EVALUATING METHODS FOR MULTI-LEVEL SYSTEM DESIGN OF A SERIES HYBRID VEHICLE

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EVALUATING METHODS FOR MULTI-LEVEL SYSTEM DESIGN OF A SERIES HYBRID VEHICLE

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Contents

List of Tables

List of Figures

Nomenclature

α	Linear Approximation Coefficient for $\pi(\vec{z})$
η	Efficiency
μ_k	Karush-Kuhn-Tucker Multiplier
ω	Speed in rad/s
$\phi_i(\vec{y}_i)$	Objective Function for Subsystem i
$\pi(\vec{x})$	System Value Objective
τ	Torque in N-m
ε	Velocity Error in mph
$\vec{y}_i$	Subsystem Extensive Attributes for Subsystem i
$\vec{z}$	Composition Vector of All Extensive Attributes
$\vec{z}^*$	Preliminary System Optimum
a	Acceleration Time in s
c	Cost in USD
D	Diameter in m
d	Design Variable
$f_i\left(\vec{d}_i\right)$	Attribute Function for Subsystem i
$g(\vec{z})$	Feasibility Constraint
$h(\vec{z})$	Composition Function

i Number Of Subsystems

K Diameter Ratio

l Length in m

m_i Number of Extensive Attributes for Subsystem i

N Number of Battery Cells

n Number of System Attributes

P Power in W

p_i Number of Design Variables for Subsystem i

R Resistance in Ω

r Ratio

U Expected Utility in USD

V Voltage in V

v Velocity in mph

x System-Level Attribute

$_w$ Motor Coil Wire

$_{max}$ Maximum Value

$_{r,ext}$ Rotor Exterior

$_{r,int}$ Rotor Interior

$_{s,ext}$ Stator Exterior

$_{s,int}$ Stator Interior

CDF	Cumulative Distribution Function
CRN	Common Random Number Variance Reduction
DACE	Design and Analysis of Computer Experiments
DBD	Decision-Based Design
DC	Direct Current
DOE	Design of Experiments
DVDD	Distributed Value Driven Design
EPA	Environmental Protection Agency
GA	Genetic Algorithm
IC	Internal Combustion
INCOSE	International Council on Systems Engineering
KKT	Karush-Kuhn-Tucker Conditions
LHS	Latin Hypercube Sampling
MDO	Multidisciplinary Optimization
RA	Requirement Allocation
SOI	Subsystem of Interest
SVDD	Support Vector Domain Description
UDDS	Urban Dynamometer Driving Schedule
VDD	Value Driven Design
vN-M	von Neumann-Morgenstern Utility Theory

SUMMARY

In design and optimization of a complex system, there exist various methods for defining the relationship between the system as a whole, the subsystems and the individual components. Traditional methods provide requirements at the system level which lead to a set of design targets for each subsystem. Meeting these targets is sometimes a simple task or can be very difficult and expensive, but this is not captured in the design process and therefore unknown at the system level. This work compares Requirements Allocation (RA) with Distributed Value Driven Design (DVDD).

A computational experiment is proposed as a means of evaluating RA and DVDD. A common preliminary design is determined by optimizing the utility of the system, and then a Subsystem of Interest (SOI) is chosen as the focal point of subsystem design. First the behavior of a designer using Requirements Allocation is modeled with an optimization problem where the distance to the design targets is minimized. Next, two formulations of DVDD objective functions are used to approximate the system-level value function. The first is a linear approximation and the second is a nonlinear approximation with higher fidelity around the preliminary design point. This computational experiment is applied to a series hybrid vehicle where the SOI is the electric motor.

In this case study, RA proves to be more effective than DVDD on average. It is still possible that the use of objectives is superior to design targets. This work shows that, for this case study, a linear approximation as well as a slightly higher fidelity approximation are not well suited to find the design alternative with the highest expected utility.

Chapter I

INTRODUCTION

1.1 Problem Statement

Systems engineering seeks to bring a methodology to the design of complex systems that can be repeated across various domains and applications. The complexity of man made objects has increased substantially in the last century. Previously, a novel idea or machine could be conceived and produced by one person. But with the introduction of complex systems like aircraft, spacecraft or large energy generation facilities, the ideas and relationships of the system can no longer be fully comprehended by one person, especially when a system may include multiple technical domains [30].

The role of the system designer is to properly partition the system and supervise the integration of all the subsystems, components, subcomponents and parts. The system designer is present throughout the design process from concept exploration to maintenance and disposal. The decisions made by a system designer are of high consequence due to the scale of complex systems. A failure to meet program projections could cost millions or billions of dollars and push back final production by years [8, 9, 10]. A key task for the system designer is to effectively relay his preferences to the individual subsystem designers. It is the purpose of this thesis to evaluate two methods for communicating from the system level to the subsystem level in order to achieve the final design with the highest utility.

In order to effectively comprehend a complex system, it is partitioned into a structural hierarchy leading to multiple levels of complexity. As shown in Figure 1, the complexity decreases and the required domain expertise increases as we move down the system hierarchy. This system decomposition reduces the problem scope to be addressed by technical experts and simplifies the engineering problem that must be comprehended by the system designer.

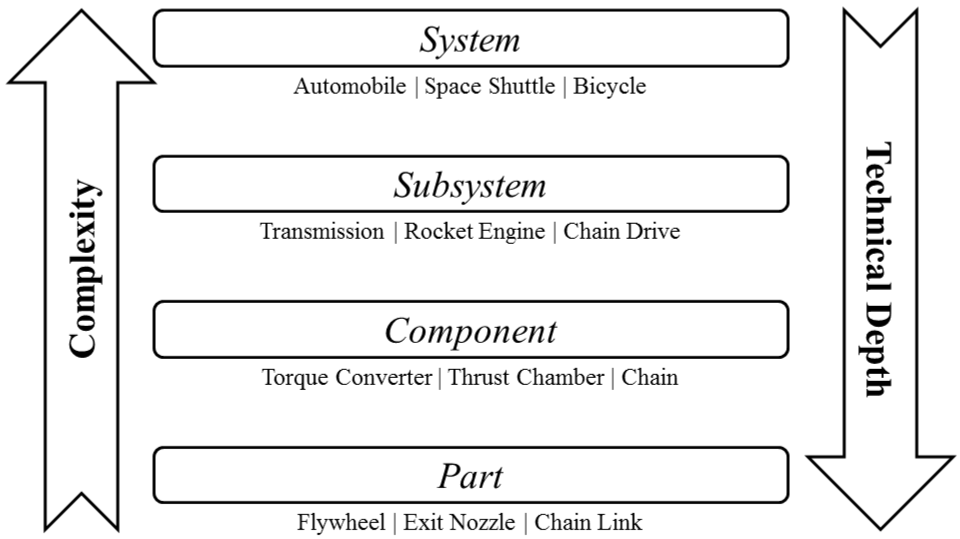

Figure 1: Change in Complexity and Technical Depth among the Levels of a Complex System

The transition of design activities from the system level to the subsystem level often occurs in the transition from preliminary design of the system to subsystem design. A system level model is constructed and multiple simplifying assumptions are made about the subsystems to evaluate possible design alternatives. Once a system design is selected, the preferences of the system designer are communicated to the subsystem designers to complete the design of the individual subsystems. Traditionally, this is done using requirements which are design targets allocated from the system level to the subsystem level.

It has been proposed by Collopy [5] that the use of design targets is a substantial reason for cost and schedule overruns that often arise in the development of complex design programs. He suggests that a value based approach and the use of an objective function at the subsystem level can lead to a system design with higher expected utility. To evaluate the superiority of one method over the other, an example system is designed using both Requirements Allocation (RA) and Value Driven Design (VDD), yielding quantitative metrics used for comparison.

1.2 Motivation and Hypothesis

The thought exercises and theory proposed by Collopy prompts the need for further study of multi-level system design. The systems engineering process has long relied on the use of requirements and design targets at every level of the system hierarchy. The systems engineering community has also been witness to numerous instances where the targets set could not be achieved within the allotted budget and schedule [8, 9, 10]. This motivates the evaluation of alternative approaches that may curb these shortfalls and improve the systems engineering process as a whole. The work in this thesis is driven by the following hypothesis.

> *Hypothesis:* Overall system performance can be improved by formulating the subsystem design problem in terms of objectives rather than targets.

This proposition is based on the belief that there is a better way to communicate the needs of the system designer to the subsystem designer. The two approaches of interest prescribe different ways to perform that multi-level communication. The hypothesis is rejected if, on average, the subsystem design by RA yields a higher expected utility than the subsystem design by VDD. The results of this work support or discount the claim of the hypothesis, but cannot outright declare one method superior to the other. The case study presented models the actions of system and subsystem designers, and therefore, provides representative guidance to the designers of complex system.

A computational experiment is presented and carried out to investigate this hypothesis. The experiment is defined by completing a common preliminary design followed by the design of an individual subsystem using each method and examining the expected utility of the design resulting from each approach. The example system is modeled with varying levels of fidelity to approximate the assumptions made by the system designer during preliminary design and the subsystem designer during subsystem design. In the approach of Requirements Allocation, design targets are assigned to the subsystem attributes based on the preliminary design. In the approach of Value Driven Design, a weighted sum value function is derived from the preliminary design and applied at the subsystem level. Each approach is then used to optimize the subsystem under uncertainty yielding the overall expected utility of the system. Finally, the expected value and distribution of the utility is used to compare each method and highlight the key factors that may support or discount the motivating hypothesis.

1.3 Thesis Organization

In this chapter, the problem is defined as a deficiency in current methods used to design complex systems. A new approach is proposed based on the previous work of other researchers and a need is identified to evaluate the possible advantages of the proposed approach. The motivating hypothesis is presented and the means of accepting or rejecting the hypothesis is discussed. The next chapter provides a review of current systems engineering practices including the use of design targets as well as the background and development of value-based approaches. Chapter 3 defines in detail the computational experiment used to evaluate each method. Chapter 4 discusses the construction and implementation of an example system used to carry out the experiment. This includes the key assumptions made to model the interactions that go on between the system designer and the subsystem designer. In Chapter 5, the results of the computational experiment are provided and discussed in the context of the motivating hypothesis. Finally, in Chapter 6 the contributions of this work are summarized and possibilities for future work are proposed.

Chapter II

REVIEW OF CURRENT AND LEGACY METHODS

This chapter looks at the current methods employed by the systems engineering community and points to certain deficiencies that could be mitigated by new methods. A review of RA is provided and examples are given that suggest the source of cost and schedule overruns that are prevalent in the development of large complex systems . Decision Theory is introduced as a framework to ensure rational choices are made when comparing possible alternatives. Utility Theory is discussed as a means to implement Decision Theory. In seeking a solution to the problems caused by design targets, Value Driven Design is proposed as a way reform current system engineering practices and ensure compliance with the foundations of Decision Theory and Utility Theory.

2.1 Requirements Allocation and the Use of Design Targets

Requirements Allocation is the process of transferring the needs and desires of the system level designer to the subsystem level designer which results in derived requirements. In the traditional method of systems engineering, system requirements will be developed based on stakeholder input and available resources. As the design process moves toward design of subsystems and components, the practice of RA is used to partition the system as well as the system requirements [13]. This is a systematic process to determine the requirement values that are eligible for allocation and how that is to be carried out. Those requirements with numerical definitions can be related to the system as a whole through a mathematical hierarchy. An example system hierarchy partitioned by subsystem is shown in Figure 2.

The International Council on Systems Engineering (INCOSE) provides the most

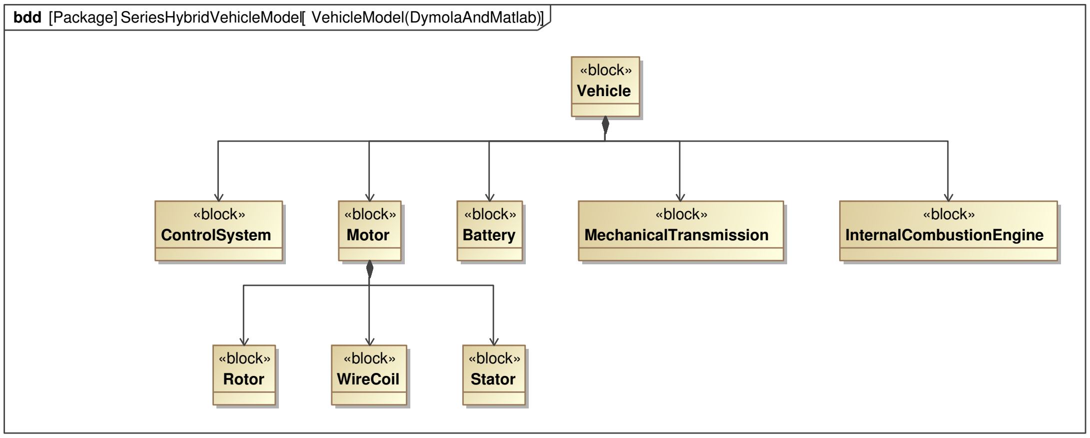

Figure 2: Hierarchical System Decomposition for a Series Hybrid Vehicle

basic implementation of RA [14]. A specification tree is completed using the system hierarchy as the structure. Completeness is measured by "the inclusion of all items required in the system." The specification tree now provides the entire system specification and subsystem requirements are crafted using language and rhetoric consistent with the system level requirements. While some numerical values can be transferred easily, subjective input can be introduced by the engineer in requirements that have a performance value associated with them. Guidance is provided by INCOSE to make this process as consistent as possible, but falls short of providing a mathematically derived or automated method for ensuring consistency across the multiple domains of a system. Some work has been done to improve this process and is discussed below.

Grady [13], not the first by far, but one of the most thorough, provides the idea of requirement margins. Margins are defined as the difference between the design target and the maximum error value, known as the threshold. While targets have always been employed in requirement specification, thresholds provide leeway if needed and imply a direction of improvement. Grady also suggests the practice of margin account transfers between subsystems. In the case that one subsystem cannot reach the threshold while another passed the target, a margin transfer allocation may be made to keep both subsystem requirements satisfied as well as the parent requirement at the system level. At first, this appears to be a suitable alternative to violated requirements. However, additional inconsistencies often arise that cannot be accounted for in a swift and agile form within the systems engineering process.

In spite of a well established method of requirement specification and the the discipline of systems engineering, large and complex systems continue to fail at meeting cost and schedule targets. A 2001 report found that the US Army Comanche helicopter encountered numerous problems throughout the acquisition process [9]. The issues described include five program restructurings, a ten year extension to the production schedule, and a 38% reduction in total planned aircraft. Similar examples exist with the US Air Force B-2 Bomber and the Department of Defense Joint Strike Fighter programs [10, 8]. In [4], Collopy provides an aerospace example to illustrate this problem which is typical of many complex systems. A turbo-pump housing manufacturer has exceeded the cost target and is far within the weight budget. The pump manufacturer chooses a new design that reduces the cost by \$10, but increases the weight by 40 lbs. and the housing is now within the cost and weight specification. Conversely, the payload ring manufacturer has exceeded the weight limit by 10 lbs. To combat this, the ring company uses a new design that reduces the weight by 15 lbs, but increases the cost by \$80, so that the payload ring is also now within the specification. This example is illustrated at the component level, but is analogous for the subsystem level as well. Although the actions by both contractors are rational with respect to their own interests, it is clear that the requirement specification did not adequately provide information from the system level to the subsystem level to achieve the highest value system (see Table 1). Collopy suggests that the use of an objective function, instead of specification-based design, can lead to improvements in both cost and production time while still utilizing domain specific experts and concurrent engineering practices.

It is the goal of this thesis to show that there are superior methods to system

Table 1: Summary of the Changes to a Fictional Aerospace System Due to Requirement Violations [4]

	Weight Δ	Cost Δ
Housing	+40 lbs.	-$10
Ring	-10 lbs.	+80
Total Δ	+25 lbs.	+$70

design and decomposition which have a basis in Utility Theory and Decision Theory. We propose that an objective function is needed to better communicate the needs of the system designer to the subsystem designer. This inherently implies that the system designer has preferences for possible outcomes and also has beliefs about the probability of certain outcomes occurring. From this, we can conclude that Decision Theory with the aid of a utility function would be a good place to start in looking for a solution to the shortfalls of RA. The next section provides a foundation for these concepts.

2.2 The Application of Decision Theory to System Design

Decision Theory can be applied to many other domains, but is especially well-suited to design due to the systematic method that can be used for any decision in any context. In the context of system design this discipline is known as Decision-Based Design (DBD) [15, 27]. With a mathematical foundation in Utility Theory, Decision Theory is directed at the allocation of resources by choosing alternatives under uncertainty [18]. Hazelrigg [16] provides a thorough introduction to Decision Theory motivated by the idea that all engineering activities are decisions with uncertain outcomes.

Every engineering activity, or decision can be decomposed into the choice between a set of alternatives, the uncertain outcome of each alternative, and the personal preferences of the decision maker with respect to each outcome. The decision alternatives are all the possible options from which the engineer may choose, but he may only choose one. The decision outcome is the result of any one alternative and can have multiple terms. For example, the engine choice in a vehicle will have a mass element, cost element, physical form factor element, and power element. This outcome can never be deterministic. As Hazelrigg suggests, this would imply a perfect knowledge of the future. For this reason, outcomes are treated as random variables formed by the decision maker's prior beliefs. The last component of any decision is the preference of the decision maker which is associated with the possible outcome of each alternative. The decision maker holds no preference for the alternative, but only the outcome that is caused by choosing that alternative. Under the assumption that the decision maker is rational, he would choose the alternative that provides him with the greatest utility and because uncertainty is present, this becomes expected utility. An illustration of Decision Theory is shown in Figure 3.

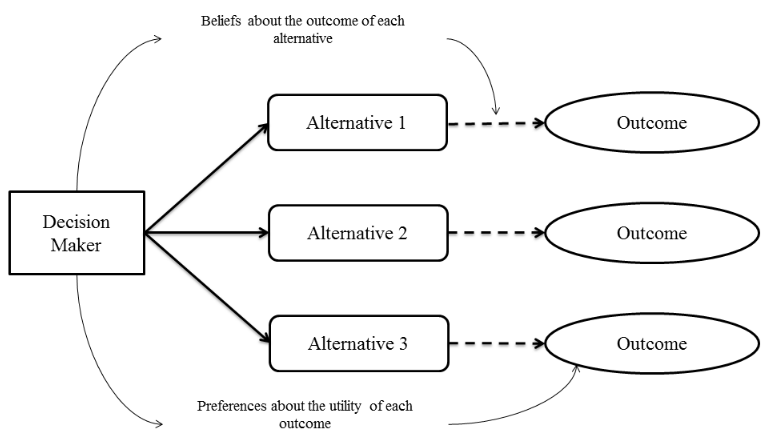

Figure 3: Illustration of Decision Theory Using a Decision Tree

The decomposition of choices as described above requires the ability to characterize and implement the preferences of the decision maker under uncertainty. Utility theory is an appropriate method to complete this task since it allows the preferences of the decision maker to be elicited under uncertainty enabling the selection of the alternative with the highest expected utility. Decision Theory provides the systematic decomposition of the problem and Utility Theory provides the means to find the best alternative under uncertainty. Recall that we are currently forming the foundation required to obtain an objective function that provides the most complete information the subsystem designer from the system designer. The axioms and foundations of Utility Theory are provided below.

2.2.1 Utility Theory as a Means of Implementing Decision Based Design

Previous work by Hazelrigg [15], Thompson and Paredis [32], and Lee [22] has shown that Utility Theory, based on logical axioms, is suitable for making decisions in the context of system design which is inherently completed with imperfect knowledge. Utility Theory states that the decision maker should select the alternative with the highest expected utility. This is purely based on the preferences of the decision maker and is elicited using a utility function. There are five axioms of Utility Theory which are provided in Table 2. These axioms were defined as the foundation of Utility Theory in 1944 by von Neumann and Morgenstern [34] and were built upon by other investigators with similar conclusions [17, 2, 24, 26]. This is known as von Neumann-Morgenstern Utility Theory (vN-M).

The vN-M axioms express characteristics of the decision maker's preferences that must be satisfied, thereby qualifying the decision maker as *rational*. The first axiom proposes that the decision maker has preferences for each possible outcome and those preferences can be communicated clearly. The second axiom states that the preferences of the decision maker must be transitive and consistent. The third through fifth axioms are concerned with a vN-M lottery. A vN-M lottery is defined as a choice between n alternatives with uncertain outcomes A_1, A_2, ..., A_n where the outcomes are ranked from most to least preferred. Each outcome has a probability of occurrence p_1, p_2, ..., p_n where $(0 < p < 1)$. The third vN-M axiom states that the decision maker's preferences must be continuous over a region. With respect to the lottery, this means

Table 2: The Axioms of Utility Theory [34]

1. Complete Ordering
For any *(u,v)*: either $u \succ v$ OR $u \prec v$ OR $u \sim v$
2. Transitivity
For any *(u,v,w)*: if $u \succ v$ AND $v \succ w$ THEN $u \succ ww$
3. Continuity
For any *(u,v,w)* such that $u \succ w \succ v$, then for some α where $0 < \alpha < 1$, $w \sim \alpha u + (1-\alpha)v$
4. Convexity
For any *(u,v)* such that $u \succ v$, then for any α where $0 < \alpha < 1$, $u \succ \alpha u + (1-\alpha)v$
5. Combining
For any *(u,v)* where $(0 < \alpha\beta < 1)$ and $\gamma = \alpha\beta$, $\alpha(\beta u + (1-\beta)v) + (1-\alpha)v \sim \gamma u + (1-\gamma)v$

(u, v, w) are outcomes. (α, β) are probabilities. $u \succ v$ indicates that outcome u is preferred to outcome v. $u \sim v$ indicates that outcomes u and v are equally preferred.

that any lottery with two possible outcomes can be reduced to a single equivalent certain outcome. The fourth vN-M axiom states that preferences must be convex. In a vN-M lottery if an specific outcome is preferred, then a higher probability of receiving it must always be preferred over a smaller probability of receiving it. The last vN-M axiom proposes that compound lotteries can be reduced to a single lottery.

These axioms, above all, impose rationality on the decision maker. This is not always the case for real world decisions, but it is assumed that an engineer or system designer in will continuously seek rationality in design activities. So long as the decision maker observes these axioms and preserves rationality, his or her behavior can be modeled by maximizing the expected value of the resulting utility function. These axioms would be violated in a case when the decision maker deliberately chooses an alternative that is not based on their elicited preferences. An example of this may occur if the decision maker does not actually have the authority to allocate design resources.

2.2.2 The Elicitation and Use of Utility Functions

In addition the the axioms of Utility Theory, von Neumann and Morgenstern also defined the basis of utility functions. Two forms of these functions have been developed; one to analyze single objective design problems and another to analyze problems with multiple objectives.

Single attribute utility functions determine the utility of an alternative based on one objective that includes all other parameters of the design problem. Equations 1 and 2 show that Y is the single attribute over which preference is elicited and is defined as a function of $\vec{X}$. One criticism of this formulation is that the decision maker will rarely have enough knowledge about the alternatives to provide a rational preference over a single attribute. However, if the formulation of system parameters can be successfully aggregated, this method has been shown to be useful in conveying a decision maker's preference [16].

$$U = Pref(Y) \tag{1}$$

$$Y = f(X_1, X_{2,...}, X_n) \tag{2}$$

A widely accepted method for aggregating preferences of multiple objectives was developed by Keeney and Raiffa [20] in 1993. Preferences of the decision maker are elicited over multiple objectives and then combined to create a single measurement of effectiveness for each design alternative. The utility aggregation is performed using an additive utility function (Eqn. 3) or a multiplicative utility function (Eqn. 4).

$$u(f_1(\vec{X}), \ldots, f_n(\vec{X})) = k_1 u_1(f_1(\vec{X}) + k_2 u_2(f_2(\vec{X})) + \cdots + k_n u_n(f_n(\vec{X})) \tag{3}$$

$$1 + ku(f_1(\vec{X}), \ldots, f_n(\vec{X}) = \prod_{i=1}^{n}(1 + kk_i u_k(f_i(\vec{X}))) \tag{4}$$

Scaling constants are represented by k_i to show the relative importance of moving from the worst to the best value of attribute i. One assumption made using this theory is that the preference for a vN-M lottery attribute does not depend on the preference of other attributes. For example, in the decision to purchase a new vehicle, the buyer's preferences for back seat leg room are independent of his preference for top speed. While this method has been found to be more accurate than single attribute utility functions, it has also been criticized for requiring too much effort to acquire preferences without introducing additional subjectivity [11].

2.2.3 Design Targets in the Context of Decision Theory

An example of inconsistencies due to requirements allocation is given in Section 2.1 and now we will look at a more general case that shows that irrationality is the cause of those inconsistencies. Abbas and Matheson [1] showed that when using targets[1] to determine the allocation of resources, the preferences of the decision maker will change depending on events within the design process. If, according to the decision maker, the target will be achieved, the decision maker becomes risk averse to preserve the successful element. Conversely, if the target appears to be out of reach, the decision maker will take a risk seeking preference often trying radical or new methods to reach the target.

This inconsistency is illustrated in Figure 4 using probability distribution functions. There exists some component with an attribute of mass where less is better. 4(a) shows that during preliminary design there is some normally distributed uncertainty associated with the mass of the artifact. If simple targets are used and no margins are set (the difference between objective and threshold), then the requirement is set at the expected value. The subsystem design phase is now shown in 4(b)

[1] In this context, the term *target* is expanded from engineering system requirements to anything that may be of concern to an organization like expenditure budgets, project time lines or quarterly profits.

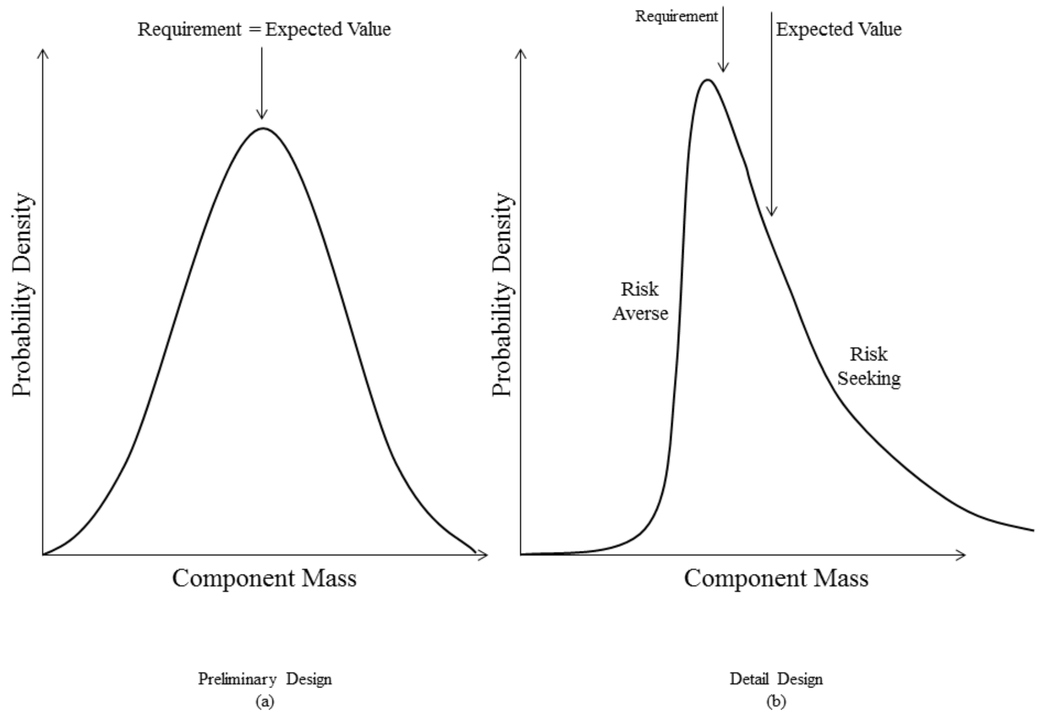

Figure 4: Effect of Altering Risk Preference during the Design Process (derived from [5])

where the decision maker will adopt either risk averse or risk seeking preferences. If it appears that the requirement will be met, he will adopt risk averse preferences attempting to preserve the successful design. Due to the increased risk, this causes the left side of the probability distribution to contract toward the mean which, in turn, causes the mean to shift right. If the subsystem design leads to the conclusion that the requirement will not be met, the decision maker adopts risk seeking preferences in an attempt to return to a successful design. This causes the right side of the distribution to spread outward, further increasing the expected value of the component mass. By imposing a mass target on the component, the expected value of the mass has increased simply because of the change in preference between design phases. At this point a Engineering Change Order would be completed to either choose a new preliminary design or alter the mass target of another component. Mass is often minimized, but in the case of an attribute being maximized such as utility, 4(b) would be mirrored across the design target. This is possibly one of the leading causes for the extensive schedule delays and cost increases that often occur in the development of complex systems [5].

Recalling the axioms of Utility Theory and the importance of rationality, it is suggested that target based design leads the decision maker to choose alternatives that do not maximize the expected utility and cause inconsistencies due to irrationality. This thesis aims to support efforts that propose the use of a properly derived objective function to avoid these inconsistencies.

2.3 Building on Decision Based Design with Value Driven Design

It is now clear that rationality is extremely important to system design and especially over the chronological life-cycle of the design process. It is also clear that when traditional methods of systems engineering employ design targets, the decision maker is not guaranteed to maximize the expected utility of the system and, therefore, suffer monetary, time and performance losses in the system life-cycle. In light of these deficiencies, Distributed Value Driven Design (DVDD) has been proposed as a formal framework by Collopy [4] which follows the axioms of Utility Theory as well as the process of decision analysis provided by DBD. It also employs quantitative financial metrics to further remove subjectivity from the comparison of design alternatives.

2.3.1 Using Distributed Optimization to Optimize the Value of a Design Alternative

In addition to assigning value to a design alternative, VDD also seeks to derive an objective function for each subsystem from the system level objective function. This method has roots in the field of multidisciplinary optimization (MDO) developed primarily by Sobieski et al. [31] and Cramer et al. [7]. MDO integrates predictive models with a system decomposition optimization structure. Although this method looks for the "best" design at the system and subsystem levels, it often employs constraints similar to design targets which of course lead to suboptimal alternatives from which to choose.

VDD relies heavily on *distributed optimization* which dictates that instead of designing subsystems to be feasible and adequate, they should be optimized with respect to the parent system. Recalling the axioms of Utility Theory, the decision maker should choose the alternative with the highest expected utility and, thus, the use of distributed optimization for complex systems is appropriate. The objective function derived from VDD is referred to as the Distributed Value Driven Design objective function due to its distributed nature from the perspective of the system designer.

VDD requires a few assumptions that set the standard practices of the engineering firm as well as the current position within the design process. First, it is assumed that preliminary design of the system has been completed and the general architecture is set. This allows for approximately 10% deviation in attribute values, but does not allow for attributes to be deleted or appended. VDD also requires that the system already be decomposed into some fixed hierarchical structure where all subsystem interfaces have been specified. Lastly, the extensive attributes must be specified. *Extensive attributes* are defined as subsystem attributes that collectively impact the overall attributes of the system. In RA, these are the attributes that are assigned targets based on system level requirements like subsystem mass or component cost.

2.3.2 System Value as a Means of Comparing Alternatives

Value based design methods have been proposed by many researchers since the work of von Neumann and Morgenstern [34], but have not penetrated into the practice of complex system design until recently. Sage [29] was one of the first to apply value-centric ideas to decision analysis of complex systems. He proposed Value System Design as a way to extract extrinsic valuation of a system from the system properties. Sage also noted the need for methods that promote rational decision making in design.

It was suggested by Hazelrigg [15] that any engineering firm is ultimately only concerned with profit and, therefore, systems should be optimized with an objective to maximize profit. This has been contested with the argument that profit is an improper measure of effectiveness for domains such as scientific research or national security. If we take the perspective of the engineering firm, there will always be a customer paying for the firm's products and services. Regardless of the end-user's specific needs, a price has been placed on the capabilities of the system and it is the role of the engineering firm to capitalize on those needs. This is illustrated in Figure 5 by the framework for optimal product design developed by Hazelrigg. In an influence diagram, square boxes denote design choices, rounded boxes denote a decision consequence and ovals denote a chance event.

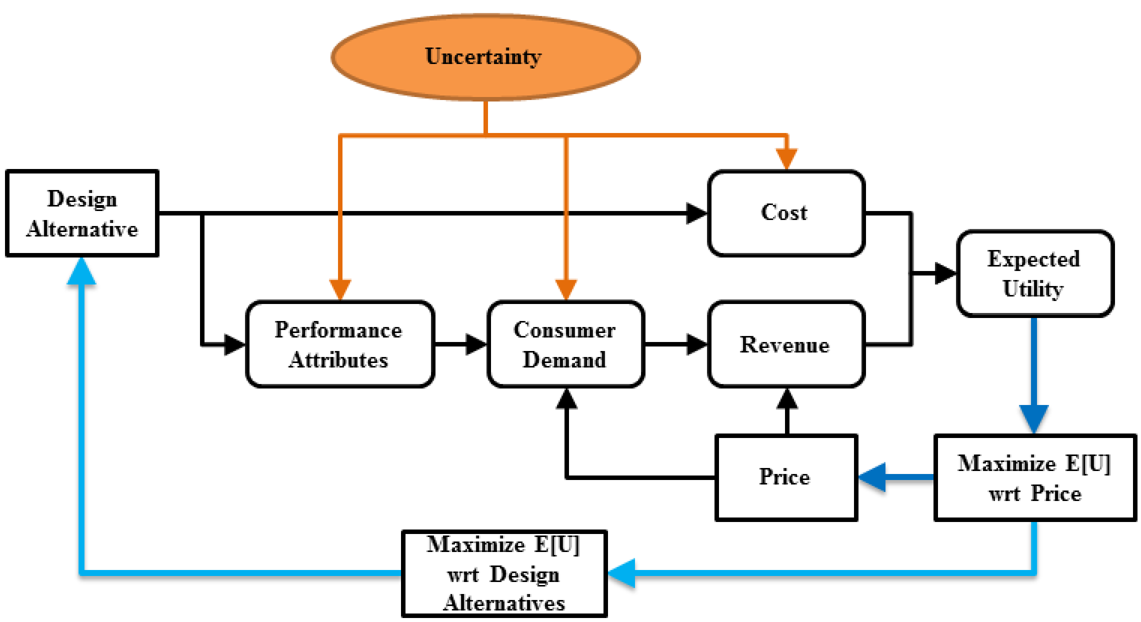

Figure 5: Framework for Optimal Product Design (derived from [16])

Along these lines, Collopy [6] argued that system utility and monetary value are equivalent and, therefore, the decision maker should prefer the design with the most value in monetary units. This further imposes rationality that is required by Utility Theory and Decision Theory since it allows for the use of traditional financial goals and quantitative metrics such as net present value and reservation price.

2.4 Summary

In this chapter, the current methods of systems engineering are reviewed, revealing inconsistencies in the design process. It has been suggested that design targets obtained by Requirements Allocation ensure a suboptimal system due to actions taken by the subsystem designers as well as the system designer. Subsystem designers will act rationally with respect to their own interest and system designers will change their risk preference based on the current state of the design; both actions having a negative effect on the final design of the system. Decision Theory is introduced to provide a process for any design decision and the axioms of Utility Theory are given as a means of design under uncertainty. Upon these ideas, Value Driven Design is introduced as a proposed solution to the suggested inconsistencies present with current methods. VDD assigns extrinsic value to system properties and further promotes rationality by using distributed optimization to ensure that if each subsystem is optimal, the overall system will also be optimal.

Chapter III

DEFINITION OF THE COMPUTATIONAL EXPERIMENT

The primary contribution of the work presented in this thesis is to support the motivating hypothesis which states that a better subsystem design, and therefore a better system design, can be achieved by using an objective function derived from Value Driven Design rather than design targets.

The comparison is completed through a computational experiment which models the actions of subsystem designers implementing each approach. The flow of information between the system and subsystem designers is illustrated in Figure 6. Past research and the experience of technical experts provides the system designer with feasibility constraints on each subsystem. The system designer then uses this information during preliminary design to select the design alternative with the highest expected utility. In order to achieve this design alternative, the system designer must communicate his needs to the subsystem designers. This work compares two possible approaches for relaying this information from the system level to the subsystem level; Requirements Allocation using targets and DVDD using an objective function. Since the initial feasibility constraints are a prediction, the true optimum will always differ from the prediction. Uncertainty is introduced to model this plausible variation and the two approaches are compared to evaluate performance with respect to the motivating hypothesis.

RA involves the assignment of targets to subsystems and components while DVDD assigns a weighted sum objective function to each subsystem or component. This is completed by using a common starting point and then evaluating the expected utility of the final system design that results from each approach. This chapter explains

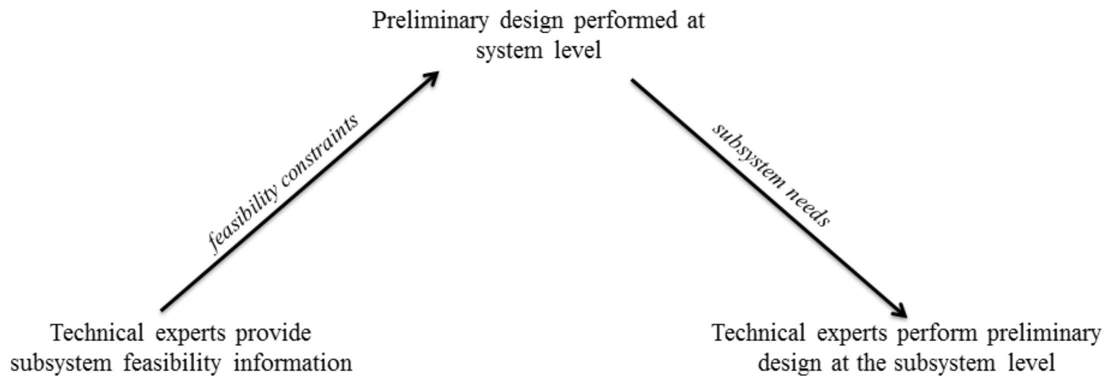

Figure 6: Information Flow Between the System and Subsystem Designers

the computational experiment used to test the hypothesis and highlights the key similarities and differences between each method. This experiment will be applied to a specific design problem in the next chapter with a discussion of the results in Chapter 5. Figure 7 shows the process flow for the computational experiment.

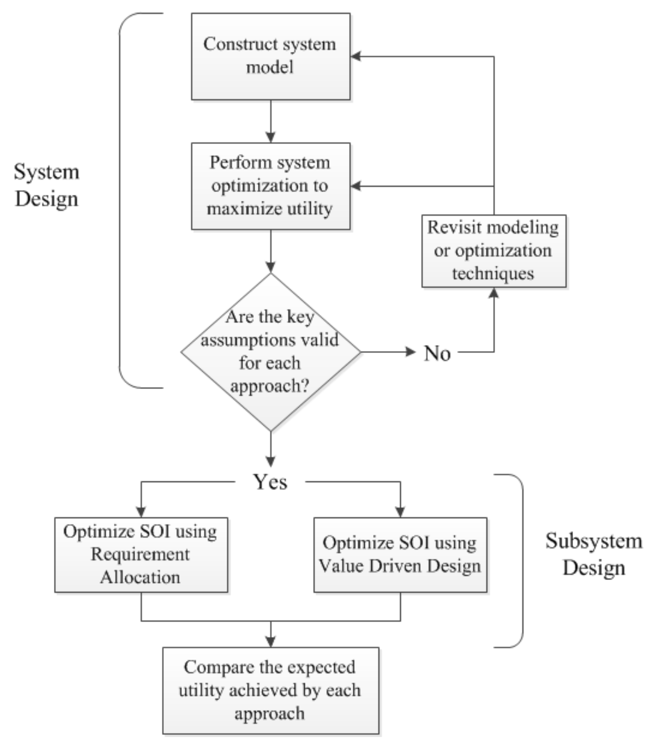

Figure 7: Computational Experiment Process Flow Diagram

3.1 Establishing the Context for a Comparison of Methods

The two methods of interest in this computational experiment fall within a larger process of design. The early stages of design as well as later stages are not included in this discussion since each is unaffected by the method used for subsystem design. It is assumed that the stages up to preliminary system design have been completed. This provides a system level design as a starting point for the two methods of interest. Similarly, once the subsystem design has been completed, the same actions are taken to produce, distribute and maintain the system.

Both approaches assume that a decomposition of the system has been completed. A structural decomposition partitions the system hierarchically into subsystems and components which conserves computational resources during optimization. Refer to Figure 2 for an example of a structural system decomposition. To ensure consistency, the targets and objective functions from each approach are applied to the same subsystem while all other subsystems are kept constant.

The key difference between Requirements Allocation and Value Driven Design is the form of information used to communicate the needs of the system designer to the subsystem designer. RA utilizes design targets that are selected based on a system level model. This provides an extremely high incentive to meet the targets but little incentive to exceed the targets if possible. Specifics of implementing this method including the construction of the optimization problem used to model the actions of the subsystem designer will be discussed in Section 3.3.2.

Value Driven Design, on the other hand, provides the subsystem designer with more information about the needs of the system level designer. The objective function for this case is based on the partial derivatives of the system model with respect to the subsystem attributes. This provides richer information to the subsystem designer which can quantify design trade-offs faced during subsystem design [4].

3.1.1 Defining the Mathematical Formulation of the System and Subsystem Relationships

Prior to the design of the system and subsystems, a mathematical foundation must be provided to understand the role of the system and subsystem design within the experiment as a whole.

The system level value is defined by the objective function $\pi(\vec{x})$ where the vector $\vec{x}$ is composed of the system level attributes $x_1, x_2, \ldots, x_n$ contained in the attribute space $\mathbf{X}$. Each system level attribute influences consumer demand and therefore influences value. The attributes in $\mathbf{X}$ would be most familiar to the consumer of a specific system (e.g. top speed and efficiency of a consumer vehicle). Each system attribute is a function of the *extensive attributes*, which are defined as the subsystem attributes that collectively affect the overall system attributes.

The extensive attributes of subsystem i are defined by $y_{i,1}, y_{i,2}, \ldots, y_{i,m_i}$ composing the vector $\vec{y}_i$ in the extensive attribute space $\mathbf{Y}_i$. In the example of a consumer vehicle, these attributes would include the engine power or the mechanical driveline efficiency. We define the composition vector function $h(\vec{z})$ where $\vec{z}$ is the concatenation of all the extensive attributes. This allows use to relate the extensive attributes of the subsystems to the system objective function by Equation 5.

$$\pi(\vec{x}) = \pi(h(\vec{z})) \tag{5}$$

At the system level the extensive attributes are treated as design variables. However, they must be in accordance with the constraints of the initial feasibility model, $g(\vec{z})$, which is provided by the technical experts of each subsystem. This is due to the fact that the extensive attributes are not independent of each other. This interdependency is defined explicitly by the function v in Equation 6. $g(\vec{z})$ is then defined as the implicit form of v in Equation 7 to model the feasible attribute space as a whole.

$$v(z_2, z_3) = z_1 \tag{6}$$

$$g(\vec{z}) = v(z_2, z_3) - z_1 \text{ where } g(\vec{z}) \geq 0 \tag{7}$$

We will establish a * notation to identify the specific design that has been chosen as the most preferred system alternative. This yields the system attribute vector $\vec{x}^*$ with corresponding subsystem extensive attribute vectors $\vec{y}_i^*$ for each subsystem i. The composition of these extensive attribute vectors is referred to as $\vec{z}^*$. These vectors are known once the optimization of the system model has been completed. The preliminary system attribute vectors remain static for the duration of the design process and are used to derive the design targets and DVDD objective function.

Once the system level relationships have been established we can define the subsystem objective function as $\phi_i(\vec{y}_i)$ where the vector $\vec{y}_i$ is composed of the extensive attributes of subsystem i in $\mathbf{Y}_i$. The two approaches being compared differ in the construction of the objective function ϕ_i for each subsystem. In each approach and throughout the computational experiment, the length of the subsystem attribute vector $\vec{y}_i$ must remain constant. More intermediate variables may be introduced to increase the fidelity of the subsystem model, but the same extensive attributes are used to convey subsystem merit with respect to the system as a whole. During subsystem design, the constraints from the system-level design are neglected and a higher fidelity model, f_i, is used to determine the extensive attributes for each subsystem. The design variables of this model are exclusive to that subsystem. In the example of a consumer vehicle, the design variables for the internal combustion engine may be the displacement in liters or the intake valve radius in inches.

$$\vec{y}_i = f_i(d_{i,1}, d_{i,2}, \ldots, d_{i,p_i}) \tag{8}$$

With the mathematical relationships between the system and subsystems defined, we will move on to the preliminary design at the system level.

3.2 Defining the Preliminary System Design

Maximizing the utility at the system level to establish the preliminary design is imperative to both Requirements Allocation and Value Driven Design. This is more than an overall system architecture definition that may be determined during concept exploration and as is noted below, must be a good approximation of the final subsystem design. This requires a full computational model that has at least some estimation for every subsystem.

3.2.1 Constructing the System Model

The computational experiment is used to model the actions of the design participants. In practice, assumptions and approximations are made to provide a starting point for design. This means the decision maker has incomplete knowledge about the design problem and there exists uncertainty about the future of the system [16]. Any model of the system or subsystems is an approximation of the real world, but in this experiment, one specific subsystem will be approximated with the knowledge that new information will be obtained during subsystem design. In practice, new information would become available during the design process for every single component. For this work, we are concerned with how the subsystem design may differ from the needs of the system designer due to this new information.

In the computational experiment, which particular subsystem is chosen is not important; however, we must have separate models with varying levels of fidelity (i.e., new information) to perform the subsystem design on that particular element. With this in mind, the Subsystem of Interest (SOI) used in the computational experiment should be determined before the system model is constructed to ensure that a more accurate subsystem design can be completed following the preliminary design.

Once the SOI is determined the system level model is constructed with a separate model for each subsystem based on the structural decomposition. A very simple model could decompose the system into the SOI and the rest of the system while a more realistic decomposition would break the system into multiple subsystems based on the task performed or technical domain, one of which being the SOI. The models used for the subsystems can vary in fidelity so long as values can be found for every system level attribute that contributes to the overall utility. In this experiment, some subsystems are modeled using a curve fit from market data and others use more detailed physics-based equations to model behavior of the subsystem. Once the model is constructed, the system can be optimized to maximize utility.

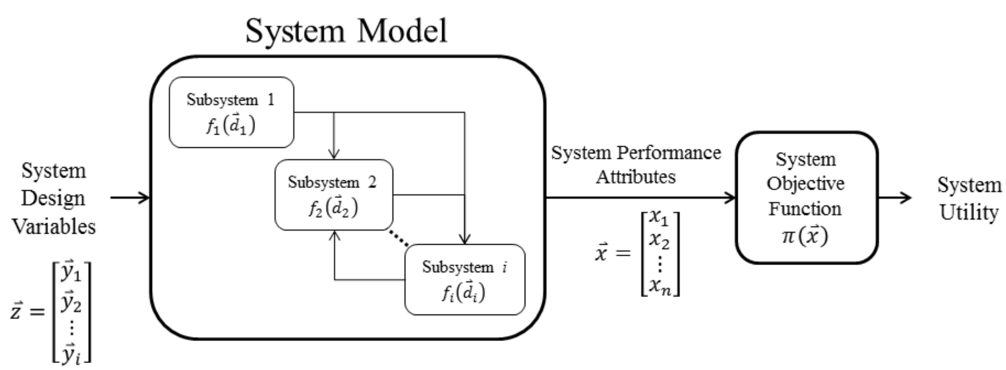

Figure 8: Preliminary Design System Model

Figure 8 shows a generic system model that is used for this experiment to model the actions of the system designers. Note that during preliminary design the subsystem functions f_i are abstracted away using feasibility constraints initially provided by the technical experts. The *objective function* is any function that may determine the goodness of a preliminary design. For the reasons outlined in Chapter 2, this work will employ the axioms of Utility Theory for the objective function. Utility Theory is only useful when uncertainty is present and although uncertainty is not used in the preliminary design, it is present in the evaluation of each subsystem design so it must be employed in the preliminary system model.

3.2.2 Maximizing the Utility of the System Model

This experiment relies on a deterministic global optimum found using a constrained optimization algorithm. The optimization formulation is as follows.

$$\begin{aligned} \text{Find:} \quad & \vec{z} = \{\vec{y}_1, \vec{y}_2, \ldots, \vec{y}_i\} \\ \text{That Maximizes:} \quad & \pi\left(h\left(\vec{z}\right)\right) \\ \text{Subject To:} \quad & g\left(\vec{z}\right) \geq 0 \end{aligned}$$

The extensive attributes of the subsystems are treated as design variables and are subject to the feasibility constraints provided by the domain experts. This solution $\vec{z}^*$, to this optimization formulation must satisfy the Karush-Kuhn-Tucker (KKT) conditions [21]. The KKT conditions are outlined in Equation 9 below[1].

$$\nabla\pi\left(\vec{z}^*\right) + \sum_{j=1}^{k}\mu_k \nabla g_k\left(\vec{z}^*\right) = 0 \tag{9}$$

where

$$\begin{aligned} g_k\left(\vec{z}^*\right) \geq 0 \quad & \forall k \\ \mu_k \geq 0 \quad & \forall k \\ \mu_k g_k\left(\vec{z}^*\right) = 0 \quad & \forall k \end{aligned}$$

In modeling the actions of the system designers, the KKT conditions express that the negative gradient of the objective must exist inside the simplex of all the gradients of the active constraints. An illustration of the system optimum in light of the KKT conditions and a single active constraint is given in Figure 9.

For this work, extra care was taken to make sure that the global system optimum was found prior to moving on in the computational experiment. This is important because the authors may not know exactly where the optimum exists on the Pareto

[1]This problem has been formulated as a maximization instead of a minimization as originally prescribed by the KKT conditions. However, the constraint inequality has also been reversed, so the KKT conditions remain the same overall.

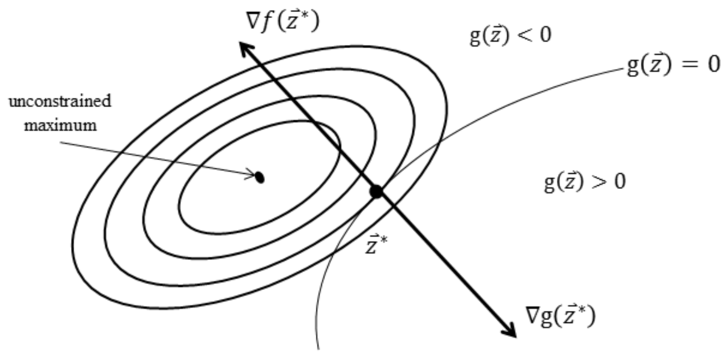

Figure 9: System-Level Optimization Problem for One Active Constraint

frontier for the computational experiment. However, it is assumed that system designers familiar with the problem domain would have the knowledge and experience to quickly find the neighborhood of the global optimum.

3.3 Defining the Subsystem Design

3.3.1 Applying Uncertainty to the Subsystem Design Stage

As noted previously, both of the proposed approaches define a format used to relay information from the system level to the subsystem level. The initial feasibility constraints provided to the system designer from the technical experts are predictions. The difference between the predictions of the domain experts and the actual feasibility realized through subsystem design is modeled using uncertainty. The effect of this uncertainty on the ability of the subsystem designers to reach the system optimum is illustrated in Figure 10.

If the subsystem design were completed deterministically in this experiment, it would be implied that the system designer has perfect knowledge about the entire system. Then the design targets would be reached every time and would be guaranteed to be the alternative with the highest attainable utility. But since this is not the case and the knowledge about the system is imperfect, uncertainty is introduced and it is the goal of the optimization to maximize the expected value of the system

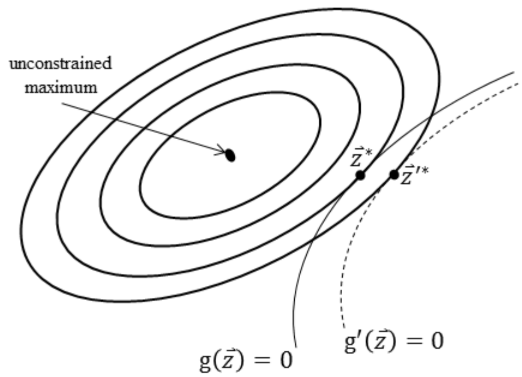

Figure 10: Shift of $g(\vec{z})$ Due to Differences Between the Predicted Feasibility and Actual Feasibility

utility. Sources of this uncertainty include technological advances, logistical or inventory problems, economic changes, or political instability. The uncertainty present shifts the feasibility constraint $g(\vec{z})$ with respect to $\vec{z}^*$. Favorable uncertainty, like recent technological advancement, may shift $g(\vec{z})$ towards the unconstrained optimum. This would make the design point $\vec{z}^*$ easily attainable. Conversely, unfavorable uncertainty as shown in Figure 10 shifts $g(\vec{z})$ to the extent where $\vec{z}^*$is no longer attainable. Unfavorable uncertainty may model realities such as an increase in material costs.

For the design of the SOI, various constants in the SOI model are treated as random variables with a specific distribution. The choice and characteristics of the distribution are based on the beliefs of the decision maker about the possible values that may result from the sources listed above. The distribution chosen for each variable need not be the same type and is only dependent on the beliefs of the decision maker. It is acceptable to apply a normal distribution to one variable and a triangular distribution on another. Rarely does the decision maker have enough information to use a specialty distribution like a beta or gamma distribution. Likewise, he usually has at least some belief about the possible outcome for each alternative so a uniform distribution is seldom appropriate.

The Common Random Number [19] sampling technique is used to reduce the number of samples that are needed. The statistical technique takes uses the exact same sample to evaluate each approach. This means that given the same true feasibility during the subsystem design, it can be evaluated which approach will provide the maximum utility. Evaluating this over the entire set of uncertainty values provides the information needed to determine which approach yields the highest expected utility. A Latin Hypercube Sampling (LHS) method is used to generate the random variables in this experiment. LHS takes advantage of randomization, but also employs stratification of the sample space to ensure that the system attributes are not dominated by a select few variables [28].

3.3.2 Subsystem Design by Requirements Allocation

This section will define the experiment used to model subsystem design using RA. In this scenario, the subsystem designer is provided targets based on the preliminary system design. The subsystem designer is rewarded if he can meet or exceed the targets. However, due to the cost-minimizing nature of designers, it is not expected that the targets will ever be exceeded. Exceeding the targets would require additional resources without additional incentive. Recall that the literature suggests the behavior of the subsystem designer will depend on his current beliefs about the probability of reaching the target. Because of this, the actions of the subsystem designer are modeled as an optimization problem which seeks to minimize the distance between the current design and the target.

This can be modeled mathematically by Equation 10 where the goodness of an alternative is evaluated based on the distance between the design targets and the current extensive attributes of the system. In general, requirements are specified at the system level by the optimal extensive attribute vector $\vec{z}^*$ which was selected by optimizing $\pi(\vec{z})$. The subsystem level targets are taken directly from the $\vec{y}_i$ components of $\vec{z}^{*}$.

$$\phi_i(\vec{y}_i) = \sum_{k=1}^{p_i} \left(\frac{y_{i,k} - y^*_{i,k}}{y^*_{i,k}} \right)^2 \tag{10}$$

The resulting optimization problem is given below, with the recognition that reaching the target perfectly results in a function output of zero.

$$\begin{aligned} \text{Find:} \quad & \vec{d}_{SOI} = \left\{ d_{SOI,1}, d_{SOI,2}, \ldots, d_{SOI,p} \right\} \\ \text{That Minimizes:} \quad & \phi_{SOI}(\vec{y}_{SOI}) = \sum_{k=1}^{p_{SOI}} \left(\frac{y_{i,k} - y^*_{i,k}}{y^*_{i,k}} \right)^2 \\ \text{Subject To:} \quad & \vec{y}_{SOI} = f\left(d_{SOI,1}, d_{SOI,2}, \ldots, d_{SOI,p} \right) \end{aligned}$$

Under the uncertainty that is used to model the difference in predicted feasibility and actual feasibility, there are two distinct possible outcomes. First, the uncertainty realization is favorable and the presumed system optimum, $\vec{z}^{*}$ is achieved. Second, the uncertainty realization reflects that of Figure 10 and $\vec{z}^{*}$ cannot be reached and the subsystem is designed as close to the targets as possible. In either case, the vector $\vec{z}\,'$ represents the true subsystem design realization. In order to compare this result with the result of DVDD, we evaluate the system value objective $\pi\left(h\left(\vec{z}\,'\right)\right)$ at this new design point.

3.3.3 Subsystem Design by Value Driven Design

Modeling Value Driven Design is very similar in process to Requirements Allocation, but a different optimization formulation is used to model the actions of the subsystem designers. The behavior being modeled is as follows. Based on the alternative found during preliminary design, an objective function is provided to the subsystem designer which reflects how the system-level value is affected by changes in the extensive attributes of the subsystem. Instead of a "pass/fail" incentive structure as is used with design targets, the incentive for the subsystem designer in value-based design is monotonically increasing and proportional to the result of maximizing the objective function.

The best evaluation of DVDD would be provided by designing the SOI strictly using the system value objective. This would create an objective function of the form $\pi\left(\vec{z}^{*}, \vec{y}_{SOI}\right)$ where $\vec{z}^{*}$ contains all the optimal extensive attributes except for those associated with the SOI. A Genetic Algorithm or similar optimizer could be used to perform a global search. In most cases, however, this would be extremely computationally expensive. Because of this, the system value objective must be approximated.

This behavior of the subsystem designer under a value-based incentive structure is modeled mathematically for the SOI by choosing the subsystem design variables $\vec{d}_{SOI}$ that maximize the system-level value while the extensive attributes of the other subsystems remain constant (at $\vec{z}^{*}$).

$$\begin{aligned} \text{Find:} \quad & \vec{d}_{SOI} = \left\{d_{SOI,1}, d_{SOI,2}, \ldots, d_{SOI,p}\right\} \\ \text{That Maximizes:} \quad & \phi_{SOI}(\vec{y}_{SOI}) = \pi\left(h\left(\vec{z}\right)\right) \\ \text{Subject To:} \quad & \vec{y}_{SOI} = f\left(d_{SOI,1}, d_{SOI,2}, \ldots, d_{SOI,p}\right) \end{aligned}$$

The evaluation for this formulation can be computationally expensive so the system value objective is approximated. Two types of approximations are proposed for the computational experiment. The first is a linear approximation at $\vec{z}^{*}$ and the second is a higher order approximation, also at $\vec{z}^{*}$.

Collopy [4] proposes a linear approximation using a Taylor expansion around $\vec{z}^{*}$ which results in the following optimization problem.

$$\begin{aligned} \text{Find:} \quad & \vec{d}_{SOI} = \left\{d_{SOI,1}, d_{SOI,2}, \ldots, d_{SOI,p}\right\} \\ \\ \text{That Maximizes:} \quad & \phi_{SOI}(\vec{y}_{SOI}) = \nabla^{\mathrm{T}}\pi\left(\vec{z}^{*}\right) \cdot \vec{y}_{SOI}\left(\vec{d}_{SOI}\right) \end{aligned}$$

This approach assumes that in the neighborhood of $\vec{z}^{*}$, the higher order terms of the system value objective Taylor series expansion are zero. In this case study, this assumption is tested to determine if a linear approximation of $\pi\left(\vec{z}^{*}\right)$ is appropriate.

It is possible that if a global optimization method is used such as a Genetic Algorithm (GA), the result will converge on a design very far from the location of the Taylor expansion yielding a system utility much worse than that obtained with $\vec{z}^*$.

In response to this possibility, we propose an alternative approach that accounts for some of the nonlinearities in the system value. This is done by replacing the linearized gradient with a function to approximate the system value function around $\vec{z}^*$ yielding the following optimization formulation.

$$\text{Find:} \quad \vec{d}_{SOI} = \left\{d_{SOI,1}, d_{SOI,2}, \ldots, d_{SOI,p}\right\}$$

$$\text{That Maximizes:} \quad \phi_{SOI}(\vec{y}_{SOI}) = S\left(\vec{z}^*, \vec{y}_{SOI}\left(\vec{d}_{SOI}\right)\right)$$

where the function S includes some of the higher order terms of the Taylor approximation.

Again, to allow for the comparison of RA with DVDD, the resulting design $\vec{z}'$ is used to evaluate the system value objective, $\pi\left(h\left(\vec{z}'\right)\right)$ for each uncertainty realization.

3.4 Summary

In this chapter, a computational experiment is proposed to model the actions taken by subsystem designers employing either RA or DVDD during subsystem design. The predictions of technical experts are provided to the system designer in the form of initial feasibility constraints. The preliminary system design is completed under these constraints. Then subsystem design is performed using two approaches. The two approaches being evaluated differ in the form of information that is passed from the system level to the subsystem level to convey the needs of the system designer. Each approach provides a different incentive structure for the actions of the subsystem designers and these actions are modeled in the computational experiment by the formulation of optimization problems. The actions of the subsystem designer using RA are modeled by an optimization problem that seeks to minimize the distance between the current design and the targets. DVDD provides an incentive structure that encourages the subsystem designer to find the subsystem design variables that maximize the overall system value objective. This can be done in multiple ways, and in this work is completed by accounting for the higher order derivatives of the system value objective near $\vec{z}^*$ found during preliminary design. Each approach results in an design $\vec{z}'$ which is used to evaluate the system value objective yielding the expected utility of the system. This allows for the comparison of each approach.

Chapter IV

CASE STUDY: A SERIES HYBRID VEHICLE

This chapter provides and overview of the example system used to evaluate the two approaches proposed for the subsystem design. The example system is a series hybrid vehicle. The system and subsystem relationships of Chapter 3 are applied to this hybrid vehicle and the modeling techniques used to approximate the actions of the system and subsystem designers using each approach are discussed. Chapter 5 then summarizes the results of the computational experiment.

4.1 Concept Development and Initial Assumptions of the Example System

The two proposed methods can be applied to many different complex systems. In this work, a consumer hybrid vehicle was chosen as the example system based on the past experience of the author. The architecture in Figure 11 is used due to its simplicity compared with the more popular parallel hybrid architecture. Because there is only one energy path through the system, the vehicle control system is simplified and the mechanical gearing can be approximated by a simple gear box instead of a full transmission. Energy is initially converted from chemical to rotational to electrical in the Internal Combustion Engine and Generator. The electrical energy is then stored in the Battery before being regulated and transmitted to the four Electric Motors. Finally, the Electric Motor converts the electrical energy to rotational energy at the Wheel.

The fidelity of the system model is such that there are four subsystems with extensive attributes that affect the overall value of the system. These are the Electric Motor, Gearbox, Internal Combustion (IC) Engine, and Battery. The computational

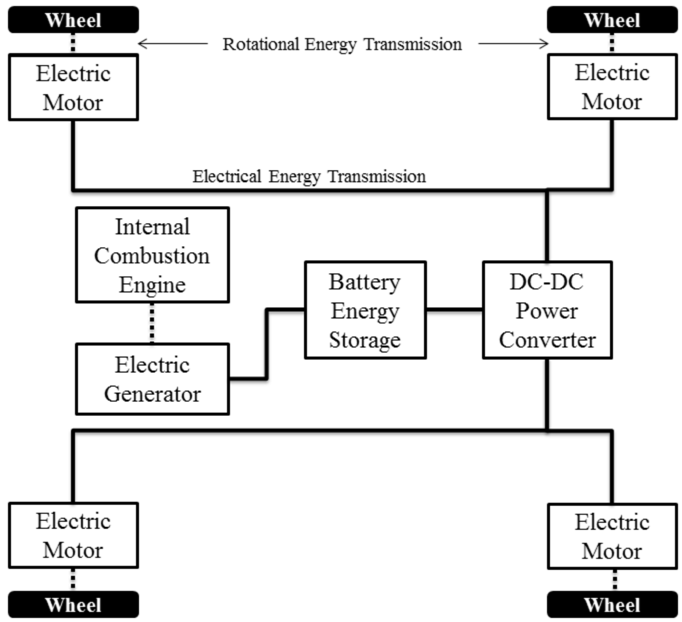

Figure 11: System Architecture of the Series Hybrid Vehicle

experiment requires a System of Interest (SOI) to be chosen as the focal point of subsystem design. The SOI must be easily approximated at the system level during preliminary design, but it should also be fit for higher fidelity modeling during subsystem design. Here, the Electric Motor subsystem is chosen as the SOI since it can be modeled using simple power relationships as well as from first principles using geometric relationships.

4.1.1 Defining the Design Variables, System Attributes and Extensive Attributes

A mathematical foundation of the system and subsystem relationships was provided in Section 3.1.1 and is now applied to the example system. Tables 3, 4, and 5 provide a summary of the design variables and attributes used for the respective models and system value objective. Specifics about each variable and model are provided in the next section.

Table 3: System Attributes of the Series Hybrid Vehicle

Attribute	Name	Description	Units
x_1	v_{max}	maximum sustainable speed of the vehicle	mph
x_2	a_{max}	acceleration of the vehicle from 0 - 60 mph	s
x_3	η	fuel economy of the vehicle	mpg
x_4	ε_{err}	drive cycle error	mph

The system attribute vector, $\vec{x}$ is summarized in Table 3. These attributes are used in the system objective function, $\pi(\vec{x})$, to determine the overall utility of a particular vehicle design.

Table 4: Extensive Attributes for Each Vehicle Subsystem

Extensive Attribute	Name	Description	Units
$y_{1,1}$	τ_{stall}	electric motor stall torque	N·m
$y_{1,2}$	ω_{max}	electric motor no-load speed	rad/s
$y_{1,3}$	c	electric motor cost	USD ($)
$y_{2,1}$	r_g	total gear ratio	-
$y_{3,1}$	P_{IC}	IC engine max power	W
$y_{4,1}$	N_s	battery cells in series	-
$y_{4,2}$	N_p	battery cells in parallel	-

The extensive attributes in Table 4 compose the vector $\vec{z}$. During preliminary design, this vector is varied to find the system design that maximizes the total utility. Feasibility and the nonlinear relationships between each variable are determined by the system model discussed in Sections 4.2 and 4.3, respectively. Variables $y_{1,1}$, $y_{1,2}$, and $y_{1,3}$ describe the electric motor, $y_{2,1}$ describes the gearbox, $y_{3,1}$ describes the internal combustion engine, and variables $y_{4,1}$ and $y_{4,2}$ describe the battery. In the method of Requirements Allocation, targets are set for $\vec{y}_{SOI}$ whereas in DVDD, an objective function is provided to optimize $\pi\left(\vec{z}^{*}\right)$ with respect to $\vec{y}_{SOI}$.

Table 5: Design Variables of the Electric Motor Subsystem

Variable	**Name**	**Description**	**Units**
d_1	$D_{s,int}$	interior stator diameter	m
d_2	D_w	wire diameter	m
d_3	l	axial length	m
d_4	K_{D_s}	stator ratio where $K_{D_s} = \frac{D_{s,int}}{D_{s,ext}}$	-
d_5	K_{D_r}	rotor ratio where $K_{D_r} = \frac{D_{r,ext}}{D_{r,int}}$	-

Table 5 summarizes the design variables of the SOI. The vector $\vec{d}$ defines the basic geometry of the electric motor. The physics-based model used to determine the electric motor extensive attributes from the design variables is discussed in Section 4.4.

Now that the variables and attributes have been established using the conventions of the previous chapter, the construction of the vehicle and electric motor models are reviewed.

4.2 Initial Feasibility Model of the Electric Motor

Prior to the modeling of the system or subsystem, technical experts provide guidelines to the system designer as to what is feasible. This is always a prediction based on the beliefs of the technical experts and reflects the Pareto frontier of possible design alternatives. There are many ways to model this prediction, but in this work it comes in the form of a kriging model. Kriging models [23] are a type of surrogate model sometimes referred to as Design and Analysis of Computer Experiments (DACE) approximations. It is an interpolation technique used to approximate a high fidelity model that is computationally expensive to evaluate and can provide feasibility as an explicit constraint. The method of Support Vector Domain Descriptions (SVDD) [25] was also investigated as a possible means of providing the initial feasibility model, but as an implicit constraint, it was found to be insufficient in approximating the Pareto frontier.

Table 6: Definition of the Electric Motor Design Space, **D**

Design Variable	Units	Lower Bound	Upper Bound
$D_{s,int}$	m	0.04	0.25
D_w	m	0.1	0.01
l	m	0.10	1.0
K_{D_s}	-	1.01	1.50
K_{D_r}	-	0.10	0.35

In approximating the feasible region, a full-factorial Design of Experiments (DOE) was performed across the design space **D** for the electric motor subsystem. The bounds of the electric motor design variables are provided in Table 6. Four views of the electric motor design space are provided in Figure 12.

As mentioned above, the initial feasibility constraint that is ultimately passed from the technical experts to the system designer is in the form of a kriging model. This can be used to model the stall torque as a function of the no-load speed and the motor cost in Equation 11. The function is then converted to an implicit design constraint by Equation 12 (generalized as $g(\vec{z}) \geq 0$ in Chapter 3).

$$\tau_{max} = Q(\omega_{max}, c) \tag{11}$$

$$Q(\omega_{max}, c) - \tau_{max} \geq 0 \tag{12}$$

The kriging model of the extensive attribute Pareto frontier around the global $\vec{z}^*$ is shown in Figure 13. In comparing this with the SVDD approximation, it is clear that

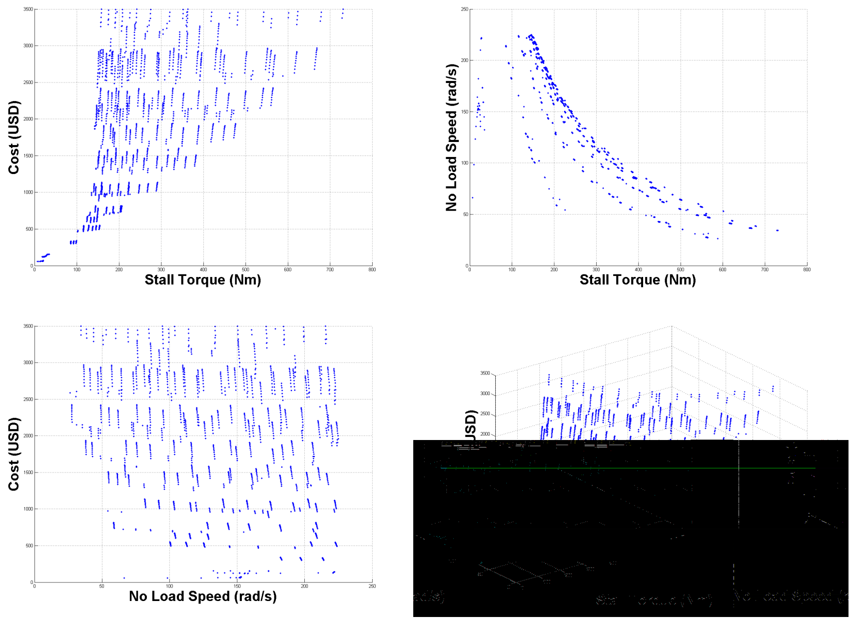

Figure 12: Electric Motor Extensive Attribute Space

an explicit model is much less expensive once the general area of the global optimum is known. Since the technical experts can be assumed to have prior knowledge of this region of the attribute space, it is valid to use a kriging model as the feasibility constraint during preliminary design.

4.3 Preliminary Design at the System Level

This section will discuss the system vehicle model and the methods used to optimize $\pi(\vec{z})$ during preliminary design. From the perspective of the system designer, there is a relatively simple approximation for each subsystem based on the initial feasibility guidelines provided by the technical experts. The model in Figure 14 is constructed in ModelCenter which is a computational tool used to connect various simulations and perform optimizations of many different forms.

The *KrigingTauPredictor* is the model of the initial feasibility constraint in Equation 11 provided by the electric motor domain experts. This provides the feasible torque and motor speed used in *MotorParameters* to get the specific characteristics

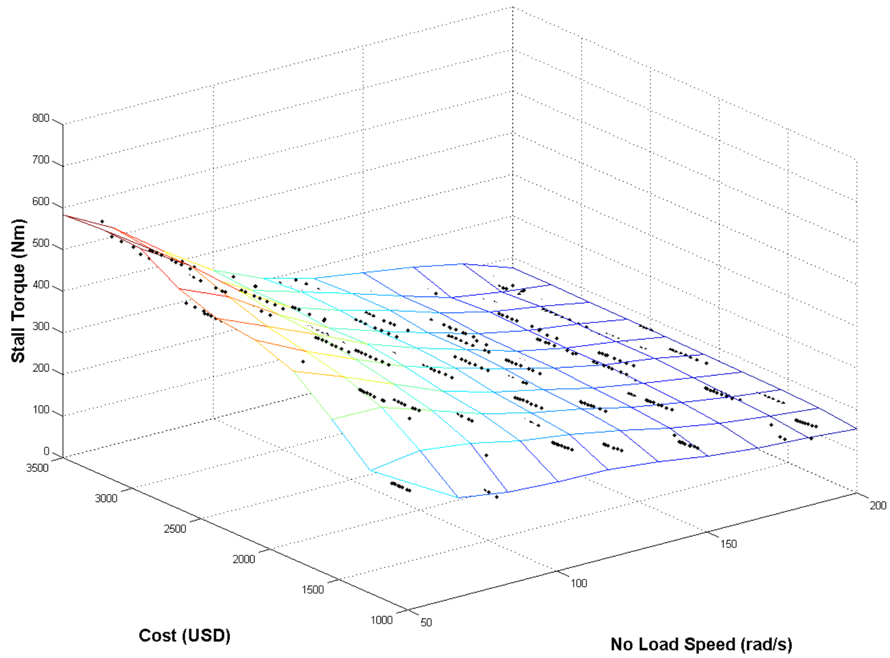

Figure 13: Kriging Approximation for the Electric Motor at $\vec{z}^*$

of the motor. Then using the motor characteristics as well as the extensive attributes of the other subsystems, *DymolaPHEV* simulates the design alternative to determine the system attributes, $\vec{x}$. After a unit conversion, the system attributes and the vehicle cost information are used in the *DemandModel* to calculate the overall value in terms of profit for that alternative. The last model, *UtilityConverter* simply applies a penalty function to alternatives with a large drive-cycle error. Each subsystem model and the use and necessity of this penalty function are described below.

4.3.1 The System-Level Vehicle Model

The series hybrid vehicle system is dynamically modeled using Dymola. Dymola is a commercial modeling and simulation environment based on the Modelica programming language. A series hybrid vehicle crosses many different disciplines including the mechanical, electrical and control domains. Because of Dymola's unique capability to model components from multiple domains, it is a suitable engineering tool for this

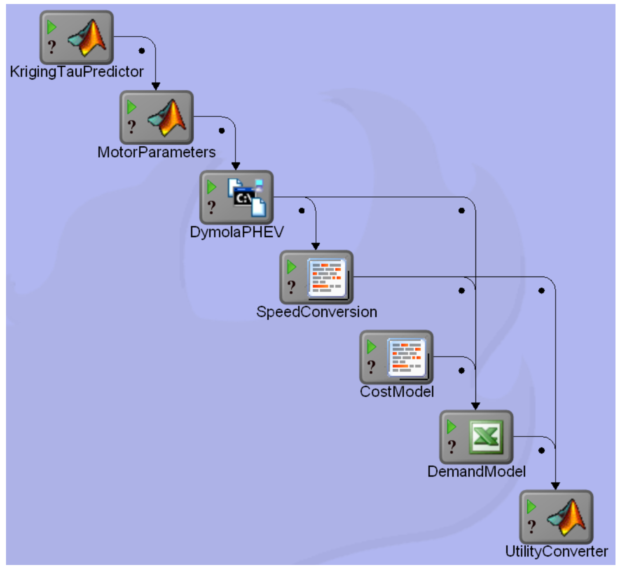

Figure 14: ModelCenter Model Used to Optimize $\pi(\vec{x})$ in Preliminary Design

work.

The Dymola diagram for the system model is provided in Figure 15. Each connector color represents a specific domain. Blue denotes electrical, black denotes rotational, green denotes translational and dark blue denotes the control domain. Each block contains a set of equations and equalities to relate the block inputs to the block outputs.

Initial observations reveal that there is one electric motor in the model while the vehicle being modeled contains four. To simplify the simulation, the three extensive attributes for the electric motor can be used to model four electric motors in series along a single shaft. Recall the electric motor extensive attributes are stall torque, no-load speed and cost. This series motor setup will multiply the torque and cost by four, but leave the speed the same. However, when considering the initial feasibility model, only one motor should be modeled since the same assumption cannot be made for the specific physical phenomena that occur inside the motor.

The vehicle model is first provided a velocity command which is the input for a simple limited PID controller. The limited PID controller allows for proper control

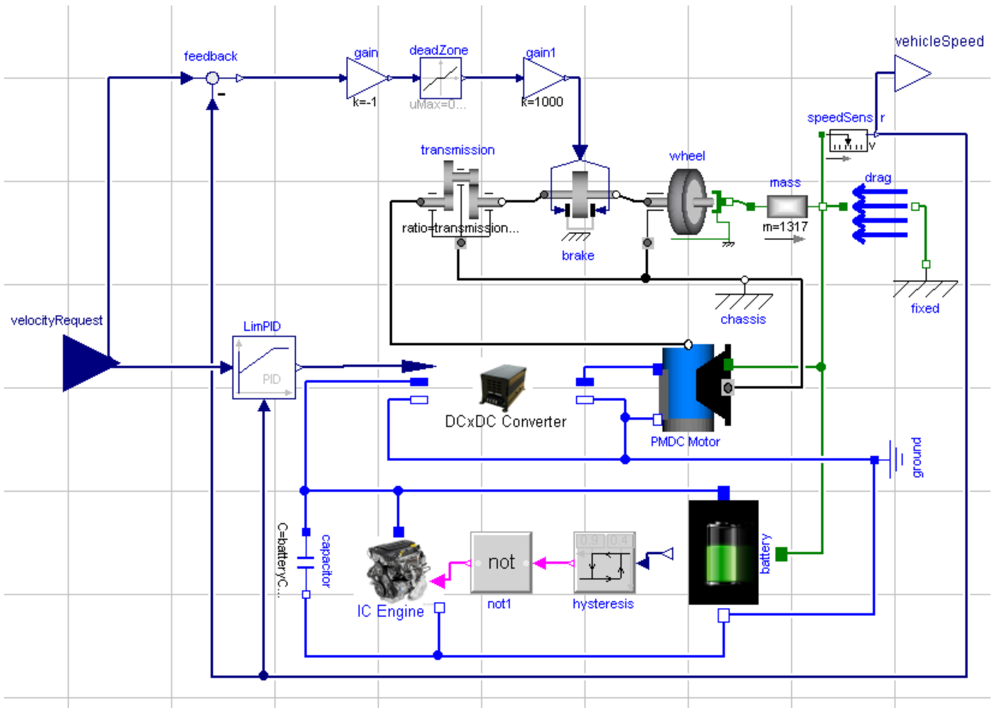

Figure 15: Simulation Model for the Series Hybrid Vehicle

during braking as well as during acceleration. The overall speed of the vehicle is regulated by the voltage provided to the electric motor by the DC-to-DC power converter. The DC-to-DC power converter is limited to a maximum current of 500 A and operates at an efficiency of 85%. All the variables for the power converter remain constant throughout the experiment and its cost is aggregated into the fixed cost of the vehicle.

The energy flow through the system originates in a parallel circuit containing the battery and internal combustion engine. The vehicle being modeled is said to have a plug-in architecture since the battery is initially at full charge. The battery has been modeled with a Lithium-Polymer chemistry and the design variables for the battery are the number of cells in series and parallel. For each cell there is an associated cost and mass which is constant. If the total number of cells increases, so too will the cost and mass of the battery according to their respective per cell rates.

The IC engine is essentially a generator so that it can be assumed to operate at single speed where power is most efficient. This efficiency is set at 35% to reflect a state-of-the-art motor common to hybrid vehicles. Engine cost is solely a function of engine power (Equation 13). This was derived from a market survey of commercial IC engines with various configurations and a power rating between 40 kW and 160 kW. A hysteresis loop controls the IC engine such that if the battery state of charge drops below 40%, it generates electrical power until the battery returns to a 90% state-of-charge. The data collected in the market survey of internal combustion engines is provided in Appendix A.1.

$$engine\,cost = 0.0177 \cdot P_{IC} + 850.6 \tag{13}$$

From the energy generation and storage circuit, the system energy flow moves from through the DC-to-DC power converter and into the electric motor where it is converted into rotational energy. The electric motor is essentially modeled by a set of two equations that relate the torque and speed to the motor resistance and torque constant.

$$R_m = \frac{V_{max}^2}{\omega_{max} \cdot \tau_{stall}} \tag{14}$$

$$k_\tau = \frac{V_{max}}{\omega_{max}} \tag{15}$$

where V_{max} is the maximum voltage in V, ω_{max} is the no-load speed in rad/s, τ_{stall} is the stall torque in N·m, R_m is the motor resistance in Ω, and k_τ is the torque constant in $^{V \cdot s}/_{rad}$. The initial feasibility model provides the possible configurations of torque, speed and cost for the motor and these are used (sans cost) to find the motor parameters.

Once converted into rotational energy by the electric motor, energy flows through the gearbox and wheels to the road. The gear ratio, r_g, is the only design variable associated with the gearbox and is used to regulate the feedback error that may occur with different motor design alternatives. Since any gear ratio can be used with the same mass and cost, these values are kept constant and are accounted for in the fixed vehicle cost. Similarly, the wheel radius of a vehicle is often determined by the size of the vehicle and predicted use case. Since every vehicle design alternative will have the same exterior body and consumer use case, the wheel radius is held constant at 0.27 m.

Finally, the environment is accounted for by a model for air drag. Once again, the frontal area of the vehicle is kept constant throughout the experiment so this subsystem model is only dependent on the speed of the vehicle and uses physical constants as parameters.

4.3.2 Vehicle Performance Tests

Recall that the system attributes that directly affect value are vehicle speed, acceleration, efficiency and drive cycle error. These attributes are determined by simulating the Dymola system model using two test cases. The first tests for acceleration and sustainable top speed and the second test uses a standard drive cycle to determine fuel efficiency and drive cycle error.

Figure 16 provides a time vs. speed plot of the acceleration and top speed simulation where time is in seconds and speed is in $^{m}/_{s}$. A step function from 0 to 100 m/s is provided as a request velocity. The acceleration of the vehicle is measured by the time in seconds to reach 26.8 m/s (60 mph) from rest. The velocity request remains at 100 m/s for the duration of the simulation to determine the maximum sustainable speed. The absolute maximum speed of the vehicle is a result of using only the battery before the state of charge is depleted to 40% and the internal combustion engine is engaged. Since the velocity request is so high, the battery continues to deplete even with the IC engine engaged. The final sustainable speed is reached after the battery charge

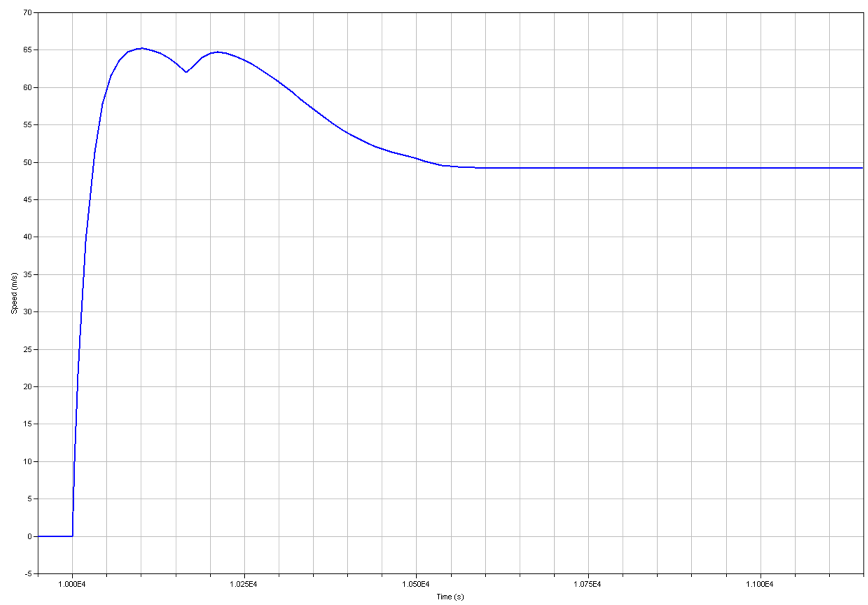

Figure 16: Vehicle Speed for Acceleration and Top Speed Tests

has been fully depleted and the IC engine is the sole power source. While the initial peak speed is higher than the sustainable top speed, a consumer would ultimately judge value based on sustainable top speed.

The second system test employs the use of the Urban Dynamometer Driving Schedule (UDDS) as a means of determining the vehicle fuel efficiency and ability to follow a predetermined drive cycle. The UDDS is an Environmental Protection Agency (EPA) standard driving schedule used for light duty vehicles in a city environment [33]. The system vehicle is shown following the the UDDS drive cycle in Figure 17. When testing a vehicle against its ability to follow the drive cycle, it is assumed that the overall vehicle value will drop off significantly if the actual speed deviates more that 1 mph from the standard. The vehicle fuel efficiency is calculated using the distance traveled and the fuel used to fully recharge the battery after completion.

4.3.3 Modeling Consumer Demand

Once the performance tests are completed and the system attributes are determined, a consumer demand model is used to find the value of the resulting design alternative.

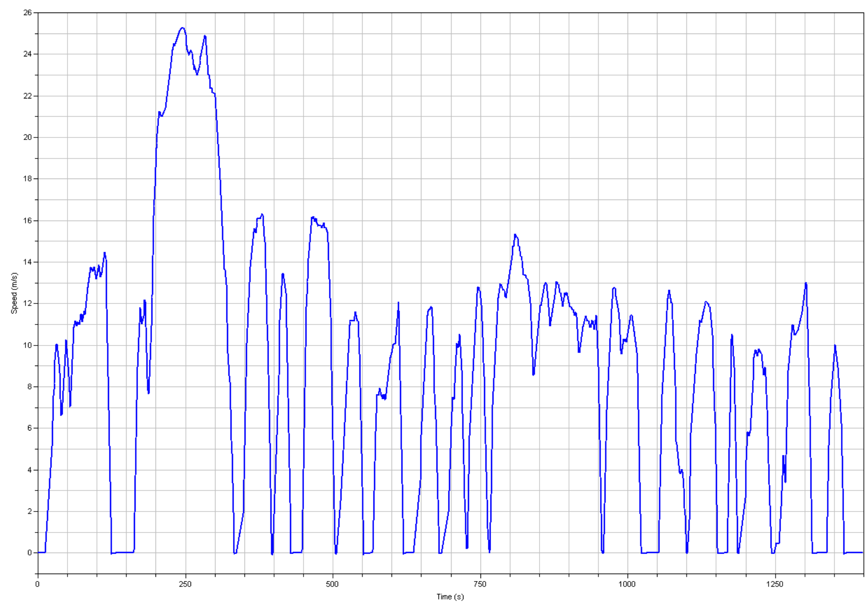

Figure 17: Vehicle Speed According to the UDDS Drive-Cycle Test

The consumer demand model employed in this work was proposed by Hazelrigg [16]. The background of this application is provided in Chapter 2 and is now applied to the example system.

Figure 18 shows the framework for optimal product design applied to the example system. During preliminary system design, the vector $\vec{z}$ is selected and the system attributes $\vec{x}$ are calculated. During subsystem design, the electric motor extensive attributes are optimized according to each approach. The expected utility of the system is used to quantify each approach and provide a means of comparison.

Consumer demand is modeled by surveying possible car buyers to elicit their preferences with respect to the system attributes. Various design alternatives are provided to the respondents, for which they must give a price they would be willing to pay for that alternative. This provides a function of the system attributes and vehicle cost that yields the price at which the total profit will be maximized.

As mentioned above, there exists an additional penalty function applied to the system utility which depends on the vehicle drive-cycle error. Since it is difficult to elicit the preferences of a consumer for more than three system attributes, it would

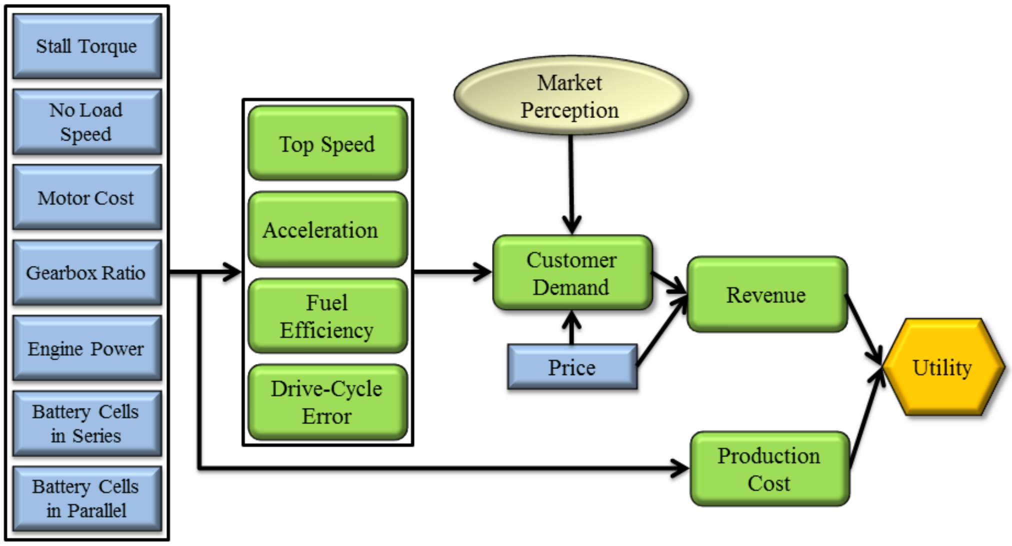

Figure 18: Influence Diagram for the System Value Objective

be nice to account for this outside the survey by making a simple assumption. It is clear that this is important to consumers, but only to the extent that the vehicle can complete a standard driving schedule. This allows for the assumption that if the vehicle does not complete the drive-cycle within 1 mph of the target schedule, the value would drop off to the end user. A plot of the utility penalty function is provided in Figure 19.

The demand model accounts for the total number of vehicles that would be sold given the survey results. This first results in an overall profit on the order of billions of dollars. From this, the risk preference of the decision maker is applied to the profit, yielding an expected utility. In this work, the risk preference of the decision maker is assumed to be neutral (i.e., neither risk seeking or risk averse). Because of this, the expected system utility can be expressed as expected system profit in US dollars.

4.3.4 Computing the Design Targets and DVDD Objective Function

Once the system level preliminary design is found, the design targets and DVDD objective function can be determined. For Requirements Allocation, the optimization problem defined in Chapter 3 models the behavior of a subsystem designer that is

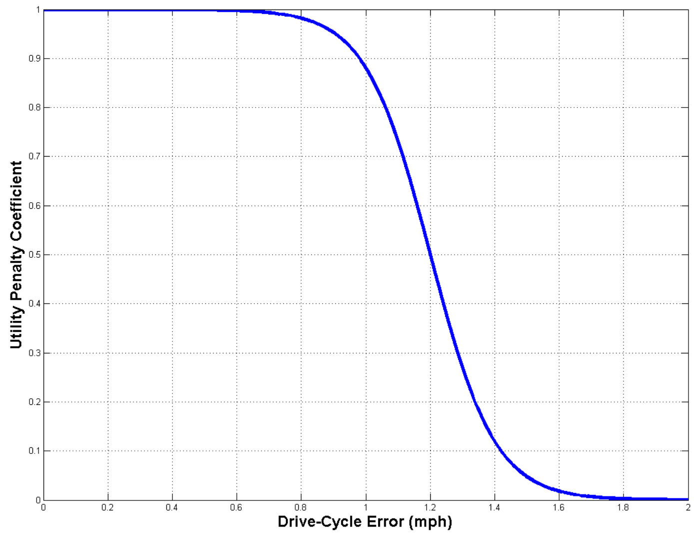

Figure 19: Utility Penalty Coefficient as a Function of Drive-Cycle Error in mph

provided targets as a design goal. The targets for the SOI of the example system are the electric motor stall torque, no-load speed and motor cost. From the perspective of the subsystem designer, these are simply the vector $\vec{y}^{*}_{SOI}$ containing the optimal extensive attributes above.

On the other hand, additional modeling is required to provided an objective function used to model the DVDD approach. Two objectives are calculated for the example system. The first follows the approach proposed by Collopy in [4] where $\pi(\vec{z})$ is approximated by a first-order Taylor series expansion. The second objective function proposed by the author accounts for some of the nonlinearities in $\pi(\vec{z})$.

The linear approximation is achieved by performing a central difference approximation of the gradient where these gradients are the coefficients α_m for the subsystem objective function. Equations 16, 17 and 18 show this approximation for the electric motor extensive attributes where h_m is 0.1% of the extensive attribute at $\vec{z}^{*}$.

$$\alpha_\tau = \frac{\pi\left(\vec{z}^{*}, \tau^{*}_{stall} + \frac{1}{2}h_\tau\right) - \pi\left(\vec{z}^{*}, \tau^{*}_{stall} - \frac{1}{2}h_\tau\right)}{h_\tau} \tag{16}$$

$$\alpha_\omega = \frac{\pi\left(\vec{z}^*, \omega^*_{max} + \frac{1}{2}h_\omega\right) - \pi\left(\vec{z}^*, \omega^*_{max} - \frac{1}{2}h_\omega\right)}{h_\omega} \tag{17}$$

$$\alpha_c = \frac{\pi\left(\vec{z}^*, c^* + \frac{1}{2}h_c\right) - \pi\left(\vec{z}^*, c^* - \frac{1}{2}h_c\right)}{h_c} \tag{18}$$

The approximation of the system value objective proposed by the author seeks to account for some of the nonlinearities that may occur in the above approximations. For this example system, the no-load speed is the extensive attribute that is approximated with more fidelity. This replaces the coefficient α_ω with the function $S\left(\vec{z}^*, \omega_{max}\right)$. The specific form of this function and the values for α_m are provided in Chapter 5.

4.4 Subsystem Design of the Electric Motor Subsystem

Since the electric motor is the SOI for the computational experiment, extensive efforts were made to model it with high fidelity from basic geometry. Figure 20 provides an approximate schematic to describe the geometry of the permanent magnet DC brushless motor. The first design variable, $D_{s,int}$ is the stator interior diameter in meters. The other three diameters are derived directly from this by Equations 19, 20 and 21.

$$D_{s,ext} = \frac{D_{s,int}}{K_{D_s}} \tag{19}$$

$$D_{r,ext} = k_g \cdot D_{s,int} \tag{20}$$

$$D_{r,int} = K_{D_r} \cdot D_{r,ext} \tag{21}$$

where

$$
\begin{aligned}
D_{s,ext} &= \text{stator exterior diameter in m} \\
K_{D_s} &= \text{stator ratio} \\
D_{r,ext} &= \text{rotor exterior diameter in m} \\
k_g &= \text{air gap ratio} \\
D_{r,int} &= \text{rotor interior diameter in m} \\
K_{D_r} &= \text{rotor ratio}
\end{aligned}
$$

The length, l in meters, is taken along the shaft of the motor and is normal to the $D_{s,int}$. The diameter of the wire used in the motor coils, D_w in meters, dictates the number of coil turns that are possible within the space between each shoe as well as radially between the interior and exterior diameters of the stator. The volume of each motor component is used to calculate the mass and cost based on the physical density and the commoditized cost of each material, respectively. The three primary materials in the motor are steel for the housing, copper for the wire coil and neodymium iron boron for the magnetic core. The result of this model is the extensive attribute vector $\vec{y}_{SOI}$ containing the motor stall torque, no-load speed and cost.

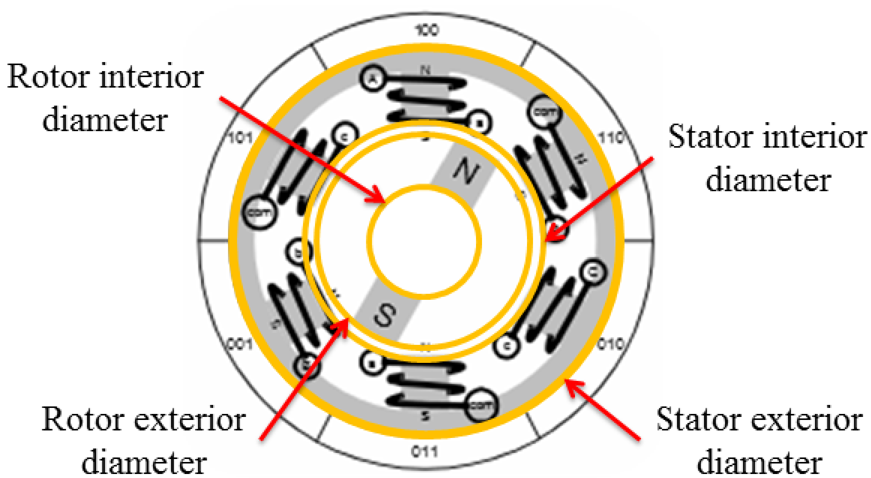

Figure 20: Basic Electric Motor Geometry Schematic [3]

The primary equations used to model the electric motor are derived from Gieras [12] and the source code is provided in Appendix A.2. The DOE used for the initial feasibility constraints on the extensive attributes of the motor was completed using this Matlab model across the design space **D**.

The ModelCenter model in Figure 21 is similar to the one used in preliminary design, but the *KrigingTauPredictor* is replaced with the high fidelity electric motor model which is optimized according to the two approaches being evaluated. The uncertainty used to model the difference between the initial predictions of the technical experts and the reality of current feasibility is the input to the the *MotorOptimization* element.

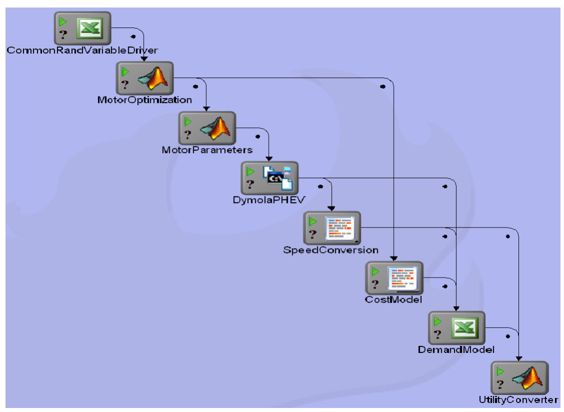

Figure 21: ModelCenter Model Used to Perform Subsystem Design

To model the uncertainty, Various parameters of the electric motor are sampled using a Latin Hypercube Sampling method. A symmetric triangular distribution is applied to each uncertain parameter where the peak is equal to the value in the initial feasibility model and the bounds are equal to $\pm 2.5\%$ of the original value. In order to effectively evaluate the two methods for subsystem design, the uncertainty samples are constant across the application of each approach. This uses the technique of Common Random Numbers (CRN) [19] which allows a smaller number of evaluations to yield statistically significant data. Since the computational experiment is such that the rest of the subsystem extensive attributes are kept constant, the rest of the model remains consistent with the form used during preliminary design.

The optimization formulations used to model each approach were provided in

Table 7: Uncertain Motor Parameters

Parameter	**Description**	**Default Value**	**Units**
p_α	pole pitch-shoe ratio	0.84	-
B_r	remanence magnetic field	1.45	T
k_w	coil winding factor	0.926	-
k_g	air gap coefficient	0.98	-
k_c	Carter's coefficient	1.05	-
$R_{external}$	sum of external resistance	1	Ω
$k_{v,stator}$	stator volume coefficient	1	-
$k_{v,rotor}$	rotor volume coefficient	1	-
c_{steel}	cost of steel housing	0.787	$^{\$}/_{kg}$
c_{mag}	cost of magnetic core	5.4E+05	$^{\$}/_{m^3}$
c_{copper}	cost of copper wire	7.90	$^{\$}/_{kg}$

Chapter 3. In RA, the subsystem designer seeks to obtain the target, but has little incentive to push beyond the provided target. In DVDD, the subsystem designer is provided with an objective function which is some approximation of $\pi(\vec{z})$.

4.5 Summary

This chapter defines the example system as a series hybrid vehicle with an individual electric motor at each wheel. The initial feasibility constraint provided to the system designer by the technical experts is modeled as a kriging model although an implicit model called an SVDD approximation is also investigated. The vehicle simulation performed in Dymola was discussed as well as each subsystem and its respective extensive attributes. This simulation results in the performance attributes of the vehicle which are maximum sustainable speed in m/s, acceleration from 0 to 60 mph in seconds and fuel efficiency in mpg. A consumer demand model is proposed as a means of measuring the value of a system in terms of profit. The process of communicating the needs of the system designer to the subsystem designers is defined for the example system using each approach. Finally, the subsystem design of the electric motor is summarized and the differences between the application of RA and DVDD are provided.

Chapter V

COMPARING REQUIREMENTS ALLOCATION WITH VALUE DRIVEN DESIGN

The motivating hypothesis for this work suggests that in the transition from system preliminary design to subsystem design, an alternative with higher expected utility will result if a DVDD objective function is used rather than design targets. In the previous chapter, the computational experiment is reviewed and the example system is established as a series hybrid vehicle. The results of performing the computational experiment on the example system are now discussed. First, the results of the preliminary system design are presented from which the design targets and DVDD objective function are derived. Then subsystem design is performed using each approach and the results are interpreted.

5.1 Preliminary System Design

Recall the high level actions for complex system design from Figure 6 that are being modeled by the computational experiment. Prior to performing the system level optimization, the kriging model is constructed to approximate the feasibility predictions of the technical experts with respect to the SOI. The results of this model have been summarized in the previous chapter. The system level optimization is carried out using a Algorithm (GA) which is somewhat expensive, but is more likely to find the global optimum. Table 8 summarizes the resulting system attributes found during preliminary design. The corresponding extensive attribute vector, $\vec{z}$, is provided in Table 9.

This system design corresponds to an overall expected utility of 1.173E+09. For

Table 8: System Attribute Values for Preliminary Design

Attribute	**Value**	**Units**
Top speed	110.0	mph
0 to 60 mph Acceleration	10.62	s
Fuel Efficiency	40.48	mpg
Drive-Cycle Error	0.883	mph

Table 9: Extensive Attribute Values for Preliminary Design

Extensive Attribute	**Value**	**Units**
τ_{stall}	284.7	N·m
ω_{max}	122.0	rad/s
c	2,132	USD ($)
r_g	1.226	-
P_{IC}	60,000	W
N_s	155	-
N_p	15	-

this experiment, the preference of the decision maker has been assumed to be risk neutral so that the expected utility can be interpreted as an expected annual profit of $1.173 billion.

From this design point, the design targets and DVDD objective for the SOI are derived. The extensive attributes of the other subsystems remain constant throughout the rest of the experiment. For Requirements Allocation, design targets are taken directly from $\vec{z}$ and provided to the subsystem designer. In the case of the DVDD objective function, the approximation of $\pi\left(\vec{z}\right)$ at $\vec{z}^{*}$ must be completed. The details of this method are given in Section 5.2.2. In examining the electric motor extensive attribute space, we can see the location of the SOI preliminary design in Figure 22.

5.2 Subsystem Design

With the system preliminary design completed, the results of each proposed approach are given and the comparison is evaluated.

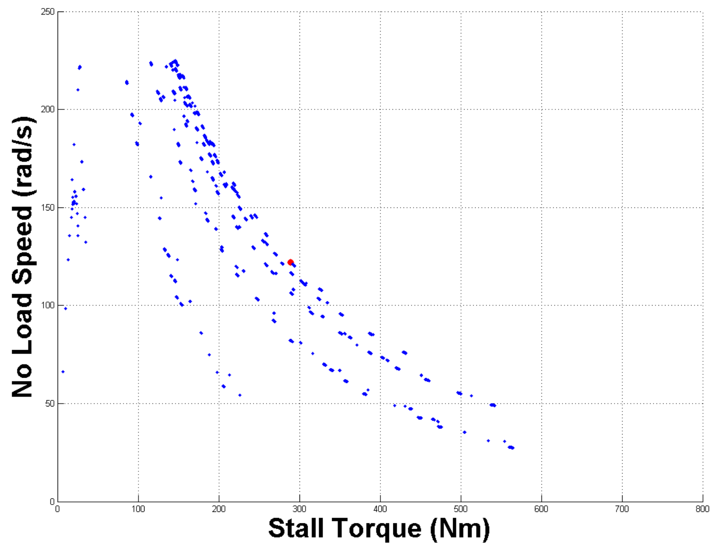

Figure 22: SOI Preliminary Design Relative to Other Feasible Motor Alternatives

5.2.1 Subsystem Design Using Requirements Allocation

In employing design targets, two possible scenarios will result. These are due to changes in the actual Pareto front from the initial prediction that is used during preliminary system design. If the changes to the Pareto front are favorable, the target will be reached. This may occur due to technological advances or a decrease in material costs. But if the actual Pareto front shifts to a point such that $\vec{z}^*$ is no longer attainable, the design alternative closest to the target will be selected. This instance would occur in the case of rising prices or programmatic disruptions to the development process.

The actions of a subsystem designer using design targets are modeled by optimizing the electric motor to the design alternative closest to the targets. Since the system preliminary design depends on the prediction of the technical expert's prediction for the Pareto frontier of feasibility, there will be very few designs for which the closest alternative has a better expected utility than the target. Figure 23 provides the Cumulative Distribution Function (CDF) of expected utility for subsystem design using RA. This is the result of 1000 LHS uncertainty samples. The red line shows the target value.

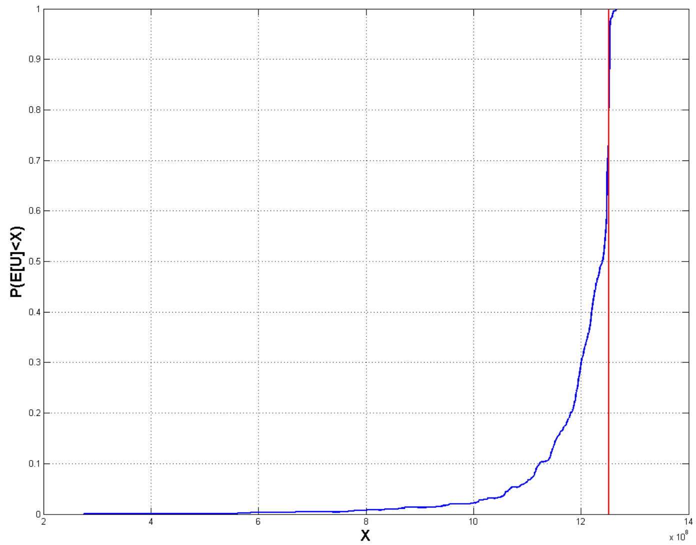

Figure 23: Expected Utility CDF for Subsystem Design Using RA

From this figure, it is clear that regardless of the nature of the uncertainty, the use of RA will only reach the target 30% of the time. Chapter 2 proposes that the use of design targets are a possible cause for the extensive budget and schedule shortfalls of current complex system development. This CDF supports that claim and shows that using design targets effectively places a ceiling on the possible improvements that may be made during subsystem design. Note that a select few designs do have an expected utility greater than the design target. In the optimization, this point happens to be the closest to the target, but this is also an accurate outcome for the scenario being modeled. In some cases, there are simply no extra resources required for the subsystem designer to surpass the target. And so in select circumstances, the subsystem design may actually be better than the target set during preliminary system design.

5.2.2 Subsystem Design Using Value Driven Design

Before the the DVDD objective function can be applied to the electric motor for subsystem design the approximations for the system value objective with respect to the extensive attributes must be completed.

The central difference approximation for each extensive attribute of the electric motor is given by Table 10 and visualized in Figure 24. Recall that there are two ways of formulating the DVDD objective function. The first, proposed by Collopy [4], is a first-order Taylor series approximation around $\vec{z}^{*}$. The second is an approximation proposed by the author to account for some of the nonlinearities in the system value objective.

Table 10: DVDD Objective Function Coefficients

Coefficient	Value
α_{τ}	1.59E+07
α_{ω}	5.00E+06
α_{c}	3.38E+05

In the visualizations of the system value function, we see that $\pi(\vec{z})$ with respect to stall torque and cost is sufficiently linear around $\vec{z}^{*}$ to justify the use of a linear approximation. However, the linear approximation for the gradient of $\pi(\vec{z})$ with respect to no-load speed is poor. Although the motor speed gradient is of similar magnitude to the gradients of the other two attributes, the linear approximation would become invalid very quickly as we move away from $\vec{z}^{*}$, the location of the Taylor series expansion. The nonlinearities associated with this extensive attribute are due to two opposing extensive attributes - max speed and fuel efficiency. Thus, the system value objective is so sensitive to changes in the motor speed that any deviation will cause a drastic drop in system utility.

One element of the computational experiment is to optimize the SOI using the DVDD objective formulation proposed by Collopy in [4]. This objective function is

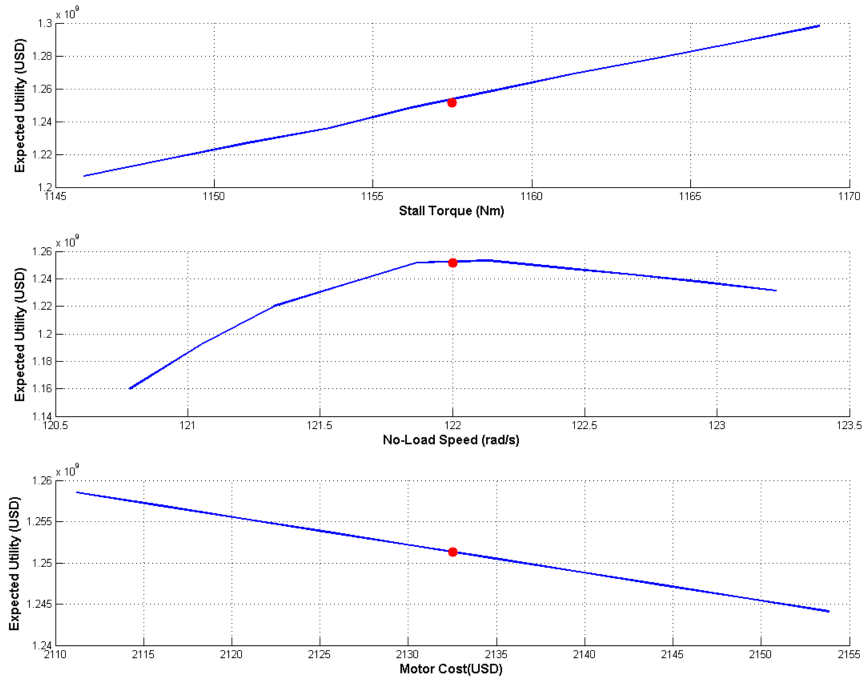

Figure 24: System Value Objective Gradient with respect to Each Electric Motor Extensive Attribute

given by Equation 22.

$$\phi_{motor}\left(y_{motor}\right) = \alpha_{\tau} \cdot \tau_{stall} + \alpha_{\omega} \cdot \omega_{max} + \alpha_{c} \cdot c \tag{22}$$

Using this objective function, the motor is optimized to a point very far from $\vec{z}^*$ and results in an expected utility of zero for the overall system. This is explained by the linear approximation around $\vec{z}^*$. The area for which it is valid is so small, that the optimizer quickly finds a design point along the approximation that seems preferred, but is actually invalid due to the shape of the system objective with respect to motor speed.

For this reason, the author proposes a new DVDD objective function that seeks to account for this problem. The gradient coefficients for stall torque and cost remain unchanged but the approximation of the gradient for the no-load speed takes the following form.

$$S\left(\omega_{max}\right) = A\left(x+\theta\right) - B\ln\left(\cosh\left(C\left(x+\theta\right)\right)\right) + s_0 \tag{23}$$

where A, B and C are approximation constants. This function is compared to the previous plot of the motor speed gradient in Figure 25. Equation 23 is specific to this problem so in future work, a more generalized method should be used to approximate the system value function when such nonlinearities are present.

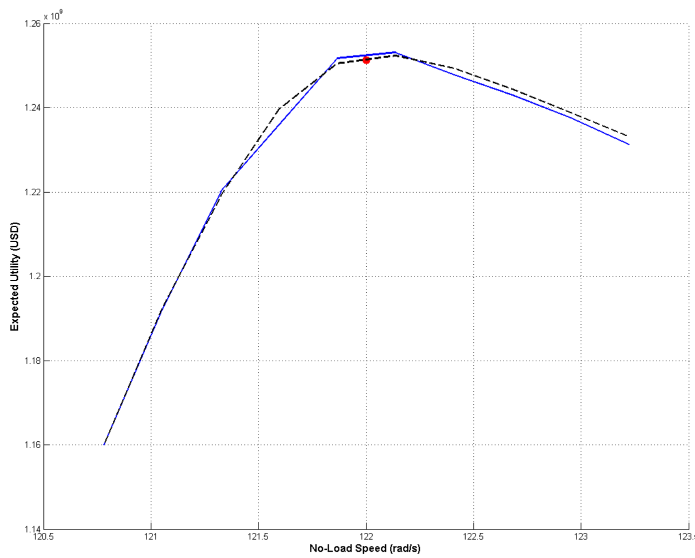

Figure 25: Higher Order Approximation for the Gradient of $\pi\left(\vec{z}\right)$ with respect to Motor Speed

Now that the system value objective has been approximated, the optimization of the SOI is completed. This is done under uncertainty, using the same sample set that was used for RA. Equation 24 provides the objective function used in terms of α_τ, α_c and motor speed approximation given above. The CDF in Figure 26 is the result of the SOI design using the previously established DVDD objective function. As a point of reference, the preliminary design design is provided by the red line.

$$\phi_{motor}\left(y_{motor}\right) = \alpha_\tau \cdot \tau_{stall} + S\left(\omega_{max}\right) + \alpha_c \cdot c \tag{24}$$

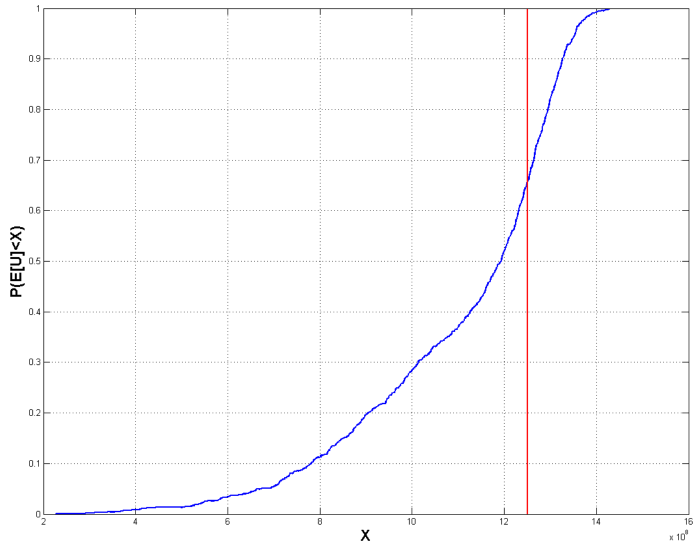

Figure 26: Expected Utility CDF for Subsystem Design Using DVDD

We see from this plot that optimization using the DVDD objective reaches the target approximately as often as with RA. However, if the system design is reached, it is almost definitely surpassed to find a design alternative with a higher expected utility. This is one advantage over Requirements Allocation which gives little possibility of finding an alternative with an expected utility greater than that specified in preliminary design. Now that the results have been provided for each method, in the next section we compare the two and interpret the findings.

5.3 Quantitative Comparison of Requirements Allocation with Value Driven Design

The hypothesis for this work is that, on average, the use of a DVDD objective function instead of design targets yields a system alternative with higher expected utility. First, we visualize the CDF's produced by each method on the same plot. This is provided in Figure 27 along with the preliminary system design as a reference.

As mentioned above, there are two possible scenarios based on the uncertain parameters in the motor. In the first case, the uncertainty is favorable, the Pareto

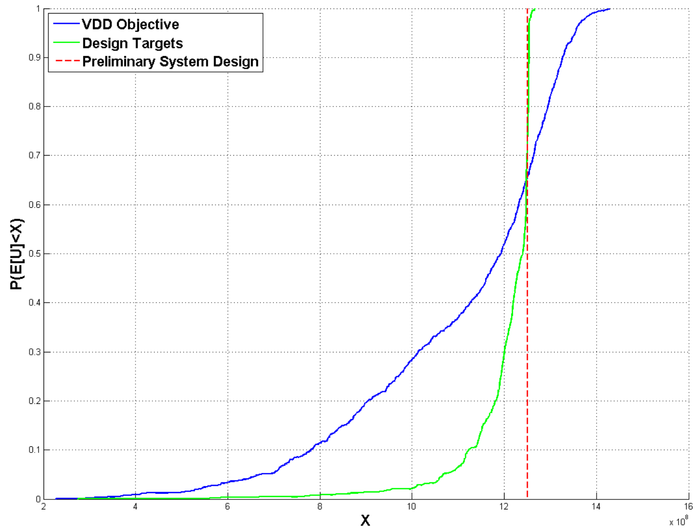

Figure 27: Expected Utility CDF for RA and DVDD

frontier is pushed beyond the preliminary design and the design target can be reached. Here, the method of Requirements Allocation will lead to an alternative at the the preliminary system design, but DVDD will lead to an alternative that is truly on the Pareto frontier and, therefore, has a higher expected utility. In the second possible scenario, the uncertainty is unfavorable and the true Pareto frontier is moved to a point with a lower expected utility than that of the preliminary design. Now as seen in the plot to the left of the target, the design target cannot be reached, but RA is much better at getting closer to the target and, thus, achieving a higher expected utility.

We can visualize this further by the plotting the difference between the expected utility obtained by DVDD and the expected utility obtained by design targets. This relationship is defined mathematically in Equation 25 and the CDF is provided in Figure 28.

$$U_{\Delta,k} = U_{VDD,k} - U_{targets,k} \quad \forall\, k = 1, 2, \ldots, 1000 \tag{25}$$

In support of the motivating hypothesis, one would hope that this difference would

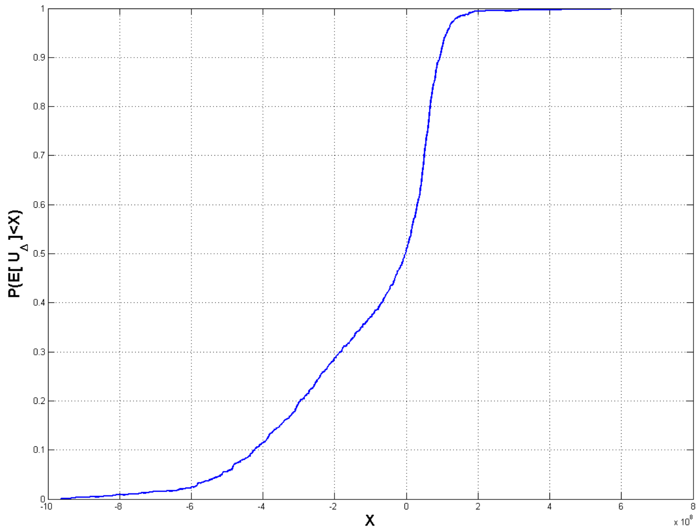

Figure 28: CDF of the Difference Between DVDD and RA

have a positive mean. We would expect DVDD to do as good, if not better, than design targets when the uncertainty is unfavorable. We would also expect this approach to surpass the design targets when the uncertainty is favorable. However, we see that on average, the use of design targets actually yields a higher utility. When the uncertain parameters are sufficiently close to their original values, the DVDD objective does produce a better design alternative than design targets. But in most cases when the Pareto frontier is shifted away from $\vec{z}^{*}$, the method of design targets is superior. Further investigation should be done to characterize the uncertainty and in cases that the uncertainty is very small, DVDD would possibly be superior. In this case, with uncertainty at $\pm 2.5\%$, it is better to use the method of design targets.

5.3.1 Further Investigation into the Approach of Value Driven Design

By looking more in depth at the attribute space, we can gain insight into the cases where the DVDD objective failed to find the highest attainable expected utility. These cases are those in which the Requirements Allocation approach determined an alternative with a higher expected utility than that of the DVDD objective.

Figure 29 provides a plot of the Pareto frontier based on the initial feasibility model for the electric motor as well as the gradient approximation with respect to stall torque and motor cost. Recall that these two gradients appeared to be sufficiently well approximated with a first-order Taylor series approximation.

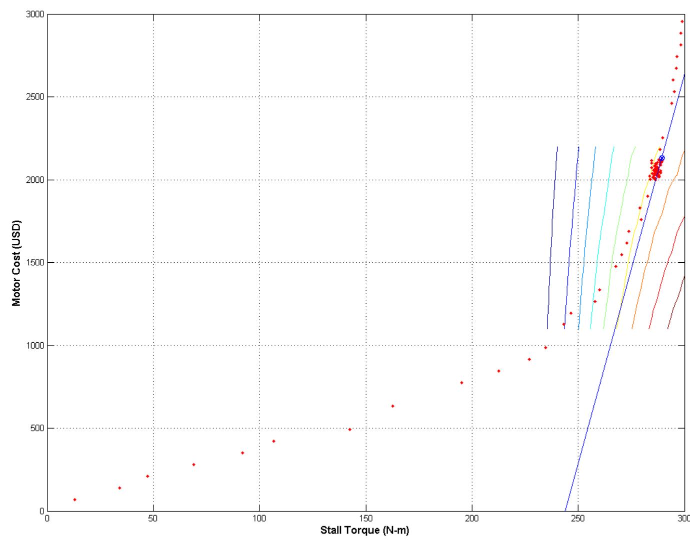

Figure 29: The Pareto Frontier of the Electric Motor Feasibility and the Linear Approximation of the System Value Objective, $\pi(\vec{z})$

It is clear that at the preliminary design, the linear approximation is sufficient, but quickly becomes inadequate as we move away from the $\vec{z}^*$. This inadequacy becomes more pronounced when uncertainty is introduced since doing so can shift, rotate or otherwise deform the Pareto frontier. With this in mind, we now turn to the results of the subsystem design using the DVDD objective in Figure 30. The orange points are the Pareto frontier determined by the initial feasibility model while the blue points are the optimal designs found using the DVDD objective under uncertainty.

The highest density cluster exists very close to $\vec{z}^*$, but many designs deviate from the area where the approximation of the system value objective is valid. In addition to the nonlinearities with respect to motor speed, this suggests that the assumption of linearity for the system value objective with respect to stall torque and motor cost

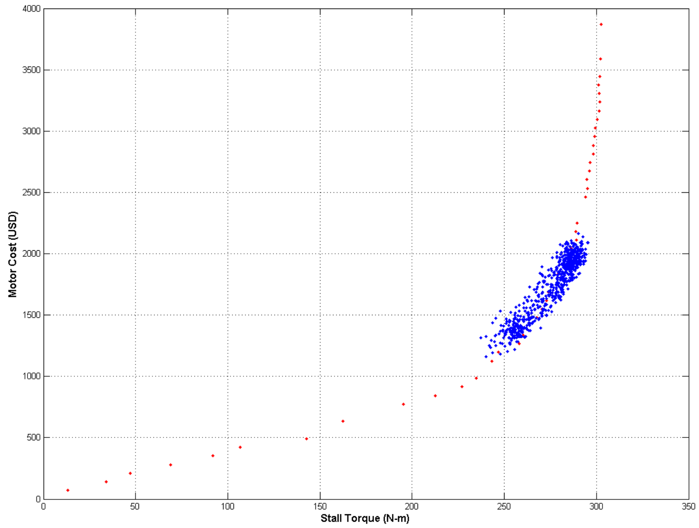

Figure 30: Result of subsystem design using the DVDD objective under uncertainty

is also invalid. The higher order terms for motor speed were accounted for, but it is clear that this should have been done for the other extensive attributes as well. A better way to account for these nonlinearities in each extensive attribute would be to use a surrogate model to approximate the gradients of the system value objective.

5.4 Summary

This chapter provides the results of the computational experiment used to compare Requirements Allocation with the use of a DVDD objective function. The preliminary system design is presented and the electric motor design at $\vec{z}^*$ is shown to exist on the edge of the Pareto frontier prediction provided by the technical experts. From this design point, the design targets are determined and the gradient information is derived for the DVDD objective. The results of subsystem design using RA confirm claims suggested in Chapter 2. These claims suggest the use of design targets as a possible source for the extensive budget and schedule shortfalls common to current system development efforts. This specific application of Value Driven Design to a series hybrid vehicle shows that a linear approximation of the system value objective is inadequate in this case. Efforts are made to perform a higher fidelity approximation of the system value function with respect to the electric motor no-load speed. If this further approximation is not performed, the motor optimization fails for every uncertainty sample. Although the DVDD objective leads to useful design alternatives near $\vec{z}^{*}$, it is not found to be superior to the use of design targets. This is primarily due to the linearized approximation of the system value objective with respect to the motor stall torque and cost. These initially appear to be sufficient, but due to the bounds of the uncertainty on the motor parameters, the true Pareto Front shifts too far from the preliminary system design for theses approximations to remain valid. Further investigation is proposed to determine if the DVDD objective is possibly superior to RA when the uncertainty is much smaller than $\pm 2.5\%$. It is also suggested that the nonlinearities present in the system value objective be accounted for by using a surrogate model instead of a Taylor series approximation.

Chapter VI

CONCLUSIONS AND FUTURE WORK

6.1 Review of the Motivating Hypothesis

A primary task of the system designer is to communicate his preferences about the system to the subsystem designers. Traditionally, this has been done through Requirements Allocation which sets subsystem design targets based on the system-level preliminary design. Relevant literature was reviewed in Chapter 2 to suggest that this process has many flaws and is possibly the source of budget and schedule overruns in the development of modern complex systems. Value Driven Design was proposed as an alternative method for relaying the system designer's preferences to the subsystem designer. This employs an objective function instead of design targets with an incentive for the subsystem designer to find an alternative that best fits the preferences of the system designer. To compare each proposed approach, the following hypothesis was provided.

> *Hypothesis:* Overall system performance can be improved by formulating the subsystem design problem in terms of objectives rather than targets.

To test this hypothesis, a model was constructed to approximate the actions of subsystem designers using each approach. To inform the system-level preliminary design, technical experts provide an initial feasibility model with respect to each subsystem. From this, the system is optimized for expected utility and the design targets and DVDD objective are derived. Subsystem design is then performed under uncertainty for each approach. This experiment is applied to a series hybrid vehicle and the electric motor is analyzed as the Subsystem of Interest.

In evaluating the motivating hypothesis, the CDF's for each approach are compared. It was found that, on average, the method of Requirements Allocation actually yielded a design alternative with higher expected utility. For this reason, the hypothesis has been rejected for this representative case study.

Additionally, the results provided in this thesis were significant in providing insight about both methods. The claim that RA is inadequate at obtaining the system target under uncertainty was supported in this case study. This was illustrated by a ceiling that is effectively placed on subsystem design when using design targets since there is little incentive for the subsystem designer to surpass the expected utility set the preliminary design. In contrast, the DVDD objective showed the possibility of surpassing the system-level preliminary design when the uncertainty was favorable. However, when the uncertainty was unfavorable, this method was inadequate in finding the design alternative with the highest expected utility.

6.2 Contributions

This work provided several contributions to the study of Engineering Design and Systems Engineering as a whole. The primary contributions are as follows.

1. A computational experiment to model the actions of designers providing insight into the incentive structure present in the design of complex systems.

2. For this case study, the common practice of Requirements Allocation is shown to be insufficient in finding a design alternative on the Pareto frontier when uncertainty conditions are favorable.

3. For this case study, the formulation of Value Driven Design proposed by Collopy

in [4] is found to be inappropriate when nonlinearities exist in the system value function at the preliminary system design point, $\vec{z}^*$.

4. A formulation of Value Driven Design specific to the example system that accounts for some of these nonlinearities is shown to find a design alternative with higher expected utility than the system-level preliminary design when uncertainty conditions are favorable.

6.3 Limitations and Future Work

This thesis as provides a representative case study to compare Requirements Allocation with Value Driven Design. Significant problems are discovered in applying Value Driven Design to the example system. Most notably, the use of a linear approximation for the system value objective is not sufficient with this degree of complexity and the amount of uncertainty present in the example system. Even when some of the nonlinearities are accounted for, extensive effort must be applied to the system-level preliminary design to ensure that it was very close to the actual Pareto frontier.

Two possible experiments could provide further insight into this issue. First, smaller bounds for the uncertainty could be assumed. The system value objective is sufficiently approximated very close to the preliminary design so if the uncertainty is small, this approximation would remain valid. Second, a better method of approximating the system value objective could be used. This work suggests the use of a surrogate model to account for the nonlinearities in a larger area around the preliminary design.

Additionally, the demand model used to approximate consumer value could be improved. For this work, a small number of survey responses were used to populate the model and the respondents were asked to make some assumptions. Future improvements could include increasing the number of respondents as well as surveying consumers that are truly in the market for a new vehicle.

Appendix A

RELEVANT SOURCE CODE AND MARKET DATA

A.1 Internal Combustion Engine (Market Survey Data)

Table 11: Internal combustion engines used to compute the engine cost-power function (Equation 13)

Name	Size (L)	Power (W)	Cost (USD)
Chevrolet G10	1.0	54,436	1,599
Honda ES2	1.8	64,130	1,699
Toyota 5EFE	1.5	69,350	2,299
Chevrolet G13	1.3	74,570	1,999
Toyota 1NZFE	1.5	79,044	3,099
Honda A20A3	2.0	82,027	1,899
Toyota 2TZFE	2.4	99,178	2,699
Toyota 1ZZFE	1.8	104,398	2,999
Honda H23A1	2.3	119,312	2,999
Honda H22A1	2.1	139,446	2,699
Toyota 2JZGE	3.0	164,045	3,999

A.2 Electric Motor (Matlab Source Code)

```
function [tauStall,omegaMax,Resistance,torqueConstant,Mass,...
    Inertia,Cost]=motor_bt(D_1in,D_w,l,kD1,kD2)

% Written by Brian J Taylor, Georgia Institute of Technology

% This code follows Example 6.2 from Gieras of an 8-pole,
% 3-phase permanent magnet DC brushless motor. The equations
% are primarily derived from the text while others are
```

```
% derived from geometry. The function input is the basic
% geometry of the motor and the function yields many
% performance and intermediate attributes of the electric motor.

% Motor Parameters
m_1=3 % *number of phases
poles=8; % *number of poles (picure pg. 171)
p=poles/2; % *number of pole pairs (eqn 6.12)
alpha=0.84; % *Pole pitch to shoe width ratio
k_f=(4/pi)*sin(alpha*pi/2);% *exitation field form
                           % factor (eqn 5.23)
mu_not=0.4*pi*10^-6;% *mag perm of free space(H/m)
mu_rec=1.05; % *recoil permiability of NdFeB (H/m)
% (www.magnetsales.com/Neo/Neoprops.htm)
mu_rrec=mu_rec/mu_not; % *relative recoil permiability (H/m)
B_r=1.45; % *remanence magnetic field (Neodymium
% Iron Boron)(T) (www.intemag.com/uploads/Rare%20
% Earth%20Magnets%20Data%20Book/Neodymium%20
% Single%20Sheets/N5311.pdf)
k_w=0.926; % *winding factor
k_p=pi*sqrt(3)/6; % *packing factor
k_g=0.98; % *gap coefficient
rho_w=1.68*10^(-8); % *resistivity of copper (ohm*meter)
density_steel=7850; % *density of steel (kg/m^3)
density_copper=8940; % *density of copper (kg/m^3)
density_magnet=7500; % *density of Neodymium Iron Boron (kg/m^3)
k_c=1.05; % *Carters coefficient k_c > 1
```

```
k_sat=1.1;% *saturation factor k_sat > 1
Rexternal=1;% *resistance of all the external components (ohms)

% Geometry
% D_1in=0.132; % stator interior diameter
r_1in=D_1in/2;
D_1out=kD1.*D_1in; % stator exterior diameter
r_1out=D_1out./2;
D_2out= k_g.*D_1in; % rotor exterior diameter
r_2out=D_2out/2;
D_2in=kD2.*D_2out;  % rotor interior diameter
r_2in=D_2in/2;
r_w=D_w/2;

% Functions

% Motor Constants
tau=pi.*D_1in/(2*p); % pole pitch (eqn 4.26)
b_p=alpha.*tau; % pole shoe width (eqn 5.4)
h_a= r_1out - r_1in; % armature pole length (derived)
N_p=floor(0.225.*tau.*k_p.*... % number of
 (r_1out-r_1in)./(pi.*r_w.^2));  % windings per  pole (derived)
N=2.*p.*N_p./m_1; % number of turns per phase (derived)
g=r_1in - r_2out; % air gap distance (derived)
h_m=r_2out - r_2in ;% magnet thickness (derived)
B_mg=B_r./(1 + mu_rec.*(g./h_m)); % max magnetic
                % flux density through the air gap (eqn 2.14)
```

```
B_mg1=k_f.*B_mg % B_mg at fundamental harmonic (eqn. 5.2)
phi_f=(2/pi).*tau.*l.*B_mg1; % excitation flux (eqn. 5.6)
phi_f_sq=b_p.*l.*B_mg; %square wave excitation flux (eqn. 6.18)
kE=8.*p.*N_p.*k_w.*phi_f_sq./(2*pi); %EMF constant (V-s)
torqueConstant=kE;  % torque constant (Nm/A)

% Resistance
l_w=N_p.*(2*(l + 0.3*tau) + ... % times 12 since there
    2*0.7*tau)*3.*p; % are 3 poles per phase and 3 phases (derived)
A_w=pi.*r_w.^2; %(derived)

% assume that the total resistance is the resistance of the
% external components + the resistance of the wire
Resistance_w=rho_w.*l_w./A_w; %(derived)
Resistance=Rexternal + Resistance_w; %(derived)

% Inductance
% armature inductance
g_prime=k_c.*k_sat.*g + (h_m./mu_rrec); %(App. A)
L_a=mu_not.*(pi/12).*(D_1in./g_prime).*(alpha.^3).*l.*...
    (N./(4.*p.*3)).^2; %(App. A)

% Volume (m^3) (not currently used)
Ao=0.225.*tau.*k_p.*... % cross sectional area taken
    (r_1out-r_1in); % up by one side of a winding %(derived)
v1=(pi.*(r_1out.*r_1out - r_1in.*r_1in) - ...
    4.*Ao.*(poles+1)).*l;  % stator volume (derived)
```

```
v2=pi.*(r_2out.*r_2out - r_2in.*r_2in)...
    .*l; % rotor volume %(derived)
vol_wire=A_w.*l_w; %volume of windings %(derived)
% Volume=v1 + v2 + vol_wire;

% Mass
mass_stator=v1.*density_steel; %(derived)
mass_rotor=v2.*density_magnet; %(derived)
mass_wire=vol_wire.*density_copper; %(derived)
Mass=mass_stator + mass_rotor + mass_wire; %(derived)

% Cost
% stator ($0.787/kg steel) (Jan '12, www.worldsteelprices.com)
statorCost=mass_stator*(0.787);
% rotor ($1050/0.00193 m^3 rare earth magnet)
rotorCost=v2.*(1050/0.0019304);
% wire ($7.90/kg copper)
wireCost=mass_wire*(7.90);
Cost=statorCost+rotorCost+wireCost;

%Moment of inertia ( not currently used)
Inertia=0.5.*Mass.*(r_2out.*r_2out + r_2in.*r_2in);

V=200;
b=0.1;
I=V./Resistance;
```

```
P=I.*V;

tauStall=torqueConstant.*V./Resistance.*min(N_p,1);
omegaMax=V.*torqueConstant./(Resistance.*...
    b+torqueConstant.*torqueConstant).*min(N_p,1);
end
```

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