Front. Eng. Manag.
https://doi.org/10.1007/s42524-022-0206-4

REVIEW ARTICLE

Tongdan JIN

Bridging reliability and operations management for superior system availability: Challenges and opportunities

Abstract Recently, firms have begun to handle the design, manufacturing, and maintenance of capital goods through a consolidated mechanism called the integrated product-service system. This new paradigm enables firms to deliver high-reliability products while lowering the ownership cost. Hence, holistic planning models must be proposed for jointly allocating reliability, maintenance, and spare parts inventory across the entire value chain. In the existing literature, these decisions are often made fragmentally, thus resulting in local optimality. This study reviews the extant works pertaining to reliability-redundancy allocation, preventative maintenance, and spare parts logistics models. We discuss the challenges and opportunities of consolidating these decisions under an integrated reliability-maintenance-inventory framework for attaining superior system availability. Specific interest is focused on the new product introduction phase in which firms face a variety of uncertainties, including installed base, usage, reliability, and trade policy. The goal is to call for tackling the integrated reliability-maintenance-inventory allocation model under a nonstationary operating condition. Finally, we place the integrated allocation model in the semiconductor equipment industry and show how the firm deploys reliability initiatives and after-sales support strategy to ensure the fleet uptime for its global customers.

Keywords system availability, product-service integration, installed base, new product introduction, service supply chain, reliability-maintenance-inventory allocation

1 Introduction

In the last decade, firms in both private and public sectors started to handle product design, manufacturing, and after-sales supports under an integrated product-service system (PSS). This new paradigm is driven primarily by customers who aspire for high system reliability and availability with low ownership cost (Kumar et al., 2007; Guajardo et al., 2012; Lin et al., 2016). High system availability is essential to daily business operations where zero downtime is extremely desirable, such as in energy generation, automobile assembly, healthcare delivery, transportation, communication network, financial services, and homeland security. For instance, an airline may incur costs of up to \$50000 per hour if a plane is grounded due to an unplanned repair (Ghobbar and Friend, 2003). Downtime costs of computer systems of a large e-commerce company or brokerage firm could be as high as \$1 million per hour (Patterson, 2002).

In fact, the after-sales service associated with maintenance, repair, and parts supply represents a lucrative income to original equipment manufacturer (OEM). Cohen et al. (2006) showed that such service could contribute as much as 40%–50% of the firm's profit. For instance, in the aviation industry, a total fleet of 39175 aircraft are projected to be in operation in 2029, up more than 42% from 27492 in 2019 (Cooper et al., 2019). The after-sales market that supports it is expected to rise to \$116 billion by 2029, up from \$81.9 billion in 2019. The global operation and maintenance market of wind industry will grow from \$30.21 billion in 2021 to \$52.74 billion in 2028 (Fortune, 2021). Similar situations are observed in other industries, such as automobile, semiconductor, and defense sectors (Thurlow, 2013).

Three approaches are often used to achieve the reliability and availability goal of a system. These methods are reliability-redundancy allocation (RRA), preventative maintenance (PM), and spare parts logistics (SPL) (Elsayed, 2021). In RRA, the product's mean-time-between-replacements (MTBR) and mean-time-between-failures (MTBF) are improved by using advanced design, durable materials, or standby units. However, a trade-off must be made among reliability, weight, volume, cost, and design

Received January 26, 2022; accepted April 10, 2022

Tongdan JIN (✉)
Ingram School of Engineering, Texas State University, San Marcos, TX 78666, USA
E-mail: tj17@txstate.edu

time. An early review on RRA models was made by Kuo and Wan (2007) and more recent ones by Coit and Zio (2019) and Si et al. (2020).

In a broad sense, PM can be classified into time-based and condition-based strategies. In time-based maintenance, systems or components are routinely checked and replaced if they reach a predefined age or fail randomly (Dursun et al., 2022). For instance, an age-based PM model has been developed to minimize the long-term cost considering imperfect repair and dynamic operating environments based on Markov process (Shen et al., 2019). Flexible age replacement policies have also been proposed to address the over- and under-maintenance issue (Jin and Yamamoto, 2017; Zhao et al., 2017; Jiang, 2019). An early survey on the PM research was done by Nicolai and Dekker (2008), and a more recent one was conducted by Alaswad and Xiang (2017). In condition-based maintenance (CBM), the equipment or component health status is monitored using in-situ sensors. The remaining useful life (RUL) is then estimated through a diagnostic and prognostic program, which is typically built upon statistical inferences, such as Bayes' theory (Zhao et al., 2018), or machine learning algorithms, such as neural networks (Peng et al., 2010; Hu et al., 2022). The replacement action is triggered once the RUL approaches, but not exceeds, a pre-defined threshold. An early review on CBM was made by Peng et al. (2010), and two recent ones were made by Li et al. (2020) and Hu et al. (2022).

SPL belongs to the service supply chain domain. It aims to reduce the mean downtime (MDT) of a system by promptly providing spare parts for proactive or failure replacement, thus ensuring the system's uptime. In SPL, the decision variables are the location of inventories and the amounts of spare parts to be stocked. Following the seminal work of Sherbrooke (1968), various SPL models have been proposed by considering the operational practices or constraints, including multi-indenture repair (Muckstadt, 1973), parts transshipment (Lee, 1987), multi-echelon location and repair (Alfredsson, 1997), and variable usage (Lau and Song, 2008). Typical performance measures include fill rate, backorders, parts availability, and inventory cost. The main challenge in managing spare parts inventory is the intermittent or sporadic demands generated from field systems. Hence, forecasting the spares demand is a key to the effective management of the spares inventory. An early survey on SPL models was made by Kennedy et al. (2002), and more recent ones can be found in Basten and van Houtum (2014) and Hu et al. (2018).

Although various models have been proposed to increase system reliability and availability, the majority are focused on one specific period of the product lifetime. For instance, RRA is limited to the product design and manufacturing phase, while PM and SPL concentrate on the after-sales market. There is a lack of holistic framework in which reliability, maintenance, and spares inventory are jointly coordinated over the product lifetime. Thus, the absence of such framework motivates us to revamp the existing research agenda and propose an integrated PSS solution with which system availability and lifetime cost are optimized simultaneously. To that end, we present three research questions: 1) how to allocate reliability, maintenance, and spares inventory concurrently under a variable installed base; 2) how to forecast the spare parts demand during the introduction of a new product with uncertain reliability and operation conditions; and 3) what are best industry practices in deploying the integrated PSS solution in manufacturing supply chain to ensure the fleet uptime in the global market.

The remainder of the paper is organized as follows. Section 2 revisits the state of the art in the interface among RRA, PM, and SPL models. Section 3 discusses the challenges and research opportunities of tackling integrated reliability-maintenance-inventory problem. Section 4 elaborates on spares demand forecasting methods, including explanatory models using installed base data. In Section 5, we present a case study for connecting the PSS model with industry best practices. Section 6 discusses the research and application of PSS in the defense or public sector. Lastly, Section 7 summarizes the paper.

2 The state of the art

2.1 A framework of integrated product-service system

Figure 1 shows a typical product-service integration framework comprising product design, manufacturing, and after-sales support. This type of manufacturing and service network is widely used for supporting durable goods or capital equipment with a typical lifetime of 10–30 years, such as wind turbines, aircraft engines, semiconductor equipment, and power generators. After a new product is released, the installed base or the fleet size increases due to market expansion, thus rendering the spares demand, maintenance service, and repair center being operated in a nonstationary condition. An OEM can adopt three approaches to attaining the reliability and availability goal of a new product: RRA, PM, and SPL. If a failed system or component can be repaired and reused, SPL is also referred to as a repairable inventory model.

The RRA problems are often formulated to maximize the system reliability or its availability under monetary, physical, and repair resource constraints. Some researchers also opt to minimize the system cost or the design resources subject to system reliability and availability constraints. Most RRA problems are revealed as NP-hard issues (Chern, 1992). Various solution techniques have been proposed, including branch and bound (Kuo et al.,

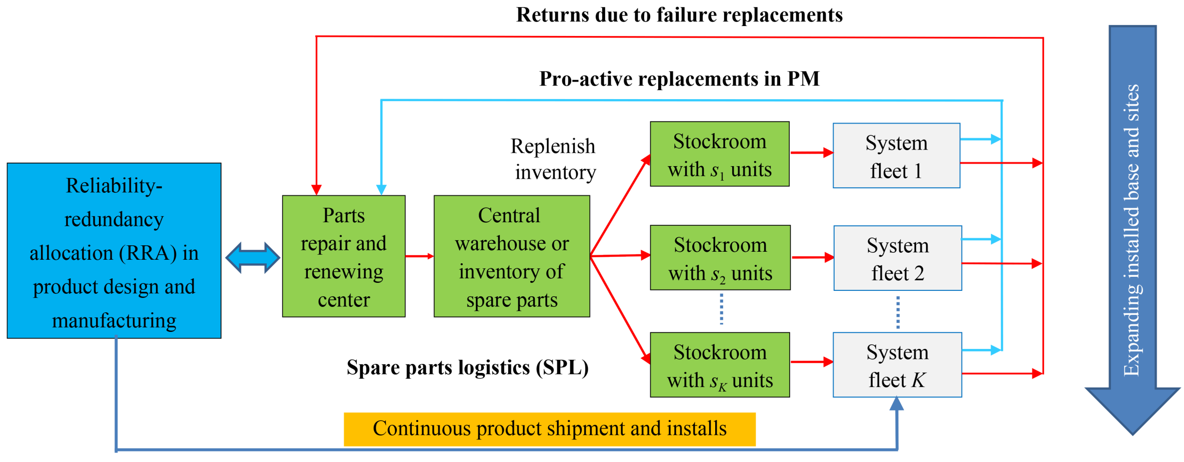

Fig. 1 Integrated product and service offering during new product introduction.

1987), genetic algorithm (Coit and Smith, 1996), multi-objective (Coit et al., 2004), Pareto optimality (Abouei Ardakan and Rezvan, 2018), Tabu search (Kulturel-Konak et al., 2003), artificial bee colony (Yeh and Hsieh, 2011), and importance measures (Si et al., 2019; 2020).

The advent of the PSS concept drives the necessity and needs of coordinating RRA, PM, and SPL under a holistic framework. In fact, this paradigm change is also driven by the emergence and implementation of performance-based contracting (PBC) in the after-sales market. In PBC, the service provider is compensated for the system reliability outcome, not the materials and labors transacted. PBC is becoming a new service delivery mechanism in the capital goods industry, especially in commercial airline, wind generation, and defense industry (Smith, 2004; Guajardo et al., 2012; Rees and van den Heuvel, 2012; Qin et al., 2021). For instance, the maintenance, repair, and overhaul (MRO) of the aviation industry is a capital- and labor-intensive service. An airline usually has to bear all the costs under traditional time- or material-based contracting. The MRO providers under PBC, however, are compensated for the achieved aircraft reliability or availability, not the actual labor and spare parts transacted. Hence, the OEM is motivated to consolidate product design, maintenance, spares, and repair under one umbrella to lower the product lifetime cost with performance warranty.

The sections below review the state of the art pertaining to three categories of joint allocation models: 1) joint decision on reliability, redundancy and maintenance, 2) joint allocation of reliability, redundancy and spares inventory, and 3) joint planning for maintenance and spares inventory. Notably, many good reviews have been made on RRA (Kuo and Wan, 2007; Coit and Zio, 2019; Si et al., 2020), PM (Alaswad and Xiang, 2017) and SPL (Basten and van Houtum, 2014). Our review differs from theirs as we focus on the interface among RRA, PM, and SPL with the goal of modeling reliability-maintenance-inventory allocation problem.

2.2 Joint decision on reliability, redundancy, and maintenance

In literature, joint optimization has been made between reliability design and maintenance policy because both decisions mutually interact and influence the system availability and cost. Levitin and Lisnianski (1999) jointly optimized component redundancy and replacement policy for a multi-state system to achieve the desired level of system reliability. A genetic algorithm is used to minimize the aggregate cost comprising capital investment, maintenance overhead, and random failures. Liu et al. (2013) solved a type of redundancy-maintenance optimization problem for multi-state systems with imperfect repair. The objective was to achieve the desired system availability through the coordination of component redundancy and replacement time by minimizing the expected cost rate. Nourelfath et al. (2012) solved a similar redundancy-maintenance optimization problem with the assumption that the repair was perfect. Moghaddass et al. (2012) compared the trade-off between redundant configuration and maintenance policy for a repairable multi-state system. A continuous-time Markov process model is proposed to maximize the system profitability per unit time subject to system availability and maintenance initiation threshold. Bei et al. (2017) formulated a two-stage, scenario-based stochastic optimization model to allocate the component type, redundancy level, and maintenance time of a series-parallel system. Subject to uncertain future stress exposures, the first stage is to select the component type and redundancy, and the second-stage determines the replacement time with the goal of minimizing the system cost.

2.3 Joint allocation on reliability, redundancy, and spares inventory

The joint reliability, redundancy, and spares allocation models can be classified into two categories: Static installed base versus variable installed base. Under a static system fleet, Louit et al. (2011) presented a number of reliability-based spares inventory models to determine the optimal stocking policy for both nonrepairable and repairable components. Three different criteria are examined: Reliability of the stock, parts availability, and cost. Öner et al. (2013) proposed an on-site, cold-standby component redundancy strategy to reduce the equipment downtime. Three performance measures are examined, namely, inventory cost, parts availability, and expected backorders. Selçuk and Agrali (2013) compared the trade-off between component reliability investment and base-stock spares inventory to minimize the cost of a multi-item system fleet. Xie et al. (2014) formulated a continuous-time Markov chain model to maximize the system availability through joint allocation of active redundant components and a base-stock inventory. Sleptchenko and van der Heijden (2016) solved a similar but more general problem in which the redundant system consists of multiple parts and spares types instead of a single part type. Zhao et al. (2019) concurrently allocated component redundancy, spares inventory, and repairmen with the intent of maximizing the availability of a cold-standby system.

The spares demand from a variable installed base turns out to be a nonstationary process with time-varying mean and variance, thus making the inventory control more difficult. Jin and Tian (2012) took an early step to jointly allocate component reliability and spares inventory to minimize the lifetime cost of a system fleet with Poisson growth. Later, Jin et al. (2017) included component redundancy, along with reliability and spares inventory, to minimize the system lifetime cost for a growing installed base. Other interesting works and related reviews on reliability-inventory planning under the variable installed base can be found in Dekker et al. (2013) and Selviaridis and Wynstra (2015). In most reliability-inventory allocation models, the aggregate spare parts demand of the fleet is often assumed as a Poisson process with a constant rate. This assumption is built upon the so-called superimposed renewal process theory. It states that as the fleet size increases, the inter-arrival time between two consecutive failures is exponential regardless of the lifetime distribution of systems (Cox and Smith, 1954; Wang, 2012). However, this assumption could be violated in a small installed base (e.g., during new product introduction). Therefore, solving the reliability-inventory allocation problem with nonhomogeneous Poisson spares demand would be more realistic, yet challenging.

2.4 Joint planning for maintenance and spares inventory

This research stream is known as maintenance service logistics. It aims to achieve high system availability by coordinating maintenance, repair, and parts provisioning at minimum cost. One research stream concentrates on consumable parts with a relatively large order quantity but less costly. The works by Zohrul Kabir and Al-Olayan (1996), Vaughan (2005), and van Horenbeek et al. (2013) belong to this stream, where parts replacement times and inventory re-ordering policy are jointly coordinated to minimize the total cost subject to random failures. Wang and Zhu (2021) investigated a joint optimization of periodic condition-based replacement and spares inventory problem for a nonrepairable k-out-of-n: F system in which the degradation of components follows the Wiener process and the gamma process, respectively. Later, Zhu et al. (2022) applied a similar model to the onshore wind turbine fleet maintenance by scheduling the shortest travel route to the failed turbines. Zhang et al. (2021) also optimized the preventive block replacement interval and spares inventory considering Wiener reliability degradation. The model differs from others in that spare parts in storage are subject to shock failure, in addition to slow deterioration.

Another research stream takes into account parts repair and renewing cost because failed items can be restored, refurbished, and reused. For instance, de Smidt-Destombes et al. (2009) jointly optimized the maintenance initiation, spare parts, and repair capacity to minimize the asset ownership cost for a k-out-of-n redundant system. Jin et al. (2015) formulated a principal-agent game model to minimize the annualized system cost for a fleet of k-out-of-n redundant systems. The model seeks the optimal allocation of maintenance time, spares inventory, and parts repair and renewing capacity. Basten and Ryan (2019) studied the impact of delay in performing planned maintenance on the optimal spares inventory policy. Attempts are also made to coordinate parts replacement time and the spares stocking policy under condition-based maintenance. For the mathematical convenience, uncapacitated repair facility is often assumed in maintenance logistics models. Given that repair capacity influences the stocking policy, Díaz and Fu (1997) and Sleptchenko et al. (2003) showed that capacitated treatment is more realistic than uncapacitated repair in this type of problem. For more studies on joint maintenance and spares inventory planning, readers are referred to the works of Wang et al. (2009a), Chen et al. (2013), and Olde Keizer et al. (2017).

3 Research challenges and opportunities

During the introduction of a new product, achieving system reliability and availability goal is rather difficult due to several reasons: 1) the installed base increases, and more spare parts and repairs are required, 2) system reliability continues to grow, but intermingled with up-and-down cycles, 3) spare parts demands are intermittent coupled with no-fault-found returns, and 4) training on the operations and diagnostics of new systems are insufficient. To cope with these challenges, three research topics are proposed as potential studies in the future.

• Developing joint reliability-maintenance-inventory allocation models.

• Optimizing spare parts logistics considering variable installed base and uncertain reliability.

• Forecasting spare parts demand considering installed base information.

3.1 Joint reliability-maintenance-inventory allocation model

Figure 2(a) shows the traditional approach to reliability resource allocation in the design, manufacturing, and after-market of capital goods. As the decisions on RRA, PM, and SPL are performed sequentially and fragmentally, the process may end up with suboptimal allocations. In fact, component reliability allocation made in the design stage will have a major influence on the maintenance cost and operational effectiveness of the system throughout its life (Carrel, 2000). To achieve the lifetime optimality, an integrated reliability-maintenance-inventory optimization model shall be proposed. Although various allocation models have been reviewed in Sections 2.2–2.4, an integrated PSS framework in which RRA, PM, and SPL are jointly coordinated remains lacking.

The integrated PSS framework proposed in Fig. 2(b) has two advantages over the sequential allocation approach. First, it allows for achieving a holistic resource optimization instead of segmented or local decision. Second, it can potentially lower product ownership cost, thus generating a win–win outcome between OEM and customers. For instance, higher product reliability requires a larger amount of upfront investment. However, a smaller amount of failures will occur during operation, thus reducing the cost of maintenance, spares, and repairs. Let A be the availability of a single-component system, then we have (Jin et al., 2015; 2021)

$$A = \frac{\int_0^{\tau} R(t)\,\mathrm{d}t}{\int_0^{\tau} R(t)\,\mathrm{d}t + t_{\mathrm{s}} + (t_{\mathrm{p}} R(\tau) + t_{\mathrm{q}} F(\tau))\Pr\{D > s\}}, \tag{1}$$

where $R(t)$ is the component reliability, $F(t)$ is the cumulative distribution function with $F(t) = 1 - R(t)$, τ is the preventive replacement time, t_{s} is the hands-on replacement time, t_{p} is the part repair turn-around time, t_{q} is the part renewing turn-around time, s is the base inventory level, and D is the random parts demand. Based on Eq. (1), the availability of a k-out-of-n redundant system is given by

$$A_{sys} = \sum_{j=k}^{n} \binom{n}{j} A^{j}(1 - A)^{n-j}. \tag{2}$$

Equations (1) and (2) represent a first-of-its-kind for modeling repairable system availability in which RRA, PM, and SPL are integrated. Namely, component reliability $R(t)$, redundancy level n, maintenance time τ, base stock inventory s, repair capacity t_{q}, and renewing capacity t_{p} are incorporated into a unified framework.

3.2 Spare parts logistics under variable installed base

After the capital equipment is installed at customer site, the spares inventory plays a vital role in sustaining its operation by providing good items for failure replacement. The demand for spare parts usually is intermittent and sporadic due to the stochastic nature of failures, uncertain system usage, and variable fleet size. During the new product introduction, more failure replacements are generated from the expanding fleet as the installed base continues growing. As a result, the spares inventory faces a nonstationary demand stream with time-varying mean and variance.

Figure 3 shows a growth profile of the installed base for a type of capital equipment starting from the initial shipment. This example is taken from the semiconductor test equipment sector. For confidentiality reasons, the data in Fig. 3 are normalized, but the trends are retained. From t = 1 to t = 130, a total of 1100 systems were

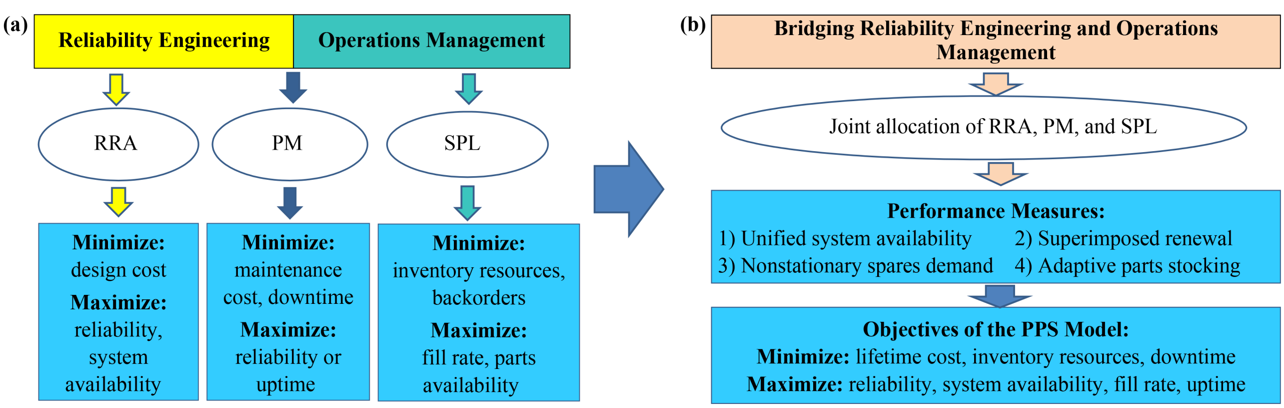

Fig. 2 (a) Sequential and segmented decision, and (b) Integrated product-service system.

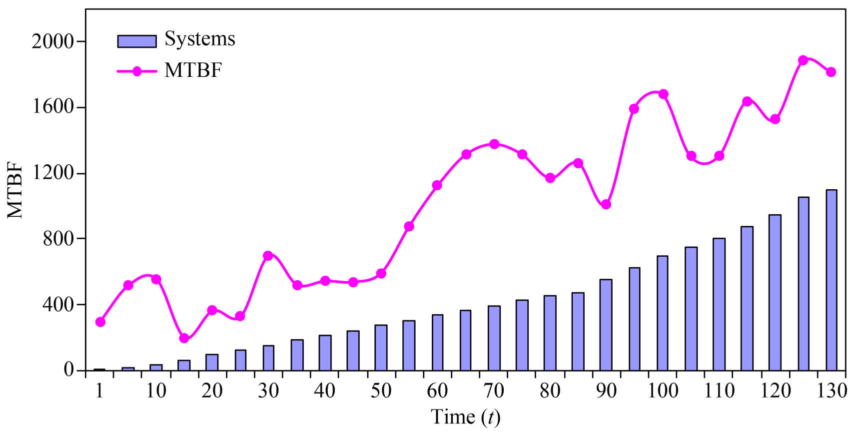

Fig. 3 Reliability growth and fleet expansion of a new product.

installed in field. The installation rate is not linear due to the stochasticity of the market. The rate between $t = 1$ and $t = 80$ is lower than that for $t = 81$ to $t = 130$. In the meantime, the system reliability manifested as MTBF is improved from about 300 at $t = 1$ to 1800 at $t = 130$. In fact, the reliability growth is highly uncertain, and multiple up-and-down cycles are observed.

Figure 4 graphically shows how the mean (E) and the variance (Var) of the lead time spares demand increase with the installed base. Lead time is the duration from when a replenishment order is placed to when the part arrives at the inventory. On the one hand, as the fleet size grows over time, the inventory needs to provide more spare items to meet the increasing failures. On the other hand, each installed system will likely reduce the spare parts demand because of reliability growth. Most spares inventory models assume the demand is a Poisson or stationary process. As a result, spares inventory models based on stationary demand becomes less effective in handling the time-varying demand during the new product introduction phase. Some researchers have focused on optimizing the stocking policy considering the nonstationary demand (Song and Zipkin, 1993; Ettl et al., 2000; Graves and Willems, 2008), but the primary interests of these studies are in production-inventory systems. Spare parts provisioning differs from production-inventory system in that the demand in the former heavily depends on the product reliability, maintenance policy, and fleet size.

4 Spares demand forecast using installed base information

A prerequisite to the effective management of spares inventory is the forecasting of intermittent parts demands. Many factors contribute to the intermittent behavior of spares demand, such as product discard (Ritchie and Wilcox, 1977; Lu and Wang, 2015), random system load (Wang et al., 2009b), operating temperature and humidity (Ghodrati and Kumar, 2005; Ghodrati et al., 2012; Nouri Qarahasanlou et al., 2019), working materials (Barabadi et al., 2014), uncertain lifetime (Hong and Meeker, 2013; Kontrec and Panić, 2017), system usage (Jin and Wang, 2012), and maintenance policy (Wang and Syntetos, 2011; Si et al., 2017). Interested readers can refer to the related topics within these works.

During the new product introduction, the installed base usually changes and increases, resulting in more failures and replacement requests. Hence, our priority of the

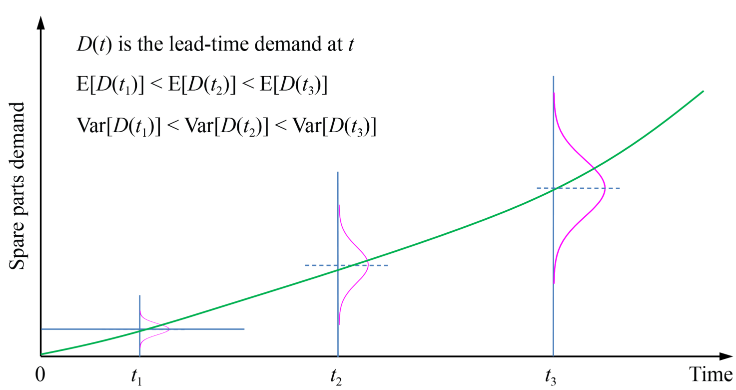

Fig. 4 Lead time spares demand under an increasing installed base.

forecasting model is focused on this period. First, we briefly review the history of the reactive spares demand forecasting method. Then, explanatory forecasting models incorporating reliability and installed base data are elaborated. Recently, van der Auweraer et al. (2019) provided a comprehensive review of the forecasting models considering installed base information. Our review differs from theirs because we present two superimposed renewal models: 1) forecasting the spares demand during the introduction of a new product with exponential lifetime; and 2) characterizing lead time spares demand of a new system fleet with Poisson expansion.

4.1 Reactive spares demand forecasting methods

In the 1970s, Croston (1972) proposed a seminal method to forecast the intermittent spares demand. Instead of predicting the mean demand per period, the author divided the demand into two separate terms: Demand occurrence and demand size. Two separate estimates are made: One for the demand inter-arrival time and the other for the spares quantity per demand occurrence. Since then, different variations of Croston's method have been developed, including Schultz (1987), Johnston and Boylan (1996), Syntetos (2001), Syntetos and Boylan (2001; 2005), Snyder (2002), Levén and Segerstedt (2004), Teunter et al. (2011), and more recently by Pennings et al. (2017).

Other reactive approaches to forecasting intermittent demand include machine learning, bootstrapping, and expert judgment. Machine learning algorithms, such as neural networks, are good at predicting nonlinear, intermittent demand data owing to the nonlinearity feature of the model (e.g., Kourentzes (2013)). Bootstrapping essentially is a nonparametric method that allows for the resampling of underlying random demand, rendering distributional assumptions unnecessary (Willemain et al., 2004). If a wealth of experience or expertise knowledge is available, an analytical model intermingled with expert judgment oftentimes results in an improved forecast result for certain part types (Wang and Petropoulos, 2016).

These aforementioned methods belong to the reactive forecasting technique and have one major drawback. They primarily leverage the historical data and passively predict the upcoming demand without explicitly considering uncertain future factors. However, future demand may fluctuate and vary considerably due to factors such as reliability growth, installed base, and system usage. It may not be sufficient to obtain an accurate forecasting result based on past information. Wang and Syntetos (2011) suggested that critical factors influencing the future demand generation, such as maintenance strategy, shall be incorporated into the forecasting procedure. Dekker et al. (2013) emphasized that spare parts management requires a level of reliability and installed base data for future forecasting, which cannot be met by reactive forecasting methods.

4.2 Explanatory spares forecasting with installed base data

The installed base is a key driver behind the generation of the intermittent spares demand, which has been discussed in Section 3.2. Figure 5 shows the installed base of a product lifecycle can be divided into three phases: Increasing, steady-state, and retirement or end-of-life. The fleet size increases during the product introduction phase, reaches a steady-state level once the market is saturated, and then decreases during the end-of-life phase. Below explanatory forecasting models are discussed corresponding to these phases.

4.2.1 Spares forecasting for increasing installed base

Fortuin (1984) investigated the future spares demand as the installed base increases during the introduction of a new product. Assuming a constant product failure rate α, the author presented a deterministic forecasting model as follows

$$Z(t) = \alpha \int_0^t n(x)\,\mathrm{d}x, \tag{3}$$

where $Z(t)$ is the cumulative spares demand of an installed base in $[0, t]$, and $n(t)$ is the fleet size at time t. The author further derived a closed form solution for $Z(t)$ assuming a linear and deterministic growth function of $n(t)$.

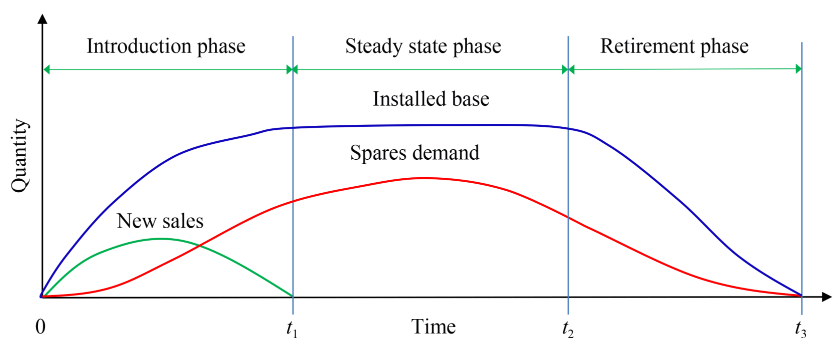

Fig. 5 New sales, installed base, and spares demand (Inderfurth and Mukherjee, 2008).

Realizing new sales are often random and uncertain because of market volatility. Jin and Liao (2009) proposed a spares forecasting model that synthesizes stochastic new installation and superimposed renewals theory. Renewal theory has important applications in reliability analysis and maintenance planning, and a review on this topic is available in Cox and Smith (1954) and Wu (2019). Assume the first product is installed at time 0. Let $N(t)$ be the random variable representing the number of new products installed in $(0, t]$. Thus, a total of $(N(t) + 1)$ products are installed by time t. Then, the aggregate spares demand of the fleet in $[0, t]$, denoted as $Z(t)$, can be expressed as

$$Z(t) = M(t) + \sum_{i=1}^{N(t)} M(t - W_i), \text{ for } t > 0, \tag{4}$$

where $M(t)$ is the renewal function for the product installed at $t = 0$, and W_i is a random variable representing the installation time of the ith product. Thus, $M(t - W_i)$ is the number of failures or renewals of the ith product in $[W_i, t]$. Essentially, $Z(t)$ is a superimposed renewal process formed by $(N(t) + 1)$ systems. Evidently, $Z(t)$ is a random variable due to the stochastic nature of $M(t)$, W_i, and $N(t)$. When the product lifetime is exponential and the fleet size follows the Poisson counting process, the mean and the variance of $Z(t)$ have been derived (Jin and Liao, 2009) and given as follows

$$\mathrm{E}[Z(t)] = \alpha t + \frac{1}{2}\alpha\lambda t^2, \tag{5}$$

$$\mathrm{Var}[Z(t)] = \alpha t + \frac{1}{2}\alpha\lambda t^2 + \frac{1}{3}\alpha^2\lambda t^3, \tag{6}$$

where λ is the product installation rate. Since Eqs. (5) and (6) are quadratic and cubic functions of time, respectively, the spares demand stream is a nonstationary process driven by a time-varying installed base. On the basis of Eqs. (5) and (6), a joint optimization problem of component reliability and adaptive stocking policy is solved under a Poisson expanding fleet (Jin and Tian, 2012).

The spare parts demand during the inventory replenish lead time is of particular interest to the OEM. Let $D(t)$ be the lead time spares demand in $[t, t+l]$, and l be the lead time duration. Then, we have $D(t) = Z(t+l) - Z(t)$. The mean and variance of $D(t)$ are obtained as follows (Jin et al., 2017)

$$\mathrm{E}[D(t)] = \alpha(1+\lambda t)l + \frac{1}{2}\alpha\lambda l^2, \text{ for } 0 \leqslant l \leqslant t, \tag{7}$$

$$\mathrm{Var}[D(t)] = \alpha(1+\lambda t)l + \left(\frac{1}{2}\alpha\lambda + \alpha^2\lambda t\right)l^2 + \frac{1}{3}\alpha^2\lambda l^3, \quad \text{for } 0 \leqslant l \leqslant t. \tag{8}$$

As Eqs. (7) and (8) effectively capture the nonstationary behavior of spares demand during the lead time, they can serve as the theoretical basis for planning spares inventory during the new product introduction.

Jalil et al. (2011) examined where to place the spare parts inventories throughout a service supply chain network. An aggregate forecast is performed for an entire region by summing up the historical spare parts demand observed at individual locations. Next, an extrapolation method, such as simple exponential smoothing, is used to derive an aggregate demand forecast for the entire region. The size of the current product fleet is then used to allocate and divide the aggregated forecasted spares demand geographically.

The method of Liu and Tang (2016) developed a spares inventory model for cost minimization under a growing installed base. Their work differs from the previous studies in that the failure processes of components or subsystems in the same system are assumed to be dependent. In addition, the possibility of reliability improvement or deterioration over time is also discussed in their work.

Qin et al. (2021) investigated a repairable inventory service network considering multi-fleet expansions in geographically dispersed locations. The repair center and the central warehouse face a nonstationary spares demand comprising failure streams from several locations or fleets. Their work represents a good effect in extending the single-site fleet expansion model to multi-location problems.

4.2.2 Spares forecasting for decreasing installed base

In the end-of-life phase, no new sales occur in the future, and the installed products could be discarded due to end of use. This line of research has been treated as the case of a discontinued product (Ritchie and Wilcox, 1977; Hong et al., 2008; Chou et al., 2015; 2016; Kim et al., 2017). The end-of-life scenario often occurs in practice, as the service period of a durable product is typically much longer than the production period. In that case, the installed base is decreasing over time. Teunter and Fortuin (1999) proposed “remove-down-to” levels for spare parts and then derived an optimal last order quantity in the final lot production. Chou et al. (2015; 2016) highlighted the importance of including the decline information of the installed base, as the part production costs during the end-of-life phase may be much larger than in the mature phase because of the limited economy of scale and scope. Moreover, overstocking is very costly as unsold parts will become obsolete.

4.2.3 Spares forecasting for both increasing and decreasing installed base

Yamashina (1989) related service parts demand to the shipment pattern of new products by implicitly assuming that each manufactured product is also installed in the field, together with the product life characteristics (i.e., when it is discarded) and the part reliability characteristics (i.e., failure rate). The installed base information includes product installation data over time, such as when they are added to the fleet and which and where products retire and leave the fleet. Thus, the entire product life cycle is addressed. However, the author only presented an approximation solution, and indicated the difficulty of calculating the demand forecast analytically when the future product sales are a stochastic process.

Minner (2011) modeled the evolution of the installed base considering the new product sales and the end-of-use of product retirement. The author determines the probability distribution, instead of a point forecast, for the one-period-ahead demand by means of recursion.

Stormi et al. (2018) introduced a forecasting model for industrial service sales, which considers the characteristics of the installed base and predicts the number of active customers and their yearly volume. The case study indicates that the installed base driven forecasting outperforms the reactive forecasting approaches suitable for similar data. Nevertheless, they pointed that a reliable forecasting requires comprehensive, up-to-date information about the actual installed base.

4.3 Spare parts procurement considering trade policy and additive manufacturing

Spare parts supply and forecast are also correlated with a nation's trade policy, political stability, and supply chain resilience. Rahmawati et al. (2019) studied the impact of import tariff on aircraft spare parts in the Indonesian aviation MRO industry. Their study showed that the import duty exemption increases domestic MRO services from 30 percent to 49 percent in 2013–2017 because of the availability of low-cost spare parts. Belhadi et al. (2021) investigated supply chain resilience in the manufacturing and service operations of automobile and airline sectors during the COVID-19 pandemic. Both sectors perceive that real-time information sharing plays a critical role in overcoming the supply uncertainties posed by the pandemic. The use of digital technologies also accelerates the cooperation among supply chain stakeholders. Hence, the future spares forecasting model can also incorporate the uncertainties in trade policy and high-impact event such as pandemic issues.

Additive manufacturing (AM) or 3D printing can potentially increase spares supply dynamics with its fast progress in precision, speed, affordability, and materials range. Several studies, such as Pérès and Noyes (2006), Holmström et al. (2010), Liu et al. (2014), and Khajavi et al. (2014), have specifically discussed the AM technologies in the spares inventory dynamics. For instance, Holmström et al. (2010) compared the cost and lead time between centralized and decentralized AM deployments in a spares supply network. Li et al. (2017) investigated the impact of AM on the spares supply chain in three scenarios: Conventional supply chain, centralized AM-based supply mode, and distributed AM-based supply mode. Their study showed that utilizing AM is superior to the traditional supply mode in terms of reducing variable cost and carbon emissions. They also noticed that the AM-based supply chain becomes less cost-effective unless the initial capital of equipment is further reduced.

5 A case study in semiconductor equipment industry

We take the automated test equipment (ATE) to illustrate the potential applications of the integrated PSS model. ATE is a high-end, capital-intensive electronics system that costs between \$1 million and \$3 million. They are widely used for wafer probing and device testing in the backend of semiconductor manufacturing. According to Market Watch (2021), the global ATE market was valued at \$4.3 billion in 2020 and will grow with a rate of 2.88% from 2020 to 2027.

To facilitate the maintenance and repair, an ATE system is typically configured by 20–40 swappable printed circuit boards called line replaceable units (LRUs). Figure 6 graphically illustrates the ATE configuration: Four high speed digital (HSD) boards, two direct-current (DC) boards, two analog boards, one radio frequency (RF) board, and one support board. The cost of an LRU varies between \$50000 and \$150000 depending on the performance and function of the board. Upon failure, the faulty LRU is replaced with a good item, and the system can resume the production immediately.

As shown in Fig. 7, the design, manufacturing, installation, and support of a global ATE fleet are carried out in a distributed supply chain network. For instance, the design of a new ATE is undertaken by engineers in Boston, MA and San Jose, CA, USA. The software application for ATE is outsourced to India. The LRU production is made by subcontractors in Charlotte, NC, USA and then shipped to a factory in Shanghai, China where the entire system is assembled. Repair centers are located in the Philippines and Costa Rica, respectively, where the

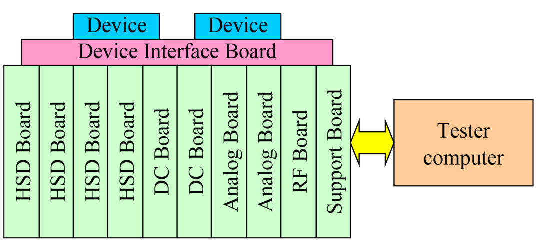

Fig. 6 An ATE system with reduced configuration.

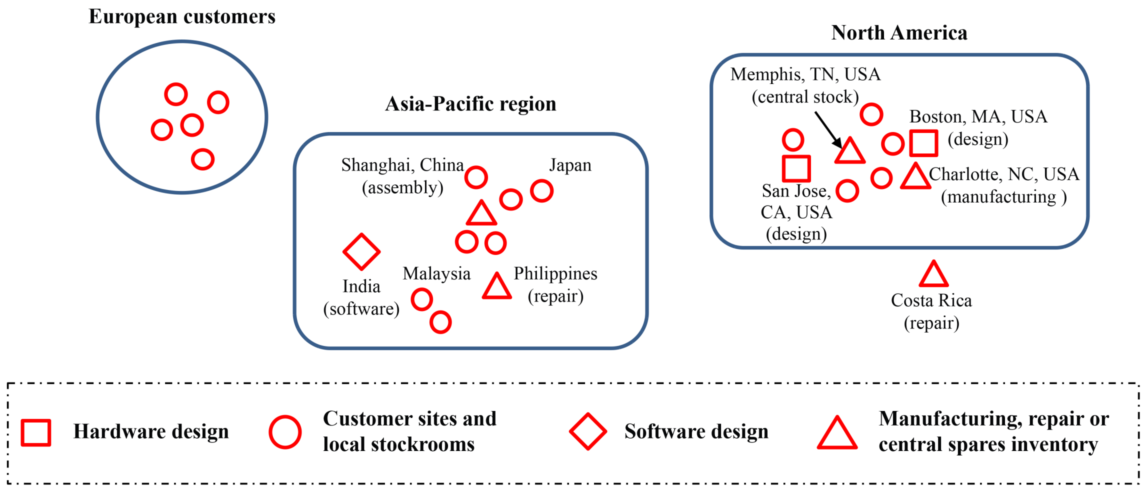

Fig. 7 Distributed ATE manufacturing and service operations (Jin, 2019).

renewal, revision, and repair of field returns are performed in 24/7 mode. All repaired items are shipped by air to the central warehouse located in Memphis, TN, USA, from where spare parts are further distributed to the regional inventory in Asia, Europe, and North America. This manufacturing and service supply chain enables the firm to leverage global resources to deliver high-quality, low-cost ATE systems.

The applications of the integrated PSS in the distributed manufacturing and service supply chain consist of four research tasks as follows:

• First, we need to predict the number of new ATE installations on the basis of the market overlook as well as the competitive edge against similar products. If some initial installation data are available, a future installed base can be estimated by relying on both future market and past shipment. In addition, smart logistics technologies, such as the Internet of Things, information technology, and artificial intelligence, enable a more efficient tracking of the location and usage of existing and new systems (Feng and Ye, 2021).

• Second, under a nonstationary operating condition, we concurrently allocate reliability, maintenance, spares inventory, and repair capacity to lower the ATE lifetime cost while assuring system operational effectiveness. Mixed integer non-linear programming is a viable approach to solve the reliability-maintenance-inventory optimization problem. Spares demand forecasting can be performed using explanatory methods incorporating installed base information. The results can be compared with reactive methods, such as time series, Markov chain Monte Carlo, deep neural network, support vector machine, and random forest.

• Third, as the product enters the retirement stage, the joint reliability-maintenance-inventory allocation model shall be refined by considering reliability degradation, repair discard, cannibalization (Salman et al., 2007), re-use or remanufacturing (Ferguson and Browne, 2001), and parts substitution (Achamrah et al., 2022). The last three options also provide the solution to address the spares supply issue for systems under mass varieties and small batch production.

• Fourth, comparing the integrated reliability-maintenance-inventory decisions between constant failure rate and time-varying failure rate products is another interesting topic to examine. A constant failure rate is often adopted after the market enters the steady state phase. However, the failure rate is non-constant and likely increases when the product enters the retirement phase.

6 Reliability and operations management in defense industry

In the US defense sector, the PSS concept is referred to as integrated product support (IPS) (DAU, 2019). It is a management technique that integrates all acquisition activities starting with requirements definition through prototyping, production, deployment, and operations to optimize the design, manufacturing, business, and supportability processes. Under performance-based logistics, IPS benefits from adopting an integrated reliability-maintenance-inventory model to minimize the total ownership cost with superior operational effectiveness (Carrel, 2000; Kumar et al., 2007). Typical operational effectiveness indexes include system availability, dependability, and capacity.

In the Chinese reliability community, Yang (1995) first proposed the concept of reliability systems engineering (RSS) in 1990s. RSS investigates the correlations between the reliability and lifetime of a product in the content of its operational environment, failure occurrence, and evolution, as well as the methods to detect, mitigate, prevent, and eliminate these failures. To that end, a variety of techniques are adopted to improve reliability, extend lifetime, and enhance operational effectiveness on the basis of reliability growth strategies, such as accelerated life testing, failure mode, effect and criticality analysis, corrective actions, and maintenance. RSS is shown to be quite effective and has been successfully adopted in the Chinese military and defense industries (Shi, 2007). The essence of the RSS is to emphasize the necessity and benefit of synthesizing reliability, maintainability, and supportability to attain superior operational effectiveness while lowering the system lifetime cost. Both reliability and availability are the basic measures to assess the operational effectiveness. They are also the key factors influencing the lifecycle cost of a product. New advancements in RSS theory have been achieved and frequently reported since its inception (Kang and Wang, 2005; 2007; Qian et al., 2020). A detailed review on the origin and evolution of the RSS methodology is available in a recent work by Wang (2021).

7 Conclusions

This study discusses the challenges and opportunities of merging reliability engineering and operations management to achieve superior system availability under uncertainty. First, we discuss the existing studies on reliability-redundancy allocation, preventive maintenance, spare parts logistics, and their extension. Second, we present a new class of a reliability-maintenance-inventory allocation problem in the context of product-service integration. Specific effort is focused on the new product introduction phase when the system installed base is growing but highly uncertain. Third, the generation of spare parts demand is a complex process that depends on product reliability, installed base, usage, operation condition, maintenance, and trade policy, among others. Explanatory forecasting models generally outperform reactive prediction methods because the former can accommodate historical data and future failure sources. For exponential failure with Poisson fleet expansion, the mean and variance of the nonstationary spares demand process can be derived analytically using superimposed renewal theory. The analytical model allows for the design of adaptive inventory policy and the provisioning of spare parts to cope with the growing installed base. Finally, a case study on semiconductor test equipment is presented to show how the integrated reliability-maintenance-inventory model can be applied to a distributed manufacturing and service supply chain. The product-service integration also plays a critical role in public sectors manifested as integrated support and reliability systems engineering in the defense industry. The reliability challenges today could nevertheless be the research opportunities of tomorrow. Hence, this study calls for new research agenda revolving around three aspects: 1) modeling and optimizing reliability-maintenance-inventory allocation problems in nonstationary conditions, 2) managing spare parts logistics under variable fleet size, and 3) forecasting spare parts demand considering installed base information.

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