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RESEARCH ARTICLE

Simultaneous Consideration of System Design and Post-Production Support Network Decisions in the Context of a Performance-Based Contract

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ABSTRACT In times of shrinking margins, researchers are looking for more cost-effective and profitable ways to improve the post-production support of large-scale, complex systems. There is an inherent tradeoff between the system design and the design's long-term support. A system's design largely determines its reliability that, in turn, influences the demands on its post-production support network necessary to maintain the proper use of the system over its intended, economic useful-life. Performance-based contracts are a successful financial instrument between suppliers and buyers for long-term support contracts. This research leverages the tenets of performance-based contracting, especially its foundation in transactional cost economics and management control theory, and agency theory, to develop and test an analytical model. This research proposes a novel, analytical model that maximizes the profit margin of a large-scale, complex system simultaneously considering its design and post-production support network. To date, these decisions are largely understudied. This model uses redundancy allocation to represent a design decision, and the post-production support network decisions are the location, quantity of spares, and logistics footprint. The post-production support network is a non-arboreal, multi-echelon sustainment network, and the design is a series-parallel configuration. The model is constrained by customer-specified, minimum reliability, mean-time-between-failure (MTBF), and a maximum logistics footprint (LF) measured in pounds. A meta-heuristic algorithm was used to address the nonlinearity of the objective function and constraints. Afterward, a numerical example was solved, and comparative experiments were conducted to test the algorithm. The results showed a profit for the supplier of $14,505.12 with 78.45 hrs of MTBF out of the 75 hours minimum allowed and a logistic footprint of 6,285.25 lb. out of the 10,000 lb allowed. The solution demonstrates the economic importance of system engineers, contract personnel, and program managers in understanding the inherent tradeoff space connecting the design and support of a system.

INDEX TERMS Inventory optimization, performance-based contracting, reliability, supply chain networks, systems theory.

I. INTRODUCTION

Increasingly the design community, often spearheaded by systems engineers, and the sustainment community is collaboratively looking for more cost-effective and profitable ways to simultaneously provide a better-performing system and improved post-production support to their customers. In times of shrinking margins, reduced funding, and increased competition, it makes sense that managers would seek innovative strategies to facilitate such competitive challenges. One such emerging strategy is performance-based contracting (PBC); especially in capital-intensive systems such as

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aerospace, defense, energy, healthcare, highway/railway, etc [1]. PBC is otherwise known as "Performance-based logistics" (PBL) [2], "Availability Contracting" [3], "Contract for Availability" [4], "Performance-based Service Acquisition" [5], and "Outcome-based Contracting (OBC)" [6].

Traditionally, post-production contracts are consistent with Transactional Cost Economics (TCE), where suppliers perform maintenance on a system and the buyer provides remuneration for each maintenance action. With PBC, the underlying theoretical lens of TCE is now replaced through agency theory and the theory of incentives, where suppliers are financially incentivized to provide outcomes to the buyer. So, the supplier is no longer compensated for each maintenance transaction completed, but rather, rewarded or penalized based on system performance outcomes [7].

As a buyer-supplier contractual strategy, the use of PBC is present in public and private sectors [8], [9]. For example, PBC is used for the procurement and maintenance of highway and railway infrastructure [10], [11], [12], [13], [14], health and social care [15], energy [16], [17], manufacturing [8], defense [18], and aerospace [19]. The U.S. Department of Defense (DoD) has been using PBC as the preferred sustainment strategy since 2001 [20]. Using PBC across different industry sectors shows a 25-40% increase in reliability, a 10-20% reduction in the cost per unit of performance, and operational availability improvements [2], [21].

PBC has been successful in generating buyer value and the supplier-buyer network profitability; most notably for complex, hight-cost systems where the cost of sustaining the system over its economic, useful-life far exceeds its cost of research, development, and production [8], [22]. PBC aims to make a supplier deliver performance outcomes as specified by key performance indicators (KPI) for the contracted work while creating incentive schemes through longer contracts and opportunities for cost avoidance [22]. For example, Rolls-Royce created a "power-by-hour" (PBH) program for its airplane engines where it is responsible for the availability of the engines, performing the necessary engine maintenance, repair, and overhaul, and the buyers of the engines pay Rolls-Royce based on each flight hour it uses its engines [6]. Another company that can exhibit how PBC generates value is General Electric (GE). They implemented a condition-based monitoring and maintenance service agreement for their pressure control equipment service business instead of having a calendar and event-based maintenance. This allowed GE to share some of the operating risks with its customers and offered a risk-adjusted value proposition while gaining more control over the condition and maintenance of its equipment.

Redundancy in spare allocation for maintenance purposes is essential to secure high system reliability and operational availability. Solving spares allocation in a multi-echelon supply chain is a complex problem because every decision made in one echelon affects both upstream suppliers and downstream buyers within the supply chain. To date, spares allocation in a multi-echelon supply chain has been solved to minimize logistics costs or maximize the availability of spares through efficient inventory placement between echelons [23]. Researchers have used a variety of constraints or requirements to solve the spares allocation problem, such as lead time variability [24], a number of service engineers needed to do the replacement [25], disruptions in different echelons of the supply chain [26], budget constraint [27], or demand variability [28], among others.

One of the main objectives of PBC is to reduce the Mean Time Between Failure (MTBF) and, consequently, improve the service process and reduce costs [7]. However, studies have focused on balancing reliability and maintenance effectiveness. A broader perspective considering sustainability aspects in multi-year contracts or including resilience is missing [29]. In addition, environmental sustainability aspects must emerge as a requirement in PBC. Wang et al. [30] developed a model for deteriorating production systems operating under PBC. In this model, the customer offers PBC payments while the supplier implements Conditioned-based maintenance (CBM), which represents periodic inspections and sets an investment for spare parts. They proposed a two-staged heuristic approach to maximize utilities for both stakeholders. PBC strategy leverages long-term relationships to turn year-after-year sustainment cost avoidance into a potential return on investment [1]. To that end, this manuscript's objective is to propose a new algorithm that, when solved, allows system engineers and managers to understand the impact that design and, mainly, system redundancy have on total life-cycle costs associated with spare inventories. The algorithm, coupled with the correct support strategy, broadens the effective "market potential" through outcome-based multi-year contracts, such as PBC.

Systems engineers are increasingly adopting a System-of-Systems approach when describing the interaction between the design of a system, the system operation, and the post-production support network necessary to sustain the operation of that system. The system and its necessary post-production support network combined provide outcome-based value (e.g., operational availability) to the buyer of the system at a profit that is acceptable to the supplier. There is substantial research in the extant literature when system design (redundancy allocation) and post-production support network (quantity and location of spares) decisions are considered separately. However, to date, the complexities of simultaneous consideration of system design and post-production support network decisions are largely understudied. A critical aspect of system design involves determining the impact of system design and redundancy on sparing. These decisions are critical to providing customer value and maximizing profit through multi-year, fixed-price contract cost avoidance [1].

This paper addresses these complexities by defining a novel, analytical model that maximizes the profit margin of a large-scale, complex system simultaneously considering its design and post-production support network. This model uses redundancy allocation to represent a design decision, and the post-production support network decisions are the location, quantity of spares, and logistics footprint (LF). The post-production support network is a non-arboreal, multi-echelon sustainment network, and the design is a series-parallel configuration. Specifically, the model is constrained by buyer-specified, minimum reliability, measured as the mean-time-between-failure (MTBF); and a maximum logistics footprint (LF), measured in pounds.

As aforementioned, redundancy allocation models in the extant literature focus only on component reliability and not the effects reliability (or non-reliability) has on spares [31]. As components fail, demands are generated on a system's post-production support network that includes spares. Our proposed analytical model considers this linkage.

The primary research question guiding this study is:

- Is it more advantageous to develop system support mechanisms and system design in conjunction rather than independently?

Along with the following sub-questions:

1) How does the integrated development of post-production support network and design impact overall system performance and reliability?
2) What are the cost implications of a conjoint development approach compared to separate development?

Compared with the extant literature, the main contributions of the present paper are summarized as follows:

- We develop an analytical model that maximizes the profit margin of a large-scale, complex system while considering its design and post-production support network.
- We propose a meta-heuristic algorithm that determines the level of redundancy in each subsystem and the quantity and location of spares to support the system's operation.
- We include environmental sustainability aspects regarding the logistics footprint as a constraint in the model.
- We evaluate the proposed model through a numerical example and compare different feasible solutions to provide a better understanding of the model and its managerial insights.

The remainder of this paper is organized as follows: Section II reviews the relevant redundancy allocation problem and PBC literature. Section III presents the notation used in this paper. It also describes the relationship between the system design and its post-production support network and briefly describes the performance metrics used in the analytical model. Section IV explains the analytical model and the proposed meta-heuristic algorithm to solve it. Section V shows a numerical study implementing the model and its results. In addition, we present several managerial insights in Section VI. Finally, this paper concludes in section VII with conclusions and future research.

II. BACKGROUND

The motivation of the present research and the relevant existing literature are presented in this section.

A. REDUNDANCY ALLOCATION PROBLEMS

Redundancy allocation is a system design problem that determines whether redundancy is necessary and, if necessary, where to locate it in the design. The intent is to optimally assign redundancy within the system design to meet a buyer-specified reliability target at a minimum cost or to maximize the system reliability given a budget constraint. The reliability allocation problem (RAP) is best addressed early in the design process, with the greatest opportunity to influence cost and performance.

Kennedy et al. [32] did a literature review on spare parts inventory for supporting infrastructures. They pointed out that a critical design decision involves choosing the ideal number of redundant equipment to design into the primary system. If there are sufficient redundant parts to achieve a reliability design target, it may be possible to replace all failed parts at a single point in time. There are other literature reviews on spare parts inventory, mostly focused on forecasting for inventory planning and spare parts classification [23], [33]. A recent literature review on solving the RAP reviewed 275 papers [34] where authors used different system configurations, performance measures, problem formulations, and solution methods. For example, several authors used a genetic algorithm (GA) to achieve a solution or a modified version of GA [35], [36], and others developed a solution space reduction procedure and a branch-and-bound algorithm to obtain a solution, which implicitly enumerates the solutions [37]. The latter method has yielded optimal results but requires potentially inefficient enumerations. Other approaches to solve the RAP include several types of simulations, from Monte Carlo simulation to stochastic simulation combined with neural networks and GA [38], [39], [40]. A recent review paper show the spares allocation gap between modelling and application and, between theory and practice. In their search, they included maintenance-policy classes and inventory optimality rules because they argue that the gap between theory and practice is growing due to the increasingly complicated mathematical problems [41].

Hemmati et al. [42] solved the RAP as a multi-objective problem, maximizing the MTBF and minimizing the system's total cost. Their multi-objective algorithm, named Multi-Objective Harmony Search (MOHS), saves CPU time compared to the Non-dominated Sorting Genetic Algorithm (NSGA-II) and Non-dominated Ranked Genetic Algorithm (NRGA). In this study, we implemented Monte Carlo simulation to generate potential series-parallel system design configurations. Later, the algorithm evaluates whether this design satisfies the MTBF and LF constraints.

Allocation of spares in isolation, without regard to the total ownership cost, invariably leads to a suboptimal design. Hadel et al. [43] point out that all system-level requirements must be addressed simultaneously to ensure those requirements are optimally addressed within design constraints. They developed a multi-step technique. First, a Customer Quality Model (CQM) is created that uses a modified Quality Function Deployment. Using the CQM, a numerical allocation of customer-specified, system-level requirements is performed. With PBC, the focus is now on the supplier to reduce the system design's present and future economic considerations while guaranteeing buyer-specified system performance.

B. PERFORMANCE-BASED CONTRACTING

PBC focuses on the supplier's post-production support of the system the supplier delivered to the buyer [44]. PBC is especially relevant for sustaining large-scale complex systems present in the aerospace, defense, aircraft, and utility industry sectors. This strategy has been adopted due to an increase in the number of end-users, operators, original equipment manufacturers (OEMs), and sustainment service providers who are faced with longer service life cycles, higher costs, and demand for improved system performance [45]. Practitioners attribute billions of dollars in post-production support savings to PBC [46].

Post-production support costs are a significant and profitable part of the economy [22]. Using a PBC strategy, supplier networks, and their buyers are adopting the traditional return on sales of repair, spare, and overhaul revenue model. Instead, these buyer-supplier partnerships engage in long-term contracts that tie compensation to performance using a return on investment business strategy. This makes sense, especially for those high-cost, repairable, complex systems (e.g., high-speed rail, defense systems, telecommunication) whose support costs often exceed their research, development, and production costs [22]. Savvy system operators and buyers see the line-by-line and year-by-year sustainment costs associated with these systems as a tool to encourage the supplier network to invest in reducing system cost while improving system performance for the buyer [22]. In the traditional post-production support strategy, not only the supplier is charged at the beginning of the project but also charged for each service it performs to sustain the system, in which the profit is linked to the post-production services of the sale of parts, equipment, transportation, and labor [21], [47].

Throughout the 1990s, companies like Toyota and General Electric demonstrated how reliability and quality addressed not only fundamental warranty issues but also increased revenue, decreased costs, and built brands [48]. PBC links design and supply chain strategy with the buyers' total life-cycle cost and performance experience. By linking supplier network decisions to life-cycle operational costs, PBC is a mechanism to focus engineers, operators, and supply managers on identifying cost-saving opportunities. Understanding the year-to-year costs associated with inventory, transportation, warehousing, repair, purchasing, and more, and linking those costs to system design and redesign through a return on investment incentive structure, provides the supplier network with a significant potential market [1], [45].

Strategies such as PBC adopt detailed year-to-year profit maximization through a cost avoidance perspective when creating design decision trade space. This view has caused designers, suppliers, OEMs, operators, and buyers to rethink their reliability, redundancy, and spare decisions during the system's design, production, operation, and support. The emergence of PBC and its multi-year performance-based strategies has highlighted research and practice gaps. Academicians and practitioners have noted that these strategies significantly increase the complexity of design decisions [1], [22], [49], [50], [51].

Academic research into PBC strategies continues to emerge and holds promise [1], [22], [49], [52], [53], [54]. To date, PBC research has focused on the business aspects of PBC and, to a lesser extent, mathematical models in support of a holistic approach to PBC. For example, Sols et al. [49] developed an n-dimensional, PBC model. Kim et al. [22] and Nowicki et al. [55] focused their research on the post-production support of a system design where inventory allocation problems were studied under a PBC.

PBC has driven a requirement for new algorithms from which to guide system design decisions that tradeoff sparing, repairing, network structure, and network cost. Previously, a supplier's post-production approach to sustainment was uncoordinated with many groups within a supplier's organization, each providing parts and services to the buyer procuring the system. Buyers pay suppliers for each maintenance, repair, overhaul, and spare support transaction, which represents a shift in how buyers purchase post-production support [56]. In contrast, a PBC is a post-production strategy that provides buyer-supplier incentives to optimize system performance through long-term contractual arrangements with clear lines of authority and responsibilities. The supplier is paid for delivering an outcome to the buyer (e.g., $/flight hour) rather than being paid to provide spares and repairs (e.g., per maintenance actions) [45], [57].

Under a PBC approach, the system integrator, which typically is the OEM, is responsible for providing an outcome for a fixed fee and incurs the cost associated with that outcome. In other words, the OEM is now responsible for the total supply chain cost required to meet a certain buyer-specified service level. As a result, the revenue model associated with production shifts significantly in comparison to traditional sustainment [21]. In traditional sustainment, the OEM and supplier increase their profits when they sell more spares or repairs, a "return on sales" revenue model [57]. On the other hand, in PBC, the integrator makes the greatest profit when the system does not fail or when the cost of maintaining the system is minimized. This drives a return on investment business model. Profits are maximized when decisions and designs are made to minimize the total life-cycle cost over the PBC contract period.

PBC's return on investment model creates a need for more accurate sparing, inventory, reliability, and redundancy algorithms. The supplier has a much larger potential return on investment concerning total life-cycle cost. While in a warranty approach, the supplier is typically responsible for just the cost of the spare part, in a PBC approach, the supplier is responsible for the total inventory, warehouse, transportation, maintenance, training, and support equipment required to recover that system when it fails. Thus, PBC design and profit decisions entail complicated multi-objective solutions to tradeoff sparing, maintenance level, and redundancy design. The industry is searching for ways to more effectively invest dollars in reducing total system life-cycle costs [9]. Under a PBC, such improvement in investment decisions represents not only increased profit but also lower out-year resource consumption, which means greater sustainability. As a consequence, suppliers will achieve an increase in their return on investment as the length of the PBC increases, leading to improved forecast accuracy. Accurate historical data helps suppliers efficiently manage performance risks [58]. Glas et al. [59] studied 12 risks associated with PBC, from dependency, misperformance, and misbehavior relationships to a lack of qualified personnel. They conclude that the higher a firm's experience with PBC, the lower its perception of risk. In this study, they consider content risk, business relationship risk, and operational risk. Researchers attempted to evaluate the impact of performance measurement in PBC. There is no exact way to evaluate performance within PBC because it depends on the industry sector and the contractual agreements [60]. Another question arises relating to the payments and the supplier's net profit. A study by Patra et al. [61] applies a first-order autoregressive moving average (ARMA) process to analyze a supplier's future net profit for linear and non-linear revenue functions. Ultimately, this approach determines the optimal system availability a supplier can provide to a buyer when the probability of loss is considered. Outsourcing has been used to minimize costs in complex projects; however, it is affected by organizational arrangements and the goal orientation of the projects [62]. We use the penalty, dead, and reward zones between the operational availability of the system and the amount of money the buyer pays the supplier [55].

III. PROBLEM DESCRIPTION, DECISION VARIABLES, PARAMETERS, ASSUMPTIONS, AND SYSTEM PERFORMANCE METRICS

This section explains the problem description, notation, assumptions, and system performance metrics.

A. PROBLEM DESCRIPTION

This research proposes a novel, analytical model that maximizes the profit margin of a large-scale, complex system simultaneously considering its design and post-production support network. This model uses redundancy allocation to represent a design decision, and the post-production support network decisions are the location and quantity of spares and their logistics footprint. The post-production support network is a non-arboreal, multi-echelon sustainment network, and the design is a series-parallel configuration, refer to Fig. 1. The model is constrained by buyer-specified, minimum reliability, measured as the MTBF, and maximum LF, measured in pounds.

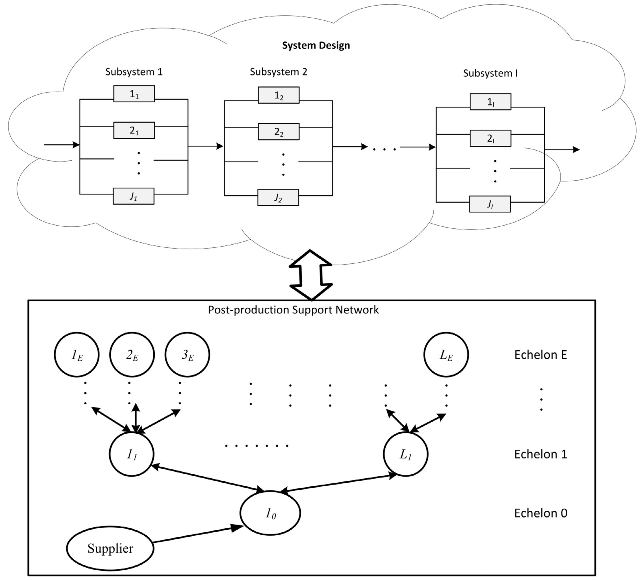

FIGURE 1. System Design and its Post-production Support Network.

The system design is a series-parallel configuration (**x**) where the system's subsystems (i^{th} subsystem of the system, where $i = 1, 2, \ldots, |I|$) are in series and each subsystem consists of components (j^{th} component of the i^{th} subsystem, where $j_i = 1, 2, \ldots, |J_i|$) in parallel. The parallel components are actively redundant. These systems are often present in the consumer electronics industry where systems use standard components, redundantly configured to improve system reliability [63]. The system presents a complex redundancy allocation problem that is combinatorial difficult. Coit and Liu [64] derive a component selection algorithm when commercial, off-the-shelf components are considered that have a known cost, reliability, and weight. Also, they argue that redundancy allocation during system design is difficult, largely due to its large combinatorial space. The system's post-production support network (**s**) is a non-arboreal, multi-echelon sustainment network that does not consider lateral resupply. The post-production support network is represented by a set of locations L_e that reside within a set of supply echelons (E); more specifically defined as the l^{th} location within the e^{th} echelon, where $l_e = 1, 2, \ldots, |L_e|$ and the e^{th} echelon in the post-production support network, where $e = 1, 2, \ldots, |E|$.

The system operates until one of its subsystems fails. Then, a corrective maintenance action is initiated, in which all components within the failed subsystems are removed and replaced with functioning spare components. This is essentially a one-for-one replenishment policy valid for large-scale, repairable systems with expensive subsystems that fail infrequently [65], [66]. If available, spare components stored at the operational location of the system are used ($l_{|E|}$). Under this scenario, the average time to operationally restore the system is the average time to remove and replace all components in the j^{th} subsystem that failed $\mu_{l_{|E|}} = \sum_{j_i=1}^{|J_i|} \mu_{j_i l_{|E|}}$. If there are no spares in stock at this location, then a replenishment action is initiated to move inventory from another supply location and echelon of support. If replenishment is necessary, the total delay includes the replenishment lead time, $LT^R_{j_i l_e}$, in addition to the components' removal and replacement time, $\mu_{l_{|E|}}$. $LT^P_{i_j l_e}$, the newly procured spare enters the support pipeline at the aggregate or central echelon of maintenance ($e = 1$).

With a series-parallel system configuration, the subassembly failure rate is not the demand rate on the post-production support network. A subassembly fails when all redundant components fail; therefore, a sub-assembly failure triggers multiple remove-and-replacement maintenance actions, one for each of its components. As a consequence, the component demand rate is the subassembly failure rate multiplied by the number of redundant components in the subassembly, $d_{j_i l_e}(t) = x_{j_i} \times \lambda_{j_i l_e}$. To determine the subassembly failure rate, a random variable T is defined to denote the time to failure and it is assumed that it follows a Poisson process, where the expected value of T, or expected time to failure, is $E[T] = MTTF_{jl_e}$ and $\lambda_{jl_e} = 1/MTTF_{jl_e}$. With the additional assumption of perfect renewals, the $E[T] = MTBF_{jl_e}$ and $\lambda_{jl_e} = 1/MTBF_{jl_e}$.

Upon failure, delays negatively impact the system's performance. The duration of the delay depends on the location and quantity of spares in the system's post-production support network. At a minimum, the system will experience a delay in removing and replacing the failed components of the failed subsystem. If spares are present in the support network, there is an additional replenishment delay. The maximum delay occurs when a procurement action is necessary to repopulate the spare pipeline.

If a component demand is unfulfilled, a backorder occurs. An unfulfilled component demand occurs when the number of demands exceeds the amount of inventory on hand at the location where the subassembly failed. The size of the backorder is the difference between the component demand and its available inventory, $d_{j_i l_e}(t) - s_{j_i l_e}$. Backorders negatively impact operational availability, a system performance metric that is agreed upon between a supplier and buyer in a PBC. The backorder is a random variable, and its expected values are defined as:

$$BO(d_{j_i l_e}(t)|s_{j_i l_e}) = \begin{cases} d_{j_i l_e}(t) - s_{j_i l_e} & \text{if } d_{j_i l_e}(t) \geq s_{j_i l_e} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

$$E[BO(d_{j_i l_e}(t)|s_{j_i l_e})] = \sum_{\alpha = s_{j_i l_e}+1}^{\inf} (\alpha - s_{j_i l_e}) \times P(d_{j_i l_e}(t) = \alpha) \tag{2}$$

This paper uses Sherbrooke [67] expected backorder to operational availability transformation, defined as:

$$A_0 = 100 \prod_{l_E}^{|E|} \prod_{i=1}^{|I|} \left\{ \frac{(1 - E[BO(d_{j_i l_e}(t)|s_{j_i l_e})])}{n_{L_{|E|}}} \right\}^{n_{L_{|E|}}} \tag{3}$$

Sherbrooke [67] transforms the backorders of the components at the system operation locations. The systems operate and fail in locations $l_{|E|} = 1, 2, \ldots, |L_{|E|}|$. The number of operating systems ($n_{l_{|E|}}$) are input into the model. Operational availability is a critical system performance metric that is commonly specified in a PBC. This study uses operational availability, reliability, and LF in the proposed meta-heuristic analytical model. These three system performance metrics are discussed in the next section.

B. DECISION VARIABLES AND PARAMETERS

The notations of the model are defined as follows:

Indices

- i — i^{th} subsystem of the system configuration, where $i = 1, 2, \ldots |I|$.
- j_i — j^{th} component of the i^{th} subsystem, where $j_i = 1, 2, \ldots |J_i|$.
- e — e^{th} echelon in the post-production support network, where $e = 1, 2, \ldots |E|$, and
- l_e — l^{th} location within the e^{th} echelon, where $l_e = 1, 2, \ldots |L_e|$.

Sets

- I — Set of subsystems in the system configuration.
- J_i — Set of components in the i^{th} subsystem.
- E — Set of echelons in the post-production support network, and.
- L_e — Set of locations in the e^{th} echelon in the post-production support network.

Variables

- $MTBF^T$ — buyer-specified mean time between failure for the system.
- LF^T — buyer-specified logistics footprint target for the supplier-provided post-production support network.
- $n_{l_{|E|}}$ — number of systems operating at location l_e in the echelon $|E|$.
- $c_{i_j l_e}$ — cost of the j^{th} component in the i^{th} subsystem located in the l^{th} location in the e^{th} echelon of the post-production support network.
- $LF_{i_j l_e}$ — logistics footprint of the j^{th} component in the i^{th} subsystem located in the l^{th} location in the e^{th} echelon of the post-production support network.

λ_{ijl_e} failure rate of the j^{th} component in the i^{th} subsystem located in the l^{th} location in the e^{th} echelon of the post-production support network.

μ_{ijle} repair rate of the j^{th} component in the i^{th} subsystem located in the l^{th} location in the e^{th} echelon of the post-production support network.

r_{ijl_e} probability of repairing j^{th} component in the i^{th} subsystem at the l^{th} location in the e^{th} echelon of the post-production support network.

$LT^R_{ijl_e}$ replenishment lead time of the j^{th} component in the i^{th} subsystem located in the l^{th} location in the e^{th} echelon, and.

$LT^P_{ijl_e}$ procurement lead time of the j^{th} component in the i^{th} subsystem located in the l^{th} location in the e^{th} echelon.

C. ASSUMPTIONS

The research problem assumptions are as follows:

1) The post-production support network is a non-arboreal, multi-echelon sustainment network without lateral supply between locations. (detailed information can be found in [68].
2) The system design is a series-parallel configuration.
3) There is a one-for-one replenishment policy.
4) To calculate operational availability, we use Sherbrooke [67] expected backorder, as shown in Eq. 3.
5) The subassembly failure rate follows a Poisson process with perfect renewals after replacing a component.

Parameters

x Vector that represents the system configuration.

s Vector that represents the post-production support network.

x_{ij} The number of the j_{th} component in the i_{th} subsystem.

s_{ijl_e} Stock level of the j_{th} component in the i_{th} subsystem located in the l_{th} location in the e_{th} echelon of the post-production support network.

$MTBF(x)$ Mean time between failure of the system configuration **x**.

$LF(x, s)$ Logistics footprint of the spares **s** needed to support system configuration **x**.

$\Pi(x, s)$ Supplier profit when the buyer purchases system **x** and the supplier sustains system **x** with post-production support network **s**.

$R[A_0(x, s)]$ Supplier revenue when the buyer purchases system **x** and pays for system availability $A_0(x, s)$.

$A_0(x, s)$ Operational available of system **x** and its post-production support network **s**.

$C(x, s)$ Supplier cost to design and produce system **x** and its corresponding post-production support network **s**.

$V(x, s)$ Buyer value of system **x** and its post-production support network **s**.

$P(x, s)$ Aggregate penalty derived if system **x** and its post-production support network **s** do not meet the buyer-specified logistics footprint and MTBF targets.

$P^{MTBF}(x, s)$ Penalty derived if system **x** and its post-production support network **s** do not meet the buyer-specified MTBF target.

$P^{LF}(x, s)$ Penalty derived if system **x** and its post-production support network **s** do not meet the buyer-specified logistics footprint target.

$BO(s_{ijl_e})$ Random variable that presents the backorders of the j_{th} component in the i_{th} subsystem located in the l_{th} location in the e_{th} echelon of the post-production support network with stock level s_{ijle}.

$E[BO(s_{ijl_e})]$ Expected number of backorders of the j_{th} component in the i_{th} subsystem located in the l_{th} location in the e_{th} echelon of the post-production support network with stock level s_{ijl_e}.

$d_{ijl_e}(t)$ Expected number of demands of the j_{th} component in the i_{th} subsystem located in the l_{th} location in the e_{th} echelon of the post-production support network during time interval t.

D. SYSTEM PERFORMANCE METRICS

Traditionally, system design performance focuses on engineering capabilities, often excluding its inherent reliability, maintainability, and supportability (RMS). For example, aircraft design generally focuses on takeoff and landing, turns, straight and level-flight in cruise, and climb. A more detailed example is an aircraft structure's stiffness and strength-to-weight ratio. The RMS of a system is central to risk and quality of its design, both critical aspects of performance. Kratz et al. [69] argue that engineering performance and RMS must be simultaneously considered and introduce the concept of System Design and Operational Effectiveness (SDOE). SDOE, as shown in Fig. 2, illustrates a holistic approach to system design where engineering performance, RMS, and process efficiency are considered, not only in the design phase of a system but throughout its entire life cycle (design, production, sustainment, and end-of-life).

From an economics perspective, SDOE uses system life-cycle cost, or total cost of ownership (TCO). A system design's TCO considers the development and design costs and the costs incurred when the design is produced, operated, and maintained. The RMS of a system design determines its frequency of failure (reliability, often measured as mean time between failures), the duration of time it takes to return the system to operation (maintainability, often measured as mean

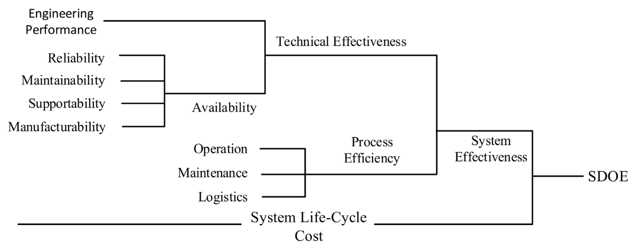

FIGURE 2. SDOE holistic perspective system design, adapted from [69].

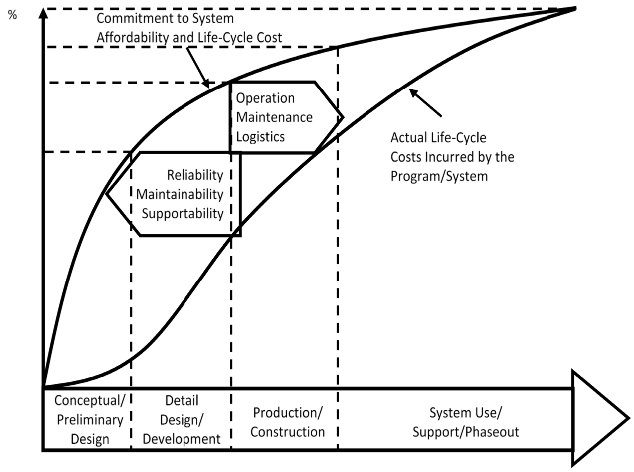

FIGURE 3. Committed vs. actual expenditures, adapted from [71].

time to perform a maintenance task), and the amount of time waiting for the necessary resource to return the system to operation (supportability, often measured as mean logistics delay time). Designing for RMS, their complex interactions, and their impact on downstream costs and revenues form the basis for TCO and inform a firm's procurement and asset management strategy [70].

Systems thinking is core to systems engineering principles and embraces a holistic approach that considers RMS, engineering performance, process efficiency, and TCO early in the design process [69]. Design decisions commit support resources and downstream costs. The earlier these linkages are understood, the better the design and post-production support network. Fig. 3 shows committed expenditures versus actual expenditures over a system lifecycle. Fabrycky [71] suggest that 85% of a system's TCO is committed early in the design process, with only 15% of the TCO's actual expenditures, consistent with Asiedu and Gu [70] assertion that minimizing TCO should focus on minimizing the system's operation and maintenance cost. When system engineers take a holistic perspective, understating the detailed linkage between system design to its enabling infrastructure, a healthier design emerges [72], [73], [74].

As shown in Fig. 4, operational availability A_0 is measured as the proportion of time a system is operating (system uptime) relative to the proportion of time it is operating or down (uptime + downtime).

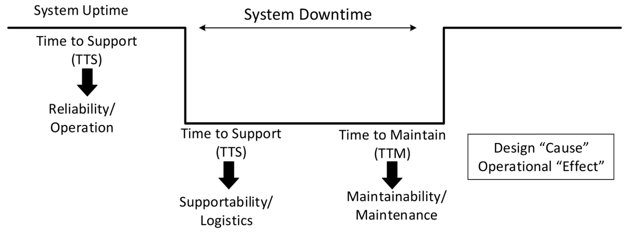

FIGURE 4. System design impact on rms and availability, adapted from [69].

The system is operational until it is down, either due to failure or a preventative maintenance task. This paper assumes a system is down only due to failure. The system remains down until it is restored to full operational status. The time to restore the system is the wait time to get all the resources (e.g., labor, material, and support equipment) necessary to perform the repair and the repair time. The operational time until failure is determined by the system's reliability, represented as the time to failure. The wait time, as determined by the quantity and location of the post-production support network resources, depends on the system's supportability, represented as the time to support. The time to repair is determined by the system's maintainability, represented as the time to maintain.

The system's operational availability is a metric that includes the system design's reliability, maintainability, and supportability. It is defined as the ratio of uptime over the summation of uptime and downtime, refer to Fig. 4. The uptime is a function of the system design's reliability, and the downtime is a function of the system design's maintainability and supportability. The denominator of A_o is a function of the system uptime and downtime. The downtime is the expected delay in waiting on resources (facilities, equipment, spares, transportation, and labor) to perform the maintenance actions to fully restore system operations [75].

Component reliability is central to our model as it determines the demand for component spares, which in turn determines, in part, the system availability, all at a cost over the system lifecycle. We assume the time to failure follows a Poisson process, and perfect renewals occur after a component is replaced or repaired. The Poisson process is selected because the average time between failures is known; however, the exact timing of failures is random. In addition, the arrival of a failure is independent of the failure before. As such, we can now define a component's failure rate as $\lambda_{i_j l_e} = \frac{1}{MTTF_{i_j l_e}}$ where $MTBF_{j_i l_e}$ is the mean time between failures of j^{th} component in the i^{th} subsystem in the l^{th} location within the e^{th} echelon. Also, the component reliability is $R_{x_{j_i}}(t) = e^{-\lambda_{j_i l_e} t}$. The system design's configuration is defined by a vector $\mathbf{x} = (x_{1_1}, \ldots, x_{j_i}, \ldots, x_{|J_I|})$, where $x_{j_i} \in (0, 1)$. The system design's configuration is series-parallel, where the components of a subsystem are in parallel (redundant) and the subsystems are in series. The reliability of the series-parallel system is $R_x(t) = \prod_{i=1}^{|I|}[1 - \prod_{i=1}^{|J_i|}[1 - R(x_{j_i}]^{x_{j_i}}]$. Assuming the reliability for all components within a given subsystem are the same ($n_j = \sum_{j_i}^{|J_i|} x_{j_i}$), the subsystem reliability is $R(\mathbf{x}) = [1 - (e^{-\lambda_{j_i l_e} t})^{n_j}]$. The subsystem reliability drives system availability, and the component failure rates create demands for the post-production support network resources. These demands, along with the post-production support network's LF, provide the performance metrics for our analytical model.

LF is the collection of resources (spares, materials, support equipment, and labor) that must be collocated with the system. As such, these resources also need to move (so, also need transportation resources) with the system when the system moves locations. LF is often measured in weight and volume, so the smaller, the better [75]. The focus on LF is prominent in the U.S. DoD, where there is a tactical advantage to having an agile, mobile system. Its support resources must be equally agile and mobile for an agile, mobile system. A reduced LF is socially responsible [76] and conforms to regulatory policies [77]. Having a higher quality of buyer-supplier relations helps to achieve a better outcome related to green practice [78]. For this research, we define LF as

$$LF(x, s) = \sum_{e}^{|E|} \sum_{l}^{|L_e|} \sum_{i=1}^{|I|} \sum_{j=1}^{|J_i|} LF_{j_i l_e} \times s_{j_i l_e} \tag{4}$$

There are costs associated with the system design and its supporting infrastructure (reliability, maintainability, supportability, availability, and LF). These costs occur throughout a system's economically useful life. We focus on the system's design, production, and support costs. The design and production costs are reflected in the components, subsystems, and system price. The support costs are the cost to provide spares (location and quantity), so the systems' post-production support network can provide the contractually agreed upon system performance from the supplier to the customer. The system design and post-production support network costs are:

$$C(x, s) = \sum_{e}^{|E|} \sum_{l}^{|L_e|} \sum_{i=1}^{|I|} \sum_{j=1}^{|J_i|} c_{j_i l_e} + (s_{j_i l_e} + n_j x_{j_i l_e}). \tag{5}$$

Systems engineers, design engineers, engineering managers, and program managers use operational availability, LF, and lifecycle costs to guide system design decisions. An inherent trade-off exists between reliability, maintainability, supportability, LF, and lifecycle cost. We introduce a meta-heuristic model that incorporates this tradeoff space so that more informed design decisions are made. This analytical model concurrently considers design and post-production decisions in the context of PBC.

E. THE MODEL

We develop a novel, analytical model that maximizes a large-scale, complex system's profit margin while considering its design and post-production support network. This model uses redundancy allocation to represent a design decision,

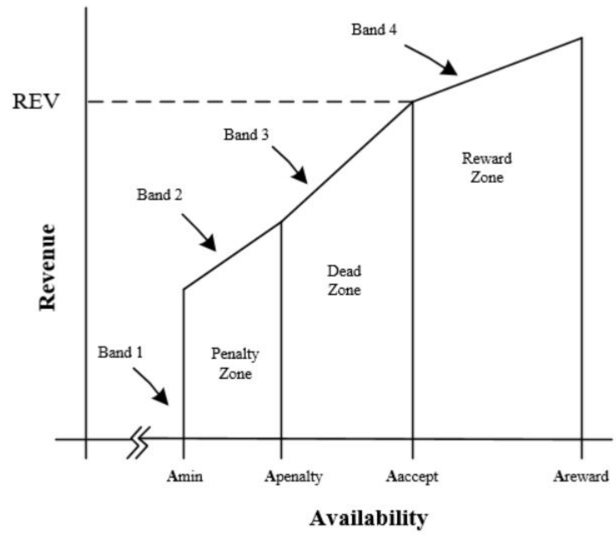

FIGURE 5. Relationship between supplier revenue and system availability, adapted from [55].

and the post-production support network decisions are the location and quantity of spares and their logistics footprint. The post-production support network is a non-arboreal, multi-echelon sustainment network, and the design is a series-parallel configuration. The model is constrained by buyer-specified, minimum reliability, measured as the MTBF, and a maximum LF, measured in pounds. The mathematical formulation of the general model follows:

$$\max \quad \Pi(x, s) = R[A_0(x, s)] - C(x, s) \tag{6a}$$
$$\text{s.t.} \quad MTBF(x) \geq MTBF^T \tag{6b}$$
$$LF(x, s) \leq LF^T \tag{6c}$$

The model determines the optimal system design configuration $\mathbf{x}$ and post-production support network resources $\mathbf{s}$ that maximize the supplier's profit without violating the buyer's reliability and logistics footprint constraints. Specifically, the model holistically examines the system design and its post-production support network to determine the level of component redundancy in each subsystem $\mathbf{x} = (x_{1_1}, \ldots, x_{j_i}, \ldots, x_{|J_I|})$, where $x_{j_i} \in (0, 1)$, and the quantity and location of spares to support the operation of the system $s = (s_{1_1 1_0}, \ldots, s_{j_i l_e}, \ldots, s_{|J_I||L_E|})$, where $s_{j_i l_e} \geq 0$.

In a PBC, the buyer compensates the supplier based on the system performance. Brown and Burke [79] introduce the notion of rewards and penalties tied to the system's performance. We use the penalty, dead, and reward zones paradigm to model the linkage between the operational availability of the system and the amount of money the buyer pays to the supplier (revenue) [55], as shown in Fig. 5. The same step revenue function was used to reflect the rewards and penalties on the suppliers' efforts to increase the availability [80].

The supplier's revenue $R[A_o(x, s)]$ is shown in equation 6a, and the supplier's cost was previously described in equation 5. The supplier revenue consists of four increments of payments the buyer pays for system availability ranging from a minimum acceptable availability to a maximum value, where the supplier will not pay any extra for exceeding this availability. We assume a linear relationship between system availability and supplier revenue within each increment. Equation 6b shows the minimum reliability measured as the mean-time-between-failure while equation 6c represents the maximum allowed logistics footprint, measured in pounds.

$$R[A_0(x,s)] = \begin{cases} 0 & \text{if } 0 \le A_0 < A_{min} \\ \alpha_1 + \beta_1 \times (A_0 - A_{min}) & \text{if } A_{min} \le A_0 < A_{penalty} \\ \alpha_2 + \beta_2 \times (A_0 - A_{penalty}) & \text{if } A_{penalty} \le A_0 < A_{accept} \\ \alpha_3 + \beta_3 \times (A_0 - A_{accept}) & \text{if } A_{accept} \le A_0 < A_{max} \end{cases} \tag{7}$$

Unfortunately, solving the aforementioned model using traditional closed-form optimization techniques such as integer programming is unsolvable since the objective function and the constraints are non-linear. For this reason, the following section explains a meta-heuristic algorithm that solves the model.

IV. SOLUTION APPROACH

We develop a meta-heuristics algorithm to solve this model, that is, to optimally determine the system design configuration and post-production support network resources that maximize the supplier's profit without violating the buyer's reliability and LF constraints. Specifically, the model holistically examines the system design and post-production support network to determine the level of component redundancy in each subsystem and the quantity and location of spares to support the operation of the system. Simultaneously solving these two problems is a key contribution to the literature. The system design configuration is a reliability allocation problem, and the post-production support network composition is a spare optimization problem. We simultaneously solve these problems by extending the performance-based, multi-echelon, multi-item spares models, accounting for a series-parallel system of [55] and [68].

The structure of a PBC often requires an agreement between the buyer and the seller on multiple system performance metrics [42], [63]. Understanding these requirements is essential during the design process through the delivery and support of the system. Our model allows for evaluating multiple system performance metrics when changes are made to the system design or the complement of post-production resources.

The developed meta-heuristic is based on an evolutionary algorithm. Evolutionary algorithms are characterized by their population-based approach, iterative and adaptability evolution to improve candidate solutions over multiple generations based on the performance of the evolving population, and then choosing the best among them to create the next generation. The algorithm will terminate until the conditions are met; otherwise, it proceeds to the next generation. The output is the best solution(s) found during the evolutionary process as the final result [81]. It is worth mentioning that inside our algorithm, we are considering the optimization of the METRIC-based spares algorithm done by Nowicki et al. [68]. As a result, the proposed, evolutionary, meta-heuristic algorithm is an iterative, four-stage process that solves the model defined in section III-E. The stages and their relationships in an algorithmic flow chart are shown in Fig. 6. Stage 1 generates system designs or populates the model with possible initial solutions. Stage 2 calculates each design's profit, spares, reliability, availability, and logistics footprint so we can choose the best system designs. Stage 3 penalizes a design if it violates the buyer's performance requirements. This part of the algorithm agrees with the phase of evolutionary algorithms by penalizing the local search when it returns to a local minimum [82]. Stage 4 determines which designs are selected to compare against the next generated design set.

A. STAGE 1: GENERATE SYSTEM DESIGNS

Monte Carlo simulation generates H potential series-parallel system design configurations. Each design configuration is defined by the vector $x^h = [x^h_{j_i}]$ for $\forall\ i \in I,\ j_i \in J_i,\ h \in H$, where $x_{j_i} \in (0, 1)$. To determine if and where component redundancy is present, we define an inclusion vector $\Omega = [\Omega_{j_i}] : \Omega_{j_i} = Pr(x_{j_i} = 1)$ where $Pr(X_{j_i} = 1)$ is the probability of inclusion. A value ζ is randomly generated using a uniform distribution, $U(0, 1)$. If $\zeta < \Omega_{j_i}$ then $x^h_{j_i} = 1$, otherwise set $x^h_{j_i} = 0$. The algorithm stops generating system designs when all initial inclusion probabilities are either zero or one, $\Omega^h_{j_i} = 1$ or $\Omega^h_{j_i} = 0\ \forall\ i \in I,\ j_i \in J_i,\ h \in H$.

We initially assign an equal likelihood of inclusion to all potentially redundant components $\Omega^0_{j_i} = 0\ \ \forall\ i \in I,\ j_i \in J_i$. Since the system configuration is series-parallel, there needs to be at least one component in each subsystem included, so we set $\Omega^0_{1_i} = 1$. The equal likelihood of initial inclusion is based on a lack of knowledge of where and how many redundant components need to be included in the system design to meet the buyer-specified performance requirements. We apply the ''Laplace principle of insufficient reason'' [83] assigning an equal chance that a redundant component is included when knowledge is lacking.

B. STAGE 2: ANALYZE THE SYSTEM DESIGNS

This stage is crucial as it ensures the system design analysis and uses the computational efficiency of the metric-based spares algorithm. The system designs, x^h, generated in stage 1 are analyzed, and the values for $\Pi(\mathbf{x}^h, \mathbf{s}^h)$, $R(\mathbf{x}^h, \mathbf{s}^h)$, $C(\mathbf{x}^h, \mathbf{s}^h)$, $MTBF(\mathbf{x}^h, \mathbf{s}^h)$, $LF(\mathbf{x}^h, \mathbf{s}^h)$, and $A_0(x^h, \mathbf{s}^h)$. are calculated. Prior to determining these values, the quantity and location of spares, $\mathbf{s}^h$, need to be derived. To derive $\mathbf{s}^h$, we use the Multi-Echelon Technique for Recoverable Item Control (METRIC) approach [67] in the context of PBC [55] using

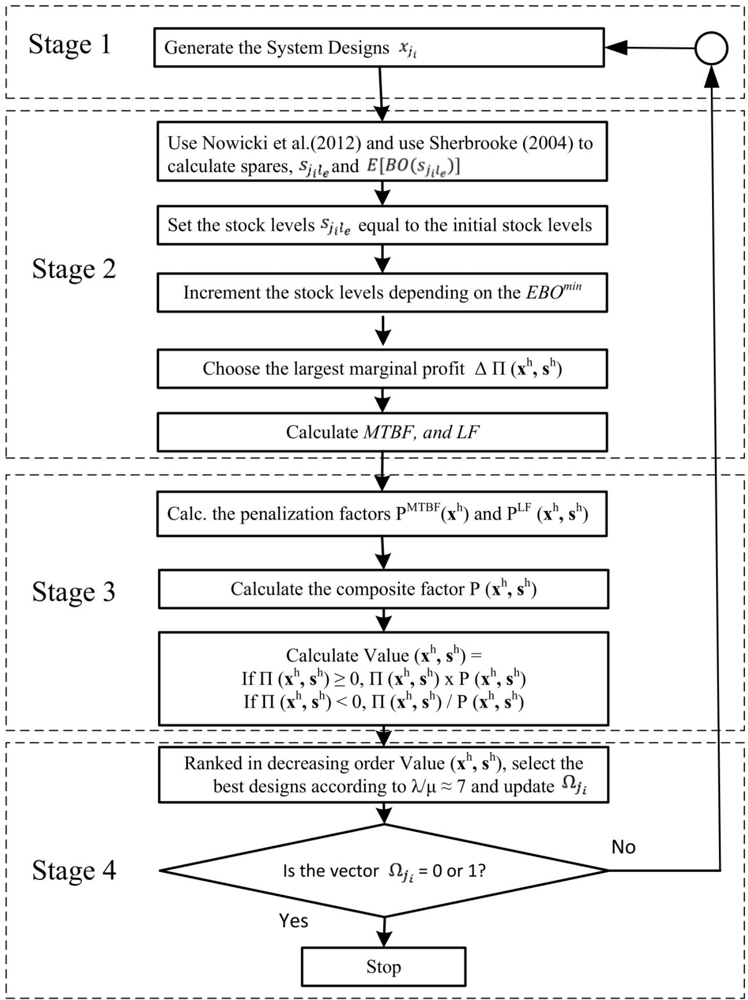

FIGURE 6. Algorithm flow chart.

computational efficiency improvements [68]. The result is a five-step process.

Step 1. Calculate $s^0_{j_i l_e}$ for each system design $\mathbf{x}^h$. First, calculate the expected backorder, $E[BO(d_{j_i l_e}(t))|, s_{j_i l_e} = 0]$ for j^{th} component in the i^{th} subsystem located in the l^{th} location in the e^{th} echelon of the post-production support network assuming there is no stock, $s_{j_i l_e} = 0$. If the $E[BO(d_{j_i l_e}(t))|s_{j_i l_e} = 0)] > EBO^{min}$, then set $s^0_{j_i l_e} = \gamma\ E[BO(d_{j_i l_e}(t)|s_{j_i l_e} = 0)]$, otherwise set $s^0_{j_i l_e} = 0$. γ is the fraction of the $E[BO(d_{j_i l_e}(t)|s_{j_i l_e} = 0)]$ that is used to determine the initial number of component spares. This approach reduces the computations needed to reach an optimal multi-item, multi-echelon, inventory solution.

Step 2. Set the stock levels $s_{j_i l_e}$ equal to the initial stock levels from step 1, $s^0_{j_i l_e}$, and then calculate the expected backorders, $E[BO(d_{j_i l_e}(t)|s^0_{j_i l_e})]$

Step 3. Increment the stock levels. The increments depend on the EBO^{min}.

If the $E[BO(d_{j_i 1_0}(t)|s^0_{j_i 1}] > EBO^{min}$ then increment by $\gamma E[BO(d_{j_i l_e}(t)|s_{j_i l_e}]$, otherwise increment by 1. So the $\Delta s_{j_i 1} = s_{j_i 1} + \gamma E[BO(d_{j_i l_e}(t)|s_{j_i l_e}]$ if $E[BO(d_{j_i l_e}(t)|s^0_{j_i l_e}] > EBO^{min}$ or $s_{j_i l_e} + 1$ otherwise. Therefore, the change in the expected backorder is $\Delta E[BO(d_{j_i l_e}(t)|\Delta s_{j_i l_e})] = E[BO(d_{j_i l_e}(t)|\Delta s_{j_i l_e})]$ - $E[BO(d_{j_i l_e}(t)|s_{j_i l_e})]$ $\forall\ i \in I,\ j_i \in J_i,\ l_e \in L_e,\ e \in E$.

Step 4. Choose the component, subassembly, location, and echelon combination (i, j_i, l_e, e) with the largest marginal profit $\Delta\Pi(x^h, \mathbf{s}^h)$. Increment the stock levels for the chosen (i, j_i, l_e, e) by $\Delta s_{j_i l_e}$. The $\Delta\Pi(\mathbf{x}^h, \mathbf{s}^h) = \Delta R(\mathbf{x}^h, \mathbf{s}^h) - \Delta C(\mathbf{x}^h, \mathbf{s}^h)$, where the $\Delta C(\mathbf{x}^h, \mathbf{s}^h) = C(\mathbf{x}, \mathbf{s}) = \sum_e^{|E|}\sum_l^{|L_e|}\sum_{i=1}^{|I|}\sum_{j=1}^{|J_i|} c_{j_i l_e} + (\Delta s_{j_i l_e} + n_j x_{j_i l_e})$ from equation 2. $\Delta R(\mathbf{x}^h, \mathbf{s}^h)$ is derived from equation 6, leveraging the relationship between expected backorders and operational available is equation 3, $\Delta A_0 = 100\prod_{L_E}^{|E|}\prod_{i=1}^{|I|}\{(1 - [E[BO(d_{j_i l_e}(t)|\Delta s_{j_i l_e})]]|n_{l_{|E|}})\}^{n_{l_{|E|}}}$

Step 5. If the optimal profit is met, stop; otherwise, start again with step 2. Profit $\Pi(\mathbf{x}^h, \mathbf{s}^h)$ is convex, where the marginal profit $\Delta\Pi(\mathbf{x}^h, \mathbf{s}^h)$, decreases until zero. Then, it is concave, with a decreasing negative marginal profit. When applying our greedy algorithm, an optimal profit is reached when the marginal profit value switches from positive to negative. the values of $(x^h, \mathbf{s}^h)$ that result in the optimal profit are then used to calculate $LF(\mathbf{x}^h, \mathbf{s}^h)$, and $MTBF(\mathbf{x}^h, \mathbf{s}^h)$.

C. STAGE 3: PENALIZE THE SYSTEM DESIGNS

The resulting supplier's profit, $\Pi(\mathbf{x}^h, \mathbf{s}^h)$, for each potential system design configuration (h) is penalized if it does not meet the buyer-specified $MTBF^T$ or LF^T contractually specified requirements. The penalty for violating the $MTBF^T$ or LF^T are:

$$P^{MTBF}(x^h) = \begin{cases} \frac{MTBF(x^h)}{(\kappa \times MTBF^T)} & \text{if } MTBF(x^h) \leq MTBF^T \\ 1 & \textit{otherwise} \end{cases} \tag{8}$$

$$P^{LF}(x^h, s^h) = \begin{cases} \frac{LF^T}{(\kappa \times (LF(x^h, s^h))} & \text{if } LF(x^h, s^h) \geq LF^T \\ 1 & \textit{otherwise} \end{cases} \tag{9}$$

In practice, PBCs may contain language suggesting the relative severity for not meeting contractually acceptable performance metrics (e.g., LF and MTBF). The factor κ represents the magnitude of the penalty for not meeting the LF and MTBF targets. Since κ is a constant, the penalties increase as the values move further from their targets. To penalize the competing, combined system design x^h and post-production support network s^h, the penalty metrics in Eq. 8 and Eq.9 are combined into a single penalty metric,

$$P(\mathbf{x}^h, \mathbf{s}^h) = P^{MTBF}(\mathbf{x}^h, \mathbf{s}^h) \times P^{LF}(\mathbf{x}^h, \mathbf{s}^h) \tag{10}$$

As specified in the model, the objective is to determine the combined system design x^h and post-production support network s^h, that maximizes the supplier's profit $\Pi(\mathbf{x}^h, \mathbf{s}^h)$ and meets the buyer-specified, performance targets, $MTBF(\mathbf{x}) \geq MTBF^T$ and $LF(\mathbf{x}, \mathbf{s}) \leq LF^T$. This is accomplished by adjusting the profit of each competing design/post-production support network combination by its penalty factor. The penalty-adjusted profit values of the competing system design x^h and their resulting post-production support network s^h are,

$$V(\mathbf{x}^h, \mathbf{s}^h) = \begin{cases} P(\mathbf{x}^h, \mathbf{s}^h) \times \Pi(\mathbf{x}^h, \mathbf{s}^h) & \text{if } \Pi(\mathbf{x}^h, \mathbf{s}^h) \geq 0 \\ \Pi(\mathbf{x}^h, \mathbf{s}^h)/P(\mathbf{x}^h, \mathbf{s}^h) & \text{if } \Pi(\mathbf{x}^h, \mathbf{s}^h) < 0 \end{cases} \tag{11}$$

D. STAGE 4: SELECT SYSTEM DESIGN

First, the penalty-adjusted profit values of the competing system design $\mathbf{x}^h$ and their resulting post-production support network are ordinally ranked, $V(\mathbf{x}^1, \mathbf{s}^1) \geq V(\mathbf{x}^2, \mathbf{s}^2) \geq \ldots V(\mathbf{x}^h, \mathbf{s}^h) \geq \ldots V(\mathbf{x}^H, \mathbf{s}^H)$. We then identify a subset of the competing system designs with the largest penalty-adjusted profit values. The subset contains the largest $\omega|H|$, where ω is the fraction of the competing designs $|H|$. Next, we update the entries of the inclusion vector $\Omega'_{j_i} = \sum_{\rho=1}^{\omega|H|} x_{j_i l_e}^{(\rho)}/\omega|H|, \forall\ i \in I,\ j_i \in J_i,\ l_e \in L_e,\ e \in E$. The updated inclusion vector, Ω, is then used as the initial conditions to generate additional system design configuration (stage 1). Our meta-heuristic algorithm (Fig.6) is consistent with the evolutionary strategy of a parent selection process, a reproduction strategy, and a substitution strategy, and its application to optimization algorithms [81]. The algorithm will stop when all the entries of the inclusion vector, Ω'_{j_i}, are either zero or one.

V. NUMERICAL STUDY

We provide a numerical study that illustrates the importance of simultaneously considering design and post-production support decisions in developing, implementing, and PBC. Fig. 7 shows the system design and post-production support system studied in the numerical example and the values used in the model (refer to the legends in Fig. 7). The system design is a series-parallel configuration with four subsystems in series, and each subsystem potentially has multiple redundant components. The post-production support system (i.e., post-production support network) is a non-arboreal, three-echelon sustainment network with one central, two intermediate, and six field locations. Similar post-production support network designs can be found in [55], [68], and [26]. The constraints have targets for MTBF of at least 75 hours, while the LF is at most 10,000 lb.

The supplier revenue model used in this example is dependent on the availability achieved when operating the system design:

$$R[A_0(x, s)] = \begin{cases} 0 & \text{if } 0 \leq A_0 < 0.70 \\ -60,000 + 300,000(A_0 - A_{min}) & \text{if } 0.70 \leq A_0 < 0.80 \\ -30,000 + 416,666(A_0 - A_{penalty}) & \text{if } 0.80 \leq A_0 < 0.95 \\ 45,000 + 100,000(A_0 - A_{accept}) & \text{if } 0.95 \leq A_0 < 1.0 \end{cases} \tag{12}$$

We apply our analytical model to derive the solution shown in Fig. 8. The optimal system design and post-production support network results in a $15,359.89 profit for the supplier with a LF of 5,904.50 lbs and an MTBF of 77.29 hours, satisfying the buyer-specified LF target of 10,000 lbs and MTFB target of 75 hours. There are two subsystems with one redundant component and two subsystems that have no redundancy reaching an availability of 0.9503.

The resulting system design vector $\mathbf{x}$ is shown in Table 1. Table 2 displays how the inclusion vector Ω evolved with each model iteration.

Table 3 shows promising, feasible solutions that may be useful in the tradeoffs in buyer-supplier PBC negotiations. These feasible solutions, captured through the iterations of the algorithm and the convergent optimal solution, provide insights into the tradeoff space between MTBF, LF, and Profit.

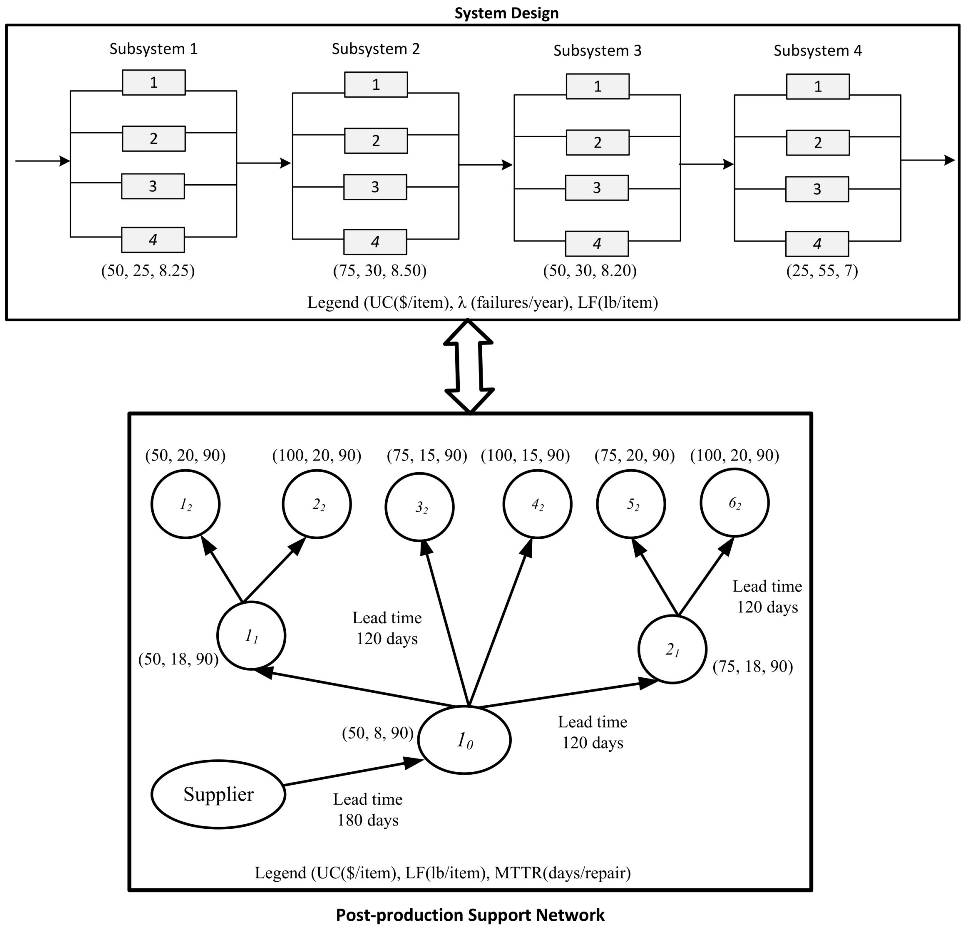

FIGURE 7. System Design and its Post-production Support Network.

TABLE 1. System design.

x_{1_1}	x_{1_2}	x_{1_3}	x_{1_4}	x_{2_1}	x_{2_2}	x_{2_3}	x_{2_4}	x_{3_1}	x_{3_2}	x_{3_3}	x_{3_4}	x_{4_1}	x_{4_2}	x_{4_3}	x_{4_4}
1	0	1	0	1	0	0	0	1	0	0	0	1	0	0	1

TABLE 2. Changes in Ω vector per iteration.

Run	Ω_{1_1}	Ω_{1_2}	Ω_{1_3}	Ω_{1_4}	Ω_{2_1}	Ω_{2_2}	Ω_{2_3}	Ω_{2_4}	Ω_{3_1}	Ω_{3_2}	Ω_{3_3}	Ω_{3_4}	Ω_{4_1}	Ω_{4_2}	Ω_{4_3}	Ω_{4_4}
1	1	0.50	0.50	0.50	1	0.50	0.50	0.50	1	0.50	0.50	0.50	1	0.50	0.50	0.50
2	1	0.40	0.50	0.35	1	0.20	0.30	0.45	1	0.45	0.30	0.45	1	0.15	0.25	0.40
3	1	0.20	0.35	0.45	1	0.20	0.25	0.30	1	0.30	0.15	0.35	1	0.05	0.15	0.30
4	1	0.10	0.40	0.20	1	0.10	0.10	0.30	1	0.30	0.20	0.30	1	0.05	0.20	0.45
5	1	0.10	0.45	0.15	1	0.10	0.05	0.20	1	0.40	0.10	0.20	1	0.05	0.15	0.55
6	1	0	0.40	0.10	1	0	0	0.20	1	0.45	0.05	0.05	1	0	0.05	0.85
7	1	0	0.65	0	1	0	0	0	1	0.30	0	0.05	1	0	0	1
8	1	0	1	0	1	0	0	0	1	0	0	0	1	0	0	1

We perform a comparative experiment showing that better decisions are made when simultaneously considering system design and the post-production support network rather than making these decisions sequentially or often independently. Tables 4 and 5 show the results of the comparative experiment, providing the details supporting the use of our proposed simultaneous analysis rather than the traditional sequential approach.

Solving the systems separately results in no satisfaction of the contractual constraints. We perform a set of experiments by first solving the system design with no redundancy, then the post-production support network optimization. We add redundancy to each subsystem one by one until we find a feasible solution that satisfies the contractual constraints of MTBF and LF. Table 4 shows the system designs of the experiments conducted, MTBF, LF, and Cost. While Table 5

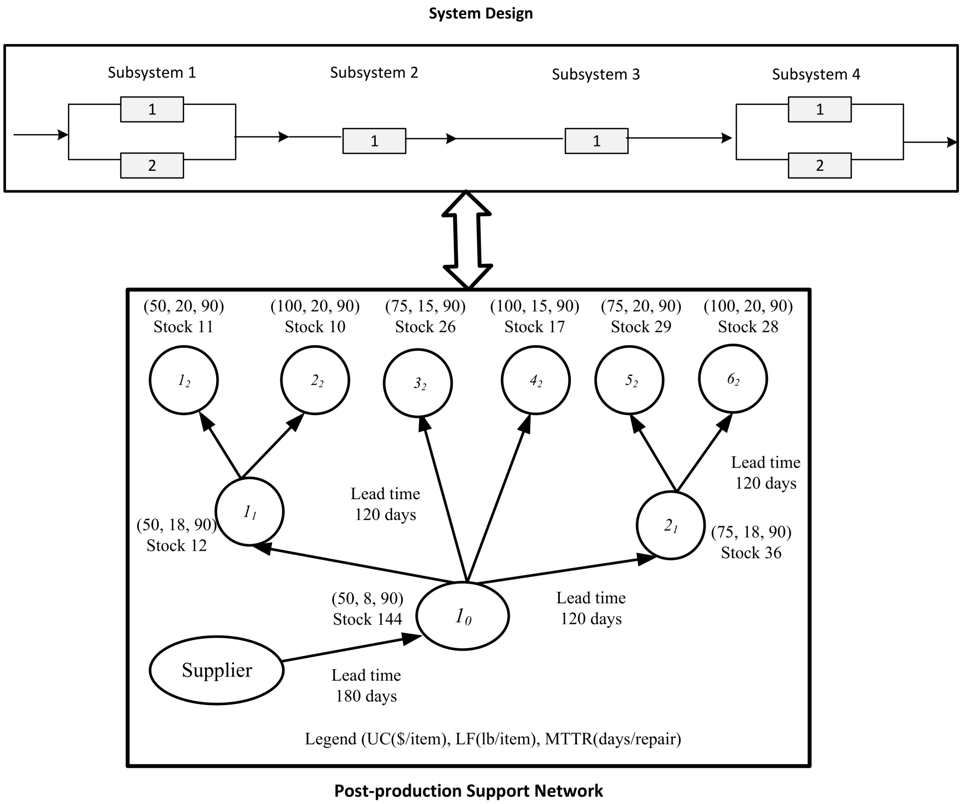

FIGURE 8. System design and post-production support network optimization.

illustrates for each run the LF, Cost, Revenue, and availability of the post-production support network optimization. Finally, the last three columns of Table 5 show whether solving the systems separately the contractual constraints are met. Up to experiment *k*, both contractual constraints are met, and the system design adds two redundant components to subsystems 1 and 2 with a MTBF of 76.17 hours and a total LF of 6,131.75 lb. Both systems result in a profit of $ 10,388.83. In addition, experiment *l* has a feasible solution. However, these runs have lower profits than solving the systems simultaneously with the proposed model.

VI. MANAGERIAL INSIGHTS

PBC is used in both public and private sectors, generating buyer value and supplier-buyer profitability. PBC is mostly used in systems where the cost of sustaining the system exceeds its research, development, and production costs. The incentive scheme is for the supplier to deliver performance outcomes for long-term contracts and increase the return on investment. The business implications for PBC are significant. Our current research focuses on evaluating the system design and its support network, which have the potential to significantly enhance the success and proliferation of PBC across multiple industry sectors. This research provides valuable insights, a roadmap, and supporting analytical models to further PBC across many industry sectors, particularly in evaluating the inherent trade-offs between system design and the network of support resources necessary to maintain these systems [84] The untapped potential of PBC offers firms (buyers) purchasing systems and firms (suppliers) designing, producing, and supporting these systems the promise of improved system performance and outcomes, cost efficiency, risk management through innovations, long-term relationships between suppliers and buyers, and most importantly, it has the power to enhance market competitiveness, driving the industry forward.

In many industries, there are often two contracts between the buyer and supplier of a system and another between the buyer and the supplier for the support network to maintain system performance and outcome, leading to suboptimal cost efficiency. With the present research, there is a promising potential to have only one contract that specifies the system design and its operating performance and outcome, thereby significantly improving cost efficiency.

The U.S. DoD has successfully employed PBC to design and post-production support large-scale, complex, repairable systems, such as aircraft. These contracts, which are often separate, could be better understood and managed by buyers and suppliers. This understanding could be contractually formalized, leading to improved performance and higher quality of service. The unique benefits of PBC in this context are evident, as it has the potential to significantly enhance

TABLE 3. Other feasible solutions to the numerical example.

Number of components per subsystem						
Subsystem 1	Subsystem 2	Subsystem 3	Subsystem 4	MTBF (hrs)	LF (lb)	Profit ($)
1	1	2	2	78.45	6,285.25	14,505.12
2	2	2	1	78.45	5,929.50	13,540.52
3	1	1	2	79.42	6,415.75	12,828.55
1	2	1	2	78.45	6,310.25	12,332.62
3	2	2	1	80.64	6,402.75	10,781.00

TABLE 4. Experiments of the system design without optimization.

System Design							
	Number of components per subsystem						
Exp.	Subsystem 1	Subsystem 2	Subsystem 3	Subsystem 4	MTBF (hrs)	LF (lb)	Cost ($)
a	1	1	1	1	62.57	1,092.25	6,375
b	2	1	1	1	66.53	1,298.50	7,625
c	3	1	1	1	68.10	1,504.75	8,875
d	4	1	1	1	68.98	1,711.00	10,125
e	1	2	1	1	67.38	1,347.25	8,625
f	2	2	1	1	72.00	1,553.50	9,875
g	3	2	1	1	73.84	1,759.75	11,125
h	4	2	1	1	74.87	1,966.00	12,375
i	1	3	1	1	69.32	1,602.25	10,875
j	1	3	1	1	74.22	1,808.50	12,125
k	3	3	1	1	76.17	2,014.75	13,375
l	4	3	1	1	77.27	2,221.00	14,625

TABLE 5. Experiments of the post-production support network optimization after the system design decision, the total cost of both systems and the validity of the contractual constraints.

Post-production support network					Both	Constraints	
Exp.	LF (lb)	Cost ($)	R[A(x,s)] ($)	A_0	Profit ($)	$MTBF \geq 75$	$LF \leq 10,000$
a	2,814	13,775	45,394.50	0.9539	25,244.50	✗	✓
b	3,107	15,400	45,104.40	0.9510	22,079.40	✗	✓
c	3,403	17,025	45,007.54	0.9501	19,107.54	✗	✓
d	3,696	18,650	45,234.16	0.9523	16,459.16	✗	✓
e	3,164	16,025	45,299.05	0.9530	20,649.05	✗	✓
f	3,462	17,700	45,034.89	0.9503	17,459.89	✗	✓
g	3,783	19,400	45,442.54	0.9544	14,917.54	✗	✓
h	3,043	20,925	45,212.19	0.9521	11,912.19	✗	✓
i	3,519	18,325	45,429.89	0.9543	16,229.89	✗	✓
j	8,812	19,950	45,193.07	0.9519	13,118.07	✗	✓
k	4,117	21,600	45,363.83	0.9536	10,388.83	✓	✓
l	4,385	23,125	45,016.18	0.9501	7,266.18	✓	✓

the success and proliferation of PBC across multiple industry sectors.

PBC contracts that simultaneously consider design and support could lead to significant innovations. For instance, an insurance company (buyer) might incentivize a health-care provider (supplier) to reduce hospital readmission rates. To achieve this, they could develop (design) new post-discharge care programs, such as remote patient monitoring systems (operation and support), which use wearable technology to track patient health data and provide real-time feedback. This innovative approach improves patient care (performance and outcome) and introduces cutting-edge technology and processes (innovation), driving the industry forward [84].

Energy companies use PBC to maintain and operate power plants [85]. For example, a power plant operator might have a PBC contract where payment depends on plant efficiency and environmental compliance. This performance-based payment structure motivates the operator to optimize operations, reduce emissions, and improve energy efficiency, leading to lower operational costs and better environmental outcomes. A PBC contract with the power plant designer and operator could improve performance and encourage suppliers to invest in innovation. Power plant operators might adopt innovative technologies such as AI-based smart grids to optimize electricity distribution and consumption to meet energy efficiency and emissions performance targets.

The industrial benefits of this research are as follows:

- Two complex systems are analyzed together. The first is a post-production support network, a non-arboreal muti-echelon sustainment network, and the second is its system design, a series-parallel configuration.
- The model maximizes a large-scale, complex system's profit margin while considering both the design and post-production support network.
- The model considers performance metrics valid to the current requirements of operability and sustainability.
- The model is constrained by minimum reliability, measured as the MTBF, and a maximum LF, measured in pounds. These contractual buyer-specified requirements can be modified according to the agreed system's availability and environmental goals.
- The demand rate is the component in the subassembly failure rate multiplied by the number of redundant components in the subassembly.

VII. CONCLUSION, DISCUSSION, AND FUTURE RESEARCH

This research aims to introduce an analytical model that simultaneously considers design and post-production support decisions in developing, implementing, and managing PBC. We are the first to create an analytical model that concurrently considers design and post-production support decisions in the context of PBC. We use the redundancy allocation problem to represent a design decision, and the post-production support network decisions are the location and quantity of spares and their logistics footprint. The post-production support network is a non-arboreal, multi-echelon sustainment network, and the design is a series-parallel configuration. The model is constrained by buyer-specified, minimum reliability, measured as the MTBF, and a maximum LF, measured in pounds. A numerical example was solved to test the model and to highlight the effectiveness of the proposed meta-heuristic by showing different feasible optimal solutions. The solution demonstrates the economic importance of system engineers, contract personnel, and program managers in understanding the inherent trade-off space connecting the design and support of a system.

The most important limitation is that detailed data about failure rates, repair time, logistics lead times, and logistics footprint is required. Gathering and maintaining this data is complex and costly. In addition, solving large-scale systems with many items and multiple echelons can make real-time or near-real-time applications challenging. Our model focuses primarily on holding costs, shortage costs, logistics footprint, and availability performance measures, such as the MTBF. It may not capture other relevant costs like transportation, administration, or downtime.

This research provides the foundation to further study collaboration between buyers and sellers, specifically how an optimal price is determined for a performance-based contract (e.g., game-theoretic models). With PBC, suppliers are incentivized to make improvements in the system's design, as long as these investments produce future rewards over the contract that exceed the investment decisions. Theoretical research is needed to understand further foundational theories such as transactional cost economics, management control theory, and agency theory that influence buyer-seller behavior in PBC's context. These incentives may spur design innovation; innovative designs that improve system reliability result in fewer failures or demands on post-production resources. The result is a more sustainable post-production support system. Consequently, future theoretical and empirical research is needed to study how PBC influences system design and post-production support innovation. Additionally, PCB impacts sustainability when management considers system designs and post-production support decisions simultaneously. Several research topics are worthy of further exploration. Resilience is one of those topics. For instance, it would be worth analyzing the impact of failures in the post-production support network regarding availability and investment needed to restore it to a satisfactory availability level [26]. It is even more important to evaluate the long-term economic effects of disruptive events, such as the COVID-19 pandemic. There is undoubtedly a linkage between design and post-production support in determining a system's resiliency. There is an opportunity to study the linkage further.

A further study could assess the implementation of new technology for spare parts replacement, such as autonomation inspection, to avoid failures [86]. Imperfect replacement or periodic inspection schemes and other performance metrics can be considered in future research, such as condition-based maintenance [30]. Our study considers only one supplier; however, suppliers often depend on other suppliers and sub-suppliers. A study evaluating these supplier dependencies and how PBC is affected would be worth analyzing [87]. A natural progression of this work is that environmental responsibility could produce interesting findings that account more for benefits for the supplier. For example, the less logistics footprint of the system, the more economic benefits there are for the supplier. Also, involving competition among suppliers for better performance metrics would be an important avenue to investigate [88]. It would be worth evaluating our model in a real-world case study to evaluate all the managerial implications and complexities of systems design.

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