Spare parts management improvement at KLM Equipment Services

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ABSTRACT

In this project a structured approach for spare parts management at KLM Equipment Services has been developed. First, a classification scheme with respect to demand forecasting is proposed and evaluated. Next, different time-series forecasting methods are initialized and compared in order to find the most appropriate method for the underlying demand pattern within a particular class. Subsequently, a classification scheme with respect to inventory control is proposed and evaluated. Special attention has been paid to the criticality analysis. Finally, this project has analyzed how to improve the logistics outsourcing relationship and scope between KLM Equipment Services and Sage Parts.
PREFACE AND ACKNOWLEDGEMENTS

This report is the result of my master thesis project in completion of the master Operations Management and Logistics at the Eindhoven University of Technology. The project has been carried out at the Engineering department of KLM Equipment Services located at Amsterdam Airport Schiphol.

I would like to thank several people that helped me during my master thesis project. First of all, I would like to thank Simme Douwe Flapper, my first supervisor, for guiding me through the process, his constructive feedback, but especially for his confidence in me. Furthermore, I would like to thank Geert-Jan van Houtum, my second supervisor, for his critical view on the project and the useful feedback.

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Anela Velagić
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EXECUTIVE SUMMARY

This report is the result of a master thesis project conducted at KLM Equipment Services (KES). KES’s main activity is the preventive and corrective maintenance of ground support equipment (GSE), that is, all vehicles and equipment necessary for ground handling of airplanes. In August, 2008 inventory control and procurement of spare parts has been outsourced to Sage Parts. Sage is responsible for the availability of components needed for maintenance on GSE. KES receives each month a report from Sage about the Key Performance Indicators (KPIs) in the previous month. These reports show every month that the actual performance is above the target values. However, this does not match with the signals KES receives from the maintenance shop – the maintenance shop is not satisfied with the availability of spare parts. KES would like to get more insight in this mismatch between the monthly reports from Sage, and the dissatisfaction at the maintenance shop.

Analysis current planning & control

First, an analysis of the current situation has been conducted. The environment in which KES operates makes spare parts management a challenging task. In order to get more insight in these challenges several people were interviewed until no new information emerged. The analysis revealed that the parts supply time is variable, the demand for spare parts is heterogeneous and irregular, and there is a gap between KES and Sage. Next, it has been analyzed how KES and Sage have set-up the current planning and control of spare parts in order to operate in the described environment and its challenges. For this analysis we have used the framework from Driessen et al. (2010) in order to find improvement possibilities. This framework distinguishes eight aspects of planning and control, that is, assortment management, demand forecasting, parts return forecasting, supply management, repair shop control, inventory control, spare parts order handling, and deployment. The analysis shows that one of the improvement possibilities is the classification of spare parts for inventory control; the current classification uses only one criterion – annual usage. Another improvement possibility is demand forecasting. From the available information we have concluded that Sage adopts “black-box forecasting”: forecasts are generated by an information system, but the specific techniques are unknown to the users. Finally, we have also seen that there are some ambiguities about the responsibilities between KES and Sage which further increases the gap between KES and Sage.

Research questions

The main research question of this master thesis project is formulated as follows: “Can spare parts management at KLM Equipment Services be improved?” The goal of this master thesis project was to find out whether spare parts management can be improved, and if so, how spare parts management can be improved. Based on the described improvement possibilities, we have formulated the following subquestions in order to answer the main research question:

1. How can we improve demand forecasting, such that it better captures the demand pattern of the spare parts?
2. How can we improve the current classification scheme for inventory control, such that it better captures the characteristics of the spare parts?
3. How can we improve the logistics outsourcing performance?
**Demand forecasting**

Currently, all items are forecasted based on historical demand but the specific technique is not known. KES would like to include also information about explanatory variables in the forecasts (e.g. maintenance planning, part failure rate). However, the use of forecasts based on explanatory variables is not always possible, nor is the use of only historical demand data always possible. In this master thesis project we have developed a classification scheme that can be used to choose between different forecasting approaches and methods. We have first selected criteria for classifying parts with respect to demand forecasting. The first classification criterion is the life cycle. Based on the life cycle phase one can choose between causal (i.e. based on explanatory variables) and time-series methods (i.e. based on historical demand) – the life cycle phase indicates whether sufficient historical data or data about explanatory variables is available for making use of these forecasting approaches. Another purpose of the classification is to determine the most appropriate time-series method for items in the *in-use* phase. Empirical investigation of the demand pattern based on the average demand interval and demand size variability revealed that the demand pattern for *in-use* items is mainly characterized by differences in demand intermittence (i.e. demand frequency). Different time-series techniques specific for intermittent demand, i.e. Croston, ES, SBA and TSB, are initialized and compared to each other for items in the *in-use* phase of the life cycle. The results reveal that the TSB method outperforms the other methods in terms of MSE and bias.

**Inventory control**

Currently, the spare parts inventory is classified by only one criterion – annual usage. When it comes to spare parts inventory management, determining the importance of a spare part by annual usage is insufficient, because spare parts are highly heterogeneous, with differing costs, service requirements, and demand patterns. In this master thesis project we have shown that the current classification scheme with respect to inventory control can be improved, such that it better captures the underlying demand of spare parts by the design of a hierarchical multiple-criteria classification scheme with respect to inventory control. First, we have selected collectively (KES’s management and the researcher) appropriate classification criteria for which sufficient information is available. We have again used the life cycle of the items, because the life cycle also influences inventory decisions. Besides the life cycle phase, another important extension of the current classification scheme is the inclusion of the criticality factor.

In order to determine the criticality we have developed a two-step-filter: in the first step vehicles are filtered based on the GSE criticality, and the type of order. In the second step, GSE vehicles are scored on the number of failures compared to the total number of failures for GSE vehicles from the same supplier type, and on the number of times that a particular item is replaced on the same GSE vehicle. To determine objective weights for the scores in the second step, we have used a multiple-attribute, DEA-like, decision model. Finally, critical items are further classified according to their part value in order to help making stock/non-stock decisions. Non-critical items are further classified according to Sage’s current classification scheme based on annual usage. No other criteria are explicitly considered at this stage for classification related purposes. Other important factors such as the supply lead time and its variability and the demand variability can be further considered in the calculation of safety stocks, when such an exercise is required.
Logistics outsourcing
Finally, we have analyzed how to improve the logistics outsourcing performance. The logistics outsourcing relationship is characterized by a lack of information exchange and shared understanding, and there are also ambiguities with respect to the responsibilities between KES and Sage. It has been explained that one can create a shared understanding by focusing on the end-customer (i.e. user of GSE). KES and Sage should aim for a low GSE downtime in order to prevent/minimize opportunistic behavior. Further, it has been explained that information exchange can be improved by making use of the developed classification schemes. The developed classification schemes create a higher awareness of spare parts characteristics and their effect on demand forecasting and/or inventory control. The current classification scheme based on annual usage does not trigger KES and Sage to exchange information about those aspects. Finally, it has been argued to reconsider the logistics outsourcing scope and activities. KES should consider taking demand forecasting and inventory control back in-house. The message is to outsource the execution, not the management.

Conclusions and recommendations
By referring back to the main research question we have concluded that it is possible to improve spare parts management by adopting a structured approach for both demand forecasting and inventory control, and by improving the logistics outsourcing performance. This master thesis project has shown the benefits of a structured approach for dealing with the considerable number of heterogeneous items. However, the developed classification schemes are only a starting point and can be used to make strategic and tactical forecasting and inventory decisions. The next step is to choose inventory policies and parameters for each class resulting from the classification scheme with respect to demand forecasting. The inventory policies and parameters depend on forecasts of demand over lead-time so inventory policies are influenced by the accuracy of demand forecasts. The classification scheme with respect to demand forecasting can be used to choose appropriate forecasting methods. Only then one can measure the real benefit of the classification schemes – that is, by integrated the outcomes of spare parts classification, demand forecasting and inventory control.

The following recommendations are made for KES (and Sage):

- Use the classification scheme in order to choose a forecasting method. In the initial phase one can estimate important characteristics by comparing the part to technically similar parts. It is recommended to use the TSB method for forecasting demand for parts in the in-use phase. For the decline phase one could for example use a regression model on the logarithm of sales against time, assuming an exponential decline in demand over time.
- Determine and compare suitable inventory policies and parameters for each class resulting from the classification scheme with respect to inventory control when the necessary data is available. The real benefit of the developed classification schemes can be tested by using the forecasted demand and the standard deviation (forecasted according to the classification scheme with respect to demand forecasting) for determining the inventory parameters.
- Collect more data on explanatory variables and validate the current data about explanatory variables in order to make causal forecasting possible (i.e. forecasting based on explanatory variables). Pay more attention to assortment management and gather parts (technical)
information from the initial phase of the life cycle instead of waiting till the in-use or decline phase.

- Consider increasing the number of preventive maintenances in order to reduce the number of corrective maintenance (i.e. repairs and breakdowns), and thus, the number of hot orders.
- In the criticality analysis we have used GSE criticality as a classification criterion. However, there were mixed signals about the criticality of a particular GSE vehicle. Create more agreement about the GSE criticality, and discuss together with fleet management and customers which GSE vehicles are really critical.
- The current KPIs do not provide sufficient insight in Sage’s actual performance. Consider eliminating the supply lead time restrictions, and using only the target values for the fill rates. Further, consider introducing a target value for the GSE downtime in order to increase the focus on the end-customer.
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IX
1 INTRODUCTION

This chapter starts with a short introduction about KLM Equipment Services and its main supplier Sage Parts (1.1). Next, the problem will be introduced (1.2). Finally, an outline of this master thesis preparation report will be given (1.3).

1.1 COMPANY DESCRIPTION

KLM Equipment Services (KES) is operating as an independent subsidiary of KLM Royal Dutch Airlines, and is based at Amsterdam Airport Schiphol since 1952. KES's main activity is the preventive and corrective maintenance of ground support equipment (GSE), that is, all vehicles and equipment necessary for ground handling of airplanes, including air conditioning units, air starter units, ambulifts, busses, cargo tractors, baggage carts, cars, catering trucks, conveyer belts, de-icers, dollies, fuelling equipment, ground power units, baggage loaders, lower and main deck loaders, pallet transporters, passenger steps, push back tractors, toilets trucks, tow bars, vans, and water trucks. The maintenance division can be subdivided into: motorized equipment, non-motorized equipment, truck maintenance, aircraft refueling equipment, battery maintenance, hoisting maintenance, and service repair shop on the ramp. KES is maintaining about 1500 GSE vehicles that can be subdivided in 250 different groups of vehicles. Maintenance activities are not only focused on KLM's GSE vehicles, but also on GSE vehicles from other fleet owners operating at Amsterdam Airport Schiphol such as Transavia and Martinair.

In August 2008, inventory control and procurement of spare parts has been outsourced to Sage Parts (hereafter Sage). Sage is responsible for the availability of parts needed for maintenance on the GSE vehicles. More than 90% of the SKUs is under Sage's responsibility, whereas the remaining 10% (e.g. oil and raw materials) is controlled by KES. Sage is focused on cost-reduction, high quality spare parts, and high know-how. Moreover, Sage has a geographically widespread distribution network in the GSE parts marketplace. Sage has an onsite parts location at KES. By bringing parts closer to their point of use, Sage is helping KES to reduce shipping costs and time, but also to avoid or eliminate costly GSE downtime.

1.2 INTRODUCTION TO THE PROBLEM

KES receives each month a report from Sage about the Key Performance Indicators (KPIs) in the previous month. These reports show every month that the actual performance is above the target values. However, this does not match with the signals KES receives from the maintenance shop – the maintenance shop is not satisfied with the availability of spare parts. KES would like to get more insight in this mismatch between the monthly reports from Sage, and the dissatisfaction with the availability at the maintenance shop. The main goal is to improve spare parts management in order to increase the availability of spare parts at rather low costs. By increasing the spare parts availability one can decrease the costly downtime of GSE vehicles. However, the environment in which KES operates makes spare parts management a challenging task. In order to get more insight in these challenges, several people were interviewed (amongst others KES's director, maintenance manager, director production support, senior consultant, and Sage Parts' branch manager) until no new information emerged. Based on the information from the interviews, an overview of the main observations with respect to the environment in which KES operates is given in Figure 1.1.
Figure 1.1 expresses that spare parts management has to deal with a variable spare parts supply time and demand. The variable spare parts supply time is influenced by the external supplier reliability, spare parts in the end of the spare parts life cycle, and spare parts specificity. The heterogeneous and irregular demand is influenced by spare parts specificity, seasonal factors, and corrective, inspection based maintenance. Further, Figure 1.1 shows that spare parts management is depended on the success of the logistics outsourcing relationship between KES and Sage. In Section 1.2.1 we will explain the mismatch between the demand and supply side. In Section 1.2.2 we will discuss the problems caused by the logistics outsourcing relationship.

1.2.1 Supply vs demand
The first observation from Figure 1.1 is that spare parts management is influenced by a variable spare parts supply time for spare parts that are out of stock or not kept on stock at all. Spare parts that are required for old GSE vehicles, and for GSE vehicles that are delivered by small, non-established original equipment manufacturers, have a long and unreliable part supply time. The number of available (reliable) external spare parts suppliers is limited for these vehicles. The part supply time for spare parts that are in the initial and in-use phase of their life cycle, and for standard spare parts is shorter and more reliable. However, in the final phase of the life cycle they do encounter problems, because of the restricted number of external spare parts suppliers. The length and uncertainty of the parts supply time are higher in the final phase of the life cycle. According to Sage, the lead time uncertainty is, among others, caused by the (un-)reliability of the external spare parts suppliers. The differences in reliability of external suppliers lead to supply lead time uncertainty. To sum up, spare parts management is complicated by the length of and uncertainty in spare parts supply lead time related to spare parts in the last phase of the spare parts life cycle and non-standard spare parts, but also by the external supplier reliability.
Figure 1.1 further shows that spare parts management is complicated by the demand pattern KES and Sage have to deal with. GSE vehicles are not highly complex, but the high number of different groups of GSE vehicles (i.e. KES is maintaining about 1500 GSE vehicles that can be subdivided in 250 different groups of vehicles) makes spare parts management complex, because of the low commonality between spare parts. The demand for spare parts is highly heterogeneous because of the high diversity in GSE vehicles. High spare parts heterogeneity makes demand forecasting and inventory control difficult. One of the reasons for the high number of different groups of GSE vehicles is the fact that the GSE vehicles, maintained by KES, are delivered by various, also small, suppliers. In addition, some GSE vehicles are insufficiently developed and engineered at the moment they are delivered by their supplier. In that case, KES has to make additional development and engineering steps in order to make the vehicle functioning well. This implies that some GSE vehicles are unique which makes spare parts management even more complicated. Further, maintenance activities, and thus the need for spare parts, are affected by seasonal factors. The number of corrective maintenance activities is higher during the Fall/Winter period (de-icers are for example only operated during the Winter) than during Spring/Summer period. Finally, the rate of corrective maintenance is high compared to preventive maintenance. Demand resulting from corrective maintenance has stochastic demand arrivals which makes demand forecasting and inventory management difficult. To sum up, given the high number of different and specialized GSE vehicles, the seasonal factors, and high rate of corrective maintenances compared to preventive maintenances, spare parts management has to deal with a heterogeneous and irregular demand for spare parts.

1.2.2 Logistics outsourcing

As is discussed, spare parts management is also influenced by the success of logistics outsourcing to Sage. From the interviews it follows that there is a gap between KES and Sage. One of the possible reasons for this gap between KES and Sage is the lack of (necessary) information exchange between KES and Sage. Sage states that they do not have all necessary information for appropriate spare parts planning and control. They expect from KES to give them more, timely, information related to the KES’s maintenance activities. One of the reasons for the lacking information exchange is the fact that KES’s and Sage’s information system are not real-time aligned with each other. However, KES and Sage are already working on this issue. Another possible reason for the gap between KES and Sage is the lack of shared understanding between the maintenance, and inventory control functions. Maintenance people are not concerned with the costs related to stocking parts with a low demand; they are more concerned with the availability of spare parts. On the other hand, inventory control tries to reduce the costs while maintaining a satisfying spare parts availability level. Both parties acknowledge that the communication and coordination between them should be improved. A holistic perspective on system performance, where the demand and supply side are integrated with each other is missing, because spare parts management and maintenance are two separate entities in the current situation. They should be better linked with each other in order to increase the availability of spare parts.

Overall, the main observations from Figure 1.1 are the (i) parts supply time variability, (ii) heterogeneous and irregular demand, and (iii) the gap between KES and Sage. These observations explain the challenges for appropriate spare parts management.
1.3 OUTLINE OF THE REPORT

In this master thesis project we will analyze whether spare parts management can be improved, and if so, how spare parts management can be improved. This master thesis project starts in Chapter 2 with an analysis of the current situation to identify improvement possibilities by using a framework for planning and control of the spare parts supply chain (Driessen, Arts, Van Houtum, Rustenburg & Hulsman, 2010). Driessen et al. (2010) point out that the framework can be used to increase efficiency, consistency, and sustainability of decisions on how to plan and control a spare parts supply chain, which in turn should minimize maintenance delay due to unavailability of required spare parts. In Chapter 3 the research design and methodology will be discussed. Chapter 3 starts with the problem statement and scope, after which the research questions, project approach and the deliverables of the project will be presented. Next, Chapter 4 will describe how to classify spare parts with respect to demand forecasting, after which different time-series forecasting methods (i.e. forecasting based on historical demand data) will be compared to each other in order to select the most appropriate forecasting method(s) per class. Chapter 5 will present a classification scheme with respect for inventory control. As part of this classification scheme, a criticality analysis will be performed. Chapter 6 will describe how the logistics outsourcing performance can be improved in order to foster a better link between the demand and supply side of spare parts. In Chapter 7 an implementation plan will be presented. Finally, in Chapter 8 the main conclusions, limitations, and recommendations from this master thesis project will be given.
2 Current Planning & Control

In this chapter it will be analyzed how KES and Sage have set-up the planning and control of spare parts in order to identify improvement possibilities. All aspects from the framework of Driessen et al. (2010) for spare parts planning and control will be discussed (2.1), that is, assortment management (2.2), demand forecasting (2.3), parts return forecasting (2.4), supply management (2.5), repair shop control (2.6), inventory control (2.7), spare parts order handling (2.8), and deployment (2.9). Finally, the improvement possibilities will be elaborated (2.10).

2.1 Framework

In the first chapter of this report we have explained that the monthly reports from Sage show a good performance, whereas the maintenance shop is actually not satisfied. In order to identify improvement options, we will first have to understand how KES and Sage have set-up the planning and control of spare parts. For this analysis we will use the framework from Driessen et al. (2010) in order to find improvement possibilities. Note that this analysis is not the same as the analysis in Section 1.2 where we have introduced the problem - Section 1.2 explains the environment in which KES operates, whereas this analysis will show how KES and Sage have set-up the planning and control of spare parts in order to operate in the environment that we have described in Section 1.2.

Before we start with the analysis, we will explain the framework from Driessen et al. (2010). Driessen et al. (2010) have developed a detailed framework that can be used for planning and control of the spare parts supply chain. Their framework presents a clustering of the involved tasks and decisions, and the mutual connections between the task and decisions. They separate eight different processes and within each process one can distinguish different decision levels, i.e. strategic, tactical, and operational decisions. The processes are assortment management, demand forecasting, parts return forecasting, supply management, repair shop control, inventory control, spare parts order handling, and deployment. The framework is shown on the next page in Figure 2.1.

First of all, Driessen et al. (2010) express that different return rates can influence control in different ways, and that the return rates therefore should be forecasted. Based on the available (technical) information on the assortment, one can classify parts with respect to return forecasting. Besides demand forecasting, and parts return forecasting, one can also use the (technical) information on the assortment for supply management. Then, supply management is defined as 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. Supply management is not only dependent on the connection with assortment management, but also on demand forecasting, and repair shop control. It is also explained that at the interface with supply structure management, agreements should be made on lead times for the repair of each repairable, and also on the load imposed on the repair shop so that these lead-times can be realized. Further, it is pointed out that spare parts classification and demand forecasting (including parts return forecasting) should be related to stock control policies. That means that inventory management should adopt a differentiated approach by assigning different inventory policies among the spare parts classes.
Figure 2.1 Overview and clustering of decisions in maintenance logistics control (from Driessen et al., 2010, pp. 8)
Furthermore, inventory policies should be developed based on the information from demand forecasting. One should also be aware of the interface with supply management which is among others related to the repair of repairables. Finally, it is explained that one needs to define preconditions and rules to manage the spare parts order handling steps. The process of replenishing spare parts inventories is explained by describing the definition of the preconditions order process and the management of procurement and repair orders.

Having shortly explained the framework and the processes, we will now analyze each of these processes for the current situation at KES. In this analysis references will be made to the operational manual. The operational manual is a report in which the topics (a) contact persons; (b) meeting structure KES and Sage; (c) management information; and (d) process flows and/or descriptions are covered, and are officially agreed on by both parties. Note that the analysis is also based on several interviews with both KES and Sage (with amongst others KES’s managing director, maintenance manager, director production support, senior consultant, and Sage Parts’ branch manager).

2.2 ASSORTMENT MANAGEMENT
Assortment management is concerned with the decision to include a spare part in the assortment and maintaining technical information of the included spare parts (Driessen et al., 2010). Driessen et al. (2010) emphasize that the decision whether or not to include a part in the assortment is independent of the decision to stock the part. For KES and Sage it is not a static decision. More specifically, in GSE, the sub-components and sub-assemblies change over time, and as such the assortment needs to be reviewed on a constant basis. The assortment is driven by the original equipment manufacturers (OEMs) and the various parts and components they choose to use in the production of the GSE vehicles.

2.2.1 Define spare parts assortment
In the Sage/KES relationship, Sage manages the assortment, but with communication and input from KES. The ultimate decision is driven by KES as they are confronted with the costs. Once the assortment is determined, it is Sage’s responsibility to ensure that proper part levels are maintained. In practice, whenever there are new GSE vehicles introduced to the KES vehicle database, KES has to inform Sage about it. It is agreed that in an early stage of the project Sage has to receive technical information concerning these vehicles. According to the operational manual, KES has to inform Sage about the maintenance planning and modifications, and provide technical information about the manufacturer, serial numbers, engine manufacturer, engine number, parts needed for preventive maintenance, and recommended parts list (RSL). Sage in turn should create a stock level based on this information. However, at this moment this information is not, sufficiently or not at all, exchanged. A part is only included in the assortment when the part is also stocked. One of the reasons for this lack of information exchange is the fact that KES does not have all the necessary information; OEMs do not always provide useful RSLs and technical information.

2.2.2 Gather parts (technical) information
Once a part is included in the assortment, information of the part should be gathered and maintained (Driessen et al., 2010). There are no “specific” agreements regarding what information should be maintained. Sage believes that the OEMs should be providing much of this information to the vehicle
owner (KES/KLM). In that case, KES should have certain information, such as parts manuals, service instructions and critical parts lists, and use it to order parts and to assist in deciding what parts should be kept available despite no or low use. However, in reality, the amount of information that is received from the OEMs is limited. Further, Sage believes that it is Sage’s responsibility to maintain information about the supplier, alternative supplier, parts commonality, substitution, reparability and specification information, along with lead time, costs, etc. There is however some ambiguity about the responsibility for collecting (technical) information. KES considers Sage as the one who is responsible for collecting the (technical) information, whereas Sage considers both companies responsible. Uncertainty about the responsibility for collecting and maintaining the necessary information might result in insufficient and/or incomplete information for appropriate spare parts management.

While “knowledge maintenance” costs are always a factor in the decisions, Sage thinks it is beneficial to gather information on all parts. Knowledge is frequently the key to improving cost, availability and inventory challenges. Historically, GSE equipment is used in the market place much longer than the average lifespan of other or similar capital equipment. Suppliers and OEMs do evolve and parts and components that were used in the production are now no longer available, or maybe alternatives are available. Sage points out that they present options about price, lead time, reliability or quality information it is aware of to the end-user, and in most cases make a recommendation. However, they believe ultimately it is the customer’s capital equipment and they need to make the final decision regarding the product that is installed on their equipment.

2.3 DEMAND FORECASTING

Since KES rarely gives Sage future demand data, Sage’s forecasting is for 100% based on historical data and utilizes algorithms that take into account dozens of data points across a wider range of products than that owned by KES. However, it is not know how the demand is actually forecasted (i.e. which forecasting methods are used). Additionally, Sage proactively works with their customers to identify certain items that should be in stock due to criticality, as well as to identify parts that might need replacement due to the age or utilization of the equipment.

While sophisticated demand plans can take into account information about the maintenance planning, parts price, data on historical and unplanned demand, active parts assortment, installed base, mean time between failures, failure rates, reliability tests, degradation of parts, substitution, redundancy, commonality, etc., Sage believes it is more practical to start simple and build up. Sage does not get sufficient reliability or even usage data (i.e. hours that the equipment is actually used) from KES regarding its upcoming demand, but Sage realizes that KES is provided very little information from the actual manufactures of the equipment. In a perfect world, the manufactures of the equipment have “service” plans that would predict parts failure and schedule replacement in advance of that failure. Unfortunately, the low volumes of similar equipment and the lack of resources of the manufactures do not allow them to provide this information to the end-user. Many end-users are more proactive as they have large fleet management departments and large fleets of the same vehicle type and they perform reliability analysis and develop their own maintenance plans which attempt to replace the parts before the failure occurs. Sage believes it is not practical to expect such sophisticated information from KES or any customer, it is practical to expect information on the service plans for service parts requirements.
(basic maintenance plans). Sage does receive this visibility from many of its customers, both large and small. Sage believes it would be extremely helpful if KES could develop a pre-defined maintenance kit for various service checks for the common and/or critical equipment types. If the kits could then be provided with a 30 day plan, they could load this information into the demand system and pre-build the kits and have the parts waiting when the equipment comes in for the planned maintenance. This would guarantee 100% availability as well as reduce the time it takes for Sage staff to pick the various components as they would be pre-kitted.

2.4 PARTS RETURN FORECASTING

Driessen et al. (2010) suggest that one needs to account for return rates and hand-in-times in the planning and control of spare parts. At KES, it is possible and common for parts not used to be returned to Sage. Sage believes they have a very liberal policy for KES whereby for a part to be returned to stock, it must be in good order, unused, re-sellable and a stock item. They also take back repairable parts that are then sent out for repair and put on the shelf for future use. With respect to new parts, for parts to be returned to a supplier they must also be in original packaging free from damage and dirt. Parts that are “deemed usable by the KES technicians”, even though used, can be returned to Sage’s warehouse for future use by KES. KES is responsible for getting the parts back to the Sage stores and ensuring that Sage has the correct data to allow the parts to be credited to the right job, etc. Sage is responsible for reviewing the “worthiness” of the parts and placing them in the correct ownership store, or returning to the supplier for full/partial credit (making the disposition). Additionally, Sage provides information on parts that were ordered by KES personnel and not yet picked up. This information is useful in alerting all parties of potential parts that may not be used. However, Sage does not plan or measure “return times” since the volume currently does not necessitate such detail. Sage’s demand plan does take into account the net use and net frequency, so they do “plan” for regular returns.

2.5 SUPPLY MANAGEMENT

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 lead time and underlying procurement contracts (Driessen et al., 2010).

2.5.1 Manage supplier availability & other characteristics

Several supply types are used to supply spare parts: (i) internal repair shop, (ii) external repair shop, (iii) external suppliers, (iv) internal development, and (v) sporadic re-use of parts. Updating and maintaining current contracts with external suppliers is a dynamic process, with multiple layers of triggers, internal source/price reviews, stock reviews, lead time reviews, supplier price files, obsolescence, etc. If there is no supply source available anymore, it becomes a collective effort for finding an alternative supply source for all parts that need future resupply. Sage believes that in theory, the OEMs should take responsibility. However, due to the age of the equipment some OEMs exit the business during the life of the equipment, or stop supporting it after several years with the hopes this will drive new equipment purchases. As a parts supplier, Sage claims that they will do their absolute best to find alternatives or options when parts are no longer available. Sage believes they have resources with experience and knowledge, a supply base that can assist, but they are always open to assistance and other sources of knowledge (including KES’s
staff). In some cases portions of the equipment might need a slight redesign to accommodate what is available in the marketplace. In those cases Sage utilizes their in-house engineers, along with any support from the OEM and the customer that is available. Sage points out that it is not possible for any one organization to stand alone in this - it is a team effort.

When the only supply source is known to disappear, one needs to decide whether to search for an alternative supply source or to place a final order at the current supply source. Sage believes that they are in almost all cases, the starting point on finding alternatives when supply is no longer available. Sage’s supply chain and sourcing groups are daily working on finding solutions for dozens of parts and components that are no longer available or in limited supply. In practice, KES is the one is responsible for deciding what to do when the only supply source of a part is known to disappear. Usually KES’s engineering department is asked to analyze what one should do; one could for example decide to modify the vehicle and/or to place a final order. To make the decision about the final order, KES makes a cost trade-off.

2.5.2 Control supply time & other supply parameters
Sage explains that GSE equipment requires working with many dysfunctional suppliers/manufactures. They use the lead times to assist in controlling their inventory and to fulfill commitments to service levels. Sage points out that they been able to insulate their customer base from product shortages, supplier factory closedowns/relocations by maintaining the proper inventory positions to account for these factors as well as supplier reliability. Sage does this by holding inventory, smart forecasting, blanket orders which scheduled releases and other methods.

However, the supply lead time of spare parts that are backordered is uncertain. KES believes that they do not get information about the actual supply lead time in a timely manner. However, Sage believes that they do inform KES about the actual supply lead time in a timely manner. According to Sage the lead time uncertainty is, among others, caused by the (un-)reliability of the external spare parts suppliers. Most suppliers are unrealistic in the lead time they quote or commit to. Sage points out that they are mainly having problems with inventory management for old GSE equipment. On the other hand, they are successful in fulfilling the service levels for newer GSE equipment. The number of available external spare parts suppliers is limited for older GSE equipment, and in some cases there are no external suppliers at all. Sage is working with a classification scheme to rank the external suppliers of spare parts, but KES does not have sufficient insight in this classification scheme. Sage has acknowledged that they are willing to give more information about the external suppliers to KES. For example, if the parts are from a C supplier, it would be useful for KES to know in advance that the supply lead time might be unreliable. Exchange of external supplier information was previously not possible, because KES and Sage work with two different systems that are not real-time aligned, but they are working on this IT-issue right now.

2.6 Repair shop control
Repaired items might have different warranty terms and prices than new parts. Evaluation of the price and life cycle of the parts should make clear whether or not it stays a repairable item. Whenever the repair price is higher than 60% of the new price, Sage has to deliver new, unless the delivery time of the new part is too long. In practice KES is the one who makes the decision whether to make an item a
repairable or not. KES believes that Sage should be the one doing this, because Sage claims that they have a worldwide network, and, KES believes that Sage has more information about external repair in order to make the right trade-off decision - Sage knows for example where the part could be externally repaired, at what price, lead time, etc., whereas KES has only knowledge about internal repair. On the other hand, Sage believes that KES should decide about the repairability of the part. According to Sage, KES has more knowledge about the repair possibilities.

Driessen et al. (2010) further describe that at the interface with supply structure management, agreements should be made on lead times for the repair of each repairable. At the moment, there are no agreements about the planned repair times at KES. KES does not determine the capacity of the repair shop, and the repair jobs are not scheduled. The capacity of the repair shop depends on the number of employees present in the maintenance shop. Internal repairs are performed ad hoc when there is sufficient capacity left. However, this is not a major problem, because the number of repairables is small compared to the total number of SKUs. For example, the number of unique SKUs requested during 2011 is 58, while the total number of unique SKUs requested during 2011 is 8273.

2.7 INVENTORY CONTROL

The inventory control process is concerned with the decision which parts to stock, at which stocking location, and in what quantity. Inventory control is primarily Sage’s responsibility. There are agreed service levels and critical parts list. This needs to be balanced with the cost of capital to keep inventory. That said, the list changes continuously, as one would expect in a dynamic maintenance environment. Sage considers the responsibilities clear. KES is aware of all items stocked by Sage systems as well as of the items stocked as a result of KES direction or input. For example, over the last year, each team in the maintenance shop identified items they would like to see stocked. Each list was reviewed by both Sage and KES with subsequent stocking decisions being made. Additionally, other items were stocked to support new equipment such as the Powerstow and Safearo units. Furthermore, whenever KES receives the information that some vehicles will be redundant or no longer will be maintained/repaired by KES, it is agreed on that Sage should receive this information as soon as possible. In the operational manual it is pointed out that on a mutual agreement with the responsible team Sage will have to make a proposal to lower the stock accordingly to avoid financial losses due to obsolete parts. Driessen et al. (2010) indeed suggest that information on parts redundancy decreases the number of stocked spare parts as it is known in advance that part failure does not cause immediate system breakdown. However, because of the gap between KES and Sage, KES does not always inform Sage about vehicles that will be no longer maintained/repaired by KES.

2.7.1 Classify parts

Sage classifies the spare parts by the annual usage resulting in classes A, B, C, and D. For example, spare parts from class A are items with a demand rate of more than 24 items per month. Those items are also called fast-movers, and they have the highest service level. On the other hand, C-items are slow-movers, and they have the lowest service level. The exact classification and the corresponding service levels as reported in monthly report from Sage, are presented in Table 2.1. However, KES does not know how this classification scheme is derived, because the contract with Sage is set-up by the previous management team.
### Classes

<table>
<thead>
<tr>
<th>Class</th>
<th>Usage</th>
<th>KPIs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class A</td>
<td>24+ units per year</td>
<td>Immediate fill 99%</td>
</tr>
<tr>
<td>Class B</td>
<td>12-23 units per year</td>
<td>Successful fill at 95% within one business day</td>
</tr>
<tr>
<td>Class C</td>
<td>4-11 units per year</td>
<td>Successful fill at 80% within three business days</td>
</tr>
<tr>
<td>Class D</td>
<td>1-3 units per year</td>
<td>Successful fill at 65% within seven business days</td>
</tr>
<tr>
<td>Class E</td>
<td>Manually controlled products with product/min/max levels</td>
<td></td>
</tr>
<tr>
<td>Class N</td>
<td>New products for the reporting location</td>
<td></td>
</tr>
</tbody>
</table>

*Table 2.1 Sage’s spare parts classification with KPIs*

#### 2.7.2 Select replenishment policy and parameters

Sage is responsible for defining the replenishment policy and parameters. In the operational manual it is defined that Sage will manage the stock level to fulfill the KES requirements. Whenever there comes a request from KES to increase the stock level above the quantity defined by Sage’s calculation, it should be approved by KES’s management. Sage’s customers have input by means of “forecast demands, critical parts lists, project planning”. Sage’s systems are designed to take into account requests/requirements from customer, in their planning. A key component of inventory management is fiscal responsibility of the current inventory levels and risk of obsolescence. It is a delicate balancing act between all components. When the team leader asks for stock increase Sage should follow this advice. When, after a period of one year, there is less than X sold, Sage should move the part to KES owned warehouse. Sage is allowed to purchase KES Inventory from KES and sell it to other customers provided that: (a) KES agrees that such products may be sold to other customers, and (b) KES and Sage agree upon a methodology for sharing the purchase price payable by the other customers of such products. With the exception of KES owned inventory, Sage owns the inventory of spare parts maintained in the storeroom. Risk of loss with respect to the spare parts, within the KES owned inventory, remains with Sage until actual delivery to KES.

#### 2.8 Spare parts order handling

Driessen et al. (2010) suggest that the first decision in handling spare parts orders is to accept, adjust or reject the order. KES orders products from time to time by means mutually determined by Sage and KES, including in-person, through the eSage website, by facsimile transmission, printed request or by phone. Each order for products which is acknowledged by Sage will constitute a contract for the purchase and sale of such products. If a part is not on stock, a “backorder” is created. When ordering new parts (not known in the KES system), KES supplies all relevant information to Sage to make it easier to obtain the part through original source of alternative suppliers. In practice all orders are accepted as they come in electronically from KES. There are however some problems with the order priorities. On average there are 10 “rode meldingen” (hereafter RMs) per day. That is, spare parts which are not on stock when requested. A RM becomes a real problem if the vehicle is out of operation when required, i.e. hot order. Usually one defines a hot order as a purchase request for a vehicle that is not operational due to the missing part. Sage has to do their outmost to collect this part. The urgency is superior to the price. The extra costs for these parts will be for KES when these parts are non-stock items or when there is an abnormal high usage of the stock items. However, the problem is that not all hot orders are real hot orders, because sometimes maintenance people assign an order as “hot” just to speed up the delivery. Also, pressure from the end-customer leads to situations where orders are assigned as “hot”, while they are not real “hot orders”.

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2.9 DEPLOYMENT
Sage sets replenishment parameters quarterly, but there are events that occur real time between these quarterly reviews, and the KES/Sage’s branch personnel are allowed to make decisions, including all non-stock purchasing. These events include customer requirements and information, but also supplier issues such as holidays, inventory, closure, product shortages, etc.

2.10 IMPROVEMENT POSSIBILITIES
In the first chapter of this report we have explained the difficulties with spare parts management caused by the variable parts supply time, heterogeneous and irregular demand, and the gap between KES and Sage. In order to identify the improvement possibilities we have analyzed the current planning and control of spare parts. From this analysis we can make the following conclusions:

- First of all, we can state that parts return forecasting is not a big issue, nor is repair shop control, because the number of returned and repaired items is limited.
- Further, assortment management can be improved by increasing the information exchange between KES and Sage. However, as is discussed, KES does not receive sufficient information about technical information and recommended parts from the OEMs. In order to improve the information exchange about the technical information and recommended parts, KES will have to demand more information from the OEMs. Further, KES should provide KES with more information about planned maintenances. Overall, we can conclude that we do not need to perform a research in order to analyze how to improve assort management – it is clear what has to be improved and how it can be improved.
- One of the improvement possibilities that we can identify from the previous analysis is the classification of spare parts for inventory control. The current classification scheme uses only one classification criterion, that is, annual usage. By using only one classification criterion, it is difficult to discriminate all the control requirements of different parts as the variety of control characteristics of parts increases. Recall that in the introduction of this report we have expressed that the environment in which KES operates is characterized by a variable supply lead time and heterogeneous and irregular demand. Classification based on only annual usage cannot capture the variability in the supply lead time and demand.
- Another improvement possibility is demand forecasting. From the available information we can conclude that Sage adopts “black-box forecasting”: forecasts are generated by an information system, but the specific techniques are unknown to the users. Furthermore, we know that forecasts are for 100% based on historical demand data. However, in the literature study it is pointed out that forecasts based solely on historic data are not accurate in every situation (Velagić, 2012).
- Finally, we have seen that there are no major problems with supply management, spare parts order handling, and deployment. Those processes will not be analyzed in this master thesis project.
Overall, we can conclude that there are improvement possibilities with respect to demand forecasting and inventory control. This also means that the master thesis project will focus on the demand side instead of the supply side. Moreover, the demand side is also the area where KES has most input. Recall that we have explained that Sage’s customers have input by means of forecast demands, and critical parts lists. The supply side (e.g. supply management and spare parts order handling) is Sage’s responsibility and Sage does not depend much on input from KES. Finally, from the previous discussion we can also conclude that there some ambiguities about the responsibilities between KES and Sage which further increases the gap between KES and Sage that we have discussed in the introduction chapter of this report. We will therefore also analyze how the logistics outsourcing performance can be improved.

To summarize, this master thesis project will analyze how demand forecasting, inventory control, and the logistics outsourcing performance can be improved such that it better matches the environment in which KES operates, and the corresponding challenges in this environment (see also Chapter 1). In the next chapter we will describe the research design and the methodology of this master thesis project.
3 \textbf{RESEARCH DESIGN AND METHODOLOGY}

This chapter discusses the research design and methodology. First, the problem will be defined (3.1) and scoped (3.2), after which the research question will be introduced (3.3). Finally, the project approach (3.4) and the deliverables of the project will be presented (3.5).

3.1 \textbf{PROBLEM DEFINITION}

From the analysis of the current planning and control of spare parts in Chapter 2, we have concluded that there are improvement possibilities with respect to demand forecasting, inventory control and logistics outsourcing performance. In order to define the problem we will extend this analysis by focusing specifically on inventory classification, demand forecasting and logistics outsourcing.

- \textbf{Inventory classification:} In Section 2.7 of this report we have presented the current inventory classification, and the agreed KPIs for each class. As introduced in Chapter 1, KES receives monthly reports from Sage about the KPIs per class. These reports show each month that the actual performance is above the target values. However, the reports do not reflect the dissatisfaction with spare parts availability in the maintenance shop. KES would like to get more insight in this mismatch between the monthly reports from Sage, and the negative signals from the maintenance shop. An explanation for Sage’s high performance, according to the monthly reports, whereas the maintenance shop is dissatisfied with the spare parts availability is the choice of classification criterion - the inventory is classified according to the annual usage. In the introduction of this report we have described the environment in which KES operates. KES and Sage carry a large amount of items in stock. These items are highly heterogeneous, with differing costs, service requirements, and demand patterns. When it comes to spare parts inventory management, determining the importance of a spare part by annual usage is insufficient. Huiskonen (2001) points out that one-dimensional spare parts classification does not discriminate all the control requirements of different parts as the variety of control characteristics of parts increases. The traditional (i.e. one-dimensional) ABC-analysis is not able to provide a good classification of inventory items in practice. This is also true for Sage’s ABC-classification of KES’s spare parts based on annual usage. Sage applies this ABC-classification worldwide, and it has shown to be a successful classification scheme. However, it is important to note that Sage’s operations are mainly focused on the US market where the standardization among the GSE vehicles is higher compared to the European market. For spare parts supply in European market it might not be sufficient to classify spare parts merely on annual usage.

- \textbf{Demand forecasting:} Spare parts classification has also implications for the applied forecasting method(s). In Section 2.3 it has been explained that Sage makes forecasts based on historic demand data. Sage points out that the accuracy of the forecasts is presented by their published service levels on stocked items. The high accuracy of Sage’s forecasts based on historic demand data can be explained by the used classification. Given that the inventory is classified according to the annual usage, one can suffice with historic demand data for forecasting the demand for each class. In the literature study it is discussed that forecasts based solely on historic data are not accurate in every situation (Velagić, 2012). KES would like to extend demand forecasting by also
including information about explanatory variables which makes it possible to look forward (e.g. part failure rate) instead of looking backward to the historical demand. However, both demand forecasting based on historical demand data and demand forecasting based on explanatory variables, are not appropriate for all spare parts. Forecasting techniques and methods should be differentiated among different classes of spare parts.

- **Logistics outsourcing:** In Chapter 1 of this report we have explained the gap between KES and Sage caused by the lack of information exchange and lack of shared understanding. Because of this gap it is difficult to link the demand and supply side of spare parts. Furthermore, in Chapter 2 we have seen that there are also some ambiguities about the responsibilities between KES and Sage which further increases the gap between KES and Sage. For appropriate spare parts management, it is important to bridge this gap – KES and Sage have to cooperate.

From the analysis of the environment in which KES operates and the analysis of the planning and control of spare parts, we can conclude that classification is an important step for spare parts management - different kinds of parts (according to the classification step) are treated with different demand and inventory management techniques. The focus of this master thesis project will be on spare parts classification and its relation with demand forecasting and inventory management in order to improve the availability of spare parts. Furthermore, we will analyze how to improve the logistics outsourcing performance in order to improve the link between the demand and supply side of spare parts.

### 3.2 Scope

This master thesis project is only focused on spare parts that are supplied by Sage, because KES experiences especially problems with spare parts management related to the parts that are outsourced to Sage Parts (more than 90% of the spare parts). The parts that are not outsourced to Sage are not influenced by the gap between KES and Sage Parts, they do not have the described specific spare parts demand pattern, and they are not influenced by the spare parts life cycle. Therefore, they will not be considered in this master thesis project. In addition, even do we will analyze inventory control, the replenishment policies and replenishment policies parameters are out of scope, because there is no information available about the replenishment lead times and the cost structure.

### 3.3 Research Question

At the moment KES and Sage do not know how to deal with the (i) gap between KES and Sage, (ii) heterogeneous and irregular demand, and (iii) the part supply time variability. KES would like to improve spare parts availability, but Sage’s monthly reports about the fulfillment of the service levels do not show what is exactly going wrong. However, the service levels are defined based on a classification scheme that is too basic to deal with KES’s heterogeneous and irregular demand, except for fast-moving spare parts. Time and effort are lost, while the maintenance shop is still dissatisfied because of the unavailability of spare parts. Insights in spare parts availability and its relation to the availability of critical GSE vehicles, should lead to a differentiated, tailor-made, spare parts management scheme. This project analyzes the relation between spare parts classification, demand forecasting and inventory management in order to improve spare parts management. As a result, the research question can be defined as follows:
Can spare parts management at KLM Equipment Services be improved?

More specifically, the research question can be split up in the following sub-questions:

1. How can we improve demand forecasting, such that it better captures the demand pattern of the spare parts?
   a. What are useful criteria for classifying parts with respect to demand forecasting?
   b. Which forecasting methods are applicable to forecast the characterized demand processes?
2. How can we improve the current classification scheme for inventory control, such that it better captures the characteristics of the spare parts?
   a. What are useful criteria for classifying the spare parts assortment into different subsets with respect to inventory control, such that each subset of spare parts has the same stocking strategy?
   b. How can the classification criteria be combined, such that the spare parts assortment is clustered in homogeneous classes of items?
3. How can we improve the logistics outsourcing performance?

3.4 PROJECT APPROACH

This section will elaborate on the line of the work in an operational project plan. The operational project plan is a set of subsequent steps that has to be executed during the master thesis project in order to answer the research question(s). The project plan is based on three building blocks of the master thesis project which are the scientific literature, analysis of the current situation at KES, and the redesign. Note that a review of the scientific literature is already presented in the master thesis preparation report (Velagić, 2012). The remaining research steps are as follows:

- **Analysis of current spare parts management (Chapter 2):** Analysis of current spare parts management difficulties and possible causes.
- **Specification of a classification scheme with respect to demand forecasting (Chapter 4):** It is necessary to identify and select the criteria that influence the choice for a specific forecasting approach and method.
- **Selection of forecasting method(s) (Chapter 4):** Based on the identified classes one should select the most appropriate forecasting method, and set the parameters for the selected forecasting method.
- **Specification of a classification scheme with respect to inventory control (Chapter 5):** It is necessary to identify and select the criteria that influence logistics-related choices about inventory management. The chosen criteria will be analyzed in detail and cut-off points will be determined.
- **Specification of improvement options for the logistics outsourcing performance (Chapter 6):** In order to improve the link between the demand and supply side, possible improvements for the logistics outsourcing performance will be specified.
• **Implementation plan (Chapter 7):** Based on the findings from the master thesis project, it will be explained how to apply the findings in practice. Furthermore, a reclassification framework will be developed, because over time spare parts can move to other classes.

• **Conclusions and recommendations (Chapter 8):** The main conclusions and recommendations will be presented.

### 3.5 DELIVERABLES

In this master thesis project a structured spare parts management scheme with respect to demand forecasting will be designed and evaluated. Based on the resulting classes recommendations will be given about the use of forecasting method(s). Further, also a spare parts management scheme with respect to inventory control will be designed and evaluated. As part of this classification scheme, a criticality analysis will be performed. Then, it will be discussed how the logistics outsourcing performance can be improved, such that a better link is created between the demand and supply of spare parts. Finally, a change plan will be presented.
4 DEMAND FORECASTING

In this chapter first the approach for demand forecasting will be explained (4.1). Next, the importance of classifying spare parts for demand forecasting will be explained, after which the spare parts will be classified (4.2). Based on the different classes resulting from the classification step, different time-series forecasting methods will be described (4.3), initialized (4.4), and compared to each other in order to identify the most appropriate forecasting method (4.5).

4.1 APPROACH

In this section we will shortly explain the different decisions and steps that have to be taken with respect to demand forecasting. First, spare parts have to be classified in order to determine appropriate forecasting methods. In Section 4.2 we will select classification criteria and set cut-off values for each criterion (4.2.1). The selected classification criteria and their cut-off values will then be applied on a real dataset (4.2.2). Based on the resulting classification scheme, one can choose between different forecasting approaches and methods. However, there is still no conclusive and practitioner-oriented indication on which is “the best” forecasting method (Bacchetti & Saccani, 2011). We will therefore focus on choosing specific forecasting methods. To be more specific, we will focus on time-series forecasting methods, because there is not sufficient data available for causal forecasting method (i.e. based on explanatory variables). Section 4.3 will explain the time-series forecasting methods that we will compare to each other. Also, their forecasts will be given, it will be explained how to set smoothing constants, and how to calculate the seasonality effects. Then, in Section 4.4 we will explain why one should initialize forecasts and how to initialize forecasts. Finally, in Section 4.5 the choice of the time-series methods will be discussed.

4.2 CLASSIFICATION FOR DEMAND FORECASTING

Different spare parts are associated with different underlying demand patterns, which in turn require different forecasting methods. Consequently, there is a need to classify spare parts and apply the most appropriate method in each class. Forecasting methods may be broadly divided into two categories: time series and causal methods. Time series methods are dependent on historical demand data, whereas causal methods are dependent on explanatory variable(s). The choice for a forecasting approach is mainly determined by the availability of data on explanatory variables such as part failure rate and the timing of preventive maintenance activities. However, the choice for a forecasting approach is also driven by the availability of demand history data which, in turn, is determined by the stage of part’s life cycle. (Boylan and Syntetos, 2008). In the literature study we have discussed three phases that can be distinguished in the life of spare parts, and each has special characteristics for spare parts demand:

- **Initial**: in this phase simultaneous to the introduction of a new technology, new types of parts, components and sub-assemblies are being introduced. Very little is known about their failure behavior. As there is no historical data available, demand forecasting relies on data from other items or judgmental forecasting (Fortuin, 1980).
- **In-use**: during this phase information about demand patterns is still scarce, but some experience has been gained for parts used longer than the initial phase. The difference with the initial phase
is that there exist some historical data that can be used for statistical forecasting. In that case statistical forecasting can be reliable for fast-movers (Fortuin & Martin, 1999).

- **Decline**: spare parts might not be available for long, and service managers are usually at the beginning of the final phase obliged to place a final order (Fortuin & Martin, 1999; Teunter & Fortuin, 1998).

Causal methods are particularly useful in the initial phase, when the part is introduced, since the lack of an adequate length of demand history precludes the use of extrapolative time-series methods. However, in the initial phase data about explanatory variables is also limited, but important characteristics can still be estimated by comparing to technically similar parts. In the in-use phase, causal methods also have an important role, if data on explanatory variables is available. However, at the moment historical data for the explanatory variables, such as timing of preventive maintenance, usage rate or failure rate, is not valid or not available at all. In that case it is more appropriate to use time-series methods. In the final phase, when a last time buy from a supplier is required, regression-based extrapolations have been recommended, assuming an exponential decline of demand. Example is a regression model on the logarithm of sales against time, assuming an exponential decline in demand over time (Boylan & Syntetos, 2008).

However, within these two main categories of forecasting approaches, i.e. time-series and causal approach, there are different forecasting methods one can choose from. Classification based solely on the life cycle phase does not assist the choice among these methods. Moreover, besides the life cycle phase, the specific method that should be employed depends also on other factors that characterize the demand pattern. So a second goal of classification, for the in-use phase, is to determine the most appropriate forecasting method. More specifically, to determine the most appropriate time-series forecasting method, because not sufficient valid data is available for causal forecasting. In order to assists the choice for a specific time-series method for items in the in-use phase, we will further classify these items by examining their demand pattern. Syntetos’s (2001) has identified two key variables, namely the average inter-demand interval (ADI) and the variability of the demand sizes - typically expressed through the squared coefficient of variation of the demand sizes (CV²). Comparisons between forecasting methods yield regions of superior performance were the cut-off values are set at ADI = 1.32 and CV² = 0.49 (Syntetos, Boylan & Croston, 2005). Figure 4.1 shows the four demand pattern classes, i.e. intermittent, erratic, slow moving, and lumpy demand. These four classes can be defined as follows:

- **Lumpy demand**: occurs at random, with many time periods having no demand. Moreover, demand, when it occurs, is (highly) variable. Thus, both the moment of demand and demand size is uncertain.
- **Erratic demand**: (highly) variable, where the erratic nature relates to the size of demand rather than to the demand per unit time period. So the quantity of demand is uncertain, whereas the moment of demand is not uncertain.
- **Intermittent (hereafter slow) demand**: random, with many time periods having no demand. In other words, moment of the demand is uncertain, but quantity demanded is not uncertain.
- **Smooth (hereafter fast) demand**: occurs at random, with many time periods having no demand. Demand, when it occurs, is for single or very few items. Thus, there is no great variation in inter-demand intervals and in the demand size.

![Diagram of demand pattern classification scheme]

**Figure 4.1 Demand pattern classification scheme**

### 4.2.1 Cut-off values

In this section we will determine the cut-off values between the life cycle phases, and demand patterns. Next, in Section 4.2.2 we will apply the cut-off values in order to develop the classification scheme with respect to demand forecasting.

**Life cycle phase cut-off values:**

Given the importance of the product life cycle for the selection of a forecasting method, but, as we will discuss later on, also for the selection of stock control policies, cut-off values between the life cycles phases have to be set. The cut-off values are as follows:

- **Initial → in-use**: In Chapter 1 of this report we have discussed that seasonality influences the demand pattern. In Appendix B it is confirmed that there are indeed seasonal effects. Given that there are seasonal effects, one should adjust demand forecasts accordingly. However, in order to calculate the seasonal effect one needs at least one complete year of demand history. We will set the cut-off value between the initial and in-use phase at one year so that we can differentiate demand data for which the seasonal effects can be calculated from the demand data for which it is not yet possible.

- **In-use → decline**: To determine which item belongs to the decline phase instead of the in-use phase, we will analyze their demand pattern by distinguishing between declining demand, and sudden decline – demand for spare parts suddenly drops to zero after years of constant demand. Furthermore, only items that have not been demanded in the past year (e.g. 2011) will be considered appropriate for the decline phase in order exclude any seasonal factors. The remaining items will be denoted as in-use.
**Demand pattern cut-off values:**

Syntetos et al. (2005) point out that demand classification according to the average inter-demand interval and the variability of the demand sizes can be linked directly to forecasting and stock control decision-making. Recall that the $ADI$ cut-off value is set to 1.32 review periods, and $CV^2$ to 0.49. It is important to note that those cut-off values are set to provide guidelines for choosing between two main intermittent demand estimators: Croston’s method and Syntetos–Boylan Approximation (SBA). However, if the objective of classification is the identification of the most appropriate methods then it is according to Heinecke, Syntetos, and Wang (2012) more logical to first compare alternative methods for the purpose of identifying regions of superior performance and then classify demand patterns based on the results. We will only use the classification from Figure 4.1 to identify the underlying demand patterns, but we will not use the recommended forecasting techniques for these four classes (i.e. Croston for smooth demand, and SBA for erratic, lumpy, and intermittent demand). Depending on the results of the demand pattern classification, we will compare alternative forecasting methods for the different classes.

Furthermore, we could also choose the cut-offs arbitrarily, but we prefer using the Syntetos et al. (2005) scheme. This scheme provides insights into the behavior of the demand patterns, and it is also useful for decision-making with regard to other aspects of an inventory system, such as the inventory policies to be used (Heinecke et al., 2012). Figure 4.2 shows a decision-model for determining the demand pattern. First, one will have to check the number of demand occurrences, because at least two time periods with a demand occurrence are needed for the calculation of $CV^2$. Those items with only one demand occurrence are classified as sporadic. The remaining parts are classified according to $ADI$ and $CV^2$, resulting in fast, erratic, slow, and lumpy parts.

![Figure 4.2 Determination of the demand pattern](image-url)
4.2.2 Application classification scheme for demand forecasting

In this section we will apply the classification factors and their cut-off values in order to develop the classification scheme with respect to demand forecasting. The data we will use contains information on over 200,000 orders at KES during the period from 01-01-2007 till 31-12-2011. For each order the item number, date of the order, item description, job card (i.e. type of order), equipment, quantity, item price, and the sales value are recorded. In total 21,097 different items are ordered during this period.

First, items are classified according to the defined boundaries for the product life cycle, resulting in 2,626 different items in the initial phase, 16,546 different items in the in-use phase, and 1,925 different items in the decline phase. In Appendix C we have shown that the life cycle phase does a good job in classifying the spare parts; it is helpful in understanding the underlying demand pattern and the cause of RM and hot orders. Next, the items in the in-use phase are further classified by analyzing their demand pattern. For the calculation of the ADI at least one demand occurrence is needed, but at least two time periods with a demand occurrence are needed for the calculation of CV². The items in the in-use phase are therefore first classified according to the number of demand occurrences, where items with only one demand occurrence are classified as sporadic (i.e. items with a very high average inter-demand interval – only one demand occurrence). The number of items with a sporadic demand pattern is 8,543, which is more than 50% of all in-use items. This high number of sporadic items is one of the reasons forecasting the demand is difficult. Finally, Table 4.1 shows the final classification of the in-use items. As one can see, most items are either sporadic or intermittent (i.e. items with slow-moving and lumpy demand patterns). Furthermore, the number of items with high demand variability (i.e. lumpy and erratic items) is only 6% of the total number of items. Given the low number of items with a high demand variability and for practical purposes (too many classes is not practical), we will not consider the variability of the demand in the further analysis – we will take the aggregates of the slow-moving and lumpy items, and classify them as intermittent (i.e. high average inter-demand interval – low demand frequency), and the aggregates of the fast and erratic items and classify them as non-intermittent (i.e. low average inter-demand interval – high demand frequency).

<table>
<thead>
<tr>
<th>Demand pattern</th>
<th>#Items</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sporadic</td>
<td>8,543</td>
</tr>
<tr>
<td>Slow</td>
<td>6,813</td>
</tr>
<tr>
<td>Lumpy</td>
<td>918</td>
</tr>
<tr>
<td>Fast</td>
<td>210</td>
</tr>
<tr>
<td>Erratic</td>
<td>62</td>
</tr>
<tr>
<td>Total</td>
<td>16546</td>
</tr>
</tbody>
</table>

Table 4.1 Classification in-use items

By combining the life cycle and demand pattern analysis, the decisions on the classification for demand forecasting can be presented as in Figure 4.3. The figure shows that one first has to check the life cycle phase. For items in the in-use phase one has to check the number of demand occurrences in order to filter out sporadic items. Finally, one can determine the intermittence of the demand by checking average demand interval, where items with an average demand interval greater than 1.32 are classified as intermittent, and items with an average demand interval lower than 1.32 are classified as non-intermittent.
4.3 TIME-SERIES FORECASTING METHODS

In Section 4.2 we have discussed that one can choose between time-series and causal forecasting methods by analyzing the part life cycle. For items in the in-use phase it is argued to use time-series methods, because not sufficient (valid) data is available about explanatory variables in order to perform causal forecasting. In order to choose an appropriate time-series method, in-use items are further classified into sporadic, intermittent and non-intermittent items. In Section 4.2.2 we have seen that most in-use items have an intermittent or sporadic demand pattern. Forecasting intermittent demand patterns request special attention given the importance of demand forecasting on stock control. Also, maintenance related decisions and consequently production efficiency as well are directly affected by such forecasts. In addition, given that the intermittent items are often the items with the greatest risk of obsolescence, improvements in forecasting and stock control may be translated to significant reductions in wastage or scrap (Babai, Syntetos & Teunter, 2011).

The occurrence of (many) periods with zero demand renders traditional time-series forecasting techniques such as simple exponential smoothing or simple moving average unsuitable (Teunter, Syntetos & Babai, 2011). Croston (1972) proved the biased nature of simple exponential smoothing (SES) when applied in an intermittent demand context and he proposed a method that relies explicitly upon estimates of the inter-demand intervals and demand sizes. Croston (1972) suggested separately updating the estimates of the inter-demand interval and demand sizes through simple exponential smoothing (SES). Teunter et al. (2011) state that the Croston method is often applied in practice to forecast intermittent demand requirements. The method is incorporated in Enterprise Resource Planning (ERP) type of solutions such as SAP and specialized forecasting software such as Forecast Pro. The method was claimed to be unbiased, but Syntetos and Boylan (2001) showed it to be positively biased (i.e. over-forecasting mean demand) and they subsequently proposed an approximately unbiased estimator: SBA.
This estimation procedure applies a deflating factor to the Croston estimates in order to take away the bias. A little bias though still remains, on the opposite side (i.e. slightly under-estimating mean demand). Another disadvantage of the Croston method and SBA is that the forecasts are only updated after periods with positive demand. According to Teunter et al. (2011) these methods are therefore not up-to-date after (many) periods with zero demand and cannot be used to estimate the risk of obsolescence and deal with the removal of excess/dead stock.

Teunter et al. (2011) have suggested a new forecasting procedure (called TSB after Teunter, Syntetos and Babai) that links naturally to the issues of inventory obsolescence. TSB uses separate simply exponential smoothed estimates of the demand probability and demand sizes. The estimate of the probability of occurrence is updated every time period, whereas the estimate of the demand size is only updated at the end of periods with positive demand (Teunter et al., 2011). Then, the product of the estimates for demand size and demand probability provides the forecast of the demand per period. Two different smoothing constants are required – both for updating the probability and the demand size. The use of two separate smoothing constants for demand probability and demand size, makes it possible to “tune” the TSB method for demand processes with different levels of non-stationarity (Teunter et al., 2011). Teunter et al. (2011) show in their numerical investigation that TSB is suitable for situations with both stationary and non-stationary demand – which allows to use data with increasing/decreasing trend without having to eliminate the trend effect. In this chapter we will test whether the TSB is superior to the Croton’s forecast method (CR), and the Syntetos-Boylan approximation (SBA), but also for which class of items. Furthermore, will also include the exponential smoothing method (ES) in our analysis, even though this forecasting method has important shortcomings for intermittent demand (there are no separate estimates for demand probability and demand size obtained, although these are essential for inventory control), it does respond quickly to situations with sudden obsolescence or decreasing demand. Before we initialize and compare these forecasting methods, we will first describe the forecasts of each forecasting method in Section 4.3.1, we will discuss the issues with selecting appropriate smoothing constant(s) in Section 4.3.2, and finally, we will discuss seasonality in Section 4.3.3.

4.3.1 Forecasts

All methods forecast monthly demand for each type of spare part separately. Therefore, we use the phrase demand instead of demand for spare parts of type i throughout this section. First, we give an overview of the notation that we will use, with abbreviations of related methods between brackets (Teunter et al., 2011).

\[
\begin{align*}
\hat{x}_t & \quad \text{forecast at the beginning of month } t \text{ of demand in month } t; \\
d_t & \quad \text{demand in month } t; \\
\hat{k}_t & \quad \text{forecast in month } t \text{ of number of months between consecutive positive demand (CR, SBA);} \\
k_t & \quad \text{number of months since the last positive demand at the beginning of month } t \text{ (CR, SBA);} \\
\hat{s}_t & \quad \text{forecast of demand in month } t, \text{ provided this demand is positive (CR, SBA, TSB);} \\
\hat{P}_t & \quad \text{forecast of the probability of a positive demand in month } t \text{ (TSB);} \\
p_t & \quad \text{indicator variable that indicates whether or not there is a positive demand in month } t \text{ (TSB);} \\
\alpha, \beta & \quad \text{smoothing constants } (0 \leq \alpha, \beta \leq 1).
\end{align*}
\]
- **Exponential smoothing (ES)**
  The exponential smoothing forecast (ES) uses the demand in month \( t \) and the forecast for month \( t \) to predict demand in month \( t + 1 \). The ES forecast is
  \[
  \hat{x}_{t+1} = (1 - \alpha)\hat{x}_t + \alpha d_t. \tag{4.1}
  \]

- **Croston’s forecast method (CR)**
  Croston proposes to update the demand size, \( \hat{s}_{t+1} \), and the demand interval, \( \hat{k}_{t+1} \), separately, using
  \[
  \hat{s}_{t+1} = \begin{cases} 
  \hat{s}_t & \text{if } d_t = 0 \\
  (1 - \alpha)\hat{s}_t + \alpha d_t & \text{if } d_t > 0,
  \end{cases}
  \tag{4.2}
  \]
  \[
  \hat{k}_{t+1} = \begin{cases} 
  \hat{k}_t & \text{if } d_t = 0 \\
  (1 - \beta)\hat{k}_t + \beta d_t & \text{if } d_t > 0,
  \end{cases}
  \tag{4.3}
  \]
  where \( 0 \leq \alpha, \beta \leq 1 \). The Croston forecast (CR) is
  \[
  \hat{x}_{t+1} = \frac{\hat{s}_{t+1}}{\hat{k}_{t+1}}. \tag{4.4}
  \]

- **Syntetos-Boylan approximation (SBA)**
  Syntetos and Boylan (2001) show that Croston’s method is positively biased. They propose to deflate the Croston forecast by a factor \( 1 - \alpha/2 \) to approximately correct for that bias. Thus, the SBA forecast is
  \[
  \hat{x}_{t+1} = \left(1 - \frac{\alpha}{2}\right)\frac{\hat{s}_{t+1}}{\hat{k}_{t+1}}. \tag{4.5}
  \]

- **Forecasting method of Teunter et al. (2011) (TSB)**
  Teunter et al. (2011) propose an alternative to Croston’s method that is able to handle obsolescence issues. They do not update the demand interval, but rather the probability of a positive demand. The probability and the demand size are updated using,
  \[
  \hat{s}_{t+1} = \begin{cases} 
  \hat{s}_t & \text{if } d_t = 0 \\
  (1 - \alpha)\hat{s}_t + \alpha d_t & \text{if } d_t > 0,
  \end{cases}
  \tag{4.6}
  \]
  and
  \[
  \hat{p}_{t+1} = (1 - \beta)\hat{p}_t + \beta p_t. \tag{4.7}
  \]
  where \( 0 \leq \alpha, \beta \leq 1 \). The forecast of Teunter et al. (2011) (TSB) is
  \[
  \hat{x}_{t+1} = \hat{p}_{t+1}\hat{s}_{t+1}. \tag{4.8}
  \]
4.3.2 Smoothing constants
In this section we will discuss how to set a value for the smoothing constant(s). A common objective in forecasting is to find the minimum variance, unbiased estimator, but this can only be achieved if the underlying demand process is known (Teunter et al., 2011). However, in practice, especially for intermittent demand, this is typically not the case – it is often unclear whether the demand process is stationary or non-stationary (Teunter et al., 2011). Teunter et al. (2011) explain that a forecasting method that adapts quickly is preferable if demand is suspected to be highly non-stationary. This is achieved by choosing “sufficiently large” smoothing constants. Croston (1972) recommend the use of $\alpha$ values in the range 0.05-0.20, when demand is intermittent. He suggested that higher values of $\alpha$, in the range of 0.20-0.30, may be found properly only if there is high proportion of items that is known to be non-stationary. However, given the fact that we do not have perfect knowledge of the underlying demand process, one cannot determine the optimal smoothing constants analytically. In that case, empirical optimization based on the demand history offers an alternative. For the Croston and SBA methods, values between 0.05 and 0.2 are usually recommended if the demand is close to stationary, and higher than that if the demand tends to be non-stationary (Syntetos and Boylan, 2005). Further, Babai et al. (2011) suggest for the TSB method to set $\beta$ smaller than $\alpha$, because the demand probability is updated more often than the demand size. So if the demand is very intermittent, that is, the demand probability is very low since the demand intervals are high, $\beta$ should be much smaller than $\alpha$ (Babai et al., 2011). In other words, if the demand is stationary we could set $\alpha = \beta = 0$ and use simple averages. However, further research is needed, and we will empirically investigate the most appropriate smoothing constants for the underlying demand pattern. In order to analyze the forecasting methods, we will vary the smoothing constant $\alpha$ from 0.05 to 0.30 in steps of 0.05. The same values are also used for $\beta$. However, given that Babai, Syntetos, and Teunter (2011) recommend considering also smaller values for $\beta$ because the demand size is updated less often than the demand probability for the TSB method, we will additionally consider $\beta$ values from 0.01 to 0.04 in steps of 0.01.

4.3.3 Seasonality
In Appendix B we have already shown that seasonal effects are present, and one has to properly separate out the seasonal effects in the historical data before making any forecasts. We will use the most commonly used method, that is, the ratio-to-moving-average procedure (Silver, Pyke & Peterson, 1998). Silver et al. (1998) state that his method can effectively handle changes in the underlying trend during the historical period. Furthermore, it tends to eliminate cyclical effects. For statistical purposes it is desirable to have several seasons worth of data because each specific seasonal period occurs only once per season. Silver et al. (1998) point out that this is especially true for slow-moving items, or for items with highly erratic demand, because the noise in the data can obscure the underlying seasonality. However, using too much history increases the risk of the seasonal pattern having changed during the history which makes the early portion no longer representative of current and future conditions. The minimum for calculating the seasonal factors is two complete seasons. Silver et al. (1998) recommend using a minimum of four complete seasons, but we will check for each item separately the number of complete seasons and determine the seasonal effects based on the available data. The seasonal effects can subsequently be updated every year.
We will calculate seasonal effects per month, because our period is “month”. The first step is to make an initial estimation of level (including trend) at each historical period. To estimate the seasonal factors we first have to remove the trend effect (Silver et al., 1998). The trend point for any particular month \( t \) is estimated by a moving average of a full season (that is, 12 months) centered at period \( t \). By using a full season we can have the moving average free of seasonal effects. Given that the we have an even number of periods, \( P = 12 \), the standard 12-period moving average ends up being centered between two periods, and not right at the middle of a period as desired (Silver et al., 1998). Therefore, we will take the average of two consecutive moving averages. Then the estimate of the seasonal factor for any particular period \( t \) is obtained by dividing the demand \( d_t \) by the centered moving average. Furthermore, in order to dampen the random effect we will average the seasonal factors for similar periods in different years. Silver et al. (1998) express that the averages need not add up to exactly 12. Thus, we will normalize to obtain estimates of seasonal factors that total to 12. From the figures in Appendix B we can also see that there is up-ward trend. However, in order to estimate the level and trend we will have to fit a regression line. We will not determine the trend, as the TSB is able to forecast demand for non-stationary demand data. This implies that the TSB method is able to deal with the increasing trend. Later on we will see whether the TSB method is superior to the other methods.

4.4 Forecast Initialization

When it comes to model fitting to the historical data, the model may fit very well, but do a terrible job forecasting actual demand (Chase, 2009). A model that fits the demand history with an error close to zero does not imply that it will do a good job forecasting actual demand. Several methods require therefore an initial forecast to generate forecast during the performance evaluation period. In order to initialize the forecast, we will divide the demand history into two datasets: an initial modeling set also known as the in-sample dataset and a test dataset, or out-of-sample data (Chase, 2009). The in-sample data will be used to estimate the parameters, including the smoothing constant(s), and initialize the method. Then we will create and compare demand forecasts against the out-of-sample test dataset. Chase (2009) explains that since the test dataset will not be used as part of the model-fitting initialization using the in-sample dataset, these forecasts are actual projections created without using the values of the observations. This way, forecasts can “stabilize” during the updating stage of the initialization. The forecast errors are measured only for the out-of-sample test dataset. Chase (2009) recommends to hold-out one third of the most current demand history as the out-of-sample dataset, and to fit the different models to the oldest two thirds of the demand history. Given that we have 60 monthly periods of demand periods, we will hold out the most current 24 months of history as our out-of-sample test dataset, and fit the different models to the oldest 36 monthly periods. Then we will forecast the 24 most recent periods comparing the forecasts to the out-of-sample test dataset to see how well the model is forecasting. Note that spare that are not demanded during the initialization period are left out of examination. Also, the seasonality effects will be separately calculated for the in-sample test dataset. Before we present the choice of a time-series forecasting method, we will first give the initial forecasts for the different methods. The initial forecast for the ES method is the mean over the first 36 months, i.e.,

\[
\hat{x}_{36} = \frac{1}{36} \sum_{t=1}^{36} d_t.
\]
For CR, SBA and TSB, the initialization is as follows – if we let $T$ denote the set of months in the first 36 months (i.e. in-sample dataset) with a positive demand then

$$\hat{\kappa}_{36} = \frac{36}{|T|}$$  \hspace{1cm} (4.10)

$$\hat{s}_{36} = \frac{1}{|T|} \sum_{t \in T} d_t$$  \hspace{1cm} (4.11)

$$\hat{p}_{36} = \frac{|T|}{36}$$  \hspace{1cm} (4.12)

### 4.5 Choice forecasting method

This section shows the comparative results for the forecasting methods discussed in Section 4.3. The forecasting methods are initialized during the initialization period as explained in Section 4.4. In order to compare the methods to each other, we will a measure for the bias and the variance. These measures are MSE ($\{\hat{x}_t - d_t\}^2$), and ME ($\hat{x}_t - d_t$). ME estimates the bias of the forecasting method, and the MSE is an estimator of the variance. We are aware that more sophisticated performance measures are available, but the benefit of MSE is that it can be defined for both zero and non-zero demand which is important in an intermittent demand context. In addition, the MSE links naturally to inventory control (safety stocks are determined based on the MSE), and is a commonly used measure. However, it is a scale dependent measure, especially prone to distortion due to outliers, and as such it may lead to many difficulties in interpreting its results (Heinecke et al., 2012). However, for comparative purposes this is not a major issue. For each value of the smoothing constant considered and each estimation method, the MSE, and ME empirical results are calculated across time for all time-series data. An arithmetic average is then used in order to summarize results across all series. In this section we report the ME and MSE results for intermittent and non-intermittent items, respectively.

In order to examine the effects of the smoothing constants on the performance of the methods, we first focus on the ME results. The ME differences are more pronounced and ME played an important role in the development of the various forecasting methods (Babai et al., 2011). Afterwards we will also discuss the MSE results in relation to the smoothing constants. The results in Table 4.2 show that for non-intermittent items, when $\alpha$ increases, the bias of Croston’s and SBA’s method increases. The lowest value of the bias for these two estimators corresponds to $\alpha = 0.05$. The bias of the ES method is also low when $\alpha = 0.05$. Overall, the results show that $\alpha = 0.05$ can be a good smoothing constant that gives the lowest bias for the Croston and SBA estimates. This confirms what is discussed about stationary demand and what has been recommended in the academic literature. For the TSB estimate, when $\beta$ is fixed, the bias is an increasing function of $\alpha$, and the lowest bias is obtained for $\alpha = 0.10$. When $\alpha$ is fixed, the bias is a decreasing function of $\beta$, i.e. the lowest bias are obtained for high values of $\beta$.

The results in Table 4.3 show that for intermittent items (i.e. both slow and lumpy demand), when $\alpha$ increases, the bias of Croston’s estimate decreases. So, in this case the lowest bias for the Croston estimate is obtained for $\alpha = 0.30$. For the SBA and ES method we also see an decreasing bias for higher values of $\alpha$. The lowest bias for the SBA method is obtained for $\alpha = 0.20$ and for the ES estimate for
\(\alpha = 0.15\). For the TSB estimate, when \(\beta\) is fixed, the bias is an decreasing function of \(\alpha\), and the lowest bias is obtained for \(\alpha = 0.30\). When \(\alpha\) is fixed, the bias is an decreasing function of \(\beta\), i.e. the lowest bias are obtained for high values of \(\beta\). Recall that larger smoothing constants are better for “less stationary” demand patterns. The fact that we find higher smoothing constants for intermittent items than for non-intermittent items is an indication that intermittent items are indeed less stationary. Non-stationary is a cause of additional intermittence and lumpiness (Babai et al., 2011). This is an indication that the naïve method provides the best ME performance for intermittent items, as this method can be seen as a special case of the TSB method with both smoothing constants set to 1. The naïve estimator is updated at every time period, in this case the last actual demand, zero or not, becomes the forecast for the next time period.

<table>
<thead>
<tr>
<th>Estimator</th>
<th>(\alpha) smoothing constant – ME</th>
<th>(\beta)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SBA</td>
<td>0.05 -0.05758 -0.1624 -0.36678 -0.61011 -0.86746 -1.1289</td>
<td></td>
</tr>
<tr>
<td>Croston</td>
<td>0.196258 0.353122 0.410837 0.428472 0.431099 0.429065</td>
<td></td>
</tr>
<tr>
<td>ES</td>
<td>0.111401 0.174315 0.166338 0.143416 0.12146 0.103501</td>
<td></td>
</tr>
<tr>
<td>TSB</td>
<td>0.271843 0.48608 0.564405 0.583279 0.577514 0.56274 0.05 -0.53525 -0.35961 -0.30054 -0.29422 -0.31043 -0.33639</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.222805 0.438605 0.51925 0.540415 0.536592 0.523329 0.02</td>
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</tr>
<tr>
<td></td>
<td>0.178777 0.357368 0.441831 0.466886 0.466443 0.455878 0.03</td>
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<tr>
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<table>
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<tr>
<th>Estimator</th>
<th>(\alpha) smoothing constant – ME</th>
<th>(\beta)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SBA</td>
<td>0.05 -0.53525 -0.35961 -0.30054 -0.29422 -0.31043 -0.33639</td>
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<tr>
<td></td>
<td>-0.27649 -0.09935 -0.04053 -0.02472 -0.02178 -0.02077 0.30</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.2 ME results for non-intermittent items

Table 4.3 ME results for intermittent items
When we analyze the MSE results for non-intermittent items in Table 4.4, it appears that MSE for the Croston, SBA and ES decreases when $\alpha$ increases, i.e. the lowest value is obtained for $\alpha = 0.30$. For the TSB estimate, when $\alpha$ is fixed, MSE is an decreasing function of $\beta$, i.e. the lowest MSE are obtained for high values of $\beta$, whereas the optimal value for $\alpha$ is obtained for $\alpha = 0.05$. The MSE results in Table 4.5 for intermittent items show that MSE is lowest for $\alpha = 0.05$ for the Croston, SBA, ES, and the TSB estimators, and the optimal value for $\beta$ is obtained for $\beta = 0.01$ which is in line with the expectations, based on the fact that the demand probability is updated more than the demand size for intermittent demand.

<table>
<thead>
<tr>
<th>Estimator</th>
<th>0.05</th>
<th>0.10</th>
<th>0.15</th>
<th>0.20</th>
<th>0.25</th>
<th>0.30</th>
<th>$\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>SBA</td>
<td>571,2595</td>
<td>566,4571</td>
<td>562,1832</td>
<td>557,7181</td>
<td>553,1121</td>
<td>548,7871</td>
<td></td>
</tr>
<tr>
<td>Croston</td>
<td>573,2836</td>
<td>571,869</td>
<td>571,6095</td>
<td>571,391</td>
<td>571,0362</td>
<td>570,8886</td>
<td></td>
</tr>
<tr>
<td>ES</td>
<td>566,9604</td>
<td>556,6471</td>
<td>549,5284</td>
<td>545,0455</td>
<td>542,6674</td>
<td>542,1758</td>
<td></td>
</tr>
<tr>
<td>TSB</td>
<td>581,7706</td>
<td>586,8485</td>
<td>587,0741</td>
<td>584,3974</td>
<td>580,6532</td>
<td>577,1618</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>577,3176</td>
<td>581,9879</td>
<td>582,5505</td>
<td>580,4007</td>
<td>577,1973</td>
<td>574,1321</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>573,4791</td>
<td>577,7346</td>
<td>578,5479</td>
<td>576,8589</td>
<td>574,12</td>
<td>571,4495</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>570,1431</td>
<td>573,9824</td>
<td>574,9763</td>
<td>573,6768</td>
<td>571,3515</td>
<td>569,0463</td>
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</tr>
<tr>
<td></td>
<td>556,8718</td>
<td>558,367</td>
<td>559,5489</td>
<td>559,8555</td>
<td>558,9584</td>
<td>558,3278</td>
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<tr>
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<td>550,8264</td>
<td>550,6997</td>
<td>551,4807</td>
<td>551,8772</td>
<td>551,9967</td>
<td>552,2522</td>
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</tr>
<tr>
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<td>547,2681</td>
<td>545,8331</td>
<td>546,046</td>
<td>546,4607</td>
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<tr>
<td></td>
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<td>542,9018</td>
<td>542,5006</td>
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<tr>
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<td>544,678</td>
<td>541,3936</td>
<td>540,3846</td>
<td>540,3321</td>
<td>540,96</td>
<td>542,2716</td>
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</table>

Table 4.4 MSE results for non-intermittent items

<table>
<thead>
<tr>
<th>Estimator</th>
<th>0.05</th>
<th>0.10</th>
<th>0.15</th>
<th>0.20</th>
<th>0.25</th>
<th>0.30</th>
<th>$\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>SBA</td>
<td>103678,7</td>
<td>104880,9</td>
<td>105772,4</td>
<td>106581,2</td>
<td>107379</td>
<td>108177,6</td>
<td></td>
</tr>
<tr>
<td>Croston</td>
<td>103692,6</td>
<td>105091,7</td>
<td>106300,7</td>
<td>107547,3</td>
<td>108918,2</td>
<td>110438,3</td>
<td></td>
</tr>
<tr>
<td>ES</td>
<td>105138,8</td>
<td>107842</td>
<td>110551,9</td>
<td>113538,1</td>
<td>116842,8</td>
<td>120469,3</td>
<td></td>
</tr>
<tr>
<td>TSB</td>
<td>103475,1</td>
<td>104598,1</td>
<td>105787,1</td>
<td>107194,5</td>
<td>108855,6</td>
<td>110777</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>103647,3</td>
<td>104779,4</td>
<td>105954,1</td>
<td>107347,9</td>
<td>109000,3</td>
<td>110917,3</td>
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</tr>
<tr>
<td></td>
<td>103811,3</td>
<td>104954,3</td>
<td>106117,3</td>
<td>107499</td>
<td>109143,3</td>
<td>111056,3</td>
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</tr>
<tr>
<td></td>
<td>103966,6</td>
<td>105122,7</td>
<td>106276,4</td>
<td>107647,6</td>
<td>109284,6</td>
<td>111193,9</td>
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</tr>
<tr>
<td></td>
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<td>107147,3</td>
<td>108487,2</td>
<td>110097,6</td>
<td>111992,2</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>105208</td>
<td>106597,5</td>
<td>107782,5</td>
<td>109130,6</td>
<td>110739,5</td>
<td>112632,3</td>
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</tr>
<tr>
<td></td>
<td>105590,2</td>
<td>107111,8</td>
<td>108362</td>
<td>109740,7</td>
<td>111363,4</td>
<td>113263,6</td>
<td>0.20</td>
</tr>
<tr>
<td></td>
<td>105915,5</td>
<td>107573,9</td>
<td>108905,8</td>
<td>110331,6</td>
<td>111981,2</td>
<td>113897,4</td>
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<tr>
<td></td>
<td>106206</td>
<td>108003,5</td>
<td>109428,8</td>
<td>110914,9</td>
<td>112602,7</td>
<td>114543,4</td>
<td>0.30</td>
</tr>
</tbody>
</table>

Table 4.5 MSE results for intermittent items
In addition, we have also analyzed the ME and MSE performance of the different estimators for sporadic and declining parts (see Appendix D). The TSB method outperforms the other methods for both *declining* and *sporadic* demand. Only ES outperforms the TSB method for *declining* items in terms of bias. However, ES is not useful for inventory planning, because there are no separate estimates for demand probability and demand size obtained, although these are essential for inventory control. Overall, in terms of both ME and MSE, the TSB method outperforms SBA and Croston for both intermittent and non-intermittent demand. Therefore, we recommend using the TSB method for forecasting the demand. However, as we have discussed, the optimal values for \( \alpha \) and \( \beta \) are not the same for the bias and MSE. Therefore, we will have to make a trade-off, as there are no exact recommendations in the literature available. By combining the optimal values for \( \alpha \) and \( \beta \) for the ME and MSE performance, we obtain \( \alpha = 0.05 \) and \( \beta = 0.04 \) for non-intermittent items, and \( \alpha = 0.25 \) and \( \beta = 0.15 \) for intermittent items.

The developed classification scheme with respect to demand forecasting is only a starting point for spare parts management. It can be used to make strategic and tactical decisions with respect to demand forecasting. The next step is to use the forecasted demand for the development of inventory policies - the inventory policies and parameters depend on forecasts of demand over lead-time. So the choice of the forecasting approach (time-series or causal) and forecasting method affects the inventory policies and parameters. The real benefit of the developed classification scheme with respect to demand forecasting is reflected in the accuracy of the inventory policies and parameters set.
5 INVENTORY CONTROL

In this chapter a classification scheme with respect to inventory control will be designed (5.1). An important classification factor is criticality. Currently, no information is available about spare parts criticality. Therefore, we will perform a criticality analysis (5.2). Finally, we will apply the developed classification scheme on a real dataset (5.3).

5.1 CLASSIFICATION FOR INVENTORY CONTROL

KES and Sage carry a large amount of items in stock. These items are highly heterogeneous, with differing costs, service requirements, and demand patterns. An important operational issue in spare parts management is the classification of relevant SKUs in order to determine service requirements for different spare parts classes and for facilitating the allocation of the most appropriate forecasting method and stock control policies. In Chapter 4 we have already built a classification scheme with respect to demand forecasting. In this chapter we will develop a classification scheme for facilitating the allocation of the most appropriate inventory policies and service requirements. Note that we will not develop any inventory policies, because we do not have the necessary data. In Section 5.1.1 we will first select the classification criteria. Next, in Section 5.1.2 we will discuss classification techniques. An important criterion is the criticality of an item which is at this moment not yet defined. In Section 5.2 we will describe and apply the criticality factor. Finally, in Section 5.3 we will apply all the classification factors in on a real dataset.

5.1.1 Classification criteria

Many papers recognize that a one-dimensional ABC-analysis is easy to use. It is especially appropriate for the inventory management of spare parts that are fairly homogenous in nature and differ from each other mainly by unit price or demand volume (Huiskonen, 2001). That is why ABC-analysis has retained its popularity among the practitioners in directing the control efforts (Huiskonen, 2001). However, Huiskonen (2001) points out that one-dimensional ABC-analysis does not discriminate all the control requirements of different parts as the variety of control characteristics of parts increases. One-dimensional ABC-analysis may not be able to provide a good classification of inventory items in practice. This is also true for the Sage’s one-dimensional classification of KES’s spare parts based on the annual usage. Sage applies this one-dimensional classification worldwide, and it has shown to be a successful classification scheme. However, it is important to note that Sage’s operations are mainly focused on the market in the US where the standardization among the GSE vehicles is higher compared to the European market. For spare parts supply in European market it might not be sufficient to classify spare parts merely on annual usage. Huiskonen (2001) states that using several criteria as a basis is especially useful for spare parts that do possess several distinctive characteristics. Also in the literature study it is pointed out that most papers propose using multiple criteria for classification of spare parts (Velagić, 2012). The table in Appendix A can be used to choose the most promising criteria for classifying the spare parts. As one can see, criteria that are frequently reported are the value, criticality, supply characteristics, demand volume, and demand variability. Other criteria that are less frequently reported (see last column of the table), but that also should be considered for the classification of spare parts are specificity, life cycle phase, and repair efficiency.
Bacchetti and Saccani (2011) observe that little attention has been paid to identifying the context in which one criterion may be preferable to others. This is a very important issue and one that has been under-exposed in the academic literature. The criteria that are judged to be important for the purpose of classifying KES’s spare parts are selected collectively (between KES’s management and the researcher). For the classification of KES’ spare parts a multi-criteria approach will be used with the following criteria:

1. **Spare parts life cycle**: Parts are clustered in three main groups based on their remaining life cycle: initial, in-use, and decline. Boundaries between these classes are already explained in Chapter 4. The spare parts life cycle does not influence only the selection of the forecasting technique, but also decisions on inventory management.

2. **Criticality analysis**: At this moment KES has not yet a defined the criticality of spare parts. (Process) criticality is an important factor because it can be directly linked to the availability of GSE vehicles. Moreover, criticality can be directly linked to the service level requirements. In Section 5.2 we will analyze the criticality of an item based on a number of sub-criteria that cover the essentials of GSE vehicles maintenance.

3. **Part value**: The cost of an item influences the overall inventory holding cost. The part value can be used in order to dimension the parameters of order-up-to level policies and to make stock/non-stock decisions. The boundaries will be determined based on the average price.

4. **Demand frequency**: Demand classification has been shown to link directly to forecasting and stock control decision-making; in particular the average inter-demand interval (ADI) and the variability of the demand sizes have been shown to be important from a theoretical point of view (Syntetos et al., 2005). However, Boylan and Syntetos (2007) showed, by means of experimentation on a large dataset, that the variability of the demand sizes may not necessarily be important in the real world. In Section 4.2.1 we have shown that this is also true for KES’s case. On the other hand, the average inter-demand interval is not only relevant in real world practices, but it is also an insensitive criterion with regards to the cut-off value assigned to it (i.e. 1.32 review periods).

5. **Annual usage**: This criterion refers to Sage’s one-dimensional spare parts classification, where class A is defined as 24+ units per year, class B as 12-23 units per year, class C as 4-11 units per year, and class D as 1-3 units per year (see also Table 2.1). It is however not known how Sage has determined these cut-off values between the A, B, C and D-classes.

No other criteria are explicitly considered at this stage for classification related purposes. Management can change the number and nature of the criteria depending on their preferences. Other important factors such as the supply lead time and its variability and the demand variability will be further considered in the calculation of safety stocks, when such an exercise is required. Having selected the criteria that collectively are judged to be the most appropriate for the purpose of classifying spare parts, the next step is to classify the spare parts. In the next section we will discuss different classification techniques.
5.1.2 Classification techniques

In the literature study we have discussed several classification techniques (Velagić, 2012). It has been pointed out that one can distinguish between quantitative and qualitative techniques. One of the most popular quantitative techniques is the ABC approach (Pareto). Silver et al. (1998) suggest to list all SKUs in descending order by demand frequency, volume or value. The ranked SKUs can then be divided into relevant categories (A, B, C, etc.). For example, items from category A are assumed to be the most critical, and, therefore, they require the highest service levels. However, Silver et al. (1998) were focused on only one criterion for the ABC classification. Various methodologies have been proposed to implement multi-criteria ABC classifications, including weighted linear programming, matrix models, artificial neural networks, weighted Euclidian distance with quadratic optimization, and the fuzzy logic (Bacchetti & Saccani, 2011). Besides ABC classification, there are also other quantitative techniques. Syntetos (2001) proposes a demand-based classification. Yamashina (1989) proposes product-still-in-use quantity curves and service part demand curves as inputs for spare parts classification, while Porras and Dekker (2008) propose a hierarchical two- or three-dimensional quail-quantitative classification.

Besides quantitative techniques, one can also use qualitative techniques. Bacchetti and Saccani describe qualitative techniques as techniques that “[...] try to assess the importance of keeping spare parts in stock based on information on the specific usages of spares and on factors influencing their management (costs, downtime, storage considerations, etc.)” (2011, pp. 2). A simple technique, but prone to subjective judgments, is the VED technique. VED stands for vital, essential, and desirable, respectively (Mukhopadhyay, Pathak & Guddu, 2003). VED is prone to subjective judgments, because it is done in consultation with experts. Bacchetti and Saccani (2011) suggest combining VED with systematic procedure for classifying spare parts in order to reduce the problem with the VED technique. They refer to Gajpal, Ganshed and Rajendran (1994) who have proposed an AHP model for performing VED analysis. AHP is a model developed by Saaty (1980) and stands for Analytic Hierarchy Process. It is a multi-criteria decision-making tool to find out the relative priorities or weights to be assigned to different criteria and it can effectively handle both qualitative and quantitative data. AHP involves the principles of decomposition, pair-wise comparison, and priority vector generation and synthesis (Saaty, 1980). AHP can be used to obtain absolute measurements of the criticality of spare parts, after which these measurements can be compared to specific limits in order to classify spare parts as vital, essential, or desirable (Gajpal et al., 1994). Besides VED analysis, there are also some other techniques that have been combined with AHP analysis, e.g. reliability centered maintenance (RCM) (Braglia, Grassi & Montanari, 2004).

Studies that consider the comparative benefits of various approaches to classification (e.g. ABC vs. other techniques) are lacking. Several authors recommend using multiple criteria ABC-analysis. We have tried to apply a multiple criteria ABC-analysis with frequently recommended criteria like criticality, value-usage, unit cost, lead time, etc. (see Appendix A). However, this approach does not allow differentiating between different items – not all criteria are relevant for classifying for all items. An approach that is more suitable for KES is to apply selected criteria hierarchically in order to define homogeneous spare parts classes. By applying a hierarchical approach, one can differentiate the criteria among the different spare parts (sub-classes). Figure 5.1 shows the resulting hierarchical multi-criteria spare parts
classification framework allowing the identification of 10 final homogeneous spare parts classes. As one can see, not all criteria affect the selection of the final classes. Class 1 contains all items in the initial phase of life cycle, class 2 are items with a sporadic demand in the in-use phase of the life cycle, class 3 are critical items with a low price, class 4 are critical items with a high price and high demand frequency, class 5 are critical items with a high price and low demand frequency, class 6, 7, 8 and 9 are A-, B-, C-, and D-items according to Sage’s classification, respectively, and finally, class 10 are items in the decline phase of the life cycle.

![Spare parts classification with respect to inventory control](image)

**5.2 Criticality Analysis**

When it comes to spare parts inventory management, determining the importance of a spare part by annual usage becomes insufficient. Classification by annual usage relies only on historic demand data – it does not differentiate between critical and non-critical spare parts. Criticality, as a classification criterion, does not only rely on demand data, it includes also information about explanatory variables (e.g. failure rate). Immediate action is needed in case of a failure caused by an item with a high criticality but which is not on stock, whereas some lead time is allowed to correct a failure caused by an item with a mediate criticality (Huiskonen, 2001). Furthermore, Huiskonen (2001) distinguishes process and control criticality. Process criticality is defined as “[…] the consequences caused by the failure of a part on the process in case a replacement is not readily available” (Huiskonen, 2001, pp 130). Process criticality can be evaluated by down time costs of the process. Control criticality is based on the possibilities to control the situation, including predictability of failure, availability of spare part suppliers, lead-times, etc.
In order to perform the criticality analysis we will first select relevant criticality factors in Section 5.2.1. Next, in Section 5.2.2 we will discuss how to combine the criticality factors in order to determine the criticality of an item. Finally, in Section 5.2.3 we will evaluate the results of the criticality analysis.

5.2.1 Criticality factors
The first step of the criticality analysis is the identification of relevant criteria impacting item criticality. We analyze the criticality of an item based on four sub-criteria, that is, GSE criticality, maintenance type, ratio of GSE failures, and the number of item failures. These factors are selected by collectively (between the company’s management and the researcher) judging their relevance for maintaining GSE vehicles, but the selection is also influenced by the availability of the necessary data. Other criticality factors like commonality and substitutability have also been considered. Commonality was defined as a measure of how frequently the same part is used on different GSE vehicle. However, the impact of the resulting commonality measures was negligible compared to the other criteria. Substitutability was defined as the total number of GSE vehicles that a particular part has a use. First of all, this definition of substitutability is a rough estimate of the real substitutability, and might bias the result. There was no data available to make better estimates of substitutability. Furthermore, the resulting substitutability measures highly impacted the result, because substitutability was given a high weight compared to other factors. We have therefore decided to leave this measure out of the analysis. Finally, it is important to note that the four selected criteria are measures of process criticality, whereas control criticality is neglected. Not sufficient data was available to include a factor for control criticality, such as the number of available suppliers for a part. The selected criticality factors are defined as follows:

1. **GSE criticality:** GSE criticality refers to the criticality of the GSE vehicles. Criticality of the GSE vehicles can be defined by the position of the GSE vehicle in the chain. The chain position describes the importance of a vehicle for handling the aircraft on the ground. GSE vehicles that are directly related to processing the aircraft on the ground are critical. Those vehicles should be up and running when necessary in order to minimize the turnaround time of the aircraft on the ground. Three degrees of criticality might be distinguished on the following basis:
   a) High: Availability of this GSE vehicle is of high importance. Failures have to be corrected and the spares should be supplied immediately.
   b) Moderate: Non-availability of this GSE vehicle can be tolerated with temporary arrangements for a short period of time, during which the failure can be corrected and the spare supplied.
   c) Low: This GSE-vehicle is not critical for ground-handling of an aircraft. The failure can be corrected and the spares can be supplied after a long period of time.

Çelebi et al. (2008) suggest that quantification of the given critically degrees can be done by assigning a penalty index ($\alpha_n$) for each item $n$ and setting it to 1 for critical vehicles, to 0.01 for a non-critical vehicles, and to 0.50 for a moderately critical vehicles. The criticality levels are determined in discussion with management.
2. **Maintenance type**: Another aspect of criticality is the type of maintenance performed on the equipment. In order to determine the type of maintenance we will look at the job card code (i.e. type of order). The different job card codes and their description are given in Table 5.1. Only two job card codes are considered to be important for the criticality analysis, namely repair and breakdown, because these two job cards codes refer to corrective maintenance, which is difficult to plan. In case a breakdown has occurred or repair is executed on the vehicle, an item is considered to be of a higher criticality level in comparison to an item for which an inspection is considered. In case of an inspection (i.e. preventive maintenance) one is capable to prevent failures or to measure indication of failures (Molenaers, Baets, Pintelon & Waeyenbergh, 2011). In addition, items for which damage repair is considered are not critical, because the necessary items for damage repair are rather aesthetic than functional. Items for modifications are also not considered to be critical, because their demand can be planned separately. Further, job cards “banden”, “lekkage” and “fuelling” are not considered for the criterion maintenance type, because these activities do not require any items. The remaining job card codes are not relevant, given their low frequency as shown in Table 5.1.

<table>
<thead>
<tr>
<th>Job card code</th>
<th>Description</th>
<th>#Job cards</th>
</tr>
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<tbody>
<tr>
<td>B</td>
<td>Banden</td>
<td>5216</td>
</tr>
<tr>
<td>C</td>
<td>Claim</td>
<td>48</td>
</tr>
<tr>
<td>E</td>
<td>Error by operator</td>
<td>5258</td>
</tr>
<tr>
<td>H</td>
<td>Damage repair</td>
<td>11527</td>
</tr>
<tr>
<td>I</td>
<td>Inspection</td>
<td>29825</td>
</tr>
<tr>
<td>L</td>
<td>Lekkage</td>
<td>1383</td>
</tr>
<tr>
<td>O</td>
<td>Modification</td>
<td>5949</td>
</tr>
<tr>
<td>R</td>
<td>Repair</td>
<td>8337</td>
</tr>
<tr>
<td>S</td>
<td>Breakdown</td>
<td>35194</td>
</tr>
<tr>
<td>T</td>
<td>Fuelling</td>
<td>2</td>
</tr>
<tr>
<td>X</td>
<td>Runner service</td>
<td>0</td>
</tr>
</tbody>
</table>

*Table 5.1 Number of job cards per job card code*

3. **Ratio of GSE failures**: Another measure of GSE criticality, and, therefore, the related spare parts, is the number of GSE failures. The number of GSE failures can be calculated by counting the number of “breakdown” and “repair” job cards based on the available job card data. We will compare the number of “breakdown” and “repair” job cards for a GSE vehicle to the total number of “breakdown” and “repair” job cards for all GSE vehicles within the same GSE supplier type (i.e. type fabrikant). This ratio expresses which GSE vehicle is really critical within a particular GSE supplier type. We will use a normalizing function which is useful for making all criteria data between [0,1]:

$$
\beta_i = \frac{e_{ij} - e_{\min}}{e_{\max} - e_{\min}} \quad (5.1)
$$

The GSE failure index, $\beta_i$, has a positive impact on the importance of item $i$ where $e_{ij}$ represents the total number “breakdown” and “repair” job cards on vehicle $j$. Here, $e_{\max}$
stands for the highest number “breakdown” and “repair” job cards, while $e_{\text{min}}$ stands for the lowest number of “breakdown” and “repair” job cards.

4. **Item failures:** There is no exact information available about the item failure rates. In order to get some information about the item failures, we will analyze how often a particular item is replaced on the same GSE vehicle. We will again use a normalizing function which is useful for making all criteria data between [0,1]:

$$\gamma_i = \frac{f_{ij} - f_{\text{min}}}{f_{\text{max}} - f_{\text{min}}}$$

(5.2)

The item failure index, $\gamma_i$, has a positive impact on the importance of item $i$ where $f_{ij}$ represents the total number of item changes on vehicle $j$. Here, $f_{\text{max}}$ stands for the highest number of item changes on the same vehicle, while $f_{\text{min}}$ stands for the lowest number item changes on the same vehicle.

5.2.2 **Multi-criteria criticality scheme**

Having selected the criteria, the next step is to calculate the weights and the scores of the different parts in order to determine the criticality. We analyze the criticality based on a multi-criteria criticality scheme consisting of three steps:

**Step 1.** First, GSE vehicles are filtered by GSE criticality and maintenance type. Only GSE vehicles with a criticality level of 1 will remain, because these, critical, GSE vehicles should be up and running when necessary. In addition, only “breakdown” and “repair” job cards will be used, because the necessary parts are most unpredictable.

**Step 2.** Second, GSE vehicles, and indirectly parts, are scored on the number of failures compared to the total number of failures for all GSE vehicles within the same GSE supplier type, and on the number of item failures on that GSE vehicle. However, it is difficult to determine objectively the weight for these two factors. Therefore, we will use a weighted linear optimization model which is usually used for multi-criteria ABC inventory classification, but it can be applied in different settings. The model we will use is an improvement on the model developed by Ng (2007) which we will call the Ng-model. The Ng-model converts all criteria measures of an inventory item into a scalar score, and with proper transformation, the Ng-model can obtain the scores of inventory items without a linear optimized, which is of course beneficial for practical purposes (Hadi-Vencheh, 2010). Ng converts first all measurement in [0,1]. To facilitate the classification under multiple criteria, Ng defines a non-negative weight $w_{ij}$ which is the weight of contribution of performance of the $i$th decision alternative with respect to the $j$th criteria. The purpose is to aggregate multiple performance scores of a decision alternative into a single score for the subsequent classification, like ABC inventory classification (Hadi-Vencheh, 2010). The score of $i$th decision alternative (denoted as $S_i$) is expressed as the weighted sum of performance measures under multiple criteria. The weighted linear optimization Ng-model is as follows for each item $i$: 
where $y_{ij}$ is the normalized attribute value of the $i$th decision alternative with respect to the $j$th criteria (e.g. performance of $i$th inventory item with respect to the $j$th classification criteria). After the necessary transformations, the maximal score $S_i$ of the $i$th decision alternative can be easily obtained as $\max_{j=1,2,...,J} \left( \frac{1}{J} \sum_{k=1}^{J} y_{ik} \right)$. Similar to the idea in Data Envelopment Analysis (DEA), the Ng-model avoids subjectiveness in determining weights and provides an objective way for multi-attribute decision making. However, as one can see from the score of each attribute, the Ng-model leads to a situation where the score of each item is independent of the weights obtained from the model. In other words, the weights do not have any role for determining total score of each item, and this might lead to wrong classifications. Hadi-Vencheh (2010) has proposed an extended version of the Ng-model by considering weights values for multi-criteria classification which we will use for the classification. The resulting multi-attribute decision making model is as follows (Hadi-Vencheh, 2010):

$$\max S_i = \sum_{j=1}^{J} s_{ij} w_j$$

$$s.t. \sum_{j=1}^{J} w_j^2 = 1$$

$$w_j \geq 0, j = 1,2,...,J$$

where $s_{ij}$ is the normalized attribute value of the $i$th decision alternative with respect to the $j$th attribute, and $w_j$ the relative importance weight attached to the $j$th criteria ($j = 1,2,...,J$) (Hadi-Vencheh, 2010). The analytical solution to the model is as follows:

$$w_j^* = \frac{s_{ij}}{\sqrt{\sum_{j=1}^{J} s_{ij}^2}} \quad j = 1,2,...,J$$

This analytical solution can only be used if there are no ordering constraints, otherwise one will have to use a software package. For particular purposes we have not defined any ordering constraints, because it is not easy to determine any order constraint, and for practical purpose it is more easy to use the analytical solution.
Step 3. The first two steps are performed on vehicle level. However, in order to determine the criticality of an item we will have to transform the findings on item level. Given that some items are used on more than one vehicle, we will have to calculate the average of the criticality scores on vehicle level (i.e. average of the scores calculated in step 2) to obtain the criticality score on item level. Based on this score we will perform a Pareto-analysis, that is, we will apply the 20/80 rule to find the most critical items.

5.2.3 Application of the criticality analysis
Before we present the results of the criticality analysis, it is important to note that the criticality analysis is based on demand data between 01-01-2010 and 31-12-2011 which contains 7,046 different items. The demand data from 2009 and earlier does not contain information about the job cards, which is required for determining the criticality analysis (see also Section 5.2.1). In order to find the most critical spare part we have performed the three steps of the multi-criteria criticality scheme. In the first step we have analyzed the GSE criticality level and the maintenance type. The following vehicles have a criticality level of 1, and are considered for further examination: air conditioning units, air starter units, container loaders, de-icers, ground power units, oil service units, pallet loaders, toilet service units, transportbanden, vliegtuigtrekkers, water service units, and fuel service units. Vehicles with criticality levels of 0.5 and 0.01 are left out of further examination. Subsequently, the demand data is filtered on job card type, where only orders with “repair” and “breakdown” job cards are left. In this first step about 60% of the items are filtered out. In the second step, we have employed the multi-attribute decision making model. According to the third step, we have transformed the resulting scores from vehicle to item level in order to determine the item criticality. The Pareto analysis shows that 41.35% of the remaining items from the first filter determines 80% of the criticality. In other words, 16.83% of all items determines 80% of the criticality which is a good approximation of the 20/80 rule. In the following section we will show the benefits of the criticality analysis over the current one-dimensional spare parts classification scheme.

5.2.4 Benefits of the criticality analysis
Here, we will analyze the comparative benefits of the criticality analysis with regards to the current practices employed by Sage. In order to show the benefits of the criticality analysis we will make use of the available demand data of the first four months 2012. The used dataset is limited, because only the most recent historical demand data contains information about the RMs and hot orders (to be more precise, KES started collecting information about RMs and hot orders in November 2011). Note that the results are only illustrative, more data is required to confirm the results that we will discuss in this section.

First, we start in Table 5.2 were the demand and the RMs are classified as critical and non-critical. Then, each class is further classified according to Sage’s classification based on annual usage. The table shows that more than 50% of the A-items are critical – both from the criticality perspective and Sage’s service level, these parts should be fulfilled immediately. It is however more interesting to check the classes B, C, and D, as these classes do not require immediate fill, whereas critical items do. In other words, the critical B-, C- and D- items should be fulfilled as soon as possible.
In order to get an idea of the performance of Sage’s classification and the classification we proposed, we will simulate both classification schemes for the demand during the period between 01-01-2012 and 30-04-2012. Table 5.3 shows that Sage’s KPI performance is almost 99% for all classes, which is way better than the required service levels as defined in the contract (see Table 2.1). The 7th column shows the number of hot orders for critical parts. As is discussed, critical parts should be fulfilled immediately or as soon as possible. If this is under control, the number of hot orders for critical parts should be zero. The 8th column shows the KPI’s for the new classification scheme, that is, the classification scheme with the criticality factor, which means that all critical parts should be fulfilled immediately – there should be no hot orders. The last column shows the KPI improvement when the criticality factor is added to the classification scheme. As one can see, the improvement over the current service level is minimal.

One explanation for the limited improvement of the new classification scheme over the current classification scheme is the fact that there is no much room for improvement given the high KPI performance. This still does not explain why the maintenance shop is dissatisfied with the availability of spare parts. We will therefore analyze the KPI performance from a different perspective. We will take the perspective of the maintenance shop – the maintenance shop wants spare parts to be there as soon as possible. Let us know consider the KPI performance without the agreed spare parts supply lead times. In that case, A-items should be fulfilled immediately (not within one day as in the current situation) at 99%, B-items at 95%, C-items at 80%, and D-items at 65%. From Table 5.4 one can see that Sage’s KPI performance is lower now, but still above the 99%, 95%, 80%, and 65% target service levels for A-, B-, C-, and D-items, respectively. We will again compare the performance of the new classification scheme with the current classification scheme. From the last two columns one can see the improvement over the current classification scheme, but the improvement is again limited.

---

**Table 5.2 Distribution of critical and non-critical parts for January-April 2012**

<table>
<thead>
<tr>
<th>Class</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Critical</td>
<td>3005</td>
<td>255</td>
<td>345</td>
<td>178</td>
<td>3783</td>
</tr>
<tr>
<td>Non-critical</td>
<td>5240</td>
<td>1317</td>
<td>1979</td>
<td>1192</td>
<td>9728</td>
</tr>
<tr>
<td>Critical rood</td>
<td>12</td>
<td>4</td>
<td>8</td>
<td>17</td>
<td>41</td>
</tr>
<tr>
<td>Non-critical rood</td>
<td>34</td>
<td>38</td>
<td>128</td>
<td>190</td>
<td>390</td>
</tr>
</tbody>
</table>

**Table 5.3 Performance based on current service levels**

<table>
<thead>
<tr>
<th>Sage class</th>
<th>Demand</th>
<th>#Rood</th>
<th>#Hot</th>
<th>KPI Sage</th>
<th>#Critical rood</th>
<th>#Critical hot</th>
<th>KPI New</th>
<th>Change %</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>8245</td>
<td>46</td>
<td>24</td>
<td>99,71</td>
<td>12</td>
<td>6</td>
<td>99,78</td>
<td>0,07</td>
</tr>
<tr>
<td>B</td>
<td>1572</td>
<td>42</td>
<td>14</td>
<td>99,11</td>
<td>4</td>
<td>1</td>
<td>99,17</td>
<td>0,06</td>
</tr>
<tr>
<td>C</td>
<td>2324</td>
<td>136</td>
<td>30</td>
<td>98,71</td>
<td>8</td>
<td>1</td>
<td>98,75</td>
<td>0,04</td>
</tr>
<tr>
<td>D</td>
<td>1370</td>
<td>207</td>
<td>20</td>
<td>98,54</td>
<td>17</td>
<td>0</td>
<td>98,54</td>
<td>0,00</td>
</tr>
<tr>
<td>Total</td>
<td>13511</td>
<td>431</td>
<td>88</td>
<td>99,35</td>
<td>41</td>
<td>8</td>
<td>99,41</td>
<td>0,06</td>
</tr>
</tbody>
</table>

---

42
To understand the real improvement, we should recall the goal of the criticality analysis. (Process) criticality is directly linked to the availability of the vehicles. Process criticality is defined as “[...] the consequences caused by the failure of a part on the process in case a replacement is not readily available” (Huiskonen, 2001, pp 130). In Table 5.5 we have therefore analyzed the number of hot orders (i.e. vehicle has to wait in the maintenance shop for the part), and more precisely, the number of hot orders for critical parts. The critical hot orders should be close to zero, given that critical parts should be fulfilled immediately and otherwise as soon as possible. In the ideal situation, where the number of critical hot orders is reduced to zero, a total reduction of circa 10% in the number of hot orders can be obtained. Overall, we can conclude that the use of the criticality factor outperforms the current classification scheme in terms of the number of hot orders. It is however not possible to express the reduction of the hot orders in monetary terms.

Table 5.4 Performance without the supply time

<table>
<thead>
<tr>
<th>Sage class</th>
<th>Demand</th>
<th>#Rood</th>
<th>Critical</th>
<th>KPI Sage</th>
<th>#Critical rood</th>
<th>KPI New</th>
<th>Change %</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>8245</td>
<td>46</td>
<td>3005</td>
<td>99,44</td>
<td>12</td>
<td>99,59</td>
<td>0,15</td>
</tr>
<tr>
<td>B</td>
<td>1572</td>
<td>42</td>
<td>255</td>
<td>97,33</td>
<td>4</td>
<td>97,58</td>
<td>0,26</td>
</tr>
<tr>
<td>C</td>
<td>2324</td>
<td>136</td>
<td>345</td>
<td>94,15</td>
<td>8</td>
<td>94,49</td>
<td>0,36</td>
</tr>
<tr>
<td>D</td>
<td>1370</td>
<td>207</td>
<td>178</td>
<td>84,89</td>
<td>17</td>
<td>86,13</td>
<td>1,44</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>13511</td>
<td>431</td>
<td>3783</td>
<td>96,81</td>
<td>41</td>
<td>97,11</td>
<td>0,31</td>
</tr>
</tbody>
</table>

Table 5.5 Reduction of the number of hot orders

<table>
<thead>
<tr>
<th>Sage class</th>
<th>#Hot</th>
<th>#Critical</th>
<th>#Critical hot</th>
<th>% Reduction hot orders</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>28</td>
<td>3005</td>
<td>6</td>
<td>21,43</td>
</tr>
<tr>
<td>B</td>
<td>28</td>
<td>255</td>
<td>2</td>
<td>7,14</td>
</tr>
<tr>
<td>C</td>
<td>78</td>
<td>345</td>
<td>7</td>
<td>8,97</td>
</tr>
<tr>
<td>D</td>
<td>137</td>
<td>178</td>
<td>11</td>
<td>8,03</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>271</td>
<td>3783</td>
<td>26</td>
<td>9,59</td>
</tr>
</tbody>
</table>

5.3 APPLICATION CLASSIFICATION SCHEME FOR INVENTORY CONTROL

Having performed the criticality analysis, we now have all the necessary data to apply the complete classification scheme on a real dataset. From Figure 5.1 one can see that critical items are further classified according to their part value and demand frequency, whereas non-critical items are classified according to Sage’s classification based annual usage. These three items are dependent on the time horizon. Given that Sage uses a time horizon of one year to determine their spare parts classification, we will also use one year to evaluate and compare the resulting classification scheme to Sage’s classification scheme. To be more precisely, the evaluation and comparison is based on the demand data between 01-01-2011 and 31-12-2011. Table 5.6 shows on the left-side the resulting classification of critical parts, and on the right side the classification of non-critical parts.
Table 5.6 Result classification scheme for 2011

<table>
<thead>
<tr>
<th>Criticality</th>
<th>Critical</th>
<th>Non-critical</th>
</tr>
</thead>
<tbody>
<tr>
<td>Part value</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Demand Frequency</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>Usage</td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>#Items</td>
<td>250</td>
<td>2</td>
</tr>
</tbody>
</table>

As one can see from Table 5.6, the number of non-intermittent (i.e. high demand frequency) critical items with a high price is rather low. Further classification of critical items based on demand frequency is not necessary as more than 99% of the critical items with a high price have an intermittent demand pattern. Figure 5.2 shows the final, modified and simplified, classification scheme with respect to inventory control. Class 1 contains all items in the initial phase of life cycle, class 2 are items with a sporadic demand in the in-use phase of the life cycle, class 3 are critical items with a low price, class 4 are critical items with a high, class 5, 6, 7 and 8 are A-, B-, C- and D-items according to Sage’s classification, respectively, and finally, class 9 are items in the decline phase of the life cycle.

![Diagram](image)

Figure 5.2 Final spare parts classification scheme with respect to inventory control

However, from Table 5.6 it is not directly clear what has changed compared to the current classification scheme. Therefore, we have compared the results of the new classification scheme with Sage’s classification scheme in Table 5.7. Table 5.7 shows on the left-side the number of critical items that are classified as A, B, C or D in the current classification scheme. As one can see, 58.09% of the items are currently classified as D, which means that they have to be successfully filled at 65% within seven days. However, according to the criticality definition, those items should be fulfilled immediately and otherwise
as soon as possible. This high number of critical items that are classified as D, but also as C and B, shows why it is not sufficient to classify items only with one criterion. By classifying spare parts according to the annual usage, important information about the part is not included. Adding criticality as a classification criterion changes the resulting classes. The other classification criteria, i.e. part value and annual usage, are added to manage the inventory control of critical and non-critical spare parts, respectively. The next step is to determine inventory policies and parameters for each class. However, as is already pointed out, we do not have any information about the replenishment lead times and the cost structure.

<table>
<thead>
<tr>
<th>Class</th>
<th>Critical</th>
<th>Non-critical</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>#Items</td>
<td>%</td>
<td>#Items</td>
</tr>
<tr>
<td>A</td>
<td>142</td>
<td>11.97</td>
<td>383</td>
</tr>
<tr>
<td>B</td>
<td>85</td>
<td>7.17</td>
<td>365</td>
</tr>
<tr>
<td>C</td>
<td>270</td>
<td>22.77</td>
<td>1192</td>
</tr>
<tr>
<td>D</td>
<td>689</td>
<td>58.09</td>
<td>3920</td>
</tr>
<tr>
<td>Total</td>
<td>1186</td>
<td>100.00</td>
<td>5860</td>
</tr>
</tbody>
</table>

*Table 5.7 Sage’s classification of critical parts*
6 Logistics Outsourcing

In this chapter first it will be discussed how to bridge the gap between KES and Sage (6.1). Next, recommendations will be given regarding the logistics outsourcing scope and activities (6.2).

6.1 Logistics Outsourcing Relationship

In the previous chapters we have developed spare parts classification schemes with respect to inventory control and demand forecasting, in order to create a manageable number of control groups to focus management efforts more effectively. However, the developed classification scheme covers only one part of supply chain – it is focused on internal control factors. The controllability of spare parts also depends on external factors, like supplier performance. In Chapter 2 we have discussed the current planning and control of spare parts and we have concluded that there are no major issues with the supply link (e.g. supply management and spare parts order handling). For appropriate spare parts management the demand and supply link should be linked to each other. In the first chapter of this report we have introduced the problems with the logistics outsourcing relationship between KES and Sage which impedes the integration of the demand and supply link, that is, lack of information exchange and lack of shared understanding. Tsai, Lai, Lloyd and Lin (2012) reveal in their research that poor communication and lack of shared goals are the most significant reasons precipitating relationship risk (i.e. possibility of relationship failure). In the following sections we will discuss how relationship risk can be reduced by improving the communication, and by creating alignment between KES and Sage. More specifically, in Section 6.1.1 we will discuss how the information exchange between KES and Sage can be improved, and in Section 6.1.2 we will discuss how KES and Sage can create a shared understanding.

6.1.1 Information exchange

In Chapters 1 and 2 we have introduced the problems of the lack of information exchange between KES and Sage. Tsai et al. (2012) point out that for relationship risk, the presence of poor communications is the most important antecedent of the partner relationship, which in turn puts the involved parties at risk for their asset specific investments and service strategy development. Knemeyer and Murhpy (2004) explain that those firms desiring to establish closer long-term relationships between their firm and a logistics provider (i.e. Sage) in order to achieve possible benefits of this closeness (increased performance) should realize that they may need to establish managerial components (activities and processes that management establishes and controls) that demonstrate a higher level of trust toward their provider and/or facilitate more effective communication with their provider.

In this section we want to explain that the new classification schemes can also be used as managerial component for increasing the communication between KES and Sage. Unlike the current classification scheme based on the annual usage, one cannot just rely on historic demand data for the new classification schemes. More specifically, for appropriate classification based on the life cycle, KES has to inform Sage about the introduction of new parts, planned maintenance activities, modifications and redundancy. Further, given that the criticality analysis is among others based on information about the GSE vehicles and the maintenance types (that is, information that Sage does not have), KES has to perform the criticality analysis and provide Sage a list with the critical items, or KES should provide Sage the necessary information so that Sage can perform the criticality analysis. Both options require
information exchange. Further, in Chapter 2 about the current planning and control of spare parts we have also discussed that KES does not provide Sage sufficient reliability or even usage data (i.e. hours that the equipment is actually used), but Sage does understand that is difficult to provide such information because of the low volumes of similar equipment and the lack of resources that the GSE vehicle suppliers have. Sage believes it would be helpful if KES could develop at least a pre-defined maintenance kit for various service checks for the common and/or critical equipments types. It is possible to develop these kits, because KES has been working with such kits in the past. It is recommended to develop these kits and to provide them with a 30 day plan so that Sage can load this information into their demand system and pre-build the kits and have the parts waiting when the equipment comes in for the scheduled service. Sage points out that this would guarantee 100% availability as well as reduce the time it takes for Sage’s staff to pick the various items as they would be pre-kitted.

Further, Gadde and Hulthén (2009) express that in the short-term efficiency of the logistics outsourcing relationship is dependent on coordinated flow of information. They refer to Piplani, Pokharel and Tan (2004, pp. 40) who claim that for logistics service providers to be successful “[...] it would become imperative that they integrate [their information systems] with the IT-systems of their partners and customers in order to increase the effectiveness of the systems and to get the real value out of them”. Currently, Sage and KES are working on the integration of the IT-systems, which is thus a good initiative.

To sum up, the developed classification scheme(s) can be used to guide the information flow between KES and Sage, as it creates more awareness about the spare parts characteristics and it triggers the information exchange between KES and Sage. It is also important to further integrate the IT-systems of both parties.

6.1.2 Shared goals
Besides the lack of information exchange, we have also pointed out that there is lack of shared understanding because KES and Sage have no shared goals. Lack of shared goals reflects the contrast of organization cultures and goals that may impede successful interaction with the relocated function (Tsai et al., 2012). Differences in priorities between KES and Sage can trigger the onset of relationship risk. In order to create alignment between KES and Sage, they should focus on the end-customer (i.e. owner of the GSE fleet). Both parties have to realize the importance of a shared goal otherwise it might result in opportunistic behavior where KES’s goal is to pay as low as possible for Sage’s services, whereas Sage’s goal is to maximize the revenues. By joining forces, KES and Sage can work together to take costs out of the logistics system, mutually boost profitability, and improve service to the end customer. To assure that operations of KES and Sage are synchronized, information exchange is essential, as joint performance towards shared goals requires open disclosure (Knemeyer & Murphy, 2004).

Focusing on the end-customer impacts also the output related agreements in the contract – the goal is to reduce the GSE downtime. GSE downtime is lost time and lost money. In terms of spare parts management, one should aim for minimizing the number of hot orders, i.e. purchase request for a vehicle that is not operational due to the missing part. Reduction of the hot orders, results also in a reduction of the expensive GSE downtime. KES and Sage should consider to include the number of hot orders in the month end report and to set a target value for the number of hot orders. Note that the developed
classification scheme with respect to inventory control is useful for focusing on the end-customer. In Section 5.2.4 it has been shown that the real benefit of the criticality analysis is not the improvement over the current service levels, but rather the reduction of the number of hot orders. In other words, by making use of the criticality analysis one is more focused on what really matters for the end-customers – GSE availability.

Overall, we recommend creating common goals and compatible interests by focusing on the end-customer, to further improve the compatibility of the information systems, to frequently communicate and exchange information where the new developed classification scheme can serve as a trigger to exchange information. These measures should help bridging the gap between KES and Sage and reducing the relationship risk.

6.2 Logistics Outsourcing Scope & Activities

In the current situation, both demand forecasting and inventory control are outsourced to Sage. However, as we have argued, there are improvement possibilities with respect to both demand forecasting and inventory control. In this research we have developed spare parts classification schemes for demand forecasting and inventory control in order to improve demand forecasting and inventory control, respectively. Following from this research we recommend KES to reconsider the scope and the type of activities to be outsourced. The new classification schemes express that Sage is highly dependent on information from KES. With the current classification scheme based on annual usage this is not apparent, because Sage can rely just on historical demand data. KES should think about bringing demand forecasting and inventory control back in-house. By taking demand forecasting back in-house, KES can more easily use installed base information (e.g. usage data, preventive maintenance planning, redundancy of vehicles and modifications) for forecasting demand without being dependent on Sage.

Further, in terms of inventory control, KES should think about setting the base-stock levels by themselves. Sage has already asked KES to help them with setting appropriate base-stock levels. Moreover, KES has more knowledge about and expertise with the demand characteristics and the link with maintenance then Sage does. In order to benefit from this knowledge KES should consider setting the base-stock levels by themselves, whereas the actual procurement of parts can still be done by Sage.

Instead of also bringing the procurement back in-house, KES can benefit from Sage’s geographically widespread distribution network in the GSE parts marketplace and quantum discounts. Also, Sage minimizes the number of suppliers KES has to deal with. Further, in terms of inventory control KES can benefit from the fact that Sage is allowed to purchase KES Inventory from KES and sell it to other customers - for example parts that are not useful anymore because of a modification, can still be useful for Sage’s other customers. Recall that in the analysis of the current planning and control of spare parts we have pointed out that there are no major problems with respect to Sage’s procurement activities (e.g. supply management and spare parts order handling), and, therefore, there are no major reasons to doubt Sage’s procurement activities. To summarize, KES should think about bringing demand forecasting back in-house and set the base-stock levels by themselves, while procurement activities can be performed by Sage. Overall, we want to express that KES should consider focusing on the strategic side and let Sage focus on the executive side of spare parts management – Outsource the execution, not the management.
7 IMPLEMENTATION

In this chapter it will be described how the results of this master thesis project can be implemented in order to improve spare parts management at KLM Equipment Services. First, recommendations with respect to demand forecasting (7.1) and inventory control (7.2) will be given. Subsequently, it will be described how to update the developed classification schemes (7.3). This implementation plan can be used as a guideline by KES or Sage (depending on the outsourced activities – see the discussion in Section 6.2) to implement and use the developed classification schemes in the daily activities.

7.1 DEMAND FORECASTING

In this section we will describe how the results with respect to demand forecasting can be implemented in the daily activities. The first step of the plan is to determine the transition point between the initial and in-use phase of the life cycle, and between the in-use and decline phase. In Section 4.2.1 we have explained how to derive the transition points and in Appendix E we have explained how one can use Excel to determine the items in initial, in-use and decline phase. In this master thesis project it is explained how the different life cycle phases can be used to choose a forecasting approach. The following recommendations can be given with respect to demand forecasting:

- Initial phase: For the initial phase it is explained that the lack of an adequate length of demand history precludes the use of extrapolative time-series methods. Also, data about explanatory variables is limited. Important characteristics can still be estimated by comparing to technically similar parts. Further, it has been explained that KES is provided little information from the GSE vehicle suppliers about failures rates, reliability tests, degradation of parts, substitution, commonality, etc. Some suppliers do not provide RSLs or the RSLs contain limited information. KES should, at the introduction of a new GSE vehicle, put more effort on negotiating with the GSE suppliers on the supply of RSLs and reliability information.

- In-use phase: For the in-use phase it is explained that causal methods also have an important role, if data on explanatory variables is available. However, at this moment historical data for the explanatory variables, such as timing of preventive maintenance, usage rate or failure rate, is not valid or not available at all. In that case, it is more appropriate to use time-series methods. We have compared several time-series methods and recommended to use the TSB forecasting method. The value of the smoothing constants is depended on the intermittence of the demand. The demand intermittence can be calculated as explained in Appendix E. In Section 4.5 we have determined the optimal values for \( \alpha \) and \( \beta \); for non-intermittent items we have obtained \( \alpha = 0.05 \) and \( \beta = 0.04 \) and for intermittent items \( \alpha = 0.25 \) and \( \beta = 0.15 \). However, we have seen that there are also seasonal effects. The seasonal effects can be determined as explained in Section 4.3.3. In Appendix E it is explained how the seasonality effects can be calculated in Excel. Finally, in Appendix E we have explained how the demand can be forecasted according to the TSB forecasting in Excel.

- Decline phase: We have seen that the TSB method is able to forecast obsolescence. The TSB method can be used to determine the transition point between the in-use phase and the decline phase. However, in the decline phase it is required to make a last time buy from a supplier. Here,
it is recommended to use regression-based extrapolations have been recommended, assuming an exponential decline of demand. Example is a regression model on the logarithm of sales against time, assuming an exponential decline in demand over time.

Finally, given that KES does not want to rely only on historical demand data for forecasting demand, they should collect more data on explanatory variables and validate the data they have in order to generate forecasts using explanatory variables. The benefit of the causal/reliability based forecasting is that it can cope with changes in the installed base and varying operating decisions (Driessen et al., 2010). It is applicable in the initial, in-use and in the decline phase of the life cycle. KES should pay more attention to assortment management and gather parts (technical) information from the initial phase of a part’s life cycle instead of waiting till the in-use or decline phase.

7.2 INVENTORY CONTROL
Having forecasted the demand, the next step is inventory control. In this master thesis project we have developed a spare parts classification scheme in order to establish inventory decisions. Because of the lack of data about the cost structure and replenishment lead times, we could not develop and test inventory policies and parameters. However, we have used the different life cycle phases to guide the development of the inventory policies. We will therefore only shortly discuss inventory control on a strategic and/or tactical decision level:

- **Initial phase**: In the initial phase, when the part is introduced, there are two decisions: i) should the item be stocked and ii) if so, what are the initial stock requirements? The initial phase is characterized by a high number of new parts that are most probably needed for recently introduced vehicles. New parts for recently introduced vehicles require a high service level, which necessitates the satisfaction from stock even if the demand may be particularly low and sporadic. However, data-shortage does not allow the calculation of an effective safety stock.

- **In-use phase**: In the in-use phase, an inventory policy must be determined and the parameters estimated. If an Order-Up-To (OUT) policy is adopted, for example, then the Order-Up-To-Level must be calculated. The main benefit of the new classification scheme is the inclusion of the criticality factor which results in a lower number of hot orders. In Section 5.2 we have explained the criticality analysis and in Appendix E it is explained how to perform the criticality analysis in Excel. The criticality factor can be used to determine service level requirements. For critical parts with a low price safety stocks should be calculated. For critical parts with a high price Sage should set-up time-guaranteed supplies from established suppliers (Huiskonen, 2001).

- **Decline phase**: Based on the replenishment lead time one can make the decision whether to stock the part or not. If the replenishment lead time is smaller or equal to the supply lead time, it is not necessary to stock the part. For the parts that are currently stocked decisions should be made whether to dispose the items or not. 4118 Of the items are classified as decline, from which 1129 are still in stock, that is, more than 25% of the items in the decline phase. Furthermore, as the part nears the end of its life, suppliers may become reluctant to manufacture small volumes. In this decline phase, a decision must be taken on the size of a single order to cover all remaining demand (sometimes known as an “all time buy”).
In this master thesis project we have also discussed how to improve the outsourcing relationship between KES and Sage. In Section 6.2 we have explained that KES should consider bringing demand forecasting and inventory back in-house. However, if KES does not want to change the current outsourcing contract, they will have to increase the information exchange between KES and Sage as recommended in Section 6.1. More specifically, collect and provide Sage with installed base information, give them information about the maintenance timing, develop a pre-defined maintenance kit for various service checks for the common and/or critical equipments types, determine the criticality of spare parts and provide this information to Sage, inform Sage about changes in the installed base and operating conditions.

7.3 RECLASSIFICATION

Finally, the designed classification scheme for demand forecasting and inventory control needs to be updated during its application in order to allow for the re-classification of items. Figure 7.1 shows possible reclassification scenario’s for the classification scheme with respect to demand forecasting. An initial item (i.e. item in the initial phase of its life cycle) should move to the in-use phase after one year (the cut-off value between the initial and in-use phase is one year). The item should then be classified as sporadic, non-intermittent or intermittent. Figure 7.1 shows that a sporadic part in the in-use phase can become intermittent if there is more than one demand occurrence. An intermittent demand becomes an non-intermittent item if the average demand interval is smaller or equal to 1.32, whereas a non-intermittent part becomes an intermittent part if the average demand interval is larger than 1.32. At this moment, Sage analyzes the classification of items every three month. If KES decides to bring demand forecasting back in-house, they have to decide whether they will also use the 3-month review period or not. If KES decides to make also use of the 3-month review period, KES should check the intermittence of parts every three months. Figure 7.1 also shows that parts can become a decline part (i.e. part in the decline phase of the life cycle). Recall that only parts that have not been demanded in the past year will be considered appropriate for the decline phase. So KES/Sage can check once a year whether a part should be transferred to the decline phase. Note that parts can be earlier migrated to the decline phase if it is known that the parts will not be required anymore. Overall, we recommend setting the reclassification between initial, in-use and decline phase at once a year.

Also for the classification scheme for inventory control one should migrate initial parts to the in-use phase after one year, and if necessary in-use parts to the decline phase. In addition, the criticality analysis of spare parts should also be updated, but the criticality is not dynamic like the demand, and does not have to be updated too often. From a practical point of view, one can decide to update the criticality once a year, together with update of the life cycle phases. Note that after one year a part will migrate from the initial phase to the in-use phase. For these parts one will have to determine the criticality – one can at the same time update the criticality factor of all other items in the in-use phase.
Figure 7.1 Migration between the different spare parts classes with respect to demand forecasting
8 CONCLUSIONS AND RECOMMENDATIONS

This chapter first discusses the key conclusions of this master thesis project (8.1). Then, the limitations will be shortly discussed (8.2). Subsequently, the academic relevance will be explained (8.3). Finally, recommendations are given for both KES and for further research (8.4).

8.1 CONCLUSIONS

This section summarizes the main conclusions of this master thesis project, by giving answers to the research questions formulated in Chapter 3. The main research question as stated in Chapter 3 was:

“Can spare parts management at KLM Equipment Services be improved?”

This research question has been split in three sub-questions that are focused on demand forecasting, inventory control, and the logistics outsourcing contract between KES and Sage, respectively. The conclusions are structured accordingly:

- **Demand forecasting:** The sub-question regarding demand forecasting was formulated as follows: “How can we improve demand forecasting, such that it better captures the demand pattern of the spare parts?” Currently, all items are forecasted based on historical demand data, but KES would like to include also information about explanatory variables in the forecasts. However, in order to choose between specific forecasting approaches and methods, parts should first be classified with respect to demand forecasting (Driessen et al., 2010). First of all, one can use the life cycle to choose between forecasting approaches: causal or time-series. For items in the initial and decline phase of the life cycle phase it is recommended to use causal forecasting, because there is not sufficient data for time-series forecasting methods. For the in-use phase one can also use causal forecasting, but only if there is sufficient (valid) data on explanatory variables available. At this moment, there is not sufficient (valid) data about explanatory variables available, and one will have to rely on time-series methods. Items are further classified according to their intermittence in order to choose the most appropriate time-series method for items in the in-use phase.

Different time-series techniques specific for intermittent demand, i.e. Croston, ES, SBA and TSB, are initialized and compared to each other for items in the in-use phase of the life cycle. The results reveal that the TSB method is most appropriate for forecasting intermittent and non-intermittent items in the in-use phase. For sporadic items in the in-use phase it is more appropriate to use a reactive approach (i.e. order the part when it is requested) because the demand history is limited. Finally, we have tested the TSB method also for items in the decline phase of the life cycle. The results show that the TSB method is able to forecast obsolescence. To summarize, in this master thesis project we have shown that demand forecasting can be improved, such that it better captures the underlying demand pattern of spare parts by first classifying spare parts with respect to demand forecasting, and then, to choose appropriate forecasting approach(es) and method(s) for the resulting classes. The real benefit of the new approach can be determined by forecasting the demand according to the recommendations resulting from the classification scheme, and to use the forecasted demand for inventory control.
**Inventory control:** The subquestion regarding inventory control was formulated as follows: “*How can we improve the current classification scheme with respect to inventory control, such that it better captures the characteristics of the spare parts?*” At this moment, the inventory is classified according to only one criterion – annual usage. KES and Sage carry a large amount of items in stock. These items are highly heterogeneous, with differing costs, service requirements, and demand patterns. When it comes to spare parts inventory management, determining the importance of a spare part by annual usage is insufficient. The current classification scheme is first of all extended by the life cycle, because inventory decisions directly relate to a life cycle phase classification. By using the life cycle phase one creates more awareness for the provisioning decisions in the *initial* phase of the life cycle. Especially, given the fact that some GSE vehicle suppliers do not provide RSLs or the RSLs contain limited information. In the *in-use* phase the inventory policy and appropriate parameters must be determined. The inventory policies and parameters depend on forecasts of demand over lead-time. Here, the importance of choosing appropriate demand forecasting methods is expressed – demand forecasting impacts the accuracy of the inventory policies. Finally, classification scheme based on the life cycle creates also more awareness about the final order decisions and the obsolescence issue.

Besides the life cycle phase, another important extension of the current classification scheme is the inclusion of the criticality criterion. The classification scheme is not anymore based on only historical demand data, because the criticality analysis includes also information about the maintenance type, vehicle and the part. A test, on a rather small sample of 4 months, shows that the inclusion of the criticality criterion does not improve the service levels much, but it does reduce the number of hot orders by 10%. Further, the criticality classification can be used to support decisions about service level requirements - critical parts should be fulfilled immediately and otherwise as soon as possible. Overall, we have shown in this master thesis project that the current classification scheme with respect to inventory control can be improved, such that it better captures the underlying demand pattern of spare parts by the design of a hierarchical multiple-criteria classification scheme with respect to inventory control, including the life cycle phase and a criticality analysis.

**Logistics outsourcing:** The subquestion regarding the logistics outsourcing was formulated as follows: “*How can we improve the logistics outsourcing performance?*” Currently, there is a gap between KES and Sage, because there is insufficient information exchange and there is a lack of shared understanding. In order to improve the logistics outsourcing relationship KES and Sage should focus on the end-customer – the focus should be on reducing the GSE vehicle downtime instead of focusing on self-centered goals. Unlike the current classification scheme, the new classification schemes create a higher awareness of spare parts characteristics and their effect on demand forecasting and/or inventory control. For appropriate classification based on the life cycle, KES has to inform Sage about the introduction of new parts, planned maintenance activities, modifications and redundancy. Given that the criticality analysis is among others based on information about the vehicle and maintenance types (that is, information that Sage does not have), KES has to perform the criticality analysis and provide Sage a list with the critical items, or
KES should provide Sage the necessary information so that Sage can perform the criticality analysis. In other words, the new classification scheme can be seen as a trigger for improving the information exchange. The current one-dimensional classification scheme based on annual usage does not trigger KES and Sage to exchange information about those aspects.

KES should also consider taking demand forecasting and inventory control back in-house. The new classification schemes express that Sage is too much depended on information from KES. With the current classification scheme based on annual usage this was not apparent, because for Sage it was sufficient to rely on historical demand data. The new classification schemes show it is not sufficient to just rely on historical demand data – it requires also installed base information, and therefore more information exchange between KES and Sage. KES should consider focusing on the strategic side and let Sage focus on the executive side of spare parts management – *outsourcing the execution, not the management*.

By referring back to the main research question we can now conclude that is possible to improve spare parts management by adopting a structured approach for both demand forecasting and inventory control, and by improving the logistics outsourcing performance. This master thesis project has shown the benefits of a structured approach for dealing with the considerable number of heterogeneous items. However, the developed classification schemes are only a starting point for making strategic and tactical decisions. The next step is to choose inventory policies and parameters for each class resulting from the classification scheme with respect to demand forecasting. The inventory policies and parameters depend on forecasts of demand over lead-time. In other words, the accuracy of inventory policies and parameters is influenced by the used demand forecasting methods. The classification scheme with respect to demand forecasting can be used to choose appropriate forecasting methods. Only then one can measure the real benefit of the classification schemes – that is, by integrated the outcomes of spare parts classification, demand forecasting and inventory control.

### 8.2 LIMITATIONS

Several limitations can be recognized in this master thesis project:

- The main limitation is that is not known how Sage exactly forecasts the demand. We only know that Sage’s forecast is for 100% based on historical demand data. Given that we do not know the exact forecasting method, we were not able to compare the time-series forecasting method that we proposed, that is, the TSB method, to the current time-series forecasting method(s).
- Another important limitation is the lack of necessary data. No information was available about the cost structure, supply and replenishment lead times. Since KES only recently started with the collection of supply lead time information, we had only useful supply lead time information from 01-11-2011 till now, whereas no information was available about the cost structure and the replenishment lead times.
- Given that we did not have any information about the replenishment lead times and the cost structure, we could not analyze the performance of appropriate inventory policies. Furthermore, we did not have any information about the inventory policies that Sage applies.
A limitation of the classification scheme with respect to inventory control is the lack of information about the supply and/or replenishment lead time. Lead time information is useful for making stock-non stock decisions.

Note that the selected criteria for the criticality analysis are measures of process criticality, whereas control criticality is neglected. Again, there was not sufficient data available to include a factor for control criticality, like the number of available suppliers for a part, etc.

In this master thesis project we have tried to evaluate the new classification scheme by comparing it to the current classification scheme for inventory control (see Section 5.3). For this evaluation we have used demand data from 2011, but this data did not contain information about the actual classification of spare parts in 2011 (i.e. we did not know whether an item was a A, B-, C or D-item during 2011). Therefore, we have “simulated” Sage’s classification scheme by following Sage’s classification rules for A-, B-, C- and D-items.

8.3 ACADEMIC RELEVANCE
Aspects about spare parts management that were only limited addressed in the literature, but that were discussed in more detail in this master thesis project, are as follows:

- Bacchetti and Saccani (2011) suggest that research should devote great effort to evaluate how complex quantitative models for spare parts management can be taken into practice. They encourage the use of case study methods for this purpose, as well as to facilitate the transferability of the developed solutions. This master thesis project can be seen as case study for this purpose.

- Teunter et al. (2011) have recently suggested a new forecasting procedure (i.e. TSB method) that links naturally to the issue of inventory obsolescence. The performance of this method was assessed through an extensive simulation study on theoretically generated data and it was shown to compare very well to the other methods discussed in the literature. However, this method has never been evaluated on a real dataset. The empirical results in this project with regards to MSE allowed us to gain some insight into the methods’ performance. Furthermore, Teunter et al. (2011) suggest that an important avenue for further research is to empirically test the performance of TSB against that of other methods. In this project we have compared the TSB method to exponential smoothing, Croston and the SBA method. Again, the empirical results give some insight into the methods’ performance compared to other methods.

- One of the classification criteria for classifying spare parts with respect to inventory control is item criticality. Item criticality, has been recognized in literature, but is not well defined and certainly no consensus has been reached for measuring it (see for a discussion Molenaers et al., 2011). Evaluating the criticality of items is not an easy task because various characteristics can have an impact on the degree of criticality. In order to effectively deal with this multi-criteria problem, we have proposed a combined methodology in this master thesis project. The model presents the multi-criteria classification problem in a logic decision diagram where a multiple-attribute decision model (DEA model) is proposed to solve the multi-criteria decision problems at decision nodes of the diagram. The basic idea is to develop a decision diagram, which guides the analyst towards the best criticality class of a spare part.
8.4 RECOMMENDATIONS
This section can be split into two sections, namely recommendations for KES, but also for Sage, and then, recommendations for further research.

The following recommendations can be made for KES and Sage:

- In this report we have presented a classification with respect to demand forecasting and explained how one can use the classification scheme in order to choose a forecasting approach and method. In the initial phase one can estimate important characteristics by comparing to technically similar parts. It is recommended to use the TSB method for forecasting demand for items in the in-use phase. For the decline phase one could for example use a regression model on the logarithm of sales against time, assuming an exponential decline in demand over time. Next, we have presented a classification scheme for inventory control and shortly discussed an inventory strategy for each class. However, because of the lack of data about the cost structure and the replenishment lead times, we could not calculate and compare inventory policies and parameters. It is recommended to determine and compare suitable inventory policies and parameters for each class resulting from the classification scheme with respect to inventory control as soon as one has the necessary data. The real benefit of the developed classification schemes can be tested by using the forecasted demand and standard deviation (forecasted according to the classification scheme with respect to demand forecasting) for determining the inventory parameters.

- Given that KES does not want to rely only on historical demand data for forecasting demand, they should collect more data on explanatory variables and validate the data they have in order to forecasts using explanatory variables. The benefit of the causal/reliability based forecasting is that it can cope with changes in the installed base and varying operating decisions (Driessen et al., 2010). It is applicable in the initial, in-use and in the decline phase of the life cycle. KES should pay more attention to assortment management and gather parts (technical) information from the initial phase of the life cycle instead of waiting till the in-use or decline phase.

- In Appendix C it has been shown that a considerable number of hot orders is linked to parts required for repairs and breakdowns. KES should consider increasing the number of preventive maintenances in order to reduce the number of corrective maintenance (i.e. repairs and breakdowns), and thus, the number of hot orders. Also, a high number of hot orders are linked to parts required for damage repair. It is not possible to predict damages, but this issue does require more attention. The damages are not only caused in maintenance shop, but also on the platform where the vehicles are used by the end-customers. KES should therefore discuss with end-customers the need for better prevention of damages.

- If KES wants to continue as in the current situation, it is recommended to reconsider at least the current KPIs. As is discussed in this master thesis project, Sage’s performance seems perfect with the current KPIs. In Table 2.1 we have seen that the service levels decrease as the demand for an item decreases. Furthermore, the table shows that the required supply lead time also decreases as the demand decreases. For example, D-items have to be successfully filled at 65% within seven business days. It is no surprise that Sage has a high performance, because both the required
service levels and supply lead times decline as the demand declines. The current KPIs do not provide sufficient insight in Sage’s actual performance. We recommend to eliminate the supply lead time restrictions, and to use only the required fill rates. The modified KPIs are presented in Table 8.1. Further, consider introducing a target value for the GSE downtime in order to increase the focus on the end-customer.

<table>
<thead>
<tr>
<th>Classes</th>
<th>Usage</th>
<th>KPIs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class A</td>
<td>24+ units per year</td>
<td>Immediate fill 99%</td>
</tr>
<tr>
<td>Class B</td>
<td>12-23 units per year</td>
<td>Successful fill at 95%</td>
</tr>
<tr>
<td>Class C</td>
<td>4-11 units per year</td>
<td>Successful fill at 80%</td>
</tr>
<tr>
<td>Class D</td>
<td>1-3 units per year</td>
<td>Successful fill at 65%</td>
</tr>
<tr>
<td>Class E</td>
<td>Manually controlled products with product/min/max levels</td>
<td></td>
</tr>
<tr>
<td>Class N</td>
<td>New products for the reporting location</td>
<td></td>
</tr>
</tbody>
</table>

*Table 8.1 Modified Sage classification with KPIs*

- In the criticality analysis we have used the GSE criticality as a classification criterion. However, there were mixed signals about the criticality of a particular GSE vehicle. We recommend to create more agreement about the GSE criticality, and to discuss together with fleet management and end-customers which GSE vehicles are really critical.
- In the analysis of the current planning and control it has been concluded that parts return forecasting is not a big issue, nor is repair shop control, because the number of returned and repaired items is limited. In the future, KES should consider looking more conscious to parts return and repair shop. At this moment both parts return and repair shop are not structurally managed and controlled. Lack of parts returns forecasting and (indirectly) repair shop control impacts inventory control negatively, because parts are “randomly” returned and repaired. The lack of parts return forecasting influences also inventory control as it might lead to obsolescence.

*The following recommendations can be made for further scientific research:*

- By using separate smoothing constants for the demand probability and demand size, the TSB forecasting method can be “tuned” for demand processes with different (suspected) levels of non-stationarity. Empirical investigation confirmed that the TSB method is suitable for situation with both stationary and non-stationary demand. However, further research on what values to use for the smoothing constant is still required. Moreover, further research should lead to recommendations on what values to use under which circumstances.
- From a methodological point of view, unlike a simple ABC-approach, multi-criteria classifications models allow for the consideration of the specificity of a company’s environment. However, this does raise issues related to their generalization and applications in different contexts. Further research should analyze the trade-offs between various possible approaches for classifying spare parts.
- Finally, it would be interesting to assess the relevance of the classification criteria proposed in this project in similar companies, smaller/bigger companies, or other industrial contexts.
REFERENCES


LIST OF ABBREVIATIONS

ADI    Average Demand Interval
CR     Croston
CV²    squared Coefficient of Variation of the demand sizes
GSE    Ground Support Equipment
ES     Exponential Smoothing
KES    KLM Equipment Services
RM     Rode Meldingen
RSL    Recommended Supplier List
SBA    Syntetos–Boylan Approximation
TSB    Teunter-Syntetos-Babai
### List of Definitions

<table>
<thead>
<tr>
<th>Term</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Erratic demand</td>
<td>Demand is (highly) variable, where the erratic nature relates to the size of demand rather than to the demand per unit time period.</td>
</tr>
<tr>
<td>Fast demand</td>
<td>Demand occurs at random, with many time periods having no demand. Demand, when it occurs, is for single or very few items.</td>
</tr>
<tr>
<td>Hot order</td>
<td>Purchase request for a vehicle that is not operational due to the missing part.</td>
</tr>
<tr>
<td>Intermittent</td>
<td>High average inter-demand interval (low demand frequency)</td>
</tr>
<tr>
<td>Job card code</td>
<td>Type of order</td>
</tr>
<tr>
<td>Lumpy demand</td>
<td>Demand occurs at random, with many time periods having no demand. Moreover, demand, when it occurs, is (highly) variable</td>
</tr>
<tr>
<td>Non-intermittent</td>
<td>Low average inter-demand interval (high demand frequency)</td>
</tr>
<tr>
<td>Rode melding</td>
<td>Part that it is not on stock when requested</td>
</tr>
<tr>
<td>Slow demand</td>
<td>Demand is random, with many time periods having no demand.</td>
</tr>
<tr>
<td>Sporadic</td>
<td>Very high average inter-demand interval (only one demand occurrence)</td>
</tr>
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APPENDIX A: CLASSIFICATION CRITERIA

In this appendix we will discuss the results of a literature study about spare parts classification criteria (Velagić, 2012). The literature study shows that traditionally, classification of spare parts is based on a single criterion. However, most papers propose using multiple criteria (e.g. Flores & Whybark, 1987; Partovi & Burton, 1993; Ramanathan, 2006; Ng, 2007, Zhou & Fan, 2007; Petrovic & Petrovic, 1992). Bacchetti and Saccani (2011) show in their literature review that the most applied criteria for classifying spare parts are parts criticality and parts costs/price (e.g. Duchessi, Tayi & Levi, 1988; Porras & Dekker, 2008; Zhou & Fan, 2007). Other frequently applied criteria for spare parts classification are amongst others the demand (e.g. Porras & Dekker, 2008; Zhou & Fan, 2007; Syntetos, Keyes & Babai, 2009), different supply characteristics, e.g. certainty of supply and lead time (e.g. Persson & Saccani, 2009; Zhou & Fan, 2007; Ng, 2007), and demand variability (e.g. Cavalieri, Garetti, Macchi & Pinto, 2008; Yamashina, 1989). Other criteria that are proposed by fewer studies are part life cycle phase (e.g. Persson & Saccani, 2009; Yamashina, 1989), specificity (e.g. Huiskonen, 2001), and reliability (e.g. Yamashina, 1989).

The Table A.1 shows the criteria that have been suggested and/or used for a policy in scientific articles. The disadvantage of using multiple criteria for classification is that it becomes more difficult to optimize, and to implement the classification system (Syntetos et al., 2009). It is a balance between precision and adequacy, and comprehension and simplicity. If all criteria are applied, the model will get enormous and impracticable. However, if some criteria are not taken into account, it could lead to suboptimal solution. Thus, one should find the right balance between classification adequacy and the ease of implementation. The criteria that can be applied for the classification of KES’s spare parts depend on several factors. Some criteria can be combined with other criteria, like demand volume and demand variability. Further, some criteria might not be interesting with regard to availability, and the costs. Moreover, some criteria may create different classifications, but that does not immediately means that one will have to apply different policies for these classes. The table can be used to choose the most promising criteria for classifying the spare parts. As one can see, criteria that are frequently reported are the value, criticality, supply characteristics, demand volume, and demand variability (Bacchetti & Saccani, 2011). Other criteria that are less frequently reported (see last column of the table), but that also could be considered for the classification of spare parts are specificity, life cycle phase, and repair efficiency.
<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Year</th>
<th>Classification criteria employed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Value</td>
</tr>
<tr>
<td>Braglia et al.</td>
<td>2004</td>
<td>X</td>
</tr>
<tr>
<td>Cavalieri et al.</td>
<td>2008</td>
<td>X</td>
</tr>
<tr>
<td>Duchessi et al.</td>
<td>1988</td>
<td>X</td>
</tr>
<tr>
<td>Flores et al.</td>
<td>1988</td>
<td>X</td>
</tr>
<tr>
<td>Gajpal et al.</td>
<td>1994</td>
<td>X</td>
</tr>
<tr>
<td>Huiskonen</td>
<td>2001</td>
<td>X</td>
</tr>
<tr>
<td>Ng</td>
<td>2007</td>
<td>X</td>
</tr>
<tr>
<td>Partovi et al.</td>
<td>2002</td>
<td>X</td>
</tr>
<tr>
<td>Persson et al.</td>
<td>2009</td>
<td>X</td>
</tr>
<tr>
<td>Petrovic et al.</td>
<td>1992</td>
<td>X</td>
</tr>
<tr>
<td>Porras et al.</td>
<td>2008</td>
<td>X</td>
</tr>
<tr>
<td>Ramanathan</td>
<td>2006</td>
<td>X</td>
</tr>
<tr>
<td>Syntetos et al.</td>
<td>2009</td>
<td>X</td>
</tr>
<tr>
<td>Yamashina</td>
<td>1989</td>
<td>X</td>
</tr>
<tr>
<td>Zhou et al.</td>
<td>2006</td>
<td>X</td>
</tr>
</tbody>
</table>

Table A.1 Classification criteria employed (from Bacchetti & Saccani, 2011, pp. 3)
Appendix B: Seasonality

This appendix assesses the seasonality of the demand. In Chapter 1 we have stated that maintenance activities, and thus the need for spare parts, are affected by seasonal factors. The number of corrective maintenance activities is higher during the Fall/Winter period (de-icers are for example only operated during the Winter) than during Spring/Summer period. To illustrate this effect, Figures B.1, B.2 and B.3 show time-series, for all parts demanded between 2007 and 2011, on a yearly, monthly, and daily level, respectively. Figure B.2 shows that each year the demand is lowest during May, June and July, the demand is increasing between December and March, the highest demand is obtained during March, and the demand decreases again after March. This confirms the information obtained from the interviews: high demand during the Fall/Winter period and low demand during the Spring/Summer period. Thus, we can conclude that there are indeed seasonal effects and demand forecasts will have to be adjusted for seasonality. Note that all three figures also show an upward trend – increasing demand over time. Given that the TSB method is able to forecast non-stationary demand, this is not an issue.

![Figure B.1 Seasonality analysis - yearly level](image-url)
Figure B.2 Seasonality analysis - monthly level

Figure B.3 Seasonality analysis - daily level
APPENDIX C: LIFE CYCLE PHASE

In this appendix the benefits of the life cycle criterion will be shown by making use of available demand data of the first four months of 2012. We use only these four months, because only the most recent demand data contains information about the “rode meldingen” (RMs) and hot orders which we want to use to analyze the benefits. The first column of Table C.1 shows the different classes that we have identified in the demand data from 2012. As one can, we have added the class “New 2012”. Those are items that have not been demand during 2007-2011 – the demand history data that we have used for classifying the items according to the life cycle phases. Most “New 2012”-items are items that have not been asked before, except for a few very sporadic items for which we do not have any information. Further, we have separated the sporadic items from the remaining in-use items. As one can see, more than 80% of the demand is in the in-use phase. However, more than 50% of the RMs and hot orders are linked to new parts. This high number of RMs and hot orders can be explained by the demand unpredictability of new parts. Furthermore, in the literature study it has been pointed out that the spare parts life cycle follows the vehicle life cycle. We have added the 6th, 7th and 8th column to check whether the RMs are linked to vehicles that are younger than two years. However, the last column shows that only 5% of the RMs can be linked to “new” vehicles.

<table>
<thead>
<tr>
<th>Class</th>
<th>Demand</th>
<th>#Rood</th>
<th>#Hot orders</th>
<th>KPI</th>
<th>Vehicle age &lt; 2 yr</th>
<th>#Rood</th>
<th>% of total</th>
</tr>
</thead>
<tbody>
<tr>
<td>New 2012</td>
<td>1201</td>
<td>493</td>
<td>323</td>
<td>58,95</td>
<td>196</td>
<td>23</td>
<td>4,67</td>
</tr>
<tr>
<td>Initial</td>
<td>1121</td>
<td>196</td>
<td>136</td>
<td>82,52</td>
<td>73</td>
<td>11</td>
<td>5,61</td>
</tr>
<tr>
<td>Sporadic</td>
<td>296</td>
<td>106</td>
<td>75</td>
<td>64,19</td>
<td>6</td>
<td>2</td>
<td>1,89</td>
</tr>
<tr>
<td>Decline</td>
<td>149</td>
<td>24</td>
<td>21</td>
<td>83,89</td>
<td>2</td>
<td>0</td>
<td>0,00</td>
</tr>
<tr>
<td>In-use</td>
<td>13800</td>
<td>497</td>
<td>308</td>
<td>96,40</td>
<td>318</td>
<td>6</td>
<td>1,21</td>
</tr>
<tr>
<td>Total</td>
<td>16567</td>
<td>1316</td>
<td>863</td>
<td>92,06</td>
<td>595</td>
<td>42</td>
<td>3,19</td>
</tr>
</tbody>
</table>

*Table C.1 Distribution of items among the life cycle phases*

To get more insight in the relative high number of hot orders for new spare parts, we have analyzed the number of RMs and hot orders among the different job cards codes (i.e. type of order). The different job card codes and their description are given in Table C.2.

<table>
<thead>
<tr>
<th>Job card</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>B</td>
<td>Banden</td>
</tr>
<tr>
<td>C</td>
<td>Claim</td>
</tr>
<tr>
<td>E</td>
<td>Error by operator</td>
</tr>
<tr>
<td>H</td>
<td>Damage repair</td>
</tr>
<tr>
<td>I</td>
<td>Inspection</td>
</tr>
<tr>
<td>L</td>
<td>Lekkage</td>
</tr>
<tr>
<td>O</td>
<td>Modification</td>
</tr>
<tr>
<td>R</td>
<td>Repair</td>
</tr>
<tr>
<td>T</td>
<td>Fuelling</td>
</tr>
<tr>
<td>S</td>
<td>Breakdown</td>
</tr>
<tr>
<td>X</td>
<td>Runner service</td>
</tr>
</tbody>
</table>

*Table C.2 Job card description*
Note that part of the items has no job card code at all. To get insight of the number of orders distributed among the different job cards, we show in Table C.3 the number of orders for the different classes among the most frequent job cards.

<table>
<thead>
<tr>
<th>Class</th>
<th>Usage</th>
<th>#Rood</th>
<th>#Hot orders</th>
<th>Modification</th>
<th>Inspection</th>
<th>Reparation</th>
<th>Breakdown</th>
<th>Damage</th>
</tr>
</thead>
<tbody>
<tr>
<td>New</td>
<td>1201</td>
<td>493</td>
<td>323</td>
<td>123</td>
<td>31</td>
<td>230</td>
<td>412</td>
<td>145</td>
</tr>
<tr>
<td>Initial</td>
<td>1121</td>
<td>196</td>
<td>136</td>
<td>240</td>
<td>29</td>
<td>189</td>
<td>362</td>
<td>107</td>
</tr>
<tr>
<td>Sporadic</td>
<td>296</td>
<td>106</td>
<td>75</td>
<td>18</td>
<td>6</td>
<td>65</td>
<td>129</td>
<td>38</td>
</tr>
<tr>
<td>Decline</td>
<td>149</td>
<td>24</td>
<td>21</td>
<td>7</td>
<td>8</td>
<td>45</td>
<td>56</td>
<td>16</td>
</tr>
<tr>
<td>In-use</td>
<td>13800</td>
<td>497</td>
<td>308</td>
<td>668</td>
<td>3249</td>
<td>3401</td>
<td>3303</td>
<td>1446</td>
</tr>
<tr>
<td>Total</td>
<td>16567</td>
<td>1316</td>
<td>863</td>
<td>1056</td>
<td>3323</td>
<td>3930</td>
<td>4262</td>
<td>1752</td>
</tr>
</tbody>
</table>

Table C.3 Distribution of the number of orders among the job card codes

Table C.4 shows the performance for the most frequent job cards – modification, inspection, reparation, breakdown, and damage repair. In the following discussion we will refer to “new” parts as parts that are totally new, but also to parts in the initial phase of the life cycle. First of all, as one can, half of the RMs for the modification job cards which are linked to new parts are hot orders – that is, half of the vehicles has to wait for the new item to be delivered before any modifications can be done. Given that modifications can be planned in advance, the number of RMs and, therefore, also the number of hot orders, can be reduced by careful planning, and by communicating the planned modifications and necessary spare parts, timely to Sage. Further, Table C.4 shows that the number of RMs and hot orders for inspections are rather small. This is according to the expectations, because inspection job cards mainly consist of preventive maintenance activities, if the BK is appropriately assigned. However, as one can see, most “hot orders” are linked to reparations and breakdowns, that is, corrective maintenance activities. More than 50% of the RMs is a hot order. We have already seen that the number of hot orders for new items is not much influenced by the introduction of new vehicles. The hot orders are rather caused by vehicles that are already in-use for some time. The high number of hot orders expresses the need for more preventive maintenance activities. Finally, from the last column one can see that almost 50% of the RMs for damage repair results in a hot order. It is not possible to predict damages, but the high number of RMs does express the need for paying more attention on this issue. Overall, we can conclude that the life cycle phase does a good job in classifying the spare parts; it is helpful in understanding the underlying demand pattern and the cause of RMs and hot orders.

<table>
<thead>
<tr>
<th>Job card</th>
<th>Modification</th>
<th>Inspection</th>
<th>Reparation</th>
<th>Breakdown</th>
<th>Damage repair</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class</td>
<td>#Rood</td>
<td>#Hot</td>
<td>#Rood</td>
<td>#Hot</td>
<td>#Rood</td>
</tr>
<tr>
<td>New</td>
<td>34</td>
<td>16</td>
<td>17</td>
<td>10</td>
<td>105</td>
</tr>
<tr>
<td>Initial</td>
<td>9</td>
<td>5</td>
<td>4</td>
<td>10</td>
<td>47</td>
</tr>
<tr>
<td>Sporadic</td>
<td>7</td>
<td>4</td>
<td>2</td>
<td>0</td>
<td>29</td>
</tr>
<tr>
<td>Decline</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>In-use</td>
<td>33</td>
<td>8</td>
<td>21</td>
<td>13</td>
<td>151</td>
</tr>
</tbody>
</table>

Table C.4 Distribution of RMs and hot orders among the BK codes
APPENDIX D: DEMAND FORECASTING

In Section 4.5 we have analyzed the performance of the SBA, Croston, ES and TSB forecasting methods for intermittent and non-intermittent demand. In order to test the benefit of the TSB method compared to the other methods, we have also analyzed the ME and MSE performance of the different estimators for sporadic and declining parts. Tables D.1, D.2, D.3, and D.3 show the ME and MSE performance for sporadic and declining demand, respectively. The TSB method outperforms the other methods for both decline and sporadic demand. Only ES outperforms the TSB method for decline items in terms of bias. This analysis confirms that the TSB method is able to deal with non-stationary demand and to forecast obsolescence.

<table>
<thead>
<tr>
<th>Estimator</th>
<th>$\alpha$ smoothing constant - ME</th>
<th>$\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>SBA</td>
<td>0.021366 0.020048 0.018731 0.017413 0.016096 0.014778</td>
<td></td>
</tr>
<tr>
<td>Croston</td>
<td>0.007871 0.006869 0.005867 0.004865 0.003863 0.002861</td>
<td></td>
</tr>
<tr>
<td>ES</td>
<td>0.004151 0.003151 0.002151 0.001151 0.000151</td>
<td>0.000151</td>
</tr>
<tr>
<td>TSB</td>
<td>0.011040 0.009048 0.007046 0.005046 0.003046 0.001046</td>
<td></td>
</tr>
</tbody>
</table>

Table D.1 ME results for sporadic items

<table>
<thead>
<tr>
<th>Estimator</th>
<th>$\alpha$ smoothing constant - MSE</th>
<th>$\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>SBA</td>
<td>0.556294 0.554684 0.553044 0.551482 0.549964 0.548488</td>
<td></td>
</tr>
<tr>
<td>Croston</td>
<td>0.548223 0.546621 0.545023 0.543425 0.541827 0.540229</td>
<td></td>
</tr>
<tr>
<td>ES</td>
<td>0.545794 0.544196 0.542698 0.541199 0.539692 0.538194</td>
<td></td>
</tr>
<tr>
<td>TSB</td>
<td>0.537718 0.536119 0.534521 0.532923 0.531325 0.529728</td>
<td></td>
</tr>
</tbody>
</table>

Table D.2 MSE results for sporadic items
### Table D.3 ME results for declining items

<table>
<thead>
<tr>
<th>Estimator</th>
<th>$\alpha$ smoothing constant</th>
<th>$\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>SBA</td>
<td>0.05 0.10 0.15 0.20 0.25 0.30</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.142116 0.137926 0.133802 0.129699 0.12561 0.121541</td>
<td></td>
</tr>
<tr>
<td>Croston</td>
<td>0.14606 0.145802 0.1456 0.145411 0.145226 0.145055</td>
<td></td>
</tr>
<tr>
<td>ES</td>
<td>0.088567 0.058761 0.04229 0.03248 0.026191 0.021889</td>
<td></td>
</tr>
</tbody>
</table>

### Table D.4 MSE results for declining items

<table>
<thead>
<tr>
<th>Estimator</th>
<th>$\alpha$ smoothing constant</th>
<th>$\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>SBA</td>
<td>0.05 0.10 0.15 0.20 0.25 0.30</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.311348 0.298244 0.286026 0.273316 0.260095 0.246803</td>
<td></td>
</tr>
<tr>
<td>Croston</td>
<td>0.324591 0.324634 0.325515 0.325589 0.324614 0.322949</td>
<td></td>
</tr>
<tr>
<td>ES</td>
<td>0.168028 0.119963 0.10041 0.090629 0.085218 0.088217</td>
<td></td>
</tr>
<tr>
<td>TSB</td>
<td>0.131335 0.13115 0.130876 0.130555 0.130216 0.129875 0.11713</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.118455 0.118299 0.118053 0.11776 0.117446 0.11713 0.102</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.107237 0.107106 0.106886 0.106617 0.106326 0.106031 0.03</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.097446 0.097338 0.097139 0.096891 0.096621 0.096346 0.04</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.059257 0.05923 0.059119 0.05896 0.058776 0.058583 0.01</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.04287 0.042872 0.0428 0.042682 0.04254 0.042387 0.01</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.033091 0.033113 0.033064 0.032973 0.032858 0.032732 0.02</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.026846 0.026846 0.026813 0.02674 0.026643 0.026535 0.025</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.022513 0.022552 0.022529 0.022469 0.022386 0.022291 0.03</td>
<td></td>
</tr>
</tbody>
</table>
APPENDIX E: IMPLEMENTATION

In this appendix we will explain how one can determine the life cycle phases, calculate the intermittence of demand, calculate the seasonality effects, forecast by making use of the TSB method and perform a criticality analysis in Excel.

LIFE CYCLE PHASE
An example of how to determine the life cycle phases is given in the spreadsheet “Status.xlsx”. In this example we have determined the life cycle phases based on the demand between 2007 and 2011 as explained in Section 4.2. Note that we have assumed that the current date is 01-01-2012. The worksheet “Parts” shows per item number the total quantity demanded per month during 2007-2011. The life cycle phase of the item is determined by the variable Status, where “N” (i.e. new) stands for items in the initial phase of the life cycle, “SPO” (i.e. sporadic) are sporadic items in the in-use phase of the life cycle, “U” (i.e. use) stands for items in the in-use phase, and both “SD” (i.e. sudden decline) and “D” (i.e. decline) stand for items in the decline phase of the life cycle. Recall that an item can only be in the initial phase of the life cycle if it is for first time demanded in the past year. In order to check this, we have added an additional variable to determine whether an item is “N” or “SPO”, that is, the variable Check. This variable calculates the number of days between the date that the price is set and one year before the current date. In the used example this is 01-01-2011, because we have assumed that the current data is 01-01-2012.

DEMAND PATTERN
The spreadsheet “Demand pattern.xlsx” shows for items in the in-use phase (except for sporadic items) how to determine the demand pattern as explained in Section 4.2. The worksheet “Demand pattern” shows per item number the total quantity demanded per month during 2007-2011. The demand pattern can be calculated as follows:

1. Use the variable $N$ to calculate the number of positive demand occurrences.
2. Use the variable Seasonality to check how many years have passed since the first positive demand occurrence.
3. Use the variable Interval to calculate the interval between the first year with a positive demand occurrence and the last demand occurrence.
4. Use the variable $ADI$ to calculate the average inter demand interval. $ADI$ is calculated as follows: $ADI = N / \text{Interval}$.
5. Use the variable Intermittence to check whether it is an intermittent or non-intermittent item.
6. Use the variable $CV^2$ if you want to check the variability of the demand.
7. Use the variable Pattern if you want to check whether an item is slow, lumpy, fast or erratic.

SEASONALITY
The spreadsheet “Forecasting in-use.xlsx” shows an example for calculating the seasonality effects based on the demand data between 2007 and 2011. The worksheet “Seasonality Int.” shows how to calculate the seasonality effects for intermittent items in the in-use phase, and the worksheet “Seasonality Non-Int.” shows how to calculate the seasonality effects for non-intermittent items in the in-use phase. The
principle is the same, only the used data is different. The seasonality effects are calculated as explained in Section 4.3.3. In order to explain the worksheet, we will refer to the used colors in the header row.

1. The columns with a gray header row show the total demand for each item during the past 60 months (2007-2011). Use the variable *Seasonality* to check how many years have passed since the first positive demand occurrence, because the calculation of the seasonality effect will be based on the number of “available seasons”.

2. Use the columns with a yellow header row to estimate the trend point for any particular month $t$ by a moving average of a full season (that is, 12 months) centered at period $t$. Given that the we have an even number of periods, $P = 12$, the standard 12-period moving average ends up being centered between two periods, and not right at the middle of a period as desired. Therefore, we will take the average of two consecutive moving averages.

3. Use the columns with a blue header row to estimate the seasonal factor for any particular period $t$ by dividing the demand (from the columns with a grey header row) by the centered moving average (from the columns with a yellow head row).

4. Use the columns with a red header row in order to dampen the random effect by averaging the seasonal factors for similar periods in different years.

5. Silver et al. (1998) express that the averages need not add up to exactly 12. Use the columns with a pink header row in order to normalize the columns with a red header row. One obtains estimates of seasonal factors that add up to 12. So the columns with a pink header row show for each item the seasonal factors for each month.

6. Finally, the columns with a green header row show the de-seasonalized demand from the columns with a grey header row. The de-seasonalized demand can be used to forecast future demand.

**TSB method**

The spreadsheet “Forecasting in-use.xlsx” shows an example for demand forecasting according to the TSB method. The worksheet “Int. deseasonalized” shows how to forecast the demand for intermittent items in the *in-use* phase, and the worksheet “Non-Int. deseasonalized” shows how to forecast the demand for non-intermittent items in the *in-use* phase. However, the principle is the same, only the used data is different. In this example we have used a 5-year of demand history data. Rather than initializing the TSB method based on the whole 5-year period, we first use only the first 3 years and we will then update the forecast for the remaining 2 years. This way, forecasts can “stabilize” during the updating stage of the initialization. The variable $T$ denotes the set of months in the first 3 year with a positive demand. Variables $s37$, $p37$, and $x37$ are the initial forecasts of the demand and probability (see Section 4.3.1 for the exact definition). Next, the columns with a yellow header row show the updating of the forecasts for the remaining 2 years.

Then, an example is given for forecasting the demand for January 2012. The same procedure can be followed for future demand forecasting. The following variables are used:

- $d_{jan}$: the actual de-seasonalized demand of January 2012
- $s_{jan}$: forecast of the demand in January provided that this demand is positive
- \( ^p_{jan} \): forecast of the probability of a positive demand in January
- \( ^x_{jan} \): forecast at the beginning of January for the demand in January
- \( p_{jan} \): indicator variable that indicates whether or not there is a positive demand in January. This variable influences the forecasts for February.
- \( x_{jan} \): actual forecast of the demand in January. This variable is calculated by multiplying the deseasonalized forecast for January \(^x_{jan}\) by the seasonal effect of January.

**Criticality Analysis**

An example of a criticality analysis is shown in the spreadsheet “Criticality.xlsx”. This example is based on demand data from 2010-2011 as explained in Section 5.2. In the worksheet “Afname” all the necessary (and more) variables for performing the criticality analysis have been collected. The variables are defined as follows:

- **Jobcard**: job card number
- **Plantype**: vehicle number
- **Item nr.**: item number
- **Item price**: price of the item
- **Entry**: job card code as defined in Table 5.1.
- **GSE criticality**: the criticality of the GSE vehicles as defined in Section 5.2.1, that is, the position of the GSE vehicle in the chain.

For the first filter we will focus on the variables **Entry** and **GSE criticality**. First of all, only item numbers with job card codes R (i.e. repair) and S (i.e. breakdown) as given in column **Entry** should be selected. Also, only items numbers with a GSE criticality of 1 should be selected. Worksheet “Results 1st filer” shows all the item numbers with job card codes R and S, and GSE criticality of 1. In this worksheet some additional variables have to be calculated, that is:

- **#Jobcards/vehicle**: number of (repair and breakdown) job cards per vehicle. Can be determined by making use of a PivotTable.
- **Size supplier**: number of vehicles within the same type of supplier
- **#Jobcards/supplier**: number of (repair and breakdown) job cards within the same supplier type
- **Ratio/jc**: ratio of the number of (repair and breakdown) job cards of a vehicle compared to the total number of (repair and breakdown) job cards within the same supplier type. This variable can be calculated by dividing the variable **#Jobcards/vehicle** by the variable **#Jobcards/supplier**.
- **#Item changes/vehicle**: number of times that a particular item is replaced on the same vehicle. Can be determined by making use of a PivotTable.

Given that all the necessary variables are determined, we can now calculate the criticality score as presented in the Worksheet “Final results”. According to the model presented in Section 5.2.2 (formula 5.5), one first has to calculate the weight for the ratio of GSE failures (i.e. \( wRatio \)) and for item failures (i.e. \( wItemChangesVehicle \)). First, the ratio of GSE failures and item failures are normalized, resulting in variables **sRatio** and **sItemChangesVehicle**. The score can be calculated as follows:
1. Use the variable $wRatio$ to calculate the weight of the ratio of GSE failures. $wRatio$ is calculated as follows: $wRatio = \frac{sRatio}{\text{SQRT(SUM}(sRatio:sItemChangesVehicle))}$.

2. Use the variable $wItemChangesVehicle$ to calculate the weight item failures. $wItemChangesVehicle$ is calculated as follows: $wItemChangesVehicle = \frac{sItemChangesVehicle}{\text{SQRT(SUM}(sRatio:sItemChangesVehicle))}$.

3. Use the variable $score$ to calculate the criticality score based on the weights. The variable $score$ is calculated as follows: $score = sRatio \times wRatio + sItemChangesVehicle \times wItemChangesVehicle$

However, the criticality score is calculated on vehicle level. In order to shift from the vehicle level to item level, one will have to use a PivotTable to calculate the average criticality score per item number. The average score is shown in column Average of score. This column is sorted from the largest to the smallest average score. The variable Pareto calculates the cumulative percentage per item number. All the items with a cumulative percentage smaller than 20% are classified as critical.