

Understanding the Impacts of Length of the Contract and Fleet Size on Spare Parts Level and Reliability Investments in Performance-based Contracting

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ABSTRACT

This essay investigates the impacts of contract features such as contract length and fleet size on reliability investment, spare parts, supplier's profit, and the annual cost of the system in performance-based contracting (PBC). The impact of each contract feature analyzed using the multi-objective genetic algorithm in a mathematical model. We found that failure rates of the systems and the annual unit cost for the buyer exponentially decrease when the fleet size or contract length becomes larger. Also, an annual profit of suppliers grows substantially with an increase in fleet size and length of contracts. Additionally, we explored that these features have little impact on spare parts in PBC. Findings of this study advance understanding of the impact of fleet size and the length of contracts on decisions made by suppliers for the reliability and inventory investments in PBC. Furthermore, practitioners will benefit from the results to build effective and efficient PBC.

Keywords: *performance-based contracting, outcome-based contract, performance contracting, performance-based logistics, length of the contract, fleet size*

1. INTRODUCTION

Performance-based contracting (PBC) offers an approach which binds the supplier's payment to accomplishment of desired performance outcomes as specified by the buyers. The fundamental structure of the PBC is built upon evaluation of outputs instead of paying for required inputs, activities, or processes (Martin, 2007). Today, PBC can be seen in many areas from manufacturing to service industries, including the private and public sectors (Hypko *et al.*, 2010a; Hooper, 2008; Selviaridisa and Wynstra, 2015).

In PBC, the contract identifies what is required, such as

availability rates of systems, but the supplier determines how to attain these objectives (Kim *et al.*, 2007). How to achieve the required outcome such as availability rate depends on the supplier's decisions about investment in quality, logistics processes, or inventory level. The number of systems and length of the contract are two critical factors that affect the supplier's decision (Straub, 2009; Randall *et al.*, 2012; Jin *et al.*, 2012; Jin *et al.*, 2014). In PBC, while buyers expect high product quality, suppliers can be reluctant to make upfront investment to increase reliability, because of uncertain expectations of relationship continuity with customers (Hypko *et al.*, 2010). While suppliers in long-term arrangements are eager to invest in quality and innovative processes, in the short term, they prefer to enhance existing processes, such as inventory management, transportation, and repair services (Randall *et al.*, 2012). On the other hand, the number of systems is another critical aspect for suppliers' decisions, since it affects suppliers' upfront investments for reliability improvement. Thus, the length of the contract and fleet size become the primary contract features that affect the selection between investment in reliability or processes. Although there are many studies that examine the trade-off between spare parts and reliability, there is dearth of research on the impact of different terms of contracts and fleet sizes on the investments of reliability and spare parts in PBC (Glas *et al.*, 2018; Hypko *et al.*, 2010a; Selviaridis and Wynstrab, 2015). Since the selection of contract length is critical in PBC for buyers to shift suppliers' focus on their benefits by aligning goals, this study investigates the various effects of contract length. Moreover, unlike previous research, this study also examines how the number of systems in the contract affects suppliers' decisions for reliability investments and spare parts.

The primary purpose of this study is to investigate how

suppliers' decisions to invest in quality improvement and inventory level are affected by the incentive structure of PBC in different terms of contracts and fleet sizes. Furthermore, it aims to exhibit the effects of these contract features on supplier profit and the buyer's annual unit cost. Especially for original equipment manufacturers for high life cycle cost systems and their buyers, such as defence industry, showing the impacts of these contract features will facilitate the success of PBC arrangements in pre-contractual and post-contractual term. To that end, this research answers the following research questions: (a) What are the effects of the contract length and fleet size on investments for reliability and level of spare parts in PBC? (b) How do these two contract features impact the supplier's annual profit and the buyer's annual unit cost?

The remaining of the paper proceeds as follows. After presenting related literature background and theoretical underpinnings of this study, research methodology and mathematical model are presented. Next, we presented the numerical example and its results, before concluding with a general discussion of theoretical and practical implications, research limitations, and suggestions for future research.

2. LITERATURE REVIEW AND THEORETICAL BACKGROUND

PBC has been offered as an exceptional model, a "win-win" solution for both buyers and suppliers (Hypko *et al.*, 2010). All efforts in PBC, such as maintenance programs and inventory management, are designed to reduce the cost of ownership for sustaining systems (Gansler and Lucyshyn, 2006; Vitasek *et al.*, 2007). PBC creates more high-profit margins for suppliers through additional revenue when they achieve desired objectives such as availability rate (Ong *et al.*, 2005). In addition, suppliers are motivated by incentives to invest in the reliability of systems, which result in high operational readiness (Gansler and Lucyshyn, 2006; Vitasek *et al.*, 2007). This investment in reliability increases the availability of systems while reducing total service costs, spare parts procurement, inventory holding costs, and the logistics footprint (Cohen and Netessine, 2007; Devries, 2005; Gansler, 2006).

Many studies have examined optimum solutions, such as the trade-off between inventory and reliability improvement for suppliers in PBC. Kumar *et al.* (2007) developed a multi-objective optimization model to optimize reliability, maintainability, and supportability criteria that are important in PBC. Nowicki *et al.* (2008) proposed an optimization model for the spare asset allocation problem under three different revenue functions: step, exponential, and linear revenue functions. They found that an optimal spares asset allocation could not be sustained without considering the associated profit stream. Using a principal-agent contracting framework, Kim *et al.* (2010) analysed efficiencies of sample-average and cumulative downtime within two contract types used in the performance-based approach. They found that when a component was highly reliable, implementation of PBC might create high agency cost. Mirzahosseini and Piplani (2011) investigated how component reliability, maintenance facility, and inventory management affected the availability of systems under PBC. They found that the base stock level of spare parts had an insignificant impact on system availability. However, they

revealed that the supplier must enhance component reliability and repair time, rather than increase the stock of spares so as to attain a minimum target availability level (Mirzahosseini and Piplani, 2011). Jin *et al.* (2012) investigated how the relationship between system cost, reliability, and spare parts under PBC affected the operational availability of a system. They found substantial evidence to conclude that these three factors were the primary drivers of system performance. Additionally, they showed that under a more extended service agreement in PBC, suppliers as original equipment manufacturers were eager to invest in reliability improvement. Also, they revealed that increasing spare parts inventory had less impact on the availability of very reliable systems. Guajardo *et al.* (2012) showed in his experimental study, based on data from the Rolls-Royce company, that product reliability was impacted by the usage of two support strategies: time and material based (T&MC) strategy and performance-based strategy. They found that the reliability of products was much higher (25%–40%) under PBC than under T&MC. Bakshi *et al.* (2015) developed a principal-agent model to investigate the interaction between reliability signalling and the vendor's unrestricted investment in spare parts inventory. They found that customers were eager to accept PBC when mature technologies were available for acquired products rather than products with newly developed technology. Kim *et al.* (2017) developed a game-theoretical model to investigate the interaction of investment in reliability improvement and spare parts under the traditional resource-based contract and PBC. They found that incentives under PBC motivated suppliers to make the upfront investment in reliability improvement, thus generating savings by reducing acquisition and holding costs in spare assets. On the contrary, under the material-based contracts, the supplier invested more in inventory and less in reliability. Additionally, Patra *et al.* (2019) developed a mathematical model to maximize supplier's profit under the PBC. They established an optimal availability which is used as a major performance metrics in their model to increase the probability of successful PBC arrangements for buyer and supplier. Also, in their mathematical model, Wang *et al.* (2019) proposed a new maintenance policy in PBC to maximize supplier's profit while maximizing the availability rates of the system.

Theoretical Background: In PBC, the buyer assigns the task of delivering the system's performance to the supplier (Helander and Moller, 2008). This relationship between supplier (agent) and buyer (principal) creates the agency problem when the preferences and goals of the principal and agent conflict (Eisenhardt, 1989). The main issues in the post-contractual term are "hidden action" and "moral hazard" (Bergen *et al.*, 1992). The problem of moral hazard in the post-contractual term stems from the buyer's inability to observe the supplier's actions in PBC because of imperfect information. The buyer's inability to observe supplier actions can be mitigated by the performance-based payment (Eisenhardt, 1989). Although buyers may have information about the supplier's capability, such as service capacity and technological ability, they cannot forecast the supplier's action in performing the work specified by the contract. Because of imperfect information about the agent's decisions, difficulties arise when it comes to ascertaining whether the supplier is performing in the buyer's best interests (Eisenhardt, 1989; Bergen *et al.*, 1992). The

performance-based payment, tied to the achievement of outcomes, enables the alignment of the buyer’s goals with the supplier’s preferences and transfers risks from the principal (buyer) to the agent (supplier) (Eisenhardt, 1989; Firchau, 1987). However, even the incentive structure of performance-based payment in PBC does not alleviate the buyer’s burden of assuming responsibility for the system’s operational performance. Also, in order to mitigate risks that emerge from agency problems, buyers can conduct outcome-based incentives in various contract types in a different revenue models (Sols *et al.*, 2007). With the incentivizing structure of PBC, buyers can motivate suppliers to act in agreement with their own interests. Thus, in PBC context, the moral hazard problem in the post-contractual term can be handled by aligning goals by tying the reward/payment to the accomplishment of performance outcomes by suppliers and reducing the information asymmetry by understanding each contractual feature.

3. METHODOLOGY AND MATHEMATICAL MODEL

In this study, we conducted an analytical model analysis through Matlab. The effects of each key contract feature (fleet size and the contract length) on spare parts and failure rates were investigated under the step revenue model, which was adapted from Nowicki *et al.* (2008). Since there were more than two decision variables, a genetic algorithm (GA) was used to examine the impact of each key contract feature on availability rates in PBC. For our research questions, the mathematical model in this study was adapted from the model of Jin *et al.* (2014).

3.1 Genetic Algorithm

As a metaheuristic approach, GA is an appropriate method to find the optimal solutions for multi-objective optimization problems by using evolutionary techniques (Horn *et al.*, 1994). Based on Holland (1973, 1992), who developed GA, the algorithm starts from the creation of a random population of solutions that builds search space in optimization. After generating the initial population, the algorithm uses three evaluation operators: selection, crossover, and mutation (Houck *et al.*, 1995). At first, better solutions are reproduced by the selection of better individuals. In GA, the term of individuals is used to represent possible solutions; and the name of the population is used to describe a set of individuals or solutions (Chiu *et al.*, 2006). Next, in the crossover process, two individuals are exchanged at random and put into the next solution to generate better individuals for optimal solutions. Finally, in the mutation process, individuals are created through random modifications based on the initial parameters of GA that are selected to process the algorithm. So, while the selection process decreases the search space within the initial population by eliminating poorer individuals, crossover and mutation processes search the initial population to find better solutions (Razali and Geraghty, 2011). In each loop, new solutions are used to change the weaker option to find better individuals. The algorithm continues until the termination of chosen criteria. The flowchart of GA algorithm is presented in **Figure 1**.

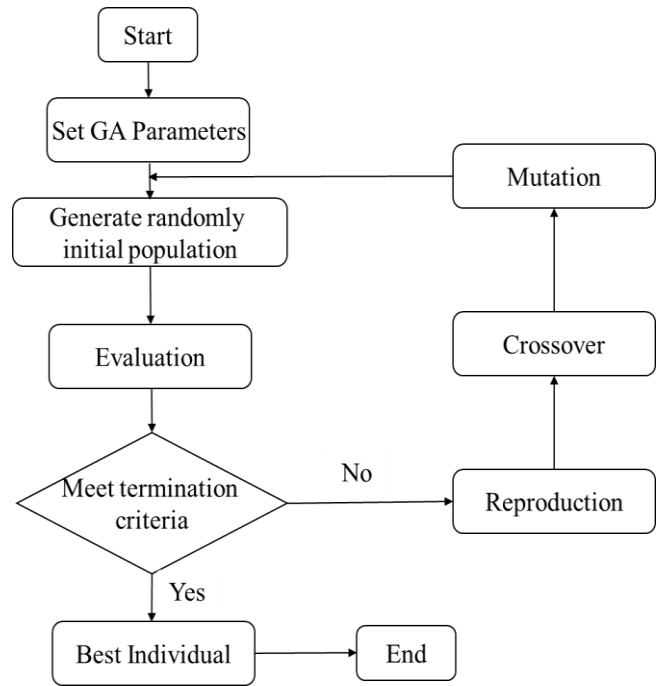


Figure 1 Genetic algorithm flowchart

3.2 Mathematical Model

Notations:

- A_s availability of system
- $A_{(i)}$ availability of subsystem where $i=1,2,3$.
- A_{min1} minimum availability of the system for the penalty zone
- A_{min2} minimum availability of the system for the award zone
- n number of systems in the contract
- λ_{max} maximum inherent failure rate (faults/year)
- λ_{min} minimum inherent failure rate (faults/year)
- λ failure rate (faults/year), decision variable
- s base-stock level of spare parts, decision variable
- τ length of contract (year)
- t_r turn-around time for fixing the broken item
- t_s repair-by-replacement time when the spare part is available
- Y a random variable for on-order spare parts
- Z a random variable for backorders for spare parts
- H a random variable for on-hand spare parts
- x a random variable for spare parts demands
- ϕ coefficient for design difficulty
- B_1 baseline design cost with the maximum inherent failure rate
- B_2 baseline unit cost with the maximum inherent failure rate

L	number of subsystems
θ	interest rate compounded annually
$R(A)$	revenue function
$c(\lambda)$	unit production cost
$D(\lambda)$	design cost
$I(\lambda, s)$	inventory cost for service logistics
$M(\lambda, n)$	maintenance/repair cost
$\Pi(\lambda, s, n)$	life cycle cost
a	fixed price
$b_{(1,2)}$	penalty rate, reward rate
$P(\lambda, s, n)$	profit function

In this model, the supplier, an original equipment manufacturer (OEM) in PBC, provides the maintenance and repair logistics of n systems. Also, as an OEM, the supplier provides system design improvements and owns the inventory. In this study, spare parts in inventory are considered at one location within the buyer site. This inventory for spare parts is managed by the one-for-one replacement policy during system failures. Also, the repairable inventory model is used for controlling expensive critical parts that are replaced correctively (Driessen *et al.*, 2010; Sherbrooke, 1968). The goal of this repair depot is to minimize inventory investment and to diminish holding or backorder costs (Jin *et al.*, 2014). After the replacement of a faulty/broken item in the failed system with a spare part in inventory, the defective part is sent to the repair depot. Working under the assumption that there are sufficient repair servers in the repair depot, the $M/G/\infty$ queue system was considered for this flow (Sherbrooke, 1992). Thus, all maintenance times are uniformly distributed with the mean value of repair time (t_r). This average turnaround repair time includes forward-and-return transportation times (Jin *et al.*, 2014). When spare parts are available in inventory, the broken item is replaced by the spare part in inventory, which is located on the buyer’s site within the average of replacement time (t_s).

Operational availability is considered one of the most significant criteria for repairable systems and is defined as the percentage of time that a system is ready for a mission (Mahon, 2007; Nowicki *et al.*, 2008). This primary performance metric, operational availability, is operationalized in Equation 1. It can be characterized as the percentage of system uptime over the total of system uptime and downtime (Wang *et al.*, 2004).

$$A = \frac{(uptime)}{(uptime)+(downtime)} = \frac{MTBF}{MTBF+MDT} \quad (1)$$

System uptime is represented by the meantime between failures (MTBF), which is the operating time between two successive failures. On the other hand, system downtime is represented by the mean downtime (MDT), which is the sum of meantime to replacement of a part and mean logistics delay time. Thus, MDT is affected by the inventory level of spare parts and waiting time for logistic services such as labor and transportation.

Based on the assumption of an exponential distribution of system lifetime, the relationship between MTBF and the failure rate, λ , can be estimated as:

$$\lambda = 1/MTBF \quad (2)$$

MDT is affected by the spare parts inventory level. If the spare parts are in stock, when the system fails, a defective part is replaced with a new part with an average time of t_s . Otherwise, an order is placed for the broken part and replacement time is lengthened until the spare part arrives (Jin *et al.*, 2014). To model these two cases, two random variables were used for spare parts availability in inventory. These are on-hand inventory (H) and backorder (Z). On-hand inventory (H) and s are related to each other through $H = \max\{0, s - Y\}$, where Y is a random variable representing the inventory level on order. Also, backorder and s are related to each other through $Z = \max\{0, Y - s\}$. A random variable for on-order spare parts (Y) can be modelled as a Poisson distribution with mean $\mu_0 = n\lambda t_r$ where $n\lambda$ represents the fleet failure rate, and t_r represents the repair time when spare part is not available (Jin *et al.*, 2014).

$$MDT = t_s Pr\{Y \leq s\} + (t_s + t_r)(1 - Pr\{Y \leq s\}) \quad (3)$$

where

$$Pr\{Y \leq s\} = \sum_{x=0}^s \frac{\mu_0^x e^{-\mu_0}}{x!}, \text{ and } \mu_0 = n\lambda t_r \quad (4)$$

Here x is the number of spare parts in demand. The expected value for on-hand quantities (H) and the backorder quantities (Z) can be predicted as follows:

$$E|H| = \sum_{x=0}^s \left((s - x) \frac{\mu_0^x e^{-\mu_0}}{x!} \right) \quad (5)$$

$$E|Z| = \mu_0 - s - \sum_{x=0}^s \left((x - s) \frac{\mu_0^x e^{-\mu_0}}{x!} \right) = n\lambda t_r - s - \sum_{x=0}^s \left((x - s) \frac{(n\lambda t_r)^x e^{-n\lambda t_r}}{x!} \right) \quad (6)$$

Finally, by exchanging Equations (2), (3), and (4) into Equation (1), operational availability can be presented as:

$$A(\lambda, s, n, t_r) = \frac{1}{1 + \lambda t_s + \lambda t_r \left(1 - \sum_{x=0}^s \frac{(n\lambda t_r)^x e^{-n\lambda t_r}}{x!} \right)} \quad (7)$$

This equation combines the inherent failure rate, spare parts, fleet size, and repair time in one analytical formula.

Life cycle cost: The primary advantage of PBC depends on suppliers’ abilities to come up with future cost avoidance solutions to support systems. Therefore, it is significant for suppliers to consider all possible solutions and their interaction effects at the same time. For instance, improvement of the reliability of the system not only will affect the design cost of the system but also will affect inventory costs of spare parts. In the next models, we show how improvement in reliability impacts design and manufacturing cost.

The design cost of the system is adapted from Jin *et al.* (2012, 2014) and Mettas (2000). Design cost increases

exponentially with reliability growth (Jin *et al.*, 2012). So, in the exponential cost model, the design cost for a subsystem can be expressed as:

$$D(\lambda) = B_1 \exp\left(\varphi \frac{\lambda_{max} - \lambda}{\lambda - \lambda_{min}}\right), \text{ for } \lambda_{min} \leq \lambda \leq \lambda_{max} \quad (8)$$

where λ_{max} is the maximum acceptable failure rate specified by the customer, and λ_{min} is the best feasible rate by the supplier. In particular, B_1 is the baseline design cost with λ_{max} . The difficulties of increasing the reliability of subsystem or component (i) are represented by φ and take values between 0 and 1. This value represents challenges, such as design complexity and technological limitations, that increase the subsystem/component's reliability relative to others. The large design difficulty rate indicates that the reliability growths of the subsystems or components are difficult to improve. Additionally, this large design difficulty rate (φ) results in a high design cost to increase the reliability of the subsystems or components (Mettas, 2000).

Inventory cost and the repair cost are the primary two expenses in post-production support costs. Inventory cost is related to a number of spare parts that is affected by the reliability of systems. The inventory cost can be expressed as:

$$I(\lambda, s) = sc(\lambda) \quad (9)$$

On the other hand, transportation cost, labor cost, and repair facilities are the main dimensions of repair costs. The total repair cost during the length of the contract (τ) can be expressed as:

$$M(\lambda, n) = c_r n \lambda \vartheta(\theta, \tau) \quad (10)$$

where

$$\vartheta(\theta, \tau) = \frac{(1+\theta)^\tau - 1}{\theta(1+\theta)^\tau} \quad (11)$$

Failure rate (λ) is defined as yearly. Repair cost (c_r) per faulty/broken item includes labor costs, facility costs for repair, and transportation costs. $\vartheta(\theta, \tau)$ calculated for the present value of an annuity with interest rate (θ).

Life cycle cost consists of design cost of reliability improvement, fleet cost of systems, inventory cost of subsystems, and maintenance costs. So, the life cycle cost for the supplier can be expressed as:

$$R(A_s(\lambda, s; n)) = \begin{cases} 0 & \text{if } A_s < A_{min1} \\ a - b_1 * (A_{min2} - A_s) & \text{if } A_{min1} \leq A_s < A_{min2} \\ a + b_2 * (A_s - A_{min2}) & \text{if } A_{min2} \leq A_s < A_{max} \end{cases} \quad (13)$$

$$Max E[P(\lambda, s)] = R(A_s(\lambda, s)) - \sum_{i=1}^L (D_i(\lambda_i) - B_{1,i}) - n \sum_{i=1}^L (c_i(\lambda_i)) - \sum_{i=1}^L (I_i(\lambda_i, s_i)) - \sum_{i=1}^L (M_i(\lambda_i, n)) \quad (14)$$

Subject to

$$A_s(\lambda, s) \geq \prod_{i=1}^L A_i(\lambda_i, s_i) \geq A_{min1} \quad (15)$$

$$\lambda_{min,i} \leq \lambda_i \leq \lambda_{max,i} \quad \text{for } i = 1, 2, \dots, L \quad (16)$$

$$\pi(\lambda, s, n) = D(\lambda) + nc(\lambda) + I(\lambda, s) + M(\lambda, n) \quad (12)$$

Revenue Function: Unlike traditional material contracting, suppliers are rewarded based on their achievement of targeted outcomes in PBC. In calculating the supplier's revenue, Nowicki *et al.* (2008) devised three different revenue functions: step, exponential, and linear revenue functions. We adopted Nowicki *et al.* (2008)'s step revenue function, which is consistent with Sols *et al.* (2007)'s reward scheme for PBCs. This revenue model, which is shown in Equation (13), consists of three bands. When the system's availability reaches minimum availability of the system for the award zone (A_{min2}), the supplier receives minimum revenue, the intercept (a), and based on the incremental difference in availability, ($A_s - A_{min(i)}$), the supplier gets the additional award or penalty, which is described by the slope (b_i) (see **Figure 2**).

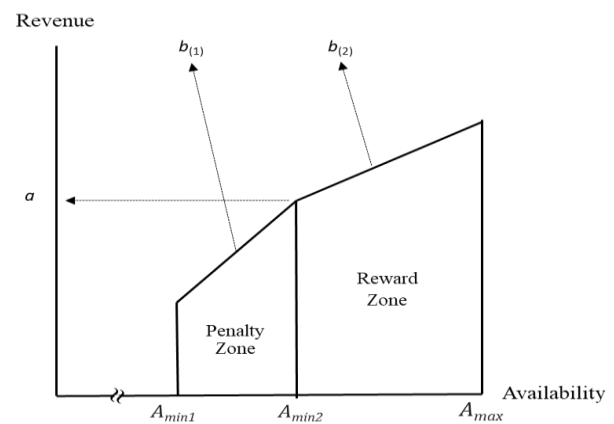


Figure 2 Revenue model (revenue and availability bands)

Revenue of Supplier: Supplier's expected profit modeled in Equation (14) and subject to target availability rates in revenue function and minimum-maximum failure rates of the each component. The number of subsystems is represented by L .

Here, the maximum profit of supplier is formulated for sustaining the entire system fleet by determining optimal failure rates and spare parts for each subsystem in the range of minimum and maximum failure rates. Considering the two decision variables within each of the four subsystems, a genetic algorithm through MATLAB was used to find the impact of each key contract feature for optimal failure rates and spare parts in PBC.

4. NUMERICAL EXAMPLE

In this study’s numerical example, the supplier is contracted to design and supply four major components of the system, which has different reliability and feasibility rates. In this model, each of the n systems consists of four sub-systems connected in a series configuration in which the system will fail if any of its subsystems collapse (**Figure 3**).

For the numerical experiment, we created the data for this study. Since PBCs have been widely used in the defence industry since 2003 (Sols *et al.*, 2007; Mahon, 2007), and considering that approximately 40% of the defence budget is consumed by operation and maintenance costs, we used similar relativity in our data for repair and attained costs of subsystems. In this example, the supplier’s objective is to maximize his profit margin by taking account of design cost, maintenance, and spare parts, while meeting the customer’s availability target under the step revenue function. The essential information about each subsystem, e.g., the baseline manufacturing cost, the acceptable maximum, and the best achievable failure rate (faults/year) are presented in **Table 1**.

In this study, the system consists of four subsystems. Subsystem 1 and Subsystem 2 have the same values, except for coefficient of design difficulty. Subsystem 3 and Subsystem 4 have the same values, except for repair cost. With this modification, we also aimed to observe the effects of difficulty rates and repair cost in the subsystems on reliability improvement and spare parts inventory.

The genetic algorithm is used through MATLAB to maximize supplier profit for the fleet and to find the optimal

or close to optimal values for failure rates and spare parts. The model was conducted with a different length of contract and fleet size under the two revenue models with different availability rates. In the numerical example, the revenue was calculated for the availability rates of 0.95 and 0.97 for A_{min1} and A_{min2} , respectively. To understand the impact of the fleet size in the numerical example, we used eight fleet sizes with 5, 10, 20, 30, 40, 50, 60, and 70. In addition, to investigate the effect of the length of the contract in each example, we conducted ten lengths of contract: 1, 2, 3, 4, 5, 6, 7, 8, 9, and 10 years.

For the fixed price, a , in the contract, the value of $\$2.53 \times 10^7$ was used for 30 units and five-year contracts. To be able to make a comparison of the profit with different values, based on the increase or decrease in fleet size and the length of the contract, award rates are increased or decreased related to this change. For the parameters of penalty and reward slopes, b_1 and b_2 , $5a$ and $4a$ are used in revenue function, respectively. In the step revenue model, the supplier will decide λ and s , subject to availability rates in revenue function to maximize his profit.

The base contract features for the length of contract and fleet size, which presents base value in this study, are five years and 30 units, respectively.

Fleet Size: Based on the values presented in **Table 1**, the optimal solution, found in GA for failure rate (λ) and spare parts (s) within a five-year agreement for the eight different fleet sizes with 5, 10, 20, 30, 40, 50, 60, and 70 unit of systems, is presented in **Table 2** and **Figure 4**.

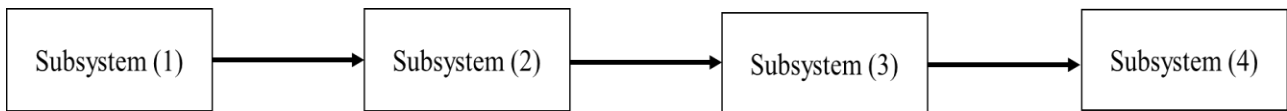


Figure 3 Serial system diagram

Table 1 Reliability and cost parameters for the system

Parameter Subsystem category	Subsystem 1 $i=1$	Subsystem 2 $i=2$	Subsystem 3 $i=3$	Subsystem 4 $i=4$
λ_{max} (faults/year)	0.4	0.4	0.4	0.4
λ_{min} (faults/year)	0.08	0.16	0.08	0.08
Φ	0.1	0.15	0.1	0.1
t_s (days)	10	10	5	7
t_r (days)	100	100	51	68
θ	0.05	0.05	0.05	0.05
c_r (dolar/repair)	55,000	55,000	24,000	32,000
B_1 (dolar)	1,600,000	1,600,000	800,000	800,000
B_2 (dolar)	160,000	160,000	80,000	80,000

Table 2 Results for the different fleet size within the five-year length of contract ($A_{min1} = 0.95, A_{min2} = 0.97, \tau = 5$)

Fleet Size(n)	5	10	20	30	40	50	60	70
Availability	0.9669	0.9695	0.9766	0.9769	0.9763	0.9742	0.9733	0.9781
Supplier Profit (\$/year)(10 ³)	299.6	308.52	478.08	811.74	1222.04	1618.54	2002.40	2513.60
Unit cost of Buyer (\$/unit/year) (10 ³)	256.68	201.64	174.36	172.88	171.42	168.89	168.56	170.52
Spare parts								
Subsystem 1	1	1	2	3	4	4	5	5
Subsystem 2	1	2	4	5	6	6	7	8
Subsystem 3	0	0	1	1	1	1	1	2
Subsystem 4	0	0	1	1	2	2	2	4
Failure rates								
Subsystem 1	0.1805	0.1600	0.1562	0.1532	0.1488	0.1407	0.1423	0.1349
Subsystem 2	0.2525	0.2523	0.2506	0.2406	0.2365	0.2252	0.2230	0.2204
Subsystem 3	0.1605	0.1467	0.1579	0.1483	0.1407	0.1349	0.1291	0.1346
Subsystem 4	0.1480	0.1338	0.1454	0.1353	0.1367	0.1317	0.291	0.1335

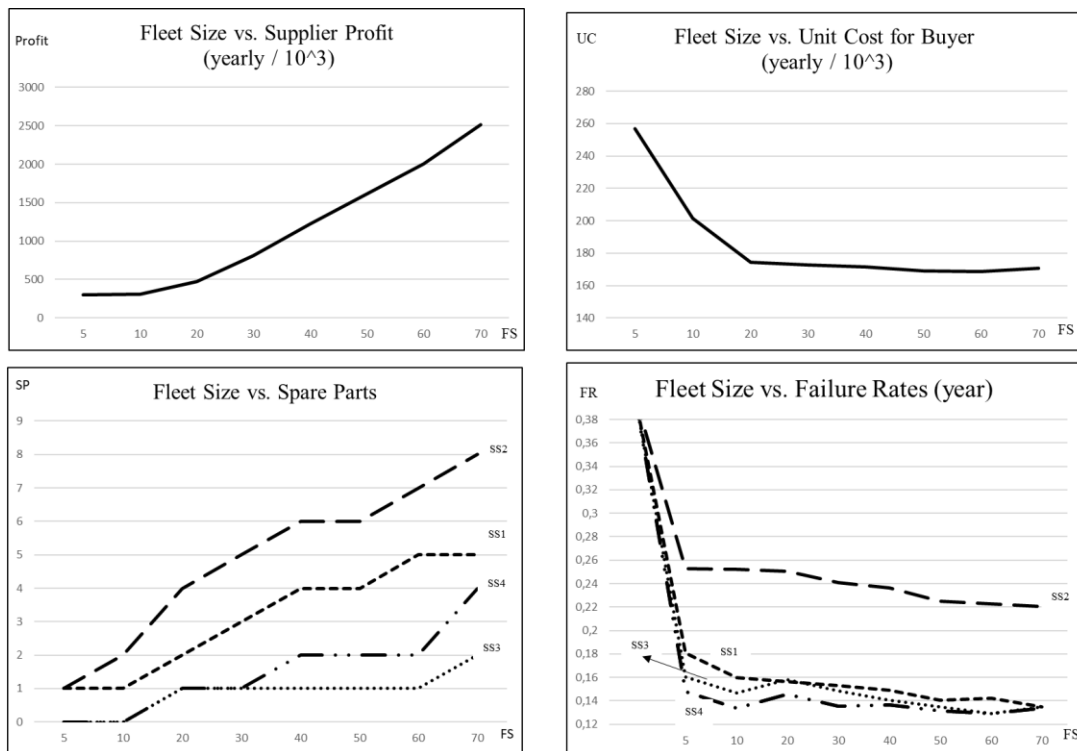


Figure 4 Results for the different fleet size within the five-year length of contract ($A_{min1} = 0.95, A_{min2} = 0.97, \tau=5$)

The results indicate that the supplier’s yearly profit grows when fleet size in the contract increases. However, in the lowest two fleet sizes with five and ten units, this increase is much smaller. The low profit in these fleet sizes is caused by the inability of suppliers to compensate for the design cost for reliability improvement. Therefore, in these two levels, failure rates are also much higher than in the other level fleet sizes. These results in the supplier decision to stay in the first zone of revenue function, which represents between two minimum availability rates (between 0.95 and 0.97) (see **Figure 2**). Therefore, based on the step revenue model, for these two lowest levels of fleet size, the supplier brings in greater profits in the first zone of revenue model. The availability rates of the systems decrease for buyers for these two smaller fleet sizes. Except for these two smaller fleet sizes, based on **Figure 4**, we can conclude that there is linear growth in the supplier’s profit alongside an increase in fleet size.

Also, as seen in **Table 2** and **Figure 4**, except with the highest level of fleet size with 70 units, for the buyer, this yearly unit cost of each system exponentially decreases with an increase in fleet size. For the lowest two fleet sizes, with 5 and 10 units, while suppliers earn less profit, the buyer must make much larger payments for each system in the fleet.

Based on the results, we can conclude that increasing the number of spare parts under the PBC doesn’t profoundly affect availability rates. A close look at each subsystem, with an increase in fleet size, for Subsystem 1 and 2, shows that growth in the number of spare parts is much higher, since they have a higher unit cost than Subsystems 3 and 4, resulting in high design cost. The Subsystem 1 and the Subsystem 2 have the same values, except for the coefficient of design difficulty. A close look at the first two subsystem

shows that an increase in spare parts for Subsystem 2 is higher than the first one because of the higher coefficient of design difficulty (50%) and design cost for improvement in reliability. Subsystem 3 and Subsystem 4 have the same values, except for repair cost. The increase in spare parts for Subsystem 4, which has a higher repair cost (50%), results in more spare parts in inventory in more than thirty-unit fleets.

Generally, we see in **Table 2** and **Figure 4** that suppliers are much more eager to invest in reliability under the PBC. And this investment shows exponential increases with the increase in fleet size. On the other hand, a close look at the subsystems reveals that the improvement in failure rates is lower for Subsystems 1 and 2, which have two times higher unit cost than Subsystems 3 and 4. Given that the calculation of the design cost is dependent on the base unit cost, an increase in reliability is a much more affordable solution when design cost is lower than the holding costs of the units. Also, when we compare Subsystems 1 and 2, we can see that the improvement in reliability for the first subsystem is higher than the second subsystem which has a more difficult design rate.

We can conclude that as the number of systems increases in the fleet, the contract becomes much more profitable for suppliers under the performance-based contract. From the perspective of the buyer, not only does the yearly unit cost of the system decrease, but also the buyer gets more reliable systems, which increases the readiness of the system.

The length of the contract: Optimal values, found in GA for failure rate (λ) and spare parts (s) for the thirty-unit fleet for the ten different lengths of the contract with 1, 2, 3, 4, 5, 6, 7, 8, 9, and 10 years, are presented in **Table 3** and **Figure 5**.

Table 3 Results for the different length of contract for thirty-unit fleet size
 ($A_{min1} = 0.95, A_{min2} = 0.97, n = 30$)

Length of the contract (τ) (year)	1	2	3	4	5
Availability (A_s)	0.9699	0.9699	0.9768	0.9777	0.9769
Supplier Profit (\$/year)(10^3)	35.206	46.160	455.866	703.175	811.740
Unit cost of Buyer (\$/unit/year) (10^3)	621.30	336.50	239.10	199.10	172.88
Spare parts					
Subsystem 1	2	2	3	3	3
Subsystem 2	5	5	5	5	5
Subsystem 3	1	1	1	1	1
Subsystem 4	1	1	2	2	1
Failure rates					
Subsystem 1	0.1473	0.1460	0.1584	0.1544	0.1532
Subsystem 2	0.2523	0.2493	0.2515	0.2446	0.2406
Subsystem 3	0.1487	0.1492	0.1490	0.1480	0.1483
Subsystem 4	0.1359	0.1352	0.1496	0.1457	0.1353

Length of the contract (τ)	6	7	8	9	10
Availability (A_s)	0.9757	0.9759	0.9741	0.9742	0.9746
Supplier Profit (\$/year)(10^3)	924.466	1025.757	1070.412	1135.333	1190.300
Unit cost of Buyer (\$/unit/year) (10^3)	154.75	144	134.160	127.970	122.070
Spare parts					
Subsystem 1	3	3	2	2	2
Subsystem 2	5	5	5	5	5
Subsystem 3	1	1	1	1	1
Subsystem 4	1	1	1	1	1
Failure rates					
Subsystem 1	0.1496	0.1496	0.1402	0.1390	0.1373
Subsystem 2	0.2384	0.2336	0.2340	0.2343	0.2311
Subsystem 3	0.1469	0.1462	0.1420	0.1405	0.1436
Subsystem 4	0.1341	0.1341	0.1311	0.1329	0.1305

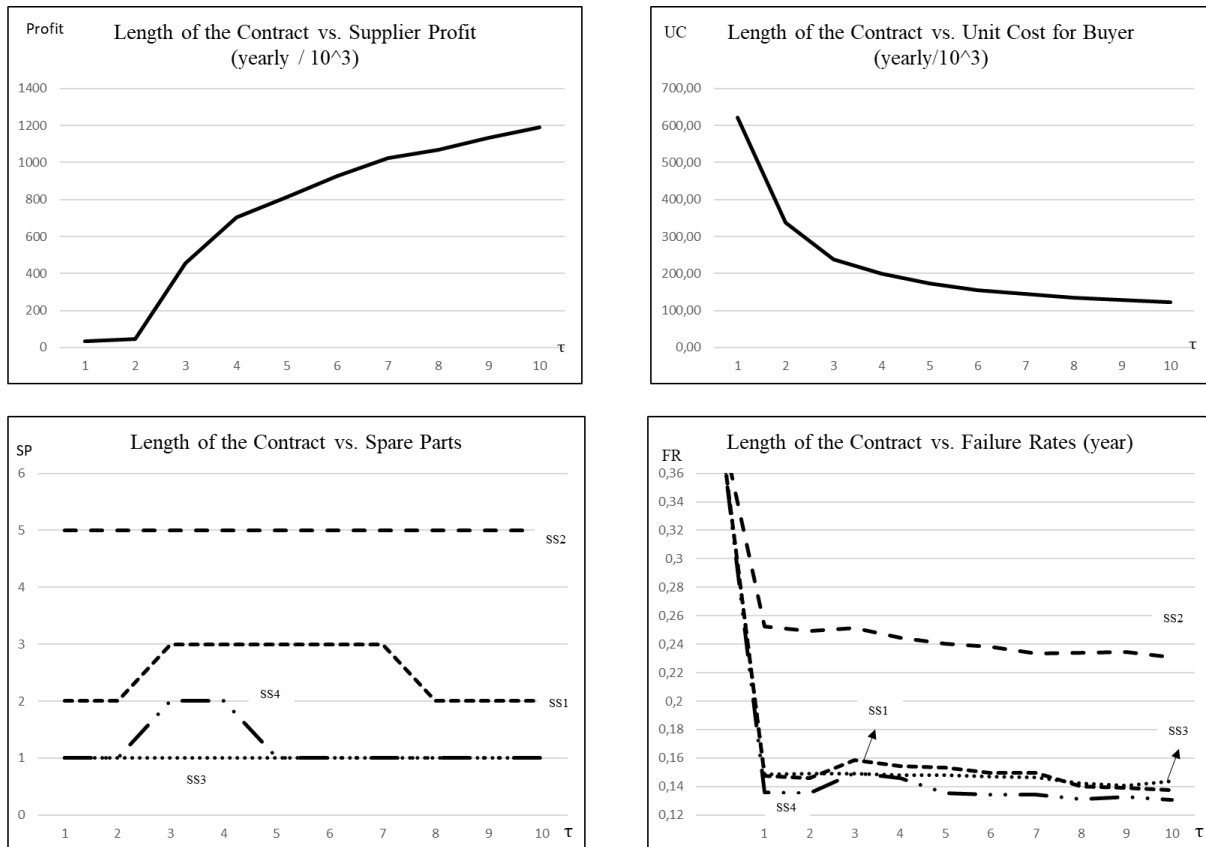


Figure 5 Results for the different length of contract for thirty-unit fleet size ($A_{min1} = 0.95, A_{min2} = 0.97, \tau=5$)

As seen in **Figure 5**, under the longer subsystem, the supplier’s yearly profit grows exponentially. However, for the one-year and two-year contracts, the supplier’s annual profit stays under \$50,000, which is close to zero in the graph. Considering that the PBC is implemented in the defence industry under a 3-5-year term with an extension option (DoD, 2014), this result confirms the disadvantages of contracts having terms less than three years. Also, at these two levels, failure rates are much higher than at the other

level of contract terms. Therefore, results show that under one and two-year contracts, the buyer must pay much more for each unit of the system with lower availability rates. Based on the step revenue model, for these two lowest levels of contract length, the supplier reaps greater profit in this penalty zone. So, the availability rates of the systems decrease for buyers for these two smaller fleet sizes.

As seen in **Table 3** and **Figure 5**, the yearly unit cost of each system exponentially decreases for the buyer with the

increase in contract length. Also, based on the results, we can conclude that the supplier is far more eager to invest in the reliability of the system than to increase spare parts under the PBC. On the other hand, failure rates show an exponential decrease with the increase in contract length. Moreover, a closer look at the subsystems reveals that they have the same aforementioned results with the increase in fleet size.

We can conclude that longer contract length is far more profitable for suppliers and buyers under the performance-based contract. From the perspective of the buyer, not only does the yearly unit cost of the system decrease, but also the buyer attains more reliable systems, which increase system readiness.

5. GENERAL DISCUSSION AND IMPLICATIONS

In this study, we examine the effects of fleet size and contract length on reliability investment, inventory level, supplier's profit and annual unit cost of the system for a buyer in PBCs. We analyze how the supplier's decision is affected by contract length and fleet size in a mathematical model, adapted from Jin *et al.* (2012), within the step revenue model, adapted from Nowicki *et al.* (2008). In PBCs, although suppliers have more freedom to act, they start to shoulder risks based on their decision on how to provide targeted performance rates (Glas *et al.*, 2019). Therefore, they have to consider all aspects of contracts' specialties that affect the outcome. On the other hand, buyers need to forecast the impacts of their decisions about contract length and fleet size. These features affect the supplier's decisions for upfront investments. Therefore, the main features of the contract, which needs to be shaped in pre-contractual terms, should be closely considered and analyzed by both parties so that the supplier chooses the best optimal solutions based on his profit in the step revenue model. This study makes the various impacts of the contract length and fleet size predictable for suppliers and buyers. So, this predictability helps to reduce information asymmetry and uncertainty that exists in agency problem in the post-contractual problem. From the perspective of buyers, unveil of the impacts of these features increases the buyer's non-coercive power to motivate the supplier to act in the best interest of the buyer. Furthermore, this predictability reduces the uncertainty of supplier's action and helps to build more efficient PBCs.

We find that there is a substantial relationship between reliability enhancement, number of spare parts, contract length, and fleet size. A general conclusion is that failure rates and the annual unit cost for the buyer exponentially decrease when fleet size or contract length increase to meet minimum targeted availability rates and to get maximum profit. This result also confirms previous studies by Jin *et al.* (2012) and Randal *et al.* (2010). However, the increase in spare parts is relatively low with an increase in fleet size and the contract length. Thus, we propose that the impact of inventory investment has little effect on desired availability rates. Additionally, the annual profit of suppliers grows substantially with an increase in fleet size and length of contracts. This growth is sustained by the supplier's ability to absorb the design cost in large fleet size and longer contract terms. Also, as seen in the examples above, the supplier's annual profit is low and almost stable with smaller fleet sizes (5 and 10) and shorter contract terms (one-year

and two-year). These results exhibit that PBC arrangements are far more convenient for longer than three-year contracts and larger fleet sizes.

PBC for a large number of systems have a positive effect on suppliers' decisions to make an upfront investment to increase the reliability of systems, from which both suppliers and buyers benefit. Considering the supplier's profit increase due to the absorption of the design and manufacturing costs in longer contract terms and larger fleet sizes, we argue that suppliers will be more motivated to sign a PBC with larger fleet size and longer contract term. Also, this results in an advantage for the buyer to acquire more reliable systems that contribute to greater system readiness.

Also, we find that long-term contracts have a positive impact on reliability enhancement. We argue that the supplier is much more eager to invest in the reliability of the system than in increasing spare parts under the PBC. Failure rates demonstrate an exponential decrease with an increase in the length of contracts. Besides, considering the rise in the supplier's annual profit and the exponential decrease in the unit cost of the system for the buyer, we conclude that a longer contract term creates a win-win situation for both the buyer and the supplier. This finding is consistent with the length of PBCs implemented by Department of Defense (DoD). Notably, in the defense industry, the DoD specified a 3 to 5-year contract term with an optional extension for their suppliers based on their performance (DoD, 2014). Consequently, we argue that an increase in contract length is much more profitable for both the buyers and the suppliers in PBC.

Although we observe that the number of spare parts was slightly increased under the long-term contract, and with larger fleet size, we conclude that increasing spare parts under the PBC does not profoundly affect availability rates. This slight increase is reasonable because of the number of systems and the longer contract period. On the other hand, we find that the growth rate in spare parts is much higher when design difficulty coefficient and repair cost are higher. Therefore, we come up with that PBC motivates suppliers to make an upfront investment for reliability improvement with powerful incentives, which leads to savings in future costs and results in higher system readiness.

In PBC, though suppliers have freedom for how to provide desired performance outcomes, buyers can lead suppliers' decisions by considering the effects of these features and reward schemes. Moreover, based on our results, we argue that PBC creates a win-win situation for both the buyers and the suppliers. For the theoretical contributions, from the perspective of principal-agent theory, we posit that the moral hazard problem in the post-contractual term can be handled by reducing the information asymmetry by understanding the effects of each contractual feature in PBC. So, moral hazard in the principal-agent theory can be handled by the incentive structure of PBC by understanding of the effect of contract length and fleet size.

From the managerial perspective, understanding the impacts of contracts features will help to build better PBC in the pre-contractual term. Also, improvement of step revenue model in this paper will help implementation of outcome-based contracts. Additionally, for the suppliers, to understand the effects of each contract features will increase the quality of suppliers' decisions for reliability improvement and inventory investment.

For the limitations of this study, we did not investigate the effects of repair and maintenance enhancement on availability rates. In future studies, the impacts of process improvement to reduce the time required for repair and maintenance services and the logistic delay time in PBC can be investigated. This study might also be extended using different reward schemes with various contract types to find the most efficient and effective contract structure.

From the scholarly perspective, we conclude that the transformation of post-production support from a traditional-based approach, which depends on sales of spare parts and maintenance service, to performance-based approach, must be considered using a holistic approach with interdisciplinary studies between engineering and supply chain management. On the other hand, from the managerial perspective, it is obvious that the PBC approach will transform manufacturing industries, which only produce goods, to provide post-production support for customers in their facilities.

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