SHA ZHU

Spare Parts Demand Forecasting and Inventory Management

Contributions to Intermittent Demand Forecasting, Installed Base Information and Shutdown Maintenance

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Vraagvoorspelling voor reserveonderdelen en voorraadbeheer: artikelen over intermitterende vraagvoorspelling, installatie-gebaseerde voorspellingen en shutdown onderhoud

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Sha Zhu
Chongqing, May 2021.

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Chapter 1

Introduction

1.1 Intermittent demand

Intermittent demand refers to demand time series with a large proportion of zero values. The term sporadic demand is roughly equivalent. In this situation, non-zero demand is often highly variable in size with low volume values interspersed with random spikes of demand that are often many times larger than the average. Intermittent demand is often observed in companies that manage large inventories of service and spare parts in industries such as aviation, aerospace, automotive, heavy machinery, process, high tech, and electronics, as well as in MRO (Maintenance, Repair and Overhaul) (Romeijnders et al., 2012).

To describe and characterize a time series of intermittent demand, parameters such as the average demand interval, average demand size, coefficient of variation of demand size are often used. Average demand interval measures the demand regularity in time by taking the average interval between two demand occurrences. Coefficient of variation of demand size measures the variation in quantities by taking the standard deviation of the demand divided by the average demand for non-zero demand periods. Syntetos and Boylan (2005) propose a formal way to categorize intermittent time series using the average demand interval and coefficient of variation of demand size. They classify intermittent demand into categories such as slow mover and lumpy demand. The former refers to very low demand per unit time period due to infrequent demand arrivals, low average demand sizes, or both. The latter describes that demand is zero in some time periods with (highly) variable demand sizes, when demand occurs.

Various data sets and reports show auto- and cross-correlation are common in intermittent demand, especially spare parts (Altay et al., 2012; Willemain et al., 1994). Different from cross-item correlation where one item's demand is correlated with the demand of another in the situation of smoothing or continuous demand, Cross-correlation is specific to intermittent demand. It refers to correlation between demand size and the inter-demand interval of an item. Positive cross-correlation indicates a high demand volume follows a long demand interval, or a short interval is followed by a low demand size. Negative cross-correlation occurs when a short demand interval is followed by a high demand size or a long interval is followed by a small demand size.

These characteristics of intermittent demand complicate demand forecasting and as result also the inventory control. Forecasting methods developed for continuous demand often perform poorly in this situation. Can we develop specific forecasting methods for intermittent demand that do better? We will review a few different methods in this chapter, and propose a new method based on an existed forecasting method in Chapter 2.

1.2 Maintenance

Many industries depend on the availability of high-value capital goods to provide their services or to manufacture their products. Failures or downtime of capital goods can have far-reaching detrimental consequences on production such as the lost of revenue, customer dissatisfaction and safety hazard. For instance, in the aviation industry, one hour of machine downtime can cost $ 8,000 (Saranga, 2004).

Maintenance is defined in British Standard Glossary of terms 3811: 1993 as the combination of all technical and administrative actions, including supervision actions, intended to retain an item in, or restore it to, a state in which it can perform a required function. Maintenance is essential to reduce costly equipment downtime, improving the efficiency of operations and ensuring safety in the workplace. The original equipment manufacturers (OEMs) and Maintenance Organizations (MOs) are the two types of operators of maintenance. In the former situation, OEMs increasingly compete on the ability to provide after-sales service rather than selling capital goods and ensuring their availability. In the latter situation, Maintenance Organizations (MOs) within companies or as independent organizations are responsible for maintaining the capital goods. This is specific in airlines, job shops, refineries, railways, electronics industries, semiconductor industries and military organizations.

Maintenance exists in different types. The simplest form is corrective maintenance. Maintenance tasks are performed only when equipment breaks down. It is a way of keeping systems in working condition, especially for assets with low risk and low impact.

Preventive maintenance typically involves regularly scheduled maintenance tasks based on time or hours used. Preventive maintenance can also be condition-based, which we describe in next paragraph. Preventive maintenance encompasses a wide range of maintenance strategies aimed at preventing failures, such as time-based preventive maintenance and on-condition maintenance. In time-based preventive maintenance a part or component is replaced periodically, e.g. after a fixed amount of time (e.g. every 6 months) or usage (e.g. every 20,000 landings of an aircraft). Time-based preventive maintenance can be planned ahead easily, and no condition information is needed to apply it, but it has the disadvantage that much of the useful life of parts may be wasted by early replacements. Another strategy under preventive maintenance is on-condition maintenance. When it is economically feasible to do so, companies inspect parts of the asset before deciding upon replacement; the part is then only replaced if degradation is above some threshold, hence the term on-condition maintenance task. Arguably, on-condition maintenance tasks are an example of condition-based maintenance, but most scholars reserve this latter term for situations where the condition is real-time monitored (Topan et al., 2018; Lin et al., 2017; Keizer et al., 2017).

Condition-based maintenance is a maintenance strategy that use tools like sensors to monitor the actual condition of an asset to decide what maintenance needs to be done. Condition-based maintenance dictates that maintenance should only be performed when certain indicators show signs of decreasing performance or upcoming failure. Checking a machine for these indicators may include non-invasive measurements, visual inspection, performance data and scheduled tests. Condition data can then be gathered at certain intervals, or continuously.

Shutdown maintenance, or overhaul, is large scale maintenance under a temporary stoppage of production for disassembly, comprehensive inspection, repairing and replacement of parts. Due to the nature of component/machine and the safety consideration of maintenance work, some preventive maintenance activities cannot be carried out under normal production conditions. Shutdown maintenance is then the only viable maintenance procedure for these activities. Shutdown maintenance is often observed in industries such as refinery and petrochemical plants. It may last for weeks and special precautions need to be taken to serve their customers in the mean time. For example, Shell advanced its Pernis shutdown maintenance process to profit from the demand drop in the Corona time. (Reuters, 2020). Though shutdown maintenance is the most expensive of all types of maintenance, it is necessary and cost-effective. The complexity in the design and building of manufacturing system increases the need for shutdown maintenance. Terms like shutdown, turnarounds and outages are used interchangeably. Shutdowns are crucial for system safety and necessary for plants to ensure their reliability. Plants will suffer consequence or a great loss if the shutdown is poorly managed, e.g. delays of shutdowns can be very costly. During shutdowns many parts are needed, hence one needs to ensure abundant part availability. If the need is only clear during a shutdown, and the likelihood of needing it is small, a difficult decision arises. This is tackled in Chapter 4.

1.3 Forecasting models

Over the years, many models have been proposed to forecast spare parts demand. In the early stage, research on intermittent demand focused on time series based models. Bootstrapping and temporal aggregation are developed for intermittent demand. Recently, models using various information for spare parts demand forecasting are developed, such as installed base information (Dekker et al., 2013; Van der Auweraer et al., 2019) and expert judgement (Syntetos et al., 2009).

Single exponential smoothing is the first time series based forecasting model applied to intermittent demand. However, as designed for continuous demand, it performs poorly for intermittent demand. Hence special forecasting methods for intermitted were developed, both parametric and nonparametric. Ad-hoc time series parametric forecasting methods starts with Croston's method. It estimates the non-zero demand and demand interval respectively. Adjusted versions of Croston's method include Syntetos-Boylan Approximation (SBA) and the Teunter, Syntetos and Babai (TSB) method (Syntetos and Boylan, 2001; Teunter et al., 2011). Syntetos and Boylan (2001) show that Croston's method is positively biased and suggest an adjustment to overcome this issue in a follow-up paper (Syntetos and Boylan, 2005). Teunter et al. (2011) propose an alternative to Croston's method that is able to handle obsolescence issues. They update the demand size and the probability of non-zero demand. For detailed overviews of this research stream, we refer to Syntetos et al. (2016). Though these methods have been widely used, they have the disadvantage of assuming a particular parametric structure of the demand distributions. Bootstrapping is a non-parametric resampling technique, which builds the lead time demand distribution by repeated sampling from observations. The so-called WSS modified bootstrapping method, see Willemain et al. (2004), resamples from past data using a Markov chain approach to switch between no demand and demand periods. Teunter and Duncan (2009) finds that bootstrapping performs equally well as the Croston's method and SBA, but is more difficult to implement. The empirical method, proposed in Porras and Dekker (2008), is a far less complex non-parametric method which uses the empirical cumulative distribution function to estimate the lead time demand distribution for fixed lead times. The empirical method was slightly extended in Van Wingerden et al. (2014) so as to cover variable lead times as well. It performs well if demand originates both from periodic preventive maintenance as well as from corrective maintenance. As the empirical cumulative distribution function only provides information for demand levels in the scope of the historical demand data, the empirical method basically breaks down for high service levels. Syntetos et al. (2015) mentions poor performance of the empirical method in such situation.

The above models depend on historical demand and respond reactively to unprecedented factors. To overcome the disadvantage, models which consider drivers of spare parts demand have been developed. Development of these drivers can often be predicted, and taking these aspects into account will improve the spare parts demand forecasting. Dekker et al. (2013) stress the importance of knowing the characteristics of installed base, such as age and usage in inventory decision. Kim et al. (2017) describe the impact of product life-cycle on spare parts demand. They argue that the demand for spare parts follows the demand for the installed product with a delay. Van der Auweraer et al. (2019) build a Poisson binomial distribution of spare parts using installed base information. Topan et al. (2018) estimate the demand distribution based on the demand signal collected from sensors. We refer to Van der Auweraer et al. (2019) for detailed overviews of the many ways to estimate demand based on installed base information. In Chapter 3, we consider maintenance plan as advance demand information in estimating the demand distribution.

1.4 Spare parts inventory problem

To reduce the downtime and facilitate maintenance of capital goods, spare components are typically stocked by maintenance organizations. Spares can be used to replace failed or aged components during maintenance of the capital good in order to improve or restore its condition. Sometimes, after repair, components are in a good condition and they can be added to serviceable. The downtime of the capital asset is limited to the replacement time as this inventory strategy allows the repair of components and the production to be simultaneous.

Availability of spares are thus essential to rapid repairs, yet redundant spares tie up a lot of capital and face the risk of obsolescence. On the other hand, inventory managers in maintenance organizations are often confronted with shortage of spares parts and budget restriction. This brings the spare part inventory problem: How should spare parts inventory management react to demand realization or estimation? What information can be used to determine the order policy of spares. In this dissertation, we formulate and analyze several of these inventory problems.

To optimize the order policy, instead of only looking at past spares demand we, as one of the first authors, consider the maintenance plan as advance demand information (ADI) in the on-condition maintenance. When maintenance tasks include parts replacement, this information can directly be used in the inventory control. In cases where the maintenance includes an inspection of the parts before deciding to replace them it is more difficult to use this information for inventory control. In our study, maintenance tasks prescribe to inspect a part of the asset. Depending on the condition of the part, it is either immediately replaced by a spare part, or it may remain in the asset. The resources that enable maintenance, e.g. mechanics and a maintenance hangar, need to be planned ahead of the actual maintenance. To enable this maintenance planning, companies specify which on-condition maintenance tasks will be performed some time periods into the future. It is this maintenance plan that we propose to use as a source of ADI. We overcome two complications when using this form of ADI to control spare parts inventories. First, on-condition maintenance tasks are a form of imperfect demand information: Only upon inspection does it become clear whether an on-condition maintenance task constitutes a spare part demand. So using the maintenance plan involves dealing with this inherent uncertainty. Second, while the need for logistics planning forces companies to plan on-condition maintenance tasks ahead of time, this plan is only available and reliable a few months into the future.

A shutdown project consists of the phases initiation, preparation, execution and termination: The initiation and preparation phases comprise determining the work scope and detailing it into tasks and activities while determining key resource requirements, for example mechanics, equipment, and spare parts (Al-Turki et al., 2019). In the shutdown maintenance, we focus on spare parts inventory decisions in the initiation and preparation phase of the shutdown project, in order to guarantee the efficient execution of a shutdown project. We focus on parts for which the replacement probability is small. Because spare parts are expensive, the stocking decision for such parts is nontrivial: Parts that are stocked but not needed cause high holding costs and may even become obsolete, while parts that are needed but not stocked lead to costly emergency orders and longer maintenance activity duration. In turn, a longer maintenance activity duration may lead to an extremely costly delay in the shutdown project, depending on precedence relations between maintenance activities and delays in other activities. We investigate the resulting trade-off between the ordering cost of spare parts and the overtime cost of the shutdown project.

1.5 Thesis outline

In this dissertation, we study spare parts demand forecasting and inventory management problem. We start with the intermittent demand forecasting and propose the empirical-extreme value theory (empirical-EVT) method. Our method inherits the advantage of non-parametric approaches without losing the ability to achieve high service levels. In addition to the time series forecast method, we also consider various information in spare parts demand forecasting and inventory management. In Chapter 3, we estimate the demand and develop the inventory policy based on the advance demand information provided by the maintenance plan. We find that such information reduces the inventory cost significantly. In Chapter 4, we optimize the ordering policy of spare parts in shutdown maintenance in which the ordering decision for a maintenance activity not only depends on itself, but also on the structure of the project network. The outline of this dissertation is as follows.

In Chapter 2 we improve the empirical method proposed by Porras and Dekker (2008) which uses historical demand data to construct the leadtime demand distribution by applying extreme value theory to model the distribution tail. The limitation of the empirical method was that it was not able to forecast spare parts needs for high service levels in case of few data points. To make the most out of a limited number of demand observations, we establish that extreme value theory can be applied to lead time demand periods computed over overlapping intervals. We consider two service levels: the expected waiting time and cycle service level. Our experiments show that the new method improves the inventory performance under the expected waiting time and cycle service level for a range of demand generating processes and service targets, when compared with the empirical method. Moreover, our method is competitive with methods such as WSS, Croston's method, and the Syntetos-Boylan approximation (SBA), in the sense that it sometimes outperforms these methods, and sometimes is outperformed by these methods, depending on the demand data and other parameters. The automotive data set described by Syntetos and Boylan (2005) and the component repair dataset by Romeijnders et al. (2012) are used in case studies. Both Croston's method and WSS perform well in the automotive data set, followed by empirical-EVT. The limited training data leads to the unsatisfactory performance of empirical-EVT since it is difficult to estimate the tail of lead time demand distribution based on 13 periods observations. However, Empirical-EVT method performs best in the component repair dataset where demand is available in 84 periods.

In Chapter 3 we study the value of maintenance plan, i.e. the planned maintenance tasks, as a source of advance demand information in spare parts ordering decision. We propose a simple forecasting mechanism to estimate the spare part demand distribution based on the maintenance plan, and develop a dynamic inventory control method based on these forecasts. The value of this approach is benchmarked against state-of-the art time series forecast methods based on data from two large maintenance organizations. We find that the proposed method can yield cost savings of 23 to 51% compared to the traditional methods.

In Chapter 4 we consider the spare parts ordering policy against this background of shutdown maintenance project planning. We present a spare parts optimization model and algorithm that includes the cost-time trade-off and precedence constraints between maintenance activities in shutdown. The objective is to balance between spare parts ordering cost and the expected project overtime cost due to waiting for spare parts. Using two-stage stochastic programming, spare parts ordering policies are determined in the first stage and a detailed project schedule is developed in the second stage. We propose a sample average approximation with importance sampling and pruning of dominated activities to solve the problem, and demonstrate that this method solves large instances quickly. We also consider heuristics, e.g. the standard project management approach based on the widely used critical path method and a heuristic that draws from spare part inventory control literature. We find both these heuristics give poor solutions.

Finally, in Chapter 5 we conclude the main findings of this dissertation.

1.6 Contribution

Chapters 2-4 are based on papers that are either published in or submitted to scientific journals. These papers are the result of a cooperation between various authors. For each chapter, the reference to the publication and the contribution of each author are given below.

Chapter 2 The research for this chapter was conducted by the first author under supervision of dr. Willem van Jaarsveld and prof.dr.ir Rommert Dekker. Dr. Alex J. Koning and Dr. Rex Wang Renjie contributed in the application of Extreme Value Theory. Fokker Services and NedTrain provided the data sets. It is based on:

Zhu, S., Dekker, R., Van Jaarsveld, W., Renjie, R. W., & Koning, A. J. (2017). An improved method for forecasting spare parts demand using extreme value theory. European Journal of Operational Research, 261(1), 169-181.

Chapter 3 The research for this chapter was conducted by the first author under supervision of dr. Willem van Jaarsveld and prof.dr.ir Rommert Dekker. Fokker Services and NedTrain provided the data sets. It is based on:

Zhu, S., van Jaarsveld, W., & Dekker, R. (2020). Spare parts inventory control based on maintenance planning. Reliability Engineering & System Safety, 193, 106600.

Chapter 4 The research for this chapter was conducted by the first author under supervision of dr. Willem van Jaarsveld and prof.dr.ir Rommert Dekker. It is based on:

Zhu, S., van Jaarsveld, W., & Dekker, R. (2021). Critical project planning and spare parts inventory management in shutdown maintenance. Working paper.

Chapter 2

An Improved Method for Forecasting Spare Parts Demand using Extreme Value Theory

2.1 Introduction

The supply of aftermarket parts is an important source of profit for companies that sell durable equipment, see Gallagher et al. (2005). Findings from Deloitte's Global Service and Parts Management Benchmark Survey show that in 2006 the service business accounted for an average of nearly 26% of revenues across the industries, see Koudal (2006). After-sales networks operate in an unpredictable marketplace because demands for repairs crop up intermittently, see Kennedy et al. (2002); Cohen et al. (2006); Syntetos et al. (2012).

An essential element in spare parts inventory control is the forecasting of the lead time demand, as the lead time is the period in which a stockout may occur when demand is larger than foreseen. Differences in the monetary values of the stock-holdings between lead time demand forecasting methods can be substantial; Eaves and Kingsman (2004) report a case in which the use of an inferior forecasting method leads to an additional investment of 13.6% of the total value of the inventory. Unfortunately, estimating the lead time demand distribution is especially difficult for slow-moving spare part types as typically only limited positive demand data points are available in practice.

The demand distribution may be estimated either parametrically or nonparametrically. Parametric methods have the advantage of being relatively simple while still showing decent empirical performance (Syntetos et al., 2015). However, as parametric estimators are derived from assumptions, they may turn out to be severely biased in case these assumptions do not hold. Therefore, nonparametric estimators are preferred, as the traditional parametric estimators have problems dealing with intermittent demand and particular patterns. Popular nonparametric approaches are the bootstrap method, see Willemain et al. (2004), which we refer to as the WSS method in this thesis, and the empirical method, see Porras and Dekker (2008) and Van Wingerden et al. (2014). Nonparametric estimators only provide relevant information for demand levels in the scope of the historical demand data of say N positive data points, and basically break down in case of extrapolation beyond this scope. In particular, the largest data point would be expected to lie at the $N/(N+1)$th percentile, and thus achieving service levels beyond this percentile may prove difficult using empirical methods. Thus, we resort to semi-parametric estimators in the tail for high service levels.

In this thesis, we propose the empirical-EVT method, which applies extreme value theory (EVT, see Beirlant et al., 2004; Coles, 2001; Reiss and Thomas, 2007) to the tail part of the distribution and handles the remainder of the distribution (the non-tail part, say) via the empirical method. The empirical distribution is used as starting point to ensure that the structure of the non-extreme part of the data is preserved. Application of EVT allows us to closely approximate the tail of a distribution using one single parameter, the extreme value index, see de Haan and Ferreira (2006). Only the largest historical demands are used to estimate the extreme value index, the other historical demands are input to the empirical method. The new method inherits the advantage of non-parametric approaches without losing the ability to achieve high service levels. As EVT allows dependence (more precisely, β-mixing dependence) between successive lead time demands, we establish that the empirical-EVT method may be applied to lead time demands computed over *overlapping* time periods. With this result, our method makes the most out of a limited demand history.

A simulation study is conducted to assess the performance of the empirical-EVT where we estimate the lead time demand distributions based on samples from a known distribution. Instead of one period forecasting error measures such as mean squared error, we employ service levels to evaluate performance, as advocated in Syntetos and Boylan (2006) and Teunter and Duncan (2009).

The experiments show that the new method improves the inventory performance under the expected waiting time and cycle service level for a range of demand generating processes and service targets, when compared with the empirical method. Moreover, the new method is competitive with methods such as WSS, Croston's method (1972), and the Syntetos-Boylan approximation (SBA) (2005), in the sense that it sometimes outperforms these methods, and sometimes is outperformed by these methods, depending on the demand data and other parameters.

We use in our empirical study the automotive data set described by Syntetos and Boylan (2005) and the component repair dataset by Romeijnders et al. (2012). Both Croston's method and WSS perform well in the automotive data set, followed by empirical-EVT. The limited training data leads to the unsatisfactory performance of empirical-EVT since it is difficult to estimate the tail of lead time demand distribution based on 13 periods observations. However, Empirical-EVT method performs best in the component repair dataset where demand is available in 84 periods.

The chapter is organized as follows. Section 2 gives an overview of the relevant literature. Section 3 briefly describes EVT theory and how to use it in our study. In section 4 a simulation study and an empirical study give insights into the differences between the empirical-EVT method, the empirical method, WSS, Croston's method and SBA. The last section presents the final conclusions.

2.2 Literature

In Subsection 2.1, we review forecasting methods for slow-moving items. In Subsection 2.2, we review extreme value theory.

2.2.1 Intermittent demand forecasting

Demand forecasting is a key issue in the field of spare parts management. For an overview on spare parts demand forecasting research, we refer to Boylan and Syntetos (2010).

Traditional forecasting methods such as simple moving average (SMA) and simple exponential smoothing (SES) fail to perform well for intermittent demand, see Syntetos and Boylan (2005). Croston's method (CR, see Croston, 1972) isolates periods with positive demands, is "robustly superior" to SES, see Willemain et al. (1994), and is biased, see Syntetos and Boylan (2001). The Syntetos-Boylan approximation (SBA, see Syntetos and Boylan, 2005), the Syntetos method (SY, see Syntetos,

2001) and the Teunter-Syntetos-Babai method (TSB, see Teunter et al., 2011) are bias-corrected modifications of the CR method. According to Syntetos and Boylan (2006), the SBA method outperforms the SMA, SES and CR methods. Teunter and Sani (2009) prefer the SY over the SB method, as the latter actually overcompensates the bias. Evidence in Babai et al. (2014) suggests that TSB does not outperform CR, SBA and SY unless the degree of intermittence is low and demand is decreasing. For other modified CR methods, see Johnston and Boylan (1996), Shale et al. (2006) and Snyder (2002). The variance of SES, CR, SY and SBA intermittent demand estimates are discussed in Syntetos and Boylan (2010). Though these methods have been widely used, they have the disadvantage of assuming a particular parametric structure of the demand distributions.

Bootstrapping is a non-parametric resampling technique, which builds the lead time demand distribution by repeated sampling from observations. The WSS modified bootstrapping method, see Willemain et al. (2004), resamples from past data using a Markov chain approach to switch between no demand and demand periods. Teunter and Duncan (2009) find that bootstrapping performs equally well as the CR and SBA method, but is more difficult to implement. Syntetos et al. (2015) conclude that the WSS modified bootstrapping method does have advantages over the SES, CR and SBA methods, but questions whether WSS is worth the added complexity.

The empirical method, proposed in Porras and Dekker (2008), is a far less complex non-parametric method which uses the empirical cumulative distribution function to estimate the lead time demand distribution for fixed lead times. The empirical method was slightly extended in Van Wingerden et al. (2014) so as to cover variable lead times as well. As the empirical cumulative distribution function only provides information for demand levels in the scope of the historical demand data, the empirical method basically breaks down for high service levels. Syntetos et al. (2015) mention poor performance of the empirical method.

Other forecasting methods supplement historical demand data with additional information. The use of installed base information is discussed in Jalil et al. (2011) and Dekker et al. (2013). Information on component repairs is first considered in Romeijnders et al. (2012). Topan et al. (2018) assess the value of the imperfect demand information and proposes a lost-sales inventory model with a general representation of demand information to find the ordering policy minimizing total inventory holding, shortage and ordering cost under imperfect information.

2.2.2 Extreme Value Theory

Extreme value theory is a branch of statistics modelling the tail behaviour of a distribution. The most prominent application is the estimation of an unknown upper quantile value corresponding to a small given exceedance probability. However, EVT also covers the estimation of an unknown exceedance probability. The determination of a safe height for the North Sea dikes in the Netherlands acted as an important driver behind the development of EVT, see de Haan (1990). Nowadays, EVT is widely used in financial risk management to estimate downward risk measures such as value at risk and expected shortfall. To our knowledge, the only previous application of EVT to inventory problems is in Kogan and Rind (2011), where the design of an inventory for critical equipment is considered. As critical equipment is characterized by *infinitely large* underage costs, they require that no stockout occurs in the coming years with high probability. Based on this requirement, they develop rules for determining inventory based on EVT, homogeneous Poisson processes, and Chebyshev's inequality.

2.3 Theory

2.3.1 Extreme value theory

Loosely speaking, EVT theory is built upon the idea that the tail behavior of many uncertain quantities that are encountered in practice can be modelled using the Generalized Pareto Distribution (GPD). We explain EVT in a precise mathematical statement in section 2.3.1.1.

2.3.1.1 Tail approximation

Let X be a random variable with cumulative distribution function $F(x) = P\{X \leq x\}$, and let $x^* = \sup\{x : F(x) < 1\}$ denote the endpoint of the support of F. Note that x^* may be either finite or infinite.

Throughout this chapter, we shall assume the existence of a positive function f such that

$$\lim_{\tau \uparrow x^*} \frac{1 - F(\tau + xf(\tau))}{1 - F(t)} = (1 + \gamma x)^{-1/\gamma} \tag{2.1}$$

for all x for which $1 + \gamma x > 0$, see condition 4 of Theorem 1.1.6 at p. 10 in de Haan and Ferreira (2006). The assumption allows the approximation of the tail of the distribution of X for a sufficiently large threshold τ,

$$1 - F(x) \approx (1 - F(\tau)) \left\{ 1 - H_\gamma \left(\frac{x - \tau}{f(\tau)} \right) \right\} \tag{2.2}$$

for all $x > \tau$, see p. 67 in de Haan and Ferreira (2006). Here H_γ denotes the cumulative distribution function of the GPD:

$$H_\gamma(x) = \begin{cases} 1 - (1 + \gamma x)^{-1/\gamma} & \text{for } \gamma \neq 0, \\ 1 - e^{-x} & \text{for } \gamma = 0. \end{cases} \tag{2.3}$$

The parameter γ of the GPD plays a central role in EVT, and hence is referred to as the extreme value index; it acts as a shape parameter of the GPD approximating the tail of the distribution. The support of the GPD is $[0, \infty)$ if γ is non-negative, and $[0, -1/\gamma]$ if γ is negative. For any distribution such that (2.1) holds, we say that the distribution belongs to the domain of attraction of $H_\gamma(x)$.

Assumption (2.1) is not restrictive because it only pertains to the tail behavior of the distribution. In that sense, it is very much weaker than (for example) stating that demand follows a negative binomial distribution, or a normal distribution, or any other specific distribution, precisely because such an assumption specifies the entire distribution.

Assumption (2.1) is satisfied by a very wide range of continuous distributions (Pickands, 1975; Balkema and de Haan, 1974). This reflects that tail behavior of many distributions allow approximate modelling by means of the GPD: this explains why the GDP occurs in the assumption. This generality is in fact one of the strongest points of EVT, and the main reason why it has been applied to a very wide range of problems: extreme sea-levels (for dike height determination), insurance losses, market risk, environmental loads on structures, etc. Moreover, according to Shimura (2012), many discrete distributions can be regarded as a discretization of a continuous distribution satisfying (2.1), and hence satisfy (2.1) themselves.

An interesting approach to test the applicability of EVT for a specific real-life scenario in which the demand distribution is unknown, would be a goodness-of-fit test. Unfortunately, goodness-of-fit in EVT is not yet fully developed, see Section 2.3 in Beirlant et al. (2012). An Anderson-Darling type test of (2.1) based on the tail empirical process is proposed in Drees et al. (2006). Several tests of (2.1) for $\gamma > 0$ are found in Koning and Peng (2008).

2.3.1.2 The basic model

The basic model on which EVT in its original form rests, assumes that $X_1, \ldots, X_n$ is a random sample of size n drawn from the distribution given by F; in other words, the observations $X_1, X_2 \ldots, X_n$ are *independent* copies of the random variable X. Let $X_{(1)} \leq X_{(2)} \leq, \ldots \leq X_{(n)}$ be the ordered sample. Choose $0 \leq k < n$, and use $X_{(n-k)}$ as an empirical threshold. That is, replace τ by $X_{(n-k)}$. To allow the derivation of asymptotic results for n tending to infinity, we assume that the choice k depends on n, and satisfies $k \to \infty$ and $k/n \to 0$ as $n \to \infty$. That is, as n grows large, k grows large but nevertheless vanishes relative to n.

Since $1 - F\left(X_{(n-k)}\right) \approx k/n$, we obtain, see Equation (3.1.4) in de Haan and Ferreira (2006),

$$1 - F(x) \approx \frac{k}{n}\left\{1 - H_\gamma\left(\frac{x - X_{(n-k)}}{\alpha}\right)\right\} \tag{2.4}$$

for all $x > X_{(n-k)}$, with $\alpha = f\left(X_{(n-k)}\right)$. In particular, this approximation continues to hold even beyond the sample maximum $X_{(n)}$.

In recent EVT literature $\alpha = f\left(X_{(n-k)}\right)$ is usually replaced by $\alpha = a(k/n)$. We also do this in our study. The functions f and a are related through the equation $f(x) = a(1/(1 - F(x)))$, see Theorem 1.1.6 at p. 11 in de Haan and Ferreira (2006); note that $1/\big(1 - F(X_{(n-k)})\big) \approx n/k$. As the parameters γ and α appearing in (2.4) are unknown, we simply replace them by estimators. We use the moment estimators proposed in Dekkers et al. (1989). Summarize the k largest order statistics via the first two "moments" $M_n^{(1)}$ and $M_n^{(2)}$ defined by

$$M_n^{(j)} := \frac{1}{k}\sum_{i=0}^{k-1}\left(\log X_{(n-i)} - \log X_{(n-k)}\right)^j \tag{2.5}$$

for $j = 1, 2$. Then, the moment estimators of the extreme value index γ and the scale α are given by

$$\hat{\gamma} := M_n^{(1)} + 1 - \frac{1}{2}\left(1 - \left(M_n^{(1)}\right)^2\left(M_n^{(2)}\right)^{-1}\right)^{-1}, \tag{2.6}$$

$$\hat{\alpha} := \tfrac{1}{2}X_{(n-k)}M_n^{(1)}\left(1 - \left(M_n^{(1)}\right)^2\left(M_n^{(2)}\right)^{-1}\right)^{-1}. \tag{2.7}$$

Until now, we have only assumed that the number $k = k(n)$ of used largest order statistics satisfies $k \to \infty$ and $k/n \to 0$ as $n \to \infty$. In practice, the choice of k is made by trading off bias and variance. For small k, only a limited amount of the information contained in the data is used, and hence the variance of the moment estimator is relatively large. Although selecting a larger value of k will reduce this variance, it is typical that the bias of the moment estimator will increase at the same time as the relevance of (2.1) diminishes. (See de Haan and Ferreira, 2006.)

Three different ways of choosing k have appeared in literature: moment estimator plot (Hill, 1975), bootstrap method (Danielsson et al., 2001; Draisma et al., 1999) and unbiased moment estimator plot (De Haan et al., 2016). For the purpose of applying EVT to inventory control, we use an automated method for threshold selection, see 2.D in the supplementary material.

2.3.1.3 Relaxing the independence assumption

The basic model assumed in the previous paragraph required that $X_1, X_2, \ldots$ is a sequence of independent and identically distributed (i.i.d.) random variables. In practice, the independence assumption may turn out to be too restrictive. As we intend to apply EVT to the lead time demands directly, the independence assumption also becomes an issue in our approach to LTD estimation. We may view lead time demands as "moving sums" of demands in subsequent time intervals (for instance, days, weeks months or year). Let D_j denote the demand in time interval j. If the window size L is fixed, then we may express the demands over window size as

$$X_i^{[L]} = \sum_{j=i}^{i+L-1} D_j, \quad \text{for } i = 1, 2, \ldots. \tag{2.8}$$

Besides constant L, multiple levels of aggregation are also applicable to our forecasting method. Various aggregation window sizes may lead to different inventory performance, see Petropoulos and Kourentzes (2015), Rostami-Tabar et al. (2013) and Rostami-Tabar et al. (2014). For a discussion of the optimal choice of aggregation window size, see Nikolopoulos et al. (2011). For the present chapter, we choose to restrict the window size to the leadtime L. We believe combining the empirical or empirical-evt approach approach with a temporal aggregation approach may be an interesting topic for further research. Whenever allowed, we shall drop the superscript $[L]$, and use the short hand notation X_i rather than the full one $X_i^{[L]}$.

Typically, the demands $D_1, D_2, \ldots$ are assumed to be i.i.d., see Croston (1972) for instance. The consecutive lead time demands $X_1, X_2, \ldots$ become dependent. In fact, $X_1/L, X_2/L, \ldots$ is a moving average process of order L, that is, an ARMA$(0, L)$ process. To avoid this dependence, one has resorted to considering "non-overlapping" lead time demands, $X_1, X_{L+1}, X_{2L+1}, \ldots$ say, see Nikolopoulos et al. (2011). (In the context of time series analysis, the construction of non-overlapping lead time demands $X_1, X_{L+1}, X_{2L+1}, \ldots$ is referred to as "temporal aggregation".)

Fortunately, the independence assumption has been relaxed in EVT, see Drees (2003), Resnick and Starica (1998) and Rootzén (2009). In essence, we should require that the sequence $X_1, X_2, \ldots$ is β-mixing instead. The β-mixing dependence condition (also known as absolute regularity or weak Bernoulli condition) was proposed in Volkonskii and Rozanov (1959), and is thoroughly discussed in Bradley (2005). Loosely speaking, β-mixing precludes long range dependence. Many random sequences in practice – among which Harris chains, ARMA, ARCH and GARCH processes – are β-mixing, see Athreya and Pantula (1986), Mokkadem (1988), Carrasco and Chen (2002), Fryzlewicz and Rao (2011). Since consecutive lead time demands $X_1, X_2, \ldots$ constructed from i.i.d. demands via (2.8) behave as an ARMA$(0, L)$ process up rescaled by a fixed factor L, it follows that these lead time demands are indeed β-mixing (the rescaling does not affect the dependence structure).

In addition, we may relax the independence between the demands, as long as we end up with β-mixing lead time demands. For example, one may show that the moving sum of an ARMA process is also an ARMA process, see Granger and Morris (1976); thus, if the demands are not independent but form an ARMA process instead, the lead time demands are still β-mixing. Recall that an ARMA process is stationary.

Autocorrelated demands have been found in intermittent industrial datasets, see Willemain et al. (1994). The simulation experiment in Altay et al. (2012) shows that the forecast accuracy and stock control performance of the SES and SBA methods are vulnerable to autocorrelated demands. The theoretical work on relaxing the independence assumption in EVT suggests that EVT-based methods are to some extent robust with respect to stationary autocorrelated demands. As EVT-based methods implicitly assume that the extreme value index stays constant over time, we do not expect EVT-based methods to work well for non-stationary demand.

After using ad-hoc arguments to conclude that the assumption of stochastic independence of lead time demands "looks highly plausible as a first approximation", results in Kogan and Rind (2011) are derived under the basic EVT model. The validity of these ad-hoc arguments is difficult to assess. Our discussion above shows that it possible to avoid ad-hoc arguments by using a comprehensive and rigorous theoretical argument. In fact, we believe that relaxing the independence assumption is essential for any application of EVT to inventory control.

2.3.2 How to apply EVT based on the empirical LTD forecasting method

In this subsection we detail the application of the empirical-EVT method using three different service levels: expected waiting time $\mathbb{E}\mathrm{WT}$, fill rate β and cycle service level CSL. These three service levels have in common that a larger base stock level yields a better service level (a smaller expected waiting time, a larger fill rate or a larger cycle service level). Thus, $\mathbb{E}\mathrm{WT}$, β and CSL are in fact monotonic functions $\mathbb{E}\mathrm{WT}\,(S)$, $\beta\,(S)$ and $\mathrm{CSL}\,(S)$ of the base stock level S.

Our aim is to determine the smallest base stock level S_{min} such that the inventory performs as least as good as some given critical service level. However, we are unable to achieve this aim since the exact relation between base stock level and service level is unknown. The best we can do is to estimate this relation using historical demand data. As a consequence, we arrive at an estimated smallest base stock level $\hat{S}_{\mathrm{min}}$ rather than S_{min} itself.

The empirical-EVT method deals with two regions: the non-tail and the tail regions, separated by an unknown threshold τ which is estimated by the empirical threshold $X_{(n-k)}$. We handle the non-tail region non-parametrically using the empirical method, and the tail region semi-parametrically by EVT. The computation of $\hat{S}_{\mathrm{min}}$ involves the following steps.

Step 1: obtain the LTD sample Obtain a sample X_1, X_2, …, X_n of lead time demands.

Typically, these lead time demands are obtained by summing demands over given time periods, as in (2.8); let $\bar{D} = n^{-1}\sum_{i=1}^{n} D_i$ denote the mean demand during the data collection period.

However, we do leave open the possibility that the sample $X_1, X_2, \ldots, X_n$ was obtained by some other data generating process (DGP), as long as EVT is still applicable; that is, the DGP should yield lead time demands which are β-mixing. (See Bradley, 2005 for β-mixing).

Step 2: construct the ordered sample Sort the sample $X_1, X_2, \ldots, X_n$ in ascending order. This yields the ordered sample $X_{(1)} \leq X_{(2)} \leq X_{(3)} \leq \ldots \leq X_{(n)}$. We shall refer to $X_{(i)}$ as the i^{th} order statistic. Remark that the information contained in the ordered sample is sufficient to construct the empirical distribution function $\hat{F}_n(x)$ appearing in paragraph 4.1.2 of Porras and Dekker

(2008), because we may write

$$\hat{F}_n(x) = \sum_{i=1}^{n} 1_{\{X_i \leq x\}} = \sum_{i=1}^{n} 1_{\{X_{(i)} \leq x\}} \quad \text{for all } x \in \mathbb{R}, \tag{2.9}$$

Moreover, as the empirical distribution function is a step function which jumps at the order statistics, we may reconstruct the ordered sample from the empirical distribution function. Thus, the ordered sample $X_{(1)} \leq X_{(2)} \leq X_{(3)} \leq \ldots \leq X_{(n)}$ carries exactly the same information as the empirical distribution function $\hat{F}_n(x)$.

Step 3: select the empirical threshold $X_{(n-k)}$ Choose k using the moment estimator plot, the bootstrap method or the unbiased moment estimator plot, as described in paragraph 2.3.1.2.

Step 4: estimate the parameters of GPD function Use the moment estimators $\hat{\gamma}$ and $\hat{\alpha}$ defined by (2.6) and (2.7) to estimate the extreme value index γ and the scale $\alpha = f(\tau)$.

Step 5: estimate the relation between S and service level This step depends on the service level used.

1. ***Expected waiting time*** If $\hat{\gamma} < 1$, estimate the expected waiting time $\mathbb{E}\mathrm{WT}(S)$ by means of the estimator $\widehat{\mathbb{E}\mathrm{WT}}(S)$ defined by

$$\widehat{\mathbb{E}\mathrm{WT}}(S) = \frac{1}{\bar{D}} \left\{ n^{-1} \sum_{i=1}^{n-k} \left(X_{(i)} - S\right)^{+} + \frac{k}{n} \hat{\mu}_{\text{tail}}(S) \right\} \tag{2.10}$$

with

$$\hat{\mu}_{\text{tail}}(S) = \left(X_{(n-k)} - S\right)^{+} + \hat{\Psi}\left(S \vee X_{(n-k)}\right) - \hat{\Psi}\left(X_{(n-k)} - \frac{\hat{\alpha}}{\hat{\gamma}}\right) 1_{\{\hat{\gamma}<0\}} \tag{2.11}$$

and

$$\hat{\Psi}(x) := \begin{cases} \dfrac{\hat{\alpha}}{1-\hat{\gamma}} \left\{ 1 + \hat{\gamma} \left(\dfrac{x - X_{(n-k)}}{\hat{\alpha}} \right) \right\}^{1-\frac{1}{\hat{\gamma}}} & \text{if } \hat{\gamma} \neq 0, \\ \hat{\alpha} \exp\left(\dfrac{-x + X_{(n-k)}}{\hat{\alpha}} \right) & \text{if } \hat{\gamma} = 0, \end{cases} . \tag{2.12}$$

For the derivation of this estimator, see 2.B in the supplementary material.

Set the estimated expected waiting time to infinite if $\hat{\gamma} \geq 1$. In this case, the waiting time distribution is classified as extremely heavy-tailed.

Although the expected waiting time $\mathbb{E}\mathrm{WT}$ is a widely used service level, it has the problematic feature of becoming infinite if $\gamma \geq 1$, or becoming extremely high for γ slightly lower than 1. This feature, which is a consequence of the fact that mathematical expectation do not exist for heavy tailed distribution, is inherited by its estimator: $\widehat{\mathbb{E}\mathrm{WT}}$ is infinite if $\hat{\gamma} \geq 1$, or extremely high for $\hat{\gamma}$ slightly lower than 1, see 2.A.

In short, the expected waiting time does not combine well with heavy tailed waiting time distributions.

2. ***Fill rate*** The fill rate $\beta\left(S\right)$ is closely related to the expected waiting time. Recall that, according to (2.8), we may view X_i as just short hand notation for $X_i^{[L]}$. Let $\mathbb{E}\mathrm{WT}^{[L]}\left(S\right)$ be the expected waiting time for $X^{[L]}$, and let $\mathbb{E}\mathrm{WT}^{[L-1]}\left(S\right)$ be the expected waiting time for $X^{[L-1]}$. Then, $\beta\left(S\right) = 1 - \bar{D}^{-1}\left\{\mathbb{E}\mathrm{WT}^{[L]}\left(S\right) - \mathbb{E}\mathrm{WT}^{[L-1]}\left(S\right)\right\}$.

   Now suppose that in Step 1 we have not only collected $X_1^{[L]}$, $X_2^{[L]}$, ..., $X_n^{[L]}$ but $X_1^{[L-1]}$, $X_2^{[L-1]}$, ..., $X_n^{[L-1]}$ as well. Note that if the demands are non-negative random variables, then $X_i^{[L]}$ is stochastically larger than $X_i^{[L-1]}$ for every i. Let $\widehat{\mathbb{E}\mathrm{WT}}^{[L]}\left(S\right)$ be the expected waiting time for $X^{[L]}$, and let $\widehat{\mathbb{E}\mathrm{WT}}^{[L-1]}\left(S\right)$ be the expected waiting time for $X^{[L-1]}$. Then, $\hat{\beta} = \hat{\beta}\left(S\right) = 1 - \bar{D}^{-1}\left\{\widehat{\mathbb{E}\mathrm{WT}}^{[L]}\left(S\right) - \widehat{\mathbb{E}\mathrm{WT}}^{[L-1]}\left(S\right)\right\}$ is an estimator of $\beta\left(S\right)$.

   The fill rate suffers from the same problems as the expected waiting time for large values of $\widehat{\gamma}$. Moreover, it also does not combine well with heavy tailed waiting time distributions. Although $X_i^{[L]}$ is stochastically larger than $X_i^{[L-1]}$ for every i, this does not imply that $X_i^{[L]} - X_{(n-k)}^{[L]}$ is stochastically larger than $X_i^{[L-1]} - X_{(n-k)}^{[L-1]}$ for every i since there is no obvious relation between $X_{(n-k)}^{[L]}$ and $X_{(n-k)}^{[L-1]}$. As a consequence, even though $\widehat{\mathbb{E}\mathrm{WT}}^{[L]}\left(S\right)$ and $\widehat{\mathbb{E}\mathrm{WT}}^{[L-1]}\left(S\right)$ decrease with increasing base stock level S, $\widehat{\mathbb{E}\mathrm{WT}}^{[L]}\left(S\right) - \widehat{\mathbb{E}\mathrm{WT}}^{[L-1]}\left(S\right)$ and $\hat{\beta}\left(S\right)$ fail to change monotonically with the increasing S, which contradicts common sense.

3. ***Cycle service level*** The cycle service level $\mathrm{CSL}\left(S\right) := P\left(X \leq S\right)$ is a service level which, in contrast to the expected waiting time and fill rate, is able to accommodate heavy tailed distributions. It is estimated by

period n	demand									
period 1-10	0	0	0	0	0	0	6	0	0	0
period 10-20	0	0	0	0	0	0	0	0	0	0
period 21-30	0	0	0	0	0	0	1	0	0	0
period 31-40	0	10	0	0	0	0	4	0	0	0
period 41-50	6	0	0	0	0	0	0	3	0	0
period 51-60	0	0	0	0	0	0	0	0	0	0

Table 2.1: Historical demands of 60 periods

means of $\widehat{\text{CSL}}\,(S)$ defined by

$$\widehat{\text{CSL}} = \begin{cases} \frac{1}{n}\sum_{i=1}^{n} 1_{\{X_i \le S\}} & \text{if } S \le \tau, \\ 1 - \dfrac{k}{n}\left\{1 - H_{\hat{\gamma}}\left(\frac{S - X_{(n-k)}}{\hat{\alpha}}\right)\right\} & \text{if } S < \tau, \end{cases} \tag{2.13}$$

For the derivation of this estimator, see 2.C in the supplementary material.

Step 6: estimate the smallest base stock level Let $\mathbb{E}\text{WT}_{\text{obj}}$, β_{obj} and CSL_{obj} denote the target waiting time, the target fill rate and the target cycle service level, repectively. Now set the estimator S_{min} equal to the smallest S satisfying one of the following service level requirements: $\widehat{\mathbb{E}\text{WT}}\,(S) \le \mathbb{E}\text{WT}_{\text{obj}}$; or $\hat{\beta}\,(S) \ge \beta_{\text{obj}}$; or $\widehat{\text{CSL}}\,(S) \ge \text{CSL}_{\text{obj}}$.

2.3.3 Example - applying EVT to the empirical LTD forecasting method

Two examples under expected waiting time and cycle service level are provided in this subsection. Example 1 shows that we can decrease the expected waiting time by applying extreme value theory. However, when the extreme value index γ is relatively large, the expected waiting time service level breaks down, due to the fat tail of the lead time demand distribution. The cycle service level does not suffer from this problem. This is illustrated in Example 2.

Example 1

Table 2.1 shows demand samples during 60 months. We set the expected waiting time target $\mathbb{E}\text{WT}_{obj}$ equal to 0.03.

Next we tally the LTD sample and compute $\hat{F}_n$ according to (2.9), see Table 2.2. According to (2.6), we construct estimators $\widehat{\gamma}_k$ using Table 2.2, see 2.1, for

LTD	frequency	proportion	$\hat{F}_n$
0	32	32/56	32/56
1	5	5/56	37/56
4	4	4/56	41/56
6	9	9/56	50/56
10	6	6/56	1

Table 2.2: Computation of EDF $\hat{F}_n$

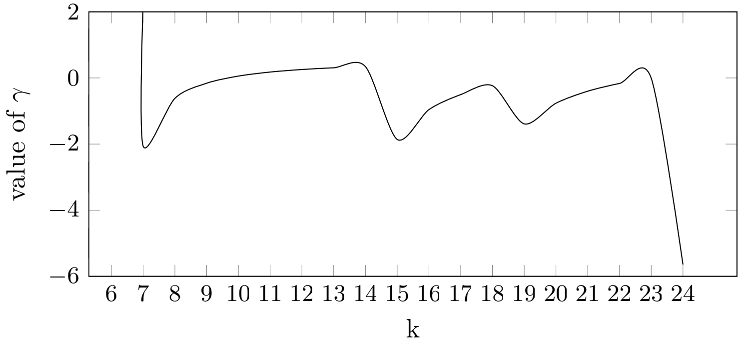


Figure 2.1: Select threshold from moment estimator plot

$k = 6, \ldots, 24$. $\widehat{\gamma}$ does not exist for $k = 1, \cdots, 5$ since the denominator in (2.6) equals to zero. We do not consider $k > 24$ in order to keep at least one positive observation in the non-tail part. The figure shows that the value of $\widehat{\gamma}$ is relatively stable when $8 \leq k \leq 14$, and we select the threshold position k equal to 10. Once the threshold is determined, we can obtain the estimates $\widehat{\gamma} = 0.056$ and $\widehat{\alpha} = 2.299$. Now (2.10) allows us to calculate $\widehat{\mathbb{E}\mathrm{WT}}\,(S)$ for any given S, which in turn enables us to determine $S_{\mathrm{EVT}}^{\mathrm{EWT}} = S_{\mathrm{min}}$, where S_{min} is the smallest S which satisfies $\widehat{\mathbb{E}\mathrm{WT}}\,(S) \leq \mathbb{E}\mathrm{WT}_{\mathrm{obj}}$. Finally, this yields $S_{\mathrm{EVT}}^{\mathrm{EWT}} = 16$.

The procedure above could be followed for other service levels as well. For instance, we obtain $S_{\mathrm{EVT}}^{\mathrm{CSL}} = 14$ under cycle service level $\mathrm{CSL}_{\mathrm{obj}} = 0.99$, see (2.13). For reference, we remark that in this example the empirical method proposed in Porras and Dekker (2008) yields $S_{\mathrm{emp}}^{\mathrm{EWT}} = 10$, $S_{\mathrm{emp}}^{\mathrm{CSL}} = 10$, see Table 2.3 for the results.

service level	S_{EVT}	S_{emp}
EWT	16	10
CSL	14	10

Table 2.3: Results of example 1

period n	demand									
period 1-10	0	0	0	0	0	0	0	0	5	0
period 10-20	0	0	0	0	19	0	0	0	0	0
period 21-30	0	0	0	0	0	0	0	0	0	0
period 31-40	0	0	0	5	0	0	0	0	0	0
period 41-50	0	0	0	0	0	0	0	0	0	0
period 51-60	0	0	0	0	0	0	0	1	0	5

Table 2.4: Historical demands of 60 periods

service level	S_{EVT}	S_{emp}
EWT	43213	19
CSL	34	19

Table 2.5: Results of example 2

Example 2

This example produces an illustration to the remark in Step 5 in Subsection 2.3.2 that the expected waiting time does not combine well with heavy tailed distributions. Table 2.4 shows another demand sample during 60 months. We use the same target and lead time as in Example 1. Following the same procedure we obtain the results in Table 2.5.

Theoretically, the tail becomes fatter when the extreme value index γ is closer to 1. As the extreme value index estimate 0.67 is already rather large, $S_{\mathrm{EVT}}^{\mathrm{EWT}}$ becomes enormous. As long as $\widehat{\gamma}$ is moderate, the expected waiting time produces reasonable results. However, if the estimated extreme value index is rather large (we have observed $\widehat{\gamma} > 0.5$), then the expected waiting time yields unrealistically high base stock levels. To avoid such extremely high base stock levels, the cycle service level should be used instead. Alternatively, we may impose an upper bound on $S_{\mathrm{EVT}}^{\mathrm{EWT}}$ to avoid the extreme cases. One could also opt to limit the parameter space of $\widehat{\gamma}$, but the upper limit needs to depend on $\hat{\alpha}$, which would make such an approach cumbersome.

2.4 Experiments

In this section, we perform experiments comparing the relative performance of the empirical-EVT method and several alternative methods. Section 2.4.1 discusses experiments where demand is generated using Monte Carlo simulation, and Section 2.4.2 discusses experiments based on real demand data.

2.4.1 Simulation

2.4.1.1 Setup

We apply a base stock policy with periodic review and full backordering. In the simulation, demand for each time period for both the *training set* and *test set* is generated according to a probability distribution that will be specified in Section 2.4.1.2. The test set is independent of the training set. Lead time demands for the training set are constructed according to (2.8). Given a target service level, the training set is used to estimate the base stock level $S_{\min}$ using various methods: empirical-EVT, the empirical method, WSS (Willemain et al., 2004), Croston (Croston, 1972) and SBA (Syntetos and Boylan, 2005). We choose smoothing constant $\alpha = 0.2$ for Croston's method and SBA. We further use the test set to obtain the estimated service level $\widehat{\mathbb{E}\text{WT}}^*$ and $\widehat{\text{CSL}}^*$ under such base stock level $S_{\min}$. Here $*$ denotes that the estimator is obtained from the training set.

Thus, the setting of our experiment conforms to the setting faced by companies in real life: forecasts and inventory levels must be set based on some past period (our training period), while the resulting base-stock levels are applied for some future period (our test period), and the quantity of interest is the performance of the base-stock level in this future period. We will vary the length of the training set, because the amount of data present may affect performance in practice. The length of the test set is fixed to 1000 periods, and the simulation is replicated for 5000 times for each parameter setting. We report the average performance over the test set for all replications.

We have three designs in our simulation experiments.

- **Design A**: In order to explore the influence of training set length n on the performance of the methods for setting base-stock levels, we set $L = 5$, fix the target service level $\mathbb{E}\text{WT}_{obj} = 0.03$ or $\text{CSL}_{obj} = 0.97$ and increase n from 60 to 500 time periods. This includes periods with both positive demand and zero demand and corresponds to 12-100 positive demand observations, since we will have positive demand in roughly 1 in 5 periods, see Section 2.4.1.2. Results are given in Figures 2.2, 2.5 and 2.7.

- **Design B**: We consider a training set length $n = 60$, $L = 5$ and different target service levels (CSL_{obj} varies from 0.85 to 0.99) to explore the impact of target service level on performance, see Figures 2.3, 2.6 and 2.8.

- **Design C**: We vary the lead time L from 2 to 6 given target service level

$\mathbb{E}\mathrm{WT}_{obj} = 0.03$ or $\mathrm{CSL}_{obj} = 0.97$ and training set length $n = 60$ to explore the influence of the lead time on the performance of the various methods, see Figure 2.4.

In Example 2 in Subsection 2.3.3, we have seen that the estimated expected waiting time may become extremely high for larger estimated extreme value indexes $\widehat{\gamma}$. To avoid this issue, we practically set an upper limit where $S_{\mathrm{EVT}} = 1.5 \cdot S_{\mathrm{emp}}$. We also use S_{emp} as a lower limit on S_{evt}. Note that very large S_{evt} does not occur when using the cycle service level (see Step 5 in Subsection 2.3.2).

2.4.1.2 Demand process

In our simulations, i.i.d intermittent demand is generated as follows. First, we consider demand generated for corrective maintenance (CM). In each time period, a positive CM demand is generated with probability $p_{nonzero} = 0.2$ and zero demand with probability $p_{zero} = 1 - p_{nonzero} = 0.8$. Next we choose one of the following distributions to represent the positive integer CM demand: (I). Geometric based compound Poisson distribution with $p = 0.5$ and $\lambda = 2.5$; (II). Truncated normal distribution with $u = 5, \sigma^2 = 3$, where we set negative values to zero. See Lengu et al. (2014) for a detailed discussion on compound Poisson distributions and their fit to spare parts demand. It is well-known that the truncated normal distribution satisfies (2.1). Note that Shimura (2012) establish applicability of EVT for the geometric distribution. Moreover, as the tail behaviour of the compound Poisson distribution is related with the right tail of the compounding distribution (Willmot, 1990), this also establishes applicability of EVT for compound Poisson demand with a geometric compounding distribution.

We also consider cases in which this CM is augmented with demand stemming from preventive maintenance (PM). PM in general may have a relatively large value. Positive integer PM demand is generated once every 12 time periods and has truncated normal distribution with $u = 12, \sigma^2 = 2$. In simulations, we thus either consider CM demand only, or we consider CM and PM together by using positive PM demand to replace the corresponding CM demand in the same period.

2.4.1.3 Results

We compare the accuracy of the various methods by evaluating the differences between the targets and the achieved service levels. We discuss underperformance (real performance does not reach target performance) as well as overperformance

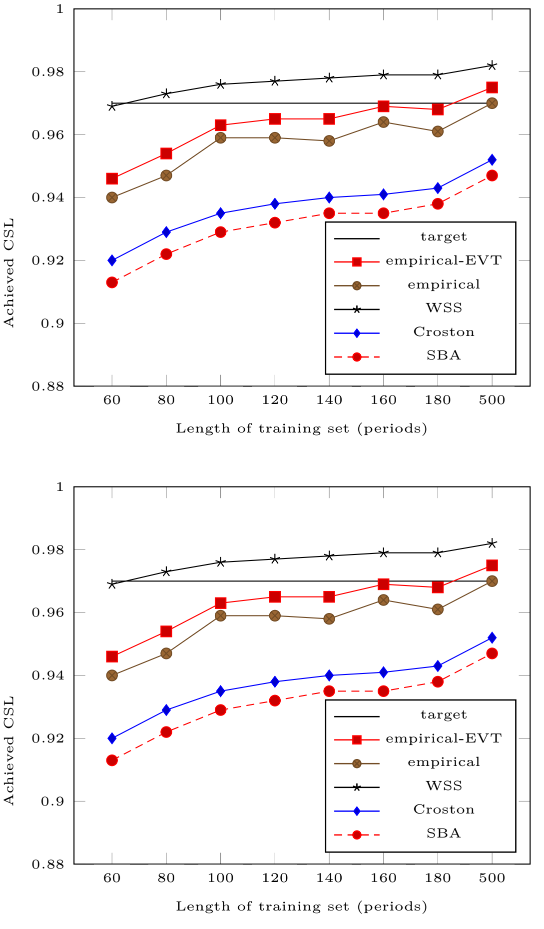
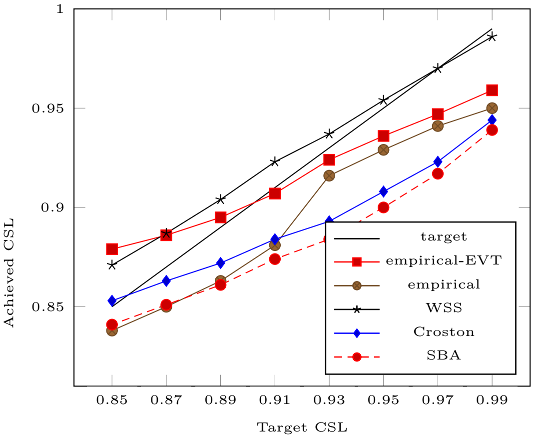


Figure 2.2: Simulation results of achieved CSL under fixed target 0.97 and different number of observations (including positive and zero demand). Only CM demand is considered. The underlying positive demand distribution is compound Poisson (left)/folded normal (right). Each result shows the average of 5000 simulations.



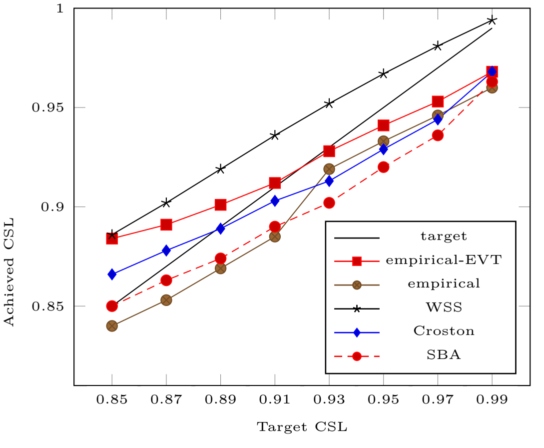


Figure 2.3: Simulation results of achieved CSL under fixed training set length 60 (including positive and zero demand) and different targets. Only CM demand is considered. The underlying positive demand distribution is compound Poisson (left)/folded normal (right). Each result shows the average of 5000 simulations.

(real performance exceeds the target).

Figures 2.2-2.6 focus on situations with CM demand only. The empirical-EVT consistently outperforms the empirical method. Both the empirical-EVT and the WSS method achieve real cycle service level that is quite close to the target. Here, WSS is closer to the target for relatively short training set length (60-80 periods - 12-16 positive demand observations), while empirical-EVT is closer to the target for more periods ($>$ 20 observations). This would give the WSS an edge in practice because the number of demand observations is typically limited there. Overperformance of

WSS is observed when the positive demand is normally distributed, see Figure 2.2 and Figure 2.3. The empirical method, Croston's method and SBA have difficulties in reaching the target. The achieved cycle service level of each approach increases as the training set length increases. Figure 2.4 shows that the empirical method and empirical-EVT are the most sensitive to the lead time, while the WSS method seems very robust to changes in the leadtime.

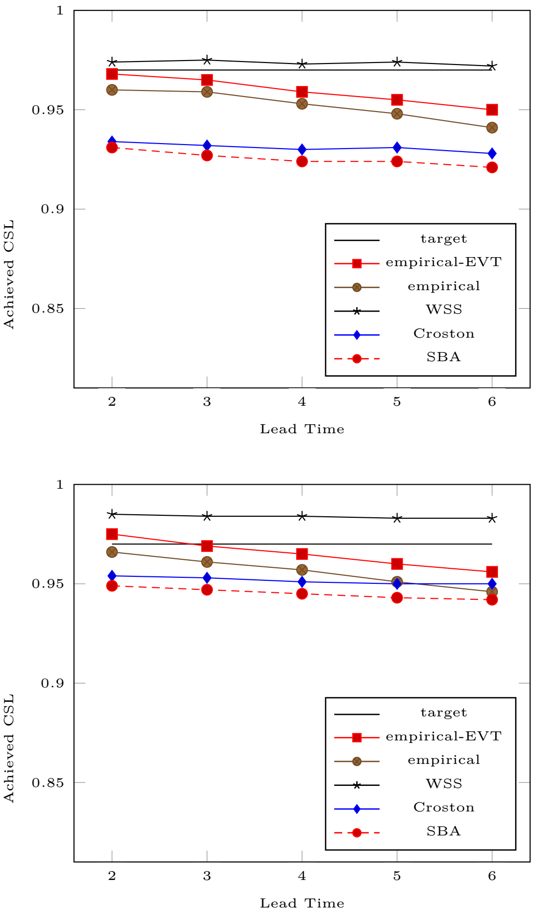
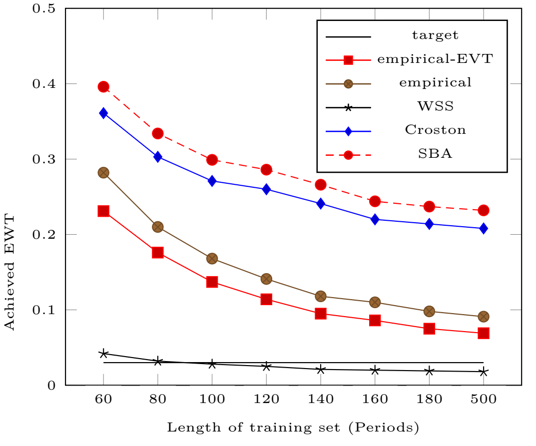


Figure 2.4: Simulation results of achieved CSL under fixed training set length 80 (including positive and zero demand), fixed target 0.97 and different lead time. Only CM demand is considered. The underlying positive demand distribution is compound Poisson (left)/folded normal (right). Each result shows the average of 5000 simulations.

Figure 2.5 and Figure 2.6 show the performance of each approach under the expected waiting time target. The performance of each approach improves with the



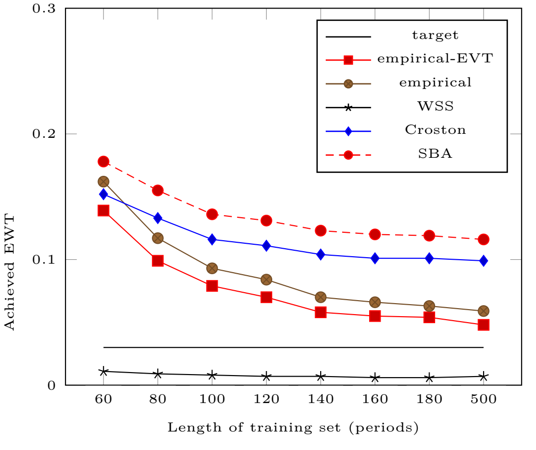


Figure 2.5: Simulation results of achieved $\mathbb{E}$WT under fixed target 0.03 and different number of observations (including positive and zero demand). Only CM demand is considered. The underlying positive demand distribution is compound Poisson (left)/folded normal (right). Each result shows the average of 5000 simulations.

increase of training set length. Empirical-EVT outperforms the empirical method, Croston's method and SBA. WSS however performs better than empirical-EVT. It has very good performance for compound Poisson demand, but it again overperforms when demand is normally distributed.

We will see in Section 2.4.2 that Croston's method and SBA attain a much higher performance for empirical datasets when compared to their results in figures 2.2-2.6 for CM only demand. A partial explanation may be given by sudden large demands in the empirical data, which may result from planned/preventive maintenance actions.

(The limited information on the empirical data can neither confirm nor rule out the role of PM in the large demands.) To test the effect of sudden large demands in a more controlled environment, we report on simulation experiments in which CM demand is augmented with PM demand, as discussed in Section 2.4.1.2.

The results are shown in Figures 2.7 and 2.8. For each demand distribution in which PM demand is considered alongside CM we find that Croston's method and SBA suddenly perform much better than in the CM only case. Additionally, SBA avoids the overstocking by Croston's method. Moreover, the cycle service level of the empirical-EVT is quite close to the target, and the most accurate of all methods for higher targets. The empirical method achieves a lower cycle service level while Croston's method, SBA and WSS result in overperformance. When the target is relatively low, overperformance happens under all approaches except for the empirical method.

2.4.2 Empirical study

2.4.2.1 Setup and parameters

To demonstrate empirical results of the proposed approach, we conduct a study based on real data. We use the automotive data set described by Syntetos and Boylan (2005) from an automotive industry and data on component repairs from Romeijnders et al. (2012). The automotive industry data set records intermittent demand of 3000 Stock Keeping Units (SKUs) over 23 time periods. The training set includes demand in the first 13 time periods and the last 10 time periods are classified as the test set.

The aircraft component repair database used in Romeijnders et al. (2012) gives spare parts usage in component repairs. We ignore the component level data and focus only on the parts used in all component repairs together. The database tracks the demand history of 11402 types of spare parts over 122 months. We set the first 84 months as the training period for each item and test the resulting base-stock levels in the last 38 periods. The data set contains many very slow moving items that might not be stocked in a real life setting. Therefore, we will consider only the parts which were used in at least 14 months in the 7 years of our training period, corresponding to at least 2 usages annually. Parts with less usage may not be stocked at all, and therefore the performance for these parts is less relevant. This results in 2549 parts that will be used in further analysis.

Except for using a different demand model, the setup of our experiments is in line

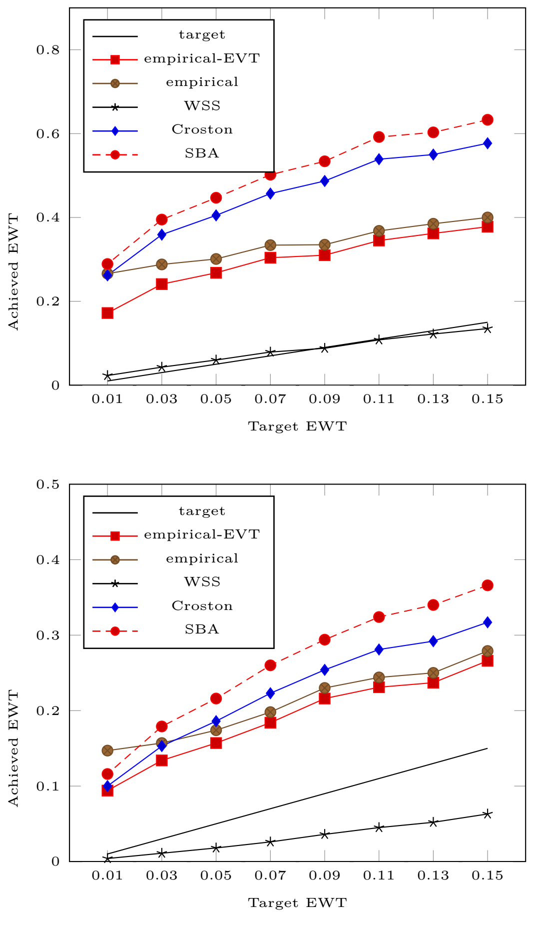


Figure 2.6: Simulation results of achieved $\mathbb{E}$WT under fixed training set length 60 (including positive and zero demand) and different targets. Only CM demand is considered. The underlying positive demand distribution is compound Poisson (left)/folded normal (right). Each result shows the average of 5000 simulations.

with the approach in Section 2.4.1. That is, we use the data in the training set to estimate the required base-stock level to achieve a certain service, and then use the test set for determining the real service level associated with that base-stock level. This approach is applied to individual each SKU or spare part and we obtain the average service level over 3000 SKUs or 2549 spare parts. We consider a constant $L = 3$ for the automotive industry data and $L = 5$ for the component repair data.

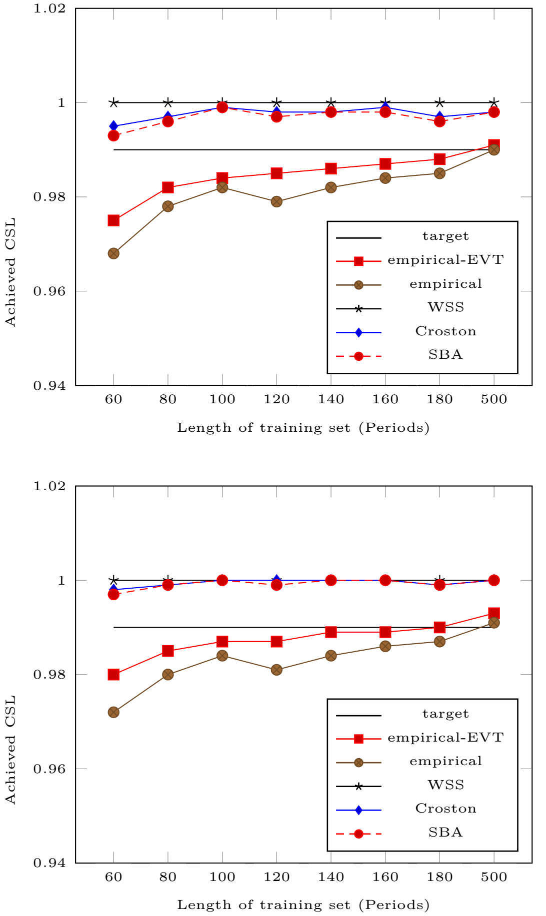


Figure 2.7: Simulation results of achieved CSL under fixed target 0.97 and different number of observations (including positive and zero demand). Both CM demand and PM demand are considered. The underlying distribution of positive CM demand is compound Poisson (left)/folded normal (right). Each result shows the average of 5000 simulations.

2.4.2.2 Results

Figure 2.9 and Figure 2.10 show the empirical result of each forecasting method for the automotive dataset and the aircraft component dataset, respectively. In the automotive case, Croston's method, SBA and WSS perform well. WSS results in an overperformance in case of low target CSL or high target $\mathbb{E}$WT. SBA has a lower achieved CSL (or higher achieved $\mathbb{E}$WT) than Croston's method since it uses the smoothing constant to adjust the estimator of mean demand. The empirical-EVT

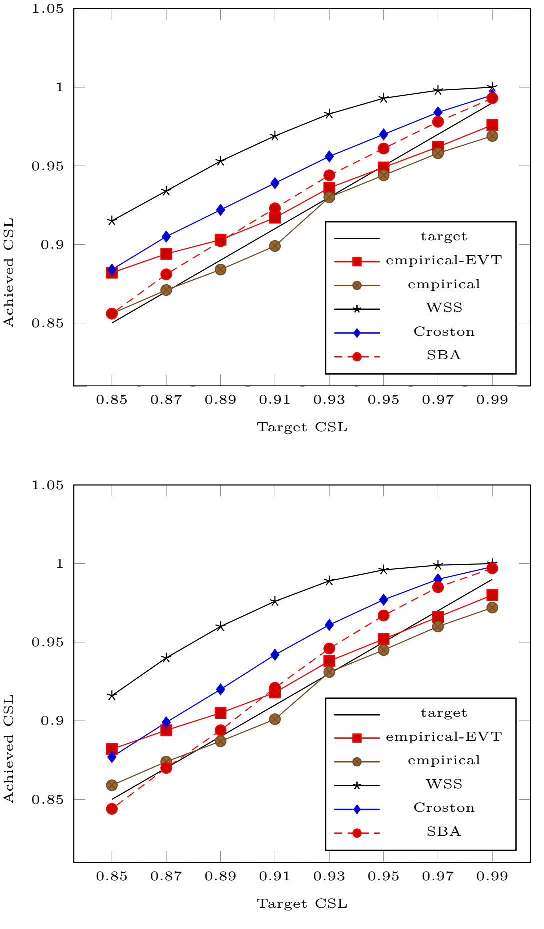


Figure 2.8: Simulation results of achieved CSL under fixed training set length 60 (including positive and zero demand) and different targets. Both CM demand and PM demand are considered. The underlying distribution of positive CM demand is compound Poisson (left)/folded normal (right). Each result shows the average of 5000 simulations.

performs slightly worse than SBA. The empirical method has difficulties in reaching the target, when compared to the other approaches. In the component repair case, the empirical-EVT method performs the best for the $\mathbb{E}$WT, while it is the joint winner for the CSL target. In general, all methods have difficulties in achieving the target. Croston's method is competitive when CSL is considered, followed by SBA, the empirical method and WSS.

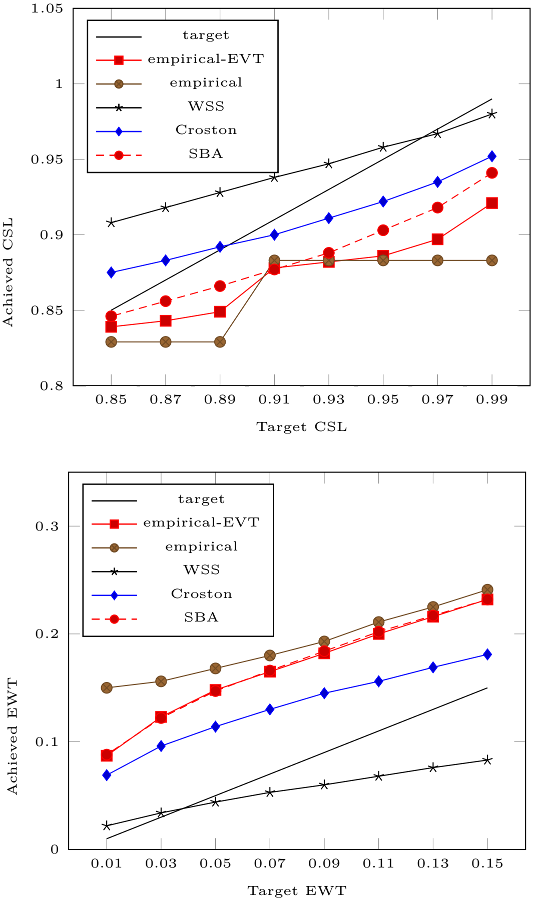


Figure 2.9: Empirical results of achieved CSL (left graph) and $\mathbb{E}$WT (right graph) for the automotive dataset.

2.4.3 Analysis and Discussion

Comparing Figure 2.7 and 2.8 with Figure 2.2 and 2.3, we found the performance of empirical-EVT is more stable than WSS, Croston's method and SBA in different situations. E.g., with the introduction of PM demand, the underperformance turns into overperformance for Croston's method and SBA. WSS as well leads to severe overperformance in the simulation in which PM demand is considered as well as CM demand. We provide two partial explanations. In general, PM demand has larger values than CM demand. WSS may select these large values repeatedly to forecast for each period and sum them up to estimate the lead time demand. The repeated selection gives rise to overestimations and hence overperformance. Besides, as the jittering process in WSS approach provides more variation around larger numbers than around smaller ones, PM results in large generated demands. As a result, the jittering process exacerbates the overperformance.

Overperformance of WSS is also observed in the situation of considering only CM demand and folded normal distributed positive demand. It results from the fact that positive demand values in this situation are relatively stable and the jittering process, in this case, loses its advantage by increasing the estimated base stock level $S_{\min}$ unnecessarily. That the overperformance in case of compound Poisson distributed positive demand is much less the overperformance for folded normal supports this explanation, the compound Poisson had double the standard deviation of the folded normal distribution for our parameters.

Lead time does not have much effect on the performance of Croston's method, SBA and WSS. The accuracy of the empirical-EVT and the empirical method decreases with lead time. These latter methods obtain lead time demand history through summing up the values within time windows of lead time length. Thus, larger lead times lead to more samples with the same value as a large proportion of the demand series is zero. This results in less variation in the sample used as input for the empirical method and the empirical-EVT method. Thus larger lead time lead to the decrease in inventory performance of empirical-EVT, when keeping the demand history fixed.

The performance of WSS is highly related to the data set. It has overperformance in case of automotive industry and underperformance in the component repair dataset. Performance of the empirical-EVT is influenced by the limitation of lead time demand. As the training set from the automotive industry gives demand in 13 time periods and provides only 11 lead time demand under the empirical-EVT approach, too few lead time demand above the threshold is available to estimate the tail. The less accurate estimation of the lead time demand tail limits the performance of the empirical-EVT approach. Data from the component repair case allow us to approximate the tail based on history in 84 periods. With more training data, the empirical-EVT leads to a better inventory performance than the benchmarks.

2.5 Conclusions

LTD forecasting is essential to spare parts inventory control but difficult as the demand has the feature of irregularity and lumpiness. Non-parametric approaches,

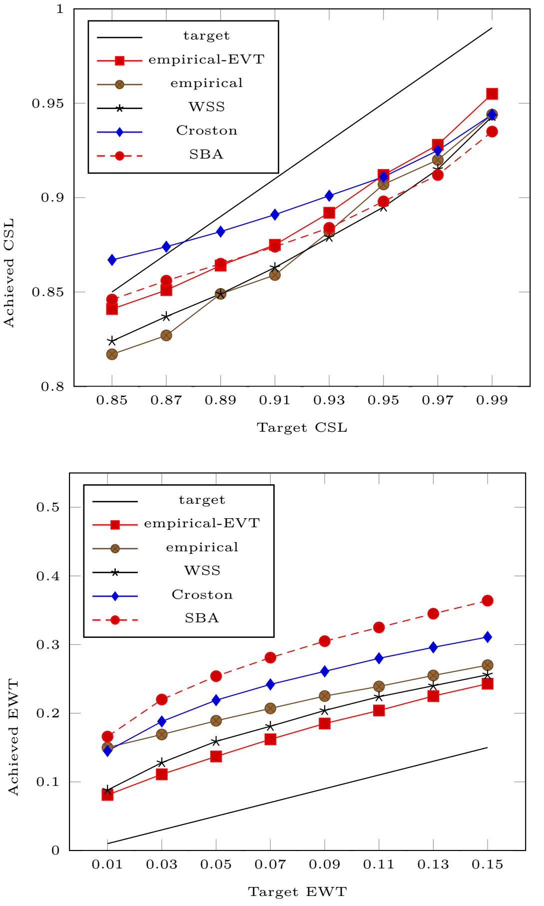


Figure 2.10: Empirical results of achieved CSL (left graph) and $\mathbb{E}$WT (right graph) for the component repair dataset.

like the empirical method, are suitable for spare parts since they can represent the erratic and lumpy demand behaviour. A limited number of observations prevents the empirical method from achieving high performance.

We propose a semi-parametric LTD forecasting method for spare parts. It is applicable for forecasting the lead time demand and determining the inventory control parameters of spare parts. The empirical-EVT method is a combination of non-parametric empirical method and EVT extrapolation. It samples LTD from actual data and uses EVT to model the distribution above a high threshold so that it can predict possible extreme values. The new method can represent the demand behaviour as well as achieve high target service levels.

We build models for different service measures and analyse their applications. Simulation shows that the empirical-EVT method has a relative good performance and avoids overperformance which regularly happens under WSS, Croston's method and SBA. Still, the empirical-EVT has performance issues with limited demand histories, and may be outperformed by WSS, and even by simpler methods such as Croston's and SBA. The empirical study based on data sets from two companies demonstrates that accuracy of WSS highly depends on the data set. Moreover, the test shows that the empirical-EVT struggles to perform well when demand history consists of only very few periods. In contrast, performance of empirical-EVT is better in cases where only relatively few demand points are available, but over many periods, as shown for our second empirical test. In those cases, the method is rather competitive. This should be taken into account when considering to apply the method in practice.

Our theoretical treatise indicates that the empirical-EVT method has a problem in estimating the fill rate. The fill rate fails to change monotonously with the increase of base stock level when applying EVT independently for the LTD with lead time L and the LTD with lead time $L-1$. Another issue arises for the expected waiting time, which can only be estimated when the extreme value index is not bigger than or close to 1. This problem is solved by considering the cycle service level instead of expected waiting time. The empirical-EVT method in combination with the cycle service level works well. However, the issues related to applying EVT with expected waiting time of fill rate may be a limiting factor when applying it.

Future research should focus on three related problems. Firstly, we observed that the empirical-EVT method might overestimate the base stock level in the case of large training set length, and it could be interesting to further investigate this convergence issue. A second issue is finding ways to apply EVT to estimate the fill rate, in order to avoid the lack of monotonicity identified in Section 2.3.2. Lastly, it could be interesting to apply EVT to other forecasting methods. E.g., in WSS it could be used to replace the jittering process in order to general lead time demand which has not been observed in the history. It is not immediately clear how to use the EVT approach with parametric methods such as Croston's method or SBA, and this too is an interesting subject for further research.

Appendix

2.A Tail approximation using EVT

Let S be a given base stock level. τ is some threshold. Denote $\mathbb{E}\left[(X-S)^{+} \mid X>\tau\right]$ by $\mu_{\text{tail}}(\tau)$. Let F denote the cumulative distribution function of X, and let $x^{*}:=\sup\{x : F(x)<1\}$ denote the (possibly infinite) endpoint of its support. Let $S\vee\tau$ denote $\max(S,\tau)$, and remark that

$$\int_{S\vee\tau}^{x^{*}} ((S\vee\tau)-S)\, dF(x) = (\tau-S)^{+}(1-F(\tau)),$$

$$\int_{S\vee\tau}^{x^{*}} (x-(S\vee\tau))\, dF(x) = \int_{S\vee\tau}^{x^{*}} (1-F(u))\, du.$$

Thus, we may write

$$\begin{aligned}
\mu_{\text{tail}}(\tau) &= \int_{S}^{x^{*}} (x-S)\, f_{x|x>\tau}(x \mid x>\tau)\, dx \\
&= \int_{S\vee\tau}^{x^{*}} ((x-(S\vee\tau)) + ((S\vee\tau)-S))\, \frac{f(x)}{(1-F(\tau))} dx \\
&= \frac{\int_{S\vee\tau}^{x^{*}} (1-F(u))\, du + (\tau-S)^{+}(1-F(\tau))}{(1-F(\tau))} \\
&= (\tau-S)^{+} + \frac{1}{(1-F(\tau))} \int_{S\vee\tau}^{x^{*}} (1-F(u))\, du. \qquad (2.14)
\end{aligned}$$

It directly follows from (2.2) that we may approximate $\mu_{\text{tail}}(\tau)$ by

$$(\tau-S)^{+} + \int_{S\vee\tau}^{x^{*}} \left\{1-H_{\gamma}\left(\frac{u-\tau}{f(\tau)}\right)\right\} du \quad \text{for all } S\vee\tau \geq \tau. \qquad (2.15)$$

Now introduce

$$\Psi_{\gamma}(x) = \begin{cases} \frac{f(\tau)}{1-\gamma}\left\{1+\gamma\left(\frac{x-\tau}{f(\tau)}\right)\right\}^{1-1/\gamma} & \text{if } \gamma \neq 0, \\ f(\tau)\exp\left(\frac{-x+\tau}{f(\tau)}\right) & \text{if } \gamma = 0, \end{cases} \qquad (2.16)$$

and distinguish between the cases $\gamma<0$, $\gamma=0$, $0<\gamma<1$ and $\gamma \geq 1$.

- For $\gamma < 0$, the endpoint x^* is finite. Rewrite (2.15) as

$$\begin{aligned}
&(\tau - S)^+ + \int_{S\vee\tau}^{x^*} \left\{1 + \gamma\left(\frac{x-\tau}{f(\tau)}\right)\right\}^{-1/\gamma} dx \\
&= (\tau - S)^+ + \left[-\frac{f(\tau)}{1-\gamma}\left\{1 + \gamma\left(\frac{x-\tau}{f(\tau)}\right)\right\}^{1-1/\gamma}\right]_{S\vee\tau}^{x^*} \\
&= (\tau - S)^+ + \left[-\Psi_\gamma(x)\right]_{S\vee\tau}^{x^*} \\
&= (\tau - S)^+ + \Psi_\gamma(S\vee\tau) - \Psi_\gamma(x^*). \qquad (2.17)
\end{aligned}$$

- For $\gamma = 0$, the endpoint x^* can be finite or infinite, see de Haan and Ferreira (2006). Assume x^* is infinite. (2.15) is transformed to

$$\begin{aligned}
&(\tau - S)^+ + \int_t^\infty \exp\left(\frac{-x+\tau}{f(\tau)}\right) dx \\
&= (\tau - S)^+ + \left[-f(\tau)\exp\left(\frac{-x+\tau}{f(\tau)}\right)\right]_{S\vee\tau}^\infty \\
&= (\tau - S)^+ + \left[-\Psi_\gamma(x)\right]_{S\vee\tau}^{x^*} = \Psi_\gamma(S\vee\tau) \qquad (2.18)
\end{aligned}$$

- For $0 < \gamma < 1$, $x^* = \infty$, see de Haan and Ferreira (2006), (2.15) can be written as

$$\begin{aligned}
&(\tau - S)^+ + \int_{S\vee\tau}^{\infty} \left\{1 + \gamma\left(\frac{x-\tau}{f(\tau)}\right)\right\}^{-1/\gamma} dx \\
&= (\tau - S)^+ + \frac{f(\tau)}{\gamma-1}\left\{1 + \gamma\left(\frac{x-\tau}{f(\tau)}\right)\right\}^{1-1/\gamma}\Bigg|_{S\vee\tau}^{\infty} \\
&= (\tau - S)^+ + \frac{f(\tau)}{1-\gamma}\left(1 + \gamma\left(\frac{S\vee\tau-\tau}{f(\tau)}\right)\right)^{1-1/\gamma} \\
&= (\tau - S)^+ + \Psi_\gamma(S\vee\tau). \qquad (2.19)
\end{aligned}$$

- For $\gamma > 1$, it is easy to see that (2.15) goes to infinity, meaning the expected shortage is infinite. So the expected waiting time is no longer valid.

Now, let $X_1, X_2, \ldots, X_n$ be a random sample of size n from the distribution given by F; that is, the observations $X_1, X_2 \ldots, X_n$ are independent copies of the random variable X. Let $X_{(1)} \leq X_{(2)} \leq, \ldots \leq X_{(n)}$ be the ordered sample. Choose $0 \leq k < n$, and set τ equal to $X_{(n-k)}$. Recall that $\left(1 - F\left(X_{(n-k)}\right)\right) \approx k/n$. As $\alpha = f(\tau)$ and γ are unknown, we simply replace them by their estimators $\hat{\alpha}$ and $\hat{\gamma}$ defined by (2.6) and (2.7).

Estimate $\Psi_\gamma(x)$ by $\hat{\Psi}(x)$ defined in (2.12).

In the special case $\gamma < 0$, we have that x^* is finite. We may estimate x^* by

$$\hat{x}^* = X_{(n-k)} - \frac{\hat{\alpha}}{\hat{\gamma}}, \tag{2.20}$$

see Equation (4) in Einmahl and Magnus (2008).

We now may estimate $\mu_{\text{tail}}(\tau)$ by

$$\hat{\mu}_{\text{tail}} = \begin{cases} \left(X_{(n-k)} - S\right)^+ + \hat{\Psi}\left(S \vee X_{(n-k)}\right) & \text{if } 0 \le \hat{\gamma} < 1 \\ \left(X_{(n-k)} - S\right)^+ + \hat{\Psi}\left(S \vee X_{(n-k)}\right) - \hat{\Psi}\left(X_{(n-k)} - \hat{\alpha}/\hat{\gamma}\right) & \text{if } \hat{\gamma} < 0 \end{cases} \tag{2.21}$$

2.B Estimation of expected waiting time

Assume that the lead time demands are constructed via (2.8), where D_j's together form a stationary process. Let $\mathbb{E}[D]$ denote the common expectation of the D_j's. According to Little's law, we may write

$$\mathbb{E}\text{WT}(S) = \mathbb{E}\text{BO}(S)/\mathbb{E}[D], \tag{2.22}$$

where $\mathbb{E}\text{BO}(S)$ denotes the expected backorders for base stock level S.

We compute the expected backorders $\mathbb{E}\text{BO}(S)$ via conditioning on the random variable $1_{\{X>\tau\}}$, where τ is again a deterministic threshold. Note that $1_{\{X>\tau\}}$ takes the value 1 if the event $\{X > \tau\}$ occurs, and the value 0 if the event $\{X > \tau\}$ does not occur. Denote $\mathbb{E}\left[(X-S)^+ \mid X \le \tau\right]$ by $\mu_{\text{non-tail}}(\tau)$.

As $\text{BO}(S)$ is in fact equal to $(X-S)^+$, the law of total expectation, see Ross (2009, p. 107), yields

$$\begin{aligned} \mathbb{E}\text{BO}(S) &= \mathbb{E}\left[(X-S)^+\right] \\ &= \mathbb{E}\left[\mathbb{E}\left[(X-S)^+ \mid 1_{X>\tau}\right]\right] \\ &= \mathbb{E}\left[(X-S)^+ \mid X \le \tau\right] \times P(X \le \tau) \qquad (2.23) \\ &+ \mathbb{E}\left[(X-S)^+ \mid X > \tau\right] \times P(X > \tau) \\ &= F(\tau)\,\mu_{\text{non-tail}}(\tau) + (1 - F(\tau))\,\mu_{\text{tail}}(\tau) \qquad (2.24) \end{aligned}$$

We use (2.4) to approximately express $\mathbb{E}\left[(X-S)^{+} \mid X>\tau\right]$ as a function of the unknown parameters α and γ, see Equations (2.17), (2.18) and (2.19).

As before, let $X_1, X_2, \ldots, X_n$ be a random sample of size n from the distribution given by F. As α and γ are unknown, we simply replace them by their estimators $\hat{\alpha}$ and $\hat{\gamma}$ defined by (2.6) and (2.7). As a consequence, we may estimate $\mu_{\text{tail}}(\tau)$ by $\hat{\mu}_{\text{tail}}$ defined in (2.21). Moreover, we may estimate $1-F(\tau)$ by k/n. It follows that the term $(1-F(\tau))\,\mu_{\text{tail}}(\tau)$ is estimated by

$$\frac{k}{n}\hat{\mu}_{\text{tail}} \tag{2.25}$$

As the $n-k$ observations below the threshold τ behave as a random sample from the conditional distribution of X given $X<\tau$, we simply estimate $\mu_{\text{non-tail}}(\tau)$ non-parametrically by

$$\hat{\mu}_{\text{non-tail}} = \frac{1}{n-k}\sum_{X_i \le \tau}(X_i - S)^{+} = \frac{1}{n-k}\sum_{i=1}^{n-k}\left(X_{(i)} - S\right)^{+}. \tag{2.26}$$

As we may estimate τ by $X_{(n-k)}$ and $F(\tau)$ by $(n-k)/n$, it follows that the term $F(\tau)\,\mu_{\text{non-tail}}(\tau)$ is estimated by

$$n^{-1}\sum_{i=1}^{n-k}\left(X_{(i)} - S\right)^{+} \tag{2.27}$$

We conclude that, for $\hat{\gamma}<1$, we may estimate $\mathbb{E}\mathrm{WT}(S)$ according to (2.10) with (2.11) and (2.12).

2.C Estimation of cycle service level

Let $X_1, X_2, \ldots, X_n$ be a random sample of size n from the distribution given by F, and let $X_{(1)} \le X_{(2)} \le, \ldots \le X_{(n)}$ be the ordered sample.

We distinguish between two cases: $S \le \tau$, and $S > \tau$, where τ is some given threshold.

- For $S \le \tau$, we can simply estimate $P(X \le S) = F(S)$ non-parametrically by

$$\widehat{P}(X \le S) = \frac{1}{n}\sum_{i=1}^{n} 1_{\{X_i \le S\}} \tag{2.28}$$

- For $S > \tau$, we first use (2.2) to approximate $P(X \leq S) = 1 - (1 - F(S))$; this yields

$$P(X \leq S) \approx 1 - (1 - F(\tau)) \left\{ 1 - H_\gamma \left(\frac{S - \tau}{f(\tau)} \right) \right\}. \tag{2.29}$$

Choose $0 \leq k < n$, and set τ equal to $X_{(n-k)}$. Replace $\alpha = f(\tau)$ and γ by their estimators $\hat{\alpha}$ and $\hat{\gamma}$. This yields the estimator

$$\widehat{P}(X \leq S) = 1 - \frac{k}{n} \left\{ 1 - H_{\hat{\gamma}} \left(\frac{S - X_{(n-k)}}{\hat{\alpha}} \right) \right\}. \tag{2.30}$$

Combining (2.29) and (2.25) yields (2.30).

2.D Selection of threshold

We choose threshold through the moment estimator plot. We let k vary from 3 to $n-3$, and obtain the corresponding extreme value index $\hat{\gamma}_{n-1},\ldots, \hat{\gamma}_{n-k},\ldots, \hat{\gamma}_3,\hat{\gamma}_2$. The threshold position which stabilizes the extreme value index γ is the i which minimizes $\sum_{j=-2}^{3}|\hat{\gamma}_{i+j} - \hat{\gamma}_{i+j-1}|$. As the empirical method obtains lead time demand by putting windows with size lead time over the demand history, it results in the repetition of lead time demand in case of intermittent demand. The repetition of lead time demand would make the moment estimator plot locate the threshold in the place where lead time demand is repeated mostly since the parameter γ there is misleadingly stable. That is, using moment estimator plot to determine the threshold directly may lead to the problem that the tail not only includes relatively large lead time demand but also contains very small values which might not be considered as tail. Therefore, we make a adjustment in applying the moment estimator plot to determine the threshold. We only consider the threshold in the last 10 percents of the LTD ascending series. That is, the threshold is as the i in the last 10 percent of the series which makes the parameter γ relatively stable.

Chapter 3

Spare Parts Inventory Control based on Maintenance Planning

3.1 Introduction

Spare parts demand forecasting is essential to controlling spare parts inventories and avoiding high spare part shortage and holding costs. Time series methods estimate demand based on history (see e.g. Syntetos and Boylan, 2005), and as such they may work well when the historical situation is comparable with the future. They respond reactively to unprecedented factors and cannot predict the timing of sudden peaks in demand. This is especially problematic for spare parts demand because of its intermittency and lumpiness (Petropoulos and Kourentzes, 2015).

Advance demand information (ADI) is information on demand, either perfect or imperfect, that is available ahead of the actual demand occurrence (see also Tan et al., 2007). This concept has been widely used in various industrial settings outside of the spare parts context, e.g. the demand forecasting of e-commerce (Ozer, 2003), customized products (Gallego and Ozer, 2001; Johnson and Whang, 2002), construction industry (van Donselaar et al., 2001). To overcome the limitations of time series methods in dealing with spare part demand intermittency and lumpiness, in this chapter we propose to use planned maintenance tasks as a source of ADI for spare parts inventory control.

We focus on maintenance tasks that prescribe to inspect a part of the asset, and depending on the condition of the part, it is then either immediately replaced by a spare part, or it may remain in the asset. Such *on-condition* maintenance tasks are a cost-effective tool for ensuring that parts continue to meet their functional and safety requirements, and they therefore constitute an important part of modern maintenance policies for aircraft, trains, and other capital assets.

The resources that enable maintenance, e.g. mechanics and a maintenance hangar, need to be planned ahead of the actual maintenance. To enable this maintenance logistics planning, companies specify which on-condition maintenance tasks will be performed some time periods into the future (see Section 3.3 for a detailed discussion). It is this maintenance logistical plan that we propose to use as a source of ADI in this paper. We need to overcome two complications when using this form of ADI to control spare parts inventories. First, on-condition maintenance tasks are a form of *imperfect* demand information: Only upon inspection does it become clear whether an on-condition maintenance task constitutes a spare part demand. So using the maintenance plan involves dealing with this inherent uncertainty. Second, while the need for logistics planning forces companies to plan on-condition maintenance tasks ahead of time, this plan is only available and reliable a few months into the future.

We contribute to literature by proposing a new approach for joint forecasting and inventory control based on the maintenance plan. The approach *endogenously* links maintenance tasks to parts usage based on maintenance data. Moreover, our approach integrates the demand forecasting model with an inventory control model. The natural approach for this would be to somehow extrapolate the demand forecast for the first few months, but this leads to myopically ordering too many parts when demand is forecasted to be high, which is very costly for slow moving parts. We contribute a method to overcome this: We extend the demand forecast using a hybrid forecasting approach, and we propose a forward-looking inventory procedure that explicitly takes into consideration the risk that parts stay in inventory for a long time after procurement. The hybrid forecasting approach combines an ADI-based approach for the first few periods with a regular forecasting approach for the remainder of the horizon. The forward-looking inventory policy solves in each period a stochastic dynamic program based on the latest demand forecasts over the horizon.

The forecasting element of our approach is conceptually related to spare parts forecasting models that use the delay-time model (e.g. Wang and Syntetos, 2011), but unlike those approaches our approach does not need the delay-time distribution of each component as input, but it estimates *from data* all parameters needed to arrive at forecasted demand distributions. Other approaches improve forecast accuracy at the expense of increasing the difficulty, the effort and the operational cost to predict demand, e.g. investing in a condition monitoring system (Topan et al., 2018), see also Driessen et al. (2010). In particular, while our method needs more data than typical time-series methods, we need considerably less data and information than approaches based on the delay-time model (e.g. Poppe et al., 2017; Wang and Syntetos, 2011) or on system monitoring systems (Lin et al., 2017; Topan et al., 2018). This reduction in the data requirements constitutes an important step towards enabling the application of ADI-based approaches in practice, and in particular towards rolling out such approaches over entire spare parts assortments.

We illustrate this by assessing the potential value of implementing our approach for inventory control based on data for thousands of parts of two companies, and compare it to a state-of-the-art time series forecasting approach (viz. Syntetos and Boylan, 2001). We find that optimizing inventory using the maintenance plan yields a very substantial cost reduction of 23-51%, compared to the benchmarks. To our knowledge, this is the first proof that an ADI-based approach yields value in a practical setting, where all parameters need to be estimated from data.

The remainder of this chapter is organized as follows. The next section gives an overview of the relevant literature. In Section 3.3 we discuss the availability of planned on-condition maintenance tasks in practice. In Section 3.4 we discuss our approach. Section 3.5 gives the setup and results of our experiments using two sets of real company data. The final conclusions are presented in Section 3.6.

3.2 Literature Review

Spare parts demand can either be forecasted based on historical data, advance demand information or a combination of both (Driessen et al., 2010). Since our ADI-based method represents an alternative to time-series forecasting methods for intermittent spare parts demand, we first briefly review literature those latter methods (for a more detailed review see Van Wingerden et al., 2014). Time series forecasting methods for intermittent demand include parametric and nonparametric methods. Croston's method (Croston, 1972) is an early example of a parametric method. Recent works analyze and improve this method (Syntetos and Boylan, 2005; Syntetos and Boylan, 2001; Teunter et al., 2011; Syntetos, 2001; Shale et al., 2006) and propose alternative parametric methods (Willemain et al., 1994; Ghobbar and Friend, 2003; Eaves and Kingsman, 2004; Romeijnders et al., 2012). For insightful discussions regarding parametric methods refer to Boylan and Syntetos, 2010 and Prak and Teunter, 2019. *Non-parametric* methods construct empirical distributions of demand, see e.g. Van Wingerden et al. (2014), Willemain et al. (2004), Porras and Dekker (2008), and Zhu et al. (2017).

We next review contributions that apply ADI in demand forecasting and inventory control. ADI may take different forms (e.g. service contract, sensor data from machines, part age, etc) and topics in literature include how to derive demand from different forms of ADI and how to respond to ADI. ADI literature can be divided into two streams: *perfect ADI* refers to situations where the quantity and timing of demand is known in advance, and *imperfect ADI* refers to cases where some information regarding demand is known, but not the exact quantity and timing.

Hariharan and Zipkin (1995) study where customers place their orders in advance (i.e. a *demand leadtime*), and show that this form of perfect ADI is mathematically equivalent to a reduction in the supply leadtime. Gallego and Ozer (2001) also study perfect ADI and show that state-dependent (s, S) policies are optimal in the periodic review model for positive set-up cost. The study gives a lower bound to its extension to a distribution system, which is studied in Ozer (2003). Gallego and Ozer (2003) consider perfect ADI in a multi-echelon system. They find that the value of ADI on each echelon is influenced by the lead time of that echelon, and prove the optimality of state-dependent, echelon base-stock policies. The key finding for perfect ADI is that the inventory position should include outstanding demand.

We now discuss papers with imperfect ADI. Tan et al. (2007) study an inventory problem with ADI that might either be realized as demand, wait in the system one more period or leave the system without demand realization with given probabilities. They show that the optimal policy is of order-up-to type, with the order-up-to level depending on the ADI information. Tan et al. (2009) consider imperfect ADI in an ordering and rationing problem with two demand classes. ADI is used to make a better rejection decision to lower class demand.

In addition to the above papers utilizing ADI to obtain (optimal) inventory policies, Abuizam and Thomopoulos (2005) and Tan (2008) apply ADI in demand forecasting. Abuizam and Thomopoulos (2005) propose a Bayesian method to update the expected amount of orders. However, Bayesian updates might fail in some problems as they rely on the distribution assumption, give one sided updates and fail to consider customer patterns (Tan, 2008). Therefore, Tan (2008) combine expert judgmental prediction and demand estimation from ADI. ADI are subject to change in time and orders are partially materialized. Historic record is used to model the order changing behavior. Van der Auweraer et al., 2018 review the forecasting methods in which ADI takes the form of installed base information. Forecasting methods are evaluated either in forecasting accuracy or in the integrated inventory system. Syntetos et al. (2010) and Boylan and Syntetos (2006) stress on the importance of considering inventory metrics rather than standard forecasting accuracy measures in evaluating the forecasting method. Simulation is the most widely used in evaluating the forecasting method and inventory performance, e.g. Wang and Syntetos (2011), Zahedi-Hosseini et al. (2017) and Poppe et al. (2017).

Using the imperfect ADI concept for improving spare parts inventory control could potentially aid practitioners to overcome the difficulties posed by spare part demand intermittency and lumpiness, and a few researchers have developed approaches in this general direction. Deshpande et al. (2006) track the age of parts in aircraft and use this information as ADI to improve spare parts inventory control. Pince et al. (2015) consider a manufacturer with contractual obligations to provide parts to its customers, and study the drop in demand rate resulting from contract expiration. Their proposed policy reduces the base stock level ahead of actual contract expiry. Basten and Ryan (2015) consider a single stocking point that satisfies demands resulting from corrective and preventive maintenance, and assume that perfect ADI is available for preventive maintenance. They propose heuristics for order and inventory allocation decisions, and find that the joint inventory requirement will be reduced due to the effect of risk pooling. Romeijnders et al. (2012) develop a two-step method that makes use of the component repairs in spare parts demand forecasting. They focus on comparing various time series forecasting methods without ADI, but mention that ADI in this setting can considerably increase forecast accuracy.

Wang and Syntetos (2011), Topan et al. (2018), Lin et al. (2017) and Poppe et al. (2017) pioneer new approaches towards spare parts inventory control driven by planned/foreseen maintenance, and as such they are arguably most closely related to our present work. These works are conceptually based on delay-time degradation models. To our knowledge, this key idea was introduced in Wang and Syntetos (2011), in the context of a block-based inspection policy. They assume that distributions for both the initial and the delay-time of the delay-time model are known. They focus solely on forecasting, and develop a forecasting model by computing the conditional probabilities of parts needing replacement during inspection and between the inspection intervals. They find that this model can reduce the forecast error substantially. Topan et al. (2018) consider an asset monitored by a real-time condition monitoring system that generates imperfect warnings that may indicate that a part is failing. They develop effective spare parts inventory control policies in this situation. Poppe et al. (2017) consider an asset monitored by a real-time condition monitoring system, and investigate the impact of adopting a condition based maintenance policy on inventory control, where they use corrective maintenance and periodic maintenance as benchmarks. In contrast, Lin et al. (2017) investigate the value of condition monitoring systems for spare parts inventory control without changing the maintenance policy, and find that it may be substantial.

All these approaches rely heavily on component degradation information, in the form of real-time condition monitoring and/or complete distributional information on the degradation process. In contrast, our approach needs no such information. Instead, we propose to directly estimate the probability that a part needs replacement in an on-condition maintenance task from data. This greatly simplifies applying our approach in practice. In addition, we are the first to use real data to test the value of ADI approaches for spare parts inventory control. Note that our tests involve assessing the value of the model for inventory control, and as such they contribute to an understanding of the potential value of our approach in practice.

3.3 On-condition maintenance tasks as advance demand information

We first discuss the on-condition maintenance concept versus other maintenance concepts, and explain how planned on-condition maintenance tasks constitute ADI. We then discuss in more detail how information regarding planned on-condition maintenance tasks arises in practice. The discussion is based on the experience of the authors working closely with two maintenance organizations (cf. Section 3.5). The second author has been working with these two companies for over 10 years. The first author conducted site visits to these and other maintenance organizations to verify the validity of the idea using maintenance plan for spare parts demand forecasting. The third author has worked with many industrial partners and accumulated deep insights to the maintenance industry. Finally, we note that Driessen et al. (2010) bring up a similar discussion based on in-depth interviews with a wide range of maintenance organizations. (Unlike us, they do not develop forecasting methods.)

The simplest form of maintenance is perhaps break-down maintenance, i.e. run-to-failure. In contrast, preventive maintenance encompasses a wide range of maintenance strategies aimed at preventing failures, and we discuss such strategies next.

In *time-based* maintenance a part or component is replaced periodically, e.g. after a fixed amount of time (e.g. every 6 months) or usage (e.g. every 20000 landings of an aircraft). Time-based maintenance can be planned ahead easily, and no condition information is needed to apply it, but it has the disadvantage that the useful life of the replaced parts may be poorly used. Therefore, when it is economically feasible to do so, companies *inspect* parts of the asset before deciding upon replacement; the part is then only replaced if degradation is above some threshold, hence the term *on-condition* maintenance task. This approach is typically motivated using a delay model for part degradation (Wang, 2011; Wang, 2012). Arguably, on-condition maintenance tasks are an example of *condition-based maintenance*, but most scholars reserve this latter term for situations where the condition is *real-time* monitored. In practice, the prevalence of real-time condition monitoring systems is still low because of their high associated cost (Topan et al., 2018).

In this chapter, we propose to use *planned* (but not necessarily periodic) on-condition maintenance tasks as spare parts ADI. This generic idea is broadly applicable across a wide range of maintenance organizations. The key and only requirements of the proposed approach are that on-condition maintenance tasks are known beforehand (e.g. 1 month into the future), and that information on past on-condition maintenance tasks and resulting spare parts usage is stored. In typical high-tech asset maintenance settings, the first requirement is satisfied in the sense that a broad range of on-condition maintenance tasks can be accurately foreseen beforehand, and data collection is often compulsory because of traceability requirements. Indeed, asset maintenance must be planned ahead of time to organize availability of the asset, qualified mechanics, tools, maintenance hangar, etc. The scope of asset maintenance is typically also known beforehand. Therefore, for those assets which have a big ratio of planned maintenance, using information on the on-condition maintenance task is very beneficial from cost perspective. Moreover, increasing adoption of maintenance management software has made data on the maintenance plan available in formats useful for automatic decision making, which has increased the potential of and need for the approach we propose. In the following, we explain in more detail the applicability of the approach for modularly designed assets. Modularly designed assets contain many line-replaceable units (LRUs) that can be removed during asset maintenance. Examples include aircraft, trains, trams, and many other high-tech machines. LRUs are typically removed periodically in order to inspect them. In particular, each LRU has an associated inspection interval and *inspection scope*. This scope consists in the on-condition maintenance tasks on *parts* of the LRU that together constitute the inspection. Both inspection intervals and degradation limits for on-condition tasks are typically prescribed by the manufacturer of the LRU, which bases its prescriptions on quantitative analysis in so-called reliability-centered/risk-based maintenance studies, see e.g. Khan and Haddara (2003) and Moubray (1997). The inspection of LRUs after removal from the asset is typically carried out in specialized repair shops. Therefore, parts of the LRU that are replaced depending on their condition are typically referred to as shop-replaceable units (SRUs). **Example:** *the manufacturer may specify that the rear servomotor (=LRU) of a certain type of aircraft must be removed for inspection every 8000 flight hours. Moreover, the manufacturer specifies that if, during inspection, it is found that the coil (=SRU) of the servomotor shows any signs of corrosion, it must be replaced.*

Asset maintenance is *clustered* in order to efficiently satisfy the component safety requirements prescribed by manufacturers. E.g. in aviation it is common practice to define maintenance with several depth levels, e.g. A, B, C and D level maintenance. In A-level maintenance the scope is small, while D-level maintenance encompasses the removal and inspection of a wide range of LRUs. The various levels of asset maintenance and their frequency are designed such that inspection intervals of individual LRUs are guaranteed. As a consequence of this careful design of the various checks, the *work scope* of such checks is typically specified beforehand, i.e. it is known which LRUs will be removed for inspection in which check. Moreover, maintenance organizations make detailed plannings of the maintenance of their fleet, in order to align availability of bottleneck resources such as maintenance hangars, mechanics and tooling, and moreover to ensure that the operational capabilities of the fleet remain at a sufficiently high level. **Example (continued):** *The fleet maintenance plan of an operator specifies that in the upcoming four weeks, each week two aircrafts of a specific type will undergo C-level maintenance, which includes removal and inspection of the rear servomotor installed in those aircraft.*

The main idea of this chapter is then to use the maintenance plan, and in particular the on-condition maintenance tasks that can be derived from the plan, as input to forecast spare parts demand. Maintenance plans may be made years in advance, but the plan is not reliable far into the future. This may for example be a consequence of cumulative forecasted usage (e.g. flight hours/kms) deviating from actual cumulative usage, or changes in the plan, etc. However, on the short term (e.g. a few months into the future instead of years) cumulative usage can be more accurately forecasted, making such deviations rare. Another reason for the plan to be more reliable on the short term is that deviations on the short term cause operational disruptions as well as unavailability and/or idle time of bottleneck resources. We propose to base ADI on this reliable time horizon, and we develop a method that reverts to time-series forecasting for periods beyond this horizon. **Example (continued):** *The coil in the rear servomotor has historically been replaced in one out of three repairs. Based on two planned removals of the rear servomotor per week, an expected demand of* $2/3 = 0.67$ *coils per week is forecasted for the next four weeks.*

To some extent, the approach can help to predict peaks in demand. **Example (continued):** *Suppose that an operator decides to inspect all servomotors in the fleet in April, to avoid any problems in the busy summer months. As a consequence, there will be 18 inspections per week for the month April. Based on this, expected demand of coils suddenly grows to* 6 *per week, or about* 24 *per month, and using the maintenance plan would enable to predict the sudden demand hike. However, note that there would still be considerable remaining variability in coil demand because of variations in actual coil replacement rates.*

We emphasize that while maintenance plans and tasks are nowadays increasingly available in maintenance management systems, such systems are not ubiquitous, and even if an investment in such systems is made, it is not necessarily trivial to extract information from such systems in a format usable for spare parts decision making. Apart from developing methods to use on-condition maintenance plans for spare parts inventory control, one of the goals of this chapter is testing their potential value in practice using data from companies in aerospace and train maintenance that were able to extract the necessary data from their system. We believe this assessment may help in driving business cases for the proposed approach.

3.4 Methods

Our approach is applicable in general for maintenance organizations that perform on-condition maintenance tasks. For concreteness, in what follows we adopt terminology of a *repair shop*. We focus on one specific LRU/component that is regularly inspected by the repair shop, which is an establishment specialized in repairs of line-replaceable units (cf. Section 3.3). Inspection consists of determining the condition of parts of the component: if a part is degraded beyond some acceptable level, then it must be removed and discarded, and replaced by a spare part. So for the repair shop, each component repair corresponds to a number of on-condition maintenance tasks: one for each part in the component.

To complete repairs quickly, the repair shop keeps a local inventory of spare parts, and our focus is on inventory control of one specific spare part that may be used in the component. In case the part is needed but out of stock, an emergency order is placed, and after the emergency leadtime the repair continues. Emergency orders are a common way to avoid very long and costly delays of maintenance, and the emergency order leadtime is understood to be much shorter than the regular leadtime. Note that placing an emergency order is (mathematically) equivalent to a lost sale, and we take this latter perspective. We consider the penalty costs for the lost sale to be c_e, where c_e includes emergency order cost and costs of delaying the repair. Note that delaying a component repair may be costly as it requires the mechanic to store the inspected component, and to later retrieve it, which is time-consuming. As is customary in industry (cf. Romeijnders et al., 2012), inventory is reviewed periodically, resulting in a periodic-review, single-item, lost-sales inventory system. We denote periods by $t \in \{1, \ldots, T\}$. Here, T is the last period before the end of the horizon.

We consider a constant lead time L for a regular order. Parts ordered at the start of period t arrive at the start of period $t + L$. We let $L = 1$, which corresponds to a situation where parts ordered one period are available in the next period. This is reasonable because repair shop inventory is replenished from a central warehouse every period. Moreover, since many SRUs are relatively inexpensive, it is affordable to avoid stock-outs in this central warehouse. More importantly, focusing on this assumption avoids very technical inventory models and allows us to focus on the exposition of the key ideas regarding the integration of ADI and inventory control. For the same reasons, we assume no economies of scale in ordering. Inventory has holding cost h per part per time unit, and since we work with a finite horizon, leftover inventory at the end of period T is penalized with cost s per part. This penalty may either reflect the cost of scrapping the inventory (in case this is really the end of the horizon in which the part is used), or it may reflect the cash tied up in inventory at the end of the horizon, which causes a potential loss of opportunity, cf. Section 3.4.2.

As described in Section 3.3, we focus on cases where the repair shop knows the number of on-condition maintenance tasks (component repairs) that will be carried out some periods in advance. In particular, at the start of period t, the repair shop knows the number of on-condition maintenance tasks for periods $t, t + 1, \ldots, t + T_m$, where T_m corresponds to the number of periods that tasks are known in advance. Note that the spare part demand for period t is only revealed during period t: only upon inspection does it become clear whether a part needs replacement. Also, we assume that the repair shop keeps track of past on-condition maintenance tasks and the resulting spare parts demand. (This is often required for quality assurance reasons anyhow.)

3.4.1 Forecasting

The goal of this section is to arrive at a demand forecast for upcoming periods that can serve as a basis for inventory control. Note that for this latter purpose, a demand *distribution* forecast rather than a point estimate is needed. Let d_t denote the actual spare part demand in period t, and let A_t denote the number of maintenance tasks in period t. At the start of period t, we know the values d_{t+i} and A_{t+i} for $i < 0$, because those periods are in the past. We also know A_{t+i} for $0 \leq i \leq T_m$: this is the ADI.

Conceptually, an on-condition maintenance task results in a spare part demand with some (failure) probability p. In practice, such a probability needs not not be stationary; it may be subject to change as the components age, and as their usage pattern changes, etc. Moreover, the precise value of this probability is unknown. We therefore suggest to estimate the value of this unknown probability from data, by updating the forecasted failure probability $\widehat{p}_t$ in every period t as follows:

$$\widehat{p}_t = \begin{cases} (1-\alpha)\widehat{p}_{t-1} + \alpha \dfrac{d_{t-1}}{A_{t-1}} & \text{if } A_{t-1} > 0 \quad (3.1) \\ \widehat{p}_{t-1} & \text{if } A_{t-1} = 0 \quad (3.2) \end{cases}$$

Here, α is a smoothing factor. $\widehat{p}$ could be initiated as 0, or using the first few months of the demand history.

To forecast demand more than T_m periods in advance (that is, d_{t+i} where $i > T_m$) in our proposed method, we revert to standard time-series methods to forecast the average demand per period, which will be denoted by λ_t. We opt for the well-studied Syntetos-Boylan approximation (SBA) (Syntetos and Boylan, 2001), which is an improvement to Croston's method (Croston, 1972):

$$\widehat{\lambda}_t = (1 - \frac{\alpha'}{2})\frac{\widehat{S}_t}{\widehat{k}_t} \tag{3.3}$$

Here, α' is a smoothing parameter. The estimated demand size $\widehat{S}_t$ is updated by

$$\widehat{S}_t = \begin{cases} (1-\alpha')\widehat{S}_{t-1} + \alpha' d_{t-1} & \text{for } d_{t-1} > 0 \quad (3.4) \\ \widehat{S}_{t-1} & \text{for } d_{t-1} = 0 \quad (3.5) \end{cases}$$

and the estimated demand interval $\widehat{k}_t$ is updated by

$$\widehat{k}_t = \begin{cases} (1-\alpha')\widehat{k}_{t-1} + \alpha' k_{t-1} & \text{for } d_{t-1} > 0 \quad (3.6) \\ \widehat{k}_{t-1} & \text{for } d_{t-1} = 0 \quad (3.7) \end{cases}$$

At the start of period t, to arrive at a forecasted demand *distribution* $\widehat{D}_{t,t+i}$ for some upcoming period $t+i$, we distinguish between the cases $i > T_m$ and $i \leq T_m$. For $i \leq T_m$, the spare parts demand has a binomial distribution with A_{t+i} trials and success probability p. Since p is unknown, we substitute the estimated value $\widehat{p}_t$ to obtain for $0 < i \leq T_m : \widehat{D}_{t,t+i} \sim B(A_{t+i}, \widehat{p}_t)$, where $B(n,p)$ denotes a binomial distribution with parameters n and p. For $i > T_m$, A_{t+i} is not available. Because the Poisson distribution is a good fit on spare part demand in general, for $i > T_m$ we forecast the demand distribution as $\widehat{D}_{t,t+i} \sim \text{poisson}(\widehat{\lambda}_t)$.

We note that there are substantial difference between using $B(A_{t+i}, \widehat{p}_t)$ for forecasting, versus using $\text{poisson}(\widehat{\lambda}_t)$. Most importantly, $B(A_{t+i}, \widehat{p}_t)$ reacts immediately to a large number of planned maintenance tasks, while $\text{poisson}(\widehat{\lambda}_t)$ only changes after the maintenance tasks have been executed. Secondly, using the binomial distribution $B(A_{t+i}, \widehat{p}_t)$ has the advantage that we explicitly know an upper bound on the number of replacements, which may help reduce the stock in certain situations.

3.4.2 Inventory optimization

We develop an approach for determining the amount x_t of spare parts to order in some arbitrary period t. Since demand is non-stationary, x_t should not myopically depend on the forecasted demand during leadtime alone, but it should be forward looking. This is easily seen based on an example: *Let* $T_m = 1$ *and consider two situations at time t: 1)* $\widehat{p}_t = 0.2$, $\lambda_t = 0.01$, $A_t = 10$, $A_{t+1} = 10$; *2)* $\widehat{p}_t = 0.2$, $\lambda_t = 2$, $A_t = 10$, $A_{t+1} = 10$. *In both cases, demand on the short term is likely around* 2 *since* $\hat{p}_t A_{t+1} = 2$, *but in the first case, demand is expected to go down to* 0.01 *in subsequent periods, while in the second case, demand is expected to remain around* 2. *That means that any items remaining at the end of period* $t+1$ *will likely stay in stock longer in the first case than in the second case, which should be reflected in the order decision.*

To arrive at a forward-looking policy, in each period t we solve a stochastic dynamic program (SDP) over periods $t+i \in \{t, \ldots, T\}$. This SDP uses the demand distributions over said periods, but the exact demand distribution is unknown. Instead, it is natural to use the forecasts constructed in period t: $\widehat{D}_{t,t+i}$. In the following, we briefly summarize the steps that occur in each period, and we subsequently give the SDP used to determine the order quantity x_t in each period t. For summarizing the steps, we introduce y_t and y'_t to denote the on hand inventory at the beginning and the end of period t, respectively. Here, y_t is understood to include the items that arrive in period t.

In each period, first the order placed in the previous period arrives. Thus $y_t = y'_{t-1} + x_{t-1}$. Then the order amount x_t is decided. Next, spare part demand D_t happens. Demand is satisfied by on hand inventory y_t. Thus at the end of period t we have on hand inventory $y'_t = (y_t - D_t)^+ = (y'_{t-1} + x_{t-1} - D_t)^+$. The holding cost $h \cdot y'_t$ and emergency ordering costs $c_e \cdot (D_t - y_t)^+$ are incurred. Subsequently, the next period starts.

To arrive at an SDP equation for deciding x_t, let $f_{t,t+i}(y_{t+i})$ denote the optimal total discounted cost from period $t + i$ until the end of the time horizon T, when the starting inventory in that period is y_{t+i}, and based on the forecasts obtained in period t. Then $f_{t,t+i}$ satisfies the recursive equation:

$$
\begin{aligned}
f_{t,t+i}(y_{t+i}) = \min_{x_{t+i} \in \{0,1,\ldots\}} & h \sum_{d=0}^{\infty} P(\hat{D}_{t,t+i} = d)(y_{t+i} - d)^+ && (3.8) \\
& + c_e \sum_{d=0}^{\infty} P(\hat{D}_{t,t+i} = d)(d - y_{t+i})^+ \\
& + \sum_{d=0}^{\infty} P(\hat{D}_{t,t+i} = d) f_{t,t+i+1}(y_{t+i+1}) && (3.9) \\
= \min_{x_{t+i} \in \{0,1,\ldots\}} & g_{t,t+i}(x_{t+i}) && (3.10)
\end{aligned}
$$

where $y_{t+i+1} = (y_{t+i} - d)^+ + x_t$, and with the boundary condition $f_{t,T+1} = -s \cdot y_{T+1}$. This boundary condition reflects that, in our approach, we assume that at the end of the horizon, inventory must be scrapped. This is in line with assumptions in our numerical experiment. However, even in situations where the end of the horizon does not necessarily correspond to part obsolescence, it may be wise to add a penalty to ending the last period with inventory, since this may avoid large procurements near the end of the horizon because of the end-of-horizon effect. So we believe that having this penalty is wise, even if not all inventory would be scrapped at the end of the horizon. Note that (3.10) implicitly defines $g_{t,t+i}(x_{t+i})$. We then obtain the amount to order in period t as $x_t \in \arg\min_x g_{t,t}(x)$. Note that $f_{t,t+i}(y_{t+i})$ corresponds to *estimated* costs based on the forecast constructed at the start of period t. Hence, after updating the forecast, at the start of each period a new SDP is constructed to arrive at x_t.

We next discuss the computational effort required to solve the SDP defined in (3.9) using backward induction. A practical upper bound for the maximal planned optimal on-hand inventory (i.e. $y_t + x_t$) can be obtained by using a very high percentile of the demand distribution, because it cannot be optimal to order an amount that will only be used with negligible probability. In particular, a Poisson random variable with mean $\bar{\lambda}$ exceeds $U(\bar{\lambda}) = \bar{\lambda} + 10 + 10\sqrt{\bar{\lambda}}$ with almost vanishing probability for the Poisson case; for the Binomial case we could use the natural bound A_t. y_t can then be bounded by $2U(\bar{\lambda})$. Then backward induction for each inventory decision involves computations over $T - t + 1$ periods, with $2U(\bar{\lambda})$ states for each period. Computing the value for each state involves at most a constant times $U(\bar{\lambda})$ computations, so computation time for each decision (i.e. solving the SDP) can be bounded by some constant times $U(\bar{\lambda})^2T$. For the experiments that we report in Section 3.5.2, computation time was (much) less than a second for each decision.

3.5 Assessment of potential value of the method

In this section we use data from two maintenance companies in order to quantify the potential value of the ideas and methods developed in this paper. In Section 3.5.1 we discuss the data and the setup of the experiments. Section 3.5.2 gives the results.

3.5.1 Data and experimental setup

We first briefly describe the two companies and their data, and then discuss the experimental setup. The first company is Fokker Services (FS). FS provides comprehensive in-house component maintenance, repair and overhaul support to aircraft operators in dedicated repair shops. Components are typically delivered to FS according to the aircraft operator maintenance plan. FS subsequently determines the condition of parts during initial inspection. Failed parts generate demand for spare parts, which are delivered from a warehouse next to the repair shop. (The warehouse is replenished from a central warehouse in the Netherlands, but this replenishment is left out of the scope of this study.)

Repair data over a period of 134 months are available. Data are cleaned by removing some parts which are not applicable in our model, e.g. if the bill of material coefficients are larger than one for the part/if the part is used in a quantity larger than one in a single repair. Each type of component and each type of spare part has a unique serial number. In our analysis, we use the following information that is gathered about component repairs: Period in which the component arrived at the repair shop, component serial number, which spare parts (serial numbers) were used in the repair operation. As a component might generate demand of different spare parts types, we call the component and each corresponding type of spare part as one spare part-component pair. The data set includes 24,455 different spare part-component pairs.

We designate the first 84 months as the training set. Within this training set, we use the average of the first 48 months to arrive at an initial estimate for the model parameters. We then use the approach discussed in Section 3.4.1 to update the parameters (e.g. parts failure probability) for the remaining 36 months in the training set. The test set contains the last 50 months of data, i.e. months 85-134. In the test set, we keep updating the parameters, and we record performance statistics such as holding costs and emergency ordering costs.

Real SRU prices are not available. In the experiment, we consider the following 4 parameters as the experimental factors: (i) holding cost per item per time unit h, (ii) emergency shipping cost c_e, (iii) scrapping cost at the end of horizon s, (iv) maintenance plan lead time T_m.

For the *base case*, we use the following parameters. At 24% holding costs per year, a typical low part price of 5 euros amounts to $h = 0.1$ euros/month. Costs for scrapping parts at the end of the horizon are set at $s = 5$ euros, because the costs of scrapping are dominated by the lost investment. Regarding the emergency costs, we found in discussions at various repair shops that delaying repairs is inconvenient because it typically requires the mechanic to temporarily store the component, and to later retrieve it. Additionally, even relatively short repair delays may harm customer satisfaction. As a consequence, we set the penalty costs for an emergency shipment as $c_e = 20$ euro. Finally, we set $T_m = 3$. We design our experiments around these base case parameters, and a sensitivity analysis is conducted to explore the effect of changes to the base case.

Since each component constitutes an on-condition maintenance task that may result in usage of the part, we can directly apply our methods for each spare part-component combination. Our method is used to determine the replenishment quantity in each period. Subsequently, we simulate the dynamics of the system using the real demand and maintenance data (cf. Section 3.4.2), and obtain holding, emergency shipping, and scrapping costs for all parts. To assess the value of ADI, we will use as a benchmark a method that does not use ADI. Like the method proposed in this chapter, the benchmark uses the recursive approach (3.9-3.10) to set spare parts orders. However, the benchmark uses the time series forecast $\widehat{D}_{t,t+i} \sim \text{pois}(\widehat{\lambda}_t)$ for *all* future periods, including those with $0 < i \leq T_m$. Note that the value of A_t is not needed for the benchmark, and note that the Syntetos-Boylan approximation is used to determine λ_t. So the benchmark represents the state-of-the-art time-series method.

Note that our experiments compare holding, emergency shipping, and scrapping costs for both the proposed approach and the benchmark. Thus costs for performing the actual on-condition maintenance tasks (i.e. labor costs & downtime of equipment) are not considered in either approach. This is reasonable, since the latter costs are exogenous to the model, and should be considered as sunk costs.

We also test our approach at another company: the Netherlands Railways (NS). NS is by far the largest operator of passenger railway transport in the Netherlands. The maintenance department of NS tracks the repair actions of main components of trains over 35 months, and we obtained that data. The history covers information over 138,347 repair actions on main components. At NS components may either be replaced as part of the maintenance plan, or upon unplanned failure. The former covers 2,727 types of components and 749 types of parts, and the latter covers 3,935 types of components and 1,485 types of spare parts. Ideas in this chapter are applicable to the former case, and we only use that data. We designate the first 25 months of demand as training data, and the last 10 months as test data. Out of the training set the first 20 periods are used for initialization of forecast parameters, and the last 5 for updating those parameters. The other settings are the same as in the FS case.

We mainly evaluate the proposed approach and benchmarks using inventory control metrics, but to provide a broader perspective, we also assess the performance of the proposed forecast approach in isolation using the root-mean-square-error (RMSE) and mean-absolute-deviation (MAD). In evaluating the forecasting accuracy we use the point forecast of demand rather than the demand distribution. Therefore, we consider the mean of the binomial distribution estimated in 3.4.1 and the benchmarks include moving average (MA), exponential smoothing forecast (ES), Croston's forecast method (CR), Syntetos-Boylan approximation (SBA) and forecasting method of Teunter et al. (Teunter et al., 2011) (TSB). The length of moving periods in the MA method is set to be 12. The smoothing constant in ES is 0.2. We give 0.2 to both the smoothing constant of the demand size and that of the demand interval in CR and its modification SBA. The smoothing factors of the demand size and the probability in TSB is set to be 0.2 and 0.1 respectively. The initial forecast in the benchmarks is made over the first 48 months in the Fokker case and 20 months in the NS case.

3.5.2 Results

We compare the total cost of all spare parts of our proposed approach to the costs of the benchmark that only uses time-series forecasts. Figure 3.1 shows the relative cost reduction of all the spare parts at Fokker Services, in the Total Costs (TC), Holding Costs (HC), Emergency Costs (EC), and Scrapping Costs (SC). Figure 3.2 does the same for NS. Each column in Figure 3.1 and 3.2 represents a single setting of parameters: For each case the base values of parameters are $h = 0.1$, $p = 0$, $c_e = 20$, $s = 5$, $T_m = 3$. Figure 3.4 and 3.5 show the forecasting performance measures for the Fokker Service and the NS respectively. Average over all types of spare parts are given.

As the FS case has a relatively long demand history, we can make a relatively accurate categorization of spare parts based on the number of months with positive demand during the training period (84 months) to explore the value of the maintenance plan on each category. The three categories are very-slow moving (1-5 months with positive demand), slow-moving (6-20 months), and fast moving (21-84 months). We have 24,455 types of part - component combinations in total. Very-slow moving includes 21,011 combinations, slow moving covers 2,846 combinations and relatively fast moving has 598 combinations. Figure 3.3 shows the cost reduction in each category. We have the following observations.

- We observe that our approach reduces the total cost compared to the benchmark by 48% and 23% in average for Fokker Services and NS, respectively. This illustrates that the value of the maintenance plan is very high in inventory control. In eight out of ten instances in the FS case and in nine out of ten instances in the NS case, our approach outperforms the benchmark with regard to all three cost components. Cost reductions are mainly driven by reductions in emergency shipping cost, followed by the holding cost and scrapping cost. The emergency shipping cost contributes 89% to the total saving in the Fokker case and 68% in the NS case. Note that since many spare parts are very reliable, and since components have a life cycle of 5-20 years, scrapping costs may be a substantial part of total costs because even with low stocks there is always a risk of leftovers (cf. van Jaarsveld and Dekker, 2011). This explains the substantial costs of scrapping for the cases. However, note that the scrapping costs difference between the ADI method and the benchmark is minimal, which implies that the assumption of scrap costs is not essential for our results. Finally, we note that the cost reduction for Fokker Services is higher than the

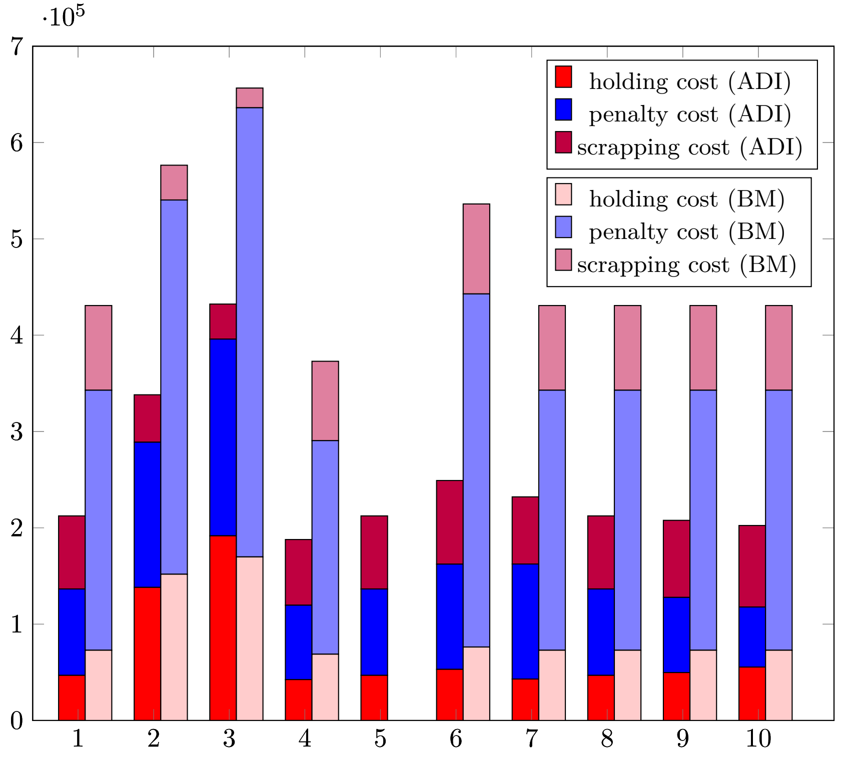


Figure 3.1: The effect of parameters on the value of maintenance planning (Fokker Service). Numbers 1-10 on the horizontal axis represent experiments with $\mathrm{h} = 0.1$, $\mathrm{h} = 0.5$, $\mathrm{h} = 1$, $\mathrm{c_e} = 15$, $\mathrm{c_e} = 20$, $\mathrm{c_e} = 30$, $\mathrm{T_m} = 1$, $\mathrm{T_m} = 3$, $\mathrm{T_m} = 5$, $\mathrm{T_m} = 38$ respectively

cost reduction for NS. This is mainly due to the fact that the maintenance plan is more stable for NS, which reduces the value of ADI, cf. Section 3.4.1.

- The holding cost rate h has more effect on our method than the benchmark while the emergency shipping cost c_e has larger impact on the benchmark. When h is increased from 0.1 to 0.5, the cost of our approach is increased by 59% while 34% for the benchmark in the Fokker case. For h from 0.5 to 1, it's 28% for our approach and 14% for the benchmark. The effect of h is monotonic in general. For c_m from 15 to 20 and to 30, the cost of our approach is increased by 13% and 17% respectively, while for the benchmark it's 16% and 24%. Therefore, we can conclude that our approach on average orders more than the benchmark as to have less penalty and holding cost. The method apparently orders at the right moment. When h/c_m is large enough, the value of the maintenance plan vanishes since the optimal policy under both methods

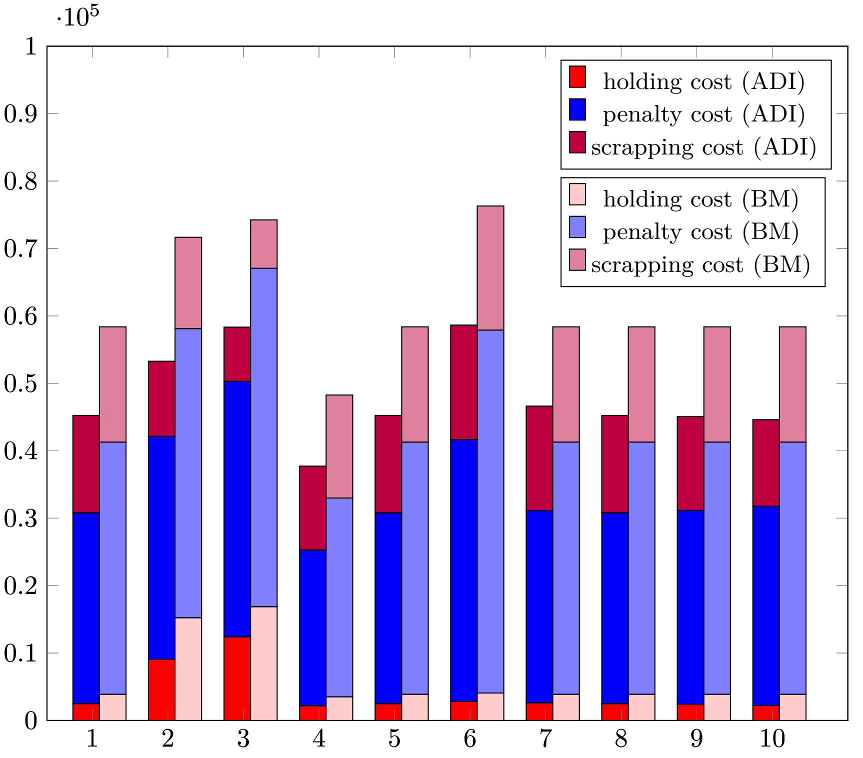


Figure 3.2: The effect of parameters on the value of maintenance planning (NS). Numbers 1-10 on the horizontal axis represent experiments with h = 0.1, h = 0.5, h = 1, $c_e = 15$, $c_e = 20$, $c_e = 30$, $T_m = 1$, $T_m = 3$, $T_m = 5$, $T_m = 38$ respectively

does not place any order. When c_m/h is large, both of the methods have larger stocks. However, using the maintenance plan yields an upper bound for the spare parts demand while the benchmark does not have access to such an upper bound. In addition, the benchmark might place an order in the period when there is no component arrivals as it only uses the history demand in forecasting. Again, the ADI method places timely orders. This is verified by the observation of the increase in the holding cost reduction with the increase of c_m in both Figure 3.1 and 3.2.

- The value of maintenance plan is not sensitive to T_m. In the Fokker case, obtaining the maintenance plan one lead time ahead achieves 46% in cost reduction, while obtaining it 5 lead times ahead achieves a 52% cost reduction. In the NS case, the cost reduction increases from 20% to 24% by increasing T_m from 1 to 10. The marginal benefit decreases dramatically with the increase of

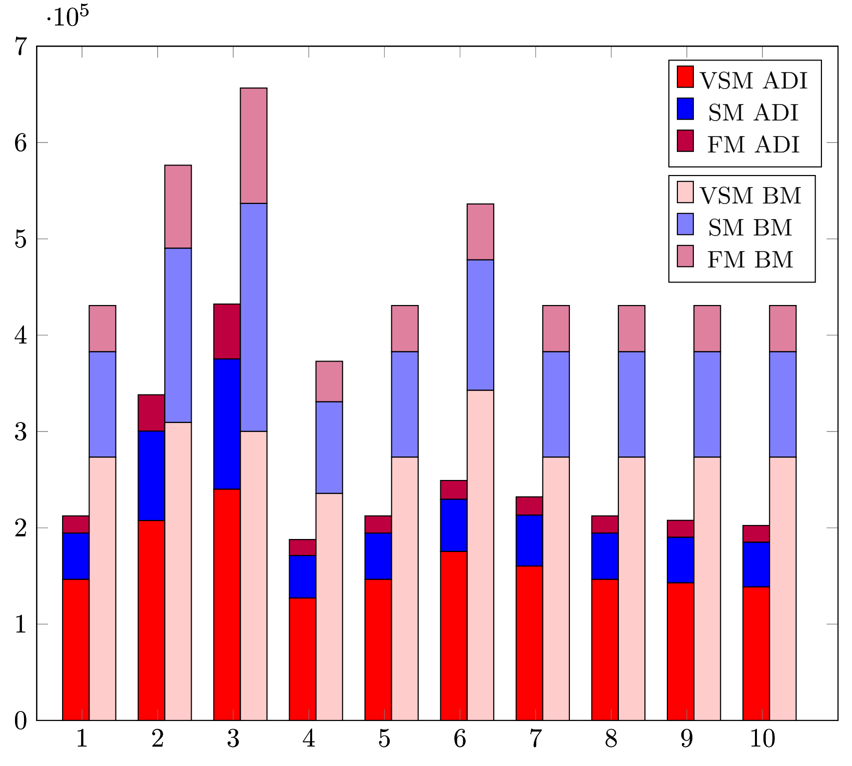


Figure 3.3: The effect of parameters on the value of maintenance planning, for the part categories very slow moving (VSM), slow moving (SM), and fast moving (FM) (Fokker Service). Numbers 1-10 on the horizontal axis represent experiments with $h = 0.1$, $h = 0.5$, $h = 1$, $c_e = 15$, $c_e = 20$, $c_e = 30$, $T_m = 1$, $T_m = 3$, $T_m = 5$, $T_m = 38$ respectively

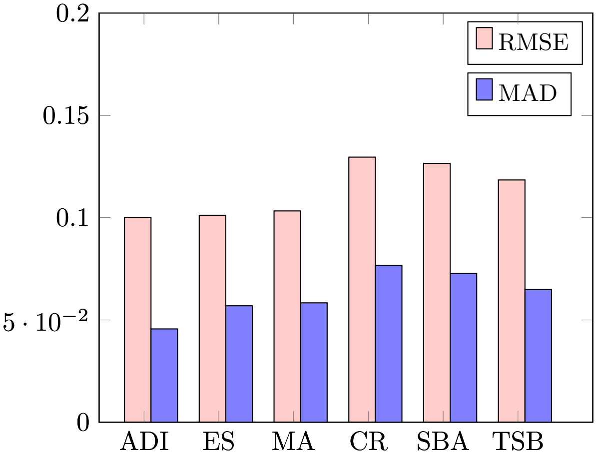


Figure 3.4: RMSE and MAD for the Fokker Service

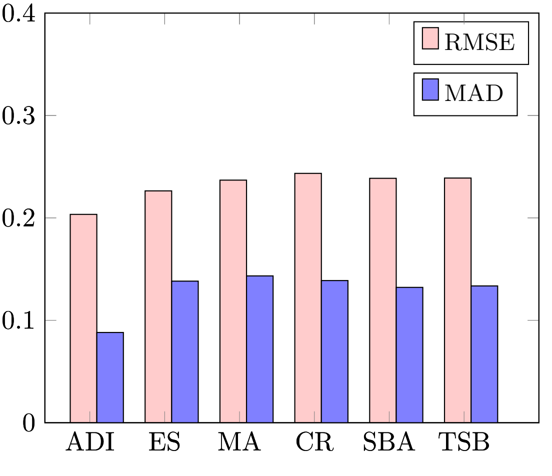


Figure 3.5: RMSE and MAD for the NS

T_m. Therefore, we conclude that it is necessary to obtain the maintenance plan in advance as it brings substantial cost saving. However, obtaining the maintenance plan one lead time ahead contributes the most to the inventory cost. It is not very cost effective to invest more in order to obtain the maintenance plan much earlier.

- Figure 3.3 shows that costs reductions are substantial over all categories, and relative cost reductions increase only slightly for faster moving categories. The biggest *absolute* contribution to the total cost savings is made by the very slow moving parts: 53% (averaged over the various cost parameter settings). This is because the very-slow moving category accounts for a large proportion of the parts. It is interesting that our approach performs well for the very-slow moving category, because that category is very hard to forecast using traditional techniques. Note furthermore that the very-slow moving category is less sensitive to the holding cost rate h than the other two categories in both the ADI method and the benchmark. This is because holding cost accounts for a smaller proportion of the total cost for very-slow moving items.

- In addition to the inventory metrics, our ADI-based forecasting approach also performs better comparing to the time series methods in the evaluation of forecasting accuracy. The method ADI has an advantage over all other time series approaches in both RMSE and MAD in each case, shown in Figure 3.4 and 3.5. Note that as we update λ_t for Poisson distribution by SBA in Section 3.4.1, the point forecast by SBA method in evaluating forecasting accuracy is exactly the mean value of the Poisson distribution used in the inventory control system. Therefore, our approach which considers ADI leads to less cost in the inventory system and a better forecasting accuracy than the benchmark in which demand is estimated to be Poisson distributed and its corresponding point forecast.

- The results are consistent with an intuitive interpretation. The proposed method can better take into account the time interval between positive demands. Therefore, it prevents the system from keeping redundant stocks. This leads to less inventory holding cost, as we observe in both cases. The proposed approach differentiates spare part demand forecasts in different time periods by building the dependence between spare part demand and its origin, component arrivals. By responding to the maintenance plan, our approach makes the spare part demand forecasting more accurate and the inventory decisions more appropriate. As a result, we have less penalty cost for emergency shipment and less scrapping for leftover stocks at the end of time horizon. In this way, our approach can better achieve the goal of having the right amount of stocks at the right moment. We expect the value of our approach in practice to be highest for the very slow moving items, because especially such items are notoriously difficult to control for human decision makers.

3.6 Conclusions and future research

Spare parts demand forecasting is essential to spare parts inventory control but difficult as the demand has the feature of irregularity and lumpiness. We proposed and tested ideas to apply ADI, in the form of planned on-condition maintenance tasks, to improve spare parts inventory control under these circumstances. Incorporating this form of ADI into forecasting makes the demand forecast nonhomogeneous over the forecast horizon. Accordingly, as argued in this chapter, the inventory control must become forward looking, and we propose an inventory optimization approach to reflect this. We determined the potential value of the combined forecasting and inventory optimization approach using industry data, and found that potential savings are very substantial: 51% for the aerospace maintenance case, and 23% for the train maintenance case.

Some comments are needed to put these figures into perspective. First of all, while aircraft component maintenance typically results from checks planned by the operator, this information is currently only shared on an ad hoc basis, e.g. maintenance organizations inform the repair shop in advance when they expect a substantial number of removals of a specific component in a short time interval. This is mainly in their own interest: If the repair shop is prepared, then spare part shortages are rare. The present research solidifies these findings and underlines the economical value of such information sharing in the supply chain. Moreover, the study provides compelling evidence that investing in a more structured sharing of information, e.g. in the form of a data platform, can simultaneously reduce inventory and increase part availability. Train maintenance organizations likewise inform the repair shop typically on an ad hoc basis. The present study shows that it would be better to more structurally organize this, as structural sharing of information would allow for a substantial reduction in the mismatch between spare parts demand and supply. Finally, it is interesting to note the rather marked difference in cost reduction for Fokker Services and NS, though in both cases cost reductions are substantial. We believe that this is caused by a more uneven maintenance pattern in the aircraft industry compared to train maintenance.

Our approach focuses on the most common case: If parts are used in an on-condition maintenance task, they are used in quantity 1. While this holds for the vast majority of parts, one could generalize it to situations where multiple parts of the same type may be replaced in a single maintenance task (van Jaarsveld et al., 2015). Another direction for future research is related to our forecast method: Suppose many on-condition maintenance tasks are upcoming, i.e. A_{t+i} is high. This will likely increase future demand, so future demand is likely to be higher than $\hat{\lambda}_t$. It would perhaps be interesting to adapt the forecasting method for $\hat{\lambda}_t$ such that it already responds to expected changes in demand. Finally, any experience on a broad implementation of the ideas pursued in this chapter would likely teach us valuable lessons that cannot be learned from this preliminary study alone.

Chapter 4

Critical Project Planning and Spare Parts Inventory Management in Shutdown Maintenance

Chapter 5

Summary

Capital goods are expensive machines or products that are used by manufacturers to produce their end-products. Examples include computers, production equipment, aircrafts and lithography machines that are used by semi-conductor manufacturers. Availability of spare parts is essential to facilitate their maintenance both to correct failures as well as to prevent these. Large spare parts inventories however, tie up significant capital and face the risk of obsolescence. Hence smart decisions are needed on inventories: when to stock and in which quantity. These decisions should be based on good forecasts.

In this dissertation, we present three contributions to this problem. First, a new method based on extreme-value theory is developed to aid companies in forecasting the spare parts demand distribution. Next, we analyze the inventory control problem for on-condition maintenance and shutdown maintenance. We propose a new approach for joint forecasting and inventory control based on probabilistic information on the maintenance plan. We found the value of this plan to be significant in preparing the repair shop by catching the irregularity and lumpiness of spare parts demand. Finally, we model the spare parts ordering problem against the background of shutdown maintenance project planning. Decision makers need strategies which consider the interdependence of maintenance activities. Our new stochastic programming approach is able to give much better advice than traditional methods and hence meets the requirement of real-life shutdown projects.

In chapter 2, we study the leadtime demand forecasting problem of spare parts. We improve the empirical method by applying extreme value theory to model the tail of the leadtime demand distribution. We propose a semi-parametric leadtime demand

distribution forecasting method (empirical-EVT). It is applicable for forecasting the lead time demand and determining the inventory control parameters of spare parts. The empirical-EVT method is a combination of non-parametric empirical method and EVT extrapolation. It samples LTD from actual data and uses EVT to model the distribution above a high threshold so that it can predict possible extreme values. The new method can represent the demand behaviour as well as achieve high target service levels. We build models for different service measures and analyse their applications. We find that the empirical-EVT method has a relative good performance and avoids overperformance which regularly happens under WSS, Croston's method and SBA. Still, the empirical-EVT has performance issues with limited demand histories, and may be outperformed by WSS, and even by simpler methods such as Croston's and SBA. The empirical study based on data sets from two companies demonstrates that accuracy of WSS highly depends on the data set. Moreover, the test shows that the empirical-EVT struggles to perform well when demand history consists of only very few periods. In contrast, performance of empirical-EVT is better in cases where only relatively few demand points are available, but over many periods. In those cases, the method is rather competitive. This should be taken into account when considering to apply the method in practice. Our theoretical treatise indicates that the empirical-EVT method has a problem in estimating the fill rate. The fill rate fails to change monotonously with the increase of base stock level when applying EVT independently for the LTD with lead time L and the LTD with lead time $L-1$. Another issue arises for the expected waiting time, which can only be estimated when the extreme value index is not bigger than or close to 1. This problem is solved by considering the cycle service level instead of expected waiting time. The empirical-EVT method in combination with the cycle service level works well. However, the issues related to applying EVT with expected waiting time of fill rate may be a limiting factor when applying it.

In chapter 3, we proposed and tested ideas to apply advance demand information (ADI), in the form of planned on-condition maintenance tasks, to improve spare parts inventory control. For many maintenance organizations, on-condition maintenance tasks are the most important source of spare part demand. An uneven distribution of maintenance tasks over time is an important cause for intermittency in spare parts demand. and this intermittency complicates spare parts inventory control severely. We propose a simple forecasting mechanism to estimate the spare part demand distribution based on the maintenance plan, and develop a dynamic inventory control method based on these forecasts. We determined the potential value of the combined forecasting and inventory optimization approach using industry data, and found that potential savings are very substantial: 51% for the aerospace maintenance case, and 23% for the train maintenance case. We contribute to literature by proposing a new approach for joint forecasting and inventory control based on the maintenance plan. The approach endogenously links maintenance tasks to parts usage based on maintenance data. Moreover, our approach integrates the demand forecasting model with an inventory control model. Currently, while aircraft component maintenance typically results from checks planned by the operator, this information is only shared on an ad hoc basis, e.g. maintenance organizations inform the repair shop in advance when they expect a substantial number of removals of a specific component in a short time interval. This is mainly in their own interest: If the repair shop is prepared, then spare part shortages are rare. Our research solidifies these findings and underlines the economical value of such information sharing in the supply chain. Moreover, the study provides compelling evidence that investing in a more structured sharing of information, e.g. in the form of a data platform, can simultaneously reduce inventory and increase part availability. Train maintenance organizations likewise inform the repair shop typically on an ad hoc basis. The present study shows that it would be better to more structurally organize this, as structural sharing of information would allow for a substantial reduction in the mismatch between spare parts demand and supply.

In chapter 4, we consider the spare parts ordering policy against this background of shutdown maintenance project planning. We investigated the order policy of spare parts in the initial/preparation phase of the shutdown maintenance. In the shutdown project, the delay due to the shortage of spare part in each activity propagates along with the path in the project network, which may lead to a large overtime cost. We investigate the case where the demand probability of each part is small, which complicates the order decision. We developed a two-stage integer linear stochastic program to obtain the optimal order size. We find that for activities that are never on the critical path, the optimal solution can be expressed in closed form. In solving the problem, we proposed sample average approximation with importance sampling for the activities that can be on the critical path. We also proposed removal and stock heuristics for the problem, yet they are not faster nor more accurate. We find that scenario based heuristics give an acceptable approximation. The solution of the heuristic based on standard critical path with normal distributed project time assumption is far away from the optimum.

In summary, we use statistics with empirical method to build an improved forecasting method for intermittent demand. We also use optimization methods to find solutions to spare part ordering problem under on-condition maintenance and shutdown maintenance respectively. In chapter 3, we show the value of maintenance plan which can be obtained without large investment in on-condition maintenance. In chapter 4, we study the spare parts management in project planning and propose an optimization model which considers the structure of shutdown project.

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Nederlandse Samenvatting (Summary in Dutch)

In dit proefschrift bestuderen we vraagvoorspellingen van reserveonderdelen en methodes van voorraadbeheer. We beginnen met onderzoek naar de voorspelling methode voor intermittende vraag. In hoofdstuk 2 stellen we een nieuwe voorspelling methode voor op basis van extreme-waardetheorie (EVT). Deze methode blijkt minstens op gelijke voet te zijn met de state-of-the-art methoden voor een reeks van vraagverdelingen. Hoofdstuk 3 richt zich op de geavanceerde vraaginformatie uit het on-condition onderhoud. We bestuderen de waarde van dergelijke geavanceerde vraaginformatie in het voorraadbeheer van reserveonderdelen. Onze resultaten laten zien dat, op basis van de datasets van Fokker Services en NedTrain, de waarde van vooraf beschikbare gevraagde informatie van 23 tot 51% kan oplopen. In hoofdstuk 4 onderzoeken we het probleem van het bestellen van reserveonderdelen in de planning van shutdown-onderhoud projecten. Onderscheidend van de standaard voorraadbeheersingstheorie van reserveonderdelen, waar aangenomen wordt om beslissingen voor elk onderdeel afzonderlijk te nemen (een opvullingspercentage vast te stellen of een stock-out boete te introduceren), zijn er in onze setting geen duidelijke stock-out verbonden kosten of opvullingsdoelstelling voor het reserveonderdeel en de gevolgen van een stock-out van één onderdeel kunnen ook afhangen van de beschikbaarheid van andere onderdelen. In tegenstelling tot unimodale activiteitsduur die voornanamelijk in de literatuur wordt toegepast, beschouwen we bimodale (met twee pieken) activiteitsduren die de totale projecttijd een multimodaal maken in plaats van unimodaal. We vinden dat heuristieken op basis van scenario's een acceptabele benadering geven, terwijl de standaard aanpak van project management op basis van de veel gebruikte Critical Path-methode in onze setting veel slechtere resultaten oplevert. We gebruiken technieken en methoden uit zowel het operationele research als de

statistiek om deze problemen aan te pakken.

Curriculum Vitae

Sha Zhu (1987) obtained her Bachelor's degree in Transportation Planning and Management from Jilin University in 2010. In 2013 she received her Master's degree in Logistic Engineering in Shanghai Jiao Tong University.

Sha Zhu joined the Erasmus Research Institute of Management (ERIM) in October 2013 as a PhD student under the supervision of prof. dr. ir. Rommert Dekker and dr. Willem van Jaarsveld. She worked on spare parts demand forecasting and inventory management problems. Her work has been published in European Journal of Operational Research and Reliability Engineering & System Safety. She has presented her research at various national and international conferences, including IFORS, EURO and ISIR International Symposium on Inventories. Her research interests include operations research, demand forecasting and inventory management.

During her PhD project she assisted in various courses, primarily Advanced Inventory Supply Chain Management and Production Planning and Scheduling.

Portfolio

Publications

Peer-reviewed journal articles:

Zhu, S., Dekker, R., Van Jaarsveld, W., Renjie, R. W., & Koning, A. J. (2017). An improved method for forecasting spare parts demand using extreme value theory. European Journal of Operational Research, 261(1), 169-181.

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Working papers

Zhu, S., van Jaarsveld, W., & Dekker, R. (2021). Critical project planning and spare parts inventory management in shutdown maintenance.

Zhu, S., van Jaarsveld, W., & Dekker, R. (2021). A life-time extension model with an application to PC upgrading.

Pan. F., **Zhu. S.**, Zhou. W., Fan. T. (2021). Dual packaging strategy for perishable products.

Teaching

Tutorial lecturer:

Advanced Inventory Supply Chain Management, graduate level, Erasmus University Rotterdam, 2015-2017.

Production Planning and Scheduling, graduate level, Erasmus University Rotterdam, 2015-2017.

Logistics and Supply Chain Management, graduate level, Erasmus University Rotterdam, 2016

Quantitative Methods for Logistics, undergraduate level, Erasmus University Rotterdam, 2015

PhD courses

Stochastic Programming
Inventory Management in Supply Chains
Noncooperative Games
Cooperative Games
Integer Programming Methods
Convex Analysis for Optimization
Advanced Inventory Supply Chain Management
Stochastic Dynamic Optimization
Scientific Integrity
English: CAE level
English: CPE level
Publishing Strategy

Conferences attended

ISIR International Symposium on Inventories, 2014, Budapest, Hungary

ISIR Summer School on Value-Driven Inventory Management in Logistics and Supply Chains, 2015, Hamburg, Germany

ISIR International Symposium on Inventories, 2016, Budapest, Hungary

International Institute of Forecasters Workshop Supply Chain Forecasting for Operations, 2016, Lancaster, UK

LNMB Annual Conference, 2014-2017, Lunteren, the Netherlands.

IFORS Conference, 2017, Quebec City, Canada

ISIR Summer School on Competitive Advantage through Resource Efficiency, 2017, Vienna, Austria

ISIR International Symposium on Inventories, 2018, Budapest, Hungary

National OML (Operations Management and Logistics) conference, 2018, Soesterberg, the Netherlands.

EURO Conference, 2018, Valencia, Spain

The ERIM PhD Series

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In this dissertation we present three contributions to this problem. First, a new method based on extreme-value theory is developed to aid companies in forecasting the spare parts demand distribution. Next, we analyze the inventory control problem for on-condition maintenance and shutdown maintenance. We propose a new approach for joint forecasting and inventory control based on probabilistic information on the maintenance plan. We found the value of this plan to be significant in preparing the repair shop by catching the irregularity and lumpiness of spare parts demand. Finally, we model the spare parts ordering problem against the background of shutdown maintenance project planning. Decision makers need strategies which consider the interdependence of maintenance activities. Our new stochastic programming approach is able to give much better advice than traditional methods and hence meets the requirement of real-life shutdown projects.

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