Forecasting Spare Part Demand with Installed Base Information: a Review

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Abstract

The classical spare part demand forecasting literature studies methods to forecast intermittent demand. The majority of these methods do not consider the underlying demand generating factors. Demand for spare parts originates from the part replacements of the installed base of machines, which are either done preventively or upon breakdown of the part. This information from service operations, which we refer to as installed base information, can be used to forecast future spare part demand. In this paper we review the literature on the use of such installed base information for spare part demand forecasting to asses (1) what type of installed base information can be useful; (2) how this information can be used to derive forecasts; (3) what is the value of using installed base information to improve forecasting; and (4) what are the limits of the currently existing methods. The latter serve as motivation for future research.

Keywords: Spare parts, demand forecasting, literature review, maintenance, installed base

1. Introduction

Service maintenance is commonly used to extend the lifetime of capital assets, such as manufacturing equipment or heavy infrastructure, often referred to as the *installed base*. It is performed when a component breaks down and needs replacement, or the maintenance and part replacement can be performed preventively. The former type of service maintenance is known as corrective maintenance, whereas the latter is known as preventive maintenance. When the spare parts necessary to perform the maintenance action (also denoted as the service parts), are not available, the incurred shortage costs may be substantial. For instance, the unavailability of a machine part could jeopardize the productivity of a plant, inducing large time delays and thus high costs. For this reason, companies often keep stock buffers to deal with the uncertain demand of these spare parts. Having extra safety stocks on an individual stock keeping unit (SKU) basis may not necessarily be a problem: a small amount of additional stock might be sufficient to provide a good service level. However, even if only one extra unit of stock is held for many hundreds or thousands of items, this results in considerable amounts of capital tied up in safety stocks. It is common to observe companies of moderate size carrying thousands of different items in inventory, resulting in excessive holding costs (e.g., Güvenir & Erel, 1998). Donnelly (2013) described Maintenance, Repair and Overhaul inventories as accounting for up to 40% of the annual procurement budget in many organizations. Clearly, a trade-off exists here between the investment in inventories and the observed shortages. This trade-off can be translated to balancing inventory costs and the attained service level. Specialized service parts models should therefore focus on improving the availability of parts whilst limiting the investment in inventories.

Spare part demand is known to be intermittent (Dekker et al., 2013). In the literature, specific techniques have been developed to forecast intermittent spare part demand (for an overview, we refer to Syntetos et al. (2009a); Boylan & Syntetos (2010); Bacchetti & Saccani (2012)). However, these methods are mostly time series based, i.e., they rely on the historical demand pattern to generate demand forecasts, but do not take into account the factors that generate the spare parts demand. Indeed, the demand for spare parts originates from the part replacements of the installed base of machines (either preventively or correctively). We refer to the factors regulating the spare part demand (i.e., the failure behavior of the components, the maintenance policy, etc.) as the *installed base information*.

The installed base of a product is the number of sold products that can lead to demand of their spare parts (Kim et al., 2017). Dekker et al. (2013) stress the importance of knowing the characteristics of this installed base (e.g., age, usage) to make correct inventory decisions. Fortuin (1984) claims that using installed base information to forecast spare part demand can lead to up to 25% stock reductions. Auramo & Ala-risku (2005) suggest to additionally use information on the sudden and scheduled service needs of the products in the decision making process. Over time, a number of papers have been published that exploit this link between the part replacements and the demand for spare parts to forecast future spare part demand, each with its own assumptions. In this article, we review the literature on the use of installed base information for forecasting such demand.

Our work contributes to the growing body of literature reviews on spare part demand forecasting along the following lines. Babiloni et al. (2010) provide a review on intermittent demand forecasting, whereas Boylan & Syntetos (2010), Rego & Mesquita (2011), and Bacchetti & Saccani (2012) review the literature on spare parts demand forecasting specifically. The focus mainly lies on techniques based on historical demand data, and the authors hardly consider other sources of information. The work by Hu et al. (2017) presents a framework for operational research in spare parts management. This paper does take into account other factors than the time series data alone. The authors touch upon reliability based forecasting, taking into account the failure rate of the parts, the influence of the operating environment on the reliability characteristics, and the impact of different maintenance strategies, but they do not consider the impact of the evolution and status of the installed base explicitly. There also exists a review that addresses installed base information as a source of information for industrial services (Perminova-Harikoski et al., 2015), yet with no focus on its use for spare part demand forecasting. To the best of our knowledge, our review is the only one that is dedicated to the use of installed base information to forecast spare part demand. With our work, we provide the academic community with a review on literature concerning the use of installed base information for forecasting. We clarify what type of installed base information can be useful, how this information can be used to produce spare part demand forecasts, and what is the value of using installed base information to improve forecasting. Lastly, we also consider the limits of the currently existing methods, in order to provide a foundation for future research.

The remainder of the paper is organized as follows: Section 2 provides an overview of the possible avenues for forecasting spare parts demand. Section 3 covers the literature selection process. Section 4 constitutes the main part of the paper, discussing the main findings from our literature review. We provide details on the use of installed base information for spare part demand forecasting. Section 5 discusses the limitations of the current literature and gives guidance to future research directions. Section 6 provides some concluding remarks.

2. Background

2.1 Spare part characteristics

Maintenance parts have specific properties that make them different from many products. We refer to Huiskonen (2001); Kennedy et al. (2002); Boylan & Syntetos (2010); Bacchetti & Saccani (2012) for a detailed review of service parts characteristics. The most prominent part characteristics, and especially those related to difficulties in forecasting, are (1) part demands exhibit patterns that are difficult to predict, (2) they are generated by maintenance policies and part breakdowns, and (3) they are subject to obsolescence.

A first distinctive characteristic of spare parts is their demand pattern, which is quite different from the demand pattern of many other products. Even though some spare parts have a high and/or stable demand, the great majority face intermittent demand: it is often characterized by sequences of zero demands interspersed by occasional non-zero demands. Moreover, the demand size itself may be highly variable, in which case it is called *erratic*. When a demand pattern is both intermittent and erratic, it is said to be *lumpy* (e.g., Huiskonen, 2001; Boylan & Syntetos, 2010; Rego & Mesquita, 2011). Because of this intermittence and the (sometimes extreme) levels of lumpiness, resulting in a very skewed demand size distribution, the lead time demand cannot always be represented by the normal distribution (Boylan et al., 2008), which is often assumed in standard inventory models. Moreover, because of the limited number of non-zero historical demands it can be hard to estimate the distribution of the lead time demand (Hua et al., 2007). The intermittent demand pattern renders demand forecasting a challenging exercise, as standard forecasting techniques often produce inaccurate results. Therefore, specific forecasting techniques have been developed for intermittent spare part demand.

Second, spare parts differ from work-in-process or final products. Unlike end products, that have independent demand and tend to be fast moving, or parts whose demand is dependent on the product demand via the Bill-of-Materials, a spare part is required when the corresponding installed part fails or is replaced preventively (Fortuin & Martin, 1999). The consumption of spare parts is thus closely related to maintenance. The purpose of spare parts inventories is then to assist maintenance staff in keeping the equipment in operating condition. Maintenance policies and breakdowns dictate the need for spare parts inventories (Kennedy et al., 2002; Gu et al., 2015).

Thirdly, along with the life cycle of products the part specificity generates a risk of obsolescence (e.g., Cohen et al., 2006; Boone et al., 2008; Rego & Mesquita, 2011). Because most spare parts have specialized uses, they remain in inventory until their installed equipment require it (Kennedy et al., 2002). When the products for which the parts were designed are discontinued, clients can still use the product and generate demand for spare parts when asking for a repair. Heavy equipment may continue to generate a demand for spare parts even decades after the end of production (Boone et al., 2008). However, because the installed machines will be taken out of operation over time and no new machines are sold anymore, the risk of obsolescence for the parts increases (Kennedy et al., 2002; Teunter et al., 2011). Taking into account this increasing risk of obsolescence may therefore reduce unneeded stocks.

2.2 Forecasting methods for spare part demand

A seminal work for forecasting intermittent demand was written by Croston (1972). Instead of focusing on the mean demand per period, he divided demand into two separate components: demand size and demand occurrence. He then made two separate estimates; one of the inter-demand interval and one of the size of the demand when it occurs. Croston's method (CR) has been adjusted and revised by many authors: Schultz (1987), Johnston & Boylan (1996), Syntetos (2001), Syntetos & Boylan (2001) and Syntetos & Boylan (2005) (SBA), Snyder (2002), Levén & Segerstedt (2004), Teunter et al. (2011) (TSB), and recently by Pennings et al. (2017).

Next to the research stream following Croston (1972), other approaches for intermittent demand/spare part demand forecasting have been developed in literature. Bootstrapping (e.g., Willemain et al., 2004) is a non-parametric approach that permits to forecast the distribution of demand directly, rendering distributional assumptions redundant. Likewise, neural networks (e.g., Kourentzes (2013)) could provide a (non-parametric) tool to forecast intermittent demand, as they allow capturing of the interaction between non-zero demand and inter-arrival rate of demands. Judgmental forecasting (e.g., Wang & Petropoulos, 2016) is oftentimes used to adjust quantitatively derived forecasts, and can result in improved forecast accuracy (Syntetos et al., 2009b). Nonetheless, the managerial time requirement renders the method hardly applicable in a practical setting when dealing with thousands of spare parts.

Except for judgmental forecasting, all of the above discussed methods have one major drawback: They only consider historical demand and only react to what happened in the past, i.e., they are forecasting in a reactive way. However, demand might depend on many other factors, and relying only on past consumption might not be accurate (Gu et al., 2015; Beutel & Minner, 2012). Characterizing the factors that generate demand allows to forecast in a more proactive way (Wang & Syntetos, 2011), as this anticipates the future demand.

In this paper we review the literature on explanatory forecasting techniques that explicitly consider the drivers of the spare part demand; i.e., the installed base of machines that require a part replacement.

3. Literature selection and analysis

We performed a database search looking for articles concerning the use of installed base information for spare part demand forecasting. The (final) search was carried out in June 2018. We analyzed the databases of Emerald Insight, Scopus, JSTOR and Web of Science and used the keywords "spare part" or "service", in combination with "forecast" or "predict", and "installed base". We have excluded work not written in English, and papers which only appeared in conference proceedings. We studied the resulting publications and considered their relevance to the topic under study. For each paper and book chapter, we first evaluated

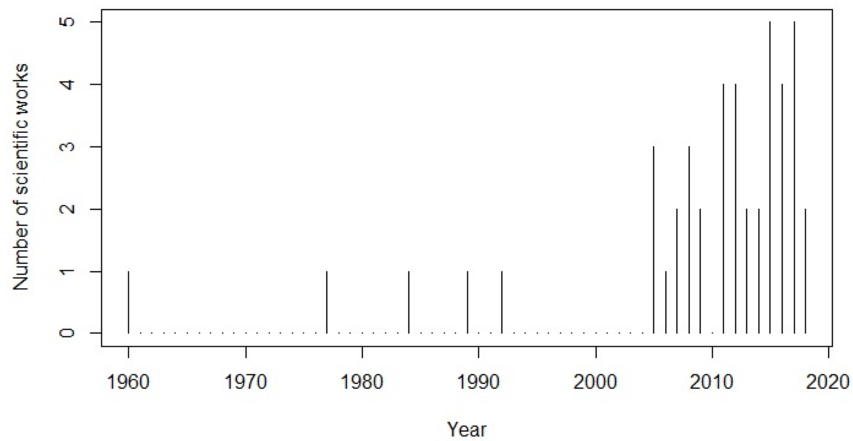

Figure 1: Evolution of the number of published works over time

the title. If this seemed relevant, we considered the abstract, and then the introduction and conclusion. If the paper was still considered relevant, the full paper was analyzed. This initial database search resulted in 11 relevant publications. To extend this number, we complemented our research with two iterations of forward and backward search[1], for the selected papers, evaluating the appropriateness of the cited and citing articles on the topic.

This search resulted in 39 relevant papers and 5 book chapters, presented in Table 1. All work is published between 1960 and 2018, as graphically presented in Figure 1. The papers are published in 25 different journals and the book chapters stem from five different books, presented in Table 2, in various research fields. We evaluated the relevance of the resulting scientific works in greater detail with regard to our research objectives: (1) What type of installed base information is relevant for forecasting purposes (size of the installed base, maintenance policy in use, failure behavior, etc.); (2) how this information can be used to produce forecasts; (3) what is the value of using installed base information to improve forecasting; and (4) what are the limits of the currently existing methods.

We identified different strands of literature during our review. First, the majority of papers focus on corrective maintenance, and how to use reliability analysis to forecast future spare part demand. A second strand of literature considers preventive and/or condition based maintenance information to enhance demand forecasting. Third, a rather separate series of scientific works focuses on the inclusion of environmental factors that affect the part reliability in the spare part demand forecasts. In addition, there are a number of scientific works that discuss miscellaneous aspects related to the use of installed base information for spare part demand forecasting. Table 3 presents the papers according to their focus: corrective maintenance, preventive maintenance, focusing on environmental factors, or representing a

[1]Backward reference searching involves identifying and examining the references or works cited in an article. Forward searching identifies articles that cite an original article or work after it had been published.

Type of scientific work	Reference
Book (chapter)	Ghodrati (2011); Minner (2011); Perminova-Harikoski et al. (2015); Kontrec & Stefan (2017); Si et al. (2017)
Paper in peer-reviewed journal	Shaunty & Hare Jr (1960); Ritchie & Wilcox (1977); Fortuin (1984); Yamashina (1989); Petrovic & Petrovic (1992); Auramo & Ala-risku (2005); Ghodrati & Kumar (2005b,a); Deshpande et al. (2006); Ghodrati et al. (2007); Hua et al. (2007); Cavalieri et al. (2008); Hong et al. (2008); Wagner & Lindemann (2008); Jin & Liao (2009); Lanza et al. (2009); Jalil et al. (2011); Wang & Syntetos (2011); Barabadi (2012); Ghodrati et al. (2012); Jin & Tian (2012); Romeijnders et al. (2012); Dekker et al. (2013); Hong & Meeker (2013); Barabadi et al. (2014); Hellingrath & Cordes (2014); Chou et al. (2015); Hu et al. (2015); Kontrec et al. (2015); Lu & Wang (2015); Chou et al. (2016); Gharahasanlou et al. (2016); Liu & Tang (2016); Lu & Hjelle (2016); Hu et al. (2017); Kim et al. (2017); Qarahasanlou et al. (2017); Andersson & Jonsson (2018); Stormi et al. (2018)

Table 1: Classification of the selected scientific works according to type

more general point of view.

4. Literature review findings

In this section we discuss the main findings and research directions that result from our literature review. We first provide an overview of the different sources of installed based information (Section 4.1). We then describe the different methods how the installed based information can be used for spare part demand forecasting (Section 4.2). Next, we summarize and discuss the reviewed papers (Section 4.3).

4.1 Definition of installed base information

The literature review shows that installed base information consists of three main sources of information, that drive spare part demand: (1) the size and status of the installed base and the status of the spare part itself; (2) the maintenance policy that depicts when a part is replaced; and (3) environmental factors that impact the part reliability. These issues are now discussed in more detail.

First, according to Yamashina (1989), three main factors are related to service parts demand: the manufacturing rate of the product, the product life characteristics, and the part life characteristics. Similarly, Minner (2011) and Auramo & Ala-risku (2005) refer to the age and status of products and systems in use as a source of information. Hong et al. (2008) add the replacement probability of the failed part, because a failed part is not necessarily replaced, or it might be replaced by an unauthorized part as well. Dekker et al. (2013) and Kim et al. (2017) argue that the demand for spare parts follows the demand for the installed product with a delay. It is thus dependent on the product life-cycle. The product life cycle and the impact on spare parts demand is illustrated in Figure 2. In the initial phase where product sales ramp up and the installed base grows, the demand for spare parts is usually rather low, as products are still relatively young. In the mature phase,

Scientific work	Amount
Journal	
European Journal of Operational Research	5
International Journal of Production Economics	3
Computers and Industrial Engineering	2
International Journal of Logistics: Research and Applications	2
IISE Transactions	2
International Journal of Simulation Modeling	2
Journal of Quality in Maintenance Engineering	2
Journal of the Operational Research Society	2
Mathematical Problems in Engineering	2
Production Planning and Control	2
CIRP Annals - Manufacturing Technology	1
International Journal of Industrial Engineering	1
International Journal of Information and Management Sciences	1
International Journal of Mining and Geo-Engineering	1
International Journal of Mining, Reclamation and Environment	1
International Journal of Performability Engineering	1
International Journal of Physical Distribution and Logistics Management	1
International Journal of Quality and Reliability Management	1
Journal of Service Management	1
Management Science	1
Operations Research	1
Production and Manufacturing Research	1
Reliability Engineering and Systems Safety	1
Technometrics	1
Transportation Research Part E	1
Book	
Data-Driven Remaining Useful Life Prognosis Techniques	1
Replacement Models with Minimal Repair	1
Service Parts Management	1
Strategic Change towards Future Industrial Service Business	1
System Reliability	1

Table 2: Classification of the papers according to the different journals

Strand of literature	Papers
Corrective maintenance	Shaunty & Hare Jr (1960); Ritchie & Wilcox (1977); Fortuin (1984); Yamashina (1989); Petrovic & Petrovic (1992); Hong et al. (2008); Jin & Liao (2009); Minner (2011); Jin & Tian (2012); Hong & Meeker (2013); Chou et al. (2015); Kontrec et al. (2015); Lu & Wang (2015); Chou et al. (2016); Liu & Tang (2016); Lu & Hjelle (2016); Kim et al. (2017); Kontrec & Stefan (2017); Stormi et al. (2018)
Preventive Maintenance	Deshpande et al. (2006); Hua et al. (2007); Wang & Syntetos (2011); Romeijnders et al. (2012); Hellingrath & Cordes (2014); Hu et al. (2015); Si et al. (2017)
Environmental factors	Ghodrati & Kumar (2005b,a); Ghodrati et al. (2007); Lanza et al. (2009); Ghodrati (2011); Jalil et al. (2011); Barabadi (2012); Ghodrati et al. (2012); Barabadi et al. (2014); Gharahasanlou et al. (2016); Qarahasanlou et al. (2017)
Miscellaneous	Auramo & Ala-risku (2005); Cavalieri et al. (2008); Wagner & Lindemann (2008); Dekker et al. (2013); Perminova-Harikoski et al. (2015); Hu et al. (2017); Andersson & Jonsson (2018)

Table 3: Classification of the scientific work according to the research focus

where product sales gradually fall back and the installed base is at its maximum size, the spare part demand is expected to rise. In the end-of-life (EOL) phase, where product sales end, the demand for spare parts can still continue to increase, before it gradually diminishes as more products reach their end-of-use (Kim et al., 2017). From this figure it can be seen that the demand for spare parts follows the demand for the product, albeit with a delay.

Second, the maintenance policy can be considered as a driver of spare parts demand. Wang & Syntetos (2011) argue that failure-based spare parts management is very different from preventive-maintenance spare parts management, as demand in the former case originates from part failures and in the latter from preventive maintenance actions. Whereas corrective maintenance is characterized by stochastic arrivals of demand, but also by a deterministic demand size (often one unit), preventive maintenance has a deterministic demand arrival, as it is known in advance, but it may have a stochastic demand size as a part is not always replaced after inspection. This distinction is illustrated in Figure 3. Dekker et al. (2013) and Poppe et al. (2017) note that maintenance information is especially important when predicting parts demand for planned maintenance, as those generate advance demand information. In practice, however, it often happens that if some demands for spare parts are planned, while others are unplanned, they are all treated as being the same, i.e., unpredictable without taking into account the maintenance policy.

Third, Ghodrati & Kumar (2005a,b) additionally identify the operating environment in which the installed base operates (e.g., the humidity or the dust) as a factor that affects part reliability and as such spare part demand. Similarly, Jalil et al. (2011) and Andersson & Jonsson (2018) use information on the regional distribution of the installed products (e.g., the installed base may be concentrated in certain regions).

Once the set of installed base information is defined, the question arises how to obtain this installed base information. Based on interviews with five companies, Auramo & Ala-risku (2005) recognize the importance of managing installed base information for the purpose of

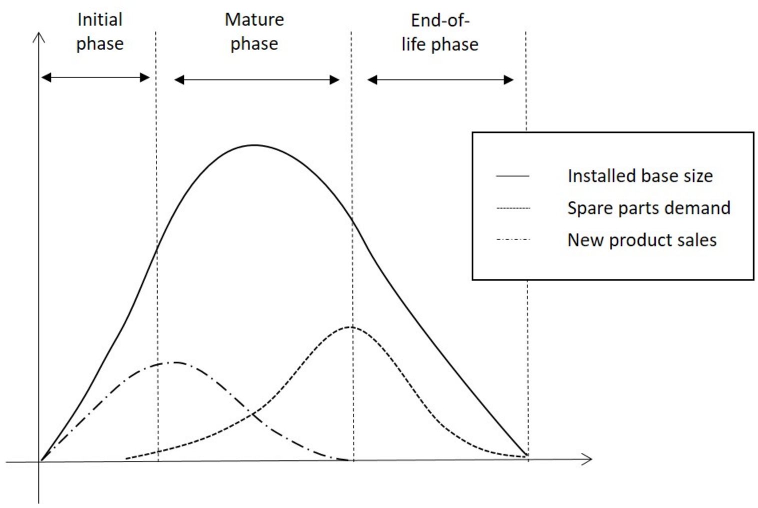

Figure 2: Product life cycle, installed base evolution, and spare parts demand (adapted from Dekker et al. (2013)).

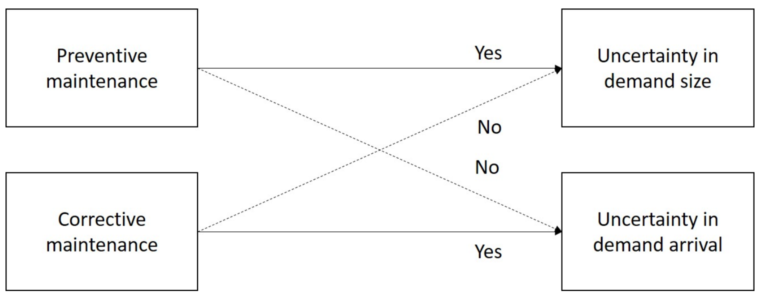

Figure 3: Corrective versus preventive maintenance

improving the management of industrial services, but at the same time they remark that having reliable information available on all the relevant products in the installed base can be very challenging. Similar insights are obtained by Wagner & Lindemann (2008), who found in a case study with seven engineering companies that most of the companies only have a 'cloudy view' of their installed base, and specific information, or even the exact number of products sold, are difficult to determine. As the installed base can consist of complex equipment with different subassemblies and parts, it is necessary to keep track of the complete composition and potential technical improvements and maintenance actions in order to keep track of the installed base (Dekker et al., 2013). Moreover, companies generally do not have information on where/how the customer uses the product. As such, they could base their forecasts on some wrong installed base information. To resolve this issue, Perminova-Harikoski et al. (2015) claim customer interactions as an important source of installed base data and an opportunity for data collection. Along the same lines, Kim et al. (2017) identify maintenance contracts as an important source of installed base information.

4.2 Methods to use installed base information for spare part demand forecasting

In a very early attempt, Shaunty & Hare Jr (1960) link spare parts demand to product usage. They investigate this connection in the specific setting of aircraft spare parts, whose demand is estimated based on the number of landings of the planes. Therefore, they estimate the failure rate of a part per 'usage', here defined as the number of landings, and multiply it with the scheduled number of landings at a certain location per time period (e.g., per week) for a certain plane type. When these part needs are summed over all planes planned to land at a given station, the forecasted need for that location is obtained.

Rather than assuming a constant installed base, several authors acknowledge the evolution of the installed base over time. As illustrated in Figure 2, the number of installs increases during the initial phase of the product life cycle (PLC), reaches a maximum level within the mature phase, and decreases during the end-of-life phase (Inderfurth & Mukherjee, 2008).

Jin & Liao (2009) claim that neglecting the increase in product installations, due to market expansion, underestimates the actual maintenance needs. This is later confirmed by Jin & Tian (2012) using simulation studies. Fortuin (1984) investigates this for the introduction of a new product, where an initial forecast for the future spare part demand is made using a rough estimate for the part failure rate and a linear increase of product demand.

Ritchie & Wilcox (1977), Hong et al. (2008), Chou et al. (2015, 2016), and Kim et al. (2017) treat the case of a discontinued product, where no new sales occur in the future and installed products can be discarded due to end of use. This often occurs in practice, as the service period of a product is typically much longer than the production period (Teunter & Fortuin, 1999). In that case the installed base is decreasing over time. Chou et al. (2015, 2016) highlight the importance of including the decline in installed base, as the part production costs during the EOL phase might be much larger than in the mature phase because of limited economies of scale and scope, and overstocking is very costly as unsold parts will become obsolete. Ritchie & Wilcox (1977) introduce the probability that a part, when it fails, is not replaced. They argue that the decrease in spare parts demand originates from the non-replacement decision for defective parts in old machines, rather than from the decay in the number of installed machines over time. Hong et al. (2008) extend the work of Ritchie & Wilcox (1977), by combining a decline in installed base with a replacement probability. Instead of using a reliability model, Chou et al. (2015, 2016) find that regression on the failure probability leads to more accurate forecasts than regression on historical part sales data. Kim et al. (2017) also present a regression methodology, to make an accurate last make/buy decision. It is noteworthy that the authors study spare part demand for consumer products, such as refrigerators and televisions, whereas most other works study capital goods, like planes or heavy equipment.

The part replacement probability is also discussed by Lu & Wang (2015), who assume that the repair willingness of a customer decreases with the cumulative number of breakdowns the product as a whole has experienced in the past. Lu & Hjelle (2016) extend this idea by evaluating whether users will have their product repaired depending on both the number of past failures and the use time.

Yamashina (1989) includes new product installations, which are added to the installed base, together with product survival, where products leave the installed base, over time, and thus addresses the entire product life cycle. He relates service parts demand to the production pattern of products containing the studied part (implicitly assuming that each produced product is also installed), together with the product life characteristics (i.e., when it is discarded), and the part life characteristics (i.e., failure rate). The author however remarks on the difficulty of calculating the demand forecast analytically when the future product sales are a stochastic process. Minner (2011) models the evolution of the installed base by the new product sales and the end-of-use of products. The author determines the probability distribution, instead of a point forecast, for the one-period-ahead demand by means of recursion.

Kontrec et al. (2015) and Kontrec & Stefan (2017) propose a reliability model where they observe the total unit time, i.e., the average life span of a part, and use it to estimate the number of parts to be kept in stock. Stormi et al. (2018) propose a regression model which only considers the size of the installed base as the driver for demand, and ignore the failure behavior of the parts. Nonetheless, the authors observe the existence of a replacement probability when applying their method in a case study. In the research of Hong & Meeker (2013) the failure occurrence is considered to be dependent on the dynamic use rate of the product, and not on calendar time.

The method of Liu & Tang (2016) differs from all previous research as it assumes that sub-failure processes of items on the same system are not necessarily independent. The authors also include the possibility of reliability improvement or deterioration over time.

Several papers discuss the impact of environmental factors on the part reliability distribution. The environmental operating conditions, such as the temperature, humidity, dust, etc., can have an influence on the reliability characteristics of the product. Ghodrati & Kumar (2005a,b); Ghodrati (2011) propose a method to obtain the expected number of spare parts using system reliability and environmental data. They adjust a baseline part failure rate with time-independent covariates that are associated with environmental factors to account for different operating conditions. Using an Event tree analysis, Ghodrati et al. (2007) find that ignoring the operating environment results in economical and production losses. Their method and findings are implemented and validated at a case company in Ghodrati et al. (2012) and Barabadi et al. (2014). In the work of Lanza et al. (2009) and Barabadi (2012) the parameters of the part reliability function are adjusted based on time-dependent covariates. Using a case study, Gharahasanlou et al. (2016) and Qarahasanlou et al. (2017) validate the importance of including (time-dependent) covariates related to the operating conditions in the spare part demand forecasts.

A different installed base approach is used by Jalil et al. (2011), who study where to place the spare part inventories throughout a service network. They make an aggregate forecast for an entire region, where they sum up the historical spare part demand observed at each location. Next, an extrapolation method is used (e.g., Simple Exponential Smoothing (SES)) to derive an aggregate demand forecast for the entire region. Information on the size of the current installed base is then used to allocate and divide the aggregated forecast geographically.

Finally, in addition to the spare part requirements for corrective (or reactive) maintenance, several authors analyze the spare part demand originating from preventive (or proactive) maintenance. Ghobbar & Friend (2002, 2003) discuss three primary (preventive)

Maintenance Process	**Papers**
Periodic maintenance (Hard-time)	Hu et al. (2015)
Periodic Inspections (On-condition)	Hua et al. (2007); Wang & Syntetos (2011); Romeijnders et al. (2012)
Condition-monitoring	Deshpande et al. (2006); Hellingrath & Cordes (2014); Si et al. (2017)

Table 4: Classification of the scientific work considering preventive maintenance

maintenance processes: hard-time (periodic maintenance), on-condition (periodic inspections), and condition monitoring. The first two involve periodic maintenance visits related with preventing failures, whereas the third only leads to a preventive maintenance visit based on the condition of the part. The classification of the studied papers considering preventive maintenance can be found in Table 4.

Hua et al. (2007) develop a regression model in which they attribute non-zero demand to the occurrence of planned maintenance actions. Hu et al. (2015) consider a two-dimensional preventive maintenance cycle, where preventive replacement scheduling is dependent on both calendar time and usage time (e.g., mileage, flight hours, etc.), to forecast future demand. Romeijnders et al. (2012) propose a two-step forecasting method, in which they separately forecast the number of repairs for each type of component and the average number of parts of the studied type needed per repair of that component.

Wang & Syntetos (2011) look at a case of preventive maintenance where items are inspected at regular intervals and can be replaced if defective and consider a delay time based model to forecast future spare parts demand. Si et al. (2017) build on the idea of Wang & Syntetos (2011) to use real-time condition-monitoring degradation data of the system instead of statistical failure data to produce their forecasts. Condition monitoring data are also used by Hellingrath & Cordes (2014) to enhance the demand forecast quality: in a first step, condition monitoring information is analyzed with regard to distribution parameters of potential breakdowns, which is then in a second step combined with a Bayesian approach (Dolgui & Pashkevich, 2008) to provide a probability distribution for the future spare parts demand.

Finally, Deshpande et al. (2006) apply a somewhat different approach using condition monitoring data to improve the predictability of service parts demand: they develop a condition based advance order policy, where each installed part with an age higher than a certain threshold generates advance demand information and triggers an advance order. The use of these advance orders improves the availability of the spare parts.

4.3 Analysis of the reviewed literature

In what follows we classify the different papers, including an overview of the assumptions made on the future development of the installed base size and the part failure behavior, a review of its evaluation methods, and its most important contributions and limitations.

Table 5 classifies the causal based forecast methods that make use of installed base information into three categories (as in Andersson & Jonsson (2018)): reliability based forecasting, regression based forecasting, and condition-based maintenance (forecasting using sensor data). The method of Jalil et al. (2011) is not included in this classification, as it uses

Category	Papers
Reliability based	Shaunty & Hare Jr (1960); Ritchie & Wilcox (1977); Fortuin (1984); Yamashina (1989); Petrovic & Petrovic (1992); Ghodrati & Kumar (2005b,a); Ghodrati et al. (2007); Hong et al. (2008); Jin & Liao (2009); Lanza et al. (2009); Ghodrati (2011); Minner (2011); Wang & Syntetos (2011); Barabadi (2012); Ghodrati et al. (2012); Jin & Tian (2012); Hong & Meeker (2013); Barabadi et al. (2014); Hu et al. (2015); Kontrec et al. (2015); Lu & Wang (2015); Gharahasanlou et al. (2016); Liu & Tang (2016); Lu & Hjelle (2016); Kontrec & Stefan (2017); Qarahasanlou et al. (2017)
Regression based	Hua et al. (2007); Chou et al. (2015, 2016); Kim et al. (2017); Stormi et al. (2018)
Condition-based	Deshpande et al. (2006); Hellingrath & Cordes (2014); Si et al. (2017)
Other methods	Jalil et al. (2011); Romeijnders et al. (2012)

Table 5: Classification of the forecast methods according to Andersson & Jonsson (2018)

the installed base information merely as an allocation method, nor is the work of Romeijnders et al. (2012), who apply a time series based forecasting, rather than a causal method. Both are added to a fourth category "Other methods". We observe that the majority of proposed methods apply reliability based forecasting. In Table 6 we give an overview of the diverse types of information considered by the different methods. Whereas regression based forecasting requires data on explanatory factors that correlate with demand (e.g., the size of the installed base, the part failure behavior, historical failures), forecasting using sensor data necessitates sensor data to be collected and analyzed. Reliability based forecasting in turn may use a variety of data: the part failure behavior, the current and future size of the installed base, the geographical location, the usage (conditions) of the installed base, the repair willingness of the customers, and the maintenance policy in place.

Tables 7 and 8 provide an overview of the different assumptions on the future development of the installed base, as also discussed in Section 4.2. We observe that almost all works consider historical product sales and historical discards, without anticipating potential future changes over time. Only six of the 37 works considers an increase in installed base over time through new product sales, and seven consider the decline because of product discards, of which two take both new sales and product discards into account. Only the latter two consider the entire product life cycle of the installed base, where the number of installs increases in the initial phase, reaches a maximum in the mature phase, and declines when the product enters the end-of-life (EOL) phase. Nonetheless, linking the product life cycle with part demand can be beneficial, as time series based methods lag behind the life cycle development (Minner, 2011). In the beginning of the life cycle, explanatory variables related to the installed base can be incorporated to anticipate the future increase in demand, and in the EOL phase, spare part stock should only be kept for items that are still operational (i.e., the active installed base), to reduce or even eliminate obsolete stock (Wagner & Lindemann, 2008). Especially when product life cycles are long, tracking the installed base may result in inventory reductions (Minner, 2011).

Tables 6 and 9 illustrate the different approaches to the part failure process. Some authors only use the observed historical failures, for example as a dependent variable in a regression analysis, but do not model the part failure behavior itself. Those are indicated with (H) in Table 6. Table 9 shows that the Exponential and Weibull distribution are commonly used to model the part failure process. Where the use of an Exponential time-to-failure distribution, or a constant failure rate, facilitates calculations, it is a simplifying assumption which does not necessarily hold in practice. The Weibull distribution, on the contrary, might be more appropriate in a practical setting, although more complex to apply (Ghodrati, 2011).

In Table 6 we observe that environmental factors are included in eleven out of 37 works. It is remarkable that none of the studied papers considers environmental factors together with an evolving installed base size. Most papers include the impact of the environment (such as humidity, dust, temperature, etc.) on the part reliability through covariates. A different approach is applied by Jalil et al. (2011), who use the environment (the geographical location of the installed base) as an allocation method for their time series based forecast.

Table 10 indicates the assumptions taken on the part replacement probability. Only six out of 37 works consider a replacement probability.

Table 11 summarizes how the different authors validate and/or evaluate their forecast methods, if applicable, together with the main results. We observe that most methods show promising performance, either in terms of increased forecast accuracy and/or reduced inventories. Nonetheless, it is remarkable that some authors do not include any means of forecast evaluation nor validation in their work, e.g., Shaunty & Hare Jr (1960); Yamashina (1989); Petrovic & Petrovic (1992); Lanza et al. (2009). These papers are excluded from Table 11. Moreover, some authors apply their method to a real dataset, but without validation to the actual demand (e.g., Ghodrati & Kumar, 2005a,b; Kontrec et al., 2015), or evaluation relative to other methods (e.g., Ritchie & Wilcox, 1977; Jin & Liao, 2009; Lu & Wang, 2015). And in those cases were the methods are evaluated, we find that very different measures (e.g., inventory costs, Mean Absolute Deviation (MAD), Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE)) and benchmark methods (e.g., current company policy, SBA, CR, SES, bootstrapping) are applied. We also observe a lack of overall comparison among the various installed base methods. That renders it hard to evaluate the performance across the different methods. An exception to this is Hong et al. (2008), who explicitly compare their method performance with the method by Ritchie & Wilcox (1977). Ghodrati (2011) also investigates the impact of using an exponential time-to-failure distribution (Ghodrati & Kumar, 2005a) versus a Weibull distribution (Ghodrati & Kumar, 2005b) when including covariates.

In Tables 12 and 13, we finally present an overview of the main contributions and limitations to the discussed scientific works. From Table 12 we clearly observe a trend towards more complexity of the proposed methods over time, through an increased amount of installed base information that is considered. This reflects a closer match between the developed methods and reality. Table 13 shows that for many papers, the main challenge lies in the proper estimation of the method parameters (part replacement probability, impact of environmental factors, evolution of the installed base, etc.). The proposed methods can only perform well if this data is available and reliable. Generally, the authors assume availability and observability of the necessary data. In practice, however, this is quite a strong assumption. To overcome difficulties with parameter estimations and limited failure data availability, Petrovic & Petrovic (1992) apply theoretical failure rates estimated from data banks or reliability handbooks in their forecast. Cavalieri et al. (2008) recommend predicting the failure rate using past failures or reliability testing. Nonetheless, they acknowledge that this requires the history of failures to be registered in a database (which is also addressed by Andersson & Jonsson (2018)). When data is missing, Lanza et al. (2009) suggest to base reliability parameters on expert knowledge.

Paper	Historical sales	New sales	Historical discards	Future discards	Failures	Replacement probability	Environment
Shaunty & Hare Jr (1960)	x		x		x		
Ritchie & Wilcox (1977)	x				x	x	
Fortuin (1984)		x			x		
Yamashina (1989)		x		x	x		
Petrovic & Petrovic (1992)	x		x		x		
Ghodrati & Kumar (2005b,a); Ghodrati et al. (2007); Ghodrati (2011); Ghodrati et al. (2012)	x		x		x		x
Deshpande et al. (2006)	x		x		x		
Hua et al. (2007)					(H)		
Hong et al. (2008)	x			x	x	x	
Jin & Liao (2009); Jin & Tian (2012)		x			x		
Lanza et al. (2009)	x		x		x		x
Jalil et al. (2011)	x		x		(H)		x
Minner (2011)		x		x	x		
Wang & Syntetos (2011)	x		x		x		
Barabadi (2012)					x		x
Romeijnders et al. (2012)					(H)		
Hong & Meeker (2013)	x		x		x		
Barabadi et al. (2014)	x		x		x		x
Hellingrath & Cordes (2014)	x		x		x		
Chou et al. (2015)	x		x	x	x	x	
Hu et al. (2015)	x		x		x		
Kontrec et al. (2015)	x		x		x		
Lu & Wang (2015)	x		x		x	x	
Gharahasanlou et al. (2016)	x		x		x		x
Chou et al. (2016)	x		x	x	x	x	
Liu & Tang (2016)	x	x			x		
Lu & Hjelle (2016)	x		x		x	x	
Kim et al. (2017)	x		x	x	x		
Kontrec & Stefan (2017)	x		x		x		
Qarahasanlou et al. (2017)	x		x		x		x
Si et al. (2017)					x		
Stormi et al. (2018)	x		x	x	(H)		

Table 6: Sources of installed base information

Paper	New sales
Fortuin (1984)	Linear growth function
Yamashina (1989)	Time dependent sales rate / Lump production
Jin & Liao (2009)	Homogeneous Poisson Process
Minner (2011)	Logistic growth function
Jin & Tian (2012)	Homogeneous Poisson Process
Liu & Tang (2016)	Deterministic

Table 7: Assumptions on the distribution of the new sales

Paper	Product Discards
Yamashina (1989)	Not specified
Hong et al. (2008)	Exponential survival function
Minner (2011)	Sum of Binomial distributions
Chou et al. (2015)	Integrated in the expression of the replacement probability
Chou et al. (2016)	Integrated in the expression of the replacement probability
Kim et al. (2017)	Exponential survival function
Stormi et al. (2018)	Exponential survival function

Table 8: Assumptions on the distribution of product discards

5. Discussion

First, Tables 6-10 show that a wide range of installed base information is considered in literature, albeit scattered over different papers. Table 12 reveals that there is a trend to develop more complex methods taking multiple sources of installed base information into account, however none of the studied methods considers all relevant demand drivers into one model. Moreover, most of the work seems to be tailored to a specific product life cycle phase; whereas this allows a simplification of the analysis, it unfortunately does not render them applicable in other life cycle phases. We also observe that environmental factors, impacting the part reliability (such as location, dust, humidity) are rarely combined with a changing installed base size. Additionally, a part replacement probability is hardly considered. Consequently, an avenue for future research is the development of a method that takes a broader number of drivers into account. It is expected that this will lead to even better performance.

Second, from the overview of the evaluation methods used in literature (see Table 11), we find that a common evaluation measure to compare the different forecasting methods is lacking; currently, many different performance measures and different benchmark methods are used. Furthermore, there is hardly any comparison between the different installed base methods. It could be interesting to establish a link between classification techniques and the use of installed base information. As regions of superior performance have been identified for SES, CR, and SBA (Syntetos & Boylan, 2005), it might also be interesting to define a region in which the inclusion of installed base information is useful. For this purpose, we consequently identify a need for a large scale evaluation of the proposed methods, to investigate their relative performance and their performance compared to traditional methods, to formally investigate potential gains, and investigate the value of (not) including different

Paper	Failure process
Shaunty & Hare Jr (1960)	Constant failure rate
Ritchie & Wilcox (1977)	Constant failure rate
Fortuin (1984)	Exponential time-to-failure distribution
Yamashina (1989)	Exponential time-to-failure distribution
Petrovic & Petrovic (1992)	Constant failure rate
Ghodrati & Kumar (2005b)	Weibull time-to-failure distribution
Ghodrati & Kumar (2005a)	Exponential time-to-failure distribution
Deshpande et al. (2006)	No distribution specified
Ghodrati et al. (2007)	Exponential time-to-failure distribution
Hong et al. (2008)	Exponential time-to-failure distribution
Jin & Liao (2009)	Exponential and Weibull time-to-failure distribution
Lanza et al. (2009)	Weibull time-to-failure distribution
Ghodrati (2011)	Exponential and Weibull time-to-failure distribution
Minner (2011)	Bernoulli process, probability dependent on part age
Wang & Syntetos (2011)	Weibull time-to-failure distribution
Barabadi (2012)	Weibull time-to-failure distribution
Ghodrati et al. (2012)	Exponential time-to-failure distribution
Jin & Tian (2012)	Exponential time-to-failure distribution
Hong & Meeker (2013)	Weibull time-to-failure distribution
Barabadi et al. (2014)	No distribution specified
Hellingrath & Cordes (2014)	No distribution specified
Chou et al. (2015)	No distribution specified
Hu et al. (2015)	Weibull time-to-failure distribution
Kontrec et al. (2015)	Rayleigh time-to-failure distribution
Lu & Wang (2015)	Exponential time-to-failure distribution
Chou et al. (2016)	No distribution specified
Gharahasanlou et al. (2016)	Weibull time-to-failure distribution
Liu & Tang (2016)	Weibull time-to-failure distribution
Lu & Hjelle (2016)	Exponential time-to-failure distribution
Kim et al. (2017)	Exponential part survival function
Kontrec & Stefan (2017)	Rayleigh time-to-failure distribution
Qarahasanlou et al. (2017)	No distribution specified
Si et al. (2017)	Wiener degradation process

Table 9: Assumptions on the failure rate

demand drivers.

Third, from Table 13 we find that most methods involve the estimation of multiple parameters, and as such they necessitate data collection and analysis. This might be a challenge when implementing the methods in a practical setting. Dekker et al. (2013) remark that obtaining the necessary information to produce forecasts using installed base information can be very difficult and time consuming. In order to benefit from installed base forecast methods, explanatory variables need to be identified and analyzed and data need to be available and of high quality (Andersson & Jonsson, 2018). Nonetheless, the IT advances and storage capacities that can permit the collection and analysis of such 'big data' exist. In automobiles, for example, more and more vehicles are linked by telematics, and the amount of data generated by those telematics is increasing (Andersson & Jonsson, 2018). More and more machines, too, are equipped with sensors that can collect various kinds of data and

Paper	Replacement probability
Ritchie & Wilcox (1977)	Exponential replacement probability distribution
Hong et al. (2008)	Exponential replacement probability distribution
Chou et al. (2015)	Exponential replacement probability distribution
Lu & Wang (2015)	Probabilities based on survey data, no distribution specified
Chou et al. (2016)	Exponential replacement probability distribution
Lu & Hjelle (2016)	Probabilities based on survey data, no distribution specified

Table 10: Assumptions on the replacement probability

allow for direct monitoring of the products in use (Furtak et al., 2015; Andersson & Jonsson, 2018). Zhong et al. (2016) present an overview of recent big data collection and analytics tools, developed by large IT companies, such as SAP, Microsoft, and Oracle. Big data analytics has emerged in recent years to provide possible solutions for data analysis, knowledge extraction, and advanced decision making. Remarkably, data management practices are hardly discussed when new methods are proposed, and they assume data to be available and observable. Therefore, a validation of the methods on real data, together with a discussion of the data collection and analysis process, could extend the current knowledge.

The ultimate goal of collecting and storing big data is to convert it into meaningful information that can be used to improve decision making (Richey et al., 2016). In some industries, data collection is regulated, dictating which information to collect. In others, however, data availability might be an issue and even basic information might be missing (Perminova-Harikoski et al., 2015). Consequently, companies tend to only have a 'cloudy' view of their installed base (Wagner & Lindemann, 2008). Even when data is available, the collected data can be heterogeneous, unstructured, or incompatible, which complicates data integration (Zhong et al., 2016). As such, even when companies build large databases, they can fail to accurately analyze the collected data. Despite this clear indication that data might be imperfect or even missing, this issue is not addressed in the studied literature. Therefore, we suggest the investigation of the impact of imperfect or missing data on the performance of the proposed forecast methods.

Lastly, as most methods proposed in literature require a large database to be available, we propose the investigation of the potential to combine installed base information together with more traditional methods, as similarly suggested by Furtak et al. (2015); Hu et al. (2017); Andersson & Jonsson (2018). Such approaches, as presented by Jalil et al. (2011) and Romeijnders et al. (2012), allow the application of a simple method that requires little (advanced) data and enrich it with installed base information. Installed base information could thus be used to adjust traditional methods, whilst reducing the need for a complex forecasting method.

6. Concluding remarks

A lot of research has already been performed on the topic of forecasting spare parts demand. A large part of this research, however, focuses on extrapolation methods which use historical demand data in order to classify and forecast parts demand. A smaller body of research exists on causal forecasting techniques, which incorporate the real drivers of spare part demand generation. In our literature review we identify 44 relevant papers or book chapters, of which 37 present a method or analysis, and 7 present a literature review or a framework, on the use of installed base information for spare part demand forecasting. Nonetheless, over the past years, interest for the topic has been increasing. When mapping the publications on a time line, we observe that the number increases from 2005 onwards: 70% has been published in the last 10 years, and 40% in the past 5 years. In our opinion, this can be explained by the fact that the use of installed base information for forecasting requires a huge amount of data to be available and to be analyzed. These days it is often stated that our most valuable resource is no longer oil, but data (The Economist, 2017). In the past decade, data collection, storage and analytics tools have greatly increased. Also the field of advanced data analytics is recently growing very fast. As such, we expect the number of papers on this topic to increase more over the coming years.

Establishing a link between the installed machines, the maintenance policy, and spare parts demand seems intuitive, and even self-evident. Therefore we believe that practitioners will appreciate its value. Causal forecasting is also particularly suited for spare parts demand forecasting. This becomes even more important in early stages of the product life cycle, when little historical demand data are available but some information on the installed base might be at hand. In the end-of-life phase, the use of installed base information allows the reduction or even elimination of obsolete stock.

Our literature review motivates the identification of a number of possible future research directions. First of all, it seems intuitive to investigate a method which combines a broad set of demand drivers, such as the preventive maintenance information in combination with the failure rate information, as this captures a large part of the demand generating process. Second, it might be interesting to establish a link between classification techniques and the use of installed base information. As regions of superior performance have been drawn up for SES, CR, and SBA, it might also be interesting to define a region in which the inclusion of installed base information is useful. Therefore, a large scale comparison of different installed base methods with each other and with traditional methods is necessary to formally evaluate their performance, strengths and weaknesses. Third, a profound discussion of data management practices would enrich current literature, as there is a need for information systems that support the data collection and analysis. Fourth, this discussion could be extended by evaluating the impact of imperfect or missing information. Fifth, there is also value in the combination of forecasting techniques. Therefore, a possible research direction could be in further investigating the combination of extrapolation techniques and causal methods.

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Paper	Evaluation	Results / comparison
Ritchie & Wilcox (1977)	Case study	Good graphical fit with real demand
Fortuin (1984)	Case study	25% stock reduction / current policy
Ghodrati & Kumar (2005b)	Case study	Difference in forecasted demand of 20% / covariates not included
Ghodrati & Kumar (2005a)	Case study	Difference in forecasted demand of 40% / covariates not included
Deshpande et al. (2006)	Empirical study	Average inventory cost reduction of 20% / exogenous lead time demand
Ghodrati et al. (2007)	Case study	Greater economical/production losses for non-inclusion of covariates
Hua et al. (2007)	Case study	Lower error ratio, percentage error / SES, CR, bootstrapping
Hong et al. (2008)	Graphical analysis	Better fit with real demand / Ritchie & Wilcox (1977)
Jin & Liao (2009)	Numerical example	Inventory control system is sensitive to time-to-failure distribution
Ghodrati (2011)	Sensitivity analysis	Exponential time-to-failure distribution more affected by covariates than Weibull
Jalil et al. (2011)	Case study	Cost improvement of 1-16% for small and 1-58% for large installed base / current policy
Minner (2011)	Simulation	Average inventory reduction of 50% / SES
Wang & Syntetos (2011)	Simulation	Reduced MAD / SBA
Barabadi (2012)	Case study	Influence of time-dependence of covariates on spare part demand
Ghodrati et al. (2012)	Implementation	Less downtime and increased efficiency when considering covariates
Jin & Tian (2012)	Simulation	Validation of the method
Romeijnders et al. (2012)	Case study	MSE and MAD reduced up to 20% / CR, SES, Moving Average (MA), TSB
Hong & Meeker (2013)	Simulation	Reduced MSE when applying use-rate data
Barabadi et al. (2014)	Case study	Hazard rate up to 1.8 times higher in different operating conditions
Hellingrath & Cordes (2014)	Case study	Reduced forecast error / SBA
Chou et al. (2015)	Case study	MAD improves 16% / other regression models
Hu et al. (2015)	Case study	Influence of usage rates on spare part demand
Kontrec et al. (2015)	Case study	No validation/evaluation
Lu & Wang (2015)	Simulation	No significant difference / simulated demand data
Chou et al. (2016)	Case study	MAD improvements of 14,27% - 51,5% / MA
Gharahasanlou et al. (2016)	Case study	50% difference in Economic Order Quantity and order point when considering covariates
Liu & Tang (2016)	Numerical example	Inventory performance is robust
Lu & Hjelle (2016)	Simulation	No significant difference / simulated demand data
Kim et al. (2017)	Case study	Relative error, MAPE and RMSPE reduced by factor 2 / AR model
Kontrec & Stefan (2017)	Case study	No validation/evaluation
Qarahasanlou et al. (2017)	Case study	Difference in forecasted demand / covariates are not included
Si et al. (2017)	Case study	Forecasted and actual demand match well
Stormi et al. (2018)	Case study	Symmetric MAPE reduces 8% / CR

Table 11: Overview of the validation/evaluation of the proposed forecast method and main results

Paper	Main contribution
Shaunty & Hare Jr (1960)	Link spare part demand to product usage
Ritchie & Wilcox (1977)	Forecast for the EOL phase and include replacement probability
Fortuin (1984)	Consider the initial supply of a part
Yamashina (1989)	Incorporate both new product sales and discards
Petrovic & Petrovic (1992)	(1) Link forecasts with inventory, (2) develop decision support software
Ghodrati & Kumar (2005b)	Consider Weibull Time-To-Failure (TTF) distribution with environmental factors
Ghodrati & Kumar (2005a)	Consider exponential TTF distribution with environmental factors
Deshpande et al. (2006)	Link part-demand database with maintenance database
Ghodrati et al. (2007)	Perform risk analysis of ignoring environmental factors in forecasts
Hua et al. (2007)	Include maintenance policy in forecasts
Hong et al. (2008)	Model decreasing fleet size with part replacement probability
Jin & Liao (2009); Jin & Tian (2012)	Model new product sales process
Lanza et al. (2009)	Include load-dependency in reliability analysis
Ghodrati (2011)	Investigate different time-to-failure distributions with covariates
Jalil et al. (2011)	Spatially (dis)aggregate traditional forecasts
Minner (2011)	(1) Develop method applicable in full PLC, (2) Forecast distribution instead of point forecast
Wang & Syntetos (2011)	Use inspection-based delay time model for forecasts
Barabadi (2012)	Investigate impact of time-dependent covariates
Ghodrati et al. (2012); Barabadi et al. (2014); Gharahasanlou et al. (2016)	Implement method of Ghodrati & Kumar (2005a)
Romeijnders et al. (2012)	Differentiate between maintenance demand and part demand
Hong & Meeker (2013)	Propose forecasts based on product use instead of calendar time
Hellingrath & Cordes (2014)	Integrate condition monitoring information and demand forecasts
Chou et al. (2015)	Investigate impact of recency versus quantity of historical data
Hu et al. (2015)	Incorporate two-dimensional (usage time and calender time) Preventive Maintenance cycle in forecasts
Kontrec et al. (2015)	Determine demand based on total unit time
Lu & Wang (2015)	Include repair willingness based on previous breakdowns
Chou et al. (2016)	Demand probability increases for some parts in EOL phase
Liu & Tang (2016)	Consider dependencies between sub-failure processes in a system
Lu & Hjelle (2016)	Extend repair willingness concept
Kim et al. (2017)	Investigate different types of installed base information
Kontrec & Stefan (2017)	Consider data availability
Qarahasanlou et al. (2017)	Validate use of time-dependent covariates in case study
Si et al. (2017)	Integrate condition monitoring information with distributional forecasts
Stormi et al. (2018)	Use installed base information to manage customer lifetime value

Table 12: Main contributions of the selected literature

Paper	Limitations/difficulties
Shaunty & Hare Jr (1960)	Empirical determination of usage weight per product necessary.
Ritchie & Wilcox (1977)	Do not model decrease of the installed base.
Fortuin (1984)	(1) Initial parameter estimates necessary, (2) not applicable in other PLC phases.
Yamashina (1989)	Hard to estimate product lifetime.
Petrovic & Petrovic (1992)	Poor accordance of failure rates from databanks with real conditions of use.
Ghodrati & Kumar (2005b,a); Ghodrati (2011); Ghodrati et al. (2012); Barabadi et al. (2014)	Definition and estimation of covariates necessary.
Deshpande et al. (2006)	Difficult to merge maintenance database with demand database.
Ghodrati et al. (2007)	Estimation of event-tree probabilities necessary.
Hua et al. (2007)	Sufficient historical failures necessary for regression.
Hong et al. (2008)	(1) Estimation of replacement probability needed, (2) not applicable in other PLC phases.
Jin & Liao (2009); Jin & Tian (2012)	(1) Computationally challenging when not using exponential time-to-failure distribution, (2) only consider increase of number of installs.
Lanza et al. (2009)	Estimation of load-dependent reliability function necessary.
Jalil et al. (2011)	Case dependent results do not necessarily hold in different setting.
Minner (2011)	Complicated method for forecasting >1 periods ahead.
Wang & Syntetos (2011)	Difficult to capture delay-time parameters in practice.
Barabadi (2012)	(1) Definition and estimation of covariates necessary, (2) complex to consider many time-dependent covariates together.
Romeijnders et al. (2012)	Separate forecast for number of repaired components is hard if they fail rarely.
Hong & Meeker (2013)	Assumptions necessary to generate predictions for non-connected parts.
Hellingrath & Cordes (2014)	(1) Sensors need to be present in all machines, (2) limited case study (5 parts, 1 period ahead)
Chou et al. (2015)	(1) Estimation of combined replacement-discard probability necessary.
Hu et al. (2015)	Estimation of relation usage-time and calendar-time necessary.
Kontrec et al. (2015)	No evaluation/validation of method performance.
Lu & Wang (2015); Lu & Hjelle (2016)	(1) Estimates of user repair willingness necessary, (2) conclusions not necessarily true for capital goods.
Chou et al. (2016)	(1) Estimate of combined replacement-discard probability necessary, (2) many data observations necessary for valid regression.
Gharahasanlou et al. (2016)	Definition and estimation of covariates necessary.
Liu & Tang (2016)	Estimation of covariates for sub-failure process dependencies necessary.
Kim et al. (2017)	(1) Long estimation period during production phase necessary, (2) preferably short EOL phase, (3) part deterioration depends on product age.
Kontrec & Stefan (2017)	No validation/evaluation of the method performance.
Qarahasanlou et al. (2017)	Definition and estimation of covariates necessary.
Si et al. (2017)	Consider only 1 installed item.
Stormi et al. (2018)	(1) Over-forecasting bias present, (2) only consider fleet size (not age).

Table 13: Limitations of the studied work