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A Multi-Objective Optimization Method for Maximizing the Value of System Evolvability Under Uncertainty

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Master of Science

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ABSTRACT

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System evolvability is vital to the longevity of large-scale complex engineered systems. The need for evolvability in complex systems is a result of their long service lives, rapid advances to their integrated technologies, unforeseen operating conditions, and emerging system requirements. In recent years, quantifiable metrics have been introduced for measuring the evolvability of complex systems based on the amount of excess capability in the system. These metrics have opened opportunities for optimization of systems with evolvability as an objective. However, there are several aspects of such an optimization that require further consideration. For example, there is a trade-off between the cost of excess capability initially built into complex systems and the benefit that is added to the system for future evolution. This trade-off must be represented in the optimization problem formulation. Additionally, uncertainty in future requirements and parameters of complex systems can result in an inaccurate representation of the design space. This thesis addresses these considerations through multi-objective optimization and uncertainty analysis. The resulting analysis gives insight into the effects of designing for evolvability. We show that there is a limit to the value added by increasing evolvability. We also show that accounting for uncertainty changes the optimal amount of evolvability that should be designed into a system. The developed theories and methods are demonstrated on the design of a military ground vehicle.

Keywords: evolvability, reconfigurability, flexibility, adaptability, optimization, multi-objective optimization, uncertainty, aleatory, epistemic, complex systems

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Finally, I thank my Father in Heaven for giving me the opportunity to make a difference, and the ability to succeed.

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NOMENCLATURE

D	Set of all system parameters
X	Excess capability
g	Benefit per unit excess capability
α	Cost per unit excess capability
B	Benefit that is added to the system
C	Cost that is added to the system
V	Value that is added to the system
NPV	Net present value
FV	Future value
r	Interest rate
E	Measure of system evolvability
σ	Standard deviation
k	Number of standard deviations allowed
p	Probability of occurrence

CHAPTER 1. INTRODUCTION

Large-scale, complex, engineered systems (hereafter referred to as complex systems) are increasingly important in our modern society. Examples of complex systems include aircraft (e.g. Joint Strike Fighter), naval vessels (e.g. Nimitz-class aircraft carrier), spacecraft (e.g. International Space Station), and power generation plants (e.g. Palo Verde nuclear power plant). Such systems have characteristically complex interactions between sub-systems [1], unusually large multidisciplinary design teams [2], and expectations of long service life [3]. Unfortunately, the development of complex systems is often plagued by exorbitant budget overruns and lengthy delays [4–7].

The cost and time associated with complex systems development is in part due to uncertainty in future system requirements. Their long service lives often necessitate changes to operating conditions and requirements that are unforeseeable during design [8]. The impact of these changes must be accounted for when making design decisions. However, Bonissone et al. note that with new complex systems there is often a lack of long-term data to corroborate predictions of future performance or evaluate the system's ability to handle emerging requirements [9]. To make matters worse, the effects of a single change can propagate throughout the entire system [10], making it difficult to predict the full impact of emerging requirements on the system [11].

Designers of complex systems need tools for developing systems that can react positively to emerging requirements instead of becoming obsolete. Evolvability, reconfigurability, and other similar attributes have been shown to improve the ability of systems to adapt to emerging requirements [12–14]. This thesis focuses on system evolvability as a way to avoid premature obsolescence. System evolvability is a measure of how well a system is able to move from one state to another to meet emergent requirements [15]. In recent years, steps have been taken to develop quantifiable metrics for measuring the evolvability of complex systems [16]. These metrics have opened opportunities for optimization with evolvability as an objective. However, such an optimization has never been attempted in the literature. This is largely due to several problems that still hinder our ability to optimize the evolvability of complex systems.

Answers to the following questions will improve the ability of designers to develop evolvable systems:

1. How can existing metrics for evolvability be implemented into an analytical optimization?

2. At what point do the benefits of evolvability outweigh the associated costs of designing for evolvability? How can this value trade-off be represented in an analytical optimization?

3. What types of uncertainty are introduced when attempting to quantify evolvability? How does this uncertainty affect the accuracy of a solution set optimized for evolvability? How can this uncertainty be minimized?

This thesis addresses these questions through multi-objective optimization and uncertainty propagation. The resulting analysis provides insight into the effects of optimizing for evolvability and highlights considerations for formulating such an optimization.

1.1 Background

Before it can be implemented into a design, evolvability must be characterized. A significant amount of research has contributed to the development of general design principles for evolvability [17–20]. Although these principles are useful in generally guiding designers, the complexity of large-scale systems often necessitates the use of computer optimization to aid in design. To optimize complex systems for evolvability, designers need quantifiable metrics for evolvability that are directly linked to system input parameters [21].

Modular design has been studied as a more tangible means of improving flexibility and evolvability [22–25]. The benefits of modularity have been proven in numerous studies, particularly in the context of product platforms [26–29]. Several metrics have been proposed for defining the modularity of a system [30–32]. However, these and other metrics for modularity rely primarily on an understanding of the interfaces between components. Unfortunately, the modularity of interfaces can be difficult to quantify or define in terms of an analytical optimization routine.

Although modularity is not an ideal candidate for early-stage optimization, related drivers for evolvability can be used. For example, excess capability often accompanies modular designs, particularly in product platform architectures [33]. Tackett et al. suggest that the amount of built-in excess capability in a system is a good indicator of the system's ability to evolve [16]. Allen et al. show that this is true as long as the capability is of the appropriate type, quantity, form, and location required to meet future needs [34].

This thesis utilizes the metrics developed by Tackett et al. for quantifying evolvability based on excess capability [16]. However, other quantifiable metrics for evolvability may be used with the principles introduced herein.

1.2 Key Research Areas and Contributions

The metrics developed by Tackett et al. focus on improving system evolvability, but do not consider the coupling between evolvability and other objectives [16]. As shown in Figure 1.1, this thesis provides a unified framework for optimizing complex systems for evolvability with consideration for the value of evolvability and the uncertainty associated with evolvability. The main contributions in these areas are outlined in the following sections.

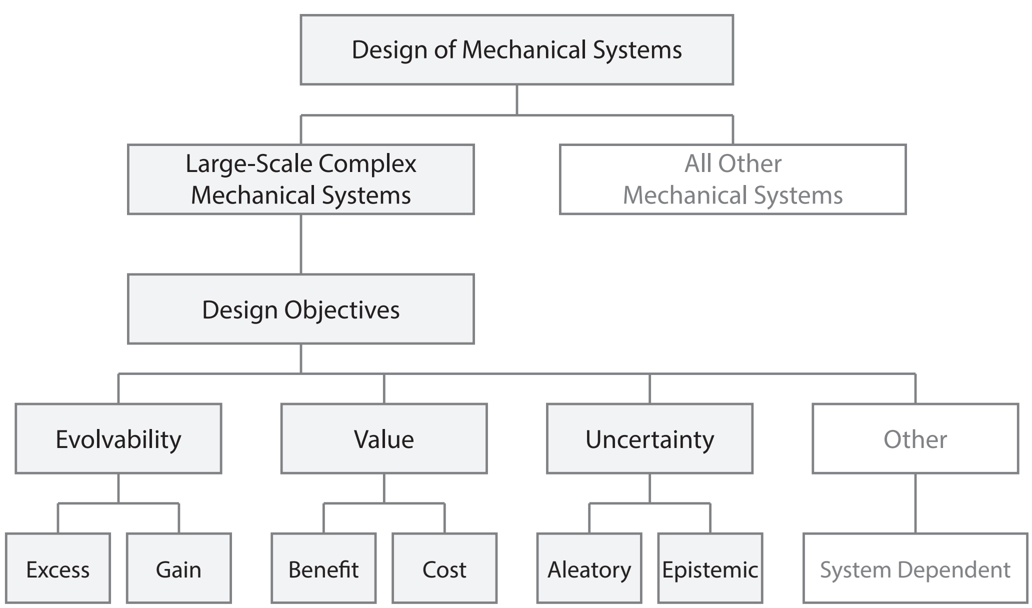


Figure 1.1: Topics covered and areas of contribution (shaded boxes)

1.2.1 Value of Excess Capability

Although excess capability can enable future evolution, it also increases the production and operating costs of the system. These costs can counter the long-term benefits of excess that is eventually used to evolve the system. System designers need to understand what parameters contribute to this value trade-off.

The value that is added by excess is highly dependent on the length of the expected service life for the system. For example, if a system is expected to remain in service for 50 years, it is more likely to encounter large requirements changes where excess capability could add benefit. A system that is only expected to last for 5 years is less likely to find opportunities to benefit from excess capability. However, it should be noted that a long expected service life also compounds the recurring costs of carrying and supporting excess capability. Dealing with these time-dependent trade-offs is an important consideration when evaluating evolvability. It can assist designers in finding the optimal amount of excess capability that will add the highest value for a given expected lifespan.

This thesis provides a framework for incorporating this value trade-off into an optimization of system evolvability. We explore the implications of this trade-off and show that there is a quantifiable point where adding more excess capability will diminish the value of evolvability. This finding expands the work done by Tackett et al. which implied that more excess capability is always beneficial.

1.2.2 Consideration for Uncertainty

Due to the unknown nature of planning for future evolution, designers can only probabilistically determine the future requirements for a system. Because quantification of system evolvability relies on an understanding of future requirements, this uncertainty results in some degree of uncertainty in any evolvability measure. It also means that the value of excess capability cannot be exactly determined.

Incorporating uncertainty analysis into our optimization will result in more realistic measures of evolvability and value [35]. Many methods have been suggested for propagating uncertainty through engineering models [36, 37]. This thesis utilizes these methods to propagate uncertainty in the input parameters and requirement predictions to find the associated uncertainty of evolvability and value of excess capability.

We are most interested in understanding the effects of uncertainty on the results of an evolvability optimization. This thesis shows that uncertainty attenuates the value that can be achieved through evolvability. The minimum time for a system to be in service before excess capability of a given amount becomes valuable is also extended. Optimizing for system evolvability without consideration for uncertainty will yield results that over value the benefits of excess capability.

1.3 Thesis Overview

This chapter has introduced the importance of system evolvability and the desire to use quantifiable metrics to optimize the evolvability of systems. We discussed the limitations of evolvability metrics and the need to consider value and uncertainty when optimizing for evolvability. The remainder of this thesis is organized as follows:

- Chapter 2 introduces a framework for optimizing system evolvability and the value of excess capability. It also explores the coupling between service life and the value of evolvability.
- Chapter 3 applies the framework from Chapter 2 to the optimization of a military ground vehicle. The trade-off between evolvability and value is developed for this system. The results of the optimization are analyzed.
- Chapter 4 discusses methods for accounting for uncertainty in our optimization framework. The general impact of uncertainty on the assumptions of Chapter 2 is examined. An improved optimization formulation is developed to account for and minimize the effects of uncertainty.
- Chapter 5 extends the example developed in Chapter 3 to include consideration for uncertainty. We analyze the effects of uncertainty on the evolvability and value of excess capability included in the military ground vehicle. The relationship between service life and the value of excess is shown to change when uncertainty is included.
- Chapter 6 discusses the importance and the efficacy of the steps made in this thesis. Limitations of the proposed approach and opportunities for future work are addressed.

CHAPTER 2. EVOLVABILITY AND THE VALUE OF EXCESS CAPABILITY

This chapter presents a framework for selecting the optimal amount of excess capability that should be included in a system to increase evolvability while still accounting for the value that is added by excess capability. This is an important addition to existing methods for calculating evolvability. Due to the enormity of complex systems, this selection process is most efficiently accomplished through optimization.

2.1 Optimization Methods

Before attempting to optimize system evolvability, we first examine the advantages and disadvantages of various optimization algorithms. In general, optimization algorithms fall in one of two categories: gradient-based and evolutionary. Zingg et al. discuss in depth the strengths and weaknesses of each type [38]. These differences should be taken into consideration when selecting the proper algorithm for each system.

Gradient-based algorithms are typically capable of reaching a minimum more quickly than evolutionary algorithms. Though their setup may be time intensive, their execution is relatively inexpensive computationally. However, gradient-based algorithms do have several drawbacks when treating complex models. In particular, gradient-based algorithms have difficulty solving problems with discrete-valued variables, a large number of variables, multiple local minima, and non-differentiable functions [39]. Depending on the system, these deficiencies could render gradient-based methods inaccurate or infeasible.

Evolutionary algorithms solve many of the problems of gradient-based algorithms. They are able to handle discrete-valued variables and discontinuous objective functions commonly encountered in complex systems [40]. Evolutionary algorithms do not converge as quickly as gradient-based algorithms, which can be problematic if an exact optimum is required. However, in the current study, we are primarily interested in generating an approximate Pareto front to inform the design process. This will allow us to discover general dependencies and relationships for enabling evolvability in our system. For these reasons, the remainder of this study will focus on the use of evolutionary algorithms.

Due to the trade-offs inherent in complex systems, it will be beneficial to optimize multiple objectives simultaneously. For this we will need to aggregate the objectives into a single fitness function. Balling suggests using the maximin fitness function to create a well distributed Pareto set [41]. The maximin fitness function is defined by:

$$\text{maximin}^i = \max_{j \neq i} \left(\min_k \left(f_k^i - f_k^j \right) \right) \tag{2.1}$$

where the maximin fitness of design i is evaluated with respect to design j for k objectives. When a single aggregate function (e.g. maximin fitness) is created from functions of different magnitude, improper scaling can bias the solutions toward a single objective. We will normalize our objectives to avoid scaling issues.

2.2 Objective #1: Maximize System Evolvability

Evolvability (E) is defined as a measure of how well a system is able to evolve to meet emerging requirements. This thesis makes use of the metrics developed by Tackett et al. that base system evolvability on the amount of excess capability available for system evolution [16, 34]. Their metrics for evolvability are adapted according to Equation 2.2.

$$E = \sum_{i=1}^{n_i} \left[\int_{X_{i\min}}^{X_i} g_i X_i dX_i \right] \tag{2.2}$$

Excess capability (X) is defined as the quantity of unused capabilities in a system with respect to current design requirements, as explained further in Section 2.3.2. The gain per unit excess (g) is a function of the design requirements and will be described in Section 2.3.3. Maximizing system evolvability thus becomes our first optimization objective. To avoid scaling issues, the evolvability is normalized for each requirement.

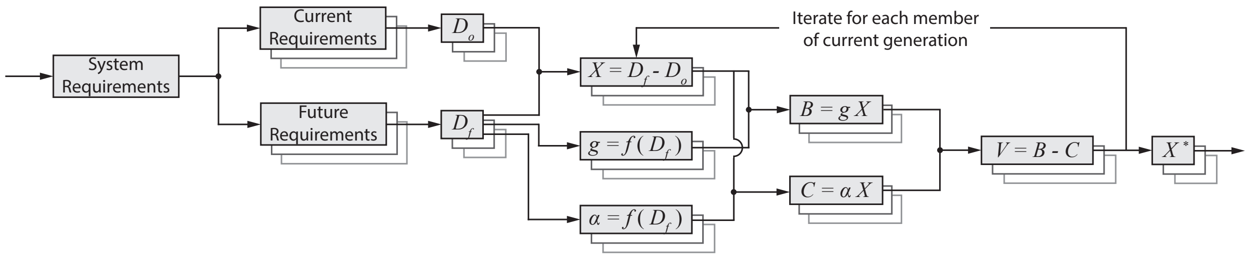


Figure 2.1: Framework for optimizing the value of excess capability in a system (D_o=capability required for current requirement, D_f=capability required for future requirement, X=excess capability, g=benefit per unit excess, α=cost per unit excess, B=benefit, C=cost, V=value, X^*=optimal amount of excess)

2.3 Objective #2: Maximize Value of Excess Capability

There is a trade-off between the cost of excess capability built into complex systems and the benefit of that excess toward evolvability. We propose that the value of excess capability can be optimized using the framework set out in Figure 2.1. As shown, the framework breaks the system into current requirements and potential future requirements. The quantity of excess capability needed for each future requirement is derived from these descriptions. The cost per unit excess (α) and benefit per unit excess (g) for each future requirement are then identified and used to compute the monetary value of adding excess capability to different system functions. These costs and benefits are constructed based on the expected service life of the system. This allows the value of the system to be computed with respect to the probability of future requirements (see Equation 2.8). It also accounts for the time-dependent value of investments (see Equation 2.9). An optimization routine is then used to select the amount of excess capability resulting in a set of evolvable designs that can be selected based on the value that they add to the system. Each of these steps is described in detail in the following sections.

2.3.1 Current and Future Design Requirements

The uncertainty of future requirements is one of the main challenges of designing complex systems [42]. It is difficult to fully define future system requirements, let alone assign a probability that the requirement will emerge within the expected lifetime. However, as Mehrabi et al. explain, it is possible to extrapolate future requirements from current situations if the drivers of change are understood [43]. Using methods such as change modes and effects analysis (CMEA), designers can identify potentially impactful requirements changes in complex systems [44, 45]. CMEA assists designers in evaluating the causes and effects of potential requirements changes. CMEA is most effective when combined with existing knowledge about trends and system-specific information. Unfortunately this information is often limited for complex systems. For the purposes of establishing a framework, we will assume that the most impactful future requirements for a complex system can be determined by informed designers using CMEA or similar methods. A non-deterministic variation on this approach, where future requirements can only be defined probabilistically, is outlined in Chapter 4.

Once future requirements are identified, they can be broken down into a description of the capabilities needed to fulfill each requirement. These capabilities (D_f) are inputs into our optimization framework, as shown in Figure 2.1. They take the form of design parameters and dimensions required to support a described future requirement.

The capabilities needed to fulfill current requirements (D_o) are also inputs into the optimization framework. As described in Section 2.3.2, the currently required capabilities act as a lower bound on the system design parameters.

2.3.2 Excess Capability

In order for systems to evolve, they must have the capability to support future requirements. In the case that future requirements are more demanding of the system than current requirements, excess capability is designed into the system initially to later be used in an evolved state. The amount of excess capability (X) is dictated by the current and future design requirements according to:

$$X = D_f - D_o \tag{2.3}$$

where D_f is the capability required to meet predicted future needs and D_o is the capability required to meet current needs. These capabilities are thus used to identify areas requiring excess (see Figure 2.1).

The amount of capability needed to fulfill a future requirement is not always a single number. Often there is an entire capability range that could satisfy the future requirement with varying benefit. Accordingly, excess capability allotted for a given potential requirement has a discrete beneficial range. For the i-th requirement, this range is dictated by:

$$X_{i\mathrm{min}} \leq X_i \leq X_{i\mathrm{max}} \tag{2.4}$$

where $X_{i\mathrm{min}}$ is the minimum amount of excess capability that can be allotted to fulfill the i-th new requirement, and $X_{i\mathrm{max}}$ is the maximum beneficial amount of excess capability that can be allotted for the i-th new requirement. The variable X_i represents the range of values that the excess capability is allowed to occupy to fulfill the i-th new requirement and add benefit to the system. Excess capability allotted outside this range has a gain of zero, as shown in Figure 2.2.

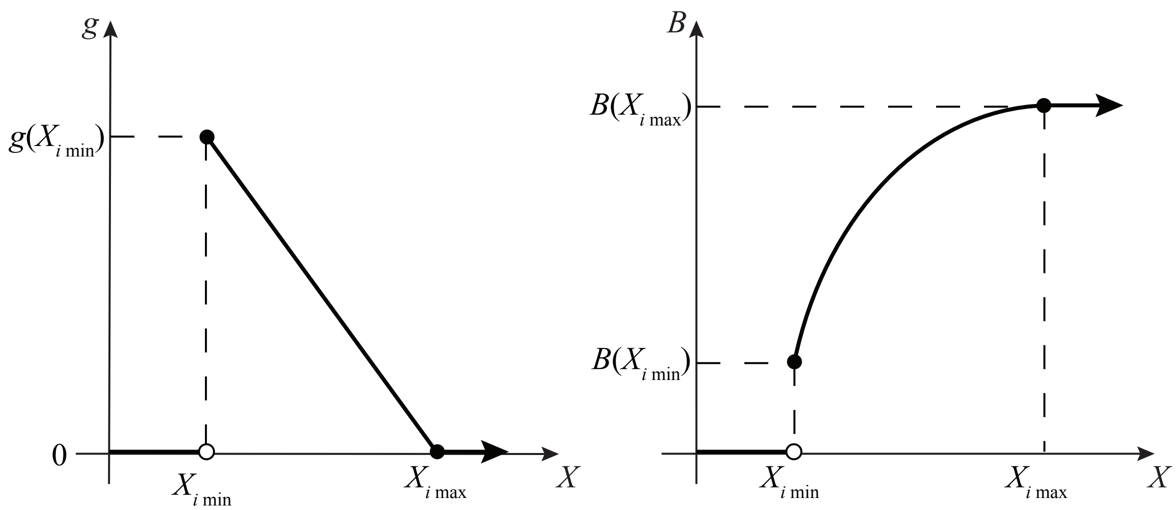


Figure 2.2: Basic illustration of functions for benefit per unit excess capability (g_i) and total benefit added (B_i)

The range of allowable excess can be understood by considering how much excess capability to add for a future heating system in the cargo bay of an aircraft. Suppose there are multiple heaters that could be installed to meet this new requirement, each of which have different spatial and electrical demands. To satisfy this requirement, excess space and electrical capability could be built into the cargo bay. Any power or space included above the amount required by the largest candidate heater would add no further value towards meeting this need. The same is true of excess capability less than the smallest available heater. Between these two values, excess capability results in a varying level of benefit per unit excess.

It should be noted that excess capabilities are not always independent in the way they benefit the system. Often increasing excess capability of one type does not add benefit to the system unless there is an increase in capability of another type. For example, in the cargo bay heater problem described above, the excess space allotted for a heater is coupled to requirements for excess payload and electrical power. Even if the maximum amount of excess space is allotted, the largest heater can not be added unless there is adequate power and payload capacity to operate and support the heater.

Some components can operate across an entire range of performance to satisfy future needs. Such variable-performance components are able to dynamically adjust their parameters between $X_{i\min}$ and $X_{i\max}$. For example, some military-contracted vehicle manufacturers have begun to use damping systems filled with magneto-rheological fluid [46]. As shown in Figure 2.3, these systems can actively change the damping coefficient of the suspension by application of a magnetic field. Used in parallel with external sensors, such damping systems are able to satisfy a range of damping needs to accommodate terrain changes. Such variable-performance components have built-in excess which allows them to evolve as requirements change.

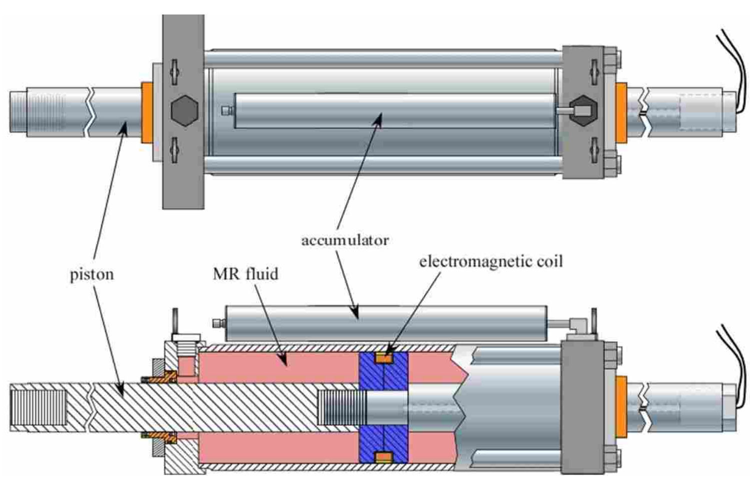


Figure 2.3: Schematic of MR fluid dampers used in vehicle suspension (www.nees.org)

2.3.3 Identifying Benefit Per Unit Excess

The gain (g_i), or benefit per unit excess, of a given design change is the benefit associated with having the excess capability to support some degree of a future evolution. As shown in Figure 2.2, the gain does not need to be constant or even continuous with respect to X_i. The gain of excess capability outside the range of allowable excess ($X_{i\min} \leq X_i \leq X_{i\max}$) is zero.

The gain function is specific to the requirement it describes. Generally, the gain represents the monetary benefits of meeting the new requirement. However, the gain can also include the economic impact from any emotional or social effects of being able to evolve to meet the new requirement. Tackett et al. suggest steps for developing the relationships for gain based on the minimum and maximum range of excess [16].

The benefit per unit excess depends on the realization of future requirements that can typically only be defined probabilistically. The effect of probabilistic requirements on the gain functions is addressed in Chapter 4. Due to the time value of money, the gain is also dependent on when the requirement emerges during the system's service life. This effect is discussed in Section 2.3.7.

2.3.4 Identifying Cost Per Unit Excess

Tackett et al. impose a constraint that requires the gain per unit excess to be greater than or equal to zero [47]. This is to imply that adding more excess capability can never make your evolvability negative. Although more excess capability may not decrease your evolvability, at some point it may have a net negative impact on the system's value, despite any benefits of being able to evolve. It is even possible that the net value of excess capability alternates between positive and negative within the allowable excess range. Therefore, we must consider the negative impact that excess can have on a system.

We therefore introduce a new variable (α_i) to account for the cost per unit excess capability with respect to the i-th future requirement. The cost per unit excess capability is the sum of the initial and recurring costs of the added excess capability. It can be evaluated by:

$$\alpha_i = \alpha_{io} + \alpha_{ir} \tag{2.5}$$

where α_{io} is the initial development and production cost of the added excess capability and α_{ir} is the recurring operating cost of maintaining and supporting the excess capability across the total life of the system. The cost of excess capability is linked to the total service life by the α_{ir} term. As such, the recurring costs of excess become increasingly impactful with increased expected service life. Figure 2.4 shows one possible set of functions for cost per unit excess (α) and total cost (C) across the allowable range of excess for meeting a future requirement.

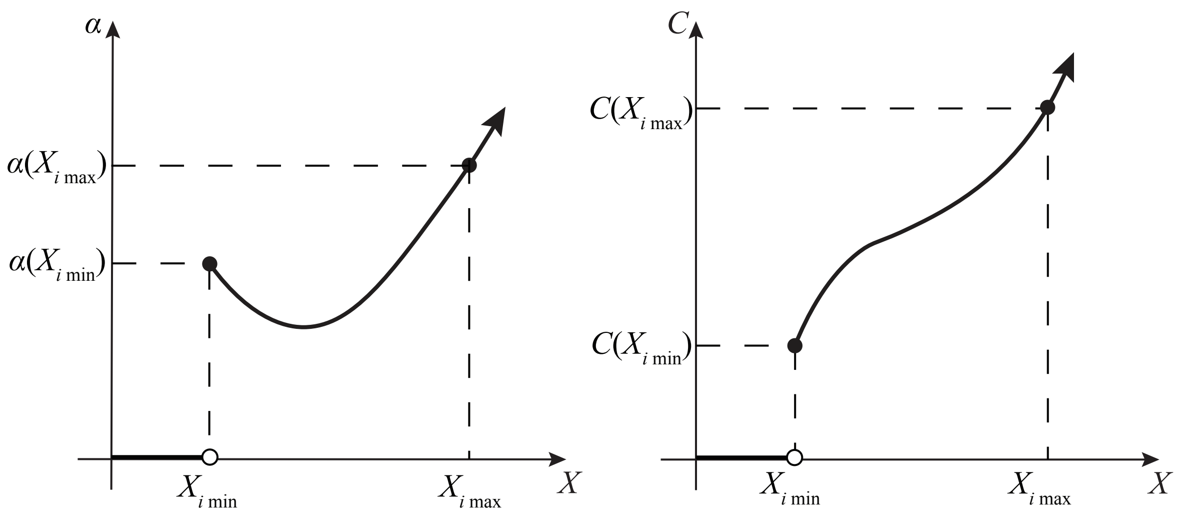


Figure 2.4: Basic illustration of functions for cost per unit excess capability (α_i) and total cost added (C_i)

Although the functions shown in Figure 2.4 are hypothetical, it should be noted that the cost per unit excess can decrease as you add more excess capability. This is typical in situations where the initial production cost of adding $X_{i\min}$ is significant (e.g. due to tooling), but where adding slightly more excess above $X_{i\min}$ results in only a small increase in the total cost.

2.3.5 Calculating Benefit Added By Excess Capability

Excess capability added into the initial system design contributes to the value of the system when that excess is used for evolution. The total benefit of this excess capability can be evaluated according to:

$$B = \sum_{i=1}^{n_i} g_i X_i \tag{2.6}$$

The benefit (B) represents the monetary amount that will be saved by adding the excess capability into the system initially, instead of redesigning the system when the new requirements take effect. As shown in Figure 2.1, the benefit of adding a given amount of excess is calculated based on the gain assigned for each requirement. This is calculated for each iteration of the optimization, depending on the amount of excess (X_i) allotted.

2.3.6 Calculating Cost Added By Excess Capability

Excess capability added into the system design adds cost both initially and across the system's service life. This cost can be evaluated according to:

$$C = \sum_{i=1}^{n_i} \alpha_i X_i = \sum_{i=1}^{n_i} (\alpha_{io} + \alpha_{ir}) X_i \tag{2.7}$$

The cost (C) represents the monetary amount incurred by adding excess capability initially and maintaining it before and after it is utilized. Similar to how the benefit is calculated for each requirement, the cost takes X and α as inputs in the framework.

2.3.7 Calculating Value and Adjusting for Time

It is important for designers to be able to evaluate whether adding excess capability into a system will be worthwhile across the lifespan of the system. This can be accomplished by computing the difference between the benefits of excess capability and its associated costs, as in:

$$V = B - C \tag{2.8}$$

We will refer to this difference as the value (V) of the excess capability associated with allotting excess for all i potential requirements. Figure 2.5 illustrates a potential relationship between cost and benefit and value and excess.

As shown generally in Figure 2.5, the cost and benefit of adding zero excess are both zero. As more excess is included, the costs begin to add up. However, you don't begin to see benefits until you have enough excess to make future evolutions possible. This means that if you are going to add excess, you need to at least add $X_{i\min}$ before the benefits begin to counter the costs. If you

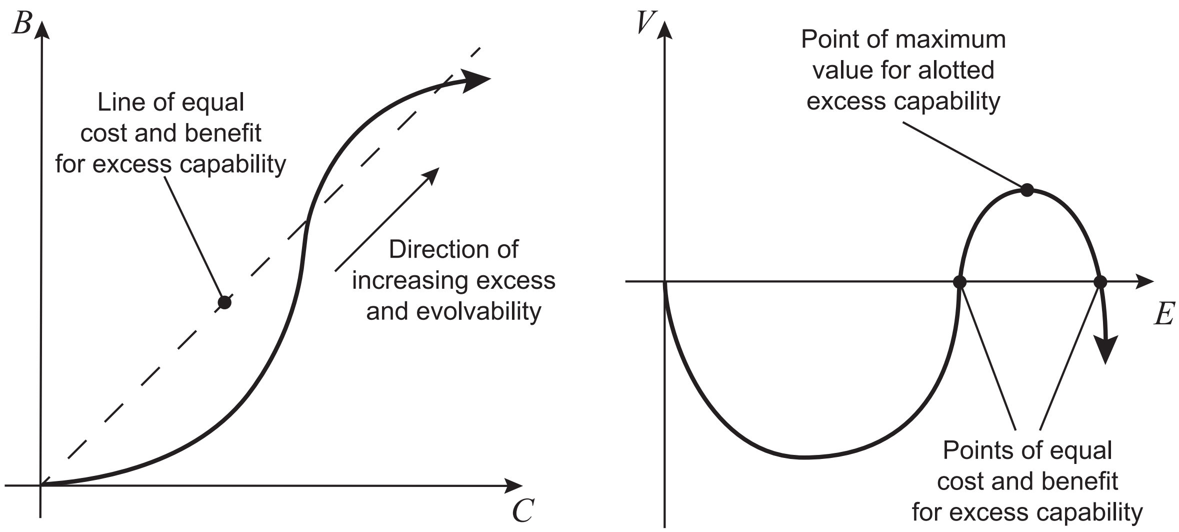


Figure 2.5: Illustration of how the benefits of excess can overcome the costs of excess

continue to add excess, eventually the costs may once again overcome any benefits that have been gained by adding evolvability.

As mentioned previously, it is important to account for the effect of time on the value of excess capability. Increased service life means that the costs of excess must be perpetuated for a longer duration. It also means that the benefits of excess capability are more likely to be realized and may have a greater impact. To account for part of this effect, the net present value of all cash flows can be computed for a given service life [48]. The net present value for a series of m cash flows can be calculated using Equation 2.9

$$\mathrm{NPV} = \sum_{i=1}^{m} \frac{\mathrm{FV}_m}{(1-r)^t} \tag{2.9}$$

where FV is the future value of the cash flow, r is the rate of inflation or interest, and t is the time until the cash flow occurs.

Including the net present value into our cost and benefit calculations results in a shift of the value curve illustrated in Figure 2.5 dependent on the service life and cost and benefit functions specified by the designers. This shift is illustrated generally in Figure 2.6.

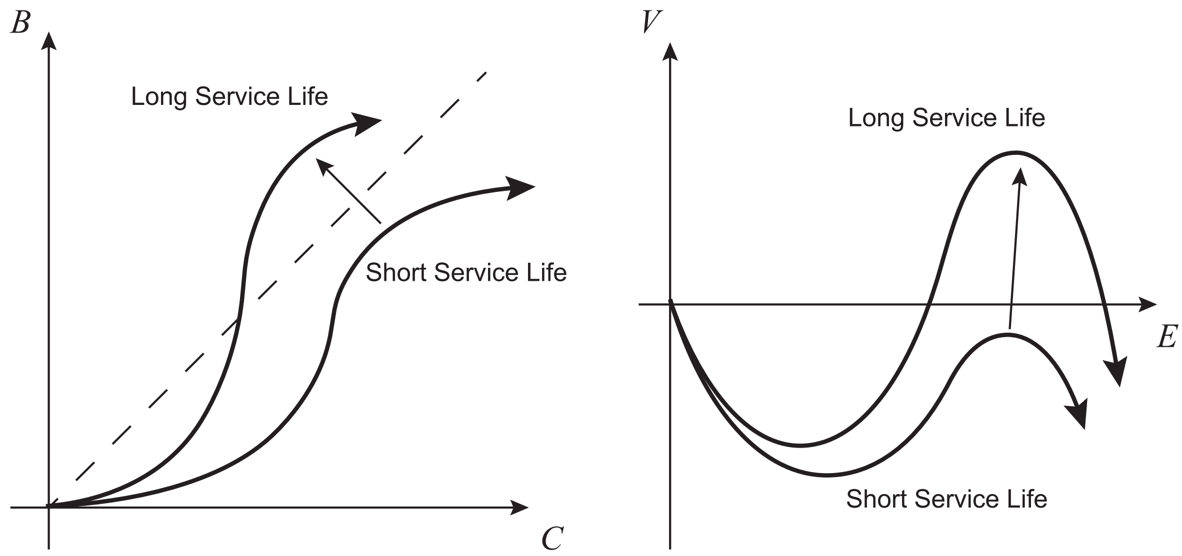


Figure 2.6: Illustration of shifting value curve due to increasing service life

2.4 Optimization Formulation

This chapter has discussed methods for evaluating the evolvability of a system and the value of excess capability in a system. Accordingly, the formulation of the optimization problem is currently given by:

$$
\begin{aligned}
\underset{\mathbf{X}}{\text{minimize:}} \quad & \text{maximin}(-E(\mathbf{X}), -V(\mathbf{X})) \\
\text{subject to:} \quad & \mathbf{X}_{\text{min}} \leq \mathbf{X} \leq \mathbf{X}_{\text{max}} \\
& G_i(\mathbf{X}) \leq b_i \\
& H_i(\mathbf{X}) = c_i
\end{aligned}
\tag{2.10}
$$

where G_i represents any inequality constraints and H_i represents any equality constraints. Typically, the feasible bounds on each type of excess will be included as inequality constraints. In Chapter 3 we demonstrate this formulation on an analytical system model. In Chapter 4 we will expand this formulation to account for uncertainty introduced into various aspects of the system model.

CHAPTER 3. CASE STUDY PART A: MILITARY GROUND VEHICLES (DETERMINISTIC)

This chapter demonstrates the methods from Chapter 2 by applying them to the optimization of military ground vehicles. For the present analysis, we assume that all parameters, functions, constraints, and events are known deterministically (zero uncertainty). In Chapter 5, we will expand this analysis to include consideration for uncertainty as outlined in Chapter 4.

3.1 Background

In 2005, the US Marine Corps submitted requests for Mine Resistant Ambush Protected (MRAP) vehicles to replace their insufficiently protected fleet of High-Mobility Multipurpose Wheeled Vehicles (HMMWV) [49]. The request was spurred by an increase in improvised explosive devices (IEDs) – a new threat that the flat-bottomed, low-clearance HMMWV is not designed to address. However, despite urgent and repeated requests for MRAP replacements, it was several years before substantial shipments of MRAP vehicles made it to U.S. troops. Weiner cites evidence that the delay was caused by an inability to reconcile current needs for greater IED protection with predicted future needs for lighter, more maneuverable vehicles [50]. Neither the HMMWV nor the MRAP were capable of being evolved to meet all potential requirements (see Figure 3.1).

Ideally, military ground vehicles should meet a broad range of emerging needs. However, many of these needs conflict with one another. For example, vehicle stability, top speed, and cargo capacity are all diminished by the addition of after-market armor added to increase protection. Even the benefits of additional armor are eventually countered by an increase in fuel consumption, and thus fuel convoy casualties [51]. For every military mission there may be many combinations of performance requirements.

The prevailing design method for military ground vehicles has been to create several variations capable of performing well on a few limited mission types. This has led to delays and costly

(a) HMMWV (b) MRAP

Figure 3.1: Two current military ground vehicle options and their associated capabilities (data from www.amgeneral.com, www.defense-update.com, www.militaryfactory.com, and www.navistardefense.com)

redesigns [52]. However, a set of optimal designs can be prepared by identifying potential future requirements and adding excess capability according to the methods set out in Chapter 2.

3.2 System Model

It is not necessary to model every system parameter to understand how excess capability will improve the evolvability of a system. Creating a simplified model of our complex system, focusing on high-level parameters of the design, allows us to gain understanding about evolvability without a computationally expensive model. A discussion of the effects of scaling with complex systems can be found in Section 6.2.3. Our model of a military ground vehicle is reduced to only consider a few key areas of excess capability that enable future evolution. The design variables of interest in this study are excess vehicle height (X_H), excess vehicle width (X_W), excess vehicle length (X_L), excess payload (X_S), and excess power (X_P). Accordingly, the construction of our vehicle is simplified to the diagram shown in Figure 3.2.

For this example, the optimization routine is allowed to create solutions within a defined range of excess volume, excess payload, and excess power. The minimum and maximum allowable value for each design variable is given in Table 3.1. Note that each area of excess refers to the area in the back of the vehicle (shown by dashed box in Figure 3.2). However, the width of the vehicle (W) and the width of the excess volume (X_W) are equivalent.

The linear dimensions of the vehicle are not allowed to go to zero due to functional geometric constraints on the vehicle (see Figure 3.2).

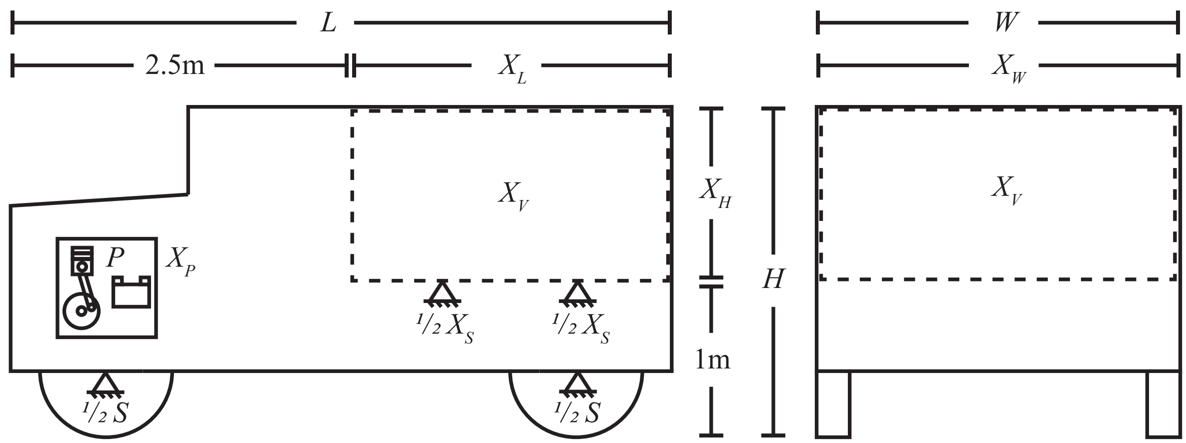


Figure 3.2: Simplified model of excess volume (X_V), excess payload (X_S) and excess power (X_P) in a military ground vehicle

Table 3.1: Minimum and maximum bounds on each type of excess capability for the military ground vehicle model

Type of Excess	$X_{\mathbf{min}}$	$X_{\mathbf{max}}$
Excess Length (X_L)	1.00 m	4.00 m
Excess Width (X_W)	2.00 m	4.00 m
Excess Height (X_H)	1.25 m	2.50 m
Excess Payload (X_S)	0 kg	3000 kg
Excess Power (X_P)	0 kW	400 kW

3.3 Future Evolution Requirements and Associated Excess Capability

Across the lifespan of a military ground vehicle, there are many states to which the system may be required to evolve. For the purposes of this analysis, we assume that four such evolutions are identified as being probable and impactful by a CMEA study. These potential evolutions are listed in Table 3.2 with their accompanying types of required excess capability.

The first predicted evolution allows the vehicle to become an armored transport vehicle capable of supporting an added armor kit and passengers. The required armor thickness is set to 50mm based on the work of Hoffenson and Arepally and Yap [51, 53]. In order for excess capability to benefit this evolution, there must be enough volume, payload capacity, and power to

Table 3.2: Potential future states to which the system may evolve (variables: n=quantity, V=volume, m=mass, ρ=density, A=area, t=armor thickness, P=power; subscripts: p=people, a=armor, te=telecommunications equipment, u=UAV, le=launch equipment, md=medical devices)

Potential Evolution	**Excess Volume**	**Excess Payload**	**Excess Power**
(1) Armored Transport Vehicle	$n_p V_p$	$n_p m_p + \rho_a A_p t_a$	$P_p + P_a$
(2) Telecommunications Vehicle	V_{te}	m_{te}	P_{te}
(3) UAV Launch Vehicle	$V_u + V_{le}$	$m_u + m_{le}$	$P_u + P_{le}$
(4) New Medical Tech Vehicle	V_{md}	m_{md}	P_{md}

support the addition of armor and at least one 80kg individual. Benefit increases as a step function with the number of individuals that can be transported (see Table 3.3).

The second predicted evolution allows the vehicle to act as a telecommunications post for military operations. The vehicle must be able to power and support any equipment used for this purpose. Unlike the piece-wise step function used for modeling the benefit for transporting individuals, the benefit for this evolution has a linear growth beginning at the smallest amount of excess that can be allotted. This is to show that the vehicle can always make use of more excess capability to add more telecommunications equipment.

The third predicted evolution allows the vehicle to launch UAVs remotely. This evolution requires a minimum excess length of 3 meters, a minimum excess width of 2.5 meters, and a minimum excess payload of 100 kilograms. If the excess in the system is at least this amount, the full benefit of this evolution is realized. Otherwise, the system receives zero benefit with respect to this evolution.

The last predicted evolution allows the vehicle to support currently unknown medical-related technology that could be developed over the service life of the vehicle. The amount of excess required for such a need is approximated based on past technology trends. The benefit is determined by a distribution about the predicted need. As the excess capability in the vehicle approaches the predicted amount, the benefit grows exponentially.

Realistically, each of these potential evolutions has a predicted probability of occurrence. Likewise, the parameters of each evolution are typically uncertain. However, for the current deterministic analysis, we assume that the probability of each evolution and the parameters required for each state are known exactly. Uncertainty in these areas is introduced in Chapter 4.

3.4 Benefit and Cost Per Unit Excess

The benefit per unit excess is based on not needing to redesign for each future state described in Table 3.2. For the current analysis we assume that the benefit per unit excess can be precisely determined. In our analysis, these values are approximately chosen with the intent to model realistic values. These values are given in Table 3.3.

Table 3.3: Benefits per unit excess for the military ground vehicle model

Benefit per unit excess (g_i)
$g_1 = \$30,000.00/\text{person+armor}$
$g_2 = \$50,000.00/\text{full support}$
$g_3 = \$10,000.00/\text{UAV}$
$g_4 = \$100,000.00/\text{approximate capability}$

The cost per unit excess is based on the actual amount of excess capability designed into the system. These costs (shown in Table 3.4) are also intended to approximate realistic values. The effect of uncertainty in these approximations is addressed in Chapter 5.

Table 3.4: Costs per unit excess for the military ground vehicle model

Initial cost per unit excess (α_{io})	**Recurring cost per unit excess (α_{io})**
$\alpha_{Vi} = \$100.00/\text{m}^3$	$\alpha_{Vr} = \$0.40/\text{m}^3/\text{year}$
$\alpha_{Si} = \$7.00/\text{kg}$	$\alpha_{Sr} = \$0.02/\text{kg}/\text{year}$
$\alpha_{Pi} = \$50.00/\text{kW}$	$\alpha_{Pr} = \$1.00/\text{kW}/\text{year}$

The values enumerated in Tables 3.3 and 3.4 are approximately chosen for illustration purposes. It is assumed that designers who have been embedded in a particular industry for many years will be capable of creating these functions either heuristically or based on known data points for similar systems and components.

3.5 Optimization Formulation

For clarification and comparison, we lay out the general parameters used in our genetic algorithm in Table 3.5. Crossover is achieved using a standard blending function [54]

Table 3.5: Genetic algorithm parameters and methods used for the military ground vehicle model

Population Size	**Tournament Size**	**Mutation Rate**	**Generations**
500	50	0.15	20

The first optimization objective is set to maximize the total system evolvability (E) [16]. As a second optimization objective, the value (V) added by included excess capability is also maximized with respect to each future evolution described in Table 3.2. The formulation of the optimization problem is given by:

$$\begin{aligned} \underset{x}{\text{minimize}} \quad & \text{maximin}(-E(X_V, X_S, X_P), -V(X_V, X_S, X_P)) \\ \text{subject to} \quad & 1.00\,\text{m} \leq X_L \leq 4.00\,\text{m} \\ & 2.00\,\text{m} \leq X_W \leq 4.00\,\text{m} \\ & 1.25\,\text{m} \leq X_H \leq 2.50\,\text{m} \\ & 0.00\,\text{kg} \leq X_S \leq 3000.00\,\text{kg} \\ & 0.00\,\text{kW} \leq X_P \leq 400.00\,\text{kW} \\ & 0.60 \leq \text{SSF} \end{aligned} \tag{3.1}$$

The objective functions are described by equations 2.2 and 2.8. The minimum and maximum bounds for each type of excess capability (see table 3.1) are set as inequality constraints. A final inequality constraint ensures that the static stability factor (SSF) remains above 0.60 as defined by Equation 3.2.

$$\text{SSF} = \frac{X_W}{2(X_H + 1)} \tag{3.2}$$

The static stability factor is a simple predictor of a vehicle's propensity to roll [55].

3.6 Optimization Results and Discussion

The described model is simulated following the optimization formulation from Section 3.5. The net present value of cash flows is calculated based on a set 5% interest rate. Calculations are made based on a service life of 20 years. For these parameters, the optimal set of designs is found to be the set of solutions described by the Pareto frontier in Figure 3.3.

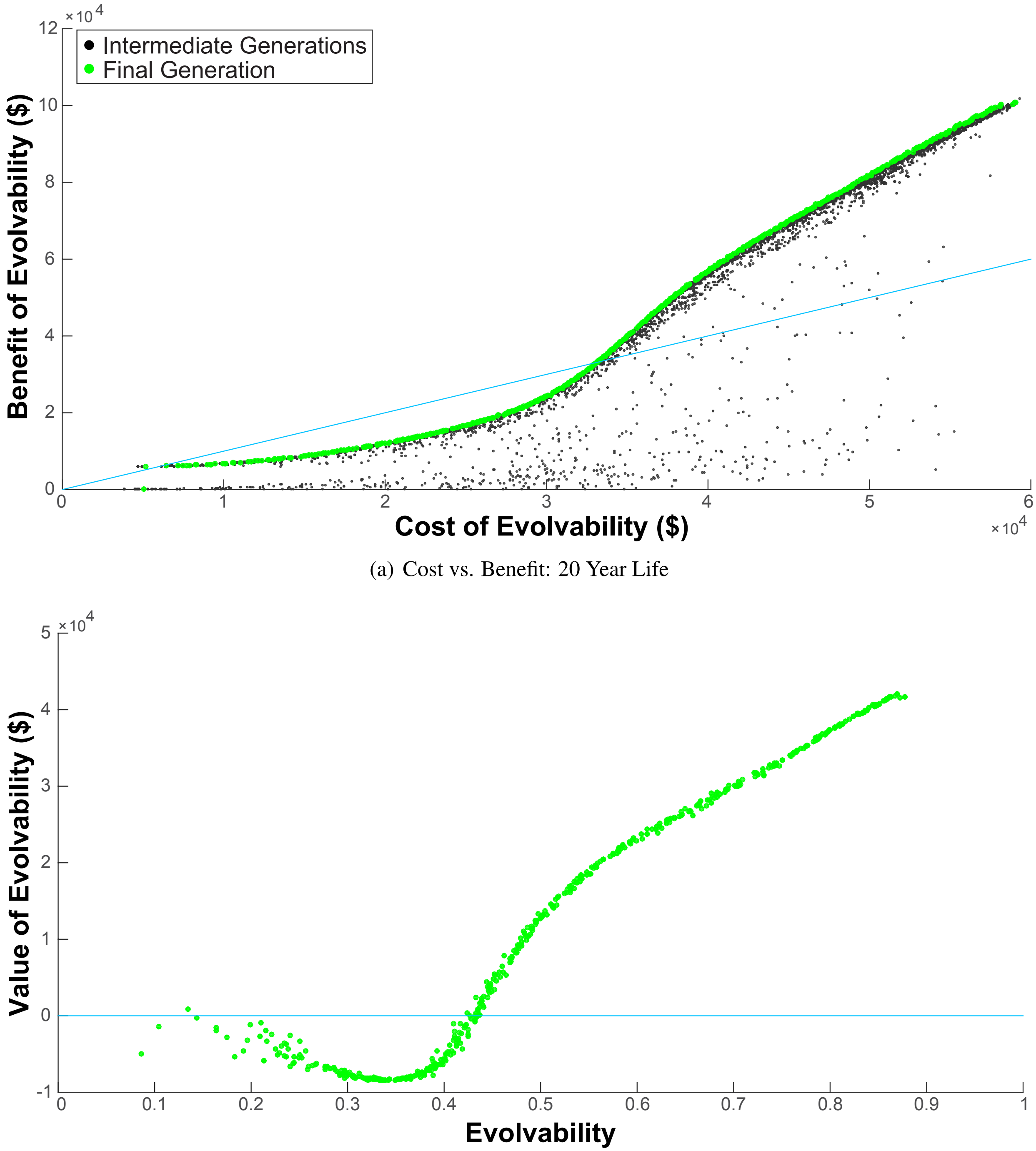
There are several factors to consider when evaluating the Pareto front and selecting a configuration. Of course, in the presence of uncertain future requirements, risk is an important consideration. However, because the current example assumes zero uncertainty, risk does not come into play (though it will in the extended case study in Chapter 5). A typical evaluation criterion is the budget allocated toward improving system longevity or evolvability. For example, if a budget of $40,000 were allocated, the point shown in Figure 3.4 would represent a configuration within budget that would yield the highest value for a 20 year service life.

This same process can be used for any budget or criteria that is measurable against the parameters of the optimization. Table 3.6 outlines the highest value configuration for three different budget constraints.

Table 3.6: Top value configuration for 3 different budget constraints for the military ground vehicle model with a 20 year service life

	$40,000 Budget	**$50,000 Budget**	**$60,000 Budget**
Excess Length (X_L)	3.98 m	3.97 m	3.97 m
Excess Width (X_W)	3.91 m	3.90 m	3.90 m
Excess Height (X_H)	2.22 m	2.24 m	2.24 m
Excess Payload (X_S)	1,999 kg	2,786 kg	2,946 kg
Excess Power (X_P)	242.53 kW	288.93 kW	333.60 kW
Cost (C)	$39,870	$49,872	$54,887
Benefit (B)	$56,150	$80,238	$91,702
Value (V)	$16,280	$30,366	$36,814
Evolvability (E)	0.52	0.71	0.81

According to Table 3.6, the optimal amount of excess volume is the same for each budget level shown. However, by moving from a $60,000 budget to a $40,000 budget, we give up a significant amount of excess payload and power. This suggests that adding excess power and



(a) Cost vs. Benefit: 20 Year Life

(b) Evolvability vs. Value: 20 Year Life

Figure 3.3: Preliminary generations and final solution set for the military ground vehicle model with a 20 year service life

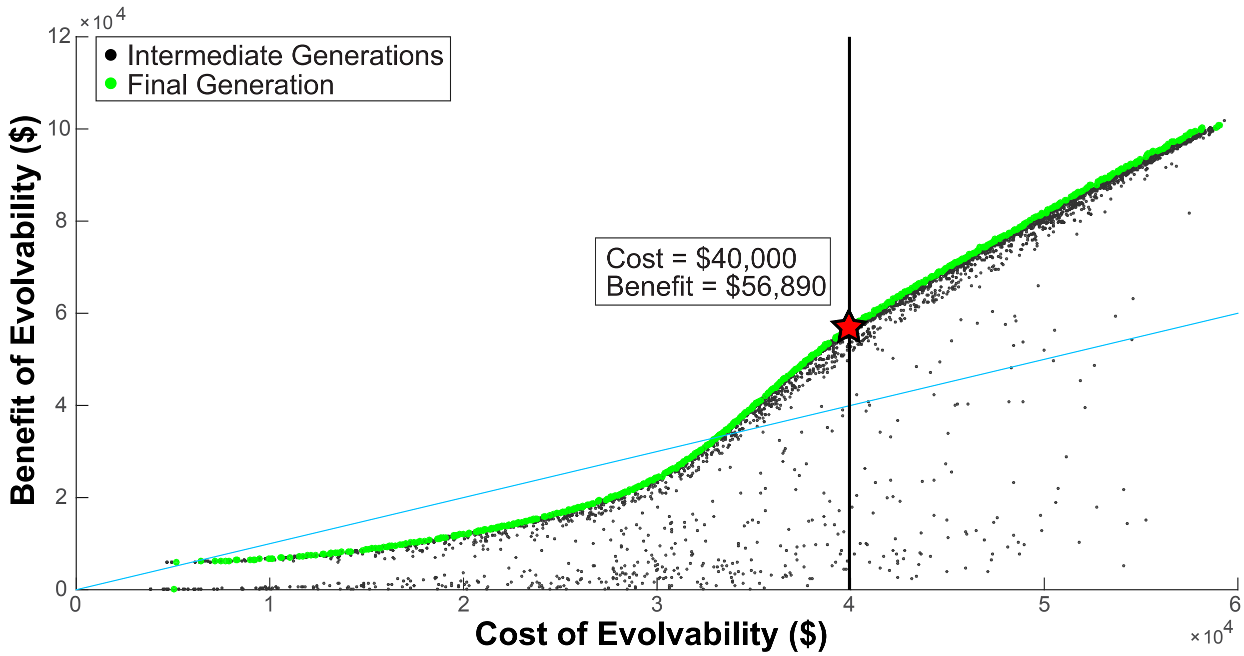
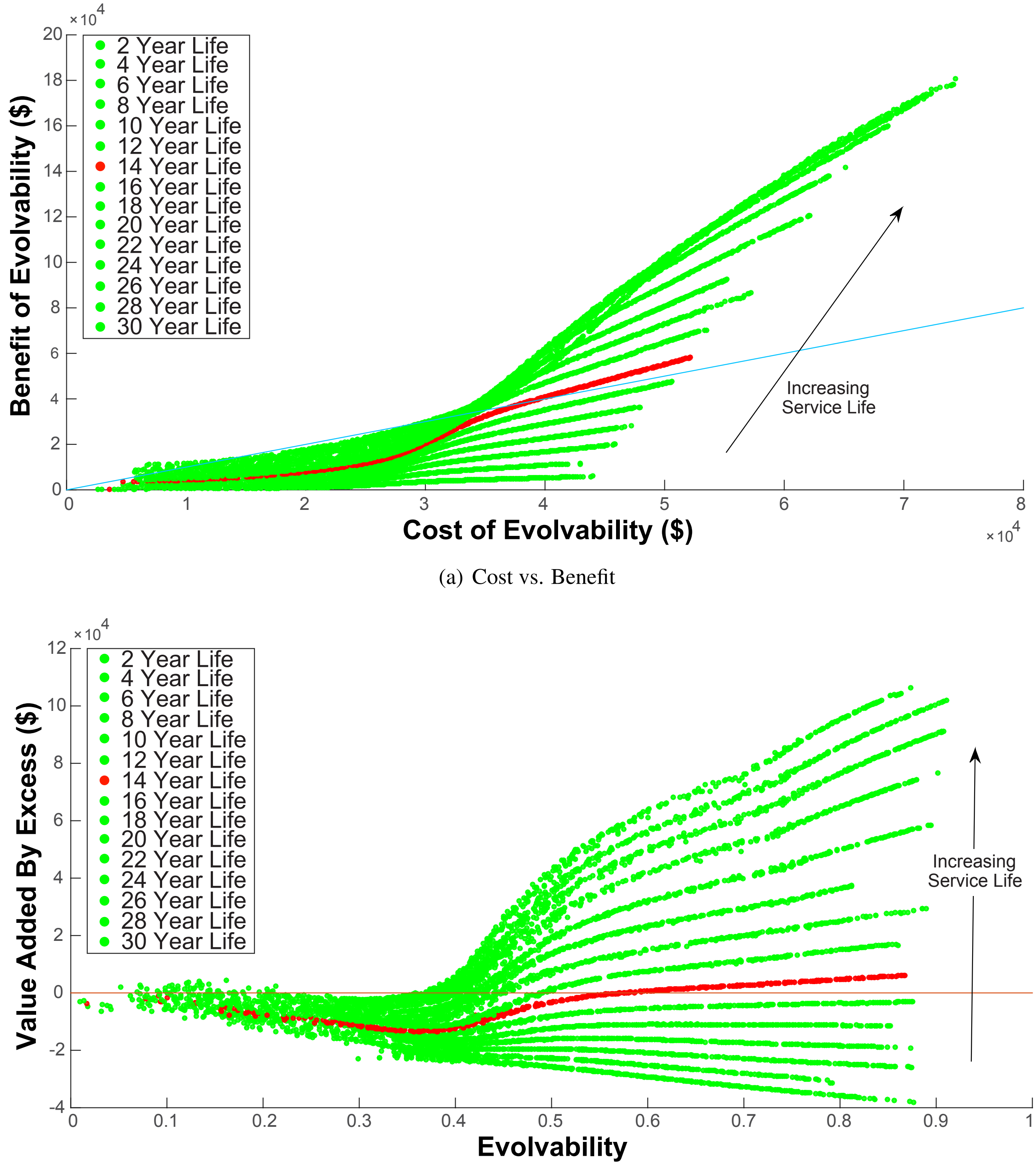


Figure 3.4: Selecting from the final solution set for the military ground vehicle model with a 20 year service life

payload in the range shown will provide a high return on investment. Additional excess volume does not appear to be the cause of changing net value between these three solutions.

The total value added by excess capability for each of these budget level solutions is positive. From Figure 3.4 it can be seen that an initial budget of around $35,000 is required to make excess capability profitable for this system. If the stakeholders are not willing to invest this much into making the system evolvable up front, they should not design excess into the system.

The solutions recorded above are based on an expected service life of 20 years. As described in Section 2.3.7, the value of excess capability is a function of predicted service life. The value of a given quantity of excess capability was proposed to be higher for systems with a longer expected service life. To illustrate this, the cost-benefit and value-evolvability curves are plotted for 15 different service life expectations in Figure 3.5. It is shown that the system must have a service life of at least 14 years in order for some amount of excess capability to be valuable. This point is dependent on the service life of the system, as shown in Figure 3.5.



(a) Cost vs. Benefit

(b) Evolvability vs. Value

Figure 3.5: Minimum service life to create a net positive value of excess capability for the military ground vehicle model

3.6.1 Final Design Selection

Once an optimal set of solutions is generated, it can be used to make decisions regarding the trade-offs between competing objectives [56]. Pandey and Mourelatos note that optimization is only meant to inform the designer, not to make the decisions for them [57]. They recommend that the designs generated by the optimization be presented to the designers for final selection based on current preferences. Now that we have generated an entire set of possible solutions, it can be used as a selection tool based on our preference criteria.

We assume that our system will remain in service for 20 years. This means that our optimal solution set is as shown in Figure 3.3. We will also assume that the stakeholders have allocated an initial budget of $50,000 to be spent on improving system evolvability. From Table 3.6 we find that the system that will yield the highest value for this budget and service life is the system shown in Figure 3.6.

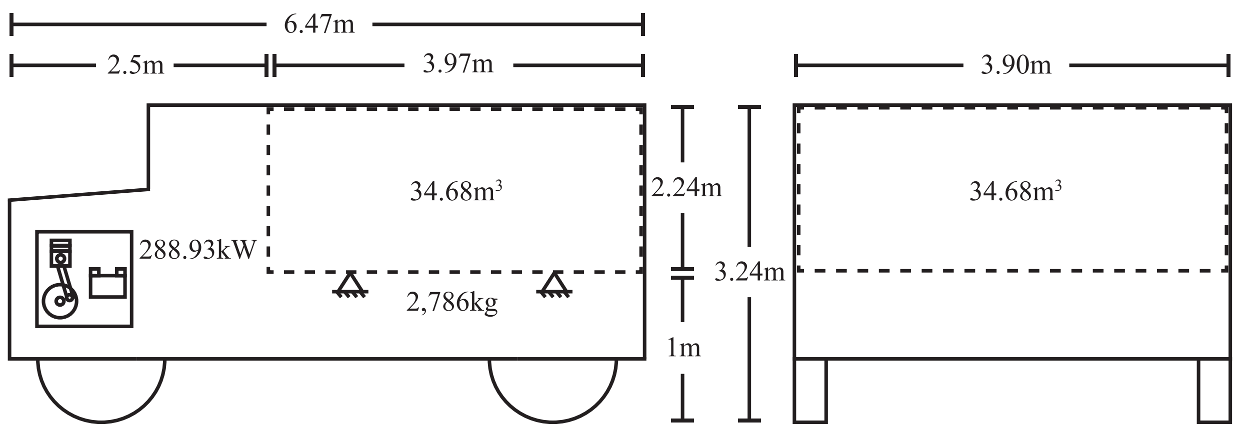


Figure 3.6: Final design for the military ground vehicle model with a 20 year service life

Although these results support the theories set out in Chapter 2, it is important to remember that they are misleadingly high because they assume zero uncertainty. In the following chapters, we introduce methods for accounting for uncertainty in our system model. This will be shown to generally decrease the expected value added by excess capability.

CHAPTER 4. OPTIMIZATION OF EVOLVABILITY UNDER UNCERTAINTY

The methods developed in Chapter 2 and demonstrated in Chapter 3 provided insight into the value trade-off associated with designing systems for evolvability. However, several assumptions were made regarding the certainty with which the system could be defined. In this chapter, we expand the methods introduced in Chapter 2 to include considerations for uncertainty in the system model and in predicting future system requirements.

4.1 Sources of Uncertainty in Complex Systems

One of the greatest difficulties when designing complex systems is dealing with the inherent uncertainty in such systems [58]. Due to the uncertain nature of planning for future requirements, evolvability metrics introduce more uncertainty into system modeling. If this uncertainty is not accounted for, numerically derived solutions can be inaccurate or misleading.

Uncertainty is often divided into two main categories: aleatory uncertainty and epistemic uncertainty [59].

Aleatory uncertainty is due to random variations in input parameters. It is generally irreducible, but it can be planned for during design. In engineering models, aleatory uncertainty is often due to variations in design parameters and dimensions that are defined by distributions.

According to Oberkampf, epistemic uncertainty is a potential deficiency in any phase of the modeling process that is due to a lack of knowledge [60]. Therefore, it can be reduced as more information is acquired or as the accuracy of models is improved. The probability that a future requirement will emerge at some point in a system's life is a primary source of epistemic uncertainty in our model for evolvability.

We will account for and mitigate both types of uncertainty in our optimization framework. The effects of uncertainty will then be analyzed to determine how including uncertainty can improve the accuracy of our results.

4.2 Propagating Uncertainty in Engineering Models

Previous research has identified several methods for optimizing engineered systems with consideration for life cycle uncertainty [35, 61–64]. One study showed that optimization with the recognition of uncertainty lead to significant improvements in system performance (greater than 10%) compared to deterministic approaches [65].

As a modification to the framework in Chapter 2, we discuss two established steps for mitigating uncertainty: shifting inequality constraints to account for probability distributions, and minimizing the variance of each objective. To apply these steps to our framework, we must first understand established mechanisms for representing and propagating probabilistic parameters.

Aleatory uncertainty is often represented by a distribution with a mean (μ) and variance (σ^2). Anderson and Mattson show that the variance can be effectively propagated through engineering models using a Taylor-series approximation [36]. The second-order Taylor-series approximation for variance propagation is given by:

$$\sigma_y^2 \approx \sum_{i=1}^{n} \left(\frac{\partial y}{\partial x_i}\right)^2 \sigma_{x_i}^2 + \frac{1}{2} \sum_{j=1}^{n} \sum_{i=1}^{n} \left(\frac{\partial^2 y}{\partial x_i \partial x_j}\right)^2 \sigma_{x_i}^2 \sigma_{x_j}^2 \tag{4.1}$$

where y is a function of x_i for $i = 1, 2, ..., n$. It should be noted that Equation 4.1 assumes that all inputs are Gaussian and independent, which may be an inaccurate assumption. Ayyub and Klir outline several other prevailing methods for propagating uncertainty for system evaluation [37]. While any propagation method may be used, the analysis in this thesis uses the Taylor-series approximation to propagate the aleatory uncertainty associated with system design parameters.

Robust optimization accounts for the variance of design parameters propagated through to the constraint functions [39]. The constraint is then shifted such that the solution set does not violate the constraint as long as the variance is within an allowable range [66]. This allows the designers to decide what percent of designs are required to be feasible.

4.3 Objective #1: Maximize Evolvability Under Uncertainty

As it is defined by Equation 2.2, evolvability is a function of the amount of excess capability in a system and the benefit per unit excess capability as it relates to future requirements. When we include uncertainty, the amount of excess capability in a system is defined probabilistically by a mean and standard deviation. Similarly, the gain is affected due to the probability of future events. Using the Taylor series approximation discussed in Section 4.2, we can calculate the variance of the system evolvability based on the variance of these two parameters according to Equation 4.2.

$$\sigma_E^2 \approx X^2\sigma_g^2 + g^2\sigma_X^2 + \sigma_g^2\sigma_X^2 \tag{4.2}$$

The variation in these parameters is discussed further in Sections 4.4.2 and 4.4.3.

4.4 Objective #2: Maximize Value Under Uncertainty

The framework developed in Chapter 2 for optimizing the value of excess capability should also be modified to account for uncertainty. The following sections describe key areas that should be considered in this regard.

4.4.1 Probabilistically Defined Requirements

As mentioned, the uncertainty associated with future requirements is epistemic, meaning it results from a lack of information. However, historical knowledge of past and current requirements can be used to help predict future requirements with some degree of confidence [62]. To model future requirements, we will assume that generally related requirements can be identified by CMEA or other methods, as discussed in Section 2.3.1. Further, we will assume that designers are able to assign each requirement a probability of occurrence within a certain life span, as well as a qualifying standard deviation for each probability. These assumptions are supported by and in line with similar studies from the related literature [67].

The definition of each requirement hence becomes a probabilistic distribution with mean and standard deviation. Thus, Equation 2.3 is modified to take the form of Equation 4.3

$$X = pD_f - D_o \tag{4.3}$$

where p is the probability associated with the requirements definition. There is also a probability associated with the occurrence of each potential requirement across the life of the system. This can be modeled with a normal cumulative distribution function with a predicted mean and standard deviation, as in Figure 4.1. The example distribution shown in this figure has a predicted mean of 15 years before occurrence with a standard deviation of 4 years. The probability of occurrence after 20 years is shown in Figure 4.1 to be approximately 90%.

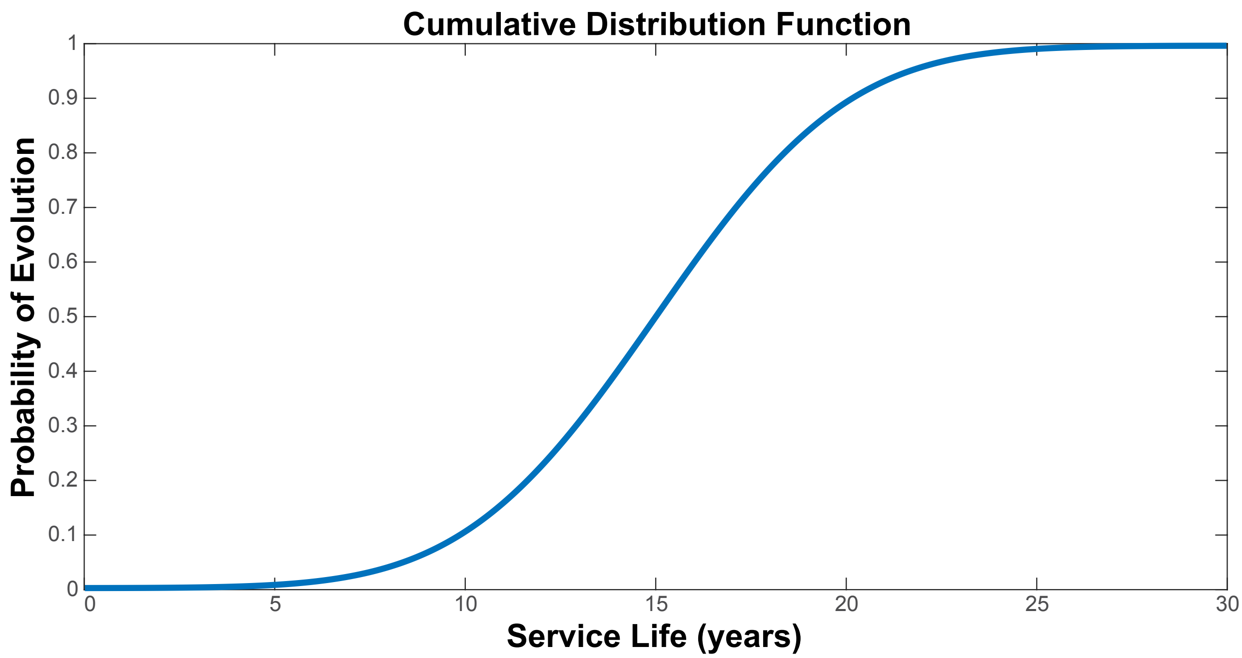


Figure 4.1: Example cumulative probability distribution with mean of 15 years and standard deviation of 4 years across the service life of the system

4.4.2 Constraints on Design Variables

As mentioned in Section 4.1, aleatory uncertainty is typical of the system design parameters. In our optimization the design parameters are the amount of excess capability in the system. Because the upper and lower limit for each capability forms a constraint in our optimization routine, the uncertainty in these parameters must be propagated through to the constraints, as explained in Section 4.2. Accordingly, Equation 4.4 is modified to become

$$(X_{i\min} + k\sigma_i) \leq X_i \leq (X_{i\max} - k\sigma_i) \tag{4.4}$$

where σ_i is the standard deviation of X_i, and k is the number of standard deviations within which results are allowable.

4.4.3 Benefit and Cost Under Uncertainty

The benefits of excess capability are only realized if the predicted requirement emerges within the system's service life. Accordingly, the benefit described in Equation 4.5 is modified to become

$$B = \sum_{i=1}^{n_i} p_i g_i X_i \tag{4.5}$$

where p_i is the probability of occurrence of the i-th predicted requirement, as described in Section 4.4.1.

The initial costs associated with excess capability are incurred immediately and whether or not the predicted future requirement ever emerges. The recurring costs of excess capability are carried across the entire service life, even after it is used in an evolved state. Therefore, the epistemic uncertainty of future events does not apply to the costs of excess. However, the recurring costs are compounded across the entire service life, meaning that the costs will be greater for a system with a longer service life.

4.4.4 Value Under Uncertainty

The probability of future events affects the value of excess capability as mentioned. If there is uncertainty in the predicted service life of the system, this will also play into the net present value calculated for each requirement. Thus, the value of excess capability is linked to both the probability of the requirement's occurrence and the duration of the system's service life. We can account for this by adjusting the net present value calculation according to Equation 4.6.

$$\mathrm{NPV} = \sum_{i=1}^{m} \frac{\mathrm{FV}_i}{(1-r)^{p_i t}} \tag{4.6}$$

Several methods have been proposed for dealing with uncertainty with respect to future cash flows [48]. The best method for accounting for this change in net present value depends on the information available during design. Engineers should use the method that works best with the information they have available.

4.5 Objective #3: Minimize Variance

Propagating uncertainty through the system model is important in understanding the accuracy of the results. However, we would like to not only be aware of the uncertainty in our model, but also minimize it as much as possible. This is possible by expanding the objectives of our optimization to include the propagated variance of our evolvability and value.

When the uncertainty of the evolvability and value are minimized, and the uncertainty of design variables is propagated to the constraints, the shape of the design space is altered. Due to the shift in constraints, the outer edges of the design space are attenuated. This results in a change similar to that shown in Figure 4.2.

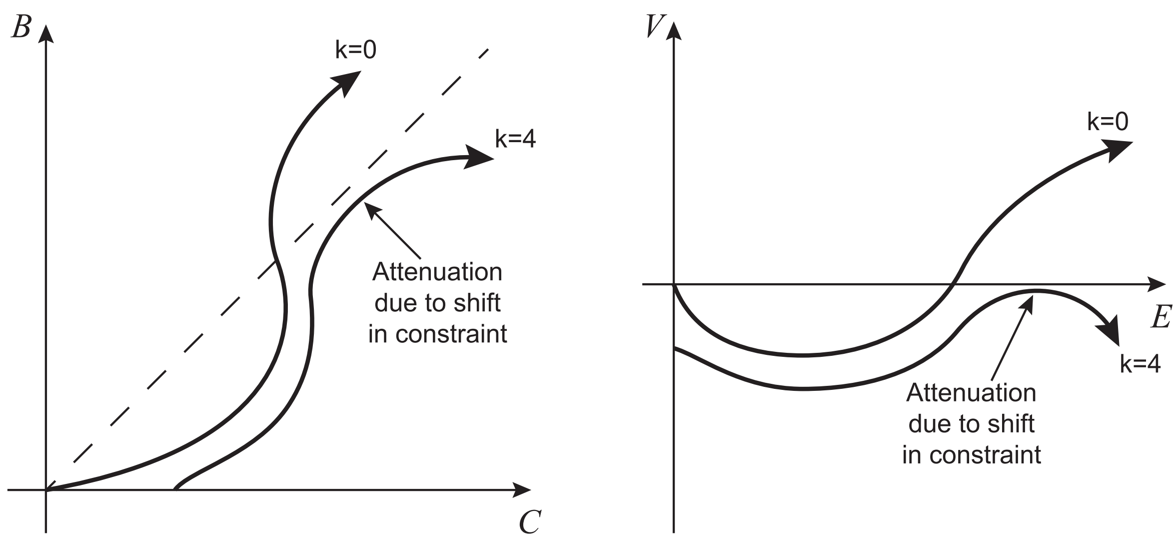


Figure 4.2: Illustration of how uncertainty can attenuate the value of excess capability

This change in the design space has important implications for planning for evolvability. It means that a given amount of excess capability will have less value toward evolution than previously calculated. With uncertainty included in our optimization, we now have a better understanding of how evolvable our system truly is.

4.5.1 Expanded Optimization Formulation

The concepts discussed in this chapter are used to expand the optimization formulation set out in Section 2.4. The new formulation of the optimization problem is thus given by:

$$\begin{aligned}
\underset{\mathbf{X}}{\text{minimize:}} \quad & \text{maximin}(-E(\mathbf{X}), -V(\mathbf{X}), \sigma_E^2(\mathbf{X}), \sigma_V^2(\mathbf{X})) \\
\text{subject to:} \quad & \mathbf{X}_{\min} + k\sigma_X \leq \mathbf{X} \leq \mathbf{X}_{\max} - k\sigma_X \\
& G_i(\mathbf{X}) \leq b_i - k\sigma_i \\
& H_i(\mathbf{X}) = c_i
\end{aligned} \tag{4.7}$$

where σ_E^2 and σ_V^2 are the variance of evolvability and value, and where k is the number of standard deviations of feasibility for the optimized solution set. All inequality constraints (G_i) are shifted by k standard deviations away from the normal constraint bound. Equality constraints (H_i) are particularly difficult to manage under uncertainty. Messac and Mattson suggest that some equality constraints must be strictly satisfied even under uncertainty, while others may be changed into inequality constraints with an allowable margin [68].

In Chapter 5 we demonstrate the importance of including uncertainty when optimizing system evolvability and value of excess. The example from Chapter 3 is continued and expanded for the purpose of comparison.

CHAPTER 5. CASE STUDY PART B: MILITARY GROUND VEHICLES (NON-DETERMINISTIC)

This chapter demonstrates the methods from Chapter 4 by applying them to the example optimization of military ground vehicles developed in Chapter 3. We accordingly expand system parameters, functions, constraints, and events to include and account for uncertainty. However, the main system model is identical for comparison purposes.

5.1 Constraints on amount of excess capability

The amount of excess capability in the system is now assumed to have a normal distribution with a known standard deviation. This is a typical form of aleatory uncertainty found in manufacturing parameters. The standard deviation of each design variable in this example is given in Table 5.1.

Table 5.1: Standard deviations for each type of excess capability for the military ground vehicle model under uncertainty

Type of Excess	**Standard Deviation (σ)**
Excess Length (X_L)	0.05 m
Excess Width (X_W)	0.05 m
Excess Height (X_H)	0.05 m
Excess Payload (X_S)	250 kg
Excess Power (X_P)	10 kW

For the current analysis, we assume that the designers have specified a minimum feasibility of 99.99% for any generated designs. This corresponds with a shift of 4 standard deviations from the mean. Therefore, as described in Section 4.4.2, we will shift each constraint (including those limiting the design variables) by 4σ.

5.2 Probabilistically Defined Requirements

As discussed in Section 4.4.1, the predicted future requirements are typically accompanied by a probability distribution. Table 5.2 outlines the probability that each future state will occur.

Table 5.2: Probabilities of potential future states to which the vehicle might need to evolve

Potential Evolutions	**Mean Probability**	**Std. Dev. of Probability**
Armored Transport Vehicle	0.95	0.05
Telecommunications Vehicle	0.80	0.10
UAV Launch Vehicle	0.40	0.10
New Medical Tech Vehicle	0.20	0.15

These probabilities are based on a 20 year service life. If the service life is more or less than 20 years, the probability of occurrence changes as demonstrated in Figure 4.1.

5.3 Uncertain Benefit and Cost Per Unit Excess

The benefit with respect to each future requirement is scaled by the probability of that requirement. The adjusted benefits are given in Table 5.3.

Table 5.3: Costs per unit excess for the military ground vehicle model under uncertainty

Benefit per unit excess (g_i)
$g_1 = \$28,500.00$/person+armor
$g_2 = \$40,000.00$/full support
$g_3 = \$4,000.00/\text{UAV}$
$g_4 = \$20,000.00$/approximate capability

As described in Section 4.4.3, the costs are not affected by the probability of future events. However, the net present value of all cash flows is affected by the service life.

5.4 Optimization Formulation

The changes discussed above are used to modify the optimization formulation used in Chapter 3. The new formulation is given by:

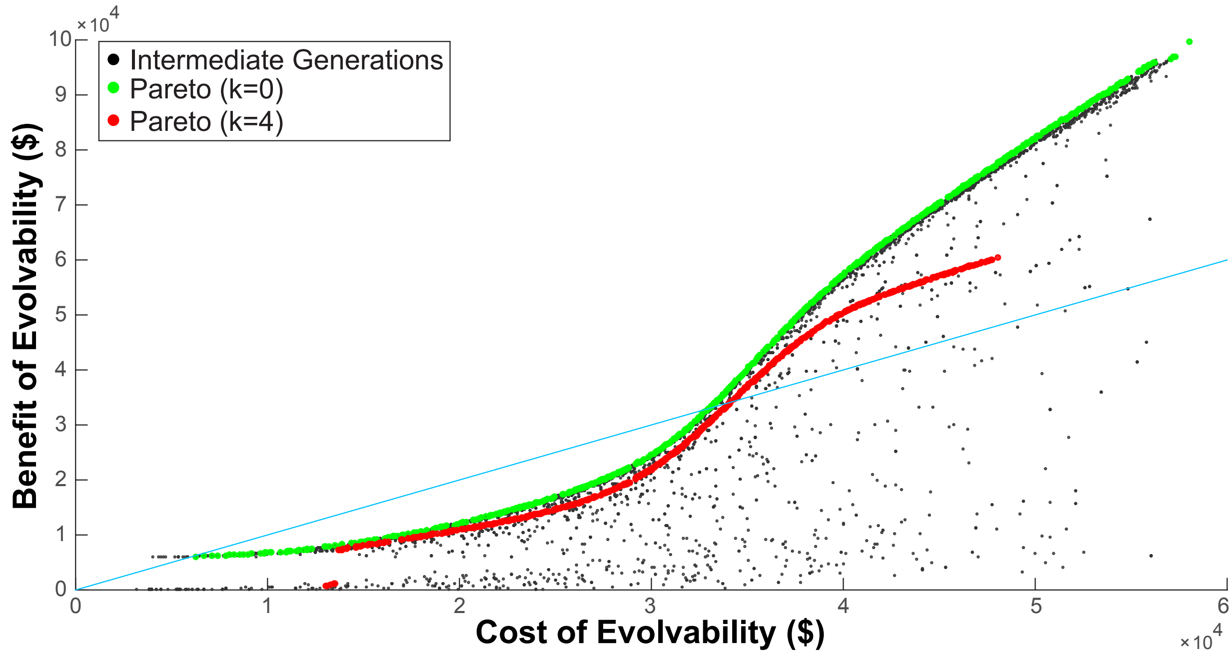
$$
\begin{aligned}
\underset{x}{\text{minimize}} \quad & \text{maximin}(-E(X_V, X_S, X_P), -V(X_V, X_S, X_P), \sigma_E(X_V, X_S, X_P), \sigma_V(X_V, X_S, X_P)) \\
\text{subject to} \quad & (1.00 + k\sigma_{X_L})\,\text{m} \leq X_L \leq (4.00 - k\sigma_{X_L})\,\text{m} \\
& (2.00 + k\sigma_{X_W})\,\text{m} \leq X_W \leq (4.00 - k\sigma_{X_W})\,\text{m} \\
& (1.25 + k\sigma_{X_H})\,\text{m} \leq X_H \leq (2.50 - k\sigma_{X_H})\,\text{m} \\
& (0.00 + k\sigma_{X_S})\,\text{kg} \leq X_S \leq (3000.00 - k\sigma_{X_S})\,\text{kg} \\
& (0.00 + k\sigma_{X_P})\,\text{kW} \leq X_P \leq (400.00 - k\sigma_{X_P})\,\text{kW} \\
& (0.60 + k\sigma_{\text{SSF}}) \leq SSF
\end{aligned}
\tag{5.1}
$$

5.5 Optimization Results and Discussion

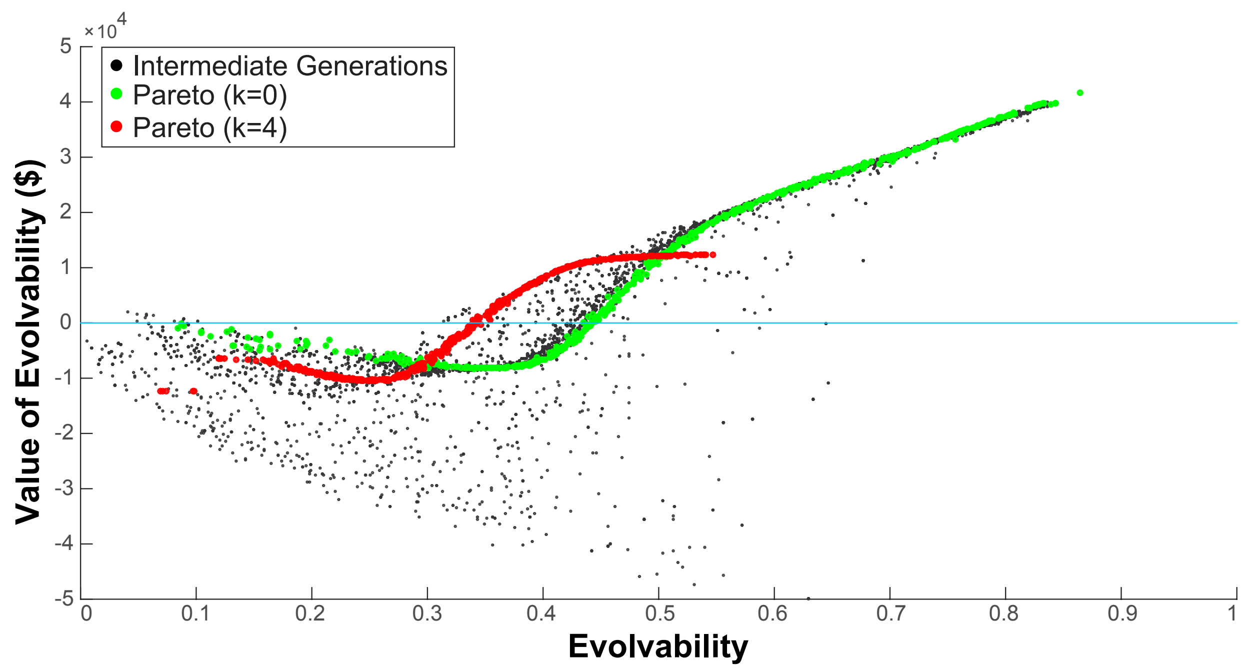
The model is once again simulated using a 5% interest rate and, initially, a 20 year service life. As stated earlier, the constraints are shifted by 4 standard deviations. Figure 5.1 shows the Pareto front of the analysis under uncertainty (red) plotted with the previous solutions from Chapter 3 (green).

As explained in Section 4.5, the plot shows an attenuation of the Pareto front at the outer extremities. A dramatic shift can also be seen in Figure 5.1(b), showing that the optimal amount of evolvability with the highest value return is less than previously thought. When the points are sampled, it can be seen that the shift and attenuation are due to the change in boundary constraints, all of which are now binding.

This modified solution set can be used to select the amount of excess capability that should be included for any given budget. It should be noted that the minimum budget that will turn a net positive value for excess added is higher than previously thought (although only slightly for this 20 year case). Figure 5.2 shows that for a budget of $40,000 the value calculated with consideration for uncertainty is significantly less than when the same value calculated without uncertainty.



(a) Cost vs. Benefit: 20 Year Life



(b) Evolvability vs. Value: 20 Year Life

Figure 5.1: Preliminary generations and final solution set for the military ground vehicle model under uncertainty with a 20 year service life

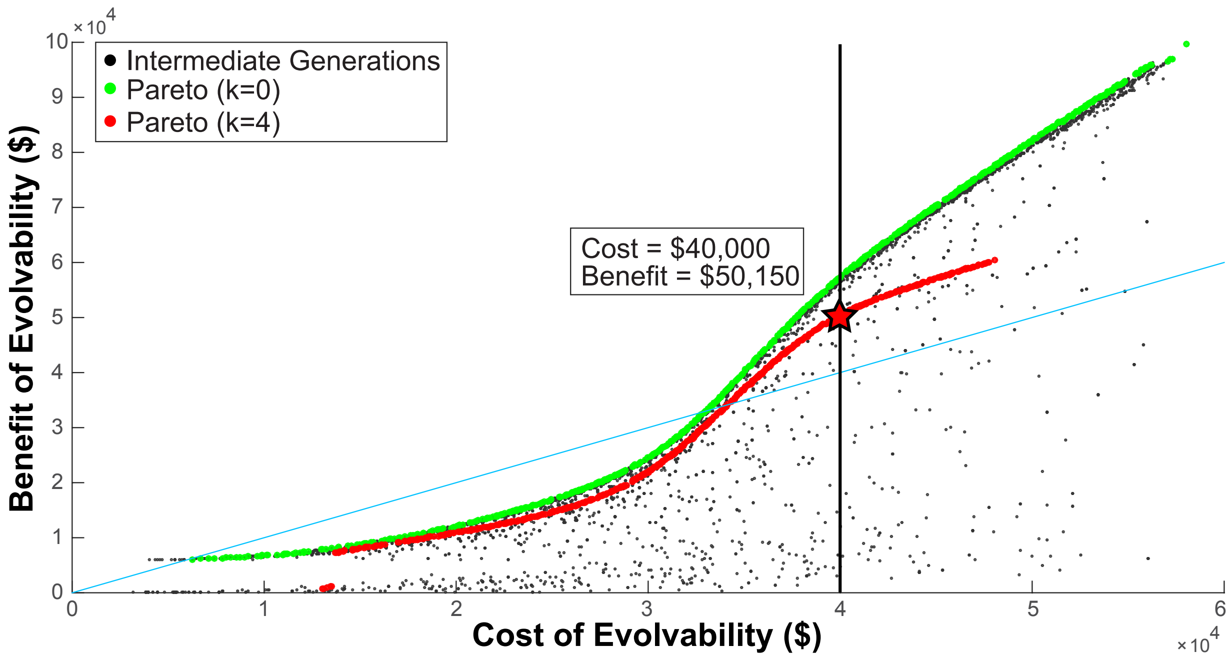


Figure 5.2: Selecting from the optimal solution set for the military ground vehicle model under uncertainty

We sample the Pareto front at the same budget levels identified in Chapter 3. However, as can be seen in the figure, no solutions exist in the \$50,000-\$60,000 range. This is due to the increased limitation on the amount of excess capability that can be added, due to shifting boundary constraints. Table 5.4 shows the optimal configuration for the budget ranges sampled.

Table 5.4: Top value configuration for different budget constraints under uncertainty

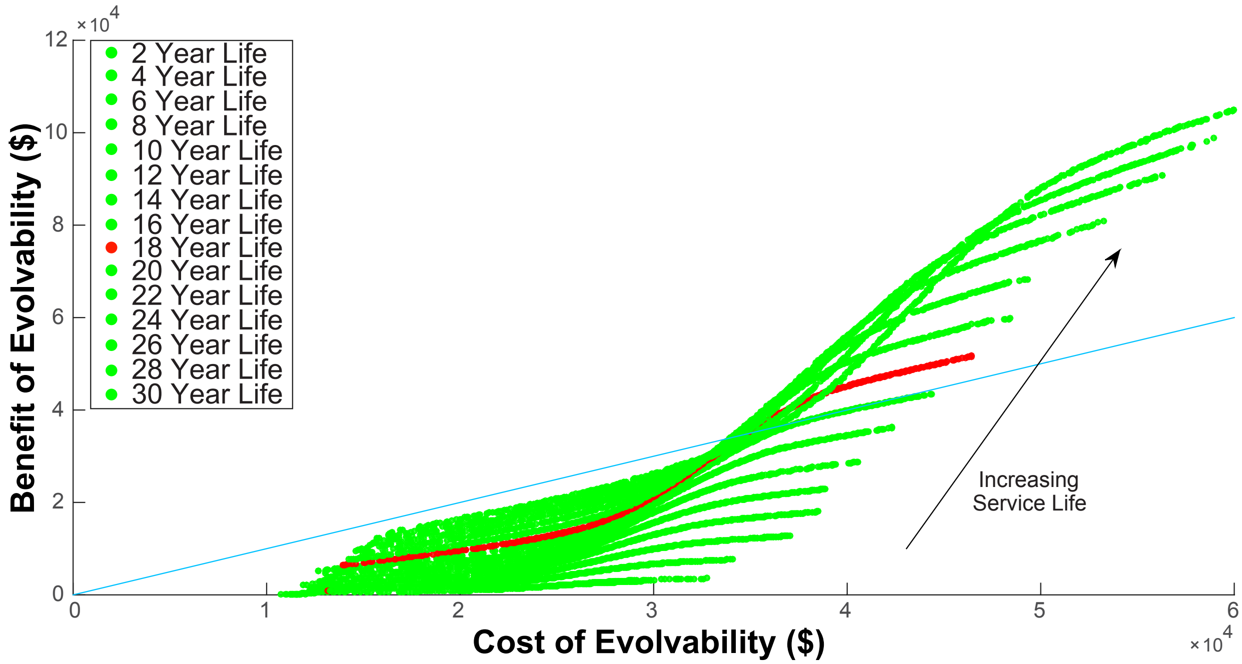
	\$40,000 Budget	**\$50,000 Budget**	**\$60,000 Budget**
Excess Length (X_L)	3.71 m	3.71 m	N/A
Excess Width (X_W)	3.78 m	3.79 m	N/A
Excess Height (X_H)	1.87 m	1.87 m	N/A
Excess Payload (X_S)	1,984 kg	1,986 kg	N/A
Excess Power (X_P)	254.55 kW	351.39 kW	N/A
Cost (C)	\$39,823	\$48,046	N/A
Benefit (B)	\$50,149	\$60,440	N/A
Value (V)	\$10,325	\$12,394	N/A
Evolvability (E)	0.42	0.55	N/A

When we compare these results with those recorded earlier we see a drastic difference. The value added by excess for a budget of $40,000 is nearly 40% less than the value predicted for the same cost in Chapter 3. The value added by excess for a budget of $50,000 is 60% less than the value predicted for the same cost in Chapter 3. This shows how optimizing without consideration for uncertainty can yield extremely unrealistic results.

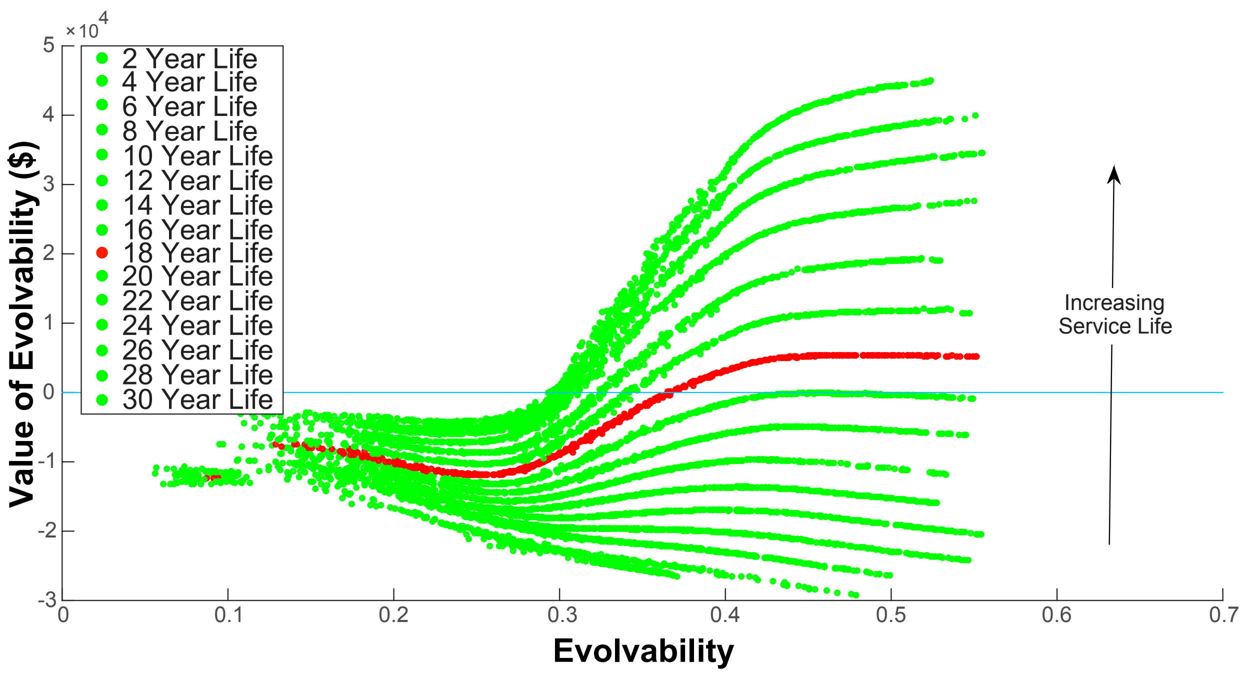
In Figure 5.3, we plot the Pareto front for 15 different service life expectations. When we compare this plot to the one shown in Chapter 3, we see an increase in the minimum service life, from 14 years to 18 years, required for excess capability to be profitable. We also note that the maximum value of excess capability is considerably decreased for a given service life, at times by a factor of two.

5.5.1 Final Design Selection

Figures 5.1 through 5.3 demonstrate the wide range of available possibilities with varying evolvability and value. To select a single optimal design, we must narrow the solution set based on our criteria. We assume that our system will remain in service for 20 years. This means that our optimal solution set is as shown in Figure 5.1. Selecting from this set can be done in several ways. We will assume that the stakeholders have allocated an initial budget of $50,000 to be spent on improving system evolvability. From Table 5.4 we find that the system that will yield the highest value, with 99.99% feasibility and a service life of 20 years, is the system shown in Figure 5.4.



(a) Cost vs. Benefit



(b) Evolvability vs. Value

Figure 5.3: Minimum service life to create a net positive value of excess capability for the military ground vehicle model under uncertainty

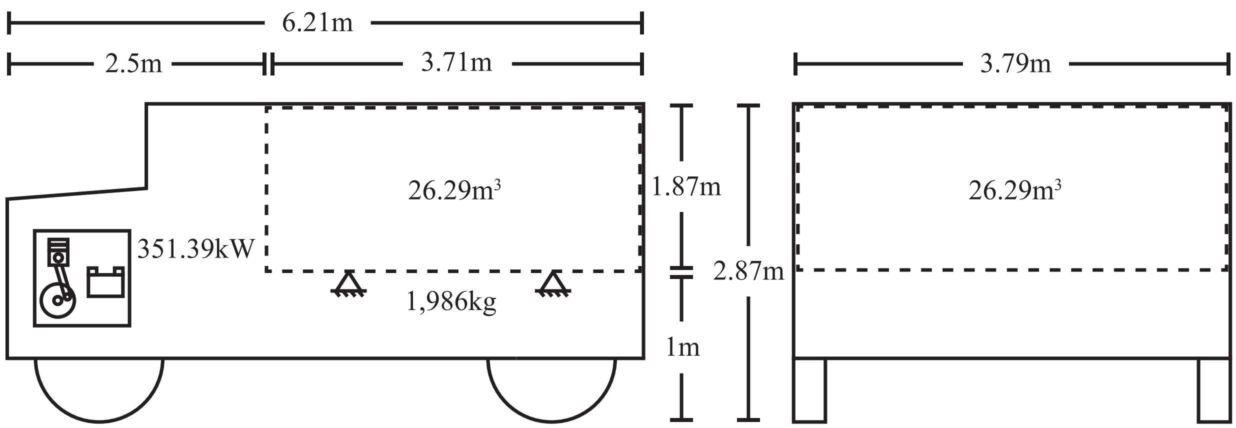


Figure 5.4: Final design for the military ground vehicle model under uncertainty

CHAPTER 6. CONCLUSIONS

Several important steps were taken in this thesis. In this chapter we will review the contributions made by the current work. We will also outline limitations of the work and opportunities for future development.

6.1 Thesis Contributions

This thesis has taken metrics developed for evolvability and placed them in a framework that can be used in system optimization. We have looked at the trade-offs present in designing for evolvability and the considerations required to effectively optimize for evolvability. We have explored the following questions, as outlined in Chapter 1:

1. How can existing metrics for evolvability be implemented into an analytical optimization?
2. At what point do the benefits of evolvability outweigh the associated costs of designing for evolvability? How can this value trade-off be represented in an analytical optimization?
3. What types of uncertainty are introduced when attempting to quantify evolvability? How does this uncertainty affect the accuracy of a solution set optimized for evolvability? How can this uncertainty be minimized?

The following sections reiterate our findings with respect to these questions, as well as other important conclusions drawn from the research.

6.1.1 Consideration for Value of Excess Capability

Previous work has frequently purported the importance of designing for evolvability as a way to mitigate the negative effects of unknown future requirements. Others have developed quantifiable metrics for evaluating evolvability. However, until now, we have not been able to understand the value trade-offs that accompany system evolvability. This thesis has shown that there is a limit to the value added by increasing system evolvability. Whereas some metrics would imply that more excess capability will always benefit the system with respect to future requirements, we have shown that in some cases it is better to redesign the system later than to pay for an evolvable system. The framework developed in Chapter 2 can assist designers in implementing evolvability metrics into an analytical optimization to select the most evolvable system at the highest possible value for a given service life. This tool can be used flexibly to meet the needs specific to the system at varying levels of abstraction. It has been demonstrated on an example of a complex system abstracted to a high-level of design parameters.

6.1.2 Consideration for Propagated Uncertainty

As described in Chapter 4, evolvability is directly impacted by aleatory and epistemic uncertainty. We have shown that optimization of evolvability and the value of excess capability can create entirely misleading results unless uncertainty is accounted for. We have suggested several ways to deal with uncertainty with respect to evolvability and value. These considerations have improved the methods developed in Chapter 2 by identifying key areas where accurate results are dependent on an understanding of the extent of information available.

6.1.3 Effects of Time

Another contribution that this work makes is creating a more tangible tie between the length of the service life of a system and the value of evolvability. We have shown that excess capability is more valuable in systems with longer service lives. We have shown that the cost-benefit curve and value-evolvability curve shift and scale depending on the required minimum service life.

6.1.4 Selecting an Evolvable Design

Prior to the current work, designing for evolvability meant heuristically incorporating general principles into a design. This made it difficult to compare the evolvability of two designs or to plan for evolvability in a concrete and measurable way. This thesis provides a meaningful look at how to select designs that will be evolvable and valuable, with minimal uncertainty from an array of possible choices.

6.2 Limitations and Future Work

The proposed methods for analyzing and assessing evolvability are not without limitations. While some of these limitations were addressed in the main body, we will review them in the following sections. These limitations offer starting points for future work.

6.2.1 Modeling Inaccuracies and Sensitivity

A key element of the described process is identifying and accurately modeling the impact of potential future requirements. Complex systems designers must carefully select functions for cost and benefit that accurately represent the value trade-off in their situation. The inability of designers to precisely establish these cost and benefit functions is a limitation of the proposed approach. Creating these functions is particularly difficult due to the unknown nature of future design requirements. However, approximate functions still provide more insight into the effects of value on evolvability than neglecting the value trade-off entirely.

Further study into the process of identifying the costs and benefits associated with future system requirements would improve the utility of the proposed methods. Also, because the value of excess capability is directly dependent on cost and benefit per unit excess, the results in this paper are very sensitive to the accuracy of these functions. Further research could investigate exactly how sensitive the solution set is to perturbations in the input parameters, particularly those that are difficult to define (i.e. cost, benefit, probability).

6.2.2 Error and Uncertainty Propagation

In Chapter 4 we explained several methods for propagating uncertainty in engineering models. However, as we noted, because these methods are approximations of the propagated uncertainty, they carry some degree of error. Decreasing this error almost always means increasing computation time and cost. When the propagated uncertainty is scaled by k standard deviations, the error in this uncertainty is also scaled. Depending on the complexity of the model, this error can potentially be very large. Engineers should understand the assumptions made for any approximations and realize that they will decrease the accuracy of results.

Alternative methods for propagating error and uncertainty have been suggested. However, many of these methods require higher computational cost. Future research could investigate the possibility of incorporating higher-fidelity propagation methods as a means of reducing total error.

6.2.3 Scalability

The examples in this thesis involved large systems modeled at a very highly-abstracted state. The number of design variables was low and the number of functions was small compared to many large systems. The computational expense of increasing model complexity can be considerable. We recommend that surrogate models or simplified models be used wherever possible. As much as possible, computationally inexpensive methods should be used to optimize the system. However, simple abstracted models can still provide insight into the evolvability of complex systems.

Future work could investigate the scalability of the proposed method through historical case studies or models with increased fidelity.

6.3 Conclusions

In-service evolution is critical to many complex systems, where long system life can lead to premature obsolescence, unless the system can be evolved. Complex systems can benefit from added excess capability that can be used to evolve towards emerging requirements. Following the framework introduced in Chapter 2, designers can optimize the value of excess capability built into complex systems. Optimized systems will be better able to meet future requirements, while still accounting for budget constraints. Including consideration for uncertainty, as described in Chapter 4, will improve the efficacy of these optimized results. As we continue to improve our understanding of the trade-offs involved in designing for evolvability, we will be able to build systems that are more resilient to emerging requirements, and as a result provide more value across their entire service life.

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