspects contribute in making spare parts a complex matter: the high number of parts managed, the presence of lumpy demand patterns, the high responsiveness required to downtime costs by customers and the risk of stock obsolescence. To address the topic of managing spare parts, Driessen et al. (2013) developed a framework for planning and control of the spare parts supply chain. Maintenance organisations can use this framework to increase the efficiency, consistency and sustainability of decisions on how to plan and control spare parts.

Within the framework of Driessen, they made a distinction between eight different processes and corresponding decisions: 1. Assortment management 2. Demand forecasting 3. Parts returns forecasting 4. Supply management 5. Repair shop control 6. Inventory control 7. Order handling and 8. Deployment. In Figure 3.1, an overview of processes is presented, including their mutual connections. Since the repairable spare parts are outside the scope we do not describe processes "3. Parts returns forecasting" and "5. Repair shop control". The order handling (process 7) contains accepting or rejecting internal spare parts orders, e.g. a maintenance repair shop request 10 spare parts at the depot. This process is also not relevant to our research and for this reason we do not describe this process. The remaining processes and spare parts decisions are discussed below, based on the paper of Driessen et al. (2013).

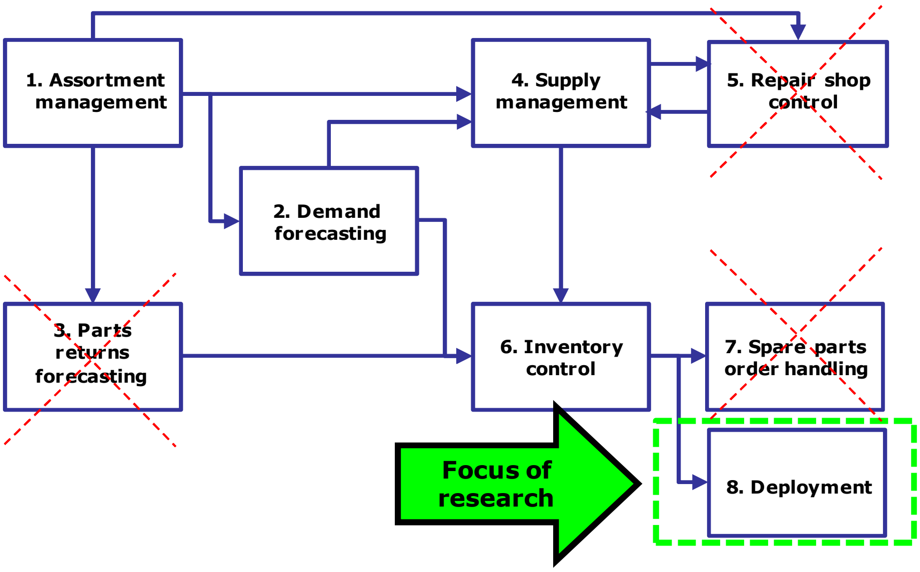


Figure 3.1 A framework for spare parts planning and control (Driessen et al., 2013).

- *Assortment management* is concerned with the decision to include (phase-in) or exclude (phase-out) a spare part (system) in the assortment. Once a part is included in the assortment, (technical) information of the part is gathered and updated when necessary. Aspects like criticality, redundancy, commonality, specificity, substitution, shelf life, position in the configuration and reparability are useful to collect.
- *Demand forecasting* concerns the estimation of demand for parts in the (near) future. The demand could be separated in planned and unplanned, where planned demand is known in advance and these parts are ordered just before the maintenance activities. For unplanned demand several forecasting methods are applicable like reliability based forecasting (based on part failure rates) and time series based forecasting (based on historical demand). Examples of time series based forecasting techniques are moving average, exponential smoothing, Croston's method and bootstrapping. The demand forecast is used to determine the number of parts to stock.

- *Supply management* concerns the process of ensuring that one or multiple supply sources are available to supply spare parts at any given moment in time with predetermined supplier characteristics, such as procurement lead time and underlying procurement contracts (price structure and order quantities).
- *Inventory control* concerns the stocking strategy (which spare parts to stock and in what quantities) and the replenishment policy (what amount to order at a certain point of time). Examples of well-known inventory policies are (s,S), (R,S) and (R,s,S)-policy. For further information about inventory policies we refer to Silver et al. (1998).
- *Deployment* concerns the process of replenishing spare parts inventories.

Since deployment is the main topic of our research, we describe this process in more detail. The replenishment policy parameters set by inventory control implicitly determine when to replenish spare parts inventories and what quantity to procure. A planner may deviate from this quantity for several reasons, e.g. based on new (daily) information not known at the time the replenishment policy parameters were set, or when exceptional procurement orders arise from exceptional inventory levels (Driessen et al., 2013). Other reasons to modify quantities will extensively researched and studied in this thesis.

Furthermore, Driessen et al. (2013) argued that maintenance organisations should set a precondition (or rules for exception management) on whether to replenish inventories with or without interventions of planners. In line with this statement, Gordian proposed an auto-order assessment system (the idea of auto-order assessment is discussed before in section 1.3). However, before we can determine preconditions on whether to intervene by planners, we will investigate how it currently works without preconditions. When we have insight in the reasons for interventions by planners, we might be able to formulate preconditions at a later stage.

3.2 Literature concerning planning decisions

In this section we seek for possible factors that could influence planning decisions in general. In subsection 3.2.1 we review scientific literature on behavioural operations. Next, in subsection 3.2.2 we review scientific literature regarding inventory management. In subsection 3.2.3 we discuss factors that influence planning decisions based on expert opinions and finally, in subsection 3.2.4 we give an overview of all factors that influence planning decisions. In order to provide an answer to sub question 1.b: *Which factors influence the planning decisions*?

3.2.1 Behavioural Operations

Recall, our main problem is that purchase requisitions generated by a planning system are often modified by planners. Consulting the scientific literature, our topic belongs to a relative new subject in the academic world, named behavioural operations. Recently, Croson et al. (2013) argued that behavioural operations have become an accepted sub-field of the discipline of operations management. This research area could be indicated as an combination of operations management and the human – behavioural - aspects of psychology.

Croson et al. (2013) defined behavioural operation as the study of potentially *non-hyper-rational actors in operational contexts*. The richness and the complexity of the operations context that distinguishes it from research on organizational behaviour. Usually, the goal of research in behavioural operations is a deeper understanding of operations processes. Many traditional papers in operations management do consider human behaviour. However, they predominantly model humans as hyper-rational beings optimising behaviour towards a single monetary goal, which is often not true. Here, hyper-rational actors are characterised by the following criteria: 1. They are mostly motivated by self-

interest; 2. They act in a conscious and deliberate manner; 3. they behave optimally for a specified objective function.
Besides research being behavioural in nature and dealing with operations context, a third aspect limits the scope of the field of behavioural operations. Research in behavioural operations analyses decisions, the behaviour of individuals, or small group of individuals.

Based on the definition and the scope of Croson et al. (2013), we conclude that our main problem can be classified as a topic of behavioural operations since we research ordering decisions made by planners in an operations context. In the next paragraphs we evaluate several papers concerning the neglect of system's recommendations by planners (paragraph 3.2.1.1) and ordering behaviour (paragraph 3.2.1.2).

3.2.1.1 Neglect of system's recommendations by planners

We found several studies that faced similar issues concerning the neglect of system's recommendations. The contexts are different, such as production planning and scheduling (Fransoo & Wiers, 2008; Wiers & van der Schaaf, 1997) forecasting decision support systems (Lawrence et al., 2002) and inventory management systems in retailing (van Donselaar et al., 2010). However, the main findings of these studies are in line with our main problem.

In the first study, Fransoo & Wiers (2008) collected data on actual planning decisions and compare them to the planning decisions proposed by the system. They conclude that planners systematically and largely neglect the system's recommendations and that the extent of neglect is larger if the planning problem is more complex. Another interesting finding of their research is that planners do not change the tactical parameters in the system, instead, they change the proposed orders of the system directly one-by-one. The authors conclude that it is not clear whether all changes made by planner really improve the performance of the production plan.

In the study of van Donselaar et al. (2010), they research the ordering behaviour of retail store managers in a supermarket chain system. They show that (i) store managers consistently modify generated order advices by advancing orders from peak days (Thu./Fri./Sat.) to nonpeak days (Mon./Tue./Wed.), and (ii) this behaviour is explained significantly (using regression) by product characteristics such as case pack size relative to average demand per item, net shelf space, product variety, demand uncertainty, and seasonality error. These factors are drivers of order advancement and are related to system inadequacy and incentive misalignment in a store. Furthermore, the paper presents evidence that managers may systematically deviate from an automated decision support system for reasons that are rational and predictable. Retail store managers may not follow order advices generated by an automated replenishment system if their incentives differ from the cost-minimization objective of the system. Incentive misalignment arises because store managers´ incentives often do not include inventory holding costs, whereas automated replenishment systems include them in their objective function. Moreover, the store manager is assessed on labour costs, whereas the system does not take these costs into account. Further, the objectives of the system differ from the incentives of the store manager even if we ignore the complexity induced by handling capacity constraints.
The regression results of this research suggest that store managers improve upon the automated replenishment system by incorporating two ignored factors: in-store handling costs and sales improvement potential through better in-stock.

The study of Lawrence et al. (2002) investigated the impact on user satisfaction and forecast accuracy of user involvement in the design of a forecasting decision support system (FDSS). Their laboratory study confirms the importance of user involvement. However, these authors argue that there appears to be a persistent problem with model based DSS: Decision makers excessively discount the value of the advice even when shown how good it is and when shown that they are unlikely to improve on it (Goodwin, 2000; Goodwin & Fildes, 1999; Lawrence & Sim, 1999; Lim & O'Connor, 1995). Instead of trusting and accepting the system advice, and only modifying it when there is evidence that it can be improved, users tend to modify it excessively, trusting there own judgement more than the system advice. The results of this behaviour are that the benefits of the system are squandered. In the paper of Lawrence et al. (2002), if the FDSS selects the optimal model to forecast the time series, the forecast advice is more accurate but the user may feel "shut out" or uninvolved and hence not accept or trust the system's forecast. As a result, this forecast is modified excessively and the potential for improved accuracy is, in effect, lost. This conundrum is not unique to the task of forecasting. The authors conclude that many complex model-based DSS can be expected to exhibit the same characteristics as a FDSS.

So far, Lawrence et al.(2002) shows that decision makers modify excessively the forecast, even when shown that the FDSS selects the optimal model to forecast and the forecast advice of the FDSS is more accurate. However, in practice, forecasters may also have access to contextual information, such as plans for a sales promotion campaign. Empirical evidence shows that, under these conditions, there are usually benefits to adjustment due to users having substantive information (Sander & Ritzman, 2001).

The papers of Fransoo & Wiers (2008), van Donselaar et al. (2010) and Lawrence et al. (2002) discussed several reasons to modify an advice, some of these reasons could also be applicable in spare parts planning. For example, behaviour that planners change orders one-by-one instead of changing the tactical parameters. In the study of van Donselaar (2010), they explained behaviour by product characteristics like case pack size and demand uncertainty (forecast error). We summarised the findings of the studies and the factors to explain these modifications in Table 3.1.

Paper	*Fransoo & Wiers (2008)*	*Donselaar et al. (2010)*	*Lawrence et al. (2002)*
Context	Production planning and scheduling	Inventory management in retail stores	Forecasting DSS
Main findings	Planners systematically and largely neglect the system's advices	Store managers systematically modify automated order advices	Decision makers modify excessively the forecast, even when the FDSS selects the optimal model
Reasons to modify?	Not investigated	Incentives differ from the cost-minimization objective, peak demand, labour capacity constraints	Trusting there own judgement more than the system advice
Factors	Changing orders one-by-one instead of changing tactical parameters	Case pack size, Net shelf space, Product variety, Demand uncertainty, Seasonality error	User involvement, Easy to use, Usefulness, Access to extra information

Table 3.1: Summary of papers on the neglect of system's advice.

3.2.1.2 Ordering behaviour

In this paragraph we provide an overview of the studies that researched specific factors that influence ordering behaviour, such as stochastic lead times (Ancarani et al., 2013) and a spike in demand (Tokar et al., 2013). Most of the studies are controlled laboratory experiments, using the well-known beer game setting or they used the newsvendor model. For background information about the beer game and the newsvendor model we refer to Appendix G. Again, we found no scientific literature that addresses ordering behaviour in spare parts planning (decisions regarding the deployment process), however, we find factors that could be relevant for spare parts planning. In the first part we consider relevant factors in the beer game context and in the second part we consider relevant factors in the newsvendor context.

Ordering behaviour in the beer game context
In this subparagraph we discuss the papers concerning ordering behaviour that use the framework of the beer game. Ancarani et al.(2013) investigated the impact of stochastic lead times. The authors conducted three human experiments by manipulating constant vs. variable demand and known vs. stochastic lead times. They compared the results of these experiments with a risk neutral virtual player (a simulation model). The first finding is that human players buy more stock than the virtual player. An explanation for this behaviour could be that a common reaction is that when people face both risk and ambiguity, they overestimate the less favourable outcomes. Another remarkable outcome is that players react to higher uncertainty (both demand and lead time) by holding fewer inventories, a behaviour consistent with the predictions of some psychological models of choice under ambiguity. Ambiguity is a type of uncertainty, i.e. a situation of which there are multiple possible outcomes whose probabilities are vague or unknown (Knight, 1921). Summarised, human players buy more stock compared to the risk neutral player when facing uncertainty in demand or stochastic lead time. However, when facing both uncertainty in demand and stochastic lead time, human players holding fewer inventories.

Sterman (1989) was the first study that investigated the Bullwhip effect, using the beer game context. The bullwhip effect stands for the fact that the demand/order variance is higher at a higher echelon in the supply chain. Sterman's experiment showed that human behaviour, such as misconceptions about inventory and demand information, may cause the bullwhip effect. The amplified order variability may be attributed to the players' irrational decision making. In contrast, Lee et al.(1997) show that the bullwhip effect is a consequence of the players' rational behaviour within the supply chain infrastructure. This important distinction implies that companies wanting to control the bullwhip effect have to focus on modifying the chain's infrastructure and related processes rather than the decision makers' behaviour. Lee et al.(1997) have indentified four major causes of the bullwhip effect: 1. Demand forecast updating; 2. Order batching; 3. Price fluctuation; 4. Rationing and shortage gaming (customers anticipate on a shortage and order more or even worse, they place duplicate order with multiple suppliers and buy from the first one that can deliver, then cancel all other duplicate orders). Later on, we discuss which factors of these "beer game" studies are relevant for spare parts planning.

Ordering behaviour in the newsvendor context
In the last decade, many papers have been published on ordering behaviour in the newsvendor problem (e.g., Schweitzer & Cachon, 2000; Lurie & Swaminathan, 2009; Benzion et al., 2010; Tokar et al., 2013; Moritz et al., 2013; Lau et al., 2013; Vericourt et al., 2013). All papers address the topic that decision makers deviate from the profit maximising order quantity. On average, decision makers order a quantity between the mean of the demand value and the expected profit-maximising quantity. Experimental research finds that the average order quantities of actual people tend to be more regressive toward the mean demand than towards the normative order quantities, a finding that has been dubbed the pull-to-center effect (Schweitzer & Cachon, 2000; Lau et al., 2013).

The study of Tokar et al. (2013) is not related the pull-to-center effect, they investigated ordering decisions when decision makers anticipated a demand shock – a spike in demand. The collective result from three (controlled laboratory) experiments identifies a bias towards over-ordering in response to a demand shock, relative to the optimal orders. The main finding is that uncertainty regarding the timing and magnitude of a demand shock leads to overstocking. The observed overstocking behaviour has two dimensions, ordering too much and ordering too early.

Summing up, several aspects of ordering behaviour have been studied recently. In Table 3.2 we provide an overview of relevant factors that influence ordering decisions with their corresponding effect.

Factors	*Effect*	*Paper*
Stochastic lead times	Increase order quantity	Ancarani et al.(2013)
Variable demand	Increase order quantity	Ancarani et al.(2013), Sterman (1989)
Stochastic lead times and variable demand	Decrease order quantity	Ancarani et al.(2013)
Demand forecast updating	Cause bullwhip effect	Lee et al.(1997)
Rationing and shortage gaming	Cause bullwhip effect	Lee et al.(1997)
Uncertainty regarding the timing of a demand shock	Place orders sooner than is optimal	Tokar et al. (2013)
Uncertainty regarding magnitude of a demand shock	Increase order quantity (over-ordering)	Tokar et al. (2013)

Table 3.2: Summary of relevant factors regarding papers on ordering behaviour.

3.2.2 Inventory management

In this subsection, we discuss factors concerning inventory planning decisions. We used the Inventory Management book of Silver, Pyke and Peterson (1998) and in addition, we reviewed the paper of Driessen et al. (2013) to find relevant factors that could influence planning decisions.

Silver et al. (1998) provides an extensive listing of potentially important factors. However, they review just three factors; replenishment lead time, demand pattern and production versus nonproduction. The factors lead time and demand patterns are also indicated as important by the studies concerning ordering behaviour (Ancarani et al., 2013; Sterman, 1989; Tokar et al., 2013). Regarding the factor production versus nonproduction, we are dealing with a nonproduction context.

Based on the extensive list of Silver et al.(1998), we find the following additional factors: *Quality of information, Timing of information, Shelf life, Substitution, Frequency of demand, Minimum order quantity (MOQ), No supplier available, Service levels, Budget constraints, Quantity discounts, Ordering costs, Shortage costs, Lateral shipment costs, Forecasting methods* (Simple, Trend, Seasonal, Slow moving) and *Inventory policies* (s,Q; s,S; R,s,S; R,S).
Later on, in subsection 3.3.1 we distillate the factors that we use in our research and in subsection 3.3.2 we give a description of these factors.

The paper of Driessen et al. (2013) discusses factors that influence decisions on how to plan and control a spare parts supply chain. However, some of these factors have also impact on planning decisions. In addition to the factors of Silver et al. (1998), we find factors as such as the *phase in* and the *phase out* of an asset, the *criticality* of parts and *commonality* of parts. In subsection 3.2.4, we summarise all relevant factors that influence planning decisions.

3.2.3 Additional factors with impact on planning decisions

So far, we reviewed literature on behavioural operations (3.2.1) and inventory management (3.2.2) to find factors that influence planning decisions. In this subsection, we use expert opinions and results from the first interviews with planners to find additional factors with impact on planning decisions. First, we discuss the results from the interviews with planners in paragraph 3.2.3.1 to 3.2.3.3. Secondly, we consider the expert opinions in paragraph 3.2.3.4.

3.2.3.1 Interviews at RET

At RET, we interviewed two planners separately to get more insights in the process of spare parts planning at this company. A complete description of RET, their spare parts planning and the ordering process can be found in Appendix C. In this paragraph, we evaluate additional factors to modify a purchase requisition. We found the following additional factors as argued by the planners:

1. *Low frequency of demand*: When the usage frequency is low (less than 2 usages per year), planners consider to decrease the proposed order quantity or even to reject the order.
2. *High unit value*: When the unit value is high, planners often decrease the proposed order quantity.
3. *Low unit value*: When the unit value is low, planners often increase the proposed order quantity.

According to our empirical results of chapter 5, see section 5.3.4, the factors *Low unit value* and *Low frequency of demand* occurs frequently at RET.

3.2.3.2 Interviews at Royal Netherlands Navy

At the Navy, we interviewed four planners separately regarding the spare parts planning. Two planners are from the Navy and two planners are from Gordian (the Navy outsourced their spare parts partially). Background information of the Royal Netherlands Navy can be found in Appendix D. In this paragraph, we evaluate additional factors that lead to intervention by planners. We found the following additional factors as argued by the planners:

1. *Rounded quantities*: Planners tend to round up or to round down order quantities to "nice" numbers. For example, the proposed order quantity is 23 and the planner adapts it to 25.
2. *Trend shift*: Planners recognised an increasing or decreasing demand pattern and anticipate on this trend shift by adapting the proposed order quantity.
3. *Long lead times*: When the lead time is long, e.g. more than 6 months, planners tend to increase the order quantity.
4. *Typical demand quantity*: Planners knows that if a demand occurs, customers order a fixed quantity. In this case, it is not smart to order less than the typical demand quantity. For example, the system proposed to order 3 spare parts but mechanics requested always 4 spare parts of this specific part.
5. *Peak in lead time*: There is a spike in the lead time. The effect is that the variability of lead time becomes much higher and the re-order level and the safety stock increases significantly. Planners anticipate by decreasing the order quantity, decreasing the re-order level or removing the peak lead time of the data.
6. *No supply information*: In this case, a supplier is known but not all information is added into the system, e.g. actual lead time of the supplier is missing.
7. *Maximum order quantity*: This is specific for the Navy since it is not allowed to exceeds the forecasted demand during 24 months (this is a policy of the management). In other words, if the EOQ is higher than the forecasted demand during 2 years, the proposed order quantity is capped on the forecasted demand in 2 years.
8. *Quadrant shift*: This is specific for Gordian's SPPT. Spare parts are classified in quadrants (based on price and frequency) and each quadrant has its own service level and inventory control settings. Spare parts can shift between quadrants which imply a new service level and (possibly) another replenishment policy. For

example, a spare part was classified as c2-item (slow mover en medium price) but due to increasing frequency of demand the spare part becomes a b2-item (medium mover and medium price). Regularly, planners adapt tactical parameters settings since the planner disagree with the quadrant shift. This kind of intervention involves for all spare parts nearby the threshold values of a quadrant.

9. *Old demand request*: This is specific for the Navy. The system is triggered by an old request or old settings, this can be considered as contaminated data. E.g. a system phased out but still the system recommends to order. Planner should check if the old request is still valid, however, often these old requests are removed from the system for several reasons.

According to our empirical results (see section 5.4.4) the factors *Rounded quantities, Old demand request* and *Typical demand quantity* occurs frequently at the Navy.

3.2.3.3 Interviews at IBM

At IBM, we interviewed the team leaders located in Amsterdam and several planners (analysers) located in Hungary. A complete description of IBM and all background information regarding their Service Parts Organisation (SPO) can be found in Appendix E. In this paragraph, we evaluate additional factors to modify a purchase requisition.

At IBM, the team leads and planners argued that factors such as substitutions, phase in of assets, phase out of assets and peak demands plays an important role by intervening. However, in addition to the factors already mentioned, IBM is dealing with one specific problem which often results in interventions. This is a combination of substitutions and commonalities and they refer to this issue as *matrix substitutions*.

1. *Matrix substitutions*: Spare parts are used in several systems and after a period there is a new spare part available that substitute the old spare part. This becomes complicated when the new spare part is not applicable in all systems (e.g. old part is used in system A, B, C and D) but only in certain systems (the new part can only be used in system A and D).
   In addition, extra complexity is introduced since some spare parts can be substituted by an upgraded part. In particular, in the IT business where technological developments change rapidly. In this case, the spare part is still in the assortment (no phase-out) and an upgraded (more expensive) part can be used if the concerned spare part is not on stock. E.g. suppose there are hard drives of 300 GB, 450 GB and 600 GB. In case the 300 GB hard drive has no available stock, a 450 GB hard drive can be used (if it is allowed to use this type of hard drive in the computer). When the 450 GB hard drive is also not available, the 300Gb hard drive can be upgraded to a 600 GB hard drive. Note that, this substitutions are not reversible (one-way substitutions).

3.2.3.4 Expert opinions

At 25th of October 2013, we spoke with expert V.C.S. Wiers. He is founder and director of consultancy company Twinlog and one day a week, he is also employed by Eindhoven University of Technology as Industrial fellow (TUE, 2013). His expertise is in the human factor in production control, in particular, the mismatch between Advanced Planning and Scheduling (APS) systems and the users of it. Background information of Wiers and a summary of the conversation with Wiers can be found in Appendix A. After the conversation, we send this summary to Wiers and based on his feedback the summary was completed.

Wiers argued that all reasons for interventions can reduced to three main categories:

1. Bad input data and/or missing data
2. Incomplete/incorrect planning model and assumptions
3. Human factor

His experience - based on research and as consultant - is that the main reasons to deviate from planning systems are the model assumptions and data issues. The influence of the human factor in planning decisions is therefore not limited to "soft" factors as such as individual differences (3), but also in correcting the mistakes that are made by the system or the planning technique (1 and 2). In subsection 3.3.2, we describe the factors used in our research and we classify whether the factor is part of data issues (1), model issues (2) or the human factor (3).

3.2.4 Overview of factors with impact on planning decisions

In this subsection, we are answering sub question 1.b; *Which factors influence the planning decisions*? Here, we summarise all 52 factors with impact on planning decisions described in the previous three subsections. An overview of all factors is given in Table 3.4 with their corresponding references.

Factors	Described in subsection	References
Case pack size, Net shelf space, Product variety, Demand uncertainty, Seasonality, Holding costs, Labour costs, Handling capacity restrictions	3.2.1.1	Donselaar et al. (2010)
User involvement, Easy to use, Usefulness, Access to extra information	3.2.1.1	Lawrence et al. (2002)
Stochastic lead times; Long lead times; Peak in lead times	3.2.1.2 3.2.3.2	Ancarani et al.(2013) Planner of Navy
Variable demand	3.2.1.2	Ancarani et al.(2013)
Demand forecast updating; Timing of information	3.2.1.2 3.2.2	Lee et al.(1997) Silver et al. (1998)
Rationing and shortage gaming	3.2.1.2	Lee et al.(1997)
Uncertainty regarding timing of a spike demand	3.2.1.2	Tokar et al. (2013)
Uncertainty regarding magnitude of a spike demand	3.2.1.2	Tokar et al. (2013)
Quality of information (data missing); No supply information	3.2.2 3.2.3.2	Silver et al. (1998) Planner of Navy
Substitution; Matrix substitutions	3.2.2 3.2.3.3	Silver et al. (1998) Planner of IBM
Frequency of demand; Low frequency of demand	3.2.2 3.2.3.1	Silver et al. (1998) Planner of RET
Minimum order quantity (MOQ), Shelf life, No supplier available, Service levels, Budget constraints, Quantity discounts, Ordering costs, Shortage costs, Lateral shipment costs, Inventory policies, Forecasting parameter settings; Forecasting method	3.2.2	Silver et al. (1998)
Phase in of asset/part, Phase out of asset/part, Criticality, Commonality	3.2.2	Driessen et al. (2013)
High unit value, Low unit value	3.2.3.1	Planner RET
Rounded quantities, Trend shift, Typical demand quantity, Quadrant shift (only for SPPT), Maximum order quantity (only Navy), Old demand request (only Navy)	3.2.3.2	Planner Navy (Gordian)

Table 3.3: Overview of all factors that influence planning decisions in general.

Note that, changing orders one-by-one instead of changing tactical parameters as argued by Fransoo & Wiers (2008), is ordering behaviour that we can observe although it is not a factor causing interventions.

3.3 Factors causing interventions in spare parts planning

In the previous section, we extensively researched factors that influence planning decisions in general. In this section, we distillate the factors that are relevant for spare parts planning in order to answer sub question 1.c: *Which factors are relevant for planning decisions in spare parts planning*?
In subsection 3.3.1, we exclude irrelevant factors for spare parts planning. Next, in section 3.3.2 we describe all relevant factors that we use in our research. In section 3.3.3, we categorise the relevant factors according to the spare part processes defined by Driessen et al. (2013) and finally, we present an adapted framework.

3.3.1 Exclude irrelevant factors for spare parts planning

In the previous subsection (3.2.4), we provide an overview of all factors with impact on planning decisions in general. In this subsection, we exclude factors that are not relevant for spare parts planning based on irrelevancy and being immeasurable. Note that, we do not exclude any factor that we found during our empirical study.

Several factors we found in our literature study - concerning planning decisions in general - are outside the scope of our research. As mentioned before in section 2.3, we focus on operational planning decisions and we assume that tactical inventory control parameters are given. Within these givens, the operational planner makes planning decisions. Therefore, we exclude the factors *service levels, inventory policies*, *forecasting parameters settings* and *budget constraints.*
The factors *user involvement*, *easy to use* and *usefulness of system* can be considered as experiences of the entire planning system by the planner. These psychological (cognitive) factors are also out of scope. Based on the same argument, we exclude the factor *rationing and shortage gaming* (recall, mechanics anticipate on a shortage in the past and order more the next time). In the study of Tokar et al. (2013), participants (planners) know in advance that a peak demand will occur but they do not know when the peak demand will occur. During our research, we do not have in-advance information about spike demands. Therefore, we exclude the factor *uncertainty regarding timing of a spike demand*.
The factors *labour costs* and *handling capacity restrictions* were found in the context of retail stores. We consider that the factor *handling capacity restrictions* is less relevant in the spare parts context and the factor *labour costs* is an aspect of the ordering costs and holding costs, discussed in the next subsection. Therefore, we also exclude these two factors. Furthermore, the factor *product variety* is irrelevant to take into account in our research.

We exclude the factor *lateral shipment costs* and *shortage costs* because of lack of data. None of the three companies, which participate in our research, measures these factors and/or take these factors into account in planning decisions. Theoretically, it is possible to derive a specific type of shortage costs (B3) from the fill rate (type of service measure), see Silver et al. (1998). However, in consultation with Gordian we decided to focus on the fill rate and not shortage costs.
When planners intervene because they have *access to extra information,* we suppose the planner might be able to improve the planning decision. However, this factor is too broad and it could be an universal answer to almost all interventions. Therefore we exclude this factor. We would like to measure concrete aspects when the planner has access to extra information. E.g. planner has more accurate knowledge about lead times, minimum order quantities, shelf life, the phase-out of an asset. Based on the same argument, we exclude the factor *Quality of data* since we want to know what kind of data is missing.

3.3.2 Factors used in our research

In this subsection, we define relevant factors concerning spare parts planning decisions. For each factor, we discuss whether we can influence the factor and we point out where we can influence the factor in order to improve spare parts planning decisions. As argued by Wiers (Appendix A), reasons for interventions can be reduced to three main categories: Data issues, Model issues or the Human factor. However, this depends on the planning system used at the participating companies where the factor can be influenced. RET uses SAP as planning system, the Navy uses the SPPT and IBM uses Servigistics, more information about these systems can be found in section 5.1.2 and appendix C, D and E. We marked the cell green if the factor can be influenced relative easy in that category. We marked the cell red if the factor is hard to influence or even can not be influenced in the corresponding category.

Data	Model	Human

1. MOQ - Minimum order quantity

Many suppliers have set a minimum order quantity (MOQ) because of the case pack size or to cover the setup costs for a new production batch. Planning systems used in our research are able to take this factor into account. Despite this fact, regularly the MOQ is missing and hence the system recommends an incorrect order quantity. During our empirical research, we recognised two effect; 1. Planners increase the proposed order to the MOQ 2. Planners consider that there is enough stock available on stock and therefore they reject the order. Regarding this factor, the first effect (increasing the order quantity) is a data issue and this can be influenced by adding the right MOQ into the system. The second effect (rejecting the order) can be considered as a human factor since the planner argues that there is enough stock available while the system would like to replenish.

Data	Model	Human

2. MOD - Case pack size

This factor is similar to the MOQ. When there is a case pack size – also called module quantity (MOD) – the order quantity has be a multiple of the case pack size. E.g. a spare part has a case pack size of 12 items, consequently the order quantity should be a multiple of 12. As with the MOQ, planning systems are able to take this factor into account. Therefore, planners intervene since the required data is missing in the system. This factor is a data issue that can be influenced.

Data	Model	Human

3. Net shelf space

Planners can intervene due to storage volume restrictions. This factor can be influenced by adding space restrictions to the model (plus information about dimensions of the spare part) or by adding a maximum inventory level for these parts.

Data	Model	Human

4. Shelf life

The shelf life of a part is the recommended time period for which products can be stored and the quality of the parts remains acceptable for usage (Driessen et al, 2013). Most planning systems do not take into account a shelf life restriction. However, in practice this is a common issue with spare parts such as batteries. This factor can be influenced by adding a shelf life restriction to the model (plus the duration of shelf life) or by adding a maximum inventory level for these parts.

Data	Model	Human

5. Substitution

Various spare parts are substituted by newer parts due to quality improvements or by functionality upgrades. Particularly in the technology business, where spare parts are substituted frequently. Advanced planning systems such as SPPT and Servigistics are able to link these parts in the system and to aggregate the demand and stock on the prime part. However, this is only feasible for straightforward substitutions as part A is replaced by part B. Regarding to SAP, this factor can be influenced by adding this functionality to the model and the corresponding substitute link.

6. Matrix substitutions (commonality) Data Model Human

This factor is a combination of substitutions and commonalities. For example, a spare part is used in several assets (commonality of spare parts) and after a period there is a new spare part available that substitute the old part. However, this becomes complicated if the new spare part is not applicable in all assets (e.g. old part is used in asset A, B, C and D) but only in certain assets (new part can only be used in asset A and D). This complexity introduced by substitutions and the characteristics of the assets is difficult to model in a system. Theoretically, it is possible to model these complex relations and to collect the data of these relationships. However, from data management point of view it might be very time consuming and inefficient to model this factor.

7. Typical demand quantity - TDQ Data Model Human

For a subset of spare parts there is a typical demand quantity. When a planner knows this information, it is practical to add this information to the system (it is comparable to the MOD, only this is a restriction on the demand side instead of the supply side). This factor should be modelled and the data should be added into the system.

8. High variability of demand - Demand uncertainty Data Model Human

Demand uncertainty and a high variability of demand can be considered as one factor. When a planner overrules a proposed order quantity because of this factor, it can be considered as a human factor. Given that historical demand is available and the planning systems used in our research apply the variance of the demand in their calculations for safety stocks and re-order levels. Planners can disagree on the proposed order quantity and order more (less) spare parts. However, this results in a higher (lower) availability of part than is required. This factor can be influenced by providing feedback to planners about the consequences of their decisions.

9. Peak in demand Data Model Human

In the study of Tokar et al. (2013), participants (planners) know in advance that a peak demand will occur but they do not know the magnitude of a peak demand. During our research, we do not have in-advance information about peak demands. However, peak demands occur frequently and we are interested in how planners deal with proposed order quantities after a peak demand occurred. From a theoretical point of view, extreme values (outliers) should be removed from the data set to make an accurate forecast. Therefore, this issue can be influenced by including an outlier detection in the model. The SPPT contains already a functionality to remove outliers from the dataset but they do not use this functionality at the Navy. Furthermore, this factor can be considered as a human factor since planners can overreact because of a peak demand (risk averse attitude).

10. Frequency of demand Data Model Human

This factor can influence spare parts decisions, especially when the frequency of demand is low (slow moving parts) as argued by the planners of RET. We make a distinction between planning systems with proper (forecasting) methods for slow movers and planning systems with regular models (SAP). Concerning SAP, the root cause is the simplified models which can be extended with more advanced models that fit to slow movers. Regarding the planning systems with advanced models, the factor can be influenced by providing feedback to the planners.

11. Seasonality Data Model Human

When a spare part is a seasonal part, planning systems can easily take this factor into account by using a seasonal forecasting method such as Winters seasonal model (Silver et al., 1998). We assume that sufficient historical demand data is available.

12. Trend shift Data Model Human

When planners see a change in the pattern of demand, often they would like to anticipate on this trend shift. Advanced planning systems are able to recognise a trend shift and take this into account in their forecasting. For planning systems with basic functionality, this factor can be influenced by modelling this aspect. Nevertheless, human judgement is still desirable in order to confirm the changing trend (or to judge that it was an exceptional demand). Besides, planners have the possibility to change the forecasting method during the review process in advanced planning systems. This can affect the proposed order quantity and therefore we also consider this factor as a human factor that can be influence by providing planners with feedback.

13. Demand data update frequency

Data Model Human

Data update frequency, timing of information or delay of information can be considered as the same factor. Occasionally, planners overrule the proposed order quantity since they have more accurate data than the planning system has. E.g. at the Navy the SPPT extract data from the ERP-system VAS. Inventory levels are updated weekly, however, other data such as the demand data is update monthly (forecast are also generated monthly). This factor can be regarded as a data issue which can be influenced by updating the data more frequently.

14. High variability of lead time

Data Model Human

Stochastic lead times and a high variability of lead time can be consider as one factor. When a planning system uses deterministic lead times, this factor can be influenced by extending the model. In advanced planning systems, the variability of the lead time is already used for the calculations of the safety stocks and re-order levels. In this case, we argue that it is unnecessary to intervene by a planner and we can influence this factor by providing feedback to planner.

15. Long lead times

Data Model Human

Planners increase the order quantity due to the long lead time. However, in our opinion, this is a overreaction of the planner since the model already determines the safety stock and the reorder level based on the lead time. Therefore, we consider this factor as a human factor and we argue that this factor can be influenced by providing feedback to planner.

16. Peak in lead times

Data Model Human

This factor is quite similar to the factor peak in demand. Extreme values should be removed from the data set to make an accurate forecast of the lead time. On the other hand, it is smart to verify with the supplier whether the peak in the lead time is an exceptional case (not structural due delivery problems at a higher level in the supply chain). From this point of view, we consider that this factor can be influenced partially by including a good outlier detection in the model. In addition, this factor can be considered as a human factor since planners can overreact due to the peak in the lead time (risk averse attitude).

17. No supplier available

Data Model Human

When no supplier (source) is available, the purchasing depart has to search for a new supplier or the mechanic has to search for a comparable spare part. This factor can not be associated with data issues, model issues or the human factor.

18. No supply information

Data Model Human

Since there is a supplier, there should also be a contract with supply information. Apparently, supply information such as the lead time of the contract is missing in the system. Therefore, this factor can be influenced by adding the supply information into the system.

19. Quantity discounts

Data Model Human

For a few spare parts, suppliers have quantity discounts based on volume. This means, there are different prices depending on the order quantity (the higher the quantity, the higher the discount usually). Planning systems used in our research do not incorporate this factor and it happens rarely that planners intervene for this reason (we found no empirical evidence). However, if necessary, this factor can be influenced by adding the price structures to the system and including this factor in the model. For more information about modelling quantity discounts, we refer to Silver et al. (1998).

Data Model Human

20. Ordering costs

When ordering, usually the planner makes a trade-off between the ordering costs and the holding costs, taking into account the forecasted demand. Aspects of the ordering costs are transportation costs, costs made by the purchasing department (preparation of offers, comparison of suppliers, creating a file), warehouse handling costs (receiving, inspection, material handling) and administration costs (invoice handling) (Silver et al., 1998). It is difficult to make good estimations of all these costs factors, this can be considered as a data issue. Gordian argues that 75 till 100 euro is usual to use as ordering costs for spare parts. Despite this fact, the planning system of RET (SAP) does not apply ordering costs in their calculations. In this case, this factor can be influenced by including ordering costs into their the model.

Data Model Human

21. Holding costs

Most important aspects of the holding costs are opportunity costs of the money invested and warehousing costs (Silver et al., 1998). Again, it is difficult to make good estimations of all these costs factors (investment opportunities can change from day to day). This can be regards as data issue. According to Gordian, the carrying rate for spare parts is between 15 and 25 percent per invested euro. Since the planning system of RET (SAP) does not use holding costs in their calculations, this factor can be influenced by including holding costs to their the model.

Data Model Human

22. Phase in of asset

When a new asset phased in, it is difficult to plan the spare parts concerned since there is no historical demand data available (or data on failure rates). This factor is hard to influence but a manual forecast could be provided.

Data Model Human

23. Phase out of asset

When an asset phased out, it depends on the context what issues can be present. Suppose, a company uses an asset and in the short term its applicability will be expired. A consequence is that the inventory levels of these spare parts should not exceed the forecasted demand until the expiry date. This aspect can be modelled and this factor can be influenced. In the context of a manufacturing company, they produce the asset concerned and after a certain period they decide to stop producing it. In this case, spare parts are still required until the end of life time. This subject is called product life cycle management and this aspect can be modelled (IBM has already made a lot of progress in this area). Therefore, we this factor can also be influenced by extending the model.

Data Model Human

24. High unit value

Planners are careful with expensive spare parts. They tend to decrease the order quantity and this can results in both lower holding costs and a lower availability of parts. From theoretical point of view, planners should not intervene because otherwise the theoretical service level will be lower than is required. We argue that this factor is a human factor and it can be influenced by providing feedback to the planner. An exception is when the planning system does not take into account the ordering and holding costs (e.g. SAP). In this case, it is unclear if the proposed order quantity is a good trade-off between ordering costs and holding costs. Consequently, the root cause is the absence of ordering and holding costs in the model. In this case, this factor can be influenced by extending the model.

Data Model Human

25. Low unit value

Concerning cheap spare parts, planners tend to increase the order quantity. Since these spare parts are cheap, we expect that the holding costs do not increase significantly. Further, as the quantity increases as well the availability of parts increases to a higher service level than is required. In advance, we expect that the impact of this intervention is small. However, this factor can be influenced by providing feedback to planner. Similar to the factor *high unit value*, an exception is when the planning system ignores ordering costs. For example, at RET we saw a proposed order quantity of 2 items with a price of 2 euro per part whereas the ordering costs are around the 50 euro. This recommendation can not be regarded as a good trade-off between ordering costs and holding costs. Therefore, the root cause is the absence of ordering costs in the model and this factor can be influenced by extending the model with ordering costs.

Data | Model | Human

26. Rounded quantities

Planners tend to round quantities to "nice looking" numbers, for example tens or hundreds. When spare parts are expensive, this rounding can have a huge impact on the holding costs and the availability of stocks (we assume that we keep just a few spare parts on stock when they are expensive). More likely, planners round quantities of cheap spare parts. For example, the proposed order quantity is 97 items and the planner decides to order 100 items. Similar to the factor low unit value, the impact of this intervention is expected to be small. This factor is a human factor and this can be influenced by providing planners with feedback on their decisions. Another option is to add a MOD (e.g. 5, 10 or 50 depending on the price of the part) into the system for these parts such that the system proposed rounded order quantities.

Data | Model | Human

27. Incorrect lead time

Several times, planners intervene for the reason that they know that the lead time is shorter in practice. In other words, the lead time in the system is too high and therefore the system is triggered too early to replenish. This factor can be influenced by adding the right lead time (data) to the system.

Data | Model | Human

28. Old demand request

This factor is typical for the Navy. In this case, the system is triggered by an old demand request. Apparently, according to the planners a couple of years ago (2 or 3 years) the system generated many purchase requisitions but these purchase requisitions where ignored since there was no more budget. This issue can be considered as contaminated data and this factor can be influenced by removing the contaminated data from the system.

Data | Model | Human

29. Quadrant shift

This factor is typical for the SPPT since this system classifies spare parts based on prices and frequencies. Planners intervene, for example, when spare parts shift from a slow mover classification to medium mover classification. The shift implies another inventory policy and a higher service level for the part concerned. However, issues arise nearby the threshold values of a quadrant. E.g. suppose a spare part had a frequency of 2 and was classified as a slow mover. Recently, there was a new demand and therefore the frequency of the spare part becomes 3. Accordingly, this spare part becomes a medium mover and it is questionable if the new classification and inventory control settings are right. For these reasons, planners intervene frequently when spare parts are positioned nearby the threshold values of a quadrant. We consider this factor as a human factor that can be influenced by providing planners with feedback.

Data | Model | Human

30. Maximum order quantity

This factor is typical for the Navy since they have a policy that the order quantity should not exceed the forecasted demand during two years. The SPPT indicates when this forecast/EOQ-ratio is below 1, this means that the EOQ is higher than the forecasted demand during two years. In this case, the planner has to decide to accept the proposed order quantity equal to the forecasted demand during two years or to adapt the quantity to the EOQ (or to any quantity between these two values). Since the management of the Navy established this rule of thumb, we consider this factor as a human factor.

31. Criticality

Data Model Human

A spare part is critical if the failure of the part results in a full system breakdown, this means that the system is non-operational for all assigned use purposes (Driessen et al., 2013). At this moment, only Servigistics (IBM) takes the factor criticality into account. As a consequence, if planners at IBM intervene, it can be considered as a human factor (assuming that the data and model are right). Regarding the other planning systems, this factor can be influenced by modelling this factor and adding data concerning the criticality of a part into the system.

3.3.3 Categorisation according to spare part processes

At this point, we have an extensive list of 31 factors that we use for our empirical research and we argued if the factor can be influenced and if it related to data issues, model issues or the human factor. Next, we categorise the factors based on the framework of Driessen et al. (2013) in order to indentify the process owner. From a management perspective it is useful to know where the root cause of a planner's intervention is situated. For example, if many interventions occur in the category supply management, it might be practical to discuss the issues with the supply relations manager.

Recall, the spare parts processes of the framework of Driessen are: 1. Assortment management 2. Demand forecasting 3. Supply management 4. Inventory control and 5. Deployment (the other three processes are not relevant for our research, see subsection 3.1.2). We discuss these processes and corresponding factors in the following paragraphs.

3.3.3.1 Assortment Management

As stated before, assortment management is concerned with the decision to include (phase-in) or exclude (phase-out) an asset (parts) in the assortment. Furthermore, (technical) information of the part is gathered and added to the planning system, including aspects such as criticality, commonality, substitution, shelf life and position in the configuration.

Based on these criteria, the following factors are associated with assortment management: *Phase in of asset, Phase out of asset, Shelf life, Net shelf space, Criticality, Substitution* and *Matrix substitution*.

3.3.3.2 Demand forecasting

As mentioned before, demand forecasting concerns the estimation of demand for spare parts in the (near) future. We regard the following factors as related to demand forecasting: *Typical demand quantity, Seasonality, Trend shift, Demand data update frequency* and *Old demand request*.

3.3.3.3 Supply Management

Recall, supply management concerns the process of ensuring that at least one supply source is available to supply spare parts at any given moment in time with predetermined supplier characteristics, such as procurement lead time, order quantities and possible price structures.

Based on these criteria, the following factors are associated with supply management: *No supplier available, No supply information, Incorrect lead time, MOQ, MOD* and *Quantity Discounts.*

3.3.3.4 Inventory Control

As mentioned before, inventory control concerns the stocking strategy (which spare parts to stock and in what quantities) and the replenishment policy (what amount to order at a certain point of time). Aspects are the settings of service levels per spare part, safety stocks, re-order levels, ordering costs and holding costs. Therefore, we regard the following factors as related to inventory control: *Ordering costs and Holding costs*.

3.3.3.5 Deployment

Recall, deployment concerns the process of replenishing spare parts inventories. The replenishment policy parameters set by inventory control implicitly determine when to replenish and what quantity to procure. A planner may deviate from this quantity for several reasons, frequently planners correct the system since the input data is wrong/incomplete or the model covers not all relevant aspects. These data and model issues are mostly related to the spare parts processes described above (Assortment, Demand, Supply and Inventory Control). When assuming that the data is correct and all relevant aspects are covered by the model, the planner may deviate from the proposed order quantity due to a human factor. E.g. Planners experience a high variability of demand (even when the planning system includes this variability in the calculations), they anticipate on a peak in the demand (while the system contains a outlier detection and excluding method) or rounding order quantities.

Based on these criteria, the following factors are associated with deployment: *Rounded quantities, Low unit value, High unit value, High variability of demand, Peak in demand, Low frequency of demand, Long lead time, High variability of lead time, Peak in lead time, Maximum order quantities (policy of management)* and *Quadrant shift.*

Note that all factors regarding the deployment process can be considered as a human factor, unless the factor is not covered by the model.

3.3.4 Overview of adapted framework

In Figure 3.2, an overview of all spare parts processes is presented, including their decision levels and mutual connections. Concerning the decision levels, we distinguish three different levels; Strategic, Tactical and Operational decisions. On a strategic level, decisions are regularly taken less frequent, i.e. once a year. Decisions on a tactical level are made more frequently, i.e. once a month or 3 months. Operational decisions are made frequently, i.e. once a day or week (Driessen et al., 2013). Note that in supply management both strategic decisions (e.g. supplier selection) and tactical decisions are made.

Regarding the mutual connections, the arcs in Figure 3.2 presents the data flows from one process to another. For example, supply lead times and demand forecasts serve as input data for inventory control. An overview of all factors per spare parts process and a brief description per factor is given in Appendix B. We used this table to collect data of interventions at the participating companies.

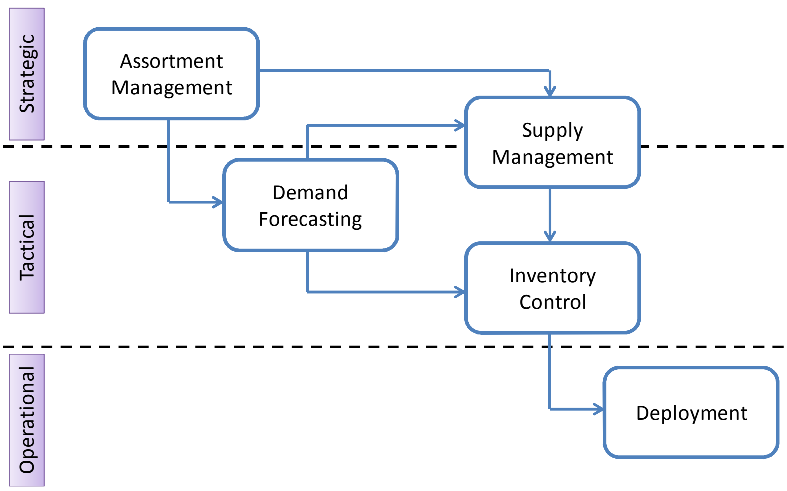


Figure 3.2: Adapted framework of Driessen et al. (2013).

Chapter summary

In this chapter we have extensively discussed the spare parts environment, planning factors in general and factors causing interventions in spare parts planning. In this final section we list the main findings of this chapter.

- We identified **five spare part processes** relevant for our research: Assortment management, Demand forecasting, Supply management, Inventory control and Deployment. **Deployment concerns the process of replenishing spare parts inventories**, this research is focussed on this process.
- This research can be positioned as a study concerning **behavioural operations** since we analyse ordering decisions of planners.
- A few papers are written regarding modifying system's recommendations and **ordering behaviour**. Unfortunately, none of these studies were conducted in a spare parts environment. Therefore, we listed planning factors in general based on scientific papers concerning behavioural operations and inventory management. In addition to the scientific papers, we used interviews with planners (RET, Navy and IBM) in order to find more factors that influence planning decisions. As result, **we found 51 factors that influence planning decisions in general**.
- From the 51 factors in general, we identified 31 factors as relevant for ordering decisions in a spare parts environment. We defined these **31 factors causing interventions in spare parts planning** and we point out where the factor can be influenced (data, model or human factor).
- We categorised the 31 factors according to the spare part processes in order to **allocate the factors to concrete process owners**.

- The factors concerning **assortment management** are: *Phase in of asset, Phase out of asset, Shelf life, Net shelf space, criticality, Substitution* and *Matrix substitution*.
- The factors related to **demand forecasting** are: *Typical demand quantity, Seasonality, Trend shift, Demand data update frequency* and *Old demand request*.
- The factors regarding **supply management** are: *No supplier available, No supply information, Incorrect lead time, MOQ, MOD* and *Quantity Discounts.*
- The factors associated with **inventory control** are: *Ordering costs and Holding costs*.
- The factors regarding **deployment** are: *Rounded quantities, Low unit value, High unit value, High variability of demand, Peak in demand, Low frequency of demand, Long lead time, High variability of lead time, Peak in lead time, Maximum order quantities (restriction of management)* and *Quadrant shift.*

4 Methods to assess ordering decisions

In this chapter we provide methods to assess ordering decisions in order to provide an answer to research question 2: "*How can we assess interventions by planners?*" The main purpose is identifying the differences in performance between the proposed order quantity of the system and the actual order quantity placed by the planner. First, in section 4.1, we define the key performance indicators (KPI) that describe this "performance". Next, we discuss an exact method to measure the impact of interventions afterwards and finally, in section 4.3, we describe an approximated method to estimate the impact of interventions at the moment of intervening.

4.1 Performance measurement

The key in spare parts planning is finding the right balance between performance and logistics costs. Here, we define performance as the availability of spare parts in order to reduce the down time of high-value capital assets. The logistics costs contain two categories, namely, holding costs and ordering costs. In the next three subsections we define these key performance indicators (KPI) which we use for the assessment of interventions.

4.1.1 Availability

Silver et al. (1998) describes several methods to manage inventories, in order to find the right balance between the risks of high inventory levels (also obsolescence risk concerning spare parts inventories) and the risk of stock-outs. One of these methods is called "safety stocks based on customer service" using a control parameter known as the *service level*. The service level becomes a constraint in establishing the safety stock of an item, i.e., minimize the inventory costs of an item, given that at least 95 percent of all demands are satisfied from on-hand stock. Well-known measures of service are:

- *Cycle service level* – Specified probability of no stock out per replenishment cycle
- *Fill rate* – Specified fraction of demand satisfied directly from shelf

There are plenty of other service measures such as the ready rate, the average time between stock out occasions and the fraction of orderliness filled. However, we discuss only the cycle service level and the fill rate since these service measures are used at the companies participating in our research. SAP uses the cycle service level as service measure and SPPT and Servigistics use the fill rate as service measure.

The cycle service level is regularly used in basic inventory management systems since the calculations are straightforward. A predetermined service level can be translated in a corresponding safety factor *k* and then the safety stock can be determined easily. However, this service level is determined *per replenishment cycle* and therefore some remarks have to be made. Consider two items, the first being replenished 10 times per year and the other once a year. If both items have the same service level of 90 percent – this corresponds to a probability of 10 percent for a stock out – then we expect for the first item one stock out per year (10*0,1). For the second item, we expect just 1 stock out per 10 year (0,1 per year). Besides, if a stock out occurs we have no information regarding the amount of backorders. Because of these down sides, we conclude that this service measure is less suitable to use.

The fill rate is defined as the fraction of customer demand that is met directly (that is, without backorders or lost sales) and this service measure has considerable appeal to practitioners. At the participating companies they use a (s,S) inventory policy with re-order level (s) and order-up-to level (S). When the actual inventory position is at the re-order or below the re-order level, a replenishment order of size Q is placed equal to order-up-to level (S) minus the actual inventory position (IP). Furthermore, there is a review period (R) of 1 week at the Navy, this means that they have a so-called (R,s,S)-

policy. Since each replenishment is of size Q, the line of reasoning is as follows concerning the fill rate:

Fraction of demand satisfied directly from shelf = 1 – Fraction backordered,
with Fraction backordered = Expected shortage per replenishment cycle [ESPRC] / Q
Therefore, the Fill rate is

$$Fill\ rate = 1 - (ESPRC\ /\ Q) \quad \textbf{Eq. 4.1}$$

Afterwards, the realised fill rate can be calculated by substituting the ESPRC by the actual number of backorders per replenishment cycle. As shown in equation 4.1, the replenishment size Q influences the fill rate. Given an expected amount of backorders, when the order quantity increases (decreases) the fill rate will increase (decrease). Furthermore, if we assume the demand is normally distributed we can easily calculate the expected shortage per replenishment cycle. This will be discussed in subsection 4.3.1. For the remaining of this report, we use the fill rate as KPI for the availability of parts.

4.1.2 Holding costs

According to Silver et al. (1998), the cost of carrying inventory contains of three main components; 1. Opportunity costs of capital 2. Warehousing costs and 3. Risk costs. Usually, the opportunity costs of capital are the largest proportion of the holding costs. In spare parts environments, the risk costs can also be a substantial part of the holding costs because of the high obsolescence risk.
To make inventory decisions more manageable both from a practical and theoretical point of view, typically, a fixed holding rate per unit value is assumed. This can easily be applied in practice although several notes need to be made. First of all, the explicit measurement of costs is a problem in practice. This problem arises because often it is not economical or even not possible (this depends on the accounting system) to trace all costs as such as handling, damage, theft, obsolescence and insurance costs. Concerning the opportunity costs, investment opportunities can change from day to day. On the other hand, Silver et al. (1998) argues that most of the decision models for inventory management are relatively insensitive to errors in the cost measurement. Second note, a fixed holding rate assumes that more expensive items are more expensive to handle or to store and expensive items have higher risk costs. Third note, this rate assumes that the value of an item is the only driver of inventory costs. Other aspects such as the size of an item or special handling requirements for an item are ignored. Despite these drawbacks, we use the holding rate to estimate the holding costs since the calculation is straightforward. As mentioned before, Gordian argues that the holding rate for spare parts is commonly between 15 and 25 percent per invested euro.

$$Holding\ costs\ per\ year = Annual\ holding\ rate * SKU\ value * Average\ inventory\ level \quad \textbf{Eq. 4.2}$$

In a continuous time re-order point inventory model, the average inventory level is Q/2 plus the safety stock (Silver et al., 1998). To calculate the exact holding costs, we suggest calculating the holding costs per day and summing up these costs for a certain period. Consequently, the realised holding costs for a certain period can be calculated according to the following formula:

$$Holding\ costs\ (T) = \sum_{i=1}^{T} Inventory\ level_i\ * Holding\ rate\ per\ day * SKU\ value \quad \textbf{Eq. 4.3}$$

With day *i* and a certain period of length *T*. We assume that the holding rate and the SKU value remains the same for period *T.*

4.1.3 Ordering costs

Ordering costs include all costs associated with a replenishment, such as costs involved by the purchasing department, transportation costs, handling costs and administration costs (Silver et al., 1998). Generally, ordering costs are assumed to be a fixed value per order. The remarks made concerning the holding costs also apply for the ordering costs concerning the explicit measurement of costs. However, since most of the decision models for inventory management are relatively insensitive to errors in the cost measurement (Silver et al., 1998), we argue that it is useful to take a constant value of the ordering costs. As stated before, Gordian argues that 75 till 100 euro is commonly used as ordering costs for spare parts.

$$Ordering\ costs\ per\ year = Ordering\ costs\ per\ order * number\ of\ orders\ \ per\ year \qquad \textbf{Eq. 4.4}$$

4.1.4 Shortage costs

This type of costs are the costs incurred when a stock out take place. In general, a stock out could result in lost revenues and/or customer dissatisfaction. In spare parts management, a stock out could result in the down time of a high-value capital asset such as a metro (RET), a data centre (IBM) or a Navy ship that has to postpone the mission. There are a number of shortage costs defined by Silver et al. (1998) such as a fixed costs per stock occasion or a fractional charge per unit short per unit time. Again, the explicit measurement of these costs is very difficult in practice. The participating companies in our research do not consider shortage costs or any down time costs, they focus on a high fill rate of spare parts. Since there are no reasonable estimations for the shortage costs and the participating companies do not take this type of costs into account, we also do not consider shortage costs.

4.2 Assessing the quality of interventions

In this section we give answer to research sub question 2.a: "How *can we measure the impact of interventions by planners?*" In subsection 4.2.1 we explain the difficulties regarding empirical assessment of planning decisions. After that, in sub section 4.2.2, we describe a proposal for an exact method to assess planning decisions. In addition, we provide an example for the assessment of an intervention empirically and we describe the data requirements.

4.2.1 Difficulties concerning empirical assessment

Ideally, we use the proposed order quantity generated by the system and the quantity actually ordered by the planner as input variables. Given these two values, we track the inventory level of the actual system (input is the quantity ordered) and we simulate the inventory level of the "automated" system (input is the proposed order quantity). Regarding the simulation, we suggest a kind of MRP approach where inventory levels are determined on a daily basis. We illustrate this idea in the following section. Next, we determine the KPIs for both systems as defined in the previous section. In this way, we want to determine the impact of modifying an order quantities.

Unfortunately, the assessment of planning decisions in an empirical way is not as straightforward as described above. Spare parts planning decisions can be considered as dynamically complex decision making tasks to be characterised by four features (Brehmer, 1992):

1. A series of decisions have to be made, not just one that finally solves a problem
2. The state of the system changes depending on decisions and exogenous effects
3. Earlier decisions affect later states of the system and, consequently, later decisions
4. The timing of decisions matters, not just their sequence.

Evaluated against this definition, the first criterion can be a point of discussion since it is arguable that planners make just one decision (the amount to order). On the other hand, planners also have to decide when to order ensuring a certain uptime of an asset. Therefore, we conclude that spare parts planning satisfy all four criteria. In practice, this implies that we require detailed data in order to track the inventory level of the actual system and to simulate the inventory level of the "automated" system. We require detailed data – on a daily basis – of demand, lead times and inventory parameters since these parameters will be updated frequently and affects the re-order levels of both systems.

Another complication is the time required for monitoring the spare parts. To make a reasonable comparison between the performance of the actual system and the "automated" system we require a long period, i.e. a year. For the reason that the majority of spare parts is slow moving and typically, lead times are longer than four months. Preferable, we require a certain period that both systems replenished, thus, both the planner and the automated system should place a second order in order to determine the performance. Only afterwards, we can determine what the impact was of the intervention in terms of availability, holding costs and ordering costs. Concerning our research, we do not have enough time to monitor the spare parts for such a long period of time.

4.2.2 Proposal for empirical assessment of planning decisions

To determine the impact of interventions by planners we suggest to track the inventory level of the actual system (input is the quantity ordered) and to simulate the inventory level of the "automated" system (input is the proposed order quantity) for a certain period. Recall, we suggest a period until both systems placed a second order. However, the length of this period should be defined in consultation with the management. Next, based on the inventory levels of both systems the impact of the intervention can be determined using the KPIs of section 4.1.

In order to illustrate our method for the assessment of an intervention, we provide a numerical example of a part of the Navy. During our research, we observed that the planning system proposed to order 28 items and the planner modified this quantity to 16 items. At the Navy they use a (R,s,S) inventory policy. The purchase requisition was generated in November 2013 and at that moment, the planner had the following information (output from SPPT):

Parameters of part	
Price (euro)	100,29
Target fill rate	70%
Safety factor k	0.204
Lead time (days)	168
Forecast per month	5
Forecast error per month	2.11
Re-order point (s)	16
Order-up-to level (S)	33
Frequency of demand per year	4
Order costs (euro)	80
Holding rate per year	15%

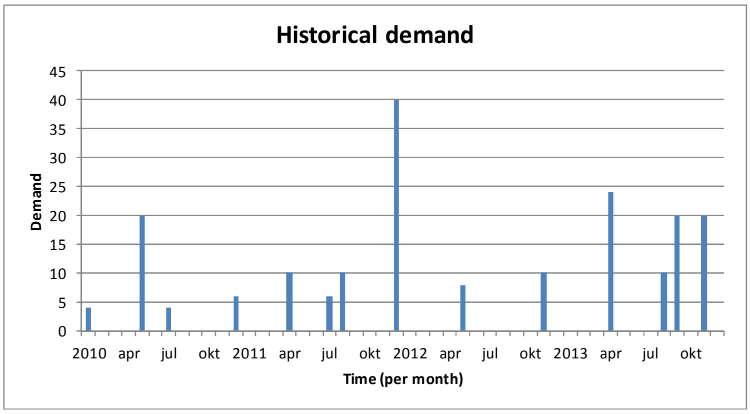


Figure 4.1: Parameters (left) and historical demand (right) of part.

As shown in Figure 4.1 (right), the demand in November 2013 was 20 items and after the demand was consumed the inventory level is 5 items. We now want to track the inventory levels for both systems (the actual system and the automated system) and afterwards we calculate the realized fill rate, holding costs and ordering costs.

Suppose we have a demand of 8, 15, 12 and 20 items in January, April, July and November respectively (in 2014) and zero demand in the other months. Further, the inventory parameters remains the same and we use a deterministic lead time of 168 days. We made these assumptions to illustrate the idea. In practice, inventory parameters will be updated over time and the actual lead times can be used. Regarding the order quantities, we assume that after the intervention the planner follows the (s,S) policy again and accept proposed order quantities of the system. In this way, we want to quantity the impact of a single intervention by a planner.

The inventory levels of both systems during the next year will be as shown in Figure 4.2. The red spikes represent the demand, the dotted line represents the on-hand inventory per day of the automated system (order quantity equals 28 at first day) and the continuous line represents the on-hand inventory per day of the actual system (order quantity equals 16 at first day).

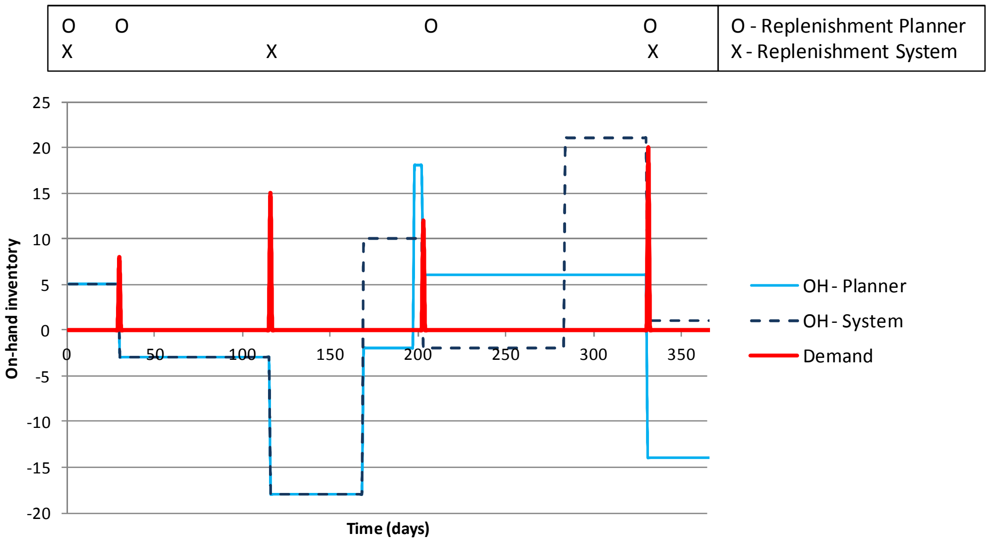


Figure 4.2: Inventory levels of actual system (planner) and automated system.

Figure 4.2 shows that the inventory levels of both systems remain the same for the first 168 days, until the first purchase order is delivered. From that moment, the inventory levels differ and the timing of replenishments differ, i.e., the planner replenishes when the first demand occur whereas the automated system replenishes when the second demand occurs. Furthermore, the figure shows that the actual system (planner) has more backorders compared to the automated system. Next, we determine the realised availability and costs of both systems using the KPIs described in section 4.1.

	Σ Backorders	*Σ Q*	*Fill Rate*	*Σ Order costs*	*Σ Holding costs*	*Total costs*
Planner	32	83	61%	€ 320	€ 41	€ 361
System	18	83	78%	€ 240	€ 61	€ 301

Table 4.1: KPIs of part (example).

In Table 4.1 we present the KPIs of both systems. In this example, the automated system performed better than the planner since the system has a higher realized fill rate (78% vs. 61%) and lower total costs (301 vs. 361). Therefore, we can conclude that it was better to accept the proposed order quantity of the system. The intervention by the planner has a negative impact on the availability of the part and the total costs.

Next, as we have these KPIs per replenishment decision (in case of an intervention), we can aggregate these results per factor in order to determine the overall impact of a specific factor. For example, determining the impact of all interventions concerning the factor “rounded quantities” or determining the impact of all interventions concerning the factor “high unit value”. A formula to aggregate the availability is described in paragraph 4.3.2.3.

Recall, these dynamically systems can not be simulated in advance since decisions affect later states of the system and later decisions. In the previous example we assume that a planner intervene and thereafter follows the old (s,S) policy again. However, since the planner decreased the order quantity and thereafter experienced a stock out it could be possible that he increase the order quantity during the next replenishment.

In order to determine the impact of interventions empirically, we require additional data for a certain period and even then, some issues remain. We sum up the requirements and potential issues.

Data requirements

- Holding rate
- Ordering costs

Per spare part:

- Unit price
- Initial inventory parameters (at least: target fill rate)
- Proposed order quantities, corresponding inventory levels and dates
- Actual order quantities, corresponding inventory levels and dates
- Reasons of interventions (using factors of section 3.3)
- Daily demand
- Delivery dates
- Changes in inventory parameters

Remaining complications

- Suppose the automated system orders more frequently than the actual system. In this case, the automated system place a "virtual" order and the lead time is unknown. Then the latest actual lead time can be used or an average lead time.
- The explicit measurement of holding costs and ordering costs, discussed before in subsection 4.1.2.

4.3 Method to estimate the impact of interventions

Since we have limited time for our research, we provide methods to estimate the impact of interventions (answering sub question 2.b: "How *can we estimate the impact of interventions by planners?*"). An advantage, in this manner we can estimate the impact at the time the decision is made. The main disadvantage, it requires several assumptions to estimate the theoretical fill rate and the expected logistics costs. First, in subsection 4.3.1 we discuss several common assumptions. Next, in subsection 4.3.2 we define formulas and methods to estimate the fill rate. At last, we describe how we can determine the expected logistic costs.

4.3.1 Assumptions for calculations

With the purpose of estimating the impact of interventions, several assumptions are required. The following assumptions are commonly made for measuring costs and measuring service according to Silver et al. (1998):

- No shortage costs
- The planning horizon is very long. In other words, we assume that all inventory parameters are constant over time.
- Costs factors do not change appreciably over time.
- A replenishment order of size Q remains the same for a long period. Thus, planners will order the same quantity in the future.
- Replenishment orders of size Q are placed when the inventory position is exactly at the re-order level. In other words, we assume that the undershoot of the re-

order level is negligible. In this case, the (s,S) policy becomes a (s,Q) policy with S = s + Q.

- Although demand is probabilistic, the *average* demand rate (forecasted demand) changes very little over time. However, decision rules used can be used adaptively (that is, parameters are updated with passage of time).
- The lead time is assumed to be deterministic.

4.3.2 Estimated fill rate

From a practical point of view and in consultation with Gordian, we distinguish spare parts with demand normally distributed and spare parts with a typical demand quantity (TDQ). For fast and medium movers (A and B items) the demand is assumed to be normally distributed. For slow movers (C items) with a demand frequency of 2 parts per year or lower, the TDQ can be characterised by a discrete compound Poisson or negative binomial distribution. However, we will use the TDQ method of Gordian. In the next two paragraphs, we provide formulas and methods to estimate the fill rate for both types of spare parts demand. In paragraph 4.3.2.3, we explain the computation for aggregated fill rates.

4.3.2.1 Fill rate under normal distribution

When forecast errors are assumed to be normally distributed, it can be shown that the expected shortage per replenishment cycle (ESPRC) is equal to the function Gu(k) multiplied by the forecast error during the lead time (Silver et al,. 1998). The function Gu(k) is a special function of the unit normal variable (μ=0, σ=1), also known as the normal-loss function, which can easily be calculated in a spreadsheet (or using a table). Using the Gu(k), equation 4.1 becomes:

$$Fill\ rate = 1 - (\frac{Gu(k)*\sigma_L}{Q}) \qquad \textbf{Eq. 4.5}$$

With σ_L as the forecast error during the lead time. However, equation 4.5 underestimates the true fill rate if σ_L is large relative to Q (Silver et al., 1998). Recall, this is often the case with spare parts since most of them have lumpy demand patterns (Bachetti & Saccani, 2012) and this result in a relative high forecast error. A more accurate formula for small values of Q/ $\sigma_{\text{Lead time}}$ is provided by Silver et al. (1998).

$$Fill\ rate = 1 - \left(\frac{\left(Gu(k) - Gu\left(k + \frac{Q}{\sigma_L}\right)\right)*\sigma_L}{Q}\right) \qquad \textbf{Eq. 4.6}$$

We use equation 4.6 for all spare parts that are identified as normally distributed, in order to estimate the fill rate. Note that, if a planner decides to reject the order (change the order quantity to zero) this formula is not applicable. In this case, *we assume that the replenishment size is equal to one,* in order to estimate the fill rate.

4.3.2.2 Fill rate using TDQ method

For slow movers, Gordian uses a TDQ method to determine the order quantity and the corresponding fill rate. We use this method of Gordian with the aim of estimating the fill rate, see Figure 4.3 for an overview of this method. The underlying idea is that a multiple of the TDQ should always be on stock in order to guarantee a certain fill rate and a (S-1, S) inventory policy is used. Furthermore, the assumption is made that if demand occurs, the quantity will be equal to one of the historical demand quantities. Accordingly, this is a kind of empirical method to determine the number of spare parts for stocking.

Next, we describe each step of the TDQ method and we provide a numerical example at each step. Suppose, for a certain part the demand quantities are 16, 8, 3, 16, 11 during the last two years (demand frequency = 5) and the lead time of this spare part is 119 days. Further, as typical demand quantity we choose 16 (TDQ=16) to illustrate the method. With the aim of determining the estimated availability, the following steps are taken:

1. Compute the average frequency of demands during the lead time.
   Numerical example: Average frequency of demand during the lead time (mean pipeline) = 119/(730/5) = 119/146 = 0.8156

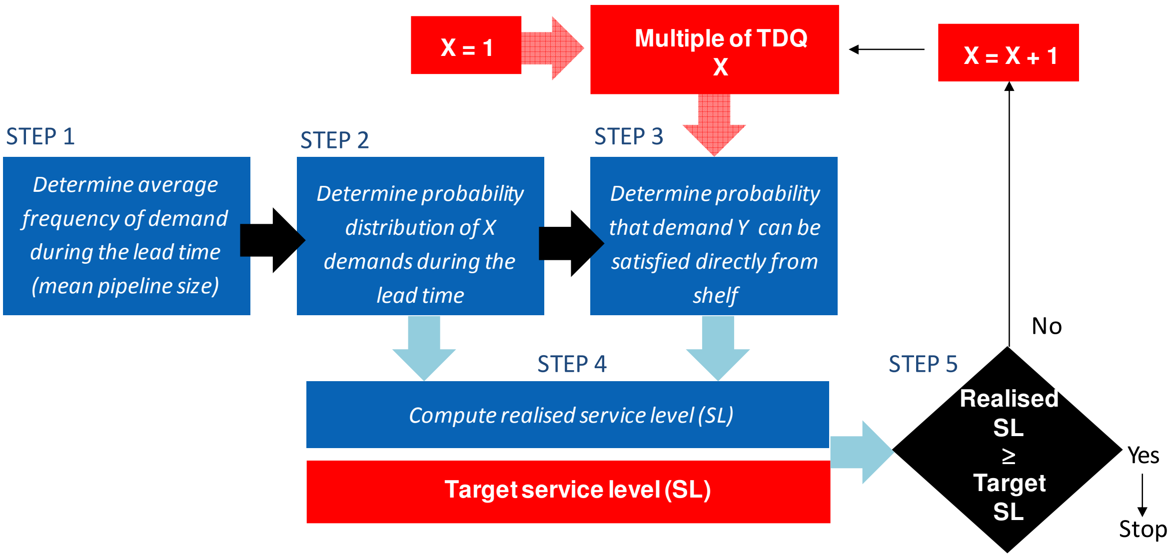


Figure 4.3: Overview TDQ-method of Gordian.

2. Determine the probability of X demands during the lead time (assuming that the arrival process can be characterised as a Poisson process, this means that the time between arrivals is exponentially distributed).
   Numerical example: Given that μ = 0.8156 during lead time, the probability of X demands during the lead time is given in Table 4.2.

X	0	1	2	3	4	5
P[X demands]	44,2%	36,1%	14,7%	4,0%	0,8%	0,1%

Table 4.2: Probability of X demands during the lead time under Poisson arrival process.

3. Given a TDQ value, determine the probability that demand Y can be satisfied directly from shelf (assuming the historical demand quantities are discrete uniform distributed).
   Numerical example: Given that TDQ is 16 and the demand is distributed uniformly, the following demand combinations can be full filled directly from shelf when a second demand occurs (1st demand during the lead time):

		2nd Demand (1st demand during lead time)					
1st Demand	*Demand*	*3*	*8*	*11*	*16*	*16*	Prob.
	3	6	11	14	19	19	1/5
	8	11	16	19	24	24	1/5
	11	14	19	22	27	27	1/5
	16	19	24	27	32	32	1/5
	16	19	24	27	32	32	1/5
	Prob.	1/5	1/5	1/5	1/5	1/5	

Table 4.3: Cumulative demand when first demand occurs during the lead time.

Note that the first demand during the lead time is the second demand that occurs. When the first demand occurs, a replenishment order is placed and the lead time commences. Table 4.3 shows that 6 of the 25 demand combinations (24%) can be full filled directly from the shelf when a demand occurs during the lead time.
When a second demand occurs during the lead time, the following demand combinations can be full filled directly from shelf: 3-3-3; 3-3-8; 3-8-3; 8-3-3 with a probability of $(1/5)^3$ each. Therefore, 4 of the 125 demand combinations (3,2%) can be full filled directly from the shelf.
Next, when a third demand occurs during the lead time, only the demand combination 3-3-3-3 can be full filled directly from shelf. This happens with a probability of $(1/5)^4$ and results in a fill rate of 0,16%.

4. Calculate the availability by the summation of the probability of the arrival process multiplied by the corresponding probability that demand Y can be satisfied directly from shelf.
   Numerical example: The fill rate is (0,444*1) + (0,361*0,24) + (0,147*0,032) + (0,04*0,0016) = 53,54%

In order to determine a TDQ, Gordian proposes a 75% percentile of the historical demands or a multiple quantity of it, satisfying the required service level. Advantages of this TDQ method are that it works well for spare parts with low frequencies of demand and the order quantities are regularly a "logical batch size" for planners. On the other hand, a disadvantage is that the computation time is long, depending on the amount of historical demands taken into account. Secondly, this method is sensitive for spare parts with just one of two demands. At last, this method assumes the lead time is deterministic.

We program this method in VBA to determine the fill rate for TDQ items, see appendix F. For the calculations, we use the historical demand from the last four years and we take the 8 most recent demands (or less if less demands occurred). Further, we assume that maximal 3 demands take place during the lead time. Here, we are aware that the calculations are less accurate when the expected frequency of demand is high during the lead time, i.e., when $\mu=2$, the probability that the frequency of demand is higher than 3 is almost 15% when assuming a Poisson distribution.

4.3.2.3 Aggregate fill rates

Using the estimated fill rates as described in the previous two paragraphs, we would like to aggregate the fill rate per factor. According to Silver et al. (1998), it is common to take the demand-weighted summation in order to calculate the aggregated fill rate. However, here the assumption is made that demand arrives one-by-one and the demand is normal distributed. Regarding the TDQ method, we determined the fill rate on order level, this means that the availability is zero if one part is missing of the order. In this case, it might be better the take a "frequency of demand" weighted summation.

Suppose we have two items, part A and part B and both items have a demand of 4 parts per year. This implies that the demand-weight for both items equals 0,5. However, for part A the demand is 1-1-1-1 and for part B the demand is 4 at once. Consequently, the frequency of demand is 4 and 1 and the frequency weight is 0,80 and 0,20 for part A and part B respectively. In Table 4.4 we illustrate the differences in the aggregated fill rates, depending on the amount of items on stock.

Amount of items on stock	Order fill rate of part A	Order fill rate of part B	Demand-weighted fill rate	Frequency-weighted fill rate
1	25 %	0 %	12,5 %	20 %
2	50 %	0 %	25 %	40 %
3	75 %	0 %	37,5 %	60 %
4	100 %	100 %	100 %	100 %

Table 4.4: Difference of demand- and frequency-weighted fill rate.

For both part A and B there are 5 demands: 4 of size 1, and 1 of size 4. Assuming that we have 3 items on stock 60% of all orders can be fulfilled from shelf which corresponds with the frequency-weight fill rate. Besides, this is more in line with the service level experienced by the customer. Note that, instead of the order fill rates, the "normal" fill rates are equal for both items. E.g. part B has 3 items on stock and the demand is 4 items. Then 3 items can be delivered directly from shelf and 1 backorder occurred. Therefore, the fill rate is 75%, equal to the fill rate of part A where the demand arrives one-by-one.

Since spare part demands rarely arrive one-by-one and the frequency-weighted fill rate is more in line with the service level experienced by the customer, we use the "frequency of demand" weighted summation to determine the aggregated fill rate.

$$Frequency\ weighted\ fill\ rate = \frac{1}{\sum_{i=1}^{n} Freq_i} \sum_{i=1}^{n} (Freq_i * Fill\ rate_i) \quad for\ i = 1..n \qquad \textbf{Eq. 4.7}$$

With part *i* and *n* number of parts.

4.3.3 Expected logistic costs

As mentioned before, the total logistic costs contain holding costs and ordering costs. In order to estimate these costs, we use a formula provided by Silver et al. (1998).
Regarding the total ordering costs, we use equation 4.4 as described earlier where the amount of orders per year can be estimated by the total demand per year divided by the order quantity (D/Q). Here, we assume that each future replenishment is of size Q. Concerning the holding costs, we use equation 4.2 where the average inventory level can be considered as Q/2 plus the safety stock (SS), see also the green line in Figure 4.3. We are aware of the fact that this estimation is not accurate for slow movers where demands rarely occur and the inventory level remains the same for a long period. Despite this drawback, we estimate the expected logistic costs (ELC) according to the following formula:

$$ELC = A * \frac{D}{Q} + \left(SS + \frac{Q}{2}\right) * vr \quad where\ SS = k * \sigma_L \qquad \textbf{Eq. 4.8}$$

With ordering costs (A), Demand per year (D), Order quantity (Q), Safety Stock (SS) consisting of safety factor (k) multiplied by the forecast error during lead time (σ_L), value of unit (v) and holding rate (r). Note that, if a planner decides to reject the order (change the order quantity to zero) this formula is not applicable. Furthermore, this formula gives extreme high values when the order quantities are relatively low compared to the total annual demand. Despite these negative aspects, we use this formula in order to estimate the logistic costs.

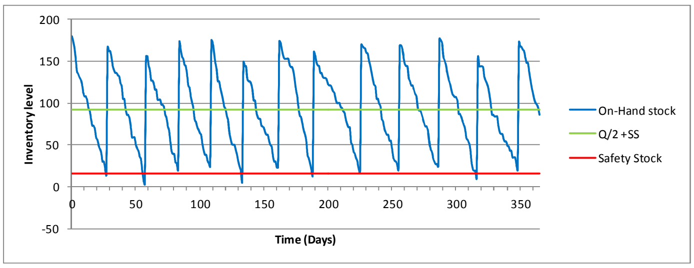


Figure 4.4: Average behaviour of inventory level for a fast mover.

Chapter summary

In this chapter we discussed methods to assess ordering decisions. We will use this methods to identify the differences in performance between the proposed order quantity of the system and the actual order quantity by the planner. This final section summarised the most important elements of this chapter.

- We use the **fill rate**, the **holding costs** and **ordering costs** as KPIs for assessing ordering decisions.
- We suggest to use the proposed order quantity generated by the system and the quantity actually ordered by the planner as input variables. Given these two values, the inventory level of the actual system (input is the quantity ordered) should be tracked and the inventory level of the "automated" system (input is the proposed order quantity) should be simulated. Based on the inventory levels of both systems, the KPIs can be determined.
- **In practice**, **it seems to be more difficult to determine the impact of intervening**. First, these planning decisions can be considered as **dynamically complex decision making tasks**, e.g. the state of both systems changes depending on decisions and exogenous effects. Moreover, earlier decisions affect latter states of the system and, consequently, latter decisions. Secondly, **another complication is the time required** for monitoring spare parts. To make a reasonable comparison between the performance of the actual system and the "automated" system we require a long period. **Only afterwards, we can determine the actual impact of an intervention in terms of availability, holding costs and ordering costs.**
- **Data requirements for the exact determination of the impact of intervening**: holding rate, ordering costs, unit price, proposed order quantities, actual order quantities, reasons of interventions, initial inventory parameters, daily demand, deliveries and changes in the inventory parameters.
- Since we have limited time for our research, **we provide methods to estimate the impact of interventions at the moment of intervening**. Main disadvantage, it requires a number of general assumptions to estimate the theoretical fill rate and the expected logistics costs.
- Regarding the **estimated fill rate**, we distinguished fast and medium moving parts (frequency of demand ≥ 3) and slow moving parts (frequency of demand ≤ 2). **For fast and medium movers, we assumed the demand is normally distributed** in order to calculate the theoretical fill rate. For **slow movers, we characterised the demand as a typical demand quantity**, assuming that if demand occurs, the quantity will be equal to one of the historical demand quantities. We used the method of Gordian in order to compute the estimated fill rate.
- The **expected logistics costs** contain estimated holding costs and estimated ordering costs.
- **Underlying assumptions regarding the estimations** are that a replenishment of size Q remains the same for a long period. In addition, if a planner rejects an order (change the order quantity to zero), the expected logistic costs can not be estimated. In order to estimate the fill rate, we assume that the replenishment size is equal to one when a planner rejects an order.

5 Empirical results

In this chapter we describe the results of the empirical data analysis in order to provide an answer to research question 3: "*What are the root causes of interventions*?" In section 5.1 we briefly describe the case studies and in section 5.2 we describe our method to analyse interventions. Next, we discuss our results per company: In section 5.3, section 5.4, and section 5.5 we discuss the results of RET, the Navy and IBM respectively. At last, we compare our case studies in order to determine the overall factors causing interventions.

5.1 Introduction to case studies

In subsection 5.1.1 we describe the main characteristics of the companies used in our research (sub question 3.a). Next, we discuss the planning systems used by the companies (sub question 3.b) and in section 5.1.3 we describe the ordering process (sub question 3.c).

5.1.1 Environments

In this subsection we briefly discuss the main characteristics of the companies cooperating in our research. More background information concerning RET, Navy and IBM can be found in appendix C, D and E respectively.

RET is a regional company that arranges the public transport in the area of Rotterdam. Their installed base consists mainly of busses, subway trains, trams, a ferry and supporting infrastructure. RET has about 25k SKUs in order to support their assets with maintenance activities. At this moment, 8k SKUs are concerned as active spare parts. This means, usage of the part has occurred in the last two years.

The Royal Netherlands Navy is part of the Dutch Ministry of Defence. Actually, we visited the "Marinebedrijf" that arranges all maintenance activities for the Navy. The installed base of the Navy consists i.e. navy ships, submarines, sensors, weapons and communication systems. We interviewed planners from the "MarTech & Material" department, they are responsible for 22k SKUs (about 10k are active spare parts).

IBM is an international company and a well-known player in the IT-business. We interviewed planners of the Service Parts Operations (SPO) department for Europe, Middle East and Africa (EMEA). Their installed base consists mainly hardware for computers and data systems. Within the EMEA network, there are around 70k active spare parts which should be managed.

5.1.2 Planning systems

An overview of the planning systems used at the companies is shown in Figure 5.1.

RET uses SAP to manage their spare part inventories which consist of a standard module for inventory management. Therefore, this can be considered as a basic planning system, this system contains no advanced planning or forecasting models to support spare parts planning.

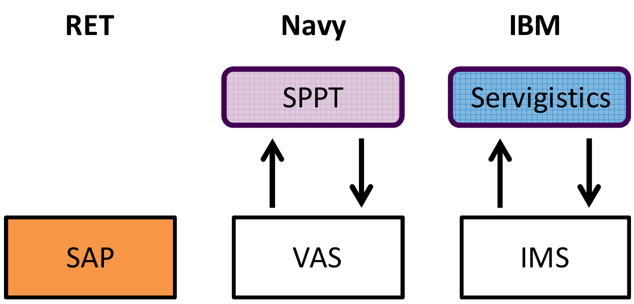


Figure 5.1: Overview of planning systems.

The Navy uses Gordian's SPPT in order to manage their spare part inventories. The data will be extracted from the ERP-system VAS, then forecasts are generated and lot sizes are determined. Next, a list of purchase requisitions will be generated by SPPT and planners will review these purchase requisitions manually. Finally, the approved purchase requisitions are transferred to VAS after which purchase orders are placed.

IBM uses Servigistics as planning system to manage their spare parts inventories. Servigistics (original name was Xelus Parts Planning) is a well-known decision support system which contains the most comprehensive features to manage spare parts, also indicated as the Rolls Royce of the spare parts planning systems. Similar to the SPPT, the data will be extracted from an ERP system (IMS) and Servigistics is used for advanced calculations. In Servigistics, most spare parts are replenished automatically (approximately 80% according to the team leads of Amsterdam) and only exceptions will arrive in the work queue of the planners. The work queue is designed to focus the planner's attention on parts that require attention (management by exception principle).

5.1.3 Ordering process

The review procedure is comparable at the participating companies, except for some small details. Generally, a purchase requisition is generated when the inventory level drops below the re-order level. An overview of the review procedure is presented in Figure 5.2. First, the planner reviews the purchase requisition and a number of aspects such as historical demand and price. There is no sequential order in the three attributes (product, demand and supply). However, in general the planner reviews all attributes and corresponding aspects.

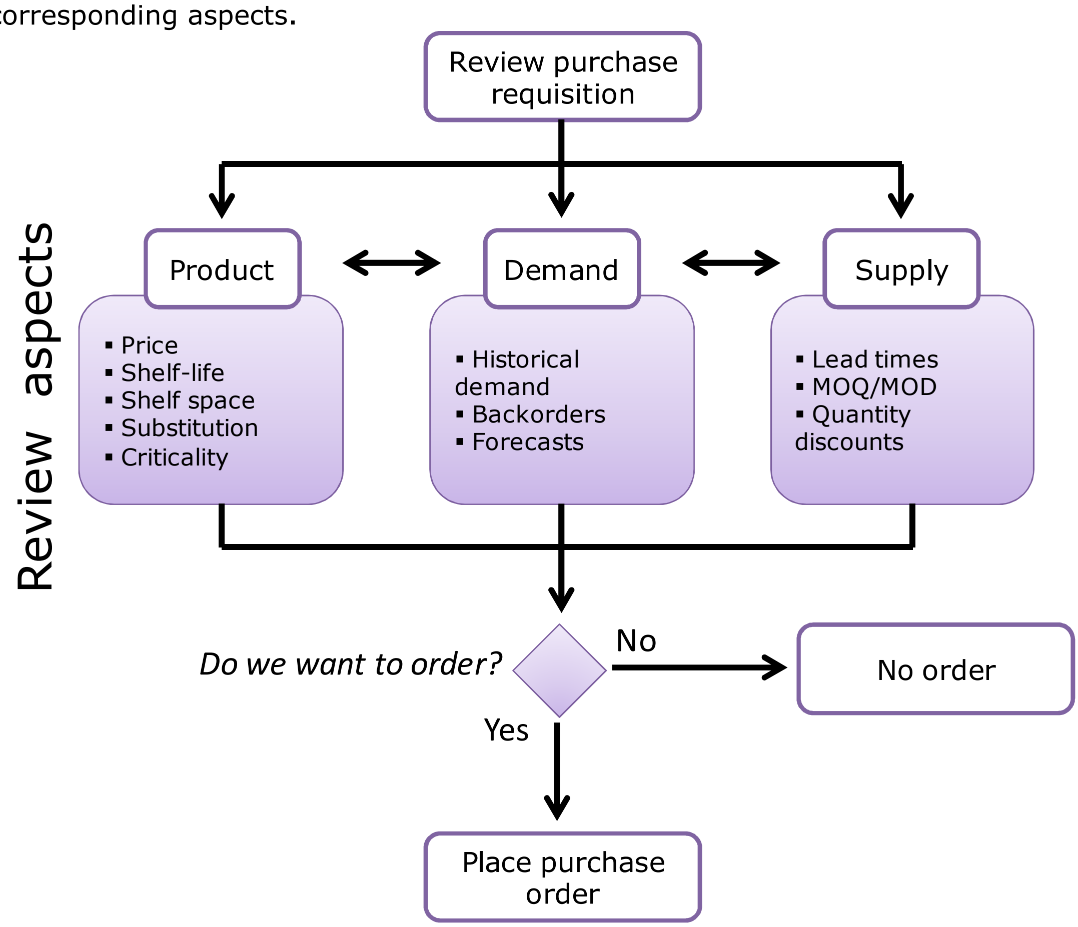


Figure 5.2: Overview of ordering process.

Regarding the three attributes, we discuss a number of aspects that a planner can review. First, the planner reviews the product aspects; the price of the unit, shelf life, shelf space, substitution relations and criticality. Secondly, the planner reviews the demand; historical demand, details of backorders and forecasts. Based on experience the planner will assess if the proposed order quantity is reasonable compared to the forecast and the historical demand. Thirdly, supply characteristics of the part are reviewed by the planner; the lead time, MOQ, MOD and quantity discounts. However, there is no sequential order and it is not required to review all aspects.

Finally, the planner decides to place an order (or not) and to modify the proposed order quantity if necessary.

5.2 Method to analyse interventions

During the period November 2013 until January 2014, we collected our data samples at RET, the Navy and IBM. Recall, the companies use planning systems to manage their spare parts and these planning systems generate purchase requisitions with a proposed order quantity for each spare part. After reviewing a purchase requisition, the planner decides to accept the proposed order quantity or to intervene (modifying or rejecting the requisition). For our research, we collected data for each purchase requisition such as the part number, the proposed order quantity of the system, the quantity actually ordered and the reason(s) for intervening. Note that the reason(s) for intervening is the interpretation of the researcher after discussion with the planner. Next, we classify the reasons according to our framework, see appendix B. In order to analyse the gathered data we conduct the steps as shown in Figure 5.3.

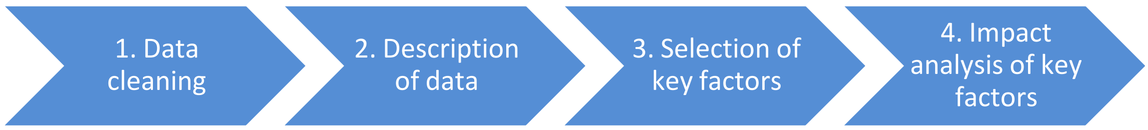


Figure 5.3: Steps for analysis of data.

Step 1: Data cleaning
First, we check the collected data for duplicate purchase requisitions. A purchase requisition is duplicated when there are multiple items with the same purchase requisition number and the same order quantities (both system and planner). Typically, purchase requisitions are duplicated when a planner rejects an order requisition and the week after the system proposes to order the same replenishment again. We remove the duplicated purchase requisitions from the data sample.

Step 2: Description of data
After removing the duplicated purchase requisitions, we describe the characteristics of the data sample: An overview of the reviewed purchase requisitions, an overview of the interventions classified on price and demand frequency, an overview of interventions on process level using the adapted framework of Driessen et al. (2013) and an overview of all factors found at the company.

Step 3: Selection of key factors
Next, we select the key factors. We argue that the factors we observed frequently have significant impact and moreover, the factors which have a high order value also have significant impact. Therefore, we select the key factors according to the following criteria:

- Select top 5 factors with the *highest number of observations*
- Select top 5 factors with the *highest order value* (summed per factor)

Step 4: Impact analysis of key factors
For each key factor, we discuss the type of interventions occurred (increase, decrease or no order), the total order value proposed by the system, and the total order value that is actually ordered by the planner. For several factors (e.g. *phase-out of an asset*) it makes no sense to estimate the fill rate and the relevant costs since the assumptions of the calculations are not valid (e.g. we assume that all inventory parameters are constant over time but this is not valid when a part is phasing out). For the other factors where the assumptions are reasonable, we estimate the fill rate of the proposed order quantity, the fill rate of the quantity actually ordered, and the corresponding expected logistic costs using the formulas and methods as described in section 4.3.

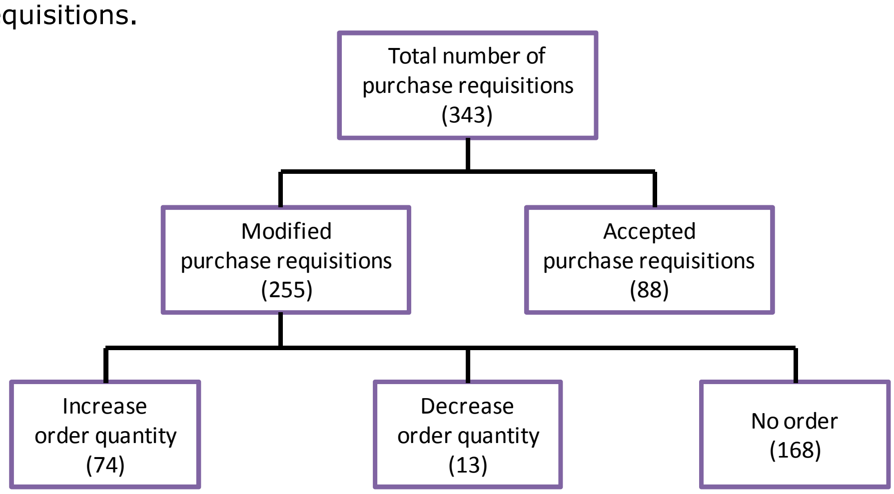
5.3 RET

In this section, we describe the empirical results of RET. First, we describe the collected data in subsection 5.2.1. Secondly, we select the key factors in subsection 5.2.2. Next, in subsection 5.2.3 we analyse the key factors and we discuss the estimated impact of the interventions. Finally, in subsection 5.2.4, we summarise the results of RET.

5.3.1 Data description

During a period of 4 weeks (week 46 until 49 in 2013) we reviewed a sample of 527 purchase requisitions. Furthermore, per purchase requisition we have detailed information about the price, service level, safety factor, safety stock, re-order level, lead time, demand forecast, forecast error, demand frequency and the historical demand aggregated per month of the last 4 years.

First, we checked the data sample of 527 purchase requisitions for duplicate purchase requisitions (Step 1). We found 184 duplicate purchase requisitions and we excluded these purchase requisitions from the data set. We continue with the remaining 343 purchase requisitions.



5.4: Overview of reviewed purchase requisitions and type of interventions at RET.

5.3.1.1 Overview reviewed purchase requisitions

In Figure 5.4 we provide an overview of the reviewed purchase requisitions and type of interventions at RET (Step 2). In this sample, 88 purchase requisitions (26%) were accepted and 255 purchase requisitions (74%) were overruled by planners. Conditioned on the interventions, 168 times the planner decided to reject the order (66%), 74 times the planner increased the order quantity (29%) and 13 times the planner decreased the order quantity (5%).

5.3.1.2 Distribution of interventions based on price and frequency classification

Next, from the initial data set of 343 purchase requisition, we excluded the purchase requisitions that were accepted (88) and we excluded the purchase requisitions where detailed information is missing (41). For the remaining 214 interventions, we classify the interventions based on the price and the demand frequency of each part, see Figure 5.5.

The threshold values for the price are the 50th and 80th percentiles of all SKU prices at RET (24.611 items). Consequently, 50 percent of all parts have a price below 25 euro, 30 percent have a price between 25 and 150 euro and the last 20 percent have a price higher than 150 euro. Concerning the frequency segmentation, we define items with a demand frequency of 10 or higher as fast movers, items with a frequency between 3 and 10 as medium mover, items with a frequency between 3 and 0 as slow mover. Here, the frequency is defined as the average frequency of demand per year, measured in the last two years. This means that a part with no demand in the last two years is classified as an extreme slow mover.

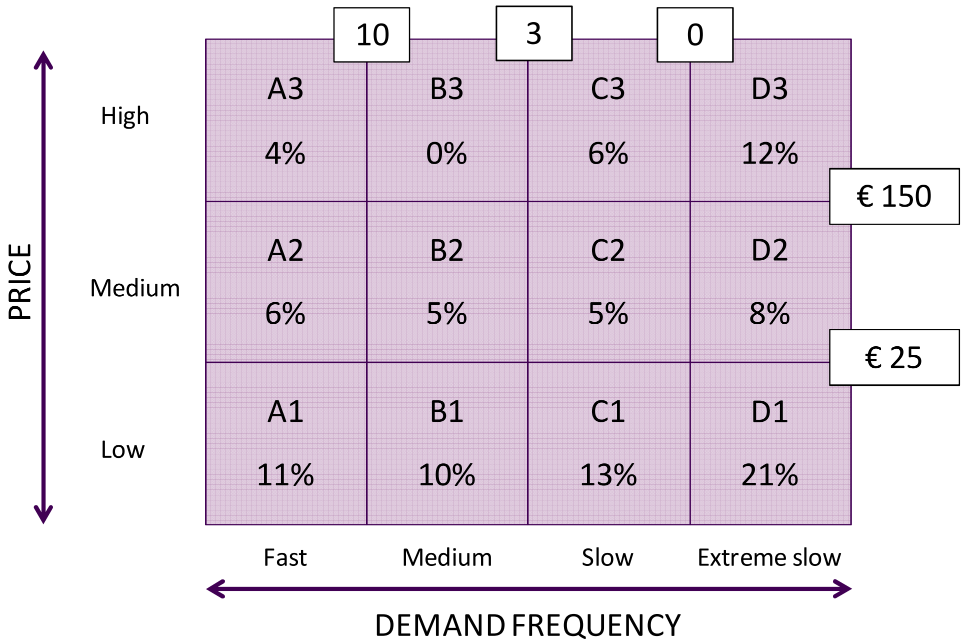


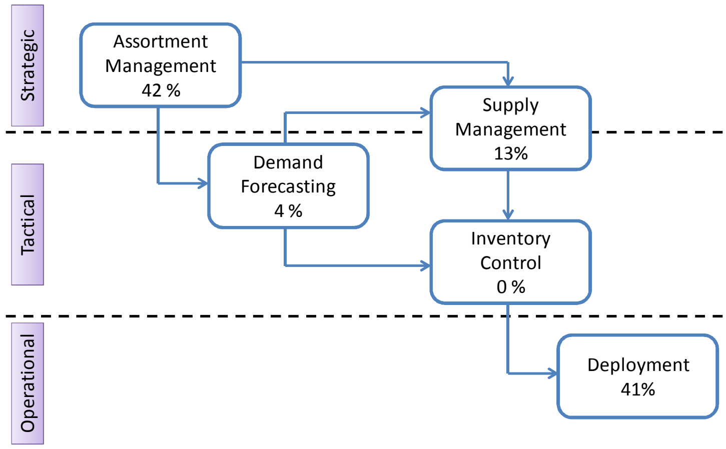
Figure 5.5: Distribution of interventions at RET according to classification.

Gordian uses this classification in order to differentiate spare parts and to apply different inventory strategies. E.g. set high service levels and use an EOQ-model for cheap spare parts with regular demand (A1, A2, B1, B2) and set a lower service level for expensive parts. In advance, we expected that most interventions would occur in the slow and extreme slow moving segment and the expensive segment.

Figure 5.5 shows that most interventions occur in the extreme slow moving segment (41%) and in the low price segment (55%). Typically, these extreme slow moving parts (D1, D2, and D3) do not have any historical demand in the last two years but in the current period a new demand arrives that triggered the system to replenish. Apparently, this happen a lot at RET and planners increase the order quantity a few times (8%) but reject the order mainly (92%). Concerning the low price segment, planners increase orders (57%) and reject orders in (43%) in quadrant A1, B1 and C1. The high percentage of rejected orders is remarkable since the gains are negligible for these cheap spare parts but this actions could have a negative impact on the fill rate. In quadrant D1 just 11% of the orders is increased and 89% of the orders are rejected.

5.3.1.3 Overview of interventions on process level

From a management perspective it is useful to know where the root cause of a planner's intervention is situated. By plotting the interventions in the adapted framework of Driessen et al. (2013), we allocate the interventions to concrete process owners. From the initial data set of 343 purchase requisitions, we exclude the purchase requisitions that are accepted (88) and we exclude the purchase requisitions that are out of the scope or no reason was given (77). Next, we classify the remaining 178 interventions in our framework, see Figure 5.6.



5.6: Interventions at RET plotted in the adapted framework of Driessen et al. (2013).

Figure 5.6 shows that most interventions are related to issues in the assortment management (42%). Main factors concerning this spare parts process are *phase-in of asset* and *phase-out of asset.* Secondly, many interventions are associated to deployment process (41%). Main factors concerning this spare parts process are *low unit value* and *low frequency of demand.* We analyse these main factors in subsection 5.3.3.

5.3.1.4 Overview of factors found at RET

An overview of all 15 factors observed at RET, the type of intervention and the total order value is given in Table 5.1.

Spare part process and factors	*Decrease*	*Increase*	*No order*	*Total*	*Sum proposed order value*
Assortment	**6**	**3**	**64**	**73**	**€ 253.921**
Phase-in of asset	6	3	42	51	€ 251.413
Phase-out of asset			21	21	€ 2.508
Substitution			1	1	N.A.
Demand/Forecasting		**7**		**7**	**€ 1.323**
Trend shift		7		7	€ 1.323
Supply management	**3**	**14**	**7**	**24**	**€ 105.389**
MOQ	2	12	5	19	€ 84.054
No supply information			2	2	€ 20.849
MOD		2		2	€ 65
Incorrect lead time	1			1	€ 420
Deployment	**2**	**45**	**24**	**71**	**€ 46.953**
Low unit value		34		34	€ 2.094
Low frequency of demand		1	18	19	€ 14.151
Rounded quantities	1	5	1	7	€ 839
Long lead time		3	1	4	€ 2.843
High variability of demand			3	3	€ 2.483
High unit value	1	1	1	3	€ 20.406
High variability of lead time		1		1	€ 4.138
Total	11	69	95	175	€ 407.587

Table 5.1: Overview of factors observed at RET.

5.3.2 Selection of key factors

At RET we observed 15 different factors that cause interventions. Next, we select the key factors based on the number of observations and order value proposed by the system (Step 3). In Table 5.2 we present the top 5 factors with the highest number of observations and the highest order value. Note that, the order value is based on the proposed order quantity of the system before the planner intervenes. Furthermore, Table 5.2 shows us that these 7 key factors represent 85,1% of the interventions observed at RET and these key factors represent 97% of the total order value (conditioned on interventions). We evaluate these key factors in the next subsection.

Key factors	*Number of observations*	*Percentage observations*	*Sum prop. order value*	*Percentage order value*
Phase-in of asset	51	29,1%	€ 251.413	61,7%
Low unit value	34	19,4%	€ 2.094	0,5%
Phase-out of asset	21	12,0%	€ 2.508	0,6%
MOQ	19	10,9%	€ 84.054	20,6%
Low frequency of demand	19	10,9%	€ 14.151	3,5%
High unit value	3	1,7%	€ 20.406	5,0%
No supply information	2	1,1%	€ 20.849	5,1%
Total	149	85,1%	€ 395.476	97,0%

Table 5.2: Overview of key factors at RET.

5.3.3 Analysis of key factors

In this subsection, we analyse the key factors found at RET (step 4). First, we provide the KPIs for each factor. Next, we briefly discuss each factor and we evaluate the impact of this factor. At last, we argue if the factor is important to tackle based on the amount of observations and the estimated impact.

In Table 5.5 an overview is given of the key factors, the total order value of the proposed order quantity (system), the total order value that is actually ordered by the planner and the savings or additional investments per factor (delta order value). We see that the planner saved a lot of money (311k euro, equals 79%) by intervening. However, decreasing and rejecting orders will result in a lower availability of parts. Only additional investments are made regarding the factor *low unit value* but these investments are negligible.

Key factors	**Number of observations**	**Σ Order value system**	**Σ Order value planner**	**Delta order value**
Phase-in of asset	51	€ 251.413	€ 10.419	€ 240.995
Low unit value	34	€ 2.094	€ 7.115	-€ 5.021
Phase-out of asset	21	€ 2.508	€ 0	€ 2.508
MOQ	19	€ 84.054	€ 56.775	€ 27.280
Low frequency of demand	19	€ 14.151	€ 0	€ 14.151
High unit value	3	€ 20.406	€ 10.203	€ 10.203
No supply information	2	€ 20.849	€ 0	€ 20.849
Total	149	€ 395.476	€ 84.511	€ 310.965

Table 5.3: Overview of order values per key factors.

Next, we estimate the fill rate and the expected logistic costs using the proposed order quantity (system) and we estimate the fill rate and the expected logistic costs using the quantity actually ordered by the planner. Recall, there are some underlying assumptions (see section 4.3 for further details) to take into account. First, a replenishment of size Q remains the same for a long period. This Q is set as a constant parameter for determining the long term fill rate. Secondly, if a planner decides to reject the order (change the order quantity to zero) we are not able to estimate the logistic costs in the long term. Moreover, if a planner rejects an order we assume that the replenishment size is equal to one in order to estimate the fill rate (also for a long period). With this in mind, the estimated impact of intervening is shown in Table 5.4. In order to estimate the fill rate and the expected logistic costs We briefly discuss each key factor in the following paragraphs.

Key factors	Number of observations	Fill rate system	Fill rate planner	Delta fill rate	ELC system	ELC planner	Delta ELC	Legend
Phase-in of asset	51	N.A.	N.A.		N.A.	N.A.		Positive
Low unit value	34	89,40%	93,99%	4,59%	€ 46.375	€ 8.360	€ 38.015	Negative
Phase-out of asset	21	N.A.	N.A.		N.A.	N.A.		Negligible
MOQ	19	94,91%	94,20%	-0,71%	€ 10.234	€ 9.394	€ 840	Unknown
Low frequency of demand	19	93,88%	91,04%	-2,84%	N.A.	N.A.		
High unit value	3	100,00%	100,00%	0,00%	€ 493	€ 821	-€ 327	
No supply information	2	N.A.	N.A.		N.A.	N.A.		
Total	149				€ 57.103	€ 18.575	€ 38.528	

Table 5.4: Overview of estimated impact per factor.

Note: Since RET does not have any approximations of the holding rate and ordering costs, we set benchmark parameters in order to calculate the expected logistics costs. According to Gordian, 75 to 100 euro is common to use as ordering costs and a holding rate between 15 and 25 percent for spare parts. For RET, we use 15% as holding rate and 80 euro as ordering costs (same parameters as with the Navy).

5.3.3.1 Phase-in of asset

The factor *phase-in of asset* is observed 51 times and mainly the planner decides to reject the order (42 times). Regarding this factor, we can not estimate the impact in terms of availability and costs since no historical data is available regarding these parts (since these are new parts). However, from the interviews we know that many parts are required for the first major overhaul of subway trains and trams (conducted every 10 year). It could be argued that this is "planned demand" for the overhaul activities but apparently it is difficult to schedule these activities. Besides, we observed that planners set manual re-order levels above the actual inventory levels with the aim of "monitoring new spare parts". In this manner, the planning system forces the planner to review these new spare parts every week since new purchase requisitions are generated weekly. Since we observed this factor the most, we argue that this factor is important to address in order to reduce the amount of interventions.

5.3.3.2 Low unit value

The factor *low unit value* is observed 34 times and in this case the planner always increases the order quantity. Increasing the order quantities results in an additional investment of 5.021 Euro. However, the impact is a higher theoretical fill rate (+4.59%) and lower expected logistic costs (€38.015). The system often recommends to order just 1 or 2 items and this result in lots of ordering costs while the value of these items are just a few Euros (low holding costs). Therefore, we conclude that the proposed order quantity generated by the planning system was worse. From the interviews we know that SAP does not contains a kind of EOQ model. Besides, holding costs and ordering costs are not taken into account in SAP. Overall, since the availability increases and the expected logistic costs decreases, we conclude that the interventions have a positive impact on the performance. We consider this factor as important to tackle.

5.3.3.3 Phase-out of asset

The factor *phase-out of asset* is observed 21 times and in this case the planner always rejected the order. It is straightforward that the planner will not order anymore since the asset is phasing out. Needless to mention, estimations for the availability and costs make no sense regarding this factor. Intervening because of this factor has a positive impact on the performance. We argue that this factor is important to meet since replenishing these parts is a waste of money as they are phasing out.

5.3.3.4 MOQ

We observed that the planner modifies the order quantity 15 times because the *MOQ* is missing. The order quantity was increased 12 times, decreased 2 times and 5 times the planner rejected the order. Table 5.3 shows that almost 27k euro (32%) is saved by intervening in the short term. In the long term, Table 5.4 shows that the estimated fill rate decreased slightly (-0,71%) and the expected logistic costs decreased slightly (€ 840). Based on the impact on the long term, we conclude that the impact of this factor is negligible on the performance and therefore we consider this factor as less important.

5.3.3.5 Low frequency of demand

We observed the factor *low frequency of demand* 19 times and once the planner decreased the order quantity and 18 times the planner rejected the order. By intervening, the impact on the estimated fill rate is little. However, we argue that the fill rate will be much lower in practice because the majority of these purchase requisitions have a replenishment size of 1 or 2 proposed by the system. As mentioned before, we assume that the replenishment size is at least one whereas the planners reject the order. Therefore the estimated fill rate is too high and not realistic. We conclude that this factor results in a lower availability and has a negative impact on the performance. We consider this factor as important to tackle.

5.3.3.6 High unit value

The factor *high unit value* is observed 3 times and once the planner increased (from 2 to 4 parts), once decreased (10 to 5) and once the planner rejected the order (6 to 0). Table 5.4 shows the estimated fill rate and the expected logistic costs of this factor. However, we argue that the estimated fill rate is too high because of the assumptions we made. In addition, based on this small number of observations it is hard to draw any conclusions regarding the impact of this factor. Since we observe this factor just 3 times and we do not know what the impact is of this factor, we suggest that this factor is less important.

5.3.3.7 No supply information

The factor *no supply information* is observed 2 times and the planner rejected the orders because of supply information that is missing. We can not estimate the impact of these interventions, however, we argue that the impact of this factor is negative on the availability of these parts. Since we observed this factor just 2 times and we do not know how large the impact is, we consider this factor as less important.

5.3.4 Summary of results RET

During a period of 4 weeks, from week 46 until week 49 in 2013, we reviewed a sample of 343 purchase requisitions at RET. In this sample, 26% of the purchase requisitions were accepted and 74% of purchase requisitions were overruled by planners. Conditioned on the interventions, we argue that a relative high number of interventions are allocated in the low price segment (55%) while we expected more interventions in the higher price segment. Furthermore, we see that most interventions are associated with assortment management (42%) and the deployment process (41%).

We find seven key factors causing interventions at RET, representing 85,1% of the interventions that occurred and 97% of the proposed order value (see Table 5.2). An overview of the key factors, the amount of observations, sum of the proposed order value, the estimated impact and if we consider the factor as important is shown in Table 5.5. Overall, we see that planners mainly reject orders and this result in a lower availability of parts whereas the expected logistic costs remains the same.

Key factors	Number of observations	Sum proposed order value	Estimated impact	Important
Phase-in of asset	51	€ 251.413	Unknown	Yes
Low unit value	34	€ 2.094	Positive	Yes
Phase-out of asset	21	€ 2.508	Positive	Yes
MOQ	19	€ 84.054	Negligible	No
Low frequency of demand	19	€ 14.151	Negative	Yes
High unit value	3	€ 20.406	Unknown	No
No supply information	2	€ 20.849	Unknown	No

Table 5.5: Summary of key factors and impact at RET.

5.4 Royal Netherlands Navy

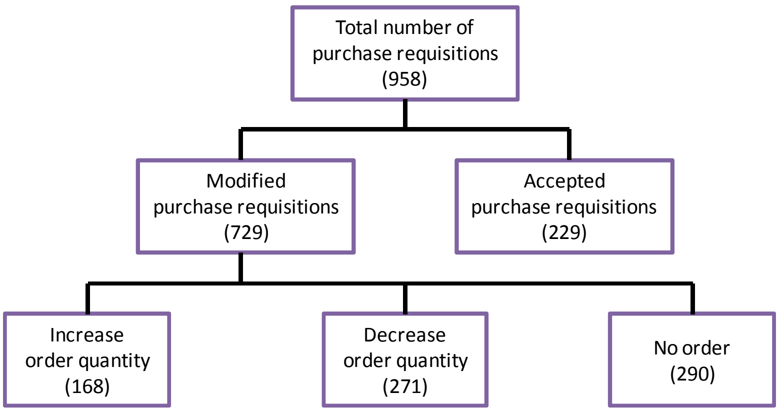
In this section, we describe the empirical results of the Navy. First, we describe the collected data in subsection 5.4.1. Secondly, we select the key factors in subsection 5.4.2. Next, in subsection 5.4.3 we analyse the key factors and we discuss the estimated impact of the interventions. At last, in subsection 5.4.4, we summarise the results of the Navy.

Remark: Since we work out the same analysis as conducted at RET, we only discuss the results and we refer to the previous section for more details of the analysis.

5.4.1 Data description

During a period of 7 weeks, from week 46 2013 until week 2 in 2014, we reviewed a sample of 958 purchase requisitions. Similar to RET, we have detailed information per purchase requisition which we use in order to estimate the fill rate and the expected logistic costs.

First, we checked the data sample of 958 purchase requisitions for duplicate purchase requisitions (Step 1). We found no duplicate purchase requisitions hence we continue with the complete data set.



5.7: Overview of reviewed purchase requisitions and type of interventions at Navy.

5.4.1.1 Overview reviewed purchase requisitions

In Figure 5.7 we provide an overview of the reviewed purchase requisitions and type of interventions at the Navy (Step 2). In this sample, 229 purchase requisitions (24%) were accepted and 729 purchase requisitions (76%) were overruled by planners. Conditioned on the interventions, 290 times the planner decided to reject the order (40%), 168 times the planner increased the order quantity (23%) and 271 times the planner decreased the order quantity (37%).

5.4.1.2 Distribution of interventions based on price and frequency classification

Next, from the initial data set of 958 purchase requisition, we excluded the purchase requisitions that are accepted (229). For the remaining 729 interventions, we classify the interventions based on the price and the demand frequency of the spare part. Similar to RET, the threshold values for the price are the 50th and 80th percentiles of all SKU prices at Navy (21.773 items). The classification of the interventions is presented in Figure 5.8.

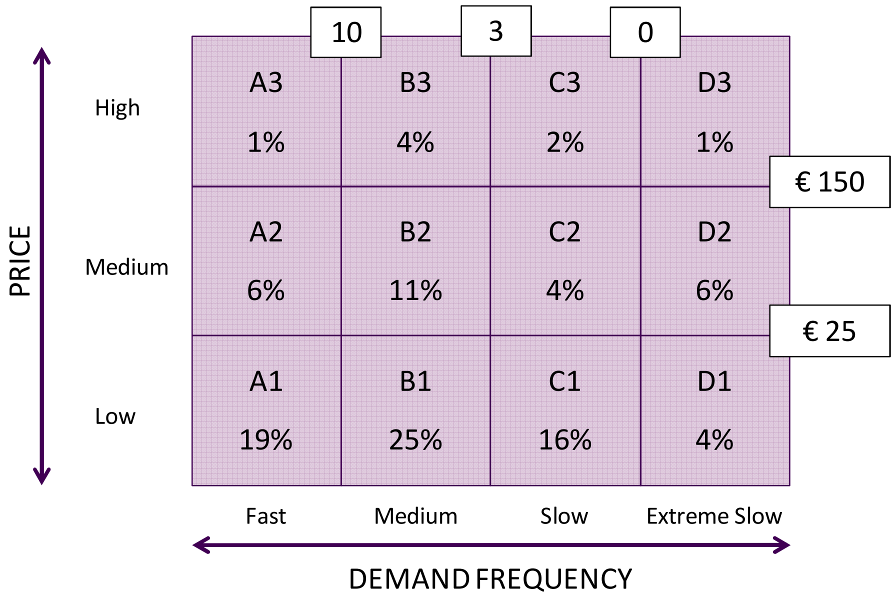


Figure 5.8: Distribution of interventions per quadrant at Navy.

On forehand, we expected that most interventions occur in the slow moving segment and the expensive segment. In contrast, Figure 5.8 shows that most interventions occur in the low price segment (64%) and in the medium moving class (40%). We present the type of interventions in the low price segment in Figure 5.9.

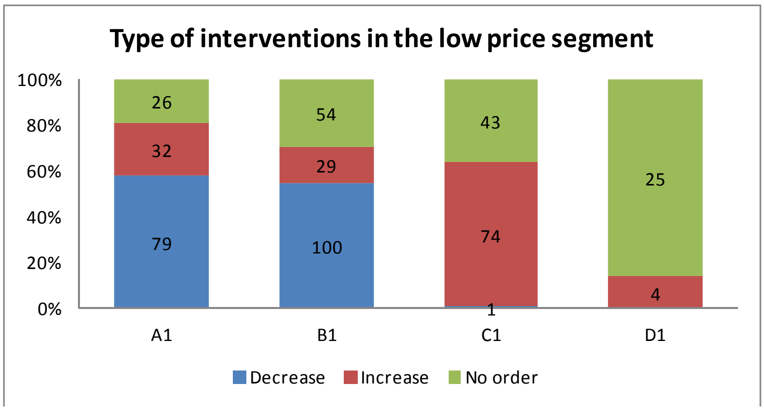


Figure 5.9: Distribution type of interventions in the low price segment.

Figure 5.9 shows that planners mostly decreased the order quantity in quadrant A1 and B1. This is remarkable since the value of the part is low (the gains are negligible) and decreasing the order quantity could result in a lower availability of parts. When planners reject the order the impact on the availability is even higher. In both quadrants, A1 and B1, about 80% of the interventions consists of decreasing or rejecting the proposed order quantity, this is counterintuitive. In quadrant C1 the planner often increased the order quantity and in quadrant D1 the orders are mainly rejected.

5.4.1.3 Overview of interventions on process level

We continue with plotting the interventions in the adapted framework of Driessen et al. (2013). From the initial data set of 958 purchase requisitions, we excluded the purchase requisitions that are accepted (229) and we excluded the purchase requisitions that are out of the scope or no reason was given (165). Subsequently, we classify the remaining 564 interventions in our framework, see Figure 5.10.

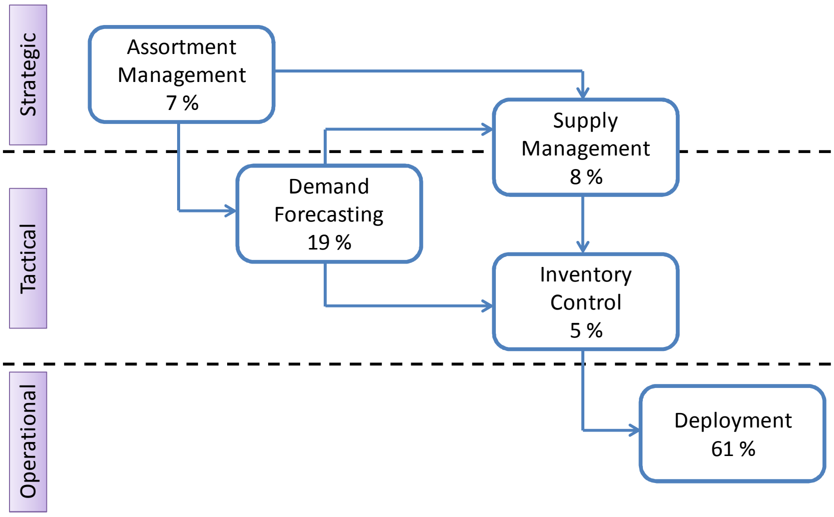


Figure 5.10: Interventions at the Navy plotted in the framework.

Figure 5.10 shows that most interventions are related to issues in the deployment process (61%). Main factors concerning this spare parts process are *rounded quantities*, *peak in demand* and *low unit value.* We discuss these factors in sub section 5.4.3.

5.4.1.4 Overview of factors found at the Navy

An overview of all 20 factors observed at the Navy, the type of intervention and the total order value is given in Table 5.6.

Spare part processes and factors	*Decrease*	*Increase*	*No order*	*Total*	*Sum proposed order value*
Assortment	**4**		**37**	**41**	**€ 77.382**
Phase-out of product	1		30	31	€ 14.992
Phase-in of asset	3		2	5	€ 7.077
Net shelf space			4	4	€ 55.188
Substitution			1	1	€ 126
Demand/Forecasting	**21**	**29**	**53**	**103**	**€ 86.295**
Old demand request			44	44	€ 60.720
Typical demand quantity	19	11	7	37	€ 23.765
Demand data update frequency	2	10		12	€ 1.084
Quadrant shift		8	2	10	€ 725
Deployment	**182**	**112**	**45**	**339**	**€ 262.553**
Rounded quantities	109	52		161	€ 117.214
Peak in demand	49	3	35	87	€ 95.251
Low unit value		47		47	€ 1.078
High unit value	11	2	5	18	€ 38.695
Low frequency of demand	5	7	4	16	€ 5.028
High variability of demand	6		1	7	€ 3.866
Peak in lead times	2			2	€ 1.323
Long lead time		1		1	€ 97
Inventory control	**26**	**1**	**3**	**30**	**€ 24.841**
Holding/carrying costs	26	1	3	30	€ 24.841
Supply management	**3**	**5**	**35**	**43**	**€ 16.949**
No supplier available			32	32	€ 3.765
MOD	2	5		7	€ 4.735
No supply information	1		3	4	€ 8.450
Total	236	147	173	556	€ 468.020

Table 5.6: Overview of factors observed at the Navy.

5.4.2 Selection of key factors

At the Navy we observed various factors that cause interventions, next we select the key factors based on the number of observations and the sum of the proposed order value (Step 3). In Table 5.7 we present the key factors, representing 71,5% of all interventions observed at the Navy and these factors represent 83,3% of the total proposed order value.

Key factors	*Number of observations*	*Percentage observations*	*Sum proposed order value*	*Percentage order value*
Rounded quantities	161	28,9%	€ 117.214	25,0%
Peak in demand	87	15,6%	€ 95.251	20,3%
Low unit value	47	8,4%	€ 1.078	0,2%
Old demand request	44	7,9%	€ 60.720	13,0%
Typical demand quantity	37	6,6%	€ 23.765	5,1%
High unit value	18	3,2%	€ 38.695	8,3%
Net shelf space	4	0,7%	€ 55.188	11,8%
Total	398	71,5%	€ 391.912	83,7%

Table 5.7: Overview of key factors at the Navy.

5.4.3 Analysis of key factors

In this subsection, we analyse the key factors found at the Navy (step 4). First, we provide an overview of the KPIs and thereafter we briefly discuss each factor. At last, we discuss if it is important to address the key factor based on the amount of observations and based on the impact (fill rate).

Key factors	Number of observations	Σ Order value system	Σ Order value planner	Delta order value
Rounded quantities	161	€ 117.214	€ 110.092	€ 7.123
Peak in demand	87	€ 95.251	€ 31.424	€ 63.827
Low unit value	47	€ 1.078	€ 2.673	-€ 1.595
Old demand request	44	€ 60.720	€ 0	€ 60.720
Typical demand quantity	37	€ 23.765	€ 7.372	€ 16.393
High unit value	18	€ 38.695	€ 16.437	€ 22.258
Net shelf space	4	€ 55.188	€ 0	€ 55.188
Total	398	€ 391.912	€ 167.998	€ 223.914

Table 5.8: Overview of order values per key factors.

In Table 5.8 an overview is given of the key factors, the total order value of the proposed order quantity (system), the total order value that is actually ordered by the planner and the savings or additional investments per factor (delta order value). We see that the planner temporarily saved 224k euro (57%) by intervening. Next, we estimate the fill rate and the expected logistic costs in the long term. As mentioned before, we made a number of general assumptions in order to estimate these KPIs, see section 4.3. Given these assumptions, the estimated impact of intervening is shown in Table 5.10. We briefly discuss each key factor in the following paragraphs.

Key factors	Number of observations	Fill rate system	Fill rate planner	Delta fill rate	ELC system	ELC planner	Delta ELC	Legend
Rounded quantities	161	94,33%	94,12%	-0,21%	€ 22.006	€ 21.845	€ 161	Positive
Peak in demand	87	95,24%	90,31%	-4,93%	€ 6.566	€ 6.907	-€ 341	Negative
Low unit value	47	72,33%	93,42%	21,09%	€ 1.623	€ 759	€ 864	Negligible
Old demand request	44	N.A.	N.A.		N.A.	N.A.		Unknown
Typical demand quantity	37	88,44%	82,90%	-5,55%	€ 2.902	€ 2.429	€ 473	
High unit value	18	62,92%	56,36%	-6,56%	€ 3.352	€ 2.927	€ 425	
Net shelf space	4	86,06%	75,48%	-10,58%	N.A.	N.A.		
Total	398				€ 36.449	€ 34.867	€ 1.582	

Table 5.9: Overview of estimated impact per factor.

5.4.3.1 Rounded quantities

We observed the factor *rounded quantities* 161 times: the planner decreased the order quantity 109 times and increased the order quantity 52 times. Table 5.8 shows that the planner saved 7k euro (6%) by intervening in the short term. Table 5.9 shows that the impact is negligible since the fill rates and expected logistic costs are almost equal. Therefore, we conclude that the impact of this factor is negligible on the performance and we consider this factor as less important.

5.4.3.2 Peak in demand

The factor *peak in demand* is observed 87 times and the planner decreased the order quantity 49 times, rejected the order 35 times and increased the order quantity 3 times. Recall, at this moment they do not use the outlier detection of the SPPT at the Navy (remove outliers before a forecast is generated). This results in a forecast that is too high and the planner anticipate regularly through decreasing or rejecting the order. We argue that these interventions are fine and this interventions can easily be prevented by using the outlier detection functionality. Given the forecast generated including the peak demands, the estimated fill rate decreases significantly (-4,93%) and the expected logistic costs increases slightly (€ 341). Based on the amount of interventions, we consider this factor as important to address in order to reduce the amount of interventions.

5.4.3.3 Low unit value

The factor *low unit value* is observed 47 times and in this case the planner always increases the order quantity. Table 5.8 shows that these interventions results in a small additional investment of 1.595 Euro. In return, the estimated fill rate increases with an impressive 21,09% and the expected logistic costs decreases with 864 euro. The large increase in the fill rate can be explained by the fact that 42 parts of the 47 parts are slow moving parts (C-items) with lower service levels settings (often 80%, 70% or 0%). By increasing the order quantity, the fill rate of 32 parts rises to 98% or higher. It seems to be that the service level settings are too low in the C1 quadrant. Overall, we see that the impact of this factor is positive on the performance and we consider this factor as important.

5.4.3.4 Old demand request

The factor *old demand request* is observed 44 times and the planner always rejected the order. Recall, the planning system is triggered by an old demand request and this can be considered as contaminated data. According to the planners, a couple of years ago (2 or 3 years) the system generated many purchase requisitions but these purchase requisitions where ignored since there was no more budget. These demand requests are still in VAS and triggers the system to generate a purchase requisition. In our opinion, these old request should be removed instead of ignoring. Since we observed this factor often we consider this factor as important.

5.4.3.5 Typical demand quantity

The factor *typical demand quantity* is observed 37 times. These interventions include 19 times a decrease of the order quantity, 11 times an increase of the order quantity and 7 times a rejection of the order. Remark, this factor does not mean that a TDQ method (paragraph 4.3.2.2) is used for the determination of the order quantity. In this case, the planner observes a typical demand pattern in the historical data. Table 5.8 shows that the planner temporarily saved 16k euro (69%) by intervening. On the other hand, Table 5.9 shows that the fill rate drops significant (-5,55%) whereas the expected logistic costs decreases slightly with 473 euro. Because of the significant drop in availability we conclude that the impact of this factor is negative on the performance. We judge this factor as important to address.

5.4.3.6 High unit value

The factor *high unit value* is observed 18 times and the planner decreased 11 times, increased twice and rejected the order 5 times. Table 5.8 shows that the planner saved 23k euro (57%) by intervening in the short term. However, Table 5.9 shows that the fill rate drops with 6,56% whereas the expected logistic costs decreases slightly with 425 euro. Because of the significant drop of the fill rate we conclude that the impact of this factor is negative on the performance. We consider this factor as important to tackle.

5.4.3.7 Net shelf space

We observed the factor *net shelf space* only 4 times and the planner always rejected the order (lack of space to store the parts). Table 5.9 shows a large drop in the fill rate, the estimated fill rate decreases with 10,58%. The expected logistic costs can not be estimated as the formula (Eq. 4.8) is not applicable. Given the large drop in the fill rate, we conclude that this factor has a negative impact on the performance and we consider this factor as important.

5.4.4 Summary of results Navy

During a period of 7 weeks, from week 46 2013 until week 2 in 2014, we reviewed a sample of 958 purchase requisitions. In this sample, just 24% of the purchase requisitions were accepted and 76% of the purchase requisitions were overruled by planners. When we focus on the interventions that occurred, we argue that a relative high fraction of the interventions (64%) are in the low price segment (value < 25 euro). Remarkable is the fact that in the A1 and B2 quadrant many purchase requisitions are decreased or even rejected (about 80%) whereas the gains are negligible (cheap parts) and the impact on the fill rate could be significant. Furthermore, we see that most interventions are associated with the deployment process (61%).

We find seven key factors causing interventions at the Navy, representing 71,5% of interventions observed at the Navy and represent 83,3% of the total proposed order value (see Table 5.8). An overview of the key factors, the amount of observations, total order value, the estimated impact and the degree of importance is shown in Table 5.10. Furthermore, we see that estimated availability drops significantly whereas the expected logistic costs slightly decreases for the majority of interventions that occurred.

Key factors	Number of observations	Sum Proposed Order value	Estimated impact	Important
Rounded quantities	161	€ 117.214	Negligible	No
Peak in demand	87	€ 95.251	Negative	Yes
Low unit value	47	€ 1.078	Positive	Yes
Old demand request	44	€ 60.720	Unknown	Yes
Typical demand quantity	37	€ 23.765	Negative	Yes
High unit value	18	€ 38.695	Negative	Yes
Net shelf space	4	€ 55.188	Negative	Yes

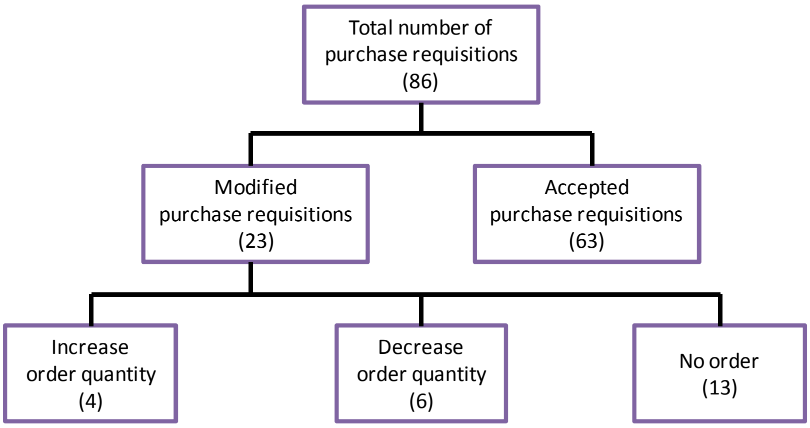
Table 5.10: Summary of key factors and impact at Navy.

5.5 IBM

In this section, we describe the empirical results of IBM. First, we describe the collected data in subsection 5.5.1. Secondly, we discuss qualitative aspects and side issues found during our visit to IBM Hungary. Next, in subsection 5.5.3 we select and discuss the key factors and finally, in subsection 5.5.4, we summarise the results of IBM.

5.5.1 Data description

During the two-day visit to IBM Hungary we interviewed 9 operational planners (analysers). These planners replenish spare parts for the hub in Venlo, the central warehouse for Europe, Middle East and Africa (EMEA). We reviewed 86 purchase requisitions and in this sample, 63 purchase requisitions (73%) were accepted and 23 purchase requisitions (27%) were overruled by planners. Regarding the interventions that occurred, the planners decided to reject the order 13 times (57%), the planners increased the order quantity 4 times (17%) and the planners decreased the order quantity 6 times (26%). An overview of the reviewed purchase requisitions is given in Figure 5.11.



5.11: Overview of reviewed purchase requisitions and type of interventions at IBM.

From the initial data set of 86 purchase requisitions, we excluded the purchase requisitions that are accepted (63) and we exclude the purchase requisitions that are out of the scope (4). These four special cases consists of purchase requisitions to send warranty items, however, no warranty items were available to send to the supplier. Therefore, we exclude these interventions from the data set. Next, we classify the remaining 19 interventions in our framework, see Figure 5.12.

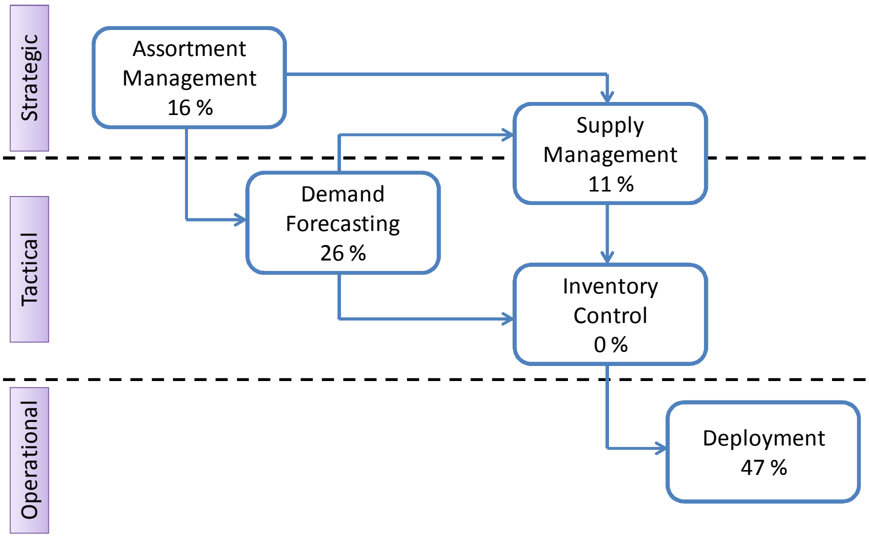


Figure 5.12: Interventions at IBM plotted in the framework.

Figure 5.9 shows that most interventions are related to issues in the deployment process (47%). Main factors concerning this spare parts process are *peak in demand* and *high unit value.* Secondly, many interventions are associated to the process demand forecasting (26%). The main factor regarding this spare parts process is *trend shift.* An overview of the factors observed at IBM and the type of interventions is given in Table 5.11.

Spare part processes and factors	*Decrease*	*Increase*	*No order*	*Total*
Assortment			**3**	**3**
Substitution			2	2
Substitution (matrix relations)			1	1
Demand and forecasting	**3**	**2**		**5**
Seasonality	1			1
Trend shift	2	2		4
Supply situation			**2**	**2**
MOQ			1	1
No supplier available			1	1
Deployment	**3**	**2**	**4**	**9**
High unit value	1		2	3
Low frequency of demand	1			1
Low unit value		1		1
Peak in demand	1		2	3
Rounded quantities		1		1
Total	6	4	9	19

Table 5.11: Overview of factors and intervention types at IBM.

5.5.2 Key factors

In this small data sample of IBM, we observed 11 different factors that cause interventions. Based on the number of observations, the major reasons to intervene are: *Trend shift* (4), *substitutions* (3), *peak in demand* (3) and *high unit value* (3).

Unfortunately, we have no additional information about the price of the parts or any historical data. Therefore, we are not able to estimate the fill rate and the expected logistic costs per factor. Consequently, it is very hard to draw any conclusion regarding the impact of these interventions.

5.5.3 Qualitative findings

During the two-day visit we spoke with 9 operational planners. Most of the planners argued that *phase-in of asset*, *phase-out of asset*, *MOQ*, *MOD* and *substitutions* are common reasons to intervene. Empirically, we found no evidence for the factors *phase-in of asset* and *phase-out of asset*. Nevertheless, planners argue that phase-in and phase-out issues frequently occur and therefore we consider these factors as important factors as well. Another remarkable finding is that Servigistics and the planners do not take ordering costs into account. However, the order value should be at least 200 dollar as rule of thumb according to the planners and the team leads of Amsterdam.

In the context of this research, one of the team leads of IBM argues that humans have the urge to generate added value with respect to the planning system, irrespectively of the quality of the proposed order quantity. This statement is in line with results described in the papers of Lawrence et al. (2002) and Wiers & van der Schaaf (1997). A common explanation is that humans knows that these techniques are imperfect and they expect that increased mental effort will increase performance (Wiers & van der Schaaf, 1997).

The team lead of IBM argues that in order to reduce the amount of unnecessary interventions, the amount of purchase orders that should be reviewed by planners should be reduced by automating the process from purchase requisition to purchase order (no manual reviewing). Suppose, planners modify 20% of the purchase requisition because of their urge to generate added value. When the planners review all generated purchase requisitions, about 20% of the purchase requisitions will be regarded as unnecessary interventions. However, when 80% is automated (this is the situation at IBM) and planners review only 20% of the purchase requisitions, about 4% (0,2*0,2) of the purchase requisitions will be regarded as unnecessary interventions caused by the human urge to generate added value.

5.5.4 Summary of results IBM

During the two-day visit to IBM Hungary we reviewed 86 purchase requisitions. In this small sample, 73% of the purchase requisitions were accepted and 27% of the purchase requisitions were modified. Concerning the interventions, we see that most interventions are associated with the deployment process (47%).

Based on the number of observations we can conclude that the factors *trend shift, substitution, peak in demand* and *high unit value* are key in causing interventions at IBM. Based on the interviews with 9 planners, we argue that the factors *phase-in of asset* and *phase-out of asset* are important factors causing interventions.

5.6 Comparison of case studies

In this section we compare the empirical results of the case studies. First, discuss the amount of interventions across the three companies in subsection 5.6.1. Secondly, we evaluate the interventions ion process level across the companies. At last, in section 5.6.3, we discuss the key factors found at the different companies.

5.6.1 Comparison of interventions

Table 5.12 shows that about 75% of the purchase requisitions are modified at RET and at the Navy. In contrast, at IBM about 25% of the purchase requisitions are adapted in the sample. Note that already 80% (approximated) of the generated purchase requisitions are automated at IBM and around 20% of the purchase requisitions are reviewed by planners. If we assume that the small sample is representative for all purchase requisitions that are reviewed we can say that roughly 5% (0,2*0,27) of all generated purchase requisitions are modified at IBM. This is quite impressive compared to the amount of interventions at RET and the Navy.

	Case studies		
Purchase requisitions	*RET*	*Navy*	*IBM*
Sample size	343	958	86
Accepted	26%	24%	73%
Interventions	74%	76%	27%

Table 5.12: Overview of purchase requisitions per company.

Concerning the fraction of purchase requisitions that is reviewed by planners at IBM, the fraction of interventions (27%) is much lower compared to the other companies. This outcome suggests that Servigistics (planning system of IBM) proposes better purchase requisitions and/or planners have more confidence in the recommendations of this system. It seems that the maturity of the planning system has influence on the degree of acceptance of the purchase requisitions. Recall, Servigistics contains the most comprehensive features to manage spare parts (Rolls Royce planning system). Unfortunately, we can not draw hard conclusions since too much external effects can influence these results (e.g. different environments, different planners with various education levels and experiences).

5.6.2 Comparison of interventions on process level

An overview of all interventions aggregated per spare part process is presented in Figure 5.13. The results of RET, Navy and IBM are marked red, orange and blue respectively.

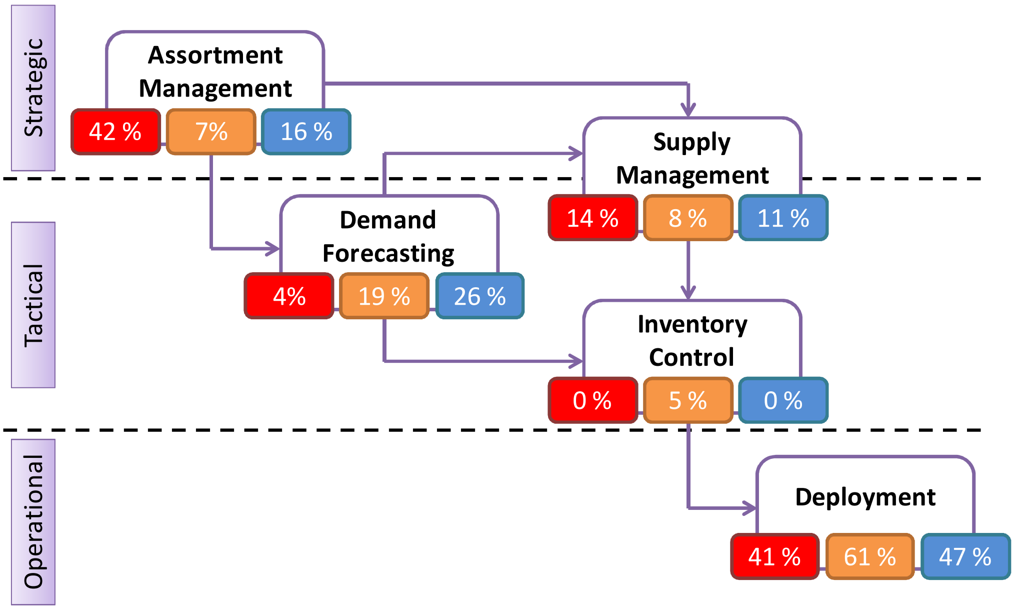


Figure 5.13: Overview of interventions per spare part process per company.

Figure 5.13 shows that across the companies, most interventions are associated with the deployment process. As stated before, deployment concerns the process of replenishing spare parts and most factors regarding this process can be considered as a human factor (paragraph 3.3.3.5). Main factors for intervening regarding the deployment process are *low unit value, high unit value, low frequency of demand, rounding quantities* and *trend shift*. Furthermore, Figure 5.13 shows a substantial part of interventions at RET are associated with assortment management. Main factors are *phase-in of asset* and *phase out of asset.*

5.6.3 Comparison of key factors

In Table 5.13 we present an overview of the key results per company and the estimated impact of intervening. When comparing all key factors we see that the factors *high unit value, low unit value* and *peak in demand* are overall key factors found at two or more companies. In particular, we conclude that the price of a part is the main driver of interventions concerning these overall factors. The remaining key factors are specific for each company.

Regarding the interventions that have a positive impact on the performance, we found the factor *low unit value* at two companies (RET and Navy). By intervening, the planners made an improvement with respect to the planning system. At RET, the proposed order quantities are worse since SAP does not contains a kind of EOQ-model (balancing ordering costs and holding costs). At the Navy, it seems that the service level settings are to low for slow movers (C1 quadrant). Interventions associated with *phase-out of asset* (RET) are caused by the fact that SAP does not take into account this factor.

Concerning the factors that have a negative impact on the performance, typically, these interventions result in a lower fill rate whereas the expected logistic costs remains almost the same.

	Impact of intervening		
Key factors	*RET*	*Navy*	*IBM*
High unit value	Unknown	Negative	Unknown
Low unit value	Positive	Positive	
Peak in demand		Negative	Unknown
No supply information	Unknown		
MOQ	Negligible		
Phase-in of asset	Unknown		
Phase-out of asset	Positive		
Low frequency of demand	Negative		
Old demand request		Unknown	
Net shelf space		Negative	
Typical demand quantity		Negative	
Rounded quantities		Negligible	
Substitution			Unknown
Trend shift			Unknown

Table 5.13: Overview key factors and impact per company.

Chapter summary

In this chapter we discussed and analysed the empirical data of our case studies. We briefly introduced the case studies and we outlined our method to analyse the empirical data. Next, we analysed the empirical data in order to find the root causes of interventions. Furthermore, we estimated the impact of interventions. In this final section we summarise the most important elements of this chapter.

- We analysed empirical data of three companies: RET, the Navy and IBM. **RET uses SAP** as planning system, this can be characterised as a basic planning system which consist of a standard module for inventory management. The **Navy uses SPPT** as planning system, this tool contains advanced models for spare parts planning. **IBM uses Servigistics**, this is a well-known planning system containing the most comprehensive features to manage spare parts.
- We collected our data samples during the **period November 2013 until January 2014**. For each purchase requisition we collected the part number, the proposed order quantity of the system, the quantity actually ordered and the reason(s) for intervening.
- **At RET,** 26% of the purchase requisitions were accepted and **74% of the purchase requisitions were modified by planners (sample size = 343)**. Conditioned on the interventions, 55% of the interventions are in the low price segment (value<25 euro) and it is remarkable that many purchase requisitions are rejected in this segment (cheap parts but the impact on the fill rate could be significant). On process level, most interventions are associated with the deployment process (48%) and assortment management (37%).
- At RET, we found **seven key factors** causing interventions, representing 85,1% of the interventions that occurred and 97% of the total order value. Based on the number of observations, the top 3 factors are *phase-in of asset, phase-out of asset* and *low unit price.*
- **At the Navy,** 24% of the purchase requisitions were accepted and **76% of the purchase requisitions were overruled by planners (sample size = 958)**. When classifying the spare parts based on price and demand frequency, we see

that 64% of the interventions are in the low price segment (<25 euro). In particular, 44% of all interventions occurred in the A1 and B1 quadrant and mostly the planners decreased or rejected the proposed order quantity. This is counterintuitive since the gains are negligible (cheap parts) and these actions could result in a lower availability of parts. On process level, by far most interventions are associated with the deployment process (61%).

- At the Navy, we found **seven key factors** causing interventions, representing 71,5% of the interventions that occurred and 83,3% of the total order value. Based on the number of observations, the top 3 factors are *rounded quantities, peak in demand* and *low unit value*.
- **At IBM, we reviewed a small sample of 86 purchase requisitions**. In this sample, 73% of the purchase requisitions were accepted and **27% of the purchase requisitions were overruled by planners**. On process level, most interventions are associated with the deployment process (47%).
- At IBM, we found **four key factors** causing interventions. These key factors are: *high unit value, peak in demand, trend shift* and *substitution*. Based on interviews with 9 planners, the factors *phase-in of asset* and *phase-out of asset* are also indicated as important factors causing interventions.
- When **comparing the case studies**, at RET and the Navy about 75% of the purchase requisitions were modified whereas at IBM just 5% (rough estimation) were modified. This outcome suggests that Servigistics proposes better order recommendations and/or planners have more confidence in the advices of this system. Secondly, **most interventions are associated with the deployment process across the companies**. Thirdly, the factors *high unit value, low unit value* and *peak in demand* are overall key factors found at two or more companies. Therefore, we conclude **the price of a part is the main driver of interventions concerning these overall factors**. The remaining key factors are specific for each company.
- Concerning the factors that have a negative impact on the performance, these interventions result in a lower fill rate whereas the expected logistic costs remains almost the same. When planners improve the system (positive impact by intervening), mainly the model does not support the (missing) factor, e.g. *phase-out of asset*.

6 Improvement areas

In the previous chapter we defined the key factors causing interventions and we determined the estimated impact. In addition, one of the main findings of the empirical results is that most interventions are associated to the deployment process. In this chapter we discuss potential improvements in order to improve the quality of planning decisions (research question 4).

In section 6.1 we briefly discuss how to reduce interventions concerning the deployment process. In section 6.2 we discuss areas of improvement and the effort required per key factor. In section 6.3, we give a prioritisation of the key factors based on impact and effort required. At last, we provide feedback on the auto-order-assessment project based on our results.

6.1 Reducing interventions in the deployment process

In all participating companies we found many interventions related to the deployment process. Recall, deployment concerns the process of replenishing spare parts inventories by planners and the majority of factors concerned this process can be considered as a human factor. The key factors of deployment found at the companies are *low unit value, high unit value, low frequency of demand, rounding quantities* and *trend shift*. It is difficult to improve the quality of these planning decisions since aspects of human behaviour are involved. It might be an option to research the cognitive factors (psychology) involved in decision making. However, we argue that planners would be able to improve their decisions if they would be able to relate their actions to the effects of their actions. Therefore, we suggest to develop a feedback mechanism to learn from own past decisions (earlier successes and failures). In this manner, planners can change their own planning behaviour and feedback improves the confidence in the planning system.

In order to realise a feedback mechanism, proposed orders and actual orders needs to be tracked and the actual impact should be determined. Based on the actual impact, planners are able to relate their actions to the effects of their actions and they would be able to improve their decisions.

6.2 Reducing interventions per factor

In this section we determine the areas of improvements per key factor and we indicate the effort that is required to reduce the number of interventions caused by these factors. Recall, in subsection 3.3.2 we already pointed out the source of influence of a factor (data, model or human) in order to improve planning decisions.

6.2.1 RET

The key factors at RET are: *high unit value, low unit value, no supply information, MOQ, phase-in of asset, phase-out of asset* and *low frequency of demand*. We briefly discuss the areas of improvements and the effort that is required to address the factor (with the aim of preventing interventions in the future).

Interventions caused by the factors *phase-in of asset* and *phase-out of asset* are required since SAP does not support solutions for these factors. The planning system can be improved by modelling these factors but this requires high effort.
Interventions caused by the factors *low unit value and high unit value* are caused by the fact that SAP does not balance ordering costs and holding costs when determining the order quantity. At this moment, the proposed order quantity is not related to the price of a part. This can be concerned as a model issue. We argue that it requires low effort to address these factors by adding an EOQ model (or another model). Concerning the factor *low unit value,* a minimum order value (e.g. 50 Euro) can be set for these parts in order to address this factor in the short term.

The missing *MOQ* and *supply information* can be categorised as data issues. These factors can easily be tackled by adding the right information into the system which require low effort.
The *low frequency of demand* can be considered as human factor. As discussed in the previous section (6.1), these effects should be monitored in practice and then feedback should be given to the planners. However, the realisation of a feedback mechanism requires lots of effort.

For simplicity, we suggest that the fraction of interventions caused by a factor is the potential gain when addressing that factor. E.g. at RET we observed that 29% of all interventions are caused by factor *phase-in of asset*. When this factor is addressed, the potential gain is a maximal reduction of interventions by 29%.
An overview of the key factors, areas of improvement, the effort required and the potential gains is shown in Table 6.1.

	Areas of improvement				Potential
Key factors	**Data**	**Model**	**Human**	**Effort**	**gain**
Phase-in of asset		X		High	29%
Low unit value		X		Low	19%
Phase-out of asset		X		High	12%
MOQ	X			Low	11%
Low frequency of demand			X	High	11%
High unit value		X		Low	2%
No supply information	X			Low	1%

Table 6.1: Overview of areas for improvement and effort required.

6.2.2 Royal Netherlands Navy

The key factors at the Navy are: *high unit value, low unit value, peak in demand, old demand requests, Net shelf space, typical demand quantity* and *rounded quantities*. We briefly discuss the areas of improvements and the effort that is required to decrease the number of interventions by addressing these factors.

The factors *rounded quantities*, *low unit value* and *high unit value*, can be considered as human factor. A general approach to address the human factor is providing feedback to the planners such that they can learn from their previous decisions. This requires a lot of effort. However, the factors *rounded quantities* and *low unit value* could also be addressed in another way. Regarding the factor *rounded quantities*, a MOD-value could be added into the system for the cheap parts (for more information about the MOD, see section 3.3) and this requires low effort. In this manner, the planning system proposed “rounded” order quantities. Concerning the factor *low unit value,* it seems that the service levels settings of the slow movers are too low (see paragraph 5.4.3.3). It could be considered to increase the service levels in the C1 quadrant and this also requires low effort.
About the factor *peak in demand*, we argue that extreme values should be removed from the data set in order to generate an accurate forecast (see section 3.3). We argue that an automated outlier filter should be implemented. The SPPT already contains this functionality for lead times, it requires low effort to implement the same method for demand.
Interventions caused by the factor *old demand request* is a data issue as mentioned before. These old request should be removed by the planners instead of ignoring. This can easily be improved by cleaning the data and this requires low effort according to the planners. Note that, in March 2014 (3 months after data collection) removing these old requests is largely already done.
The factor *typical demand quantity* can be categorised as a model issue with the corresponding data that is missing. High effort is required to address this factor.

Interventions caused by the factor *net shelf space* are required since the system does not take into account storage restrictions. This is a model issue with corresponding data requirements (e.g. dimensions of product). It requires a lot of effort to address this factor. However, in the short term this issue could be solved by adding a maximum order quantity into the system for the parts concerned. This requires low effort.

An overview of the key factors, areas for improvement, effort required and potential gain is shown in Table 6.2.

Key factors	*Areas of improvement* Data	Model	Human	Effort	Potential gain
Rounded quantities		X	X	Low	29%
Peak in demand		X		Low	16%
Low unit value		X	X	Low	8%
Old demand request	X			Low	8%
Typical demand quantity		X		High	7%
High unit value			X	High	3%
Net shelf space		X		Low	1%

Table 6.2: Overview of areas for improvement and effort required.

6.2.3 IBM

The key factors at IBM are: *high unit value, peak in demand, substitution* and *trend shift*. We briefly discuss the areas of improvements and the effort that is required to prevent interventions caused by these factors in the future.

Regarding the factor *trend shift,* planners have the possibility to change the forecasting method during the review process and this can affect the proposed order quantity. For this reason, we consider this factor as a human factor that can be influence by providing planners with feedback. It requires high effort to address this factor.
The complexity introduced by *substitutions* and the characteristics of the assets is difficult to model in a system. Theoretically, it is possible to model these complex relations and to collect the data of these relationships. However, from data management point of view it might be very time consuming and inefficient to model this factor. Therefore, to eliminate this factor it requires a lot of effort.
Concerning the factor *peak in demand*, extreme values (outliers) should be removed from the data set to make an accurate forecast. We expect that Servigistics contains a outlier detection but we are not sure. In this case, planners could overreact because of a peak demand (a human factor, risk averse attitude). In order to address this human aspect it requires a lot of effort.
At last, planners are careful with expensive spare parts. However, by rejecting these orders the fill rate of these parts drop significant very likely. The factor *high unit value* is a human factor and it can be influenced by providing feedback to the planner, this requires high effort.
An overview of the key factors and areas for improvement is shown in Table 6.3.

Key factors	*Areas of improvement* Data	Model	Human	Effort
Trend shift			X	High
Substitutions		X		High
Peak in demand			X	High
High unit value			X	High

Table 6.3: Overview key interventions and areas for improvement.

Note that we do not provide the potential gain regarding these factors at IBM since the sample is very small. However, we can argue that the potential gain will be small because of the small amount of interventions at IBM (roughly 5% of all generated purchase requisitions.

6.3 Prioritisation of key factors

Next, we reconsider if a factor is important based on the impact on the fill rate (from the previous chapter) and the effort that is required to address the factor in order to reduce the number of interventions.

An overview of the key factors of RET is given in Table 6.4. First, RET should address the factor *low unit value* since we argue that this factor is important and it requires low effort. Secondly, we recommend tackle the factors *MOQ* since this factor also requires low effort. When these two factors are tackled, we expect a 30% reduction of interventions. In the long term, the remaining key factors could be addressed in order to realise a further reduction of interventions.

Sequence	Key factors	Important	Effort	Potential gain	*Areas of improvement*		
					Data	Model	Human
1	Low unit value	Yes	Low	19%		X	
2	MOQ	No	Low	11%	X		
3	High unit value	No	Low	2%		X	
4	No supply information	No	Low	1%	X		
5	Phase-in of asset	Yes	High	29%		X	
6	Phase-out of asset	Yes	High	12%		X	
7	Low frequency of demand	Yes	High	11%			X

Table 6.4: Prioritisation of factors that need to be addressed at RET.

An overview of the key factors of the Navy is given in Table 6.5. First, the Navy should address the factors *peak in demand, low unit value, old demand request* and *net shelf space* since these factors are considered as important and require low effort to address. The potential gain is a 33% reduction of interventions by addressing these factors. The factor *rounded quantity* also requires low effort and by addressing this factor another 29% reduction could be realised. In the long term, the remaining key factors could be tackled.

Sequence	Key factors	Important	Effort	Potential gain	*Areas of improvement*		
					Data	Model	Human
1	Peak in demand	Yes	Low	16%		X	
2	Low unit value	Yes	Low	8%		X	X
3	Old demand request	Yes	Low	8%	X		
4	Net shelf space	Yes	Low	1%		X	
5	Rounded quantities	No	Low	29%		X	X
6	Typical demand quantity	Yes	High	7%		X	
7	High unit value	Yes	High	3%			X

Table 6.5: Prioritisation of factors that need to be addressed at the Navy.

Regarding the key factors of IBM, we were not able to estimate the impact in terms of fill rate and logistics costs. Since the key factors require high effort in order to decrease the number of interventions in the future, these can be concerned as factors that could be addressed in the long term. However, as mentioned before, the expected increase in the acceptance rate will be small since the acceptance rate of generated purchase requisitions is roughly 95% at this moment. For this reason, further research is needed to determine if it is efficient to address these key factors (time and costs vs. potential benefits).

6.4 Auto-order-assessment

Recall, when we start with this graduation project, Gordian would like to automate the ordering process of their SPPT partially. They proposed decision rules to assess purchase requisitions and when a purchase requisition meets these criteria the order can be processed automatically (auto-order-assessment). However, during the pilot it seems that planners modify purchase requisitions frequently for reasons that could not be verified (see section 2.1 for more information).

Currently, we know the reasons for intervening, the estimated impact of intervening and we know how to reduce the number of interventions at the Navy (using the SPPT). Regarding the auto-order-assessment project, first we recommend to tackle factor 1 until 5 (Table 6.5) with the aim of reducing interventions and this requires low effort. Next, we suggest to develop decision rules in order to select purchase requisitions that are generally accepted by planners. Thereafter, when a substantial part of purchase requisitions are automated, we suggest to monitor again the ordering decisions of planners in order the find the most important factors that cause interventions at that moment. These important factors should be addressed, new decision rules should be developed and so forth. In this manner, the fraction of interventions can be decreased and the number of automated orders can be increased.

We present an overview of our idea in Figure 6.1. During our research there was no auto-order-assessment (AOA) implemented, consequently, planners review all purchase requisitions manually. In this research we focused on the “do” and “check” phase of the improvement cycle. Gordian should continue with the “act” phase.

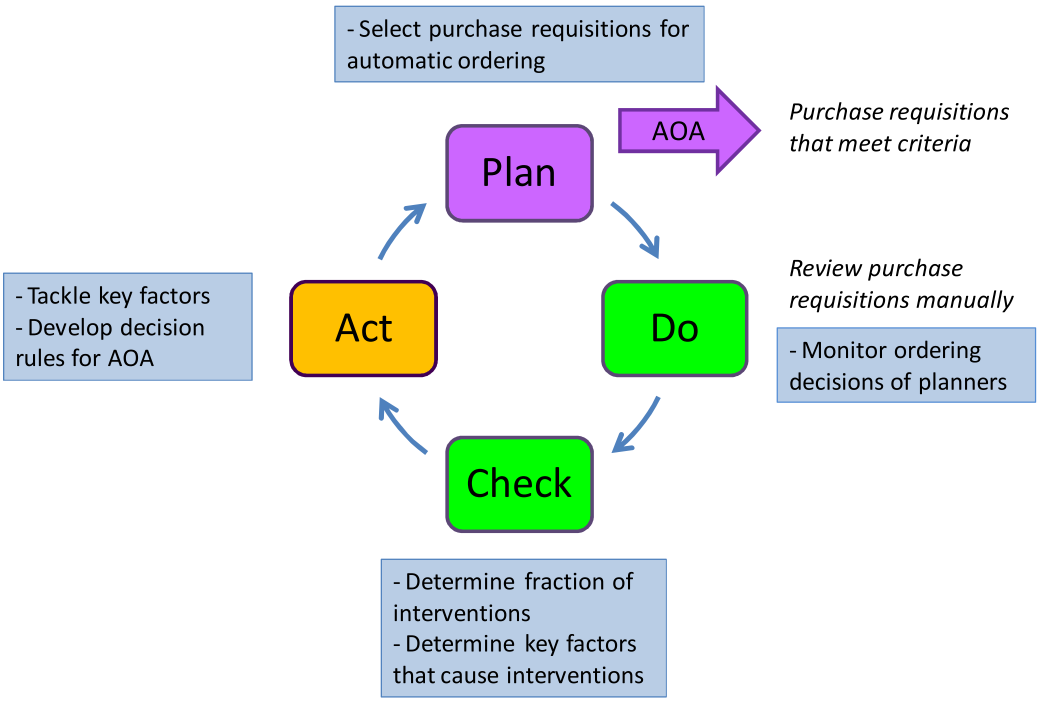


Figure 6.1: Improvement cycle in order to reduce the number of interventions.

Chapter summary

In this chapter, we discussed potential areas of improvement according to the results of our empirical analysis. We briefly discussed the idea of a feedback mechanism in order to decrease the number of interventions related to the deployment process. Furthermore, we discussed areas of improvement for each key factor and we prioritised the key factors based on impact and effort required. In this final section we summarise our main findings.

- Since many interventions are related to the deployment process at all participating companies, we suggest to develop a **feedback mechanism to learn from own past decisions.** We argue that planners would be able to improve their decisions if they would be able to relate their actions to the effects of their actions.
- Based on individual factor analysis, we determined impact on the fill rate and the effort required in order to tackle the factor concerned and thereafter we prioritise these factors. We discuss the "low hanging fruit" for the companies in order to reduce the amount of interventions:

➢ **RET**

- Tackle the factor *low unit value* by implementing an EOQ-model in SAP or by setting a minimum order value for cheap parts (potential reduction 19%).
- Tackle the factor *MOQ* by adding this values into the planning system (potential reduction 11%).

➢ **Navy (Gordian)**

- Tackle the factor *peak in demand* by implementing an automated outlier filter (potential reduction 16%).
- Tackle the factor *low unit value* by increasing the service levels in the C1 quadrant (potential reduction 8%).
- Tackle the factor *old demand request* by removing these requests from the planning system (potential reduction 8%). According to the planners this is largely already done in March 2014.
- Tackle the factor *rounded quantity* by adding a MOD into the planning system for the cheap spare parts (potential reduction 29%).

➢ **IBM**

- The key factors could be addressed in the long term. However, the expected reduction of interventions will be small (acceptance rate is already about 95% at this moment). Therefore, further research is needed to determine if it is efficient to address these factors.

➢ **Automatic order assessment**

- We recommend Gordian to tackle the key factors found at the Navy (they use their SPPT). Thereafter, decision rules should be developed in order to select the purchase requisitions that are commonly accepted by planners.

7 Conclusions and recommendations

In this final chapter we summarise the findings and conclusions of this thesis. In section 7.1 we give answers to the sub questions defined in chapter 2 and in section 7.2 we outline recommendations per company. At last, we discuss topics for further research.

7.1 Conclusions

In this section we give an answer to the central research question by providing answers to the four sub questions. Recall, the main goal of this master thesis is to gain insight into the processes of spare parts planning and the root causes of adapting or rejecting generated purchase requisitions by planners, in order to improve the planning decisions of spare parts. Consequently, we formulated the following central research question:

What are the root causes of adapting or rejecting generated purchase requisitions by planners and how can spare parts planning decisions be modified in order to improve the quality of planning and replenishment decisions?

This research can be positioned as a study concerning behavioural operations. We analysed ordering decisions of planners in a spare parts environment. For our research, we collected empirical data of ordering decisions at RET, the Navy and IBM. In order to answer the central research question, we answer the sub questions accordingly.

1. *What are the factors that influence planning decisions in spare parts planning?*

Based on an extensive literature review and interviews with planners, we found 31 factors that can influence spare parts planning decisions. The main factors found in practice we discuss later on. Further, we categorise the factors according to the spare part processes defined by Driessen et al. (2013) in order to allocate the factors to concrete process owners.

2. *How can we assess interventions by planners?*

We used the fill rate, holding costs and ordering costs as key performance indicators in order to quantify the impact of an intervention. Unfortunately, measuring the quality of replenishment decisions is not straight forward and the impact of interventions can only be measured after a long period of time. Therefore, we provided some methods to estimate the fill rate and the expected logistic costs (holding and ordering) at the moment of intervening. We distinguished fast and medium moving parts (frequency of demand ≥ 3 per year) and slow moving parts (frequency of demand ≤ 2 per year) and for both types of spare parts we described methods to determine the theoretical fill rate. Using these methods, we estimated the impact of intervening.

3. *What are the root causes of interventions?*

Based on the empirical data analysis, we determined the key factors for each company. We identified 14 different factors as key factors causing interventions at RET, the Navy and IBM. However, only the factors *high unit value, low unit value* and *peak in demand* are overall key factors found at two or more companies. Therefore, we conclude that the price of a part is the main driver of intervening. The remaining key factors are specific for each company. Based on the number of observations, another important factors across the companies are: *phase-in of asset, MOQ* and *rounded quantities*.
Regarding the impact, mainly the fill rate of parts drops by intervening (there are exceptions) whereas the expected logistic costs remains more or less the same.

Furthermore, we classified all observed factors (not only the key factors) per spare part process. Across the companies we see that most interventions are associated with the deployment process (about 50%). After reviewing the key factors concerning this process, we conclude that the majority of these factors can be considered as human factor.

> 4. *How can we improve the quality of planning decisions in spare parts planning?*

According to the empirical results, the majority of interventions can be considered as human factor. In order to reduce the number of interventions related to the human factor we suggest a feedback mechanism that planners can learn from own past decisions. We argue that planners would be able to improve their decisions if they would be able to relate their actions to the effects of their actions.
For each key factor we determined areas for improvement and the effort that is required to tackle these factors. At RET, the factor *low unit value* can be tackled by extending the model with an EOQ-model (balancing ordering and holding costs) or by adding a minimum order value. The factor *MOQ* can be tackled by adding these values into the system. In this manner, a potential reduction of 30% of interventions can be realised at RET. At the Navy, the factor *rounded quantities* can be tackled by adding MOD-values for cheap spare parts. The factor *peak in demand* can be tackled by implementing an automated outlier filter. Concerning the factor *low unit value*, the service levels in "quadrant C1" could be increased to tackle this factor. By addressing these three factors, a potential reduction of 53% of interventions can be realised at the Navy.

7.2 Recommendations

In this section we outline the recommendations that follow from this research.

1. **Tackle key factors**. We recommend to tackle the key factors in order to decrease the fraction of interventions. Most important key factors are:
   - **RET:** Tackle the factor *low unit value* by implementing an EOQ-model in SAP or by setting a minimum order value for cheap parts (potential reduction 19%). Tackle the factor *MOQ* by adding this values into the planning system (potential reduction 11%).
   - **Navy:** Tackle the factor *peak in demand* by implementing an automated outlier filter (potential reduction 16%). Tackle the factor *low unit value* by increasing the service levels in the C1 quadrant (potential reduction 8%). Tackle the factor *rounded quantity* by adding a MOD into the system for cheap parts (potential reduction 29%).
   - **IBM:** Since the expected reduction of interventions will be small (acceptance rate is already about 95% at this moment), further research is needed to determine if it is efficient to address the key factors.

2. **Track interventions and reasons of interventions**. We recommend to modify the planning systems in such a way that the following additional information will be stored: Proposed order quantities, actual order quantities and the reason for intervening (using the factors described in section 3.3). In this way, the effectiveness of the implemented improvements can be determined and ordering decisions easily be monitored in the future.

7.3 Suggestions for further research

In the final section of this report we describe several suggestions for further research.

1. **Determine exact impact of interventions**. One of the main limitations of this research is that we were not able to determine the actual impact of interventions. We described a proposal to determine the exact impact in section 4.2. However, additional data and a long period of time is required to determine the actual impact.
2. **Develop feedback mechanism**. Since major interventions are associated with the human factor, we suggest to develop a feedback mechanism that planners can learn from own past decisions. The main goal is that planners only modify purchase requisitions when there is evidence that the system can be improved.
3. **Study psychological (cognitive) factors**. In this research we explained modifications according to operational factors such as price and variability of demand. It could be interesting to investigate the cognitive factors that are involved in decision making in order to explain ordering behaviour.
4. **Include repairable spare parts**. This research focussed only on consumable spare parts. However, it is useful to extend this research with repairable parts since a considerable fraction of spare parts is repairable.

References

Bacchetti, A. & Saccani, N. (2012). *Spare parts classification and demand forecasting for stock control: Investing the gap between research and practice*. Omega, vol. 40, page 722-737.

Ancarani, A., Di Mauro, C. & D'Urso (2013). *A human experiment on inventory decisions under supply uncertainty*. International Journal of Production Economics, Vol. 142, page 61-73.

Benzion, U., Cohen, Y., Peled, R. & Shavit, T. (2008). *Decision-making and the newsvendor problem: An experimental study*. Journal of the Operational research society, Vol. 59(9), page 1281-1287.

Benzion, U., Cohen, Y. & Shavit, T. (2010). *The newsvendor problem with unknown distribution.* Journal of the Operational research society, Vol. 61(6), page 1022-1031.

Brehmer, B. (1992). *Dynamic decision making: Human control of complex systems.* Acta Psychologica, Vol. 81, page 211-241.

Croson, R., Schultz, K., Siemsen, E. & Yeo, M.L. (2013). *Behavioural Operations: The state of the Field*. Journal of Operations Management, Vol.31, page 1-5.

Cui, Y., Chen, L.G., Chen, J., Gavirneni, S. & Wang, Q. (2013). *Chinese perspective on newsvendor bias: An exploratory note*. Journal of Operations Management, Vol.31, page 93-97.

De Vericourt, F., Jain, K., Bearden, J.N. & Filipowicz, A. (2013). *Sex, risk and the newsvendor*. Journal of Operations Management, Vol.31, page 86-92.

Driessen, M.A., Arts, J.J., van Houtum, G.J., Rustenburg, W.D. & Huisman, B. (2013). *Maintenance spare parts planning and control: A framework for control and agenda for future research*. [Article in press]

Fransoo, J.C. & Wiers, V.C.S. (2008). *An empirical investigation of the neglect of MRP information by production planners*. Production Planning & Control: The Management of Operations, Vol.19(8), page 781-787.

Goodwin, P. (2000). *Improving the voluntary integration of statistical forecasts and judgement*. International Journal of Forecasting, Vol.16, page 85-99.

Goodwin, P. & Fildes, R. (1999). *Judgemental forecasts of time series affected by special events: Does providing a statistical forecast improve accuracy?* Journal of Behavioural Decision Making, Vol.12, page 37-53.

Gordian (2013). *Gordian Logistic Experts*. Found on 29 August 2013 from http://www.gordian.nl

Guide Jr., V.D.R. & Srivastava, R. (1997). *Repairable inventory theory: Models and applications*. European Journal of Operational Research, Vol.102, page 1-20.

Forrester, J. (1958). *Industrial dynamics: a major breakthrough for decision makers*. Harvard Business Review, Vol.36, page 37-66.

Kennedy, W.J., Patterson, J.D. & Fredendall, L.D. (2002). *An overview of recent literature on spare parts inventories*. International Journal of Production Economics, vol. 76, page 201-215.

Knight, F.H. (1921). *Risk, uncertainty, and profit*. Houghton Mifflin, New York.

Lau, N., Hasija, S. & Bearden, J.N. (2013). *Prototyping Newsvendor pull-to-center reconsidered*. Decision Support Systems, [Article in press]

Lawrence, M. & Sim, W. (1999). *Prototyping a financial decision support system*. Omega, Vol.27(4), page 445-450.

Lawrence, M., Goodwin, P. & Fildes, R. (2002). *Influence of user participation on decision support system use and decision accuracy*. Omega, Vol.30, page 381-392.

Lee, H.L, Padmanabhan, V. & Whang, S. (1997). *Information distortion in a supply chain: The Bullwhip effect*. Management Science, Vol.43 (4), page 546-558.

Lim, J.S. & O'Connor, M.J. (1995). *Judgemental adjustment of initial forecast: its effectiveness and biases*. Journal of Behavioural Decision Making, Vol.8, page 149-169.

Lurie, N.H. & Swaminathan, J.M. (2009). *Judgemental is timely information always better? The effect of feedback frequency on decision making*. Organizational Behavioural and Human Decision Processes, Vol.108(2), page 315-329.

Moritz, B.B, Hill, A.V. & Donohue, K.L. (2013). *Individual differences in the newsvendor problem: Behaviour and cognitive reflection*. Journal of Operations Management, Vol. 31, page 72-85.

Sander, N. & Ritzman, L. (2001). *Principles of forecasting: a handbook for researchers and practioners.* Nordwell, Kluwer Academic Publishers.

Schweitzer, M.E., Chanon, G.P. (2000). *Modelling Decision bias in the newsvendor problem with a known demand distribution: experimental evidence*. Management Science, Vol. 46, page 404-420.

Silver, E.A., Pyke, D.F. & Peterson, R. (1998). *Inventory Management and Production Planning and Scheduling (third edition).* New York, John Wiley & Sons.

Sterman, J. (1989). *Modelling managerial behaviour: Misperception of feedback in a dynamic decision making experiment*. Management Science, Vol. 35(3), page 321-339.

Strohhecker, J. & Grössler (2013). *Do personal traits influence inventory management performance? The case of intelligence, personality, interest and knowledge*. International Journal Production Economics, Vol. 142, page 37-50.

TUE (2013). *Homepage of Vincent C.S. Wiers*. Found on 29 October 2013 from http://home.ieis.tue.nl/vwiers/

Tokar, T., Aloysius, J., Williams, B. & Waller, M. (2013). *Bracing for demand shocks: An experimental investigation*. Journal of Operations Management, [Article in press].

Van Donselaar, K.H., Gaur, V., van Woensel, T., Broekmeulen, R.A.C.M. & Fransoo, J.C. (2010). *Ordering behaviour in Retail Stores and Implications for Automated Replenishments*. Management Science, Vol. 56(5), page 766-784.

Vaus, De D. (2010). *Research Design in Social Research (fourth edition)*. London SAGE Publications Ltd.

Wiers, V.C. S. & Van Der Schaaf, T.W. (1997). *A framework for decision support in production scheduling tasks*. Production Planning & Control: The Management of Operations, Vol.8(6), page 533-544.

List of abbreviations

AOA	Automatic Order Assessment
DSS	Decision Support System
EMEA	Europe, Middle East and Africa
ELC	Expected Logistic Costs
EOQ	Economic Order Quantity
ESPRC	Expected Shortage Per Replenishment Cycle
FDSS	Forecasting Decision Support System
IBM	International Business Machines Corporation
IP	Inventory Position
KPI	Key Performance Indicator
MOD	Module Quantity
MOQ	Minimum Order Quantity
RET	Rotterdamse Elektrische Tramweg (public transport of Rotterdam)
SKU	Stock Keeping Unit
SPO	Service Parts Operations
SPPT	Spare Parts Planning Tool
TDQ	Typical Demand Quantity
USP	Ultimate Spare Parts Planning
WIP	Work In Progress

Appendices

Appendices are not available in the public version of this report.