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# OPTIMAL TECHNOLOGY REFRESH STRATEGIES FOR STRATEGIC DMSMS MANAGEMENT USING RANKING AND SELECTION

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## ABSTRACT

The effects of Diminishing Manufacturing Sources and Material Shortages (DMSMS) can be excessively costly if not addressed in a timely manner. A strategic DMSMS management method that seeks to minimize the overall life-cycle cost of a system, e.g. an aircraft or ship, is presented. The goal is to select an optimal scheduling of technology refreshes over a fixed lifetime, using lifetime buys as the mitigation option. A DMSMS specific cost model is constructed that accounts for costs of multiple, diverse parts in a system and multiple technology refreshes. This study shows the efficacy of using a ranking and selection method to identify the optimal technology refresh strategy for a complex and stochastic cost function dependent upon varying refresh costs. A visual model is presented which provides the ability to quickly compare other feasible strategies.

## 1 INTRODUCTION

For sustainment dominated systems, where the system lifetime is much larger than the constituent sub-parts of the system, accounting for diminishing manufacturing sources and material shortages (DMSMS) issues in life-cycle planning is critical. If these systems are managed poorly, sustainment costs can dominate operational costs and diminish the operational readiness of the system. Retiring large systems and replacing them with newer systems is often extremely costly and should be avoided unless absolutely necessary. In order to keep military platforms operationally effective and relevant it is often necessary to evaluate strategies consisting of lower cost alternatives to complete system redesigns. The evaluation, identification, and implementation of the most cost-effective strategy is the goal of DMSMS management.

DMSMS management can be thought of as consisting of three facets: reactive, proactive, and strategic (Bartels et al. 2012). Reactive DMSMS management occurs after a part has become obsolete or is known to become obsolete in the near future. At the disposal of the DMSMS manager are a multitude of reactive options to mitigate DMSMS issues such as using existing stock, using approved parts, part substitutions, extending production, developing new sources, lifetime buys (LTBs), and technology refreshes (Defense Standardization Program Office. 2016; Bartels et al. 2012). LTBs are a commonly used mitigation technique where a DMSMS manager purchases a large enough quantity of the parts to sustain the product until the next scheduled technology refresh or the planned end of life. LTBs are also referred to as “life-of-need”, “bridge”, “last-time”, and “life-of-type” buys. Proactive DMSMS management forecasts the risk for components and uses reactive options to mitigate obsolescence issues (Sandborn 2008).

Strategic DMSMS management is defined as a “mix of reactive mitigation approaches and [planned technology] refreshes that minimizes life-cycle costs” (Sandborn 2008). A technology refresh is a predictable process for replacing old technology with new assets to avoid technology obsolescence, to save money by improving system efficiency, and to reduce failures and downtime. Other terms for technology refreshes are "design refresh", "redesign", and "technology insertion". This paper considers strategic DMSMS management plans that use a sequence of planned technology refreshes with LTBs as the intermediate mitigation option between technology refreshes.

An optimal DMSMS management plan minimizes the overall cost of a platform over the operational lifetime. For each time period (i.e. year), a decision maker must decide whether or not to schedule a technology refresh each year over the system's planned lifetime $T$. The sequence of decisions made at each time period is considered a strategy represented by the vector $y \in Y$ of length $T-1$. Each element $y_t$ in the vector $y$ is either a 0 or a 1. In DMSMS terms, if $y_t = 1$ this indicates a planned refresh at year $t$. The set $Y$ is the set of all $2^{T-1}$ possible strategies since it is assumed that a technology refresh will not be scheduled at year $T$.

Two example strategies with a combination of LTBs and technology refreshes are shown in Figure 1. The red, dashed lines represent the years with a planned technology refresh. Arrows represent the procurement lifetime of a part, or the time that a part is available for procurement in the marketplace. If a part becomes obsolete prior to a planned refresh, these shortfalls must be covered by a LTB purchase, indicated by the boxes. Costs are incurred at a planned technology refresh (vertical dashed red lines) and LTBs (boxes). The purchase quantity of the LTB must be large enough to ensure there are sufficient quantities available to meet demand until the next planned technology refresh or planned system obsolescence. The figure on the left depicts a strategy ($\langle 001000100 \rangle$) with two technology refreshes. Costs for this strategy are incurred at the planned refresh years (years three and seven) and to cover the demands represented by the LTB boxes. The figure on the right depicts a strategy ($\langle 000001000 \rangle$) with one technology refresh. This strategy only incurs one technology refresh cost at year six for the technology refresh, but will incur greater LTB costs since there is a greater amount of time to cover the LTB periods. Since there is often uncertainty in the costs for LTBs and technology refreshes, finding the optimal strategy can be difficult. This paper will introduce uncertainty in the procurement lifetimes but will assume fixed technology refresh and LTB cost rates.

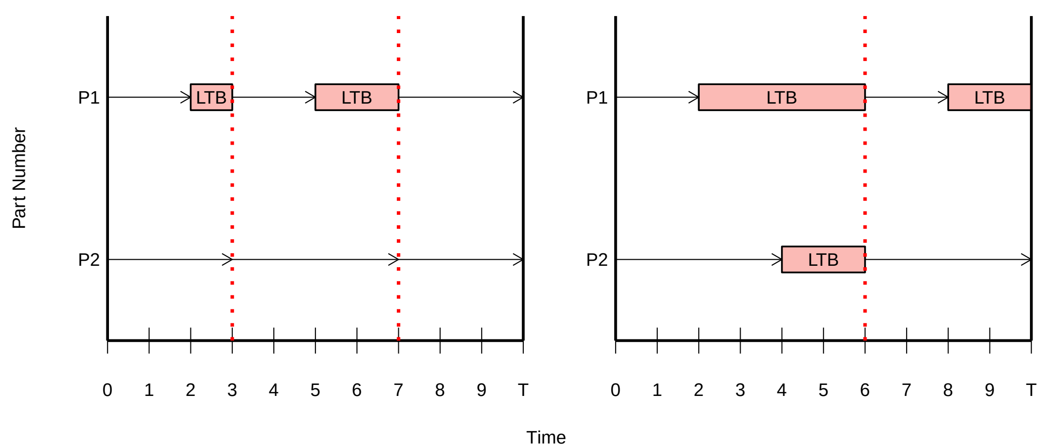


Figure 1: An example two-part (P1 and P2) system with two proposed redesign strategies. The figure on the left depicts a strategy with two technology refreshes; the figure on the right depicts a strategy with one technology refresh. Technology refreshes are depicted by red dashed lines; LTB by boxes; and procurement lifetimes by arrows.

The primary contribution of this paper is identifying the optimal strategy amongst a set of $k$ alternatives, using a ranking and selection (R&S) method. The mean cost associated with each strategy will be estimated with Monte Carlo simulation. Assuming a system has a planned operational lifetime of $T$ years, the above-mentioned strategic DMSMS framework can be translated into a finite horizon program, given by:

$$\begin{aligned} \min_{y \in Y} \quad & \mathbb{E}[C(y)], \\ s.t. \quad & y_t \in \{0,1\}, \\ & t \in \{1,2,\ldots,T-1\} \end{aligned} \tag{1}$$

where $\mathbb{E}[C(y)]$ is the expected cost associated with strategy $y$, which is a vector of length $T-1$. The optimal strategy is defined as

$$y^* \stackrel{\text{def}}{=} \operatorname*{arg\,min}_{y \in Y} \mathbb{E}[C(y)].$$

The result of solving (1) is an optimal strategy, informing the decision maker of an optimal scheduling of technology refreshes using LTBs as a mechanism to fill any shortages. A secondary contribution of this paper is providing a method to visualize strategies and their associated costs for easy comparison and is described in Section 4.3.

## 2 RELATED LITERATURE

This section will provide an overview of previous studies related to strategic DMSMS management. These will discuss how other studies have attempted to address strategic DMSMS management and discuss a simple cost function using LTBs and technology refreshes. Additionally, an overview of ranking and selection methods is discussed.

### 2.1 Strategic DMSMS Background

Other studies have evaluated the use of LTBs and technology refreshes as part of strategic DMSMS management. One study compares three strategies, programmed technology refreshes, LTBs, and re-engineering (which is defined as reactive measures other than LTBs) using a Monte-Carlo simulation (Underwood et al. 2014). They recommend programmed technology refreshes as the most cost effective, but condition their findings on the reliability characteristics used in their model. Whereas these authors evaluate three different mitigation options (separately), this paper will evaluate a combination of the two options that they evaluated (LTB and technology refreshes).

Another study uses graph theory and mixed integer programming with a combination of LTB and technology refreshes (Meng et al. 2014). They seek an optimal strategy over a fixed lifetime for a system with multiple parts. They seek to find an optimal schedule for a single technology refresh using a deterministic model. This paper will follow a similar methodology, but will take a stochastic approach in calculating the life-cycle costs as well as allowing multiple technology refreshes.

One must consider using a DMSMS specific cost function when solving (1). Feng et al. (2007) and Teunter and Fortuin (1999) present net-present value (NPV) models that evaluate the effect of the LTB quantities on the ability to support a system. The models search for an optimal LTB size for multiple parts in a system to minimize the overall life-cycle cost, accounting for LTBs, technology refreshes, holding, stock-out, and salvage costs. However, the models evaluate the effects of the overall life-cycle cost for a single, fixed technology refresh date. This current paper seeks to evaluate life-cycle costs for multiple combinations of refresh dates, taking into account various operational time-frames. A simpler cost model is presented by Bartels et al. (2012), that is based on previous work by Porter (1998). The model is a net present value model that considers the refresh cost and LTB costs for a single technology refresh date. The formulation is given by:

$$C = C_{TR} + C_{LTB} \tag{2}$$

where the total cost, $C$, is given by the costs associated with a technology refresh, $C_{TR}$, and the costs associated with LTBs, $C_{LTB}$. The cost for a technology refresh is given by:

$$C_{TR} = \exp(-rY_R)c_R, \tag{3}$$

where $c_R$ is the technology refresh cost in year 0; $r$ is the discount rate; and $Y_R$ is the year of the technology refresh ($> 0$).

The cost associated with a LTB is given by:

$$C_{LTB} = \begin{cases} 0, & \text{when } t = 0 \text{ or if } Y_R = 0, \\ c\sum_{t=1}^{Y_R} d_t, & \text{for } Y_R > 0, \end{cases} \tag{4}$$

where $t$ is the year after obsolescence; $c$ is the price of the obsolete part in the year of the LTB ($t = 0$); $d_t$ is the demand at time $t$.

The model in (2) also assumes that the part under consideration is obsolete at the beginning of the simulation ($t = 0$), whereas this paper will allow parts to be procureable. In the DMSMS literature, there have been multiple studies that seek to minimize overall life-cycle costs for a platform or system. The majority of these studies evaluate single component DMSMS risk; few evaluate DMSMS risk at the aggregate or system level (Rojo et al. 2010). This paper expands the cost model provided by Bartels et al. (2012) to account for systems composed of multiple parts and multiple technology refreshes over a fixed timeline.

### 2.2 Ranking and Selection Methods

Ranking and Selection (R&S) methods seek to find an optimal arrangement with respect to a value of interest (i.e. cost). In terms of DMSMS, this is often identifying the strategy with minimal cost over a set of alternative strategies. Popular R&S methods involve using an indifference zone (IZ) which identifies the optimal strategy within a "smallest difference worth detecting" at a given confidence level (Goldsman 2015). In terms of DMSMS the IZ is the dollar amount that the decision maker is indifferent to regarding the total cost; i.e. they consider the differences to be negligible. The IZ value will change depending upon the context of the problem, the tolerance of the procurement life distributions, and budget constraints.

Two main R&S methods are used in the case of unknown and unequal variances of the value of interest: two-stage and fully sequential methods. An example of the first method is presented by Nelson, Swann, Goldsman, and Song (NSGS) and an example of the second is Kim and Nelson (KN) (Goldsman 2015). Both methods begin by replicating all strategies an equal number of times then create a subset of the most promising strategies. The NSGS method determines the number of additional samples required for each strategy in the sub-set of the most promising strategies and then identifies an optimal strategy. Instead of performing a batch update as with the NSGS method, the KN method iteratively samples each strategy in this sub-set once and removes less promising strategies until the sub-set only includes one member. For the NSGS method, the independence assumption is satisfied by ensuring independent simulation replications and the normality assumption is reasonably satisfied when using the sample mean to estimate the value of interest such as in (1) thanks to the central limit theorem. Current work in this field revolves mostly around computational efficiency as the number of alternatives is "large"; generally speaking, "large" is on the order of one-million alternatives (Ni et al. 2014, Ni 2013). For this paper, the NSGS method is used as it is straightforward to implement and supports the DMSMS example in Section 4.

## 3 SIMULATION MODEL DEVELOPMENT

This section updates the cost functions in (3) and (4) and provides a DMSMS specific application of the NSGS method.

### 3.1 Updated Cost Function

The model in (2) assumes that the part goes obsolete at the beginning of the time period ($t = 0$) and seeks to find an optimal time to conduct a single refresh after that time. This paper considers the case where multiple parts of a system are non-obsolete at the beginning of the simulation (but can be allowed to be obsolete, if necessary). The technology refresh and LTB cost functions for a system with $N$ parts, over a finite horizon $[0,T]$, are given by:

$$C_{TR} = \sum_{t=1}^{T-1} y_t \exp(-rt)\; c_R, \tag{5}$$

$$C_{LTB} = \sum_{t=1}^{T-1}\sum_{i=1}^{N} y_t \exp\left(-rZ_{ti}(y)\right) c_i d_i S_{ti}(y) + \sum_{i=1}^{N} \exp\left(-rZ_{Ti}(y)\right) c_i d_i S_{Ti}(y), \tag{6}$$

respectively, where:

- $c_R$ is the cost of a single refresh;
- $c_i$ is the per-item cost of part $i$;
- $d_i$ is the demand, per unit time, of part $i$;
- $r$ is the discount factor rate, $r \geq 0$;
- $S_{ti}(y)$ is a random variable for the shortage time for part $i$ for a planned refresh at time $t$. The shortage time is defined as the time gap between when a part is no longer procurable (obsolete) and the next planned refresh time. Given a procurement lifetime for part $i$, $X_i$, and the time of the previous planned technology refresh, $t_{prev} \in [0,t)$, the shortage time is defined as $S_{ti}(y) = \max\{0, t - X_i - t_{prev}\}$;
- and $Z_{ti}(y)$ is a random variable for the time at which part $i$ becomes obsolete in the time period before $t$, but after the previous planned refresh. This time can be calculated with: $Z_{ti}(y) = t - S_{ti}(y)$.

(Note that the last term in (6) represents the LTB cost that will allow the system to operate up until time $T$. Since it is assumed that there will not be a technology refresh at time $T$, the sum in (5) only includes $t = 1, \ldots, T-1$. Also note $t \in \mathbb{N}$, but $X_i, S_{ti}(y), Z_{ti}(y) \in \mathbb{R}_{\geq 0}$.)

The costs from planned technology refreshes in (5) will incur a discounted cost when $y_t = 1$, at time $t$. Likewise, LTB costs will be incurred when $y_t = 1$ and when part $i$ is obsolete, as indicated by $Z_{ti}(y)$. Obsolete parts will be purchased at a discounted cost at the time when part $i$ actually becomes obsolete, $Z_{ti}(y)$. The amount purchased is given by the demand rate, $d_i$, multiplied by the shortage time, $S_{ti}(y)$. The values for the item cost, item demand, and refresh costs are assumed to be fixed in this model. They can be allowed to be dependent upon current time, $t$. Updating the model in (2) using the technology refresh costs in (5) and LTB costs in (6), the cost function, $C(y)$, is given by:

$$C(y) = \sum_{t=1}^{T-1} y_t \exp(-rt)\; c_R + \sum_{t=1}^{T-1}\sum_{i=1}^{N} y_t \exp(-rZ_{ti}(y)) c_i d_i S_{ti}(y) + \sum_{i=1}^{N} \exp(-rZ_{ti}(y)) c_i d_i S_{ti}(y). \tag{7}$$

Figure 2 shows an example system with three parts and two planned technology refresh dates, $t = a, b$ where $0 < a < b < T$. Prior to time $a$, part 1 and part 2 (P1, P2) experience obsolescence for that particular part. This difference between the planned technology refresh time and the time of obsolescence is given by $S_{a,1}$ and $S_{a,2}$ for parts P1 and P2, respectively. Similarly, the shortages before time $b$ are represented by $S_{bi}$ and shortages before time $T$ are given by $S_{ti}(y)$. The LTB costs will only be incurred when $S_{ti}(y) > 0$ and technology refresh costs at time $a$ and $b$.

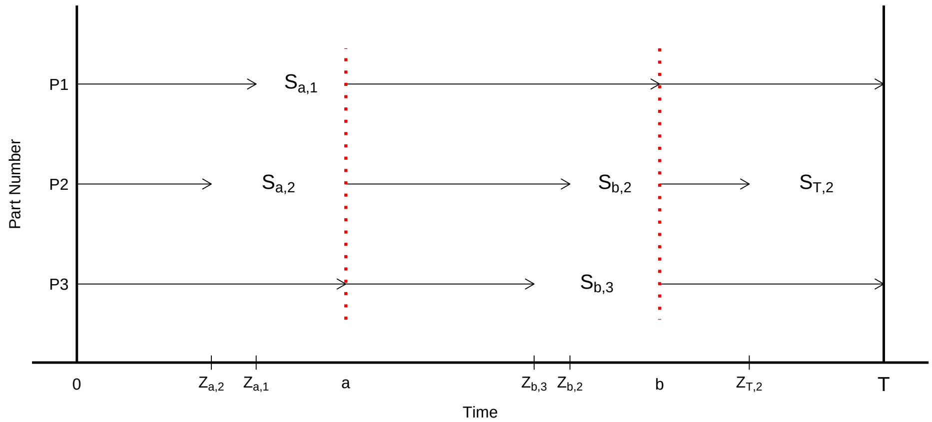


Figure 2: Example of a system consisting of three parts (P1, P2, P3) with two technology refresh dates, $a$ and $b$, where $0 < a < b < T$. LTB costs are incurred when values for $S_{ti}(y)$ are positive and technology refresh costs at the red dashed lines.

### 3.2 DMSMS Applications of the NSGS Method

Simulating the estimated values to approximately solve (1) will involve some randomness in each set of samples. The NSGS method ensures the probability of correctly selecting the optimal strategy, within an indifference zone, is greater than or equal to an overall confidence level $(1-\alpha)$ under the aforementioned assumptions. The overall significance level is defined as $\alpha = \alpha_0 + \alpha_1$, where $\alpha_0$ and $\alpha_1$ are the first stage and second stage significance levels, respectively. The first stage identifies a set of promising strategies, subject to the indifference zone, with a probability of at least $(1-\alpha_0)$ of containing the optimal strategy. The second stage consists of sampling the promising set of strategies for an appropriate amount of additional samples to ensure correctly identifying an optimal strategy at a confidence level of at least $(1-\alpha_1)$. A DMSMS application of the NSGS algorithm is as follows:

1. Select the first and second stage confidence levels, $1-\alpha_0, 1-\alpha_1$, such that the overall significance level is $\alpha = \alpha_0 + \alpha_1$. Also, choose a practically significant difference (IZ) parameter, $\delta$, for $k$ strategies. Set $t = t_{(1-\alpha_0)^{1/(k-1)},n_0-1}$ which is the $(1-\alpha_0)^{1/(k-1)}100$ percentile of the $t$-distribution with $n_0 - 1$ degrees of freedom. Also set $h$ equal to Rinott's constant, which will be discussed below.
2. Evaluate the cost $C(y)_{ij}$, $n_0$ times for each strategy ($i = 1,2,\ldots,k; j = 1,2,\ldots,n_0$).
3. Compute the first stage sample mean $\overline{C(y)}_i^{(1)}$ and sample variance $S_i^2$ of the costs for each of the $k$ strategies. Calculate a weighted $t$ statistic for each paired combination of strategies:

$$W_{ii'} = t\left(\frac{S_i^2 + S_{i'}^2}{n_0}\right)^{1/2}, \text{ for } i \neq i'.$$

4. Identify the set of strategies that are not significantly greater than the others. The set is identified by $I = \{i : 1 \leq i \leq k \text{ and } \overline{C(y)}_i^{(1)} \leq \overline{C(y)}_{i'}^{(1)} + (W_{ii'} - \delta)^+, \forall i' \neq i\}$.
5. If the set $I$ only has one strategy, stop and record that strategy as the best. If not, calculate the total number of replications required for the second stage for each $i \in I$:

$$N_i = \max\left\{n_0, \left\lceil \left(\frac{hS_i}{\delta}\right)^2 \right\rceil \right\}, \tag{8}$$

where $\lceil \, \rceil$ is the ceiling function.

6. Take $N_i - n_0$ additional replications for each strategy $i \in I$ and calculate the second stage sample means:

$$\overline{C(y)}_i^{(2)} = \frac{1}{N_i} \sum_{j=1}^{N_i} C(y)_{ij}, \quad i \in I.$$

7. Select the best system with the smallest $\overline{C(y)}_i^{(2)}$.

Rinott's constant in Step 1 can be found in tables shown in Goldsman (2015). For those values outside of these tables, it is necessary to numerically calculate the value of $h$ that gives the solution to:

$$\int_0^\infty \int_0^\infty \left[\Phi\left(\frac{h}{\sqrt{\nu(1/p+1/q)}}\right) f_\nu(p)\right]^{k-1} f_\nu(q)\,\mathrm{d}q\mathrm{d}p = 1-\alpha_1, \tag{9}$$

where $\Phi$ is the cumulative distribution function of the standard normal distribution, $f_\nu(y)$ is the probability density function of the chi-squared distribution with $\nu = k-1$ degrees of freedom. Bechhofer et al. (1995) present FORTRAN code to find a numerical solution to (9), which was later converted into Java by Ni (2013). The latter version was converted into Python for computational use in this paper.

# 4 SIMULATION STUDY

This section presents a simulation study to highlight the use of the NSGS method in DMSMS application. The scenario is that of a DMSMS manager wishing to explore possible strategies for a current system being replaced by a newer system ten years ($T = 10$) from now, assuming they only consider the LTB option to mitigate any obsolescence issues. A simple, five-part system is presented with expected procurement lifetimes, demands, and costs of the individual parts. In order to explore all alternatives, this simulation study will enumerate all $k = 2^{T-1} = 512$ strategies, representing all exhaustive strategies in a time frame of 10 years. The results of the simulation are shown in tabular and graphic formats that can provide a decision maker insights to alternate strategies.

## 4.1 Scenario Parameters

The procurement lifetime, $X_i$, for part $i \in \{1,...,k\}$ is assumed to be exponentially distributed with a mean procurement lifetime of $\mu_{X_i}$. The values for the parameters of the mean procurement lifetime (in months), annual demand, and the per-item cost are shown in Table 1.

The discount factor is set to 10%, $r = 0.10$ and the refresh costs $C_R$ are varied between \$10,000, \$100,000, and \$500,000 to evaluate the effects on an optimal strategy. Uncertainty in the LTB costs is captured by the exponentially distributed procurement lifetimes for all five parts and assumes that the annual demands and per-item costs remain fixed. Future models can allow uncertainty in the annual demand and per-item costs if desired. For the NSGS method, the overall significance level is set at $\alpha = 0.1$, with $\alpha_0 = \alpha_1 = 0.05$; the sample size in the first stage is set to 30 replications, $n_0 = 30$; and the IZ value is set to $\delta =$\$50,000, \$100,000, and \$300,000 for each refresh cost. In this example, the first IZ value represents the

Table 1: Parameters for simple, five-part system.

| | mean proc. lifetime ($\mu_{X_i}$) | annual demand ($d_i$) | per-item cost ($c_i$) |
|---|---|---|---|
| part 1 | 24 | 2000 | \$3 |
| part 2 | 36 | 1000 | \$6 |
| part 3 | 36 | 500 | \$12 |
| part 4 | 48 | 200 | \$50 |
| part 5 | 60 | 100 | \$75 |

manager being indifferent to costs equal to five technology refreshes; the second IZ value being indifferent to one technology refresh; and the final IZ value to three-fifths of a technology refresh. In reality, these values should be discussed iteratively with the DMSMS manager and should be proportionate with the manager's preference structure.

### 4.2 Simulation Results

The results for refresh costs of \$10,000, \$100,000, and \$500,000 with their respective IZ values are shown in Tables 2-4, respectively. The mean costs, strategies, total number of technology refreshes ($\sum_t y_t$), and the second stage number of replications, $N_i$, are shown. Additional five strategies with the next lowest sample mean cost values are shown in each table for comparison.

With a lower technology refresh cost of \$10,000 and a decision maker is indifferent to five technology refreshes, Table 2 indicates that it is more preferable to avoid LTBs and to conduct a refresh every year. The set of competitive strategies identified in the first stage included 45 alternatives ($|I| = 45$), but after second stage sampling only seven other strategies' mean costs were within the IZ of the optimal value. Of these, six had eight technology refreshes and one had seven refreshes. The overall total number of replications is 33,435 for both stages.

Table 2: Simulation results for technology refresh cost of \$10,000 with an IZ value of \$50,000.

| mean cost | strategy | $\sum_t y_t$ | $N_i$ |
|---|---|---|---|
| \$723,464 | $\langle 111111111 \rangle$ | 9 | 140 |
| \$745028 | $\langle 111111110 \rangle$ | 8 | 226 |
| \$757010 | $\langle 111110111 \rangle$ | 8 | 308 |
| \$759787 | $\langle 111101111 \rangle$ | 8 | 222 |
| \$760304 | $\langle 111111011 \rangle$ | 8 | 260 |
| \$763959 | $\langle 111111101 \rangle$ | 8 | 256 |

When the decision maker is indifferent to one technology refresh with a moderate cost of \$100,000, Table 3 indicates that the optimal strategy is to conduct a technology refresh twice, at years four and seven. The set of second stage strategies included 53 alternatives ($|I| = 53$) with 20 strategies within the IZ of the optimal value after second stage sampling. Of these, one strategy recommended one refresh, ten recommended 2 refreshes, and nine recommended three refreshes. The total number of replications was 34,372.

When the decision maker is indifferent to 3/5 of a technology refresh with a higher cost of \$500,000, Table 4 indicates that it is preferable to not conduct any technology refreshes and to only rely on LTB options to remedy any obsolescence issues. For this particular set of parameters, the optimal strategy did not recommend any additional second stage samples ($|I| = 1$). This will arise in the case where an optimal strategy's cost is much smaller, in the statistically significant sense, than the other alternatives. For comparison, the next five closest alternatives all had only one recommended technology refresh, but were outside of the indifference zone.

Table 3: Simulation results for technology refresh cost of \$100,000 with an IZ value of \$100,000.

| mean cost | strategy | $\sum_t y_t$ | $N_i$ |
|---|---|---|---|
| \$2,012,328 | $\langle 000100100 \rangle$ | 2 | 612 |
| \$2,013,061 | $\langle 001001000 \rangle$ | 2 | 310 |
| \$2,029,043 | $\langle 000100010 \rangle$ | 2 | 383 |
| \$2,032,522 | $\langle 000101000 \rangle$ | 2 | 386 |
| \$2,045,531 | $\langle 001010000 \rangle$ | 2 | 190 |
| \$2,047,271 | $\langle 001000100 \rangle$ | 2 | 190 |

Table 4: Simulation results for technology refresh cost of \$500,000 with an IZ value of \$300,000.

| mean cost | strategy | $\sum_t y_t$ | $N_i$ |
|---|---|---|---|
| \$3,562,830 | $\langle 000000000 \rangle$ | 0 | 30 |
| \$3,928,527 | $\langle 000001000 \rangle$ | 1 | 30 |
| \$3,998,173 | $\langle 000000100 \rangle$ | 1 | 30 |
| \$4,002,652 | $\langle 000010000 \rangle$ | 1 | 30 |
| \$4,138,701 | $\langle 000000010 \rangle$ | 1 | 30 |
| \$4,218,997 | $\langle 000100000 \rangle$ | 1 | 30 |

The total number of samples for each part $N_i$ for $i \in I$ is a function of the IZ parameter, the standard deviation of the samples, and the number of initial samples as indicated by (8). As the desired confidence level increases, or the indifference to cost decreases, the number of second stage samples will generally increase. The combination of these parameters must be chosen with an understanding of the practical implications to identify an optimal strategy.

### 4.3 Visualization of Strategies

Since the purpose of enumerating all strategies is to explore the set of (unconstrained) alternatives, the DMSMS manager may want to consider other alternatives relative to a chosen IZ value. Tabulating the strategies can provide some insights, but if the number of strategies is large it may be difficult to compare the different sequences of technology refreshes. One option to display these strategies, presented by Kiatsupaibul et al. (2016), is a one-to-one mapping of an infinite sequence $y'$ to $x \in [0, 1/2]$, using a base-3 expansion:

$$x(y') = \sum_{t=1}^{\infty} \frac{y'_t}{3^t}, \quad \forall y' \in Y', \tag{10}$$

with $y'_t \in \{0,1\}$ and $Y' = \prod_{t=1}^{\infty}\{0,1\}$ for $t \in \{1,2,\dots\}$. This mapping allows for a graphical representation, where an optimal first decision at $t = 1$ can be identified quickly, and is similar to a binary decision tree. If an optimal solution, $x^*$, for minimizing the cost is in the interval $[0, 1/6]$, then the optimal first decision is to not conduct a technology refresh; if $x^*$ is in the interval $[1/3, 1/2]$, then a technology refresh is optimal in the first decision. This can be seen by mapping the strategies where all of the decisions are 0's, the first decision is a 0 followed by all 1's, the first decision is a 1 followed by all 0's, and where all decisions are 1's, respectively:

$$x(0\bar{0}) = 0, \qquad x(0\bar{1}) = 1/6, \qquad x(1\bar{0}) = 1/3, \qquad x(1\bar{1}) = 1/2.$$

Conditioning on an optimal first decision, one can determine the optimal second decision; likewise, one can determine the optimal third decision by conditioning on the optimal first two decisions, and so on. For example, if the first decision was to not perform a technology refresh, $y_1 = 0$, focusing in on the interval $[0,1/6]$ allows the user to graphically determine the optimal second decision. Conditioning on the optimal first decision of no technology refresh ($y_1 = 0$):

$$x(00\bar{0}) = 0, \qquad x(00\bar{1}) = 1/18, \qquad x(01\bar{0}) = 2/18 = 1/9, \qquad x(01\bar{1}) = 3/18 = 1/6,$$

if $x^*$ falls between $[0,1/18]$, then the optimal second decision is to not conduct a technology refresh; if $x^*$ falls between $[1/9,1/6]$, the second decision is to conduct a technology refresh. Although described for an infinite series, using (10) for a finite series maintains the one-to-one mapping.

The results shown in Tables 2-4 only provide a handful of the overall strategies considered in the simulation; using the mapping in (10) can allow many more strategies to be plotted visually, with the capability to provide insights to alternate technology refresh schedules. Figures 3-5 show the results for the three refresh costs, \$10,000, \$100,000, and \$500,000. Figure 3 shows the optimal strategy (the larger red dot) near the value of $x = 1/2$, indicating a series of technology refreshes every year, which is the same result shown in Table 2 for a technology refresh cost of \$10,0000 with an IZ value of \$50,000. The seven other strategies that are within the IZ as mentioned in Section 4.2 can be identified by the dots below the dashed line and indicate that the first decision should be to conduct a refresh.

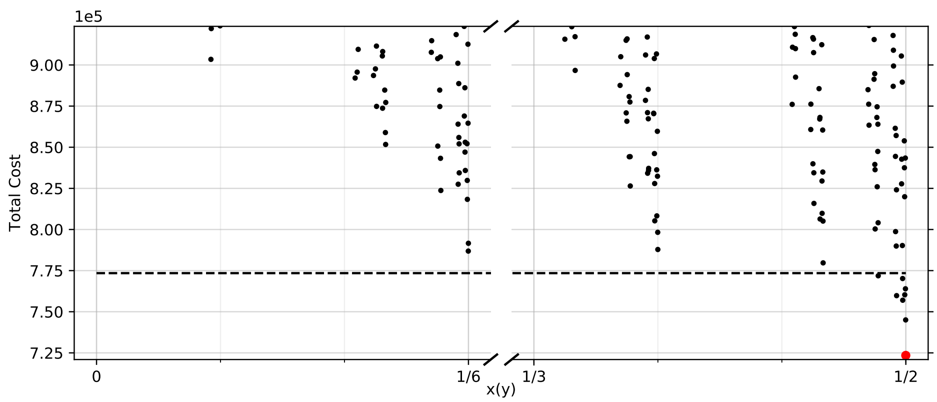


Figure 3: Visualization of the mean total costs of alternative strategies with a refresh cost of \$10,000 with an IZ value of \$50,000.

Increasing the refresh cost and IZ values to \$100,000 changes the optimal first choice to not recommend a technology refresh in the first time period. Figure 4 shows a larger number of strategies will have a lower cost when not performing a technology refresh during the first period and the optimal time to conduct the first technology refresh is in the fourth year. The 20 strategies within the IZ value are also shown in the figure and indicate that the first decision should be to not conduct a technology refresh.

When the refresh cost is increased to \$500,000 with an IZ value of \$300,000, Figure 5 shows that relying on LTB options is ideal. The optimal minimal cost and strategy are easily seen in this figure, where the mapping $x(0\cdots 0) = 0$ is on the far left of the figure. The figure shows the alternatives that may be included if the IZ were raised to a larger value.

## 5 DISCUSSION

This paper shows how a ranking and selection method can be used to identify the optimal strategy for strategic DMSMS management relative to changing technology refresh costs and IZ values. The tabular and visual results can assist the DMSMS manager in planning the sequence of technology refreshes, particularly when exploring strategies to adopt. Actual technology refresh costs should be dictated by data while the IZ parameter should be chosen by a decision maker and tied to actual budget values.

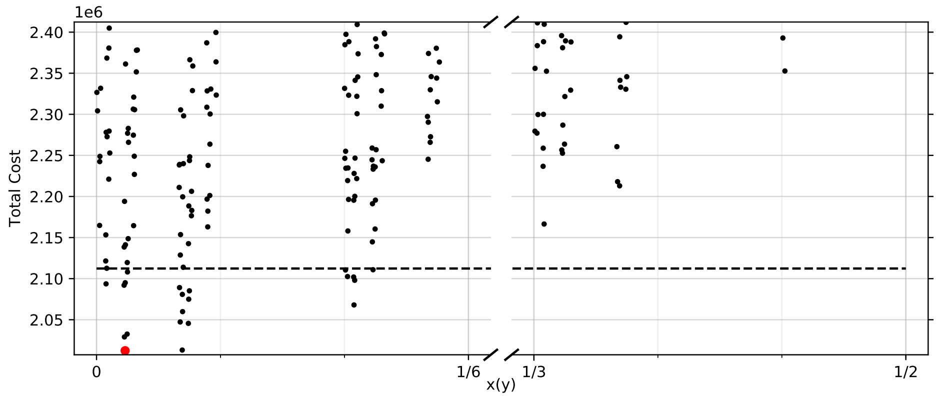


Figure 4: Visualization of the mean total costs of alternative strategies with a refresh cost of \$100,000 with an IZ value of \$100,000.

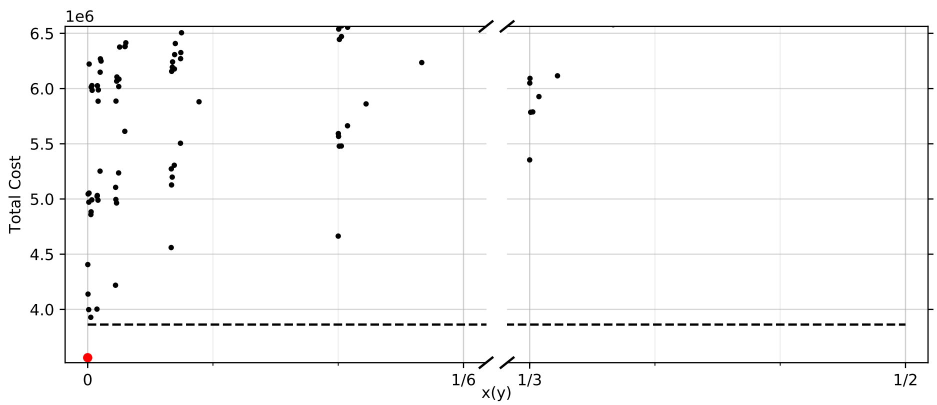


Figure 5: Visualization of the mean total costs of alternative strategies with a refresh cost of \$500,000 with an IZ value of \$300,000.

The results in Section 4 provide insights to the relationship between the LTB costs and the technology refresh costs. In general, as the technology refresh costs increase, the optimal strategy will include less refreshes and rely more on LTBs. Factoring out the similar items in (7),

$$C(y) = \sum_{t=1}^{T-1} y_t \exp(-rt) \left[ c_R + \sum_{i=1}^{N} \exp\left(rS_{ti}(y)\right) c_i d_i S_{ti}(y) \right] + \sum_{i=1}^{N} \exp\left(-rZ_{Ti}(y)\right) c_i d_i S_{Ti}(y),$$

allows for a better view of the relationship between the two costs. Since the objective is to minimize the overall costs over all strategies, there is a trade-off between the refresh costs $c_R$ and the LTB costs (the second term in the brackets and last term). As the number of technology refreshes ($\sum_t y_t$) increases the overall technology refresh costs will also increase; however, the overall LTB costs will tend to decrease as the shortage times ($S_{ti}(y)$) will also decrease. This trade-off between technology refresh and LTB costs can be investigated further in future research.

Evaluating strategies over a longer time period would not be possible to do so exhaustively as it would involve $2^{T-1}$ strategies. Thus, it would be necessary to limit the number of alternatives by only considering strategies that would be feasible in reality. One such example is removing strategies with successive (back to back) technology refreshes. Such constraints can be applied in situations where additional information is known about the particular DMSMS problem.

Future applications of the NSGS method to DMSMS applications can include uncertainty in the annual demand and the item costs. The cost function (7) can be expanded to accommodate additional mitigation options beyond LTBs, and additional costs such as holding, stock-out, and salvage costs. Examples of DMSMS specific models provided by Meng et al. (2014) can be useful for including these pertinent costs in the model if desired.

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