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Analytical Examination of Performance-Based Acquisition Strategies

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Abstract

This research, under the direction of the principal investigators and support from the Naval Postgraduate School, the Systems Development & Maturity Laboratory at Stevens Institute of Technology, and the Complex Logistics Cluster at the University of North Texas, achieved its overarching goal of developing novel models and analytical techniques to increase the defense acquisition communities' return on investment. Three studies were undertaken using a mixed methodological approach. In the first study, qualitative research methods (surveys, grounded theory, and case studies) were used to uncover key characteristics and metrics that are important for a successful performance-based contract (PBC) between a customer and a post-production service provider. In the next two studies, quantitative research methods (econometrics, operations research techniques, and diffusion models) were used to develop analytical models, incorporating the key characteristics and metrics, to assist the acquisition, design, and support communities in making informed business decisions. The analytical models determined the optimal price, length, and investment of a PBC and provided the mechanisms to allocate investment budget between system design and the post-production network needed to support the design. Key findings and business implications are discussed for each study.

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1. Introduction

This research, under the direction of the principal investigators and support from the Naval Postgraduate School, the Systems Development & Maturity Laboratory at Stevens Institute of Technology, and the Complex Logistics Cluster at the University of North Texas, has successfully

a. uncovered key characteristics and metrics that define successful performance-based contracts (PBCs; Randall, Hawkins, & Nowicki, 2011);
b. developed an analytical model to determine the optimal price, length, and investment of a PBC (Nowicki, Murynets, Ramirez-Marquez, & Randall, 2011); and
c. determined optimal investment strategies in system design and supply chain improvements;
    i. developed an algorithm to improve the computational efficiency of the Multi-Echelon Technique for Recoverable Item Control (METRIC) class of inventory optimization problems (Nowicki, Randall, & Ramirez-Marquez, 2011b);
    ii. developed a model that analyzes the trade-off between system design and supply chain performance (Nowicki, Randall, & Ramirez-Marquez, 2011a).

This technical report is organized as follows. First, we discuss performance-based acquisition strategies with an emphasis on how performance-based logistics (PBL) strategies differ from traditional logistics support strategies. We then discuss PBL successes that span across industry sectors from government (e.g., defense) to for-profit (e.g., rail, airline, housing, and utilities). Next, we present the specifics of our research. Three research objectives are addressed: (1) identify the key characteristics and metrics of successful performance based contracts (PBCs), (2) determine the optimal price and contract length of a PBC, and (3) determine optimal investment strategies in system design and supply chain improvements.

For each research objective, we provide an overview, a brief discussion of the models, key findings, business implications, and future research. Modeling and algorithmic details are in the appendices. Finally, we list our project accomplishments.

2. Discussion of Performance-Based Acquisition Strategies

Performance-based acquisition strategies are receiving increased attention in systems engineering, operations management, economic, supply chain and logistics research (Kim, Cohen, Netessine, & Veeraraghavan, 2010; Kim, Cohen, & Netessine, 2007; Ng, Maull, & Yip, 2009; Nowicki, Kumar, Steudel, & Verma, 2008; Randall, Pohlen, & Hanna, 2010; Sols, Nowicki, & Verma, 2007). Quite often, the logistics ecosystem associated with performance-based acquisition strategies, specifically a PBL strategy, is a three-tier system composed of suppliers, system integrators, and customers. We refer to this three-tier system, with its resources, technologies, policies, procedures, and flows, as the PBL ecosystem. PBL is a post-production service strategy that is highly dependent on the supply chain supporting its logistics ecosystem. Complex systems being supported through a PBL strategy rely on activities and decisions that span a broad array of functional areas, including research and development, engineering, operations, maintenance, support, logistics, purchasing, and supply chain. An example in the defense industry is the Joint Strike Fighter (JSF) with Pratt & Whitney (supplier) supplying the engines to Lockheed Martin (system integrator and original equipment manufacturer [OEM]) who will then integrate all of the components to provide mission-capable JSFs for the U. S. Department of Defense (customer) and its allied partners (F-35 Program Office, 2011). Similar relationships and structures exist in commercial industry, such as the high-speed rail industry where the operator, the end customer, and the OEM are different agencies (Siemens, 2011). Other examples can be found in the transportation sector (Transportation Research Board, 2009) and the health services sector (The World Bank, 2008).

PBL strategies have been credited with reducing life cycle costs and improving system performance when compared to more traditional, transactional approaches to post-production logistics and support. Programs that have adopted PBL have experienced system up- time increases of 40% and logistics response-time cuts of 70%, all while generating billions of dollars in savings over traditional approaches (Fowler, 2008, 2009). For instance, the U. S. Navy saved $688 million on the F/A-18 program by using PBL, and the United Kingdom's Defense Ministry saved $250 million by converting its CH-47 post-production logistics and support contract to PBL (Fowler, 2008). There are similar PBL success stories dealing with projects in the for-profit sector. For instance, one recent study of a major Dutch housing project showed that life cycle cost was reduced by 20% using a PBL approach (Straub, 2009).

In order to compare and contrast PBL with traditional approaches to logistics and post-production support, we provide a series of systemigrams. Systemigrams provide researchers with the ability to convey, in a conceptual manner, the inter-relationships of a complex system (Boardman & Sauser, 2008). Figure 1 provides a systemigram of traditional post-production logistics and support. In traditional post-production logistics and support, the major business entities are suppliers; OEMs; maintenance, repair and overall (MRO) providers; system operators; and customers. Here we use the airline and rail industries as examples of the traditional post-production support structure. The overarching concern of the system operator (e.g., airline or rail company) is to meet customer requirements while profitably operating the system. For the airline and rail industries, this means profitably operating routes and schedules at a particular price and comfort level (Flint, 2007; Siemens, 2011).

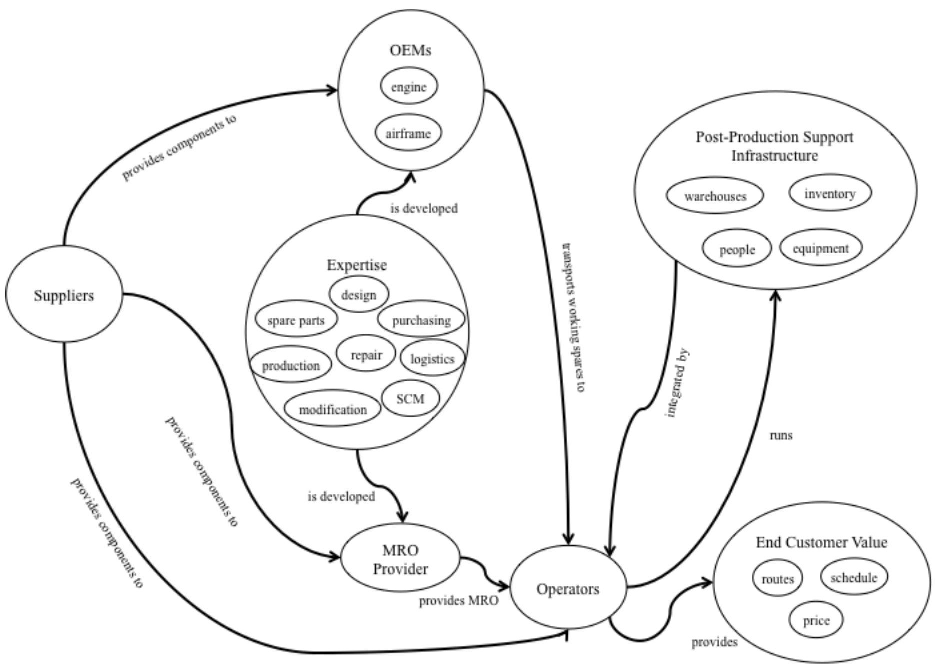

Figure 1. Representation of a Traditional Post-Production Logistics and Support Systemigram

As shown in Figure 1, the system operator's primary core competency revolves around determining profitable routes and schedules, and operating a system that meets these schedule requirements while dealing with disruptions (e.g., weather, change in customer desire, system failure) as they occur. Within a traditional post-production logistics and support system, the operators (e.g., the airline or the rail company) manage a network of warehouses, inventory, equipment, and people that keep the system in service or return the system to service when it breaks (Hypko, Tilebein, & Gleich, 2010). Considering the complexity of determining routes and price, it can be argued that running, maintaining, and integrating the post-production logistics and support infrastructure is a secondary competency of the rail and airline operator. As depicted in Figure 1, a great deal of the expertise needed to run the post-production infrastructure actually resides with the OEMs and MRO providers. Further, the operator seldom has the technical capability to control, much less reduce, cost as systems age and fatigue, manufacturing sources diminish, and corrosion takes a toll (MaClean, Richman, Larsson, & Richman, 2005).

This traditional strategy puts the end customer and the system operator at a disadvantage. They are saddled with such issues as corrosion, diminishing manufacturing sources (e.g., parts that are no longer being produced), and fatigue (MaClean et al., 2005) yet their core competency is typically not consistent with dealing with such issues (Prahalad & Hamel, 1990). As issues emerge, the system operators typically do not have the expertise, time, or funding needed to control and reduce the life cycle costs of the system ("Keeping Him Awake," 2010). Further, the operator, who is not the OEM, typically has little in-house capability to improve the reliability and design of the fielded system. In this traditional approach, the organization most capable of reducing life cycle cost, the OEM, typically moves on to the next research design and production effort, leaving post-production support in the hands of a hodgepodge of suppliers and operators (Randall, 2009).

This structure devolves into competing objectives (e.g., OEM and supplier desires to sell more spares and repairs, customer desires to reduce spending) with little incentive to invest in life cycle cost reduction beyond production (Geary & Vitasek, 2008). Without innovation and involvement from the OEM and suppliers, the efficiency of the post-production support infrastructure—characterized here as the operator's ability to integrate its warehouse, inventory, transportation, procurement, and labor functions—is limited (Randall et al., 2010).

As depicted in Figure 2, PBL corrects incentive misalignment in the post-production logistics and support network, and transfers roles and responsibilities to the entities most capable of performing these tasks efficiently and effectively. As a result, PBL manifests itself as a solution that effectively leverages the existing expertise that resides with the OEMs, suppliers, and MRO providers. PBL drives a governance structure that codifies the role of a systems integrator as the entity that establishes and performs critical supply chain integration functions across the life cycle of the system (Randall et al., 2010). Because the system integrator is now responsible for integrating and orchestrating the post-production logistics and support infrastructure (e.g., warehouses, inventory, and transportation), the operators are now free to focus on their expertise—the actual operations of the system (e.g., route scheduling and pricing).

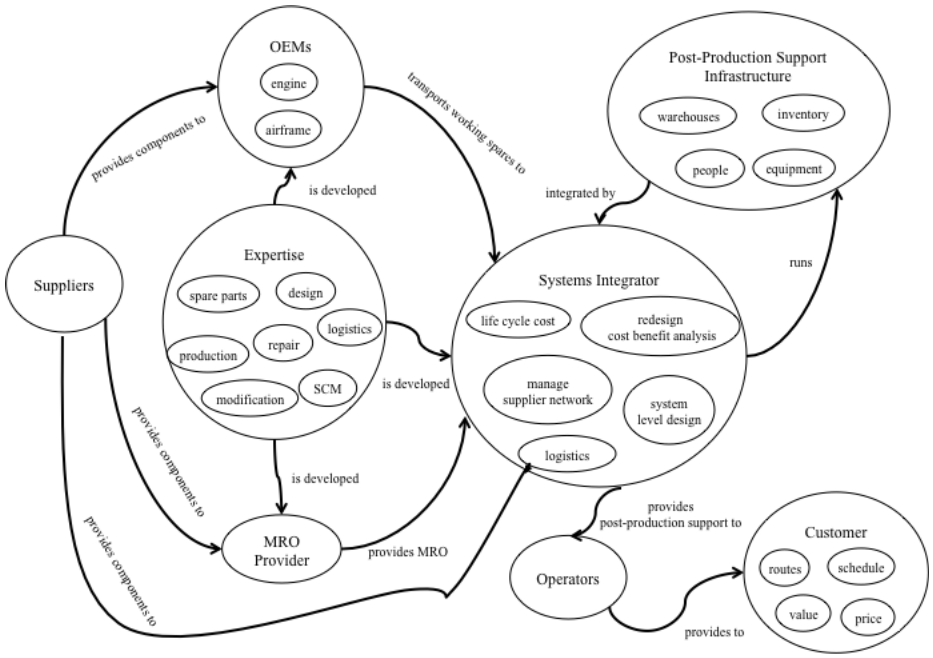

Figure 2. Representation of a PBL Post-Production Logistics and Support Systemigram

PBL integration is, therefore, particularly effective when the integrator (e.g., the OEM) keeps elements of the research, design, and production supplier network in place to manage and logistically support the system during post-production. This means that the integrator and suppliers are now capable of balancing and optimizing the cost of inventory, transportation, warehousing, on-equipment maintenance, and MRO against the potential to reduce those costs through redesign. This makes sense for a number of reasons. The OEM and the suppliers are in the best position to make initial forecasts of the reliability and subsequent demand for parts, and then to update those forecast models as the system evolves during use (Kim et al., 2010; Nowicki et al., 2008; Randall et al., 2010). Further, the OEM and suppliers are typically most capable of affordably redesigning components to drive out costs or bad actors. As new technology, materials, and logistics processes become mature, these suppliers, who are further back in the supply chain, are most capable of affordably improving the design of both consumable and repairable products. In coordination with the integration expertise of the OEM, these products can then be infused into the system as the system fails—thus, reducing future logistics costs.

There are two keys differences between a PBL contract and traditional post-production support. The first involves contracting for performance, or an outcome, rather than repeatedly contracting for discrete products and services (Geary & Vitasek, 2008). Under a PBL contract, the buyer contracts for system performance, typically characterized as system "up time," as opposed to contracting for spare parts and repair services. System up time is defined as the amount of time the system either is ready to perform (e.g., aircraft fleets) or does perform (e.g., power generation networks) divided by the amount of time possible for that system to be up. The supplier is then free to ensure this contractual up time is achieved as efficiently and effectively as possible. The second key to PBL involves its reliance on a multi-year relationship. The multi-year relationship gives the supplier network time to determine whether certain reliability issues might be better served through redesign, as opposed to continued procurement of support resources and services, such as spares and repairs. These contract dynamics of PBL result in a structure where the integration, accountability, and risk for achieving performance objectives are left with those organizations that have the greatest set of relevant knowledge, skills, and abilities.

3. Study 1: Successful Performance-Based Contracts (PBCs)—Key Characteristics and Metrics

3.1. Overview

Performance-based logistics (PBL) strategies are providing governments and for-profit organizations with a contractual mechanism that reduces the life cycle costs of their systems. PBL accomplishes this by establishing contracts that focus on the delivery of performance, not parts. PBL establishes a metrics-based governance structure where suppliers make more profit when they invest in logistics process improvements, or system redesign, that reduce total cost of ownership. While work has been done to outline an overall PBL theoretical framework (Randall et al., 2010), testing is required on the underlying theory that explains the enablers that lead to organizational and team-level, team-goal alignment associated with the PBL governance structure. The purpose of this research, therefore, was to quantitatively test previously posited relationships between enablers of PBL and PBL effectiveness. An additional objective was to explore any differences in PBL effectiveness between different business sectors.

3.2. Model

A multiple regression model was developed, tested, and validated to explain the effectiveness of PBL. The model was externally validated with exploratory cross-sectional survey data of 61 practitioners. For a detailed discussion of the theoretical development of the multiple regression model see Appendix A.

3.3. Key Findings and Business Implications

This study strongly supported recent PBL theory explaining PBL effectiveness (Randall et al., 2010). Key antecedents included investment climate, relational exchange, PBL leadership, and business sector. This investigation also found that government organizations lag behind their commercial counterparts in PBL effectiveness and PBL leadership. Model results suggested that this lag had a negative moderating effect on PBL outcomes.

PBL business arrangements are more effective in more favorable investment climates. Thus, leaders should welcome new ideas, empower employees, and encourage entrepreneurship. Because PBL effectiveness increases with relational exchange, building trust and communicating with suppliers is key. Leadership is also important to PBL effectiveness. Leaders should accept risk, focus on long-term affordability and performance, and align activities to achieve end user goals.

3.4. Future Research

This study was not without limitations. First, the research design relied upon self-reported data from respondents that may have introduced common method bias. Second, whereas the model explained 53% of the variance in PBL effectiveness, we wonder whether PBL effectiveness, while a distinct construct in the minds of the practitioners, may in fact be multi-dimensional, yet highly correlated in each dimension. There appears to be reason to consider whether PBL effectiveness is in fact an amalgamation of PBL-driven innovation and alignment. Follow-on research should address this possibility. Third, survey responses were drawn from a convenience sample, rather than a random sample, and a sample size of 61 is relatively small when making statistical inferences from the data. This could have impacted the normality of the investment climate. Fourth, the survey narrowly targeted defense industry applications of PBL. Despite its limitations, the findings are important and, as such, demonstrate the promise of this line of inquiry—which should be expounded. Indeed, the Joint Strike Fighter program will use only PBL for post-production support. With its $1 trillion life cycle cost, the Joint Strike Fighter program is the largest government program ever (Government Accountability Office, 2008). Fifth, future NPS research could test other determinants of PBL effectiveness, such as team innovation, metric appropriateness, and team learning (Geary, Koster, Randall, & Haynie, 2010). In addition, contingency theory could be applied to show contextual differences in PBL effectiveness (Bowersox, 1990; Fawcett, Magnan, & McCarter, 2008; Moorman & Slotegraaf, 1999). Differences could be explored to determine whether PBL effectiveness differs (1) by contract type (i.e., when operators and systems integrators use firm-fixed price versus cost-reimbursement contracts) and (2) by industry. Finally, future research should expand the generalizability of findings by expanding the population beyond defense systems.

4. Study 2: Determining the Optimal Price, Length, and Investment of a PBC

4.1. Overview

Performance-based contracting (PBC) has altered the fundamental relationship between buyers and suppliers engaged in the support of capital-intensive systems, such as high-speed rail, defense, and power generation. This shift is a movement away from a traditional transactional-based (return-on-sales) business approach and a movement toward a collaborative, performance-based (return-on-investment), multi-year contractual model. With PBC, the supplier is compensated for system performance, rather than for each maintenance, repair, and overhaul (MRO) transaction. The success of the PBC approach lies in the incentive structure. Under PBC, the profits are highest, performance is improved, and operator costs are ultimately reduced when smart investment decisions are made that trade year-after-year MRO costs for upfront investments that reduce total cost of ownership. The amount of money to invest in improving the system performance is both an important design decision and a critical business decision that must be made prior to engaging in a PBC. This strategic investment decision is bound by five key variables: (1) PBC contract length, (2) initial system reliability,(3) willingness of a customer to engage in a PBC at a given offering price, (4) multi-year price break, and (5) average and variability of the cost to perform a maintenance task.

4.2. Model

A decision-theoretic model was developed that determined the optimal contract length, optimal investment, and pricing strategies for performance-based, post-production service contracts that simultaneously maximize the profit to the supplier while satisfying the customer's needs. The model accounted for reliability as a function of investment and the average and variance of the cost to perform maintenance tasks, and for customers' willingness to pay for a contract depending on its length. For a detailed discussion on the decision theory and mathematical model used to determine the optimal price, contract length, and investment see Appendix B.

4.3. Key Findings and Business Implications

Optimal strategies depend on potential market size, expected cost per failure, and other parameters of the model. In summary, the following conclusions can be drawn:

- Optimal investment is an increasing function of the expected cost per failure, market size, and customers' willingness to pay, but is a decreasing function of the initial reliability.
- Optimal periodic contract fee is an increasing function of the contract's length, customers' willingness to pay, and an expected cost per failure, but is a decreasing function of the initial reliability and market size.
- Longer post-production service contracts require higher optimal investments, but provide higher system reliability.
- Optimal contract length is a decreasing function of the discount per period, expected cost per failure, and marginal investment parameter, and it is an increasing function of the market size and the maximal price that customers are willing to pay for a single-period contract.

4.4. Future Research

We believe this is just the beginning of an area of research that focuses on managerial decisions at the intersection of system design, supply chains, and sustainment. Cost avoidance strategies run the gamut from improving the reliability of a system to investing capital into spares to satisfy a customer's requirements. A possible research question is how to optimally allocate funds among competing cost avoidance alternatives? As it relates to PBC, a future area of research is to determine how to invest in these competing, and sometimes complementary, cost avoidance alternatives to increase the likelihood of contract capture and to further increase profit. We also wonder if the PBC environment represents a Nash Equilibrium, and, if so, how game theory might be used to explain and predict PBC market behavior.

5. Study 3: Determined Optimal Investment Strategies in System Design and Supply Chain Improvements

Our initial research focus was to develop analytical models to evaluate the trade-offs at the intersection of a system's architecture and its support network. Central to this problem was the ability to solve complex equations that spanned the PBL ecosystem.

5.1. Improving the Computational Efficiency of Multi-Echelon Technique for Recoverable Item Control (METRIC) Inventory Optimization Problems

5.1.1. Overview

We developed a new heuristic algorithm to improve the computational efficiency of the general class of Multi-Echelon Technique for Recoverable Item Control (METRIC) problems. The objective of a METRIC-based decision problem is to determine systematically the location and quantity of spares that either maximize the operational availability of a system subject to a budget constraint or minimize the system's cost subject to an operational availability target. This type of sparing analysis has proven essential when analyzing the sustainment policies of large-scale, complex repairable systems, such as those prevalent in the defense and aerospace industries. Additionally, the frequency of these sparing studies has recently increased as the adoption of performance-based logistics (PBL) has increased.

5.1.2. Model

We developed and validated a practical algorithm for improving the computational efficiency of a METRIC-based, inventory optimization approach. Details on the underlying theory and mathematical development of this novel, heuristic model are in Appendix C.

5.1.3. Key Findings and Business Implications

The accuracy and effectiveness of the proposed algorithm were analyzed through a numerical study. The algorithm showed a 94% improvement in computational efficiency while maintaining 99.9% accuracy.

PBL represents a class of business strategies that converts the recurring costs associated with maintenance, repair, and overhaul (MRO) into cost avoidance streams. Central to a PBL contract is a requirement to perform a business case analysis (BCA), and central to a BCA is the frequent need to use METRIC-based approaches to evaluate how a supplier and customer will engage in a performance-based logistics arrangement where spares decisions are critical. Due to the size and frequency of the problem, there exists a need to improve the efficiency of the computationally intensive METRIC-based solutions.

5.2. A System-of-Systems Design Decision under a Performance-Based Supplier-Customer Relationship

5.2.1. Overview

More often, the design community, often spearheaded by systems engineers, and the sustainment community are looking collaboratively for more cost- effective and profitable ways to provide simultaneously a better performing system and improved post-production support to their customers (Nowicki et al., 2008; Randall, Nowicki, & Hawkins, 2011; Randall et al., 2010). In times of shrinking margins, reduced funding, and increased competition, it makes sense that managers would seek innovative strategies to facilitate such competitive challenges. Performance-based logistics (PBL), also known as performance-based contracting (PBC) or power by the hour (PBH), is successfully providing new sources of customer value and supplier network profitability in the arena of complex system post-production support (also called sustainment).

A natural trade-off space exists between the system design and the makeup of the post-production support network necessary for its successful, on-going operation. Within this trade-off space reside competing investment opportunities. An example includes investing in improved system reliability (e.g., redundancy, higher quality components, etc.) with the consequence of avoiding out-year support costs (e.g., spares, transportation, etc.) On the other hand, investments in the support network (e.g., more spares, faster replenishment times, etc.) may provide the same desired system-level effect without the investment of more time and money in the research, design, and development cycles. Competing and complimentary desired system performance attributes often exist, such as reliability, maintainability, availability, life cycle cost, and logistics footprint. Design and support decisions are often made in isolation of each other and are often made with the consideration of only one system-level performance measure. We have made progress on developing multi-objective, decision support models to assist decision-makers. These models simultaneously consider the effects on system design and its post-production support network.

5.2.2. Model

We are in the process of developing a meta-heuristic model that enables optimal design decisions to be made when evaluating competing design alternatives using an analytical method capable of simultaneously considering multiple criteria. The proposed meta-heuristic model is an evolutionary algorithm defined in an iterative, four-step process. These four steps are based on the generation of the system design configuration via Monte Carlo (MC) simulation, solution analysis, and estimation of the system-level, profit-based spares algorithm to provide the necessary support to the system. This is accomplished with a new meta-heuristic algorithm that drives the simultaneous selection of a primary system configuration (where and how much redundancy to design in) and design of the enabling support network (location and quantity of spares). For details on the theoretical development of this new, evolutionary algorithm see Appendix D.

5.2.3. Key Findings and Business Implications

This is an on-going research effort. We are in the process of testing our model. When the model is complete, we will then be in a position to uncover key findings as we attempt to examine real-world problems and exercise the model to make inferences about trade-offs between system design and support network investments.

In this research, we adopted the perspective of an original equipment manufacturer (OEM) who would like to choose a design, from competing design alternatives, that simultaneously examines five fundamental systems engineering metrics—availability, reliability, maintainability, supportability, and total ownership cost. Existing design evaluation models only consider one metric, and possibly two, as an objective to make a design decision. With the continuing emphasis on PBL contracts, it is now even more imperative that design decisions are made in the presence of competing system-level performance metrics in order to judge both profitability and the ability to satisfy customer requirements.

6. Project Accomplishments

6.1. Publications

6.1.1. Journal

Nowicki, D.R., Randall, W. S., & Ramirez-Marquez, J. E. (2011a). A system of systems design decision under a performance based supplier customer relationship (Working paper).

Nowicki, D. R., Randall, W. S., & Ramirez-Marquez, J. E. (2011b). Improving the computational efficiency of metric-based spares algorithms. *European Journal of Operational Research.* Manuscript submitted for publication.

Randall, W. S., Hawkins, T. G., & Nowicki, D. R. (2011). Explaining the effectiveness of performance based logistics: A quantitative examination. *International Journal of Logistics Management*, *22*(3).

6.1.2. Conference Proceedings

Nowicki, D. R., Murynets, I., Ramirez-Marquez, J. E., & Randall, W. S. (2011). Optimal cost avoidance investment and pricing strategies for performance based post-production service contracts. In *Proceedings of the Eighth Annual Acquisition Research Symposium*. Monterey, CA: Naval Postgraduate School.

6.2. Presentations

Nowicki, D. R., & Randall, W. S. (2011). *Service and product design*. Presented at the Wharton Service Supply Chain Thought Leadership Forum, Wharton School of Business San Francisco, CA.

Randall, W. S. (2011). *A framework for a PBL system of systems approach.* Presented at the Military Logistics Summit, Institute for Defense and Government Advancement (IDGA), Washington, DC.

Randall, W. S., Geary, S. R., & Nowicki, D. R. (2010). *Profitability, competition, transaction costs, and PBL.* Paper presented at the Defense Logistics Conference: Resetting for the Future of Logistics, Arlington, VA.

6.3. Doctoral Student Research Supported/Supervised

Murynets, I. (2010). *Optimal investment and marketing strategies for technologically innovative services* (Doctoral dissertation). Available from ProQuest Dissertations and Theses database. (UMI No. 3428880)

Hernandez, I. *Emergency preparedness framework: A multi-objective approach.* Doctoral dissertation in progress.

6.4. Awards

Best Dissertation in the School of Systems and Enterprises

Awarded to Ilona Murynets for her dissertation, *Optimal Investment and Marketing Strategies for Technologically Innovative Services*. Part of her dissertation focused on investment and pricing strategies for performance-based, post-production support contracts.

Appendix A. A Multiple Regression Model used to Uncover PBC Key Characteristics and Metrics

The material we present in this appendix elaborates on the how we developed a theoretical model to evaluate the relevance of five hypotheses in uncovering key characteristics and metrics of PBL effectiveness. We tested five hypotheses using linear multiple regression:

H1: There is a positive relationship between investment climate and PBL effectiveness.
H2: Relational exchange positively influences PBL effectiveness.
H3: PBL leadership positively influences PBL effectiveness.
H4: Business sector affects PBL effectiveness.
H5: Measures of PBL effectiveness and enablers of PBL will be greater for PBL than for traditional post-production support.

Consistent with Hair, Black, Babin, Anderson, and Tatham (2010), the scale items were summed on each construct and introduced into the regression analysis. We tested the pertinent assumptions of regression (i.e., normality, heteroscedasticity, and independence of error terms) as follows. Since the sample size was small, we applied the Shapiro-Wilks test of normality. Only relational exchange was normally distributed; thus, the remaining metric constructs were transformed (PBL Effectiveness–cubed; PBL Leadership–squared; Investment Climate–squared). Only Investment Climate did not achieve a non-significant Shapiro-Wilks statistic ($p < 0.02$). Next, we tested the constructs for homoscedasticity using the Levene's test (1.59; $p < 0.25$). Results indicated satisfaction of the assumption of constant error variance. Finally, we examined the Durbin-Watson statistic (2.24) to ensure that error terms were independent. Since it was within the range of 1.5 to 2.5, we concluded that the error terms were independent. Although the independent variables were significantly correlated, all of the variance inflation factors were less than 1.7, indicating that multicollinearity did not pose a problem. Table A1 displays parameter estimates, significance levels, and the explanatory power of the model. The model is given in Equation 1:

$$Y^3 = b_0 + b_1X_1^2 + b_2X_2 + b_3X_3^2 + b_4X_4 + \varepsilon_{i,} \quad (1)$$

where:
Y = PBL Effectiveness (PBL)
X_1 = Investment Climate (IC)
X_2 = Relational Exchange (RE)
X_3 = PBL Leadership (L)
X_4 = Business Sector

Variable X_4 was a dummy variable with the for-profit firms serving as the reference group (coded 0). With a negative coefficient, the not-for-profit group shows lower PBL effectiveness (summated scale mean 31.90) than does the for-profit group (mean 37.96). As an additional test of H_4, we tested the differences in the three key enablers of PBL using ANOVA. Only PBL leadership differed ($F = 17.64$; $p < 0.001$) with the for-profit sector exhibiting significantly greater PBL leadership (mean 12.02) than the not-for-profit sector (mean 9.63). As seen in Table 1, all four predictors show significant path estimates, with relational exchange having the greatest effect on PBL effectiveness. Additionally, a respectable amount of variance in PBL effectiveness (53%) was explained by the four independent variables. Given these results, the four main hypotheses were supported. Correlations among the constructs are shown in Table 2. In nearly all items, the means of PBL exceed those of traditional post-production support. Thus, support is found for hypothesis five.

Table 1. Regression Results

DV: PBL Effectiveness	Standardized Coefficient	t	*P* > |t|	Sig.
Intercept	-8939	-0.74	0.46	
Explanatory Variables:				
Investment Climate	0.21	2.04	0.046	**
Relational Exchange	0..35	3.51	0.001	*
PBL Leadership	0..22	1.89	0.064	***
Business Sector	-0.28	-2.73	0.009	*
Adjusted R2	0.53			
Prob > F	17.86		.000	*

Note: Significance level * < 0.01, **< 0.05, ***< 0.10

Table 2. Correlation Matrix

	Investment Climate	Relational Exchange	PBL Leadership	PBL Effectiveness
Investment Climate	0.86			
Relational Exchange	0.34*	0.64		

PBL Leadership	0.44*	0.31**	0.74	
PBL Effectiveness	0.46*	0.44*	0.55*	0.94

Note: Values on the diagonal represent the construct's reliability.
*Significant, $p < 0.01$
**Significant, $p < 0.05$

Appendix B. Developing a Decision-Theoretic Model to Determine a PBC Optimal Price and Contract Length

The material we present in this appendix elaborates on how we developed the decision-theoretic model to determine the optimal price, contract length, and investment of a PBC.

Suppose a supplier offers a system for sale to its addressable market M with each potential customer having the option to engage in a post-production service contract. The salable system has an initial reliability of r_0; however, the supplier has the ability to improve the system design by investing x toward increasing the system's reliability according to $r(x)$, where $r(x) \geq r_0$. A customer purchasing the system is offered a post-production service contract at a fixed periodic fee p in exchange for a full complement of maintenance services. If the customer purchases the post-production contract, then the customer receives the system, with reliability $r(x)$, and the supplier is now responsible for the costs and risks associated with sustaining the proper operation of the system over the length (k) of the contract. A supplier's addressable market consists of M potential customers whose willingness to pay the periodic fee for the post-production service contract directly depends on the reliability of the system $r(x)$ and on the length of the service contract k. Let $w_{r(x),k}(v)$, $v > 0$ be the probability density function of reservation fees, that is, the maximum fee that a customer is willing to pay for the k-period contract if the system reliability is $r(x)$. A customer buys the post-production service contract if the supplier's actual periodic contract fee p is less than or equal to the customer's reservation fee. The fraction of the M potential customers that will engage in a post-production service contract of length k with the supplier is

$$W_{r,k}(p) = \int_p^\infty w_{r(x),k}(v)\,dv. \tag{2}$$

The total profit to the supplier, assuming the supplier invests x into improving the reliability of its system's design is

$$\Pi(x,p,k) = M\sum_{j=1}^{l}\frac{1}{(1+i)^j}(p - f(r(x)))\int_p^{\infty} w_{r(x),k}(v)dv - x\,, \tag{3}$$

where p is a periodic contract fee, i is an interest rate; and $f((r(x))$ is the total cost of all system failures for a single period within a k-period contract given that the system has a reliability of $r(x)$.

Model Notation and Assumptions

The new decision-theoretic post-production service model developed in Appendix B, is greatly influenced by the reliability of the system the supplier is contracted to sustain, the cost to the supplier each time a maintenance action is required, the supplier's total ownership cost of a system failure, and the willingness of a customer to engage into a post-production service contract with the supplier. Each of these variables are discussed Table 3 highlighting the defining assumptions and key interrelationships.

Table 3. Notation

M	number of potential customers
k	length of a contact
m	inumber of missions in a single time period of a contract of length k
r_0	initial reliability of the system for the mission time t_m
$r(x)$	reliability of the system for a cost avoidance investment of x
γ	marginal investment parameter
$f(r(x))$	total cost of all system failures for a single period, given that the system has a reliability $r(x)$
μ_c	average cost per failure
σ_c	standard deviation of the cost per failure
p	periodic contract fee
i	interest rate
d	discount per period expected by customers
λ	maximal fee that customers are willing to pay for the single-period contract if $r(x) = 1$
$w_{r(x),k}$	probability density function of customers reservation fees
$W_{r(x),k}(p)$	fraction of customers that will engage in the k-period contract with the periodic fee equal to p and the reliability of the system is $r(x)$
$\Pi(x,p,k)$	total profit to the supplier when investing capital x into the system reliability design for a k-period post-production contract with periodic fee p

We made the following four assumptions, denoted by (A1)-(A4):

(A1) The system reliability r depends on cost avoidance investment x in the following way:

$$r(x) = r_o + (1 - r_o)\left(1 - \frac{1}{x/\gamma + 1}\right) = \frac{x + r_o\gamma}{x + \gamma}, \tag{4}$$

Where $\gamma > 0$ is a marginal investment parameter, defined as the marginal investment required to achieve an incremental improvement of system reliability. The function $r(x)$ satisfies the assumption regarding the initial reliability of the equipment ($r(0) = r_0$). The signoid shape of the curve $r(x)$ describes the relationship between system reliability and investment, observed in reality fairly well (Levesque, 2000).

(A2) The cost per failure is a normally distributed random variable with the mean μ_c and variance σ_c^2.

(A3) The expected cost of all system failures per period decreases with reliability improvements is $f(r(x)) = cm(1 - r(x))$, where m is the number of missions in a single time period.

(A4) The customers' reservation fees follow the triangular distribution:

$$w_{r(x)\ k}(v) = \begin{cases} \dfrac{(\lambda(1 - d(k-1))r - p)^2}{(\lambda(1 - d(k-1))r)^2}, & 0 \le p \le \lambda(1 - d(k-1))r \\ 0, & o.w. \end{cases}, \tag{5}$$

where λ is a maximal fee that customers are willing to pay for the contract if reliability of the equipment will be improved to r(x) = 1 and d is a discount per period expected by customers if they buy a multi-period contract. The use of a triangular distribution to represent reservation fees is consistent with the current state of the pricing literature (Kirman, Schulz, Hardle, & Werwatz, 2005).

Optimization

The goal of the supplier is to identify an optimal investment x^*, optimal periodic contract fee p^* and optimal contract length k^* that maximize the supplier's expected profit $E[\Pi(x,p,k)]$ from a k-period contract ($k = 1,...,n$) :

$$E[\Pi(x^*, p^*, k^*)] = \max_{k=1,\dots,n} E[\Pi(x^*, p^*, k)], \tag{6}$$

where,

$$E[\Pi(x^*,p^*,k^*)] = \max_{\{x,p\}\in F_{x,p}} E[\Pi(x,p,k)], \tag{7}$$

with a set of feasible solutions:

$$F_{x,p} = \{\{x,p\} \mid x > 0, 0 \le p \le \lambda)1 - d(k-1)\,)r\}, \tag{8}$$

where the upper bound for the price follows from triangularly distributed customers reservation prices. Under the assumptions (A1)-(A4), an expected profit is given by

$$E[\Pi(x,p,k)] = \begin{cases} \dfrac{MI_k(p(x+\gamma) - \mu cm(1-r_o)\gamma)(p(x+\gamma) - \lambda D_k(x+r_o\gamma))^2}{\lambda^2 D_k^2 (x+r_o\gamma)^2 (x+\gamma)} - x, & 0 \le p \le \lambda L \\ 0, & o.w. \end{cases} \tag{9}$$

where $D_k = (1 - d(k - 1))$ and $I_k = (1 + i - (1 + i)^{-k})/i$.

The optimal investment x^* and the optimal periodic fee p^* for the k-period contract are either critical points determined from the first order necessary conditions:

$$\left.\frac{\partial E[\Pi(x,p,k)]}{\partial x}\right|_{(x^*,p^*,k)} = 0 \text{ and } \left.\frac{\partial E[\Pi(x,p,k)]}{\partial p}\right|_{(x^*,p^*,k)} = 0, \tag{10}$$

or belong to the boundary of the feasible set F_{xp}. With Equation 9, Equation 10 reduces to

$$p = \frac{2\mu cm(1-r_o)\gamma + \lambda D_k X}{3(X - \gamma(1-r_o))} \tag{11}$$

and

$$4M\gamma I_k(1-r_o)\left(X\lambda D_k - cm(1-r_o)\gamma\right)^2 (cm(3X + 2(1-r_o)\gamma) + X\lambda D_k) - 27X^3\lambda^2 D_k^2 (X + (1+r_o)\gamma)^2 = 0 \tag{12}$$

where $X = x + r_0\gamma$. If (x^*,p^*) is a critical point, it satisfies the second order sufficient conditions:

$$\left.\frac{\partial^2 E[\Pi(x,p)]}{\partial^2 x}\right|_{(x^*,p^*)} < 0, \text{and} \left.\frac{\partial^2 E[\Pi(x,p)]}{\partial^2 p}\right|_{(x^*,p^*)} < 0, \tag{13}$$

and

$$\left.\frac{\partial^2 \Pi(x,p)}{\partial^2 x}\frac{\partial^2 \Pi(x,p)}{\partial^2 p} - \frac{\partial^2 \Pi(x,p)}{\partial x \partial p}\frac{\partial^2 \Pi(x,p)}{\partial p \partial x}\right|_{(x^*\, p^*)} > 0. \tag{14}$$

The optimal solution (x^*,p^*) is obtained numerically for all $k = 1, ..., n$ and the optimal contracting period k^* follows from Equation 6.

Appendix C. —A Practical Algorithm to Improve the Computation Efficiency of METRIC Models

The material we present in this appendix provides the underlying theory and mathematical formulation of our new, meta-heuristic algorithm that improves the computational efficiency of METRIC models. Let us start by first defining the notation we used in developing this practical algorithm.

Table 4. Notation

Sets and Indices

E	= set of echelons within the support infrastructure, with index e = 0, 1, 2, …, $\lvert E\rvert$; where $\lvert E\rvert$ is the cardinality of set E, less one;
L^e	= set of locations within echelon e, with index l = 1, 2, …, $\lvert L^e\rvert$; and
I^{le}	= set of items at location l within echelon e, with index i = 1, 2, …, $\lvert I^{le}\rvert$.

Decision Variables

is_i^{le}	= initial stock level of item i at location l within echelon e; and
s_i^{le}	= stock level of item i at location l within echelon e.

Model Parameters

$EBO^{\min}$	= minimum expected backorder value needed to qualify an item for the preprocessing algorithm;
γ	= fraction applied to the EBO of qualified items, $\gamma \in [0,1]$;
n	= number of systems;
$BO(s_i^{le})$	= random variable (r.v.) representing the backorder of item i at location l within echelon e given stock level s_i^{le};
$\mathrm{E}\left[BO(s_i^{le})\right]$	= expected backorder of item i at location l within echelon e given stock level s_i^{le};
$N_i^{le}(t)$	= r.v. representing the demand quantity of item i at location l within echelon e in any fixed interval of length, t;
$\mathrm{E}\left[N_i^{le}(t)\right]$	= expected demand quantity of item i at location l within echelon e in any fixed interval of length, t;
λ_i^{le}	= failure rate of item i at location l within echelon e;
$MTTR_i^{le}$	= mean time to repair item i at location l within echelon e;
UC_i^{le}	= cost of item i at location l within echelon e;
Θ_i^{le}	= average quantity of item i at location l within echelon e in the overall pipeline;
$\Theta_{R\,i}^{le}$	= average quantity of item i at location l within echelon e in the repair pipeline;
$\Theta_{T\,i}^{le}$	= average quantity of item i at location l within echelon e in the transit pipeline;

$\Theta_{BO\,i}^{le}$ = average quantity of item *i* at location *l* within echelon *e* in the backorder pipeline;

r_i^{le} =probability of repairing item *i* at location *l* within echelon *e*;

$\Phi_{R\,i}^{le}$ = average time to replenish item *i* from location *l* in echelon *e-1* to location in echelon *e*; and

$F_{P\,i}^{10}$ = average time to procure item *i* from a vendor to the depot (location 1 in echelon 0).

Algorithm

The objective of the proposed heuristic algorithm is to reduce the number of iterations to determine the location and quantity of spares that are needed to meet a specified operational availability at a minimum cost. This is achieved by bounding each location's stock level from below by its mean demand during lead-time. The solution approach leverages the convexity of the expected investment cost curves beyond the mean demand during lead-time. The risk is that by artificially constraining the search space, the heuristic may never find the true optimal stock levels. This risk, however, is somewhat overstated because the impact on costs of being one or two units from the optimal should not affect the overall costs significantly. This is due to the relative "flatness" of the expected cost functions of METRIC about their minimum values. The benefit is that the number of iterations required to derive the necessary set of stock levels is drastically reduced and, therefore, the algorithm can quickly find a pseudo-optimal solution.

Figure 3 is a flow chart that graphically represents the steps and interactions of this new heuristic algorithm. The major contributions of this research are in Steps 1 and 3.The algorithm reduces the number of iterations to reach a quasi-optimal solution in two ways. First, the algorithm essentially functions as an efficient preprocessor before the augmented METRIC-based approach begins. The algorithm calculates the expected backorder (EBO) for each item at each location assuming no stock level and then identifies which (item, location) combinations are eligible for the preprocessing stage. An (item, location) combination is eligible for the preprocessing stage if its EBO exceeds the minimum EBO threshold, $EBO^{\min}$. The result of the preprocessing stage determines the initial stock levels, is_i^{le}, for each eligible (item, location) combination. The modified METRIC algorithm is then executed with its first iteration assuming these initial stock levels.

Secondly, the algorithm modifies the METRIC-based approaches by potentially adding more than one item at a particular location in a single iteration. For eligible (item, location) combinations identified in Step 1, or for an eligible (item, location) combination chosen within Step 3, the incremental number of spares of an item added to a location is determined by a fraction (γ) of its EBO. The computational efficiency algorithm is heavily influenced by the values for γ and $EBO^{\min}$. Both γ and $EBO^{\min}$ are inputs to the algorithm.

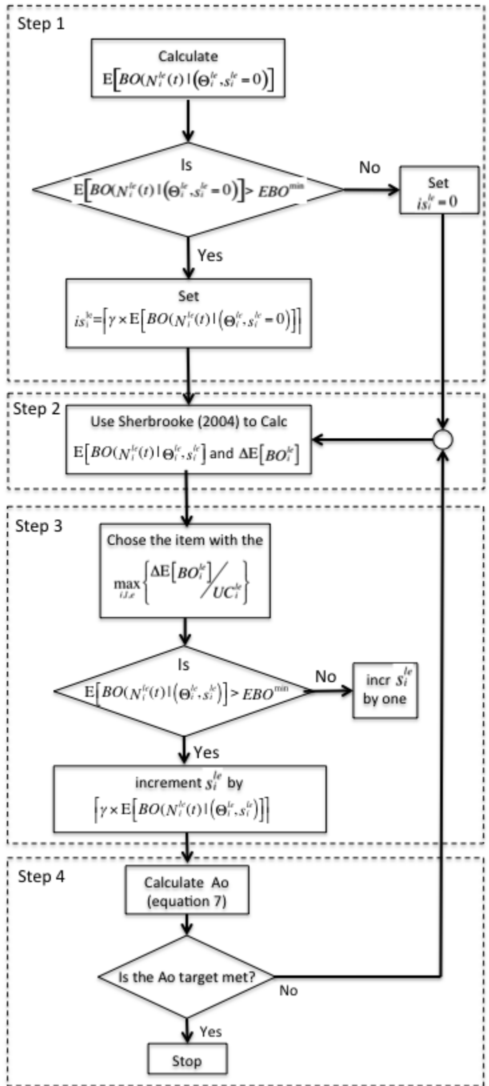

Figure 3. Flow Chart of the Computationally Efficient Algorithm

Details of the 4 step computationally efficient algorithm follow:

STEP 1. Calculate is_i^{le} for each *i*, *l*, *e* combination. For each item *i*, calculate the $\mathrm{E}\left[BO(N_i^{le}(t) \mid (\Theta_i^{le}, s_i^{le} = 0)\right] \forall i,l,e$. If $\mathrm{E}\left[BO(N_i^{le}(t) \mid (\Theta_i^{le}, s_i^{le}) = 0\right] > EBO^{\min}$ then set the initial stock level is_i^{le} to a fraction (γ) of the $E\left[BO(N_i^{le}(t) \mid (\Theta_i^{le}, s_i^{le}=0))\right] \ni is_i^{le} = \left\lceil \gamma \times E\left[BO(N_i^{le}(t) \mid (\Theta_i^{le}, s_i^{le}=0))\right]\right\rceil$; otherwise set $is_i^{le}=0$.

STEP 2. Apply Sherbrooke's (2004) METRIC model, setting the stock values of s_i^{le} equal to is_i^{le} to calculate the $E\left[BO(N_i^{le}(t) \mid \Theta_i^{le}, s_i^{le})\right]$ and $\Delta E\left[BO_i^{le}\right]$ for each I ,l ,e combination. The details of how to derive these expressions are shown in Appendix A.

STEP 3. Choose the (item, location) combination with the largest marginal benefit, $\max_{i,l,e}\left\{\Delta E\left[BO_i^{le}\right] / UC_i^{le}\right\}$, to the support network. Increment the stock level of the chosen (item, location) combination s_i^{le} by $\left\lceil \gamma \times E\left[BO(N_i^{le}(t) \mid (\Theta_i^{le}, s_i^{le}))\right]\right\rceil$ if $E\left[BO(N_i^{le}(t) \mid (\Theta_i^{le}, s_i^{le}))\right] > EBO^{\min}$; otherwise increment s_i^{le} by 1.

STEP 4. Calculate operational availability (Equation 7). If the operational availability meets its target, then stop. Otherwise go back to Step 2.

The result is a pseudo-optimal solution obtained in a fraction of the time compared with any METRIC-based algorithm.

Appendix D. Theory and Mathematical Model Development for a System of Systems Design Decision in the Presence of a Performance-Based Contract

The material we present in this appendix is a detailed discussion on the theory used and the mathematical model developed in support of simultaneously making both system design and support network decisions.

Model

The general problem formulation for maximizing the supplier's profit, within a PBL context, of a series-parallel system is presented as the general model (GM) in Table 5.

Table 5. General Model

$$
\begin{aligned}
&\max \quad Profit(\mathbf{x},\mathbf{s}) = Rev(\mathbf{x},\mathbf{s}) - Cost(\mathbf{x},\mathbf{s}) \\
&s.t. \\
&MTBF(\mathbf{x}) \ge MTBF^T \\
&LF(\mathbf{x},\mathbf{s}) \le LF^T \\
&x_{ij} \in (0,1) \quad \forall\, i \in I, j \in J^i \\
&s_{ij}^{le} \ge 0 \\
&s_{ij}^{le} = integer
\end{aligned}
$$

The intent of the GM is to determine the primary system's (PS) configuration (**x**) and spares allocation (**s**), within the existing support infrastructure (SI) that results in the largest profit to the supplier while respecting the maximum allowable customer's logistics footprint requirements LF^T and minimum mean time between failure $(MTBF^T)$requirement. The SI is represented by the vector **s** where $\mathbf{s} = (s_{11}^{10},\cdots,s_{ij}^{le},\cdots,s_{IJ}^{LE})$ and **x** is the vector representing the configuration of the PS where $\mathbf{x} = (x_{11},\cdots,x_{ij},\cdots,x_{IJ})$.

The revenue portion of the objective function is the result of the revenue paid to the supplier by the customer for the supplier's performance delivered to the customer. Nowicki et al. (2006) introduces revenue into the decision-making process to show how it has a critical impact on spares allocation decisions. The revenue model used here is the reward and penalty model (Brown & Burke, 2000) commonly used in the PBL domain. In this revenue model is expressed as a function of both the configuration of the primary system as well as of the spares profile of the enabling system. The revenue is a function of the SoS performance with $A_o \in (0,1)$ and is bounded by $a \le Rev(A_o(\mathbf{x},\mathbf{s})) \le a + b$.

$$Rev(A_o(\mathbf{x},\mathbf{s})) = \begin{cases} 0 & if \quad 0 \le A_o < A_{\min} \\ a_1 + b_1 \times (A_o - A_{\min}) & if \quad A_{\min} \le A_o < A_{penalty} \\ a_2 + b_2 \times (A_o - A_{penalty}) & if \quad A_{penalty} \le A_o < A_{accept} \\ a_3 + b_3 \times (A_o - A_{accept}) & if \quad A_{accept} \le A_o \le A_{\max} \end{cases}. \tag{15}$$

The cost is the sum of the design cost as well as the support cost. The design cost is the cost to provide items, including the redundant items, in the primary system's design. The support cost is defined here as the total cost of spares needed to populate the support infrastructure to maximize the overall system performance:

$$Cost(\mathbf{x},\mathbf{s}) = \sum_{i=1}^{I}\sum_{j=1}^{J_i}\sum_{l=1}^{L^e}\sum_{e=0}^{E} c_{ij}^{le} \times \left(s_{ij}^{le} + n \times x_{ij}^{le}\right). \tag{16}$$

Under this formulation, the GM is unsolvable using traditional optimization techniques, such as integer programming, since the objective function and the constraints are non linear in nature. The new meta-heuristic SoS algorithm proposed in Appendix D provides a good solution to the general model.

Step 1. Primary System (PS) Design Development

In the PS design development step, simulation is used to generate H potential PS series-parallel design configurations. A specific design is characterized by the vector $\mathbf{x}^h = \left[x_{ij}^h\right]$ for i = 1, …, I; j = 1, .., J_i and h = 1, …, H, where $x_{ij} \in (0,1)$. $\Omega = \left[\Omega_{ij}\right] : \Omega_{ij} = \Pr(x_{ij} = 1)$ is the initial probability of inclusion vector and defines the probability that a redundant component is included in a specific PS design, $\mathbf{x}^h$. A value, a, is randomly generated according to a U(0,1). If $a < \Omega_{ij}$, then $x_{ij}^h = 1$. Otherwise, $x_{ij}^h = 0$. The first step also contains the stopping rule of the algorithm. The algorithm will stop once $\Omega_{ij}^h = 1$ or $\Omega_{ij}^h = 0 \ \forall i \in I, \forall j \in J_i$ (i.e., once all initial "appearance" probabilities are either zero or one).

Assigning initial values to the vector Ω is based on the lack of knowledge regarding which components will actually constitute the final PS configuration to optimally solve the general model. This lack of knowledge, also known as the *Laplace principle of insufficient reason*, translates into initially providing the same probability of appearing in the final solution to each component. Thus, the initial probability of occurrence is $\Omega_{ij}^0 = 0.5 \ \forall i \in I$, where j > 1 and $\Omega_{ij}^0 = 1$ for j = 1, since at least one component in each subsystem needs to function or the system does not function.

Step 2. Performance Analysis

The second step, performance analysis, estimates the profit, MTBF, and logistics footprint for the PS potential designs previously obtained through simulation. This step derives the values for $\mathbf{s}^h$ using the profit-based, multi-echelon, multi-item spares algorithm described in Nowicki et al. (2006). As a consequence of the spares algorithm, the following values are now also known for primary operating system $\mathbf{x}^h$ and for supporting infrastructure $\mathbf{s}^h$: $Profit(\mathbf{x}^h, \mathbf{s}^h)$, $Rev(\mathbf{x}^h, \mathbf{s}^h)$, $Cost(\mathbf{x}^h, \mathbf{s}^h)$, $MTBF(\mathbf{x}^h, \mathbf{s}^h)$, and $LF(\mathbf{x}^h, \mathbf{s}^h)$.

Step 2a. Calculate the pipeline values for the lowest echelon location (i.e., the central inventory location at echelon zero). The central inventory location's pipeline value, $\Theta_{ij}^{10} = d_{ij}^{10} \times \Phi_{\mathrm{P}\,ij}^{10}$, is defined as the average number of items in repair at the central inventory location or requested for procurement from the procurement source.

The Θ_i^{10} is commonly referred to as the expected number of demands during lead-time, where the lead-time is the procurement lead-time $\Phi_{\mathrm{P}\,i}^{10}$. The expected number of demands at the central inventory location in an arbitrary time interval t is stated as

$$d_i^{10}(t) = \sum_{e=1}^{E} \sum_{l=1}^{L^e} \sum_{i=1}^{I} \sum_{j=1}^{J^i} d_{ij}^{le}(t) \times \left(1 - r_{ij}^{le}\right) \times \delta_{ab} \text{ where,}$$

$$\delta_{ab} = \begin{cases} 1 & \text{if} \quad \text{location } l_a \text{ in echelon } e_a \text{ feeds location } l_b \text{ in echelon } e_b\text{, where } a > b \\ 0 & o.w. \end{cases}.$$

Step 2b. The pipeline value is then used to calculate the expected backorder value, $\mathrm{E}\left[BO(d_{ij}^{10}(t) \mid s_{ij}^{10})\right] = \sum_{x=s_{ij}^{10}+1}^{\infty} \left(x - s_{ij}^{10}\right) \times \mathrm{P}\left[d_{ij}^{10}(t) = x\right]$, given a specified stock level at the central, s_{ij}^{10}. When $s_{ij}^{10} = 0$, the expected backorder reduces to Θ_{ij}^{10} with

$$\mathrm{E}\left[BO(d_i^{10}(t) \mid s_{ij}^{10} = 0)\right] = \mathrm{E}\left[BO(d_{ij}^{10}(t = \Phi_{\mathrm{R}\,ij}^{10})\right] = \Phi_{\mathrm{R}\,ij}^{10} \times \mathrm{E}\left[d_{ij}^{10}(t)\right] = \Theta_{ij}^{10}.$$

Step 2c. After the expected backorder for the central inventory location is derived, the expected backorder at each of the locations it supplies with inventory needs to be calculated. For echelons other than the central, the pipeline number is further broken down into three numbers, as expressed in Equation 4. Specifically, pipeline values are the sum of the average number of units in repair expressed in Equation 5, the average number of units in transport in Equation 6, and the average number of units in backorder in Equation 7.

$$\Theta_{ij}^{le} = \Theta_{R\,ij}^{le} + \Theta_{T\,ij}^{le} + \Theta_{BO\,ij}^{le} \tag{17}$$

$$\Theta_{R\,ij}^{le} = d_{ij}^{le}(t) \times r_{ij}^{le} \times MTTR_{ij}^{le} \tag{18}$$

$$\Theta_{T\,ij}^{le} = d_{ij}^{le}(t) \times (1 - r_{ij}^{le}) \times \Phi_{R\,ij}^{le} \tag{19}$$

$$\Theta_{BO\,ij}^{le} = d_{i}^{le}(t) \times (1 - r_{ij}^{le}) \times \frac{\mathrm{E}[BO(d_{ij}^{le}(t) \mid s_{i}^{le})]}{\sum_{l=1}^{L_i} \sum_{i=1}^{I} \mathrm{E}\left[d_{ij}^{le-1}(t)\right]} \tag{20}$$

Step 2d. The pipeline values are then used to derive the expected backorder values for items at each location within each echelon. The average number of units in the pipeline for a fixed period of time can be interpreted as a rate with the fixed period of time as the denominator, assuming a Poisson process. For example, if the average number of units in a pipeline is 10 over a one-year period, this is equivalent to having 10 demands per year. With this in mind, the expected backorder is represented as,

$$\mathrm{E}\left[BO(d_{ij}^{le}(t) \mid \Theta_{ij}^{le}, s_{ij}^{le}\right] = \sum_{x=s_{ij}^{le}+1}^{\infty} \left(x - s_{ij}^{le}\right) \times \mathrm{P}\left[d_{ij}^{le}(t) = x\right] = \sum_{x=s_{ij}^{le}+1}^{\infty} \left(x - s_{ij}^{le}\right) \times \frac{\left(\Theta_{ij}^{le}\right)^{x} \times e^{-\Theta_{ij}^{le}}}{x!} \tag{21}$$

When Equation 21 is evaluated for a stock level of zero, this reduces to simply,

$$\mathrm{E}\left[BO(d_{ij}^{le}(t) \mid \Theta_{ij}^{le}, s_{ij}^{le}\right] = \Theta_{ij}^{le} \tag{22}$$

Step 2e. For values of $s_{ij}^{le} > 0$, Equation 22 is difficult to solve, so the allocation problem will utilize the first difference of the expected backorder; that is, the allocation routine will evaluate the change in the expected backorder when one item is added to stock. First, differences are used to solve Equation 21 recursively, leveraging the known expression in Equation 23:

$$\Delta\mathrm{E}\left[BO_{i}^{le}\right] = \mathrm{E}\left[BO(d_{ij}^{le}(t) \mid \Theta_{ij}^{le}, s_{ij}^{le} - 1\right] - \mathrm{E}\left[BO(d_{ij}^{le}(t) \mid \Theta_{ij}^{le}, s_{ij}^{le}\right] \tag{23}$$

Step 2f. For each subsequent iteration, the quantity of the winning spare, s_{i}^{le}, will increase by $\left|\mathrm{E}\left[\gamma \times BO(N_{i}^{l}(t) \mid (\Theta_{i}^{l}, s_{i}^{l} \neq 0)\right]\right|$.

Step 3. Penalize the Design

The final step in the approach uses a penalty model to penalize the profit of a potential PS design and its corresponding enabling infrastructure when the solutions do not meet either the *MTBF* or *LF* contractual constraints. The resulting value of the penalty model is $Value(\mathbf{x}^{h}, \mathbf{s}^{h})$, representing the combined System of Systems (SoS) value of the primary system configuration, $\mathbf{x}^h$, and the enabling support infrastructure, $\mathbf{s}^h$, expressed as

$$Value(\mathbf{x}^h,\mathbf{s}^h) = \begin{cases} \Psi(\mathbf{x}^h,\mathbf{s}^h) \times Profit(\mathbf{x}^h,\mathbf{s}^h) & if \quad Profit(\mathbf{x}^h,\mathbf{s}^h) \geq 0 \\ Profit(\mathbf{x}^h,\mathbf{s}^h) / \Psi(\mathbf{x}^h,\mathbf{s}^h) & if \quad Profit(\mathbf{x}^h,\mathbf{s}^h) < 0 \end{cases} \tag{24}$$

The composite penalty factor is the multiplication of the *MTBF* and *LF* penalty factors $\Psi(\mathbf{x}^h,\mathbf{s}^h) = \Psi^{MTBF}(\mathbf{x}^h) \times \Psi^{LF}(\mathbf{x}^h,\mathbf{s}^h)$ for each randomly generated series-parallel design alternative $h = 1, \ldots, H$. The penalty factors for each of the two performance metrics *MTBF* and *LF* are defined as

$$\Psi^{MTBF}(\mathbf{x}^h) = \begin{cases} MTBF(\mathbf{x}^h) / MTBF^T & if \quad MTBF(\mathbf{x}^h) \leq MTBF^T \\ 1 & o.w. \end{cases} \tag{25}$$

$$\Psi^{LF}(\mathbf{x}^h,\mathbf{s}^h) = \begin{cases} LF^T / LF(\mathbf{x}^h,\mathbf{s}^h) & if \quad LF(\mathbf{x}^h,\mathbf{s}^h) \geq LF^T \\ 1 & o.w. \end{cases} \tag{26}$$

The solutions are then ranked in decreasing order of magnitude with $Value(\mathbf{x}^{(1)},\mathbf{s}^{(1)}) \geq Value(\mathbf{x}^{(2)},\mathbf{s}^{(2)}) \geq \cdots \geq Value(\mathbf{x}^{(h)},\mathbf{s}^{(h)}) \geq \cdots \geq Value(\mathbf{x}^{(H)},\mathbf{s}^{(H)})$. A subset of size β of the whole set of solutions (H) is then used to update $\Omega_{ij} \leftarrow \Omega_{ij} = \sum_{b=1}^{\beta} x_{ij}^{(b)} / \beta \ \forall i \in I, \forall j \in J_i$. The updated Ω is then used as the new starting condition.

The subsample size β is used to update the probabilities defined by the initial probability vector Ω. The rational for setting this value is based on work developed by Bäck and Schwefel (1996) and Schwefel and Bäck (1995) in the area of evolutionary strategies and its application to optimization algorithms that imitate certain principles of nature. In this respect, a population of individuals (a possible PS configuration in the context of the present research) collectively evolves toward better solutions by means of a parent's selection process, a reproduction strategy, and a substitution strategy.

These studies, Bäck and Schwefel (1996)and Schwefel and Bäck (1995), define a type of evolutionary strategy, where μ initial individuals generate λ offspring and selection takes place only among these λ offspring. They suggest a ratio of $\lambda / \mu \approx 7$ as a good setting for the relation between parent and offspring population size. The meta-heuristic algorithm developed in this paper works in a similar fashion since from a sample (H) of potential PS designs, the algorithm selects B among the best configurations, according to the penalized profit factor $Value(\mathbf{x}^h,\mathbf{s}^h)$.

This means that, for example, from 100 potential PS designs, the best 14 configurations are selected.

Penalization Factor (ψ)

The penalization factor (ψ) is fundamental in deriving a good solution that determines the PS design (the type and amount of redundancy in a series-parallel configuration) and its corresponding support infrastructure (quantity and location of spares). The intent is clear: maximize the supplier's profit while adhering to contractually agreed upon constraints represented in this research by *MTBF* and *LF*. With the evolutionary nature of this algorithm, it is crucial to establish a basis of comparison to evaluate competing PS design configurations. The overall objective is to decide on a PS design configuration (**x**) and corresponding support infrastructure (**s**) that maximizes profit, *Profit*(**x,s**). However, some of the competing designs may not meet specified contractual constraints and must be accessed a penalty. Herein is the underlying rationale for defining a penalization factor (ψ). The penalty factor adjusts the profit contribution of a competing design in the following manner:

$$Value(\mathbf{x}^h,\mathbf{s}^h) = \begin{cases} \Psi(\mathbf{x}^h,\mathbf{s}^h) \times Profit(\mathbf{x}^h,\mathbf{s}^h) & if \quad Profit(\mathbf{x}^h,\mathbf{s}^h) \geq 0 \\ Profit(\mathbf{x}^h,\mathbf{s}^h) / \Psi(\mathbf{x}^h,\mathbf{s}^h) & if \quad Profit(\mathbf{x}^h,\mathbf{s}^h) < 0 \end{cases} \tag{27}$$

If a profit exists, $Profit(\mathbf{x}^h,\mathbf{s}^h) \geq 0$, it is fractionally reduced by the penalty factor, $\Psi(\mathbf{x}^h,\mathbf{s}^h)$. If there is a deficit, $Profit(\mathbf{x}^h,\mathbf{s}^h) < 0$, the profit is also reduced. However, since the profit is a negative value, the value of the profit reduction is determined by dividing the profit by its corresponding penalty factor. As mentioned previously, the penalty factor is a function of not meeting one or both of the specified contractual performance parameters, LF^T or $MTBF^T$:

$$\Psi(\mathbf{x}^h,\mathbf{s}^h) = \Psi^{MTBF}(\mathbf{x}^h,\mathbf{s}^h) \times \Psi^{LF}(\mathbf{x}^h,\mathbf{s}^h) \text{ where,} \tag{28}$$

$$\Psi^{MTBF}(\mathbf{x}^h,\mathbf{s}^h) = \begin{cases} MTBF(\mathbf{x}^h) / MTBF^T & if \quad MTBF^T \leq MTBF(\mathbf{x}^h) \\ 1 & o.w. \end{cases}; \tag{29}$$

$$\Psi^{LF}(\mathbf{x}^h,\mathbf{s}^h) = \begin{cases} LF^T / LF(\mathbf{x}^h,\mathbf{s}^h) & if \quad LF^T \leq LF(\mathbf{x}^h,\mathbf{s}^h) \\ 1 & o.w. \end{cases}. \tag{30}$$

Both the *LF* and *MTBF* penalty factors only have an impact when their respective target values are not achieved, that is, when either $MTBF^T \leq MTBF(\mathbf{x}^h)$ or $LF^T \leq LF(\mathbf{x}^h,\mathbf{s}^h)$. There is no additional positive contribution to the profit margin associated with overreaching either the *LF* or *MTBF* performance metrics.

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