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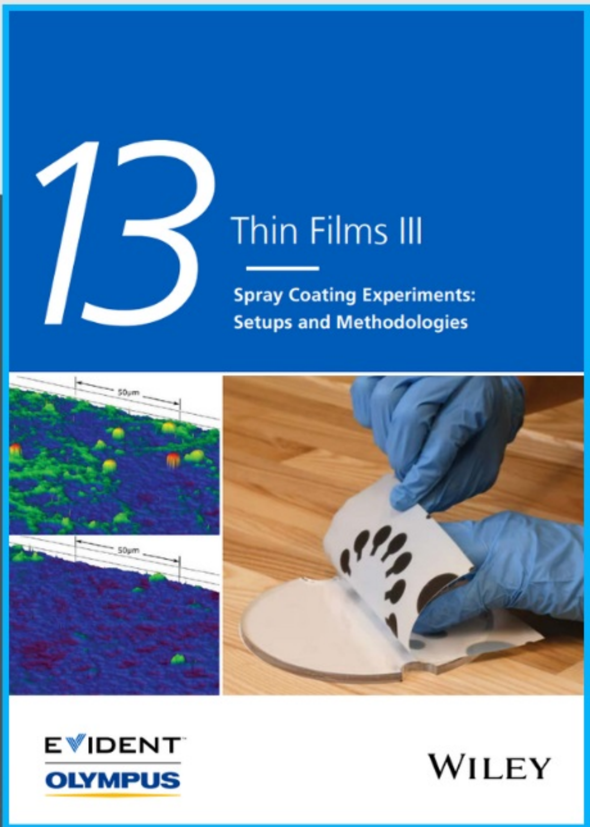

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REGULAR ARTICLE

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Multi-objective approach to forecast design refresh time due to COTS obsolescence

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Abstract

The purpose of this study is to provide program managers and systems engineers with a novel algorithm in determining the design refresh time (DRT) of sustainment-dominated systems due to COTS obsolescence. Most of the research done so far has focused on cost optimization. The main contribution of the study is two-fold. First, besides cost optimization, we have introduced efficiency optimization within a balanced approach to determine the DRT, under multiple objectives. Second, we used a set-based approach over the hypervolume quality values of solutions rather than population-based Pareto solutions. We proposed a discrete-time simulation model by using Multi-Objective Evolutionary Algorithms where the deterioration over the quality values of Pareto solution sets is used as an indicator for a DRT. We supported the proposed mathematical model in theory with empirical findings from a case study for a sustainment-dominated Naval Command and Control System that was designed in 2004 and deployed in 2007. We ran the simulation as for 2007 and conducted an analysis over the cost and operational efficiency objectives to compare the situation experienced in real life against the simulation outputs of the proposed model. The results revealed that not only the total life cycle cost but also efficient operational sustainability of a system would be increased significantly if the system had gone through design refreshes as proposed by the model. We showed that the deterioration of the Pareto optimal solutions' hypervolume quality values over time is an effective marker to decide the optimal DRT under conflicting multiple objectives.

KEYWORDS
COTS obsolescence, design refresh time, DMSMS, MOEA, set based hypervolume

1 | INTRODUCTION

The break-neck speed of technological advances within the last decades of the 20th century, especially due to the invention of semiconductors, has brought tremendous changes in our lives. In the Post-Cold War era, the competitive market focus significantly shifted from the military to consumer products.[1] Aggressive market conditions pushed the product and service providers to shorten their product design and implementation periods, which eventually lead to shorter product life cycles. This created the Commercial Off the Shelf (COTS) products as a new phenomenon, an indispensable choice for system designers and procurement agencies to use. Following the US Secretary of Defense William Perry's notice in 1994 to embrace COTS products in military systems to the maximum extent, many national defense procurement strategies aimed to increase the use of COTS products in military system designs as well.[2–5]

COTS products are both hardware and software that are available in the market with relatively lower cost and more availability as they are likely produced by multiple vendors. Program managers have been using more COTS parts in sustainment dominated systems such as the military, avionics, nuclear plants, and transportation systems due to many advantages including cost, availability, and ease of use. Despite their abundant advantages,[6] due to their shorter product life cycle (2–5 years), there are also disadvantages of using them in sustainment dominated systems whose product life cycles are 25 years on average.[7,8] Such disparity between product life cycles created "the dark side of the Moore-law."[9,10] Obsolescence affects systems differently during various phases of the product life cycle.[11] Due to the mismatch between the product life cycles of those systems and COTS parts used in them; so, it is imperative to manage maintainability issues of obsolescence. In certain cases, the COTS parts go obsolete even when the system is still in the implementation phase.[12] Any change in the original design of the sustainment-dominated systems, owing to operational continuity, usually incurs the high costs of requalification and recertification requirements. For example, the US Air Force is reported to have spent \$81 million on the F-22 program and another \$500 million on F-16 fighters' radars to mitigate obsolescence; the redesign cost of an obsolete electronic part was reported between \$26,000 and \$2 million by the Electronic Industries Alliance (EIA) Manufacturing Operations and Technology Committee.[13] The impacts of COTS obsolescence on such sustainment-dominated systems is excessive and requires a comprehensive and holistic obsolescence management plan to minimize the sustainment costs.

In order to manage the obsolescence costs, Sandborn proposed three-tiered management framework: reactive, proactive and strategic management.[14] Reactive management techniques are adopted to sustain the system until the Design Refresh Time (DRT) or retirement once the obsolescence is announced by the vendor and includes reactive responses such as Bridge Buy, Life-Time Buy (LTB), Redesign, Emulation, and Reverse Engineering. The proactive strategy monitors the system and technology as well as market trends to forecast the obsolescence using several parameters such as "Material Risk Index"[15] and proposes proactive responses before the COTS parts are announced as obsolete. The third strategy is a strategic management approach that follows comprehensive methods that can start even before the original design of the system[16] and includes longer-term forecasts as well as integrated logistics systems solutions.

While many studies on obsolescence and the deterioration of products have focused on inventory management,[17–22] the first studies on DRT due to COTS obsolescence date back to Porter's Boeing report proposing a trade-off decision model to figure out the break-even point between the amount of Last Time Buy and DRT.[23] Within the last two decades, almost all of the studies conducted about obsolescence management have focused on minimizing the costs. Researchers have developed models to forecast the DRT through data mining historical buys,[24] Bayesian networks,[15] proactive measures,[9,25–27] the ranking and selection method to find the optimal design refresh strategy among *k* alternatives[28,29] and strategic risk mitigation techniques.[30–32] Other research has focused on finding out the most appropriate set of reactive measures until DRT,[33,34] the amount of Bridge Buy and Last Time Buy,[35–37] health indicator for reactive management activities[38] and determining the end-of-repair and maintenance period.[39] Several other studies aimed at forecasting part obsolescence based on peak sales data[40] and multiple regression models.[41] In addition to that, uprating obsolete parts[42] and piggybacking on an existing product[43] were proposed as additional mitigations for COTS obsolescence.

Determining the DRT for a complex system due to obsolescence is one of the fundamental steps in proactive and strategic obsolescence management strategies. It is a challenging stochastic process since multiple conflicting decision objectives are using a number of different probabilistic decision parameters and variables. It requires a search over time domain for the optimum point as studied in previous research.[33,36,44–47] All those studies have searched for the optimum time only to minimize the product life cycles costs when determining the DRT; however in practice, this is not a single objective matter. In addition to the maintainability risks due to increased costs,[10] there are also operational efficiency[48] and security risks of using obsolete parts.[49] Particularly for military, avionics and nuclear systems, operational efficiency is of great concern for system owners. The decision to retire or refresh the design of such systems depends not only on the cost parameters but also on the efficiency of system outputs. In certain cases, it is not rare to see a very old system such as B-52 bombers still operating and maintained at whatever cost since the outputs attained from them outweigh the cost of maintenance. This situation forces decision-makers to make a trade-off among different objectives depending on their prioritization schema. Aforementioned concerns call for a multiple-objective decision-making (MODM) methodology to decide on the obsolescence management strategies including the design refresh or retirement time.

The objective of this research is to develop a model to predict the optimum DRT of sustainment-dominated systems due to COTS obsolescence. The contribution of this study has two-fold. First, in addition to cost minimization, as was the case for majority of previous studies, we have taken a balanced approach by taking additional objectives into account when proposing the optimum DRT. This is not the first study considering multiple objectives when deciding technology refresh decisions. Khanh et al developed a Markovian Decision Process using a discrete time model,[50] Adetunji et al. developed a TOPSIS model to select the optimum system based on expert judgment[51] and Bowlds et al. developed a MCDM model for software obsolescence.[52] However, the main difference of our research is that we have used the quality of the solution sets rather than fitness values of the objective functions when proposing the DRT. In other words, we used set based approach by utilizing the quality of Pareto optimal solution sets rather than using the population-based Pareto sets produced by Multiple-Objective Evolutionary Algorithms (MOEA).

The research is built on the discrete time stochastic simulation approach presented in Refs.26,44,53, and the concept of deterioration of objective values over time presented in Ref.50 We have implemented a MOEA model inside a discrete time simulation model to generate multiple Pareto optimal solution sets for each consecutive time interval. However, unlike the aforementioned foundational studies, we used multiple objectives and we did not use the optimum Pareto solutions set as an input for the decision maker to decide on DRT. Instead we have developed a set-based approach by using the hypervolume quality value of the Pareto sets as an input for decision makers to use.

The research demonstrates that the quality of the Pareto solutions produced by the MOEA can be used as a decisive indicator to forecast the DRT of the sustainment dominated system. We have developed a novel algorithm that uses the deterioration of quality values of successive Pareto solutions as a marker to propose the design refresh date. The originality of this research is that it blends the set-based preference relation approach of MOEAs into the multi-objective nature of obsolescence management and provides a flexible way for decision makers to determine the DRT.

The rest of the paper is organized as follows: In section two, we explain the theories of MODM, EAs, and the Quality Indicators (QI) of Pareto Sets. In Section 3, we explain how we applied the mentioned theories on obsolescence management, specifically on the determination of DRT time and give the details of the proposed model. In section four we give our case study, an implementation of the proposed model on a sustainment dominated naval Command and Control subsystem. The last sections give the results, discussion, and conclusions.

2 | THEORY APPLIED ON DRT FORECASTING

2.1 | Multi-Objective Decision Making (MODM)

Definition 2.1. MODM problem is the optimization of k objectives $f_i : X \to Z$ where $Z = \mathbb{R}^k$ and $1 \leq i \leq k$, is the feasible solution set in the decision space and Z is the set of objective values in the objective space. Let x be a decision vector $x = (x_1, \ldots, x_n)$ in X finite decision space such that $x \in X$ and $z = f(x)$ in the objective space.

In the MODM problems, as per Definition 2.1, the aim is to minimize (maximize) k number of objectives by finding the Pareto solution set where decision variables $\vec{x}$ are subject to a set of m constraints to find the optimum values of x_1^*, x_2^* ... ... x_n^* constituting the Pareto optimum solution set.

$$min_x f\ (x) = (f_1 (x), \ldots, f_k (x)) \tag{1}$$

s.t.

$$X = \{x | g_j (x) \geq 0,\ j = 1, 2, \ldots, m : x \in \mathcal{R}^n\}$$

where x is a vector of variable with n-dimension and $f(x)$ is a vector of multiple objectives with k-dimension.

2.2 | Multi-Objective Evolutionary Algorithms (MOEA)

Evolutionary Algorithms (EAs) are population-based algorithms based on natural selection and inspired by Charles Darwin.[54] EAs in MODM problems use the operators of initialization, fitness evaluation, selection, variation, replacement, elitism, diversity check, and termination state check. At each iteration, the fitness value for each objective function is evaluated and used in the selection process for the next generation. Fundamentals of MODM and EAs can be found in Annotated Bibliographic Surveys.[55–57]

Among those operators in EAs, the initialization and variation are problem-specific and must be coded accordingly. Fitness evaluation, diversity check and elitism are objective specific while replacement and selection are heuristic specific.[58] Various implementations of the problems, objectives, and heuristic specific operators of EAs create a wide range of different approaches to compare with each other.

Definition 2.2. Multiple-Objective Evolutionary Algorithms (MOEA): MOEA's are used to generate Pareto Sets by either population based or set based approaches. Within population-based approach, MOEA generates a new population from parent and offspring populations. On the other hand, the set based approach uses preference relation over the sets of Pareto solutions instead of individual solutions when generating the Pareto Sets.[59]

Definition 2.3. Preference Relation: Given a MOEA as defined in Definition 2.2, let a and b be two solution sets. If $a \preccurlyeq b$, a is said to be as good as b for all objectives. Preference relation is reflexive such that $a \preccurlyeq a$ and transitive such that if $(a \preccurlyeq b \wedge b \preccurlyeq c) \to a \preccurlyeq c$.

$$if\,(A \preccurlyeq B) \overset{\leftrightarrow}{iff} (\forall b \in B : (\exists a \in : a \preccurlyeq b)) \tag{2}$$

Definition 2.4. Pareto Optimality: The preference relation (Definition 2.3) $(X, \preccurlyeq_{par})$ is a set of all elements of X such that there exists no solution u with preference relation of $(x \preccurlyeq_{par\%u})$.

Definition 2.5. Pareto Front: Set of objective values of the Pareto solution set.

2.3 | Quality of Pareto solutions

While quality of a solution for a single objective problem is straightforward, comparing solutions quantitively for a multi-objective problems is a little bit trickier. We use QI (Definition 2.6) to compare multiple solutions sets. There are quite a number of different QIs to compare Pareto sets such as generational distance or C indicator for convergence, maximum spread for spread, spacing for uniformity and error ratio for cardinality.

Definition 2.6. The QI: QI of the Pareto Solution sets are used as a basis of preference relations. A single QI is assigned to each solution set A in ψ. Some of the key performance metrics to evaluate the quality of MODM algorithms are generational distance, spacing, spread and, hyper-volume values.[60] Some QIs are used to measure multiple metrics such as hypervolume (HV), inverted generational distance (IGD), ε-indicator, Integrated Preference Functional (IPF) and R Family.

Intuitively, the larger the indicator values the better.

$$A \in \psi \rightarrow \mathbb{R}^n : n = \begin{cases} 1 \text{ for unary indicator where } A \preccurlyeq B \rightarrow I(A) \geq I(B) \\ 2 \text{ for binary indicator where } A \preccurlyeq B \rightarrow I(A,B) \geq I(B,A) \\ n \text{ for } n-\text{ary indicator where } A \preccurlyeq B \rightarrow I(A_1, A_2 \cdots A_m) \geq I(A_2 \cdots A_m, A_1) \end{cases} \tag{3}$$

QI define the order of Pareto sets by mapping the solutions sets to a real value. There are multiple uses of QIs such as comparing the multiple objective optimizers, monitoring the performance metrics of parameters and stopping criteria used in the search algorithms and indicating the direction of search algorithm. The quality of a Pareto solution lies in closeness to the Pareto front (convergence), coverage on the solution space (spread), shape of distribution over solutions (uniformity), and the number of solutions (cardinality) in the set. Spread and uniformity are sometimes collectively called diversity.

Among QIs mentioned above, HV is the significant one. It represents the space that the Pareto solution set covers. While there are some critics for its bias towards extreme points,[59] it is one of the most used metrics in measuring the quality of a Pareto set because it is very practical and does not need a reference set to represent a Pareto front making it very desirable for many real-world scenarios. However, HV requires a reference point where most of the time it is selected as the maximum likely point for all objectives, in other words the worst-case solution.

Definition 2.7. Hypervolume Indicator: Let A be a set of decision vectors in the solution space ψ, $A \in \psi$, and R is the reference vector for all objectives. λ stands for Lebesgue measure and it is the extension of assigning a measure to n-dimensional Euclidean space where it represents length, area, and volume successively in one, two, and three-dimensional spaces.

Hypervolume indicator (Definition 2.7) of $I_H(A,R)$ is the Lebesgue measure of objective vectors weakly dominated by A but not necessarily by R. For a Pareto solution P, HV of P is the union of hypercubes of each solution a in the Pareto set A where the lower left vertex is the solution a and the upper right vertex is the reference point r.

$$HV(P) = \lambda \left(\bigcup_{a \in A} \{x | a \preccurlyeq x \preccurlyeq r\} \right) \tag{4}$$

$$\preccurlyeq_A (z) = \begin{cases} H(A,R)(z) \ | \exists a \in A, \exists r \in R : f(a) \leq z \leq r \\ \text{otherwise } 0 \end{cases} \tag{5}$$

Definition 2.8. Reference Vector: Assuming that the feasible region for each objective function is convex polytype bounded by linearly inequality constraints, each of the objective values are a function of the decision variables ($\vec{x}$) on those polytypes. Each of the Pareto solution set is bounded by the nadir ideal objective vectors where

$$\vec{z}^{nadir} \ni \vec{z}_i^{nadir} = \sup\{f_i(x)\} \quad \text{for all } i = 1, \ldots, k \mid x \in X$$

$$\vec{z}^{ideal} \ni \vec{z}_i^{ideal} = \inf\{f_i(x)\} \quad \text{for all } i = 1, \ldots, k \mid x \in X \tag{6}$$

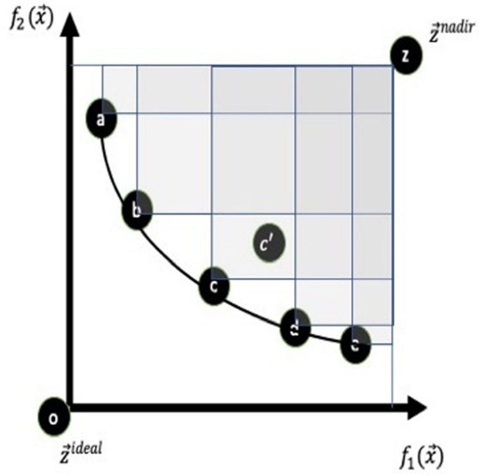


FIGURE 1 Hypervolume of a pareto solution set

Without loss of generality, let us assume a multi-objective problem with two conflicting objectives, f_1 and f_2, both minimization objective functions.

Note that solution c dominates c' because the 2D hypervolume of c contains the c', in other words $c \preccurlyeq c'$; but it is not true for other solution points in the Pareto Set since their 2D hypervolumes do not contain c'. The HV of this Pareto set is the shaded area in Figure 1.

2.4 | Application of theory on DRT due to obsolescence

Postulate 2.1. Determining the DRT for a sustainment dominated system is a MODM problem and it at least includes cost minimization and operational efficiency maximization.

Postulate 2.2. Determining the DRT for a sustainment dominated system requires selecting the best time with the optimum fitness value for the objectives throughout the product life cycle.

Postulate 2.3. Determining the DRT requires considering all system parts with a holistic view by including the system in use, system parts in inventory and system parts in maintenance.

Similar to Starling's research, we used system level approach driven by each part's availability, reliability and relevance factors.[29,61] However, we have measured the system's overall state by aggregating each part's state in the BOM and we have taken the criticality of each system part in the system configuration into account when measuring the overall systems' state.

Lemma 2.1. *Obsolete parts increases the cost factors over the product life cycle due to lack of original vendor support.*

Proof 2.1. Given in Appendix A.

Lemma 2.2. *Maintaining the obsolete products worsens the operational efficiency over the product life cycle due to lack of original vendor support.*

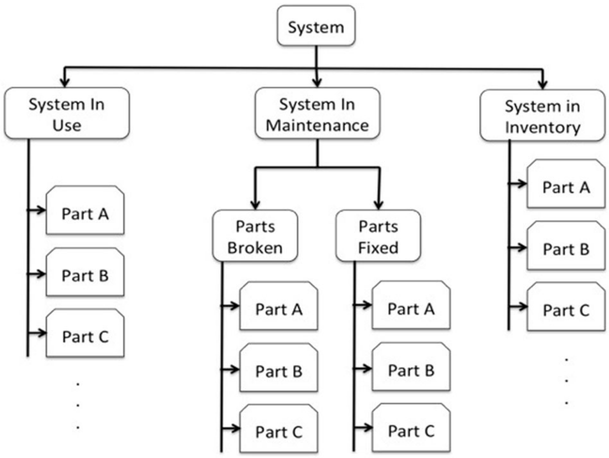


FIGURE 2 Notional representation of a system

Proof 2.2. Given in Appendix A.

Lemma 2.3. *The quality of consecutive Pareto solutions for multiple conflicting objectives (i.e., cost and performance) deteriorates over time for an obsolescence problem under the auspicious of Lemma 1 and Lemma 2.*

Proof 2.3. Given in Appendix A.

Theory 2.4. *Within the context of selecting DRT for sustainment-dominated systems due to COTS obsolescence, following the Lemma 2.1, Lemma 2.2, and Lemma 2.3, the point where the amount of deterioration reaches to a lower bound threshold value (theoretically zero) is the latest recommended time for design refresh. The threshold value is based on the risk appetite of the decision-maker.*

Based on the proofs for Lemmas 2.1–2.3, we can conclude that the area (volume for n objectives where $n > 2$) of hypervolume shrinks as the members of the Pareto solution set approaches the feasibility boundaries of objectives. The distance between the solutions and the feasibility boundary reaches notionally zero to push the solutions towards the feasibility region.

By Definitions 2.1 and 2.4, this is the time when the search algorithm cannot produce any dominating solution for at least one of the objectives in the following time intervals. When the search algorithm cannot produce any better solutions, it is best to consider a design refresh at this time. Empirical observation of the case study given in Section 4 also supports Theory 2.4.

3 | OBSOLESCENCE MODEL

3.1 | Modeling the system and its behaviors

The meta-model of the system representation is given in Figure 2. It is a conceptual model[62] to define concepts, relationships and semantics to aid in the creation of concrete models. The entities of the system parts

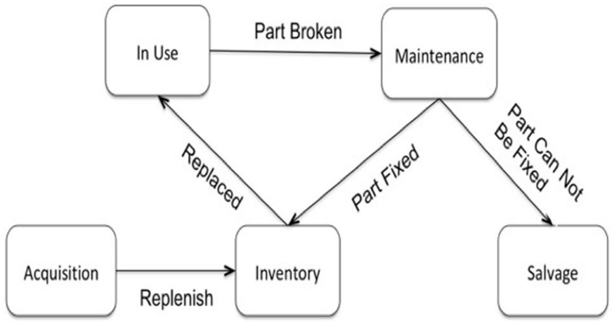


FIGURE 3 System parts flow diagrams

are modeled at the granularity of the least manageable level in the Bill of Material (BOM).[63] The overall system is composed of system parts used in operation, inventory, and maintenance.

System behavior, as its flow diagram is given in Figure 3, is modeled to move the system parts between the system in use, inventory and maintenance shop depending on the states of each system part. Each part can be in one of the following states: "functional," "broken," "under maintenance," or "inventory." The transition between these states are stochastically determined by using the MTBF and MTTR values of each part.

3.2 | Modeling the objectives and constraints

The obsolescence model developed in this research has two objectives: minimize the cost and maximize the operational efficiency.

We used the amount of Last Time Buy at a given time as the decision variable upon notified obsolescence and it represent the gene of the chromosome used in MOEA. The model can easily be extended to include new reactive strategies as additional genes into the chromosome. The model constraints are the maximum available budget and minimum operational efficiency. Those constraints represent the $\vec{z}^{nadir}$ point given above. Cost is an aggregate function of acquisition, operation, and disposal costs. Operational efficiency is the product of the relevance, reliability, and availability of the system parts in the whole system.

$$\min Cost$$
$$\max OperationalEfficiency \tag{7}$$

s.t.

$$\sum cost \leq MaxAvailableBudget$$
$$\sum efficiency \geq MinimumAcceptedEfficiencyLevel$$

Pareto solution ($P(t)$) at time t is a set of tuples with non-dominated elements of cost ($C(t)$) and efficiency ($E(t)$) values.

$$S = \{P(t) \mid P(t) = \{(C(t), E(t)) \mid C(t) = f_1(\vec{x}(t)) \text{ and } E(t) = f_2(\vec{x}(t))\}\} \tag{8}$$

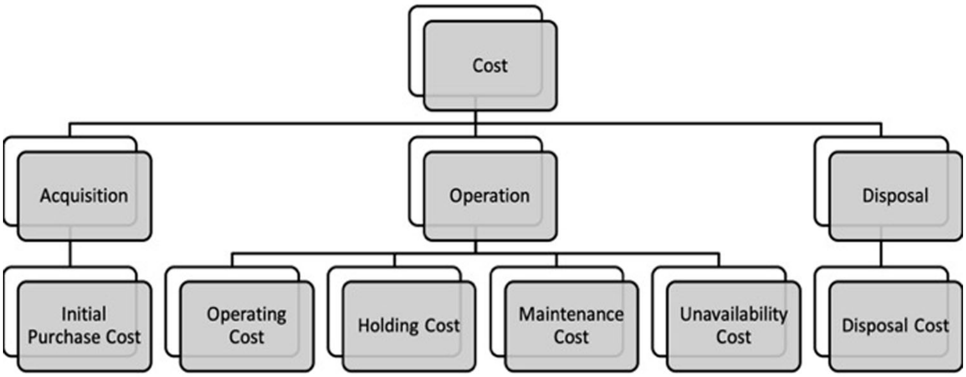


FIGURE 4 Cost model

3.2.1 | Cost model

Cost model is given in Figure 4 and includes acquisition, operation and disposal costs. Acquisition cost is the purchase cost of the part when notified as obsolete and a factor of part unit cost and the amount of Last Time Buy. The operation cost is the sum of the operating cost of the system ($C_{F(t,i)}$), holding cost for the inventory ($C_{H(t,i)}$), and maintenance cost for preventative and corrective activities ($C_{M(t,i)}$). The operating cost is the sum of fixed cost to run the system including labor, rent, electricity, security, and the variable cost that is a function of the duration and conditions of the operation. The holding cost is a function of inventory, spoilage, pilferage, labor, and storage costs. To put it simply, it is measured as a "c" percentage of the initial procurement cost. The maintenance cost is the sum of fixed costs for maintenance facilities and variable cost for routine preventative activities and corrective costs for each broken material that needs to be repaired. Disposal cost is a one-time cost in the cost model if the system is to be retired. While the unavailability cost has been used dominantly in the cost factor in the previous research, we have used this factor in the efficiency model as a penalty value by decreasing the availability of the system.

$$Cost = \sum \{ C_{Acq} + C_{Opr} + C_{Disp} \} \tag{9}$$

$$C_{Acq} = \sum_{t=1}^{T} \sum_{i=1}^{N} X_{LTB(t,i)} . P_{OV(t,i)} \tag{10}$$

$$C_{Opr} = \sum_{t=1}^{T} \sum_{i=1}^{N} C_{Op(t,i)} + C_{Manint(t,i)} + C_{Hold(t,i)} \tag{11}$$

$$C_{Op(t,i)} = C_{F\_Var(c(t),i)} + C_{F\_Fix(t,i)} \tag{12}$$

$$C_{Maint(t,i)} = C_{M\_R(t,i,c)} + C_{M\_Fix}(t, M) \tag{13}$$

$$C_{Hold(t,i)} = p_{(t,i)} .\%c \tag{14}$$

$$C_{Disp} = \sum_{i=1}^{N} C_{disp(i)} \tag{15}$$

3.2.2 | Efficiency model

Efficiency is the measurement of the extent of outputs contributed to the achievement of the system purpose at a given time. The operational efficiency model given in Figure 5 is based on the model on the effectiveness of a system proposed by Ashhab et al., however we have slightly modified the mentioned model by replacing the capability with the relevance of the system. The model is designed to include operational reliability, availability, and relevance.[64]

Availability consists of two components: material and operational availability.[65] Material availability represents the readiness of the inventory of the system to operate when it is needed. Operational availability is the readiness of operational components to perform an assigned mission.

There are various models developed to measure the availability of a system[66] some of which include point availability, average uptime availability, steady-state availability, inherent availability, achieved, and operational availability. Point availability (Equation 17) is the probability of a system being up and ready to operate at a given time. Average uptime availability (Equation 18) is the ratio of a system's availability over the period it is assured. Steady-state availability (Equation 19), also called asymptotic availability, is the limit of the availability function as time extends to infinite. When only corrective maintenance activities are considered, steady-state availability becomes inherent availability and measured by the ratio of MTBF to the sum of MTBF and MTTR. When preventive maintenance activities are taken into consideration, steady-state availability becomes achieved availability. Operational availability is measured over a period of time and includes all types of downtime periods. It is measured by taking the ratio of the uptime of the system to the total operating cycle.[66]

In this research, we assumed a constant failure rate, constant repair rate and series of N subsystems with no redundancy. We used point availability performance indicators for the expected instantaneous

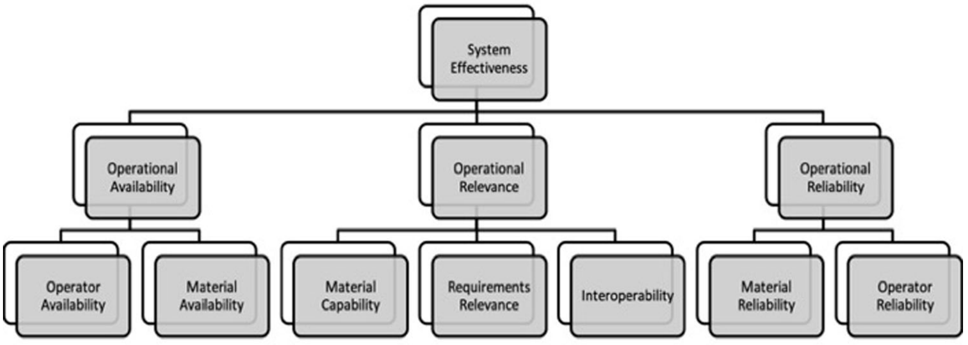


FIGURE 5 Efficiency model

availability of a system at a given time. System availability (E_{Avl}) is a function of MTBF and MTTR values and it represents the probability of the availability for both the system and operator at the time the system is needed for operation.[67,68]

The reliability of a system (E_{Rlb}) is a function of MTBF and represents the probability that the system will perform over a required period of time under specific conditions[65,69,70] when needed.

Point availability of a system part at a given time *t*, given in Equation (20) and driven from Equation (17) , covers both the reliability and availability of the part from initial time until *t*. It refers to the system's performance at a given time, but not during a duration.[69] Hence, Equation (17) also considers the reliability of a system until *t*. Reliability, as given in Equation (21), refers to a duration δt in which the part needs to operate. Reliability considers the availability as a precondition because a part's reliability would be zero during δt if it is not available at the beginning of δt. Hence, Equations (17) and (20) take the reliability of a part into account when measuring point availability. E_{Rlb} factor used in Equation (16) is the reliability of a given part at time t, that is intended to be used during an operational period δt. For example, considering the case study given in Section 4 where a discrete event simulation is modeled with monthly time intervals, assume that a part is used every Monday for 6 h and the monthly operational time is therefore 24 h a month. Equation (20) measures the availability and reliability of system part for the whole time since beginning until time *t*. Equation (21) measures the reliability of the system and its parts for the operational duration of 24 h between time *t* and *t*+1 for the duration of δt operational time units.

The system's operational relevance (E_{RIv}) is a function of the significance of the operational requirement, material, and interoperability level. The relevance of a system is measured by combining the relevance of the system's objectives and the relevance of the system with respect to its objective. In other words, it depends on the relevance of the business case and the degree of the system's meeting those defined business cases.[71]

$$Efficiency = E_{Avl} . E_{Rlb} . E_{RIv} \tag{16}$$

$$A(t) = R(t) + \int_0^t R(t-u)\, m(u)\, du \tag{17}$$

TABLE 1 Acquisition cost parameters

t	Simulations step
i	Subsystem index
T	Simulation duration
N	Total number of subsystems
C_{Acq}	Acquisition Cost
$P_{OV(t,i)}$	Original Vendor price for subsystem *i* at time *t*
$X_{LTB(t,i)}$	Last Time Buy amount at time *t* for subsystem *i*

$$\overline{A(t)} = \frac{1}{t}\int_0^t A(u)\, du \tag{18}$$

$$A(\infty) = \lim_{t\to\infty} A(t) \tag{19}$$

$$E_{Avl}(t,i) = \prod_{i=1}^{N} \frac{\mu_i}{\lambda_i+\mu_i} + \left\{\frac{\lambda_i}{\lambda_i+\mu_i} e^{-t(\lambda_i+\mu_i)}\right\} \tag{20}$$

$$E_{Rlb}(\delta t, i) = \prod_{i=1}^{N} e^{-\lambda_i \delta t} \tag{21}$$

$$E_{RIv}(t,i) = \prod_{i=1}^{N} e^{-\gamma_i t} \tag{22}$$

All parameters and variables used in the Cost and Efficiency Models are listed in Tables 1–6 and given in the Appendix B.

3.3 | Model implementation

We have implemented a stochastic discrete event dynamic system simulation over a user defined period. At each step, a state is constructed for each system part in use, in the inventory and at the maintenance shop in order to build up the system's overall status. The transition between those states are based on the MTBF, MTTR values that are fetched from the data sheets of the system parts. Skill and material

TABLE 2 Operating cost parameters

t	Simulation step
T	Simulation duration
i	Subsystem index
N	Total number of subsystems
c	Holding Cost Parameter
$p_{(t,i)}$	Price of subsystem *i* at time *t*
C_{Opr}	Operation cost
$C_{Func(t,i)}$	Functioning cost for subsystem *i* at time *t*
$C_{Maint(t,i)}$	Maintenance cost for subsystem *i* at time *t*
$C_{Hold(t,i)}$	Holding cost for subsystem *i* at time *t*
$C_{F\_Var(c(t),i)}$	Variable cost for subsystem t for conditions at time t
$C_{F\_Fix(t,i)}$	Fixed Cost for subsystem *i* at time *t*
$C_{M\_R(t,i,c)}$	Cost of preventative or corrective activity *c* for subsystem *i* at time *t*
$C_{M\_Fix}(t, M)$	Fixed cost to run maintenance shop M at time *t*

TABLE 3 Disposal cost parameters

N	Total number of subsystems
i	Subsystem index
C_{Disp}	Disposal Cost of overall system
$C_{disp(i)}$	Disposal cost of subsystem *i*

TABLE 4 Availability parameters

N	Total number of subsystems
i	Subsystem index
μ_i	Repair rate for subsystem i (1/MTTR)
λ_i	Failure rate for subsystem i (1/MTBF)
$E_{Avl}(t, i)$	Availability efficiency value for subsystem *i* at time *t;* range [0-1]

TABLE 5 Reliability parameters

N	Total number of subsystems
i	Subsystem index
λ	Failure rate for subsystem i (1/MTBF)
$E_{Rlb}(t, i) =$	Reliability efficiency value for subsystem *i* at time *t;* range [0–1]

TABLE 6 Relevance parameters

N	Total number of subsystems
i	Subsystem index
γ_i	Operational obsolescence rate for subsystem i
$E_{Rlv}(t, i) =$	Relevance efficiency value for subsystem *i* at time *t*

```
initialize system (system parts data, simulation duration(T), EA parameters)
do{
        state(t) = create states(t,MTBF,MTTR)
        Act on states(state(t))
        MOEAProblem(t) = initialize MOEA problem (t, EA method, states)
        ParetoSolutionSet(t) = findParetoSolution(MOEAProblem(t))
        S= addQualityToSet(S,findQualityOfParetoSolution(ParetoSolutionSet(t)))
while(t<T)
Φ = findFitnessDistrubution(S)
DRT = findDRT(Φ | dϕ/dt = 0)
```

FIGURE 6 Implementation Pseudocode

obsolescence depend on the attributes of the system. There are several methods proposed to measure skill obsolescence[72–74] and material obsolescence; they depend on the risk factors and remedies with regard to the part and its technology.[46,75–79]

The system's overall state is measured by aggregating the individual system parts' states. If any system part cannot be replenished from either inventory or the maintenance shop; the overall system status is lowered as a function of the criticality of the broken part.

At each step of the discrete simulation, an MOEA problem is instantiated by using the input parameters and the states developed in the previous step. The MOEA model produces the Pareto solution set for that given MOEA problem at each discrete step. Decision variables are encoded within each chromosome as the amount of the LTB. Figure 6 shows the pseudo-code of the model.

Following the initialization, for each interval (t) where t = 0,…,T, system states are calculated and parts are moved around based on the system states, the MOEA problem is generated with selected EA method (i.e., NSGA-II, PAES or PESA2], Pareto front is generated, the hypervolume of Pareto solution is measured and added to quality set. The fitness distribution function is generated based on the quality set and finally the minimum value of the distribution is proposed as DRT.

4 | CASE STUDY

In order to demonstrate the design refresh planning with the proposed approach, the case study was performed on a sub-system to a naval command and control system. The system was originally designed in 2004 and deployed in 2007. In later years, each subsystem had become obsolete as of 2010 and Bridge Buy reactive obsolescence management methods were implemented by the maintenance agency for the obsolete COTS parts as they were depleted or as informed by the original vendor as obsolete. However, in 2019 reactive obsolescence methods started failing to meet the operational objectives because of the difficulty in procuring the parts even from alternative vendors. The unit responsible for Integrated Logistics Support (ILS) was obliged to propose a tech-refresh to replace several COTS parts with the new ones in the original design. The estimated cost for the proposed solution was expected to reach roughly two million USD in 2019. Figure 7 shows the real-life events that actually took place in the life cycle of the system in use.

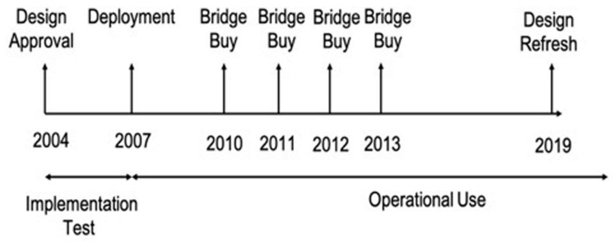


FIGURE 7 Real life events in system life cycle

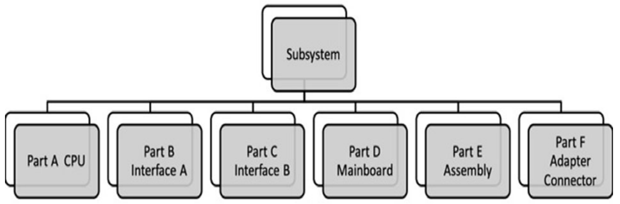


FIGURE 8 System configuration

The system is composed of the parts given in Figure 8. The lowest granularity level of the system parts is selected at Line Replaceable Unit (LRU). Each of these LRU's is produced by different vendors and all of them were announced as obsolete by the original vendors by 2010. While several second vendors have continued to provide those LRU's for a certain time, the number of second vendors dropped to only a few by 2019, some of which are offering only refurbished or open-box item. Hence, the availability and reliability of the system have significantly decreased because of the scarcity and originality of the parts.

The case study is designed as if the proposed model is run in 2007. The objective of the case study is to compare the cost and efficiency values of the system for which the situation experienced in real-life against the simulation outputs. Since the simulation is run from the past to today, we had a chance to use the exact known obsolescence dates instead of forecasted ones. In addition to that, since the simulation length is only 12 years, skill obsolescence and requirement relevance are assumed to have no impact on the system and is omitted.

The simulation was run as of 2007 January (considered as T0) for 144 months (12 years) till 2019. The holding cost rate was assumed to be 5% of the original vendor procurement cost for the parts per year. All cost values used in the simulation were adjusted with discount rate (I) of 1.3%, the average inflation rate for the 12 years. The Weighted Average Cost of Capital (WACC) is the cost of money. Sandborn showed that the different WACC values have significant impact on the optimum Bridge Buy sizes.[34] However, if investors are risk-neutral, the WACC can be set simply by risk-free interest rate to adjust the inflation. We assumed the risk-free option and used the inflation rate in place of discount rate. The actual discount rate for WACC reflects the industry standards. However, for simplicity, we adjusted the cost factors on the time domain and used Feng's approach to reflect discount rate.[35] The parameters of WACC are given in Table 7.

$$\textit{Adjusted Cost} \quad (t) = \frac{\textit{Cost}\ (t)}{(1+I)^{\left(\frac{t}{12}\right)}} \tag{23}$$

TABLE 7 WACC parameters

Adjusted Cost(t)	Adjusted cost at time t
Cost(t)	Cost at time t
I	Annual inflation rate
t	Time representing month

At each step of the simulation for 144 months, a separate MOEA problem was instantiated. For each MOEA problem, NSGA-II, PAES, PESA2 EAs were run 10,000 times with an initial population of 10,000 chromosomes representing the amount of LTB to produce the Pareto solution sets at each step. The quality value of each Pareto solution set for each EA was measured and stored at each step of the simulation.

5 | RESULTS

As a result of the analysis of the simulation for cost minimization and efficiency maximization objectives of the case study, Figure 9 shows the distribution of quality values for the Pareto solutions over 144 months of three EA algorithms. The horizontal axis shows the time intervals and the vertical axis shows the hypervolume quality values of Pareto solution sets. The quality of Pareto solutions follows a continuous deterioration over time and after a certain point; we can see that the hypervolume quality value of Pareto solutions is zero, which means that MOEA cannot produce a Pareto solution anymore for at least one of the objectives.

Figure 11 shows the deterioration of Pareto solutions over cost and efficiency objectives as time progresses. This is an empirical proof of Theory 2.4. We have normalized the cost objective values between (0 and 1) over the maximum value in the Pareto set in order to graphically show both objectives in coherence. As time progresses, the cost and the efficiency values of the Pareto optimal set worsens. As can be seen in Figure 11, when the time interval is around 70, the Pareto solution sets started to have only one solution. That means one of the objectives has reached its feasibility boundary and is not represented in the Pareto solution anymore.

Since the MOEA cannot produce a Pareto solution with a hypervolume value anymore, the system is recommended to go through a tech refresh not later than the 70th month after deployment in 2007, which is 2013.

While what exactly would go into the design refresh as of 2013 requires a thorough analysis, for simplicity, we intuitively assumed that maintaining the same functionality is a requirement and similar COTS parts would be used in the tech refresh in 2013. In order to see if there will be a need for a second design refresh between 2013 and 2019, the simulation is run again as of 2013 until 2019. Figure 13 shows the quality values of Pareto solutions for a second design refresh. The second design refresh is recommended to take place on 138th month, which is 2018.

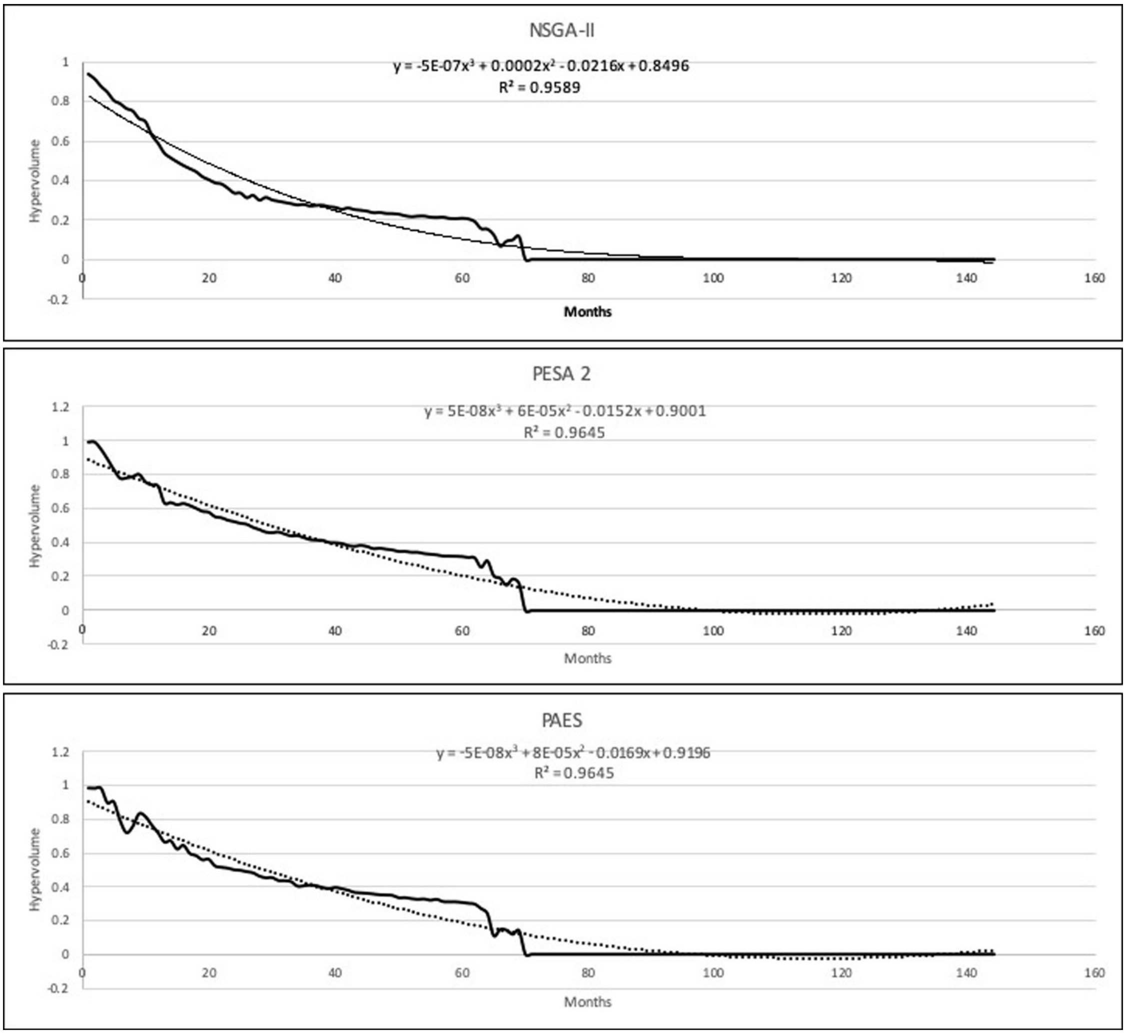


FIGURE 9 First design refresh forecast

EA Algorithms	NSGA II	PAES	PESA 2
NSGA II	1		
PAES	0,9830323	1	
PESA 2	0,97843109	0,99763779	1

ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0,29255795	2	0,14627898	2,45738577	0,08688942	3,01720189
Within Groups	25,001028	420	0,05952626			
Total	25,2935859	422				

FIGURE 10 Statistical analysis of three EA algorithms for the first design refresh forecast

In both simulations for the first and second DRTs, we note that all three EA algorithms have resulted in highly correlated, note the Anova test results in Figures 10 and 14 with alpha value .05. Since the *p* value is bigger than alpha and F_{crit} value is bigger than F value in both analyses, we cannot reject null hypothesis, hence we can conclude that the means of three hypervolume populations generated by three EA algorithms are equal. Figure 12 shows the DRTs proposed by the model.

Thereafter, we recalculated the expected cost of the system if the system had gone through design refreshes as proposed by the model in 2013 and 2018, respectively. We then compared the simulation results with the current and actual costs and efficiency. The comparison of the cost and efficiency values are given in Figures 15 and 16.

The results have shown that the cost factor would be decreased by roughly 17% and the efficiency factor would be increased significantly by 28 times.

6 | DISCUSSION

The COTS obsolescence for sustainment-dominated systems has been mostly seen as a financial issue. Numerous studies have focused on

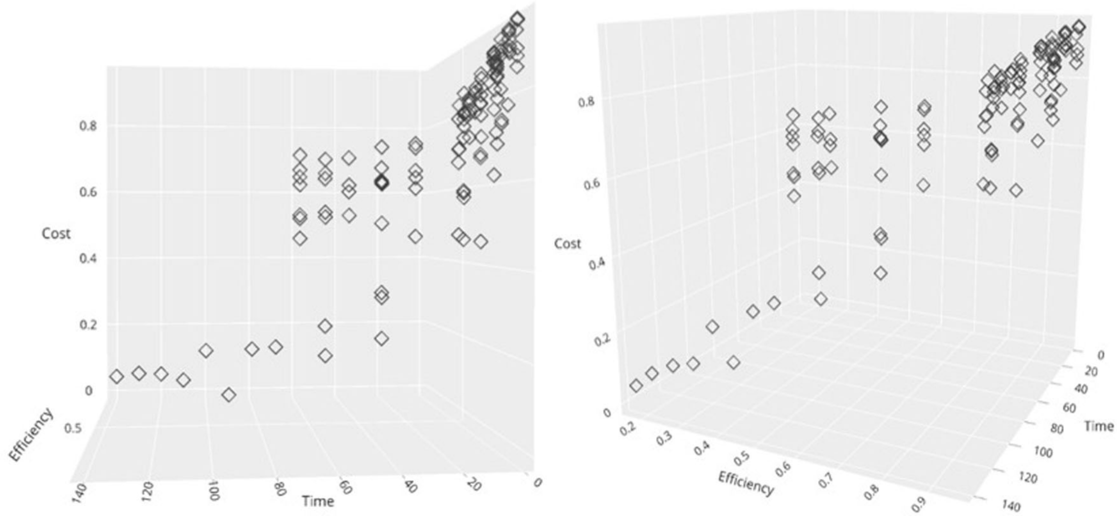


FIGURE 11 Deterioration of pareto solutions

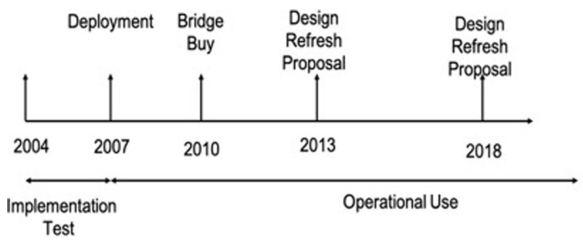


FIGURE 12 Proposed DRTs

cost minimization to find either the best set of reactive and proactive obsolescence mitigation activities or the best time to redesign the system. However, cost minimization is not the only objective for decision-makers. The operational efficiency is the core of any given business or mission objectives, and therefore maximizing or at least maintaining the operational efficiency must be taken into account as another objective.

Since those mentioned objectives conflict with each other in nature, we proposed a MODM model to balance the competing needs of financial and operational communities of interest. While the financial community or budget holders prioritize the minimum costs, the operational community aims at the efficient mission or business outputs. The decision to refresh the design due to COTS obsolescence weighs the positive and negative impacts on cost and efficiency objectives. The proposed model in this research enables the different priorities of decision makers to be included into the decision-making process. It utilizes MOEAs to generate a series of Pareto solution sets and their qualities over a discrete-time simulation model. We have shown that the quality of the Pareto sets deteriorates over time and when the deterioration of the quality values for those Pareto solutions set reaches zero or a defined minimum threshold value, it means that the solutions do not fulfill at least one of the objectives anymore. This is assessed to be an indicator to consider a design refresh or tech refresh time for that system since at least one of the objectives is not represented in the solution space.

We implemented two objectives in the model, however the model is scalable for additional objectives subject to constraints and big-O computational complexity. The computational complexity of the algorithms we used in the study is $O(n_o n_g n_p{}^2)$ where n_o, n_g *and* n_p are the number of objectives, generations and population respectively.[80] The number of objectives and generations are linearly proportional, however, number of populations used in the EA heuristics that we coded in the model is polynomial proportional to computation time. Hence, the model is scalable for the number of objectives and generations. However, as the number of populations increases, computational time increases polynomially.

The model was designed to predict the future states of a system and each of its parts. We ran the simulation in the use case starting in 2007 in order to validate the model by comparing the results against real data. However, the model can also be run as of today to inform a forward-looking state of obsolescence to predict optimum DRTs in the future. The cost model and efficiency model are predicting the states of system's parts by using listed MTBF, MTTR for efficiency model, the advertised cost values for cost model and the obsolescence state for each part. The efficiency and the cost factors for acquisition, operation, maintenance activities in future states can be estimated based on the existing obsolescence and cost forecasting models mentioned in Section 1 as well as expert judgement.

The cost and efficiency models given above can be implemented differently depending on the nature of the system, organization, the technology being used and the operational context in which the system is used. The main contribution of this research is based on the premise that, regardless of the system and the implementation of the problem specific objectives,[58] the deterioration of the quality values of the Pareto solutions generated by multi-objective problem can be used as an indicator to point DRT.

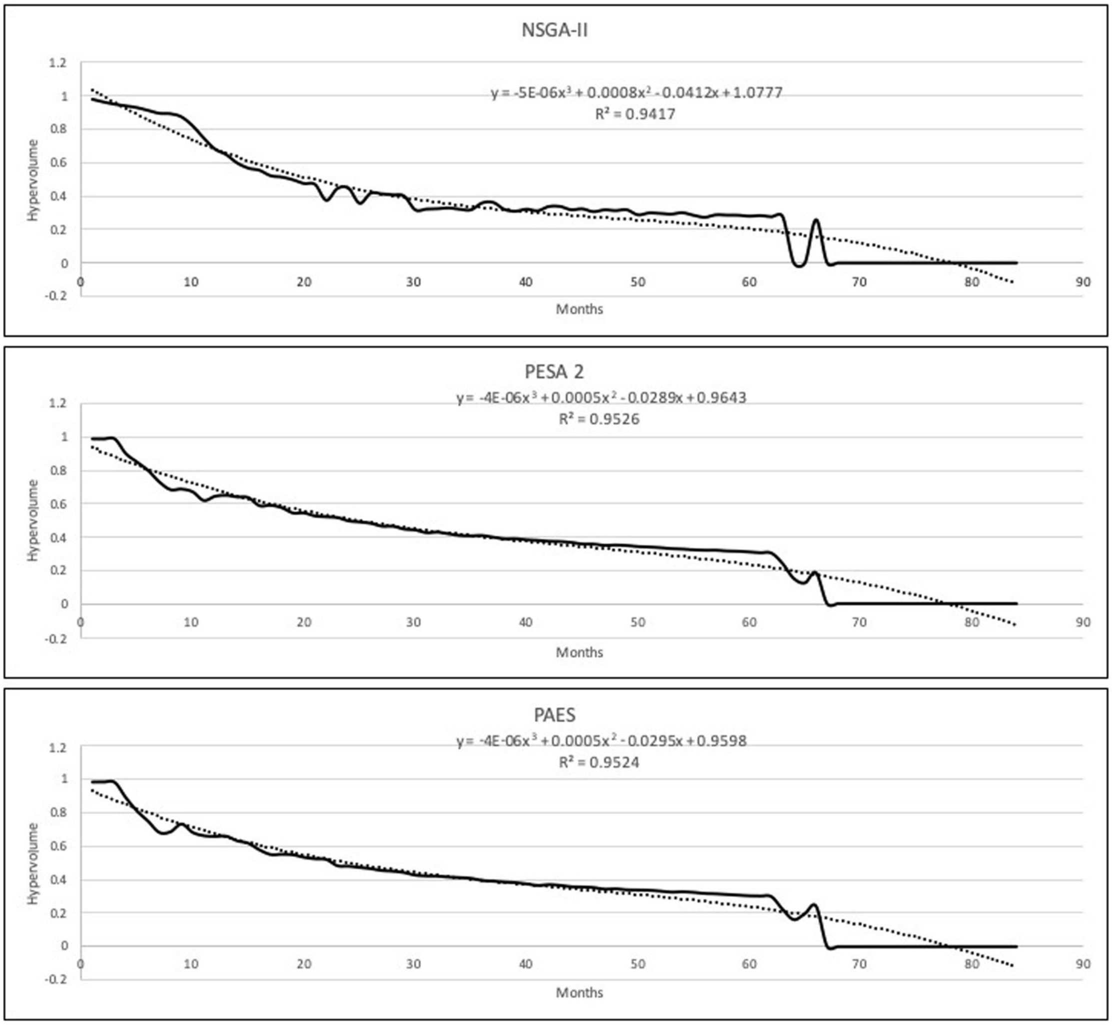


FIGURE 13 Second design refresh forecast

	PESA2	NSGAII	PAES
PESA2	1		
NSGAII	0,97134025	1	
PAES	0,99786181	0,97158882	1

ANOVA

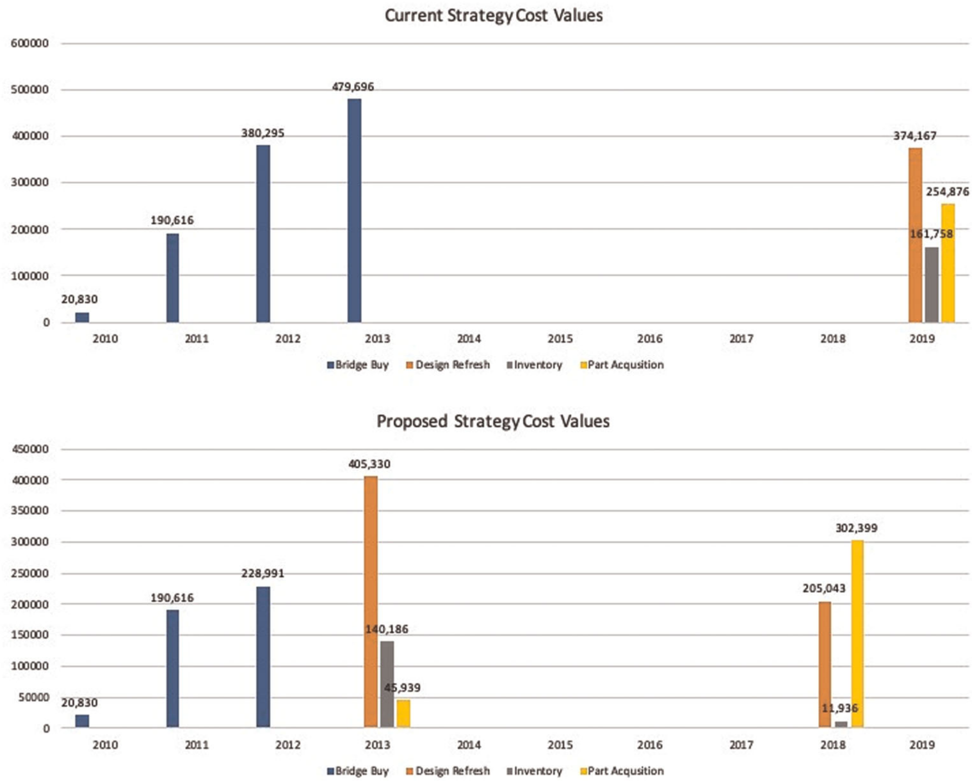
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0,0331217	2	0,01656085	0,23532456	0,79048986	3,03206492
Within Groups	17,5232541	249	0,07037451			
Total	17,5563758	251				

FIGURE 14 Statistical analysis of three EA algorithms for the second design refresh forecast

7 | CONCLUSION

The present research exhibited the application of MOEA and set based preference approach over quality values of Pareto Solution sets to determine optimum time to initiate design refresh activity for sustainment dominated systems.

The objective of this study was achieved by presenting a novel approach to forecasting the DRT of sustainment-dominated obsolete systems with a balanced approach among competing multiple objectives under resource-constrained conditions. The proposed model is scalable and extendible to include other objectives, variables, constraints, EA algorithms, and QIs. Based on both theoretical and data-driven conclusions, we showed that the hypervolume quality values of the Pareto solutions measured over time for the cost minimization and efficiency maximization objectives is a simple but decisive and realistic indicator to forecast the DRT of sustainment dominated systems with significant COTS obsolescence risk factors. Having this approach in hand, the program managers of sustainment dominated systems will



Current Strategy

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Connector	10		4	12						5
Interface A		3	4	12						5
Interface B			21							5
Assembly		2	2							2
Mainboard			8							4
CPU			4							1
Design Refresh										1
Total Cost	20830	190615,87	380294,63	479696,38	0	0	0	0	0	790800,96

Total Grand Cost	1.862.237,84

Proposed Strategy

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Connector	10		4	10					2	
Interface A		3	4							
Interface B			3							
Assembly		2	1	4					1	
Mainboard			1	4					1	
CPU			1	4						
Design Refresh				1					1	
Total Cost	20830	190615,87	228991,28	591455,09	0	0	0	0	519377,87	

Total Grand Cost	1.551.270,11

FIGURE 15 Cost values for current strategy and proposed strategy

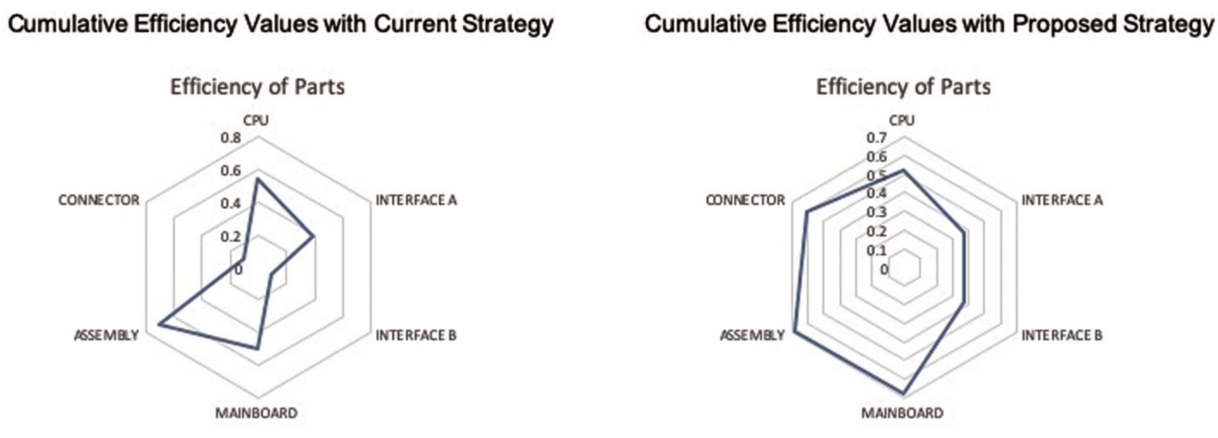


FIGURE 16 Efficiency values for current strategy and proposed strategy

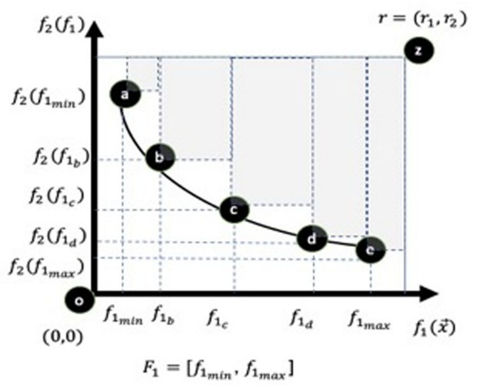


FIGURE 17 Transforming Pareto solution sets onto objectives

be capable of making more informed decisions on DRT by considering multiple objectives including but not limited to cost minimization and efficiency maximization.

DATA AVAILABILITY STATEMENT

Data sharing not applicable – no new data generated.

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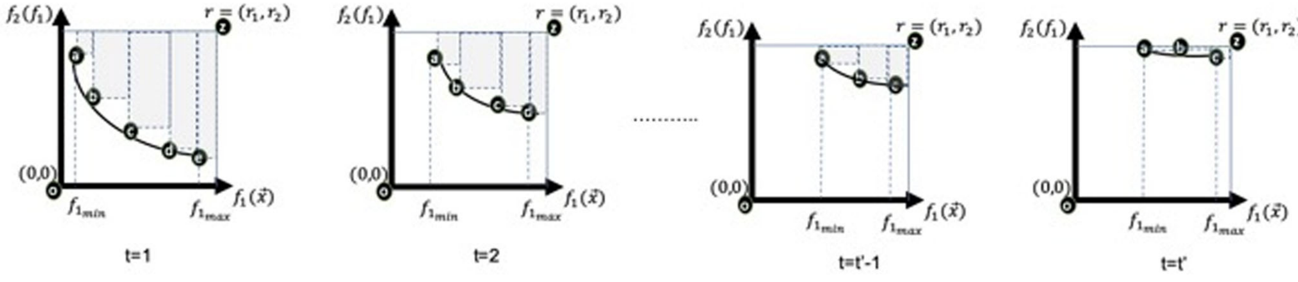

FIGURE 18 Deterioration of Pareto solutions sets over time

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APPENDIX A

Proof of Lemma 2.1. While it is straightforward, we will use proof by contradiction (reduction ad absurdum). Any obsolete part can be in one of the three state of the system: in use, maintenance or inventory.

The cost of part *i* of the system is the sum of the acquisition, operation, maintenance, and inventory costs over the product life cycle *(T)* as denoted below. Let us assume that all costs are adjusted with WACC.

$$C\,(i) = \sum_{t=0}^{T} C_{opr}\,(i,t)\,.n_{opr}\,(i,t) + C_{inv}\,(i,t)\,.n_{inv}\,(i,t) + C_{maint}\,(i,t)\,.n_{maint}\,(i,t) + C_{acq}\,(i,t)\,.n_{acq}\,(i,t) \tag{24}$$

The cost of a given part over its life cycle is sum of the cost of the part before it is called obsolete (t_o^-) and after (t_o^+).

$$C\,(i) = C(i)^{t_o^-} + C(i)^{t_o^+} \tag{25}$$

The opposite of Lemma 2.1 *(P)* is that the cost of acquisition, operation, inventory and maintenance of the obsolete parts is at most (equal or less than) the cost incurred before the parts are called obsolete. The obsolescence of parts only affects the acquisition, maintenance and inventory costs, but not the operating costs. $\neg P$ implies that $C(i)^{t_o^+}$ is less than $C(i)^{t_o^-}$ as follows:

$$C(i)^{t_o^-} \geq C(i)^{t_o^+} \tag{26}$$

1. Inventory cost: An obsolescence problem in sustainment dominated systems is a stochastic continues-review model where future demands for parts have considerable uncertainty. Continues-review models have two critical numbers: R, reorder point and Q, purchase order quantity. Inventory policy is to place an order for Q when the part amount is dropped to R. In obsolescence case, the reorder point is fixed at obsolescence time to order LTB. The main assumption of the continuous-review model is that the probability of demand is known or estimated. Purchase order quantity is

$$Q = \sqrt{\frac{2DS}{h}}.\sqrt{\frac{p+h}{p}} \tag{27}$$

where *D* is the average demand per unit time, *S* is setup cost, *h* is holding cost, *p* is shortage cost. Considering obsolescence for sustainment dominated systems, such as military, nuclear, major transportation systems, *p* is relatively a lot higher than *h*, hence the Q approaches to Q^* as in standard EOQ model.

In obsolescence model, the demand is projected over the expected life cycle of the system. MTBF is the most appropriate parameter to estimate the future demands of a part. Hence *Q*, denoting LTB, is increased by the square root of the average demand value of the part until the retirement or DRT of the system. Thus, the LTB becomes higher than the optimum value of Q^* and $C_{inv}(i)^{t_o^+}$ and increases accordingly as the total holding cost is increased for obsolete parts. Therefore $C_{inv}(i)^{t_o^+}$ cannot be less than $C_{inv}(i)^{t_o^-}$.

1. Acquisition cost: Based on Solomon's postulate that the price of obsolete parts in the typical characteristics of product life cycle at obsolescence stage as "not applicable or very high if available from aftermarket sources,"[25] since the demand will increase in the wear-out phase of the part after it becomes obsolete due to bathtub probability, [81] $C_{acq}(i)^{t_o^+}$ cannot be less than $C_{acq}(i)^{t_o^-}$.
2. Maintenance cost: Original vendors stop after-sale support once the product is called obsolete. In that case, some vendors offer special service level agreement with the system owners to continue the support only for that customer; however, such support comes with higher cost than the one before the part is called obsolete. In addition to that, second market vendors, who sell those obsolete parts also provide such after sale support with higher prices.[82] Besides, as given in the proof of Lemma 2, the reliability of the parts is decreasing with age, especially after being called obsolete and the probability of an obsolete part be broken becomes higher in than early stages of the part in its product life cycle. As, the number of maintenance activities and visit to maintenance shop for an obsolete part increases, the total maintenance cost of the system also increases proportionally. Hence, $C_{maint}(i)^{t_o^+}$ cannot be less than $C_{maint}(i)^{t_o^-}$.
3. Based on 1., 2., and 3., we can conclude that $\neg P$ is false, hence P is true and $C(i)^{t_o^-}$ is less than $C(i)^{t_o^+}$.

Proof of Lemma 2.2. Operational efficiency is a factor of system's availability, reliability, and maintainability. System availability (E_{Avl}) is a function of MTBF and MTTR values and represents the probability of availability for the system and operator at the time the system is needed for the operation.[67,68]

$$E_{Avl}\,(t,i) = \frac{\mu_i}{\lambda_i + \mu_i} + \left\{ \frac{\lambda_i}{\lambda_i + \mu_i} e^{-t(\lambda_i+\mu_i)} \right\} \tag{28}$$

The reliability of a system (E_{Rlb}) is a function of MTBF and represents the probability that the system will perform over a required period of time under specific conditions.[65,69]

$$E_{Rlb}\,(t,i) = e^{-\lambda_i t} \tag{29}$$

Both the reliability and availability of a system part at a given time are inverse exponential to the time; thus, as time increases, the availability and reliability values decreases exponentially. Performance and accrued profit of any given system will decrease in accordance with a stochastic distribution function over time and the maintenance cost will increase accordingly.[50]

When a part becomes obsolete, the original vendor stops supporting the part and the owner of system with obsolete part is left without after sale support. While there is a degree of support from second vendors, it is either a nominal support or comes with higher cost. Therefore, it is straightforward to accept that maintainability of an obsolete part decreases after the part becomes obsolete.[82]

Since reliability, availability, and maintainability values all decrease when the part becomes obsolete, the operational efficiency of a part decreases inversely proportional to the time.

Proof of Lemma 2.3. **As given in** Figure 17, **w**e can transform the Pareto set (P = {a,b,c,d,e}) given above to mapping of *f* 1 objective values onto objective values such that:

$$f_2 : f_1 \in F_1 \rightarrow f_2(f_1)$$

In this transformation, r_1 *and* r_2 are the maximum allowable values for each objective, in other words, the boundary of feasibility region of each objective. The hypervolume, I_H, of the Pareto set is the integral of shaded area bounded by (r_1, r_2) and vertices of the Pareto set $\{(f_{1_{min}}, f_2(f_{1_{min}})), \ldots, (f_{1_{max}}, f_2(f_{1_{max}}))\}$. Let n be the number of points in the Pareto set, $f_{1_{n+1}} = r_1$ and $f_2(f_{1_{n+1}}) = r_2$. Then the hypervolume of the Pareto set (*P*) is

$$I_H(P) = \sum_{i=1}^{n} \int_{f_{1_i}}^{f_{1_{i+1}}} \int_{f_2(f_{1_i})}^{f_2(f_{1_{i+1}})} df_1\, df_2 \cong \sum_{i=1}^{n} \left(f_{1_{i+1}} - f_{1_i}\right) . \left(f_2(r_1) - f_2\left(f_{1_i}\right)\right) = \Phi \tag{30}$$

On a discrete-time stochastic simulation, let *Ψ(t)* be the set of all admissible solution sets with finite size at time *t* and *P(t)* be the set of Non-dominated Pareto Solution sets where $P(t) \subseteq X$, $P(t) \in \Psi$. Then, the hypervolume of a Pareto Set at time *t* is

$$I_H(P(t)) = \breve{}\,(t) \tag{31}$$

In the context of obsolescence management, following Lemmas 2.1 and 2.2, where both cost and efficiency objectives deteriorate over time, Ψ shrinks, the members in the Pareto solution set moves towards to the feasibility region of the decision space. Deterioration of Pareto Solutions sets over time is given in Figure 18.

$$\lim_{t \to t'} \{f_2\left(f_{1_i+1}\right) - f_2\left(f_{1_i}\right)\} = 0 \tag{32}$$

There exist a time (*t*) such that t' where $(f_2(r_1(t')) - f_2(f_{1_i}(t'))) \cong 0$. Putting that in Equation (30), we find

$$\lim_{t \to t'} (I_H(P(t))) = \breve{}\,\left(t'\right) = 0 \tag{33}$$

That proves that, under the auspicious of Lemmas 1 and 2, the hypervolume of a multi-objective obsolescence problem asymptotically approaches zero as time progresses and approaches to t′.