Planning Performance Based Logistics Considering Reliability and Usage Uncertainty

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Abstract

Under performance based contracting, reliability optimization and service logistics are geared to the common objective for achieving high reliability performance for repairable systems. This paper proposes a quantitative approach to planning and contracting performance-based logistics in the presence of reliability and usage uncertainty. We focus on the circumstances where the customer purchased capital-intensive systems from the original equipment manufacturer (OEM) who also provides the after-sales services. We derive an analytical model to characterize the equipment availability by incorporating system failure rate, usage rate, spare parts level, and the size of the installed base. This analytical insight into the equipment availability allows us to estimate the system lifecycle cost taking into account the design, manufacturing, and maintenance. Two types of contracting schemes are examined under the cost minimization and the profit maximization, respectively. Numerical examples from aircraft and semiconductor industries are used to demonstrate the applicability and the performance of the proposed contracting program.

Key words: performance based logistics; repairable inventory; reliability optimization; lifecycle cost analysis
1. Introduction

Capital-intensive systems such as aircraft and wind turbines are often designed in modularity to facilitate the maintenance, repair, and upgrade. Upon failure the faulty part or the line replaceable unit (LRU) is replaced with a spare unit, and the system can be quickly restored to the production state. Downtime is often costly and even prohibitive as failures may result in production losses, injuries of human lives, or mission failures. To sustain the equipment availability and operational readiness, customers often purchase the after-sales services from the original equipment manufacturer (OEM) or the supplier by signing cost-plus contracts or warranty agreements for materials supplies. Throughout the paper, system and equipment will be used interchangeably. Meanwhile, subsystem and LRU will be used interchangeably representing a replaceable part of the system.

A paradigm shift is taking placing in conducting service business, especially in defense and aerospace industries. Performance based contracting (PBC) focusing on the outcome of the reliability performance is reshaping the conventional after-sales service model. This new contracting method is often referred as “performance based logistics” (PBL) in defense sector, or called as “power by the hour” in commercial airline industry. Instead of paying spare parts and related repair costs, under a PBC agreement the customer will buy the equipment reliability performance from the service provider (DoD 2005). Because of the complexity in technology and services in military equipment, the after-sales maintenance and repair are usually undertaken by the OEM. Recently, researches (Gadiesh and Gilbert 1998, Oliva and Kallenberg 2003, Wise and Baumgartner 1999) have been published with the purpose to assist OEM in integrating services with their core product offerings. Prior to PBL, it is not uncommon that a supplier is constantly rewarded for poor equipment reliability due to the excessive payment of repairs made
by the customer. By replacing traditionally used fixed-price and cost-plus contracting methods, PBC aims to ensure high reliability performance, and also to reduce the cost of ownership by offering financial incentives to the service providers.

There is a limited but growing literature stream on various aspects of performance based contracting. Recently some preliminary findings (Kim et al. 2007, 2010, Nowicki et al. 2008, Öner et al. 2010) have been published with respect to how such contracts could be designed and implemented, benefitting both the customer and the suppliers. For instance, in (Kim et al. 2007), the trade-off between the cost risks and the spare parts inventory level is investigated under the game-theoretic framework. In (Nowicki et al. 2008), various types of revenue models are suggested to maximize the profit margin for the service supplier in a multi-item multi-echelon repairable inventory framework. These studies use the spare parts backorders as a surrogate measure to assess the availability of field equipment.

According to the study by Richardson and Jacopinio (2006), the development and implementation of a PBC can be viewed as a four-step process. Step one is to identify the key reliability performance outcomes. System readiness, mission success and assurance of the spare parts supplying are often treated as performance outcomes. Step two is to apply reliability theory and operations management to determine the performance measures by choosing simple, meaningful and measurable metrics. Such metrics include, but not limit to, equipment availability, parts failure rate, inventory fill rate, or expected spare parts backorders. In the third step, customer should specify the reliability targets or performance criteria for the equipment. These criteria can be determined based on the specifications initially stated in the acquisition documents, or they can be determined based on the reliability performance of predecessor products. Having identified appropriate performance measures and criteria, step four
concentrates on the design of the payment plan which is able to incentivize the supplier for attaining the performance goal during the contractual period.

Based on the four-step PBC process, this paper aims to propose a quantitative approach to comprehending the performance measures and a way to attain the performance goal from a lifecycle aspect. To that end, we will define a set of performance measures comprising equipment availability, MTBF (mean-time-to-failure), and MTTR (mean-time-to-repair) to assess the reliability performance outcome. We will further show that equipment availability is jointly determined by multiple performance drivers including product failure rate, spare parts stocking level, equipment usage rate, repair turn-around time, and the size of the installed base. This analytical insight into the reliability performance allows us to evaluate the impact of individual drivers on the equipment availability. It differs from the performance measure (Kim et al, 2007, Nowicki, et al. 2008, Öner et al. 2010) where the equipment availability is simply surrogated by the probability of no spare parts backorders. In fact our study shows that spare parts inventory is only one of performance drivers influencing the equipment availability. Therefore, the surrogate model may lead to a sub-optimal PBL decision, especially in the settings where equipment reliability and utilization involve substantial uncertainties. Based on the new availability model, this paper will discuss two incentive payment programs depending on whether the objective is to minimize the lifecycle cost or to maximize the service profit.

The remainder of the paper is organized as follows. Section 2 provides the literature review on studies related to reliability optimization and repairable inventory models. In Section 3, several key reliability performance measures will be defined, based on which the equipment availability model will be further derived. Section 4 conducts the lifecycle cost analysis with concentration on the cost correlation between the product development and the reliability. In
Section 5, two contracting options are discussed in the context of minimizing lifecycle cost and maximizing service profit margins. In Section 6 numerical examples are presented to demonstrate the applicability of the proposed method, and Section 7 concludes the paper.

Notation

- \( A \): equipment or subsystem availability
- \( \tau \): service horizon or contractual period in years
- \( N \): number of installed systems or subsystems at a customer site
- \( \lambda \): inherent failure rate
- \( \lambda_a \): actual failure rate
- \( \lambda_{\text{max}} \): maximum inherent failure rate
- \( \lambda_{\text{min}} \): minimum inherent failure rate
- \( \beta \): equipment usage rate, and \( 0 \leq \beta \leq 1 \)
- \( T_c \): cumulative operating time between two consecutive failures
- \( T_s \): cumulative standby or idle time between two consecutive failures
- \( T_d \): equipment downtime duration
- \( S \): base stock level
- \( t_s \): time for performing repair-by-replacement given the spare part is available
- \( t_r \): turn-around time for fixing the defective item in base-depot-base pipeline
- \( O \): on-order spare parts, a random variable
- \( B \): backorders for spare parts, a random variable
- \( Q \): on-hand spare parts, a random variable
- \( X \): spare parts demand, a random variable with \( x = 0, 1, 2, \ldots \)
- \( \phi \): coefficient to characterize the design difficulty in reliability growth
- \( \nu \): coefficient to characterize the production difficulty in reliability growth
- \( B_1 \): baseline design cost with the failure rate of \( \lambda_{\text{max}} \)
- \( B_2 \): baseline manufacturing cost with failure rate of \( \lambda_{\text{max}} \)
- \( B_3 \): cost coefficient of the production-reliability model
- \( c(\lambda) \): unit production cost with the failure rate of \( \lambda \)
- \( D(\lambda) \): design cost
- \( M(\lambda, \beta, s, n) \): manufacturing cost per item
- \( I(\lambda, \beta, s, n) \): inventory cost for service logistics
- \( \pi(\lambda, \beta, s, n) \): lifecycle cost function
- \( P(\lambda, \beta, s, n) \): service profit function
- \( R(A) \): revenue function
- \( \theta \): interest rate compounded annually
- \( K \): number of subsystem types in the system
2. Literature Review

System availability has been widely used as a performance measure to assess the reliability performance of capital equipment. The U.S. Department of Defense (DoD 2005) recommends the equipment availability as the key performance outcome to negotiate and develop the contractual relationship with the service suppliers. The U.S. DoD defines availability as “a measure of a degree to which an item is in operable state and can be committed at the start of a mission when the mission is called for at an unknown (random) point in time.” According to this definition, equipment availability can be interpreted as the probability of being able to execute missions upon request at any random point of time.

In reliability theory (Elsayed 1996), availability is usually defined as the ratio of the equipment uptime versus its overall time. In general, the overall time is equal to the sum of the uptime and the downtime. For a repairable system having up-and-down cycles, the uptime in each cycle is characterized by MTBF, and the downtime is equivalent to MTTR. Let $A$ denote the equipment availability, then we have

$$A = \frac{MTBF}{MTBF + MTTR}$$

(1)

It is worth of mentioning that equation (1) is derived assuming that the equipment uptime is equal to the operating time. In reality, a system could also be in uptime with standby mode ready for undertaking the workloads. Obviously system availability can be improved through the increase of MTBF or the reduction of MTTR.

Two popular techniques are often applied to increase the MTBF: redundancy allocation and reliability allocation (Coit et al. 2004, Marseguerra et al. 2005). Redundancy allocation is a technique to put extra parts into the system as failure backups. The actual implementation of this
approach is often subject to design or resource constraints. In reliability allocation, components or subsystems are appropriately chosen such that the overall system reliability is either maximized or meet the design requirement. For a comprehensive review on reliability optimization, readers are referred to Kuo and Wan (2007). Both reliability and redundancy allocation models usually concentrate on material acquisition cost, design cost, and manufacturing cost. Therefore, they often result in sub-optimal solution because the after-sales services costs are ignored.

MTTR plays an important role in sustaining the maintainability and availability of repairable systems. For a multi-echelon repairable inventory model, the value of MTTR primarily depends on two factors: the repair turn-around time and the spare part stocking level. The theory of repairable inventory optimization can be dated back to 1960s when Sherbrooke (1968) derived the METRIC model to optimize the inventory resources. His contribution to the METRIC model laid a basic foundation for others to analyze multi-echelon and multi-indentured inventory problems. Since then a large body of literature has been published to address repairable inventory problems with the intention to minimize service costs or to maximize spare parts availability. These studies (Axsäter 1990, Graves 1985, Lee 1987, Wong et al. 2006) usually concentrate on simplifying computational complexity or incorporating more realistic assumptions, such as allowing for capacitated repair channels, lateral resupply, or time-varying demands. For recent surveys on this topic, readers are referred to (Kennedy 2002, Muckstadt 2005).

The implementation of PBL contracting means the concentration on the inventory cost reduction should be re-examined as service suppliers will make every effort to warrant reliability performance to gain the financial incentives. Following this direction, Kim et al. (2007) proposed
a game-theoretical approach to investigate the trade-off between the service cost and the spare parts quantity considering the risks incurred by the customer and the suppliers. Nowicki et al. (2008) investigated different reward functions and analyzed their impacts on the supplier’s profitability in a multi-echelon and multi-indentured inventory setting.

Regardless of the cost minimization or profit maximization, all repairable inventory models assume that equipment availability is equivalent to the spare parts availability. Under the PBC scheme, this surrogate model may result in a sub-optimal decision making on resource allocation. In Section 3, we will show that product inherent failure rate, usage rate, and the size of the installed base also have significant impacts on the equipment availability. Therefore, during the construction of PBL contracts, these factors must be taken into account along with the spare parts availability.

Equipment availability is jointly determined by product reliability, spare parts inventory, usage rate, and the size of the installed base. Along with this track, some preliminary studies (Jin and Liao 2009, Öner et al. 2010) have been carried out with the aim to minimize the inventory or lifecycle costs of the product. In (Jin and Liao 2009) the spare parts inventory problem is modeled and optimized in the context of reliability growth with a stochastic increment in the fleet size. In (Öner et al. 2010), the Erlang loss model (i.e. $M/G/s/s$ queue) is used to estimate the stock-out probability for a single-echelon repairable inventory, based on which a trade-off between product reliability and spare parts level is reached. Although both works made some attempts to explore the analytical relationship between product reliability and spare parts provisioning, they fail to derive an explicit performance measure that incorporates all key performance drivers: part inherent failure rate, usage rate, spare parts level, repair turn-around time, and the size of the installed base. This paper aims to derive a general equipment availability
estimate accommodating all these performance drivers, based on which optimal PBL contracts will be developed.

3. Defining Reliability Performance Measures

We will develop an optimal PBL contracting program based on the generic process suggested by Richardson and Jacopino (2006). The process consists of four steps: 1) identifying performance outcomes; 2) determining performance measures; 3) specifying performance criteria; and 4) planning PBC payment method. Among these, determining performance measures is an important step toward the successful planning and implementation of the performance-driven agreement between the customer and the suppliers.

Fleet readiness, mission success and assurance of the spare parts supplying are often treated as performance outcomes. These outcomes must be appropriately transformed into measurable means so that they can be used as basic metrics to evaluate the actual reliability performance of field equipment.

We propose a suite of performance measures comprising MTBF, MTTR, and equipment availability to assess the reliability performance of repairable systems. In our analysis, MTBF is defined as the actual equipment operating time accumulated between two consecutive failures. Obviously, this metric is able to capture the inherent product failure rate by excluding any standby or idle times. MTTR is a quantitative metric to measure how quickly a failed system can be restored to the operable state. As will be shown later, MTTR is affected by several factors including spare parts stocking level, repair turn-around time, and the number of working units in the field. Equipment availability is defined as the ratio of the uptime versus the total time during one up-and-down cycle. A distinction must be made between MTBF and uptime since the latter
is the sum of the operating time and standby (or idle) time. The advantage of using MTBF, instead of uptime, will become much clear if the equipment utilization varies over the planning horizon. These three performance measures allow the customer and service supplier to comprehend the reliability performance at various levels ranging from fleet, system, to individual subsystems.

3.1. MTBF and Equipment Usage Rate

MTBF has been widely used to model and analyze reliability performance in academe and industries due to its mathematical tractability. For repairable systems, MTBF is usually defined as the average inter-arrival time between two consecutive failures. Sometimes MTBF is simply treated as the uptime between two consecutive failures. This approximation is applicable to systems for which the standby time is relatively short compared to the operating time. Thanks to the information technology, system operating time, standby time, and repair time can be easily tracked and recorded in database systems, facilitating MTBF estimation and analysis.

Exponential distributions are often used to model the system lifetime in manufacturing industries, software development, and military sectors. The basic assumption behind the exponential distribution is that the product failure rate can be treated as constant throughout its lifetime. Although this assumption may be violated in some applications, the exponential model has been widely adopted for decades in private industries and public sectors. In fact reliability design guidelines such as Mil-HDBK-217 and Telcordia SR-332 (2001) are established upon the assumption that a constant failure rate is appropriate. If the system lifetime follows an exponential distribution, the inherent failure rate, denoted as $\lambda$, can be estimated as

$$\lambda = \frac{1}{MTBF}$$  \quad (2)
Notice that $\lambda$ is computed assuming the product is always in the operating state before it fails. Hence it represents the inherent reliability performance of the system. In reality the system state often switches between the operating mode and the standby mode before entering the failure mode. Since failures are not expected to occur when the equipment is in a standby or idle mode, the actual failure rate should be smaller. Let $T_o$ and $T_s$ be the equipment operating time and standby time, respectively. Then the actual failure rate can be estimated by

$$\lambda_a = \frac{1}{T_o + T_s} = \beta \lambda$$

(3)

Where

$$\beta = \frac{T_o}{T_o + T_s}$$

(4)

Notice that $T_o = E[T_o]$, representing the mean value for $T_o$, so does $T_s$. Here $\beta$ is the system usage rate defined as the ratio between the actual operating time and the total uptime. Obviously $\beta$ has a large impact on the actual failure rate. For example, when $\beta$=0.5 (i.e. $T_o = T_s$), then $\lambda_a$ is only a half of $\lambda$. This can be explained intuitively: since the system spends an equal amount of time in operating and standby modes, the actual failure rate is reduced by 50% compared to the one which is always in the operating mode.

3.2. Estimating MTTR

Figure 1 shows a two-echelon repairable inventory model to sustain the availability and operational readiness for $n$ systems at customer site. We assume the supplier owns the repair depot and the base inventory to provide spare parts services. The base inventory is often located at the customer site to facilitate the repair-by-replacement tasks. The repair depot and the base inventory may or may not be located in the same region. In this study, we assume the repair
depot is located in a different region as it simultaneously supports other bases which are not shown here. A centralized repair depot benefits the supplier in terms of resource sharing, tool utilization, and labor consolidation. However, the centralized repair may increase the parts turn-around time and the forward-and-backward transportation costs. Since our study focuses on capital-intensive equipment with a long useful lifetime, the additional cost generated from transportation delays are relatively small compared to part capital cost, equipment downtime losses, and actual parts repair time in the depot.

![Figure 1: An Integrated Manufacturing and Service Logistics Supply Chain](image)

The inventory maintains a base stock with $s$ spare parts, and it is operated under one-for-one replenish policy. When the equipment fails, a faulty item is immediately replaced with a spare part from the base inventory. If an on-hand spare unit is unavailable, a backorder occurs, and the equipment remains in a downtime state until a spare part arrives. Meanwhile, the defective item will be shipped to the repair depot which is modeled as an $M/G/\infty$ queue system. The average defective repair time in the depot is $t_r$, including the forward-and-return transportation times. Under the assumption of ample repair servers in the depot, all repair times are independently and identically distributed with mean value of $t_r$. Although this assumption is
quite ideal, Sherbrooke (1992) shows that this is a reasonable approximation in many repairable inventory circumstances.

Two scenarios will occur at the customer site upon the occurrence of system failures. If a spare part is available in the local stock, the repair-by-replacement job can be performed immediately. The average time used for performing this replacement job is denoted as $t_s$. If an on-hand spare item is not available, the repair-by-replacement job cannot be executed until the arrival of the spare part. In this case, the equipment downtime, hence the MTTR, is prolonged due to the waiting time for the spare unit. In the following, we will derive the MTTR model taking both scenarios into consideration.

Two important random variables are on-hand inventory $Q$ and backorder $B$, which have a substantial impact on the MTTR. Assuming the supplier sets the base stocking level as $s$ units, then $Q$ and $s$ are related with each other through $Q = \max\{0, s - O\}$, where $O$ is a random variable representing the steady-state inventory on-order. Similarly, $B$ and $s$ are related with each other through $B = \max\{0, O - s\}$. According to Palm’s Theorem, $O$ can be modeled as a Poisson distribution with mean $\mu_o = n\lambda_o t_r$. Notice that $n\lambda_o$ is the aggregate fleet failure rate, and $t_r$ is the average repair turn-around time for a defective unit. The assumption for a fixed fleet failure rate, i.e. $n\lambda_o$, is in fact an approximation, because the field-repair loop with a finite installed base means $\mu_o$ depends on the number of actual working systems in the field. This approximation is reasonable in our analysis because the condition $\mu_o << n$ usually is satisfied in practical applications. If $\bar{T}_d$ denotes the MTTR, then we have

$$\bar{T}_d = t_s \Pr\{O \leq s\} + (t_s + t_r)(1 - \Pr\{O \leq s\})$$

(5)

Where
Pr\{O \leq s\} = \sum_{x=0}^{s} \frac{\mu_o^x e^{-\mu_o}}{x!}, \text{ and } \mu_o = n\lambda rt_r \quad (6)

Here \(x\) is the number of spare parts in demand. Equations (5) provides an analytical insight into the interrelationship between the MTTR and the key performance drivers such as \(t_o\), \(t_r\), \(s\), \(\lambda ar\), and \(n\). It allows us to control or reduce the MTTR by tuning one or several parameters depending on the available resources. Notice that \(t_o\) is the time for performing the repair-by-replacement job given the on-hand spare part is available. In cases that \(t_o << t_r\) or \(Pr\{O \leq s\} \approx 0\), equation (5) can be further simplified as \(\bar{T}_d = t_r Pr\{O > s\}\), which becomes the same MTTR model given by Kim et al. (Kim et al. 2007). Finally, equations (7) and (8) below allow us to compute the expected values for \(Q\) and \(B\), respectively

\[
E[Q] = \sum_{x=0}^{s} \left( (s - x) \frac{\mu_o^x e^{-\mu_o}}{x!} \right) \quad (7)
\]

\[
E[B] = \mu_o - s - \sum_{x=0}^{s} \left( (s - x) \frac{\mu_o^x e^{-\mu_o}}{x!} \right)
\]

\[
= n\beta \lambda t_r - s - \sum_{x=0}^{s} \left( (x - s) \frac{(n\beta \lambda t_r)^x e^{-n\beta \lambda t_r}}{x!} \right) \quad (8)
\]

Similar to the MTTR, both the on-hand and the backorder quantities depend on the key performance drivers: product inherent failure rate, the base stock level, the usage rate, the repair turn-around time, and the size of installed base.

3.3. Equipment Availability-A New Perspective

As discussed previously, equipment time can be broken down into three categories: operating time, standby time, and down time. Let \(\bar{T}_o\), \(\bar{T}_s\) and \(\bar{T}_d\) be the expected value for each of these, then the operational availability can be defined as
Notice that $\beta$ is the usage rate defined in equation (4). Incorporating the usage rate into the availability model is an important step to reach a win-win contractual agreement between the customer and the service provider. Compared with equation (1), the model in equation (8) is a more realistic metric to assess the equipment availability as it takes the consideration of the usage uncertainty. OEM can make every effort to reduce the product inherent failure rate, hence increase the operational availability, through re-designs and adoption of new materials or technologies. The usage rate will assist OEM and the equipment users in reaching a realistic availability goal which might be different under different utilizations such as regular trainings and military engagements. Finally, by substituting equations (3), (5) and (6) into (9), the availability can be expressed as

$$A_o = \frac{T_o + T_s}{T_o + T_s + T_d} = \frac{T_o}{T_o / \beta + T_d / \beta}$$

(9)

Up to now, we have analytically developed a new availability model that draws upon two distinct bodies of literature. We applied the classical repairable inventory theory to estimate equipment MTTR. This metric is further evolved into a novel availability model, $A_o$, which has not been previously reported in literature. The new model elegantly brings together all key performance drivers, i.e. $\lambda$, $s$, $\beta$, $n$, and $t_o$, under a unified framework. By introducing this new assessment instrument, which has always been surrogated simply by the availability of spare parts, we have established the theoretical foundation for the operation and management of performance based service contracts.

3.4. Fleet Readiness
Assuming the fleet consists of \( n \) identical systems for which their annual usage rate is similar. Then the fleet readiness is defined as the probability that there are at least \( k \) systems available at any random point in time. This can be expressed analytically as

\[
\Pr\{N \geq k\} = \sum_{i=k}^{n} \binom{n}{i} A^i (1 - A)^{n-i}, \text{ for } k=0, 1, \ldots, n
\]  

(11)

Where, \( N \) is a random variable representing the number of available systems, and \( k \) is a predetermined integer value by the customer. For example, if \( A=0.95 \), \( n=20 \), and \( k=18 \), then \( \Pr\{N \geq 18\}=0.925 \). This implies, with probability 0.925, there are at least 18 systems in the fleet are ready for operation at any time upon the mission request. Methodologically, the fleet readiness is not new and it is simply a type of quantile estimate. But from the military point of view, it is often more concerned with the probability that enough aircrafts can fly for a particular mission, instead of the average number of mission capable aircrafts (Kang and McDonald 2010).

4. Lifecycle Cost Analysis

The new availability model in equation (10) shows that equipment availability is determined by multiple factors: the inherent reliability \( \lambda \), base stocking level \( s \), defective repair time \( t_r \), usage rate \( \beta \), and the size of the installed base \( n \). Hence, cost analysis for PBL contracting must be approached and analyzed from the product lifecycle perspective. Besides the spare parts inventory, cost factors associated with the design and manufacturing need to be assessed and incorporated into the decision model when one constructs the PBC policy. Without loss of generality, the following cost models are developed for one particular part type or LRU. The lifecycle cost for the system can be calculated by aggregating the cost of individual part types.

4.1. Design Cost versus Reliability
Although it is widely agreed that the product design cost increases with the growth of reliability, the consensus on how to describe such a relationship is still not reached in literature. Many studies such as (Mettas 2000, Yeh and Lin 2009) show that the design cost in general grows exponentially as reliability increases. Let \( D(\lambda) \) be the design cost for the product with a failure rate of \( \lambda \), then the exponential design cost model can be expressed as

\[
D(\lambda) = B_1 \exp\left( \frac{\lambda_{\text{max}} - \lambda}{\lambda_{\text{max}} - \lambda_{\text{min}}} \right), \quad \text{for } \lambda_{\text{min}} \leq \lambda \leq \lambda_{\text{max}}
\]  \hspace{1cm} (12)

Where, \( \lambda_{\text{max}} \) and \( \lambda_{\text{min}} \) represent the maximum and the minimum product failure rates, respectively. Quite often, \( 1/\lambda_{\text{max}} \) is the minimum MTBF per the customer requirement, and \( 1/\lambda_{\text{min}} \) is the best achievable MTBF by the OEM. Notice that \( B_1 \) and \( \phi \) are positive parameters. In particular, \( B_1 \) is the baseline design cost for the product with \( \lambda_{\text{max}} \), and \( \phi \) characterizes the difficulties in reducing the failure rate under materials and resource constraints. Figure 2 depicts two design-reliability cost functions for \( \phi=0.02 \) and 0.05, respectively. Both examples show that design cost will rapidly increase once the reliability reaches a certain level.

![Figure 2: Product Design Cost vs. Reliability](image-url)
4.2. Manufacturing Cost versus Reliability

Producing a highly reliable product requires adoption of new materials, improved technology and advanced manufacturing processes. As a result, the manufacturing cost increases with the reliability. Let \( c(\lambda) \) represent the manufacturing cost per unit item, then the cost can be estimated as

\[
c(\lambda) = B_2 + B_3 \left( 1 - \frac{1}{\lambda_{\text{max}}} \right), \text{ for } \lambda_{\text{min}} \leq \lambda \leq \lambda_{\text{max}}
\]

Equation (13) is a modified version of the manufacturing cost model originally proposed by Öner et al. (2010). We assume the design cycle is relatively short compared to the product useful lifetime. Hence the learning effects can be ignored in the cost model. For production cost models considering learning effects, readers are referred to Huang et al. (2007) and Loerch (1999). In equation (13), \( B_2 \) is the baseline unit production cost with failure rate of \( \lambda_{\text{max}} \). Parameters \( B_3 \) and \( \nu \) capture the incremental cost when \( \lambda \) is further reduced relative to \( \lambda_{\text{max}} \). All model parameters are positive numbers. Figure 3 presents three manufacturing cost models under \( B_2 =$10^5 \) and \( B_3 =$2,000 \) with \( \nu = 0.4, 0.5, \) and \( 0.6 \), respectively. Given the same \( B_2 \) and \( B_3 \), a higher production cost will be incurred if \( \nu \) is larger.
4.3. Service Logistics Cost

The service logistics expenditures consist of the inventory cost and the repair cost. The major portion of the inventory is the investment on spare parts. The repair costs include the part transportation fees, the labor cost, and repair facilities. Let \( I(\lambda, \beta, s, n) \) be the service logistics cost incurred in the contractual period of \( \tau \) years, then

\[
I(\lambda, \beta, s, n) = sc(\lambda) + c_r n \beta \lambda \varphi(\theta, \tau)
\]  

(14)

Where

\[
\varphi(\theta, \tau) = \frac{(1 + \theta)^\tau - 1}{\theta(1 + \theta)^\tau}
\]  

(15)

In equation (14), the first term represents the one-time base stock capital investment, and the second component represents the present value of total repair costs incurred during \( [0, \tau] \). Notice that \( c_r \) is the repair cost per defective item. It includes the costs associated with labors, repair facility, part shipment between repair depot and the base. \( \varphi(\theta, \tau) \) is the coefficient to
calculate the present value of annuity with the annual interest rate $\theta$. Since military PBL contracts often involve long-term service commitment, minimizing the lifecycle cost must take into account the effects of money in time.

4.4. System Lifecycle Cost

For the supplier, the lifecycle cost consists of the product design cost, manufacturing cost, and after-sales service logistics cost. Let $\pi(\lambda, \beta, s, n)$ denote the lifecycle cost for $n$ working units deployed in the customer site. Then the lifecycle cost for the $n$-unit fleet is given as

$$\pi(\lambda, \beta, s, n) = D(\lambda) + nc(\lambda) + I(\lambda, \beta, s, n)$$

(16)

5. Optimization for Performance Based Logistics

After the lifecycle cost model is derived, the next step for the customer is to develop the contractual payment plan. Although PBL as a logistic support strategy has been used for about ten years, there are few quantitative processes and procedures that are mature and available to guide suppliers to achieve the performance goal through optimal resource allocation. Under the PBC scheme, the service supplier will be rewarded monetarily if the equipment availability is sustained above a threshold or $A_{\text{min}}$ as defined by the customer. Depending on the rewarding methods, two options can be chosen by the service provider: cost minimization or profit maximization.

5.1. Lifecycle Cost Minimization

Cost minimization strategy is preferred if the system design is relatively new and few reliability data are available. In that case, the customer prefers to control the after-sales service payment bill as well as to mitigate the uncertainty in equipment availability. The supplier, on the other hand, may choose to minimize the total lifecycle cost of the product while meeting the
availability criterion. The following optimization model, denoted as Problem P1, is formulated to minimize the product lifecycle cost

**Problem P1:**

\[
\begin{align*}
\text{Min} & \quad \pi(\lambda, s; \beta) = D(\lambda) + nc(\lambda) + I(\lambda, s; \beta) \\
\text{Subject to} & \quad A(\lambda, s; \beta) \geq A_{\text{min}} \\
& \quad \lambda_{\text{min}} \leq \lambda \leq \lambda_{\text{max}}
\end{align*}
\] (17)

Problem P1 is formulated to determine the optimal \( \lambda \) and \( s \) such that the lifecycle cost of the fleet equipment is minimized for a period of \( \tau \) years. \( A(\lambda, s; \beta) \), \( D(\lambda) \), \( c(\lambda) \), and \( I(\lambda, s; \beta) \) are given in equations (10) and (12)-(14), respectively. Notice that constraint (18) ensures the availability being always higher than \( A_{\text{min}} \). Equation (19) specifies the product inherent failure rate must fall into the range between \( \lambda_{\text{min}} \) and \( \lambda_{\text{max}} \).

As shown in Equation (4), \( \beta \) has a significant impact on the actual equipment failure rate. It is a random variable which may vary over the planning horizon. For instance, heavier usages are often observed for military aircraft during mission engagement period compared to regular training seasons. In power industry, the utilization rate of power generation equipment also varies from hour to hour, day to day, and season to season due to the demand variability. Hence P1 actually is a stochastic programming model due to the random nature of \( \beta \). Stochastic programming problems can be solved by using simulation-based approaches or converting it into a deterministic model. Simulation approach randomly generates a usage scenario, each of which will be solved in a deterministic fashion. The final result is obtained by taking the average of the entire solution set. The result obtained from the simulation-based approach is quite accurate, but
the computational cost and time could be large as well. To solve Problem P1 in a reasonable computational time, we transform the original problem into a deterministic model, denoted as P2, by taking the expectation with respect to $\beta$ as following

**Problem P2:**

$$\text{Min } E_\beta[\pi(\lambda,s;\beta)] = D(\lambda)+nc(\lambda)+I(\lambda,s;\bar{\beta})$$  \hspace{1cm} (20)

Subject to

$$E_\beta[A(\lambda,s;\beta)] \geq A_{\min}$$ \hspace{1cm} (21)

$$\lambda_{\min} \leq \lambda \leq \lambda_{\max}$$ \hspace{1cm} (22)

Where, $\bar{\beta} = E[\beta]$ is the mean value of $\beta$. It is still difficult to compute $E_\beta[A(\lambda,s;\beta)]$ due to the analytical complexity in $A(\lambda,s;\beta)$. To make P2 mathematically tractable, yet without compromising the accuracy, $A(\lambda,s;\bar{\beta})$ will be used as an approximation for $E_\beta[A(\lambda,s;\beta)]$. Now the problem is to find the optimal $\lambda$ and $s$ such that the expected lifecycle cost is minimized while the availability criterion is still satisfied.

**5.2. Profit-centric Maximization**

Since PBL incentives are now designed to reward high operational reliability and availability of equipment, suppliers will naturally shift their concentration from purely cost reduction to profit maximization. We are going to integrate revenue function into the service decision-making model and to show how this will affect the resource allocation. We adopt the linear and the exponential models originally proposed by Nowicki et al. (2008) to allocate resources such that the supplier’s profit margin will be maximized. The linear and the exponential revenue functions are restated as follows
Both \((a, b)\) and \((\gamma, \rho)\) are parameters for the linear and exponential models, respectively. Different shapes of revenue functions can be obtained by tuning the model parameters. For instance, a larger \(b\) or \(\rho\) implies the supplier will reap more financial benefits as \(A\) increases.

Assuming a system is configured with \(K\) types of subsystems for \(i=1, 2, \ldots, K\). Each type of subsystem might be duplicated in the system due to the functional requirement. This duplicated configuration is quite common in repairable systems. For instance, a wind turbine has multiple DC/AC converters of the same type. Based on equations (23) and (24), the following profit maximization model for a fleet of systems, denoted as P3, is formulated

**Problem P3:**

Max \(E_{\bar{\beta}}[P(\lambda, s; \bar{\beta})] = R(A_i(\lambda_i, s_i; \bar{\beta})) - \sum_{i=1}^{K} D_i(\lambda_i) - B_{1,i} - n \sum_{i=1}^{K} m_i (c_i(\lambda_i) - B_{2,i}) - \sum_{i=1}^{K} I_i(\lambda_i, s_i; \bar{\beta})\)  

Subject to

\[
\lambda_{\min,i} \leq \lambda_i \leq \lambda_{\max,i} \quad \text{for } i=1,2, \ldots, K
\]

\[
A_i(\lambda_i, s_i; \bar{\beta}) = \prod_{i=1}^{K} \left( A_i(\lambda_i, s_i; \bar{\beta}) \right)^{m_i} \geq A_{\min}\)

Where, \(A_i(\lambda_i, s_i; \bar{\beta})\) is defined as the system-level availability given the availability of individual subsystems. \(m_i\) is the number of subsystem type \(i\) used in the system, and \(K\) is the number of subsystem types. The profit-centric model is formulated to determine the optimal \(\lambda_i\) and \(s_i\) for subsystem type \(i\) such that the profit margin for maintaining the entire fleet is
maximized. The objective function in equation (25) is designed to motivate the supplier to improve the product reliability through re-design or adoption of advanced manufacturing technology after the product shipment. Therefore costs for baseline design (i.e. $B_1$) and manufacturing (i.e. $B_2$) are excluded from the objective function. Numerical example will be provided in Section 6 to demonstrate the application of this model.

5.3. Solution Algorithms

Problems P2 and P3 belong to non-linear mixed integer programming problems. These types of problems are in general difficult to solve because they involve the complexity of nonlinearity and the combinatorial natures of integer programs (Gupta and Ravindran 1985). Existing algorithms generally rely on the successive solutions of closely related non-linear programming problems, and then the branch-and-bound technique to explore the integer solution. Recently, genetic algorithm and heuristic methods (Coit et al. 2004, Marseguerra et al. 2005) have shown to be effective in searching for the optimal or near optimal solution for complex non-linear programming problems within a reasonable computation time.

Since Problem P2 only involves two variables $\lambda$ and $s$, we can use the iteration method to find the optimal solution. The detailed procedure is given as follows: starting with $s=0$, we let $\lambda$ increase from $\lambda_{\min}$ and $\lambda_{\max}$ by a small step and compute the objective function. Then we increasing $s=s+1$ and repeat the same process. If the current cost is lower than the previous interaction, choose the current $s$ and $\lambda$ as the optimal solution, otherwise a new iteration begins by increase $s=s+1$. The process is repeated until $s$ reaches a reasonable level, then we stop the iteration. The iteration method cannot be applied to Problem P3 because the number of the decision variables is relatively large ($K>>2$). Therefore, we will develop a genetic algorithm to search the optimal values of $\lambda_i$ and $s_i$ for $i=1,2, \ldots, K$. 

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6. Numerical Examples

Two examples drawn from the military sector and the semiconductor industry will be used to demonstrate the PBL contracting program discussed in this paper. The first example aims to find the optimal resource allocation to product development and after-sales services such that the reliability performance of aircraft’s avionics subsystems is warranted. The supplier’s objective is to minimize the subsystem lifecycle cost by taking account of design, manufacturing, and spare parts inventory. The second example is chosen from the semiconductor manufacturing industry where equipment useful lifetime is relatively short due to the technological obsolescence. As such the goal for the OEM is to maximize the service profit margin while meeting the customer’s reliability goal.

6.1. PBL Contracting for Subsystems

In this example, the OEM is contracted to design and supply high-end avionics subsystems to the military customers. With some slight modifications, we use the avionics cost data originally given in (Kim et al. 2007) to construct the numerical example. Table 1 presents the necessary information for carrying out the cost analysis based on the optimization model in Problem P2. We assume the baseline manufacturing cost is \( B_1 = $25,000 \) per subsystem. The maximum acceptable failure rate by the customer is \( \lambda_{\text{max}} = 1.752 \) faults/year, and the best achievable failure rate by the OEM is \( \lambda_{\text{min}} = 0.876 \) faults/year. These values are selected based on the field analysis of avionics reliability in (Moreno 1990). We further assume \( t_s = 0.1 t_r \), meaning the time to replace a defective subsystem is only 10% of \( t_r \) when the spare part is available at the customer site. All other parameters are self-explained.
Table 1: Parameters for Avionics Subsystems

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta$</td>
<td>0.05</td>
<td>$B_1$ ($)</td>
<td>500,000</td>
</tr>
<tr>
<td>$\phi$</td>
<td>0.02</td>
<td>$B_2$ ($)</td>
<td>25,000</td>
</tr>
<tr>
<td>$\lambda_{\text{max}}$ (faults/year)</td>
<td>1.752</td>
<td>$B_3$ ($)</td>
<td>2,000</td>
</tr>
<tr>
<td>$\lambda_{\text{min}}$ (faults/year)</td>
<td>0.876</td>
<td>$\nu$</td>
<td>0.6</td>
</tr>
<tr>
<td>$c_r$ ($/\text{part}$)</td>
<td>5,000</td>
<td>$t_s$ (days)</td>
<td>$0.1t_r$</td>
</tr>
</tbody>
</table>

Our purpose is to help OEM analyze various contractual scenarios and make the best decision on $\lambda$ and $s$ such that the LCC (lifecycle cost) is minimized. Other variables that need to be considered include the minimum availability threshold $A_{\text{min}}$, the fleet size $n$, the repair turnaround time $t_r$, and the usage rate $\beta$. It is worth mentioning that $\beta$ usually involve large uncertainties due to the stochastic nature of military operations and engagements. Therefore, two usage rates, i.e. $\beta=0.5$ and $0.75$, are used to calculate the anticipated LCC, and the results will be compared in terms of spare parts provisioning levels.

Table 2: LCC Minimization for $\tau=5$ years and $A_{\text{min}}=0.95$

<table>
<thead>
<tr>
<th>usage rate</th>
<th>$\beta=0.5$</th>
<th>$\beta=0.75$</th>
</tr>
</thead>
<tbody>
<tr>
<td>fleet size</td>
<td>$n=200$</td>
<td>$n=500$</td>
</tr>
<tr>
<td>repair time (days)</td>
<td>$t_r=30$</td>
<td>$t_r=60$</td>
</tr>
<tr>
<td>$\lambda$ (faults/year)</td>
<td>0.9505</td>
<td>0.9373</td>
</tr>
<tr>
<td>$s$</td>
<td>0</td>
<td>14</td>
</tr>
<tr>
<td>$A$</td>
<td>0.959</td>
<td>0.951</td>
</tr>
<tr>
<td>LCC ($10^6$)</td>
<td>7.80</td>
<td>8.17</td>
</tr>
<tr>
<td>LCC/year ($10^6$)</td>
<td>1.56</td>
<td>1.63</td>
</tr>
</tbody>
</table>
Table 2 summarizes the optimal values for $\lambda$ and $s$ under a 5-year service agreement. A general conclusion is that $\lambda$ deceases and $s$ increases when $\beta$, $n$, or $t_r$ becomes larger in order to meet $A_{\text{min}}$. It is interesting to see that spare parts are not needed when $\beta=0.5$ and $t_r=30$ days. In fact there is no surprise to obtain this conclusion after we re-examine the availability metric in Equation (9). It clearly shows that a high $A(\lambda, s; \beta)$ can be attained by reducing $\lambda$, $\beta$, or $t_r$, instead of increasing $s$. The table also shows that $s$ is highly correlated with $\beta$ and $t_r$. For instance, when $\beta=0.5$, $n=500$ and $t_r=60$ day, at least 36 spare parts are required at the base inventory to support the minimum availability as opposed to $s=0$ if $t_r=30$ days. Finally the optimal failure rate $\lambda$ decreases as $n$ becomes large.

Table 2:

<table>
<thead>
<tr>
<th>$\beta=0.5$</th>
<th>$\beta=0.75$</th>
</tr>
</thead>
<tbody>
<tr>
<td>fleet size</td>
<td>$n=200$</td>
</tr>
<tr>
<td>repair time (days)</td>
<td>$t_r=30$</td>
</tr>
<tr>
<td>$\lambda$ (faults/year)</td>
<td>0.9242</td>
</tr>
<tr>
<td>$s$</td>
<td>0</td>
</tr>
<tr>
<td>$A$</td>
<td>0.960</td>
</tr>
<tr>
<td>LCC ($\times 10^6$)</td>
<td>10.64</td>
</tr>
<tr>
<td>LCC/year ($\times 10^6$)</td>
<td>0.709</td>
</tr>
</tbody>
</table>

Table 3 presents the optimal values for $\lambda$ and $s$ under a 15-year service agreement with $A_{\text{min}}=0.95$. Two distinctive observations can be made by comparing to Table 2. The annualize LCC for the long-term contract is less than 50% of the cost in the 5-year contract. This is because the design and manufacturing costs are absorbed in a longer period, making the yearly cost distribution lower than that in a short-term contract. Another observation is that a lower $\lambda$ is
more favorable to the OEM for a 15-year contract. In other words, OEM is willing to invest more resources on design and manufacturing under a long-term PBL contract. It is also observed that the contractual length has smaller impact on the level of the spare parts inventory.

Table 4: LCC Minimization for \( \tau = 15 \) years and \( A_{\text{min}} = 0.99 \)

<table>
<thead>
<tr>
<th>usage rate</th>
<th>( \beta = 0.5 )</th>
<th>( \beta = 0.75 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>fleet size</td>
<td>( n = 200 )</td>
<td>( n = 500 )</td>
</tr>
<tr>
<td>repair time (days)</td>
<td>( t_r = 5 )</td>
<td>( t_r = 10 )</td>
</tr>
<tr>
<td>( \lambda ) (faults/year)</td>
<td>0.9242</td>
<td>0.9242</td>
</tr>
<tr>
<td>( s )</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>( A )</td>
<td>0.995</td>
<td>0.992</td>
</tr>
<tr>
<td>LCC ($10^6$)</td>
<td>10.64</td>
<td>10.74</td>
</tr>
<tr>
<td>LCC/year ($10^6$)</td>
<td>0.709</td>
<td>0.716</td>
</tr>
</tbody>
</table>

Both Tables 2 and 3 show that \( t_r \) has a significant impact on the spare part quantity \( s \). To further explore the interrelationship between \( t_r, s \) and \( A_{\text{min}} \), we will minimize the LCC under an extreme scenario with \( A_{\text{min}} = 0.99 \), for which we may anticipate a high spare parts stock level. To our surprise, Table 4 shows that a small amount of spare parts are sufficient to attain a high availability level as long as we can control and reduce \( t_r \). In the worst case with \( \beta = 0.75 \) and \( n = 500 \), only 16 spares are needed for the sustainment of 99% availability if \( t_r = 10 \) days.

6.2. Contracting for Profit Maximization

Automatic Test Equipment (ATE) is a capital-intensive system widely used in wafer and device testing at the back-end of semiconductor manufacturing process. An ATE system is often designed in modularity to facilitate the repair, maintenance and upgrade. Quite often, multiple LRU of the same type will be configured into an ATE to meet the testing requirement. Upon failure, the defective LRU will be removed and replaced with a spare part of the same type. The
A defective part is then sent to the depot for repair. After repair, it becomes ready-for-use and will be sent back to the local spare pool.

PBL contracts will be investigated in terms of LRU shipping volume and unit cost in three different categories: 1) low volume and low cost (LVLC); 2) high volume and low cost (HVLC); and 3) low volume and high cost (LVHC). These categories represent the typical shipping and cost profiles for various types of LRU used in ATE systems. Parameters related to the LRU design, manufacturing, spare parts, and repairs are listed in Tables 5. Notice that costs for baseline design, manufacturing, and spare parts inventory are doubled for the high-end LRU compared to the lower-end LRU. The maximum achievable MTBF for a LRU is 25,000 hours, or equivalent to 0.3504 faults/year. The minimum MTBF required by the customer is 15,000 hours; namely 0.584 faults/year.

Table 5: Parameters for Numerical Study of ATE Systems

<table>
<thead>
<tr>
<th>index</th>
<th>( i=1 )</th>
<th>( i=2 )</th>
<th>( i=3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>subsystem category</td>
<td>LVLC</td>
<td>HVLC</td>
<td>LVHC</td>
</tr>
<tr>
<td>( m_i )</td>
<td>2</td>
<td>8</td>
<td>2</td>
</tr>
<tr>
<td>( \lambda_{\text{max}} ) (faults/year)</td>
<td>0.584</td>
<td>0.584</td>
<td>0.584</td>
</tr>
<tr>
<td>( \lambda_{\text{min}} ) (faults/year)</td>
<td>0.3504</td>
<td>0.3504</td>
<td>0.3504</td>
</tr>
<tr>
<td>( B_1 ) ($)</td>
<td>300,000</td>
<td>300,000</td>
<td>600,000</td>
</tr>
<tr>
<td>( B_2 ) ($)</td>
<td>30,000</td>
<td>30,000</td>
<td>60,000</td>
</tr>
<tr>
<td>( B_3 ) ($)</td>
<td>2,000</td>
<td>2,000</td>
<td>4,000</td>
</tr>
<tr>
<td>( \phi )</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>( \nu )</td>
<td>0.6</td>
<td>0.6</td>
<td>0.6</td>
</tr>
<tr>
<td>( c_r ) ($/repair)</td>
<td>3,000</td>
<td>3,000</td>
<td>4,500</td>
</tr>
<tr>
<td>( t_r ) (days)</td>
<td>30</td>
<td>15</td>
<td>45</td>
</tr>
</tbody>
</table>
Table 6: Comparisons Between Linear and Exponential Revenue Models

<table>
<thead>
<tr>
<th>index</th>
<th>Linear</th>
<th>Exponential</th>
</tr>
</thead>
<tbody>
<tr>
<td>category</td>
<td>$i=1$</td>
<td>$i=2$</td>
</tr>
<tr>
<td>LVLC</td>
<td>LVLC</td>
<td>LVHC</td>
</tr>
<tr>
<td>$\lambda$ (faults/year)</td>
<td>0.3645</td>
<td>0.3755</td>
</tr>
<tr>
<td>$s$</td>
<td>2</td>
<td>9</td>
</tr>
<tr>
<td>$A$ (single subsystem)</td>
<td>0.985</td>
<td>0.999</td>
</tr>
<tr>
<td>$A$ (subsystem cluster)</td>
<td>0.971</td>
<td>0.995</td>
</tr>
<tr>
<td>$A$ (system)</td>
<td>0.961</td>
<td>0.961</td>
</tr>
<tr>
<td>total profit ($10^6$)</td>
<td>3.99</td>
<td>3.57</td>
</tr>
</tbody>
</table>

The profit maximization for the ATE fleet is solved based on Problem P3. Genetic algorithm is used to search for the optimal or near optimal values for $\lambda_i$ and $s_i$, and the results are summarized in Table 6. For the linear revenue function, we set $a=5\times10^6$ and $b=5\times10^7$. Under the linear reward or revenue function, the supplier will reap nearly $4 million profit during the 5-year period by keeping the system availability at 0.961. The performance outcome is much higher than threshold $A_{min}=0.9$.

For the exponential reward function, we have $\gamma=15.42$ and $\rho=6.93$. To make a fair comparison, $\gamma$ and $\rho$ are chosen such that the base revenue and maximum revenue are the same as the linear model. Under the exponential payment scheme, the profit is reduced to $3.57 million. However, the system availability still reaches 0.961, which is the same as the linear model. This observation shows that the supplier must make more efforts to gain the same amount
of the profit under the exponential reward function. This in fact gives customer the advantage for designing the contractual payment plan while reducing the cost ownership. The inventory decision on both cases happened to be the same. Both HVLC and LVHC require a high stocking level either because of high volume shipment for HVLC or the repair turn-around time is long for LVHC.

7. Conclusion

We have proposed a general model comprehending the equipment availability in the light of several key performance drivers including product reliability, usage uncertainty, spares parts inventory, repair turn-around time, and the installed base. Under the PBC scheme, two optimization models are investigated in the context of minimizing the lifecycle cost or maximizing the service profit. Our study shows that reliability investment should be made early in the product lifecycle in order to reduce the total cost of ownership. The second observation is that quick repair turn-around time can significantly reduce the base stock level, hence increase the equipment availability. The study shows that PBL contracts must be constructed to meet the equipment availability threshold as well as the reliability goal. The latter one is often referred as MTBF or the inherent product failure rate. Although the equipment availability could be sustained by relying on a large spare items pool, this approach is not financially attractive to the supplier due to the excessive inventory cost. Meanwhile the customer is also dissatisfied with the excessive downtime failures. PBC provides lower overall sustainment costs for the equipment users, and profit growth opportunity for the service contractors. The supplier is incentivized to invest resources wisely across the design, manufacturing, and spare parts logistics such that the lifecycle cost is minimized. The availability model developed for two-echelon repairable
inventory can be expanded and incorporate more realistic conditions such as dynamic installed base, reliability growth planning, and lateral resupply. These are the potential areas we would like to concentrate on in the future.

References


