ABSTRACT

MOORE, BRADLEY MOORE. Exploring the Impact of Value Function Uncertainty in Complex Engineered Systems. (Under the direction of Dr. Scott Ferguson).

Designing and creating complex engineering systems is a difficult proposition for engineers. One of the frameworks proposed to help engineers with these difficulties is value driven design. Within the framework of value driven design, a designer maps the performance of a system to a monetary value output using a value function. However, creating correct value functions is very difficult, often leaving the designer uncertain of the exact form. If value driven design is going to be used by designers, the impact of this uncertainty must be known. This thesis explores the impact of value function uncertainty through the design of two different systems: a pressure vessel and a model rocket. The thesis first investigates how large changes to the value functions impact the optimum solution and whether or not these changes can be predicted. The results show that the changes can have a significant impact on the optimum solution and that the changes to the design can sometimes be predicted. After this, a problem is explored to identify possible solution commonalities when more realistic uncertainty ranges are applied. Results show that when faced with uncertainty there is more than one way to determine a best design. Designing towards the highest mean value is shown to create systems with better performance, while designs that are immune to uncertainty have worse performance.

Exploring the Impact of Value Function Uncertainty in Complex Engineered Systems

by
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A thesis submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the degree of
Master of Science

Aerospace Engineering

Raleigh, North Carolina

2013

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DEDICATION

To my family and friends

BIOGRAPHY

Bradley received his BS in Aerospace Engineering from North Carolina State University in 2011. In undergrad, he became interested in the design of propulsion systems and rockets. In graduate school, he spent the first semester working for Dr. Hassan studying the ablation of heat shields. After deciding that he wanted to study design and systems engineering he joined Dr. Ferguson's System Design Optimization lab. In Dr. Ferguson's lab he joined his interests of design and rockets to conduct research in the field of Value Driven Design. He looks forward to getting a job in the aerospace industry upon graduation.

ACKNOWLEDGMENTS

First I would like to thank Dr. Ferguson for all of his help and support through the process of conducting this research and turning it into a thesis. I thank him for allowing me the freedom to pick an interesting topic and explore it in a way that was very enjoyable for me. I would also like to thank him for the many hours and late nights he spent helping me edit and finish this document. I would like to thank my lab mates, Alex Belt, Dan Shaefer, Garrett Foster, and Jason Denhart for keeping the many hours spent in the lab together informative, enjoyable, and fun. I would like to thank my Mom and Dad who were always there for me through the many struggles and hard times in my college career. Finally, I would like to thank my friends who kept me sane by constantly making me laugh and enjoy myself.

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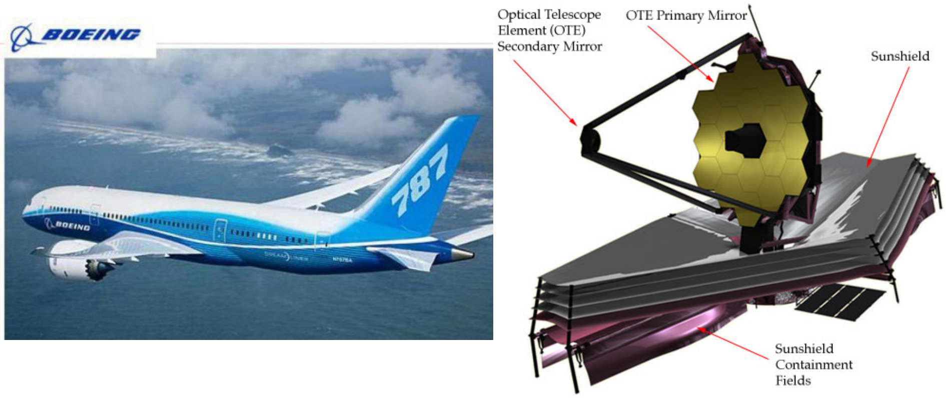
1.1 Challenges of complex system design

Designing and creating large-scale systems has become more challenging as system complexity and design team size have increased [1]. These difficulties have caused recent government and private projects to finish over budget and behind schedule. The Boeing 787 Dreamliner, for example, was $2.5 Billion over budget and over three years late from a delivery perspective [2]. This issue also has ramifications beyond the private sector. The James Webb Space Telescope was initially estimated to cost $2.4 Billion and launch in 2014. In 2008, NASA raised the price tag to $5.1 Billion, and then in 2010, the cost estimates rose to $8.7 Billion and a launch date of 2018 [3].

Taking notice of cost overruns and delivery delays, the government executed a review of all Department of Defense (DOD) projects since 1997. The report used the standard provision for cost overruns in DOD projects, which is the Nunn-McCurdy provision. A Nunn-McCurdy breach occurs when cost increases go over a certain threshold. The threshold for a significant breach is a 15% increase over the current baseline estimate, or a 30% increase over the original baseline estimate. Critical breaches occur when the increases are 25% over the current baseline or 50% over the original. It was discovered that since 1997 there have been 74 Nunn-McCurdy breaches, spanning 47 different defense acquisition programs [4]. This suggests that there is a flaw with the current methodologies for large-scale system engineering.



Boeing Dreamliner James Webb Space Telescope

Figure 1.1: Current Large System Design Difficulties

1.2 Current methods for complex system design

Delivery delays and cost miscalculations associated with today's complex engineered systems may stem from the current systems engineering approach. Here, requirements are passed down the hierarchical structure to design teams working on separate components. Passing down requirement information leads to mistakes because there is no basic form of comparison in overall performance between the different design teams [5]. The requirements are set and passed down but become difficult to meet once all of the different design teams combine their work. To explain this, consider the following hypothetical example involving a high performance car:

1. The design team responsible for the suspension system creates a new configuration that allows the team to decrease the weight by 50 lb. but increases the cost by $2000 due to the use of newer lightweight materials. These changes cause the design team to

come in slightly over budget, but feel that the reduction in weight warrants the increased cost.

2. Meanwhile, a different design team working on the engine has found a way to decrease the cost of the engine by $1800. One of the designers found that state-of-the-art materials weren't necessary in the cylinder heads, and slightly cheaper but heavier heads will suffice. The engine design was already under the weight requirement, so the team decides to use the cheaper materials. This increases the weight of the vehicle by 75 lb.
3. Taken individually, each of these decisions seems reasonable. However, as shown in Table 1.1, the net result is an increase in cost and weight for the car. The next decision is crucial. A program manager could: 1) accept these changes and the subsequent increases in cost and weight, 2) reject the changes, 3) require the two design teams to negotiate their changes toward a neutral trade in cost and weight, or 4) pass down new requirements to each design team.

Table 1.1: Car Design

	Cost	Weight
Suspension design	+ $2000	- 50 lb.
Engine design	- $1800	+ 75 lb.
Net result	+ $200	+ 25 lb.

Research into methodologies to make the design process more effective has led to many different proposed approaches. However, many of these approaches have strength in the qualitative realm, and significant limitations when used quantitatively. For example, Mitsubishi first used the House of Quality in 1972 at Mitsubishi's Kobe shipyard [6]. The House of Quality is a method that helps organize the relationships between customer needs and what the designers can accomplish. House of Quality is a powerful tool for creating qualitative discussion about the value of different concepts in design. However, this tool has serious limitations when applied in a quantitative role, as it has been shown that the numbers entered into the house are no more significant than a random process [7].

Pugh decision matrices are used in concept selection [8] by scoring the concepts in different criteria and then totaling the score. Pugh matrices have similar limitations to House of Quality in that they excel at facilitating qualitative discussion rather than quantitative comparison. This is because Pugh matrices function by scoring the concepts as better or worse when compared to a chosen datum. Yet, research has shown that this approach is vastly subject to designer opinion and the initial choice of the datum [9]

The Analytic Hierarchical Process (AHP) is a process that was designed to help in rational decision making by grouping concerns, components, and sub-components in a hierarchical manner [10]. AHP is a very attractive method for choosing concepts when given a set of alternatives. Due to how the process is set up though, it is incompatible with a set of indefinite alternatives. This shortcoming makes it unusable inside of an optimization loop and limits its effectiveness.

Toward a more rigorous and mathematically sound framework, Decision Based Design (DBD) has developed as an area of research originally presented by Hazelrigg, [11]. Decision based design is a methodology that places the design focus on the total system as opposed to individual parts. The method does this by focusing on rational decision making and optimizing around a single objective that represents the overall utility of a system. Using a single objective allows the method to be used in quantitative comparisons. However, a challenge of DBD comes in how the utility of performance attributes is modeled and how the utilities are aggregated. This is not an inherent limitation of the method, but is more of a modeling challenge to be addressed by the designer.

A methodology similar to decision based design is Value Driven Design or Value based design. Value Driven Design is similar to DBD in that it recognizes the need to focus on the optimization of a single objective. The research in this thesis focuses on Value Driven Design and how it is used. This methodology is described in more detail in the next section.

1.3 Value Driven Design

When design concepts are compared side-by-side using performance attributes, it becomes inherently difficult to choose the best design. This is due to the difficulty in comparing complex systems with a large number of performance attributes. As discussed in the previous section, there are substantial limitations to many of these approaches previously used to make these decisions [12]. The process becomes more difficult further in the design cycle as the designs become more similar. Value Driven Design (VDD) is a design framework proposed by Collopy [5] that allows a designer or design team to focus on a single metric known as “value”. Here, value is quantified in terms of a dollar amount and is used as a measure of system “success”. The framework provides a methodology that allows designs to be directly compared using value. VDD can be used in two different capacities depending on how much input the designer wants within the design cycle.

The first way is to use VDD is as a “black box”, where the value model is coded into a computer and an optimization algorithm is used to find the design with the highest possible value. This method of operation is feasible when the system being discussed can be modeled effectively with short simulation times. However, this approach may not be effective when system complexity demands simulations that take hours or days to complete. If the system in consideration is a complex system, VDD can be used as an intermediary step in the design process.

When VDD is used as an intermediary step, simulations of the complex system are used to estimate performance characteristics. These performances are then used to calculate system value. Local value derivatives can then be taken with respect to the different performance attributes to find the local gradient of the value. The local value gradient information allows designers to know which performance attributes to focus on in their next design iteration. Design engineers and corporations also prefer the iteration method because the design is not completely decided by the computer algorithm.

The second manner in which VDD can be used is for calculating the worth of a new technology [13]. When a new technology is created, it usually comes with the claim that it will either improve performance or cut costs. The value calculation with a new technology will show the exact amount of improvement in value across each of the performance attributes as well as the total system value. Knowing the exact increase in value the system shows allows the designer to see the merit of using the new technology.

1.3.1 Value Models

In order for a designer to use the VDD framework to improve the design of a system, a value model must be created for the system. In VDD, the value model is typically created in a hierarchical design process as shown in Figure 1.2. The figure shows a possible hierarchy for the design of an aircraft. The total value model for the system is the accumulation of the value of the different subsystems, which is found using the relevant performance attributes.

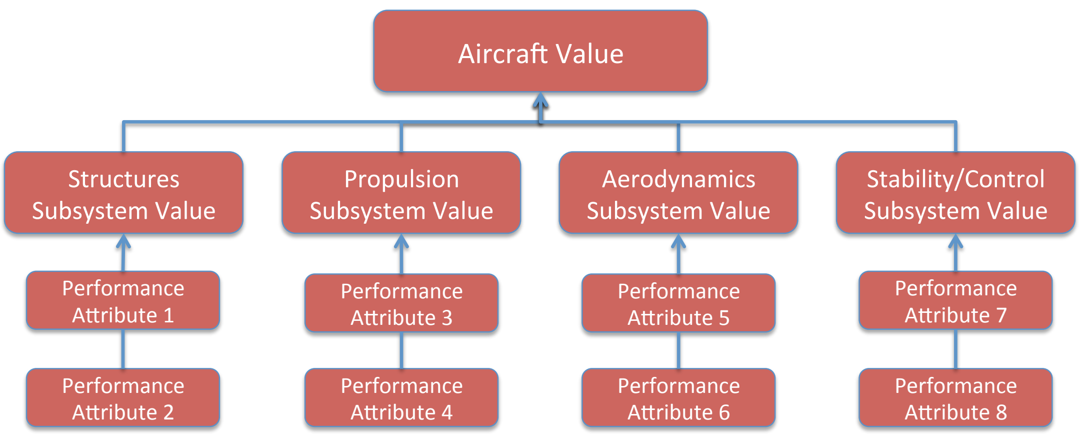


Figure 1.2: Aircraft Value Model Hierarchy

A value model is the accumulation of the preferences for performance of the system without the use of hard line requirements. In this context, preferences are viewed as an aggregation structure for the different subsystems and performance attributes. The preferences for the value model are compiled from the lead designer, board of directors of the company, the client who is purchasing the system, and economic data. Due to the complex nature of value models, there is inherently some uncertainty. This becomes clear when looking at the hierarchy in Figure 1.2. The interaction of the subsystem value functions can be difficult to correctly model and is a source of uncertainty in the value model. A second source of uncertainty in the value model is in the individual performance attribute value functions.

1.3.2 Value Functions

Value functions are the equations that translate the performance of the system in certain attributes to gained value in dollars. The designer or design team in charge of creating the system creates the value functions for each of the performance attributes of interest. An example of a performance attribute is the range of an airplane. Aircraft range is a performance attribute that would typically fall under the aerodynamics subsystem in Figure 1.2 in Section 1.3.1. The value function for range would map the possible travel distance to value in monetary terms. This value would then be combined with the value from the other aerodynamics performance attributes to find the subsystem value.

$$Value_{aerodynamics} = f(range, endurance, Lift, Drag, etc.) \quad (1.1)$$

The total system value is then found by combining the subsystem values within the preference structure.

$$System\ Value = f(\ V_{structures}, V_{propulsion}, V_{aero}, V_{stability}) \quad (1.2)$$

In current practice, the range of the aircraft would be given as a set minimum requirement. Using a value function allows the designer to potentially see that even though the airplane design may have slightly less range than the requirement, the costs go down, which increases the overall system value.

To create a value function for a performance attribute, the general tendency of the attributes worth must be known as a starting point. For the example of airplane range, it might be known that an increase in range will increase the value of the plane in dollars. This can be easily explained by the ability of the aircraft to carry a payload further without having to refuel. A plane that can go further without refueling has a higher value in dollars. Similar examples can be found for performance attributes where the value in dollars increases as the attribute decreases or one where a certain nominal performance holds the highest value in dollars [14]. Value functions can also be applied to a non-continuous performance space. Examples of this include the ability to map value in dollars to different color patterns or materials. Color may not be considered a normal performance attribute, but studies have shown that color can have a very large effect on people's willingness to buy a system [15].

1.4 Research Questions

If value driven design is going to be used in industry to help designers it must be proven to be a reliable tool that can help designers make decisions. An important characteristic of any design framework is that the same design will be produced given the same inputs [16]. Repeatability and robustness are important because they give a designer faith in his decisions if he knows that someone else will get the same results. This is also true for an optimum design being similar if small changes are made to the value model.

1.4.1 Research Question 1

How sensitive is the solution from a Value Driven Design analysis, and how predictable are expected changes when changes are made to the underlying value models?

In Sections 1.2 and 1.3, the importance of value functions in VDD and the difficulty in setting up the correct functions were described. As a designer progresses through the design process, new information is constantly being presented. This new information can be updates in customer preference or changes to the design mandated within the company itself, and can lead to different value models than the one the designer started with. It is expected that changes to the value model will cause a change in the optimum solution.

Value model uncertainty can exist in two different locations: either in the value function or in the aggregation of the different value models. If the presence of uncertainty impacts the optimum solution, it becomes important to understand the magnitude of the impact and if the change can be predicted.. If a designer knows they have to make a change to the value model, the ability to predict the change in optimum solution without rerunning the simulation would be beneficial. It is expected that general trends in the change of the design will be predictable, but not the exact degree of change. This is expected due to the complex nature of the value model, and its interaction with the system model. Along with exploring how the optimum solution is affected by uncertainty in the value model, it is also important to figure out possible methods of making sound design decisions when faced with uncertainty.

1.4.2 Research Question 2

When faced with uncertainty in the value model, how might the best design – or set of best designs – be determined?

The objective of VDD is to find the best system design. When the value model is known, the criteria for finding the optimum design is that the highest value always wins. When uncertainty is introduced into the value model, each design can have a wide variety of value scores. This research question is designed to explore if there is a way to design the system such that it can overcome uncertainty in the value models. Therefore, it is hypothesized that the mean value and the standard deviation in value of a design will be valuable metrics for finding the optimum design under uncertainty in the value model.

1.5 Thesis Preview

The questions in Section 1.4 will be investigated in the five chapters of this thesis. Chapter 1 gives an introduction to Value Driven Design and the motivation behind the research. Chapter 2 presents background information on decision making in engineering, research in VDD, and designing under uncertainty. Chapter 3 and Chapter 4 investigate the research questions and how to answer them. Chapter 3 explores the first research question while Chapter 4 explores the second research question. Chapters 3 and 4 are broken down into subsections detailing the methodology for answering the research questions and the case studies used to test the methodologies. Chapter 5 concludes the thesis with a summary of the results and ideas for future related work.

Chapter 2: Background

2.1 Precursors to Value Driven Design

As stated in the previous chapter, the research questions asked in this thesis are based around the framework of Value Driven Design. Previous work in VDD has focused on the creation of the framework and its application to different systems. Value driven design has grown from the desire to have a single objective function for a design team to optimize. Proponents of VDD believe that using a single objective function allows designers to focus on making the correct design decision, and stems from earlier work in economics and decision theory. Economists such as Debreu [17] stated that when presented with a choice, the best decision is always the one with the best possible outcome. This is not directly applicable to design however, as the outcomes are usually unknown or presented as probabilities. Work by Von Neumann [18] attempted to overcome the uncertainty in design by using utility lotteries and choosing the solution that presented the probability of largest overall utility.

Herbert Simon [19] presented the idea that designers should find the optimum value for a design, but due to computational limits believed that it was advantageous to find a less optimum design that is easier to obtain. Simon's idea is known as "satisficing" [20] and is based on the idea that a designer should try to meet an acceptability threshold that may be suboptimal. In 1977, Andrew Sage [21] built upon work performed by Keeney and Raiffa [22], exploring decision making in large scale system design. In an effort to find optimum designs faced in complicated, multi-discipline system design, the field of Multi-discipline

Design Optimization (MDO) was formed. Work by Sobieski on integrating engineering modeling codes into optimization structures [23] opened up the field. Cramer's [24] work in the field focused on how to properly set up multi-discipline engineering problems. George Hazelrigg [11] proposed a framework for decision making in engineering design that focuses on a single design objective. Hazelrigg's proposal is known as Decision Based Design (DBD), and is very similar in nature to VDD. Decision based design is presented as a method for bringing together information and presenting it in a method to help make design decisions.

Around the same time VDD was being presented by Collopy [5] and others, work on Value Based Software Engineering (VBSE) was being done by Biffl et. al. [25]. VBSE is very similar to VDD in that it focuses on making rational decisions in design, with the focus on software rather than solid systems. After presenting VDD, Collopy continued research on the subject, with others joining in the challenges of testing and using VDD on different design problems.

2.2 Research in Value Driven Design

Research in the field of VDD has focused on framework implementation and application to various design problems. After presenting the notion of VDD, Collopy then showed how the objective functions could be created using economic-based distributed design [1]. This led to the requirement of objective functions being ordinal and capable of satisfying order and transitivity properties. Potential measures of value were also presented: surplus value, net present value, and reservation price.

One of the potential objectives, surplus value, has been used in finding the optimum bypass ratio for a commercial plane [27]. Other work by Collopy has shown how VDD could have saved the government $50 billion on the Joint Strike Fighter program [28]. In 2006, the AIAA Value Driven Design committee held a workshop with the goal of applying VDD to a government style program [29]. A value model was created for a Global Positioning System (GPS), using the American people as the main benefactors of a GPS. This case study showed how the process of creating a value model is carried out. Recent efforts have also focused on how value can be used to drive the behavior of autonomous agents. Shapiro presents aligning agent objective functions with the human user's utility in order to create agents that more reliably act as the user intended [30].

The inclusion of costs in a value model makes estimating part cost important in VDD. Collopy and Eames present a new method for costing parts in aerospace systems based on the quantity of information required to accurately make the part as opposed to older methods based on mass or manufacturing [31]. A full review of approaches for cost modeling in the aerospace field was performed by Curran et al. [32] by exploring contemporary cost modeling strategies and presenting a consolidating approach called the genetic causal approach. Technology development was explored by Hong who explored the management of new technologies [33]. This research reviewed the manners in which programs for technology development were set up in order to find the successful styles.

Brown and Eremenko have proposed using a fractionalized approach to creating space systems in order to increase system flexibility [34]. The idea behind the approach is to allow the designs to adapt to uncertainty by designing the components as separate communicating modules. A proposed method of implementing the fractionated approach is to use a value based approach [35-37]. This approach allows for the flexibility of the fractionated approach to be accounted for in the value model. This is significant, as Collopy has also argued that prescribing requirements to extensive attributes, such as weight or efficiency, severely limits the design possibilities [38].

Variations on VDD have also explored model creation for evaluating technology for the Federal Aviation Administration (FAA) [39]. The models created in this work are very similar to value models. Variations in metrics have also been proposed, such as probability of success [40]. This metric is presented to replace the popular metric of 'cost per kill' for military systems that has been used for fifty years.

Applications of VDD toward aircraft have included aircraft fuselage panels [41], medium range commercial aircraft [42]., engine maintenance scheduling [43], and aero-engines [46]. VDD was applied to two components of an aero-engine, the turbine entry temperature and the turbine blade material. The results of the study show how when Surplus Value Theory is applied to VDD it leads to designs that increase profit.

In 2009, Collopy reviewed different types of value models used in industry for design optimization [16]. The work surveys and critiques some of the widely used tools for value modeling such as Quality Function Deployment (QFD), Pugh matrices, and the Analytical Hierarchy Process (AHP). The work also lays out guidelines for building a value model, listing the steps out in order. This has also led to discussions about the differences between Value-Centric Analysis and Value Centric Design [44], and how different architectures can lead to different values [45]. This work found that larger multi-mission spacecraft were fractionated into smaller simpler single mission spacecraft.

Finally, Collopy and Poleacovschi have taken the first steps in validating VDD by setting up a program with the goal of creating a fully functioning design system complete with simulated thinkers and design teams [47]. The continued work on this software will allow testers to see the effects of designers changing opinions and the flow of information between design teams and individual members during large-scale system design. This current work also looks at validating VDD, on a simplified scale, by looking at the effects of uncertainty within the value model.

2.3 Decision Making and Uncertainty in Design

Uncertainty is present throughout the entire design process. It can be found in consumer preferences, designer preferences, and simulation models. Aleatory uncertainty, or irreducible uncertainty, exists in real systems because it is inherent to the process [48]. The effects of uncertainty on design and methods of coping with variability have been researched using contemporary design frameworks [49], [50]. The reason for understanding uncertainty stems from a designer's need to make a decision when presented with incomplete information.

Decision-making is done in one of two ways, deterministically or non-deterministically. The deterministic methods such as Simple Multi-Attribute Rating Technique (SMART) [51] and value theory [52], [53] provide a way to make decisions assuming there is no uncertainty in the model or preferences. Uncertainty is inherent in design however, due to incomplete information or inadequate understanding. Decision-making under uncertainty has been studied in engineering design for many years beginning with von Neumann's [18] utility theory. Utility theory and the axioms laid out by von Neumann are the building block for many of the ideas and research in the field. Research in utility theory has led to the establishment of a single attribute utility theory (SAU) and a multi-attribute utility theory (MAU) for decision-making.

Research on uncertainty in design has focused on uncertainty existing in either the performance of the design or the state variables that define the design. Thurston and Liu explored uncertainty in multi-attribute utility theory by using beta distributions as probability density functions. The beta distributions were applied to performance attributes to observe the effect of attribute uncertainty on the desirability of alternatives [54]. Other work by Martin and Simpson presents a method for managing uncertainty during the system-level conceptual design [55]. The method proposes using Monte-Carlo simulation with the help of kriging model surrogates to introduce uncertainty in the design model inputs. Work has also been done uncertainty in decision-based design. Gurnani and Lewis created the overlap measure method by integrating over the utility function and the probability density function [56]. The overlap measure method allows designer to deal with uncertainty in many multi-attribute decision making methods.

Customer preferences and their uncertainty also play a very important role in decision making for a designer. Luo et al. have proposed a methodology for designing robust systems under consumer preference variability [57]. The proposed method uses a choice-based conjoint analysis to elicit customer preferences and then explore their variability by looking at the variance and covariance in the responses. The variance is then incorporated into the design to find robust designs.

Limitations to the existing body of research are efforts exploring uncertainty in the models being used to rate the system. These include utility functions and value models. Pundits would argue that if there is uncertainty in the objective functions being used, then the problem is not understood well enough. This may be the case, but unfortunately in industry design decisions still need to be made even if there is not a complete understanding.

Chapter 3: Solution Variability In Value Driven Design

3.1 Motivation

Value Driven Design is used as a tool to help engineers make decisions when designing complex systems. As noted in 1.4.1, the selection of a value model and value function is not an arbitrary part of the process. The value model and value functions will decide which designs are ranked higher than others, and so must be chosen correctly. The motivation for this chapter is to test how much solution variability exists for a system based on changing value functions and value models. Exploring the degree of variation between optimum solutions for a system will give insight into the solution sensitivity of VDD analysis. The solution sensitivity of a design framework is important, because it allows the designer to know the level of confidence with which they can present results. In decision based design and VDD literature it is usually assumed that the preference structure and value or utility functions are known. This is a required assumption for research focusing on the design of a particular system. However in this work, the focus is on seeing how different, but similar value models affect the outcome of the design process. This will give insight into how important the accuracy of the value model is.

3.2 General Methodology

In this section, the general methodology used to find the effect of varying value models is detailed. A flow chart of the general methodology is shown in Figure 3.1. The method shown in Figure 3.1 is applied to two different case studies in later sections. The first is the design of a pressure vessel (propane tank), which is a problem with two performance attributes and the second is a model rocket, which is a more complex problem consisting of four performance attributes.

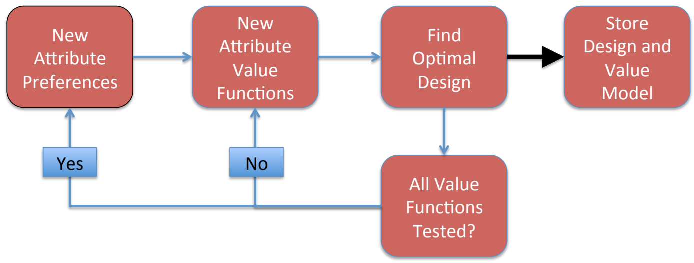


Figure 3.1: Methodology Flow Chart

3.2.1 Creating the Value Model and Value Functions

The framework for decision-making set forth by value driven design is motivated by the value model and value functions. The value model and value functions are based on economic data and designer preferences known about the system and its performance. This requires knowledge about the performance attributes of the system and their effect on the amount of dollars a system is worth. In this work, the value functions will be set up in a standardized format to allow for a better understanding of the effects of either the model preferences or value functions being altered. Here a standardized format means that the value functions are created using the same minimum and maximum value. The differences between the value functions exist in how the performance attribute range maps to the set value range.

3.2.2 Value Function Types

Value functions are used in VDD to relate the performance of a system into a value score. The value score shows how much monetary value (dollars) the performance in a particular attribute is worth. With the use of a value function, the designer does not have a set limit, or requirement, for a particular attribute. The designer has the ability to choose a design that might be removed if strict requirements were set because the ability to lower the performance in one attribute allows a large gain in another, ultimately leading to a higher overall value for the system. In this research, four different types of value functions were used, which are detailed in Sections 3.2.2.1 – 3.2.2.4.

3.2.2.1 More is Better Function

A performance attribute can be considered "more is better" if it is known that an increase in the attribute is better. There are multiple ways that the function can be formed, but the general relationship must show an increase in performance leading to an increase in value. A couple examples of attributes related to aircraft design that follow "more is better" are the range (max travel distance) and the endurance (max time aloft). The figure below shows three examples of how a value function that falls under "more is better" could be presented.

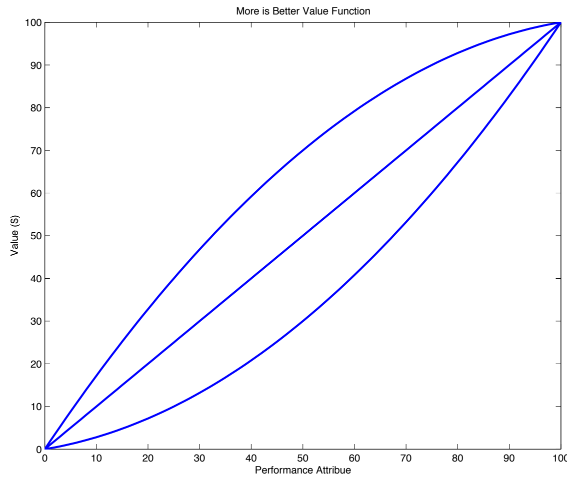


Figure 3.2: More is Better Value Function

As Figure 3.2 shows, the "more is better" curve can be expressed in a multitude of ways, as long as it follows the general trend needed. The different curves represent different preferences a designer might have within a given performance attribute.

3.2.2.2 Less is Better Function

A second general trend for a performance attribute is one in which "less is better". In this case, a lower attribute score is considered better than a higher attribute score. Examples of "less is better" for an aircraft are weight and take off distance. Figure 3.3 below shows examples of some potential forms for "less is better".

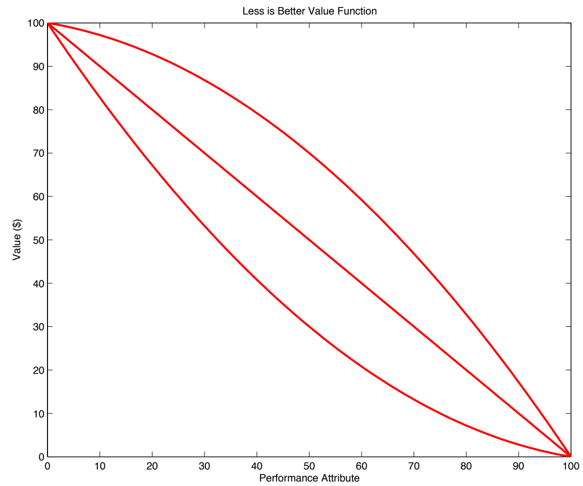


Figure 3.3: Less is Better Value Function

Similar to Section 3.2.2.1, the "less is better" trend can be expressed in a multitude of ways, varying in nature to meet the designer's preferences across a specific performance attribute. The general trend is that these value functions must have a negative slope across the performance space for an attribute.

3.2.2.3 Nominal is Better Function

The third type of value function can is set up so that a nominal value is better than any alternative. In this case, a particular score for a performance attribute is valued higher than the rest. The trend generally shows a positive slope before the nominal value, and then a change in slope sign to negative above the nominal value. An example of a "nominal is better" attribute in aircraft design is certain stability derivatives. The stability derivative needs to be very close to a certain nominal score, with scores lower or higher than this nominal score being worse. Figure 3.4 below shows some of the possible ways that a "nominal is better" attribute curve can look.

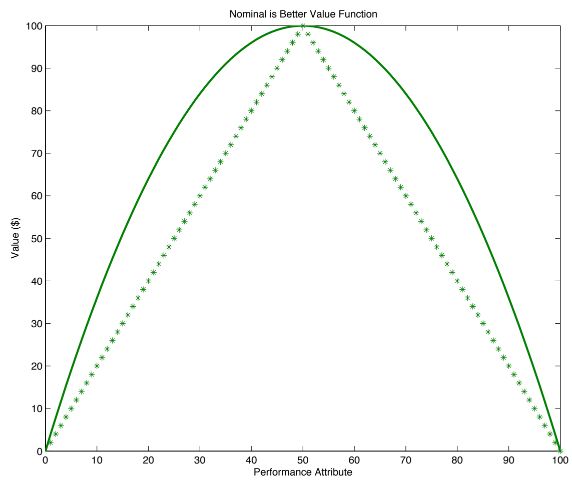


Figure 3.4: Nominal is Better Value Function

3.2.2.4 Piece Wise Function

The fourth type of value function is a piece wise function, which can be set up to meet the needs of a designer when none of the other methods can correctly convey the value of an attribute. The piece wise function can also be used to show the value for discrete attributes, such as color. Figure 3.5 below shows an example value function for a discrete performance attribute.

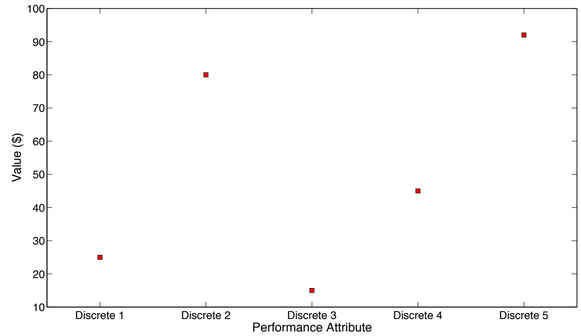


Figure 3.5: Piece Wise Value Function

3.2.3 Value Model Types

The value model consists of the combination of all of the value functions for a given system. A system can consist of multiple different disciplines working together such as aerodynamics, propulsion, and structures within the development of an aircraft. The value model sets up the connections between the different disciplines and is where the designer can apply preference for certain performance attributes over another. The method of combination is chosen by the designer to create the most accurate portrayal of the systems system. In this work a weighted sum approach is used to combine the value functions. The weighted sum approach allows all of the value functions to interact with each other as the case studies shed complexity to avoid different teams working on different disciplines.

Typically VDD is done without using weights in the summation. The importance of one attribute over another is contained within the value functions based on the possible range of the value. In this work the focus is not on creating and solving a real world problem, but rather an assessment of uncertainty in VDD. The assumption in this work of using standardized value functions and weights creates the same effect as having value functions with different ranges. The weights serve the function of changing the scale of one performance attribute to another, which is effectively the same as changing the range of the value.

The basic equation that governs VDD is the following,

$$Value(\$) = Utility(\$) - Costs(\$) \tag{3.1}$$

In the case of the weighted sum approach, the equation becomes,

$$Value_{system}(\$) = \sum_{i=1}^{j}[W_i * Utility_i\,(X) - Costs_i(X)] \tag{3.2}$$

Where there are J performance attributes, X is the system design, and W is the weighting preference for that attribute. The entire weighting preference for the model is called the aggregation structure. The equation allows the utility (in dollars) and the costs for each subsystem to be aggregated into the overall system value.

3.2.4 Testing Procedure

The testing procedure used in this chapter is designed around the concept of a sensitivity study to explore how changes to the underlying value model alter the optimum solution. This study is designed to address research question 1. The testing procedure is broken down into two different sections. The reason for this is to separately test the effects of using different value functions and different aggregation structures. The reason for testing the effects separately is that it shows how each one individually impacts the optimum solution as opposed to a combination of the multiple changes. The first step in the procedure is to identify the important performance attributes that will be used for the study, followed by testing the different value functions and aggregation structure.

3.2.4.1 Using Different Value Functions

1. Create a value function for each of the performance attributes.
2. Create a testing matrix for how the individual value functions will be combined in the value model.
3. Use an aggregation structure that gives equal weighting to each of the performance attributes.
4. Find the optimum designs for each of the combinations of value functions created in the testing matrix.
5. Compare the optimum designs in performance space.

3.2.4.2 Using Different Preference Structures

1. Select a standard or baseline value function for each of the performance attributes. These value functions will be used as the preference structure is altered.
2. Create a method for altering the aggregation structure ensuring the weighting preferences add up to 100%.
3. Find the optimum designs for each of the combinations of preference weighting structures
4. Compare the optimum design in performance space.

3.3 Case Studies

In order to test out the solution variability within VDD, two case studies were performed. In each of these case studies, the value models and value functions were created to test a subset of the entire range of possibilities. The first case study is a pressure vessel with two performance attributes and the second case study is a model rocket with four performance attributes. The purpose of this is to find out how large of an effect individual value functions and the value model can have on the optimum design output within a VDD framework. The goal is to determine how important it is to get the value model and value function correct when using VDD. The results from the case studies will give an understanding of whether it is of vital importance to get the value model and value functions correct, or if VDD is robust enough to allow for just getting the trend of the model and functions correct. The results will also indicate whether it is possible to extrapolate certain design trends, allowing a designer to make educated guesses about the response to a value model or function change.

3.3.1 Pressure Vessel: Propane Tank

The first selected case study is a pressure vessel, and specifically a propane tank designed for use on a home grill. The propane tank is being designed within the VDD framework with two performance attributes, volume and weight. The propane tank uses three design variables, thickness, inner radius, and length of cylindrical section. The propane tank model is a pressure vessel with 2:1 elliptical end caps, which is industry standard.

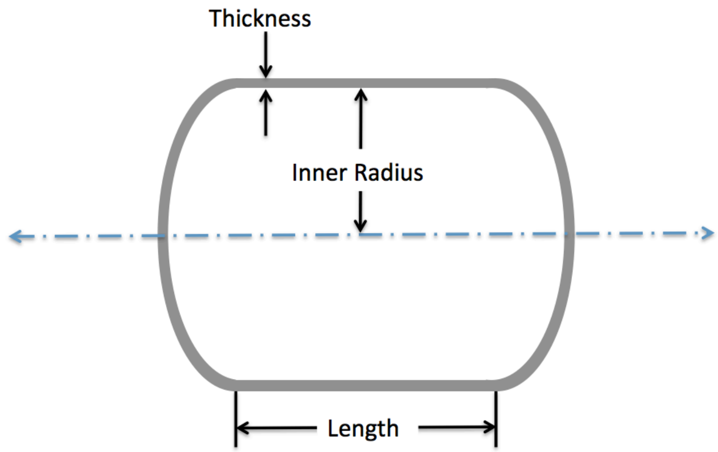


Figure 3.6: Pressure Vessel Model

The following table and equations show the variables and constants used in the propane tank case study. The equations that govern the weight and volume of a 2:1 elliptical end cap pressure vessel are from [58].

Table 3.1: Propane Tank Variables

Variables	Description
Weight	Total Weight of Propane Tank
Vol	Volume of Propane
IR	Inner Radius
T	Material Thickness
L	Length of Cylindrical Section
OR	Outer Radius
$\rho_{steel} = 0.283\ lbs/inches^3$	Steel Density
$\rho_{propane} = 4.22\ lbs/gal$	Propane Density
$Cost_{steel} = 0.25\ dollars/lb$	Steel Cost
$Cost_{propane} = 3.013\ dollars/gal$	Propane Cost

$$Vol = \frac{\pi(2*IR)^3}{12} + \pi IR^2 L \qquad (3.3)$$

$$EmptyWeight = \left[\frac{\pi(2*OR)^3}{12} + \pi * OR^2 * L - Vol\right] * \rho_{steel} \quad (3.4)$$

$$FullWeight = EmptyWeight + Vol_{gallons} * \rho_{propane} \quad (3.5)$$

$$Value(\$) = W_{vol} * Value_{vol}(\$) + W_{weight} * Value_{weight}(\$) - Cost(\$) \quad (3.6)$$

The value functions show the utility in dollars (value) for each of the performance attributes. They were created using expected performance for a typical personal use propane tank. The first performance attribute, volume is a “more is better” type of attribute, because a consumer will choose a design that has more propane with everything else being equal. The volume range used in the value function is from 0 gallons to 10 gallons. Current standard propane tanks for personal grill use are 4.7 gallons. In order to simplify the functions for ease of comparison, the value range was set to 0 dollars for 0 gallons and 100 dollars for 10 gallons.

The range for the gallons of propane in the tank was chosen based on the minimum weight required to produce a tank that would hold the propane without rupturing. At 10 gallons, the minimum tank weight was 80 lbs., which was chosen to be the maximum reasonable weight. The range used does have an effect on the outcome of the study though, as the range controls where along the value scale the typical designs fall. Ten value functions were created for the volume performance attribute and are shown in Figure 3.7 below. The ten equations used for the value functions can be found in Appendix A.

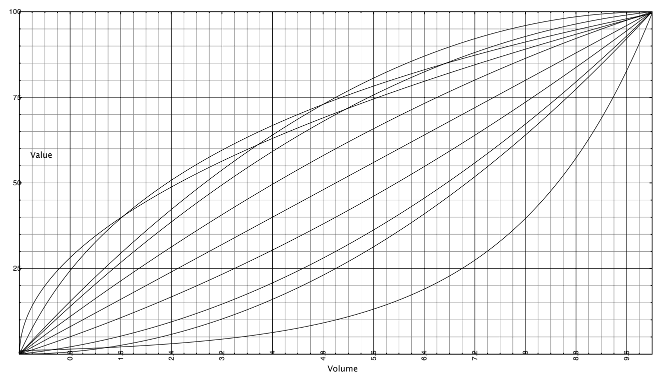


Figure 3.7: Volume Value ($) Functions

The second performance attribute for the propane tank is the total weight, including the weight of the propane. Weight is a “less is better” performance attribute so the functions chosen represent this trend. The weights used to create the value function are based on the minimum weight required to satisfy the upper and lower bounds of the volume performance attribute. The upper bound was also tested to be a reasonable weight for someone to pick up and possibly use. The value range was set to 0 dollars for a tank weighting 80 pounds and 100 dollars for a tank weighing 0 pounds. The value functions for weight can be seen in the following figure with the equations being found in Appendix A.

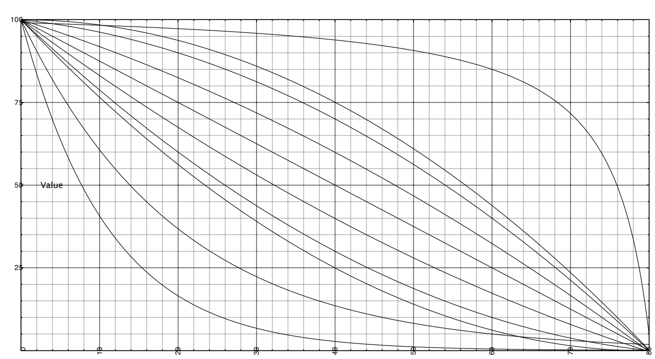


Figure 3.8: Weight Value ($) Functions

3.3.1.1 Value Function Manipulation

Using different combinations of the value functions together tests the solution variability of the optimum design in VDD. The first part of VDD that is necessary to look at is how large of an effect differing value functions has on the optimum design. Ten value functions were created for each of the performance attributes, volume and weight. For the simulation, the weight and volume performance attributes were given equal preference in the aggregation structure. The simulation was run with each of the ten value functions for volume being matched with each of the ten value functions for weight. This gave a total of one hundred optimal designs spread across the design space. This was done to find out how many possible optimal designs there were and where they exist within the design space.

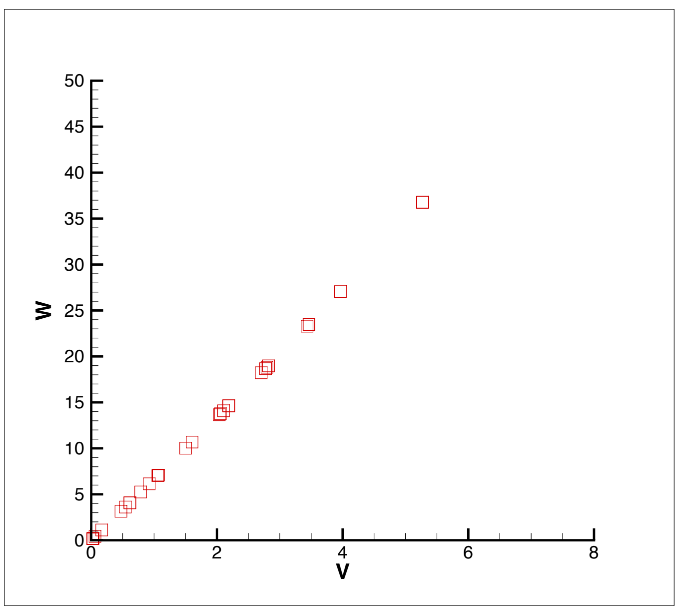


Figure 3.9: Optimal Designs in Weight (lbs.) and Volume (gal.) for Value Function Manipulation

The figure shows that there are a large number of different optimum designs possible as the different value functions are used in the optimization. It is important to note that certain designs appear more often than others. These designs are noted by the boldness of the squares representing them. It is also interesting that designs follow a pretty linear pattern in the performance space. The optimum designs represent the technology possible frontier of best possible designs. The “perfect design” exists at the bottom right of the plot, having high volume and low weight. However, due to the limitations placed on the problem not allowing designs that will rupture, the best designs exist on this frontier. The designs, while varied due not fill out the entire region between the lower left design and the upper right design. The plot shows only 21 different distinct designs, whereas the simulation found optimum designs for 100 different value function combinations.

To understand how the individual value function combinations influenced the optimum design, the value functions were broken down as risk averse, risk neutral, or risk prone for each of the performance attributes. Figure 3.10 shows the difference between the different risk profiles that will be referenced from here on. The figure is for an attribute where more is better.

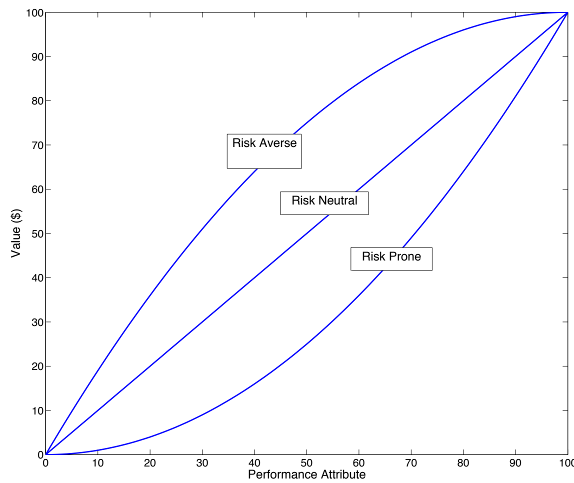


Figure 3.10: Risk Profiles

In order to group the different risk profiles for the two performance attributes (weight and volume) nine different designer types were created. The different designer types show how the different value functions for each of the performance attributes affect the optimum design. Table 3.2 below shows the breakdown for the nine different designer types.

Table 3.2: Designer Types

Designer Type	Volume Function Risk Type	Weight Function Risk Type
1	Neutral	Neutral
2	Neutral	Averse
3	Neutral	Prone
4	Prone	Neutral
5	Prone	Averse
6	Prone	Prone
7	Averse	Neutral
8	Averse	Averse
9	Averse	Prone

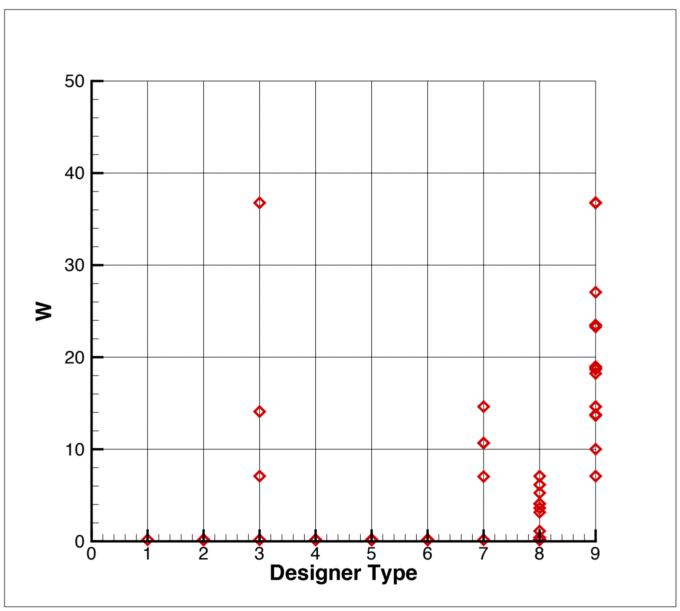


Figure 3.11: Designer Type Effect on Weight (lbs.)

Figure 3.11 shows how the different designer types affect the weight of the optimum design. As the figure shows, five of the designer types have all of their designs located at the zero weight point. The reason for this is due to the nature of the problem formulation, specifically the maximum value being normalized to $100 for each of the performance attributes. In this pressure vessel problem the cost is derived from the weight, thereby giving extra incentive to drive the vessel toward a zero weight solution. For example, designer type one is neutral for each of the performance attributes, using a linear value function. Since the model aggregates each of the performance attributes equally in this problem, the value formula becomes.

$$Value(\$) = 0.5 * \left(Value_{weight} + Value_{volume}\right) - Costs \tag{3.7}$$

Other interesting parts of this figure to note are the designer types that have a wide variety of weights for the optimum designs. Designer type three is risk neutral in volume and risk prone in weight. The risk prone weight encompasses the functions below the linear function. This means the designer is neutral towards the volume but the does not feel that there is much value until the weight is very low. This set up leads to some designs that are not located at the zero weight point, including the design with the highest overall volume found for this study. The designer type that leads to all of the designs located above the zero weight point are designer type nine. This designer type is risk averse in volume and risk prone in weight. For this designer, having a larger than average volume is very important, while he doesn't attribute much value to designs unless they are low in weight. This leads to a large range of designs that range from 6 lbs. up to 37 lbs. The next important idea to look at is how the aggregation structure of the two performance attributes affects the optimal design.

3.3.1.2 Value Model Aggregation Structure Manipulation

The next important item to explore in VDD is how much of an effect changing the aggregation structure can have on the optimal design. Changing the aggregation structure allows the designer to change the scaling of each individual value function so that one becomes more important than the other. For this study, a linear value function was used for both of the performance attributes. The use of linear value functions for this study is an arbitrary decision, and could be replaced by numerous other function forms.

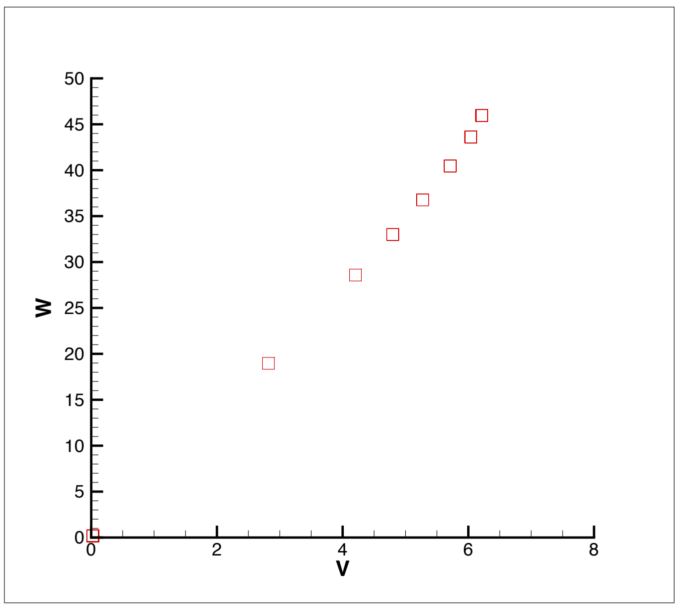


Figure 3.12: Optimal Designs in Weight (lbs.) and Volume (gal.) for Aggregation Structure Manipulation

This figure shows the optimum designs, in performance space, found when the aggregation model was altered. Similar to the study altering the value functions, there are multiple optimum designs found when the relationship between the value functions is changes. However, there is a much larger distinction between the designs in the design space, and a lower number of unique optimum designs. As Figure 3.12 shows, there are only 8 unique designs compared to the 21 unique designs found by altering the value functions. This occurs because there is only one value function being used for each of the performance attributes, which does not allow for as much nuance between designs with slightly difference performance. As the Figure 3.13 shows, there are a large number of designs at essentially the 0 weight, 0 volume location.

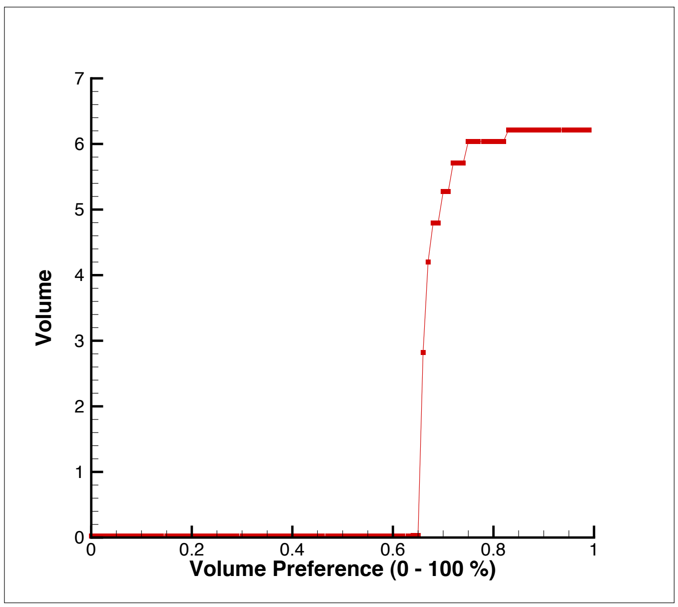


Figure 3.13: Volume (gal.) Preference Effect on Optimum Design

Figure 3.13 further shows that the optimum design stays at the zero point until the weight applied to the volume function becomes greater than 65%. This was found to occur due to the inclusion of cost in VDD and the manner in which it was implemented in this case study. Recall that the cost was a function of the amount of material used, which becomes a scaled restatement of the weight. It is believed that this problem is case specific as the weight is given double the importance in the value model.

3.3.2 Model Rocket

In the second case study a more complicated problem was chosen involving the design of a model rocket. The idea behind this problem is to make a rocket with the highest overall value using a set rocket motor. The rocket design is based on the ability to change eleven variables, altering the shape and materials of the different rocket parts. The rocket was broken down into three main components: nose cone, tube body, and fins. Simplifying assumptions made to ease the computation time were that the nose is a cone, the tube body is the same diameter as the nose cone, and the fins are rectangular in shape with a rounded front edge. The rocket variables are shown in Table 3.3.

Table 3.3: Model Rocket Variables

Variable	Description
X-1	Rocket Diameter
X-2	Nose Cone Length
X-3	Nose Cone Thickness
X-4	Nose Cone Material
X-5	Tube Body Length
X-6	Tube Body Thickness
X-7	Tube Body Material
X-8	Fins Chord Length
X-9	Fins Height
X-10	Fins Thickness
X-11	Fins Material

The performance attributes identified for the rocket are the height at apogee, the flight duration to ground, non-dimensional stability of the rocket, and payload size. Ranges for the value functions were found using a genetic algorithm (GA) to optimize each of the individual performance attributes. The first performance attribute is height at apogee and was found to be a maximum at 1000 meters. The maximum for flight duration was found to be 240 seconds. Stability is a “nominal is better” performance attribute with the goal being a stability rating between 1-2, with 2 being optimum.

This study uses twenty-one designs and rank ordering instead of optimizing the design for each value model like the pressure vessel case study. The reason for this is to demonstrate the other application of VDD - as a rank ordering or concept selection method. The goal was to find out if uncertainty in the value model would influence concept selection. The designs vary based on their focus of optimizing one or two of the performance attributes, or by focusing on a balanced rocket design. The designs were also created so that they would encompass a full swath of possible designs ranging from poor designs to high performance designs. This was done to test the affect on concept selection not only for the high-end designs but also the lower-end designs. The design specifications, and an image of the twenty-one designs can be seen in Appendix B.

3.3.2.1 Value Function Uncertainty

In this section, the effect of differing value functions is observed by looking at the rank ordering of the twenty-one designs when exposed to different value functions. Design performance was simulated using OpenRocket [59] to find the height at apogee, flight duration, and stability number. The payload size was found by using the largest possible payload that would fit in the rocket. The initial tests were completed with equal weighting on the value preference model, with each of the performance attributes being worth twenty five percent of the total value. The value function uncertainty was tested one performance attribute at a time, which allowed the rank ordering changes to be seen with respect to each value function. The value functions and the rank ordering results for each of the performance attributes can be seen in the following figures and tables.

The first performance attribute, height at apogee, is a "more is better" performance attribute. The value functions for this attribute were created by bounding the minimum and maximum heights at \$0 and \$100 respectively. The value of the median height was then allowed to change, with the functions found using 2^{nd} order polynomial fit. Figure 3.14 is a plot of the value functions that were used in the study for the height at apogee performance attribute. The curves represent a distribution of possible functions by varying the value of the middle height from 25 up to 75 by increments of 5. The procedure was to use each of these curves for the height at apogee attribute, and use set linear curves for the other attributes.

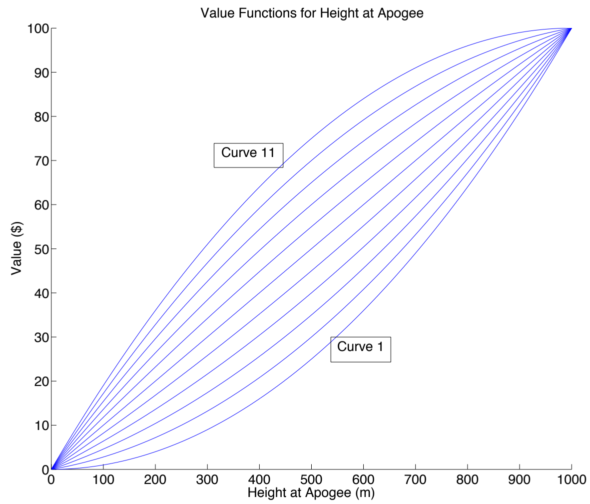


Figure 3.14: Value Functions for Height at Apogee

After calculating the total value of each of the rockets, they were rank ordered listing the highest value at the top down to the lowest value at the bottom. The rank ordered list is shown in Table 3.4 below.

Table 3.4: Rank Ordering for Height Value Function

<table>
<tr><th>Curve 1</th><th>Curve 2</th><th>Curve 3</th><th>Curve 4</th><th>Curve 5</th><th>Curve 6</th><th>Curve 7</th><th>Curve 8</th><th>Curve 9</th><th>Curve 10</th><th>Curve 11</th></tr>
<tr><td colspan="11">20</td></tr>
<tr><td colspan="11">21</td></tr>
<tr><td colspan="11">19</td></tr>
<tr><td colspan="11">15</td></tr>
<tr><td colspan="11">18</td></tr>
<tr><td colspan="11">5</td></tr>
<tr><td colspan="3">12</td><td colspan="8">6</td></tr>
<tr><td colspan="3">6</td><td colspan="8">12</td></tr>
<tr><td colspan="11">14</td></tr>
<tr><td colspan="11">8</td></tr>
<tr><td>10</td><td colspan="10">1</td></tr>
<tr><td>1</td><td colspan="10">10</td></tr>
<tr><td colspan="11">9</td></tr>
<tr><td colspan="11">11</td></tr>
<tr><td colspan="11">4</td></tr>
<tr><td colspan="11">13</td></tr>
<tr><td colspan="11">7</td></tr>
<tr><td colspan="11">16</td></tr>
<tr><td colspan="11">2</td></tr>
<tr><td colspan="11">17</td></tr>
<tr><td colspan="11">3</td></tr>
</table>

Table 3.4 shows that the rank ordering is largely unaffected by the different value functions. The first six rockets are the same regardless of which value function was used. There are two order changes that happen in this study. The first order change occurs between rockets 6 and 12. Rocket 12 has a higher value with the first 3 curves, and rocket 6 has the higher value for every curve after. Rocket 12 has a higher height at apogee, which is why it ranks higher for the first three curves. In these curves the amount of value given to higher-flying rockets is much larger compared to the curves that occur above the linear curve. In curve 1 the designer is saying that a design is only good if it has a very high height at apogee, whereas in curve 11 the designer is saying that a design is good as long as it doesn't have a very low height at apogee. The curves in between bridge the gap between these two

extremes. The second order change happens between rockets 1 and 10. For the first curve, rocket 10 has a higher value, but for the rest of the curves, rocket 1 has a higher value. The reasoning for this change is the same as for rockets 6 and 12; with the difference being rockets 1 and 10 have a much closer height at apogee. This causes only the extreme case of curve 1 to create a switch in rank ordering.

The second performance attribute, duration of flight, is also a “more is better” attribute and the value functions can be seen in Figure 3.15. Just as with the height at apogee, the duration value function curves were created by allowing the value associated with the middle flight time to vary from 25 to 75 by increments of 5. The test was also carried out only manipulating the value function for flight duration, choosing the set linear value functions for the other attributes.

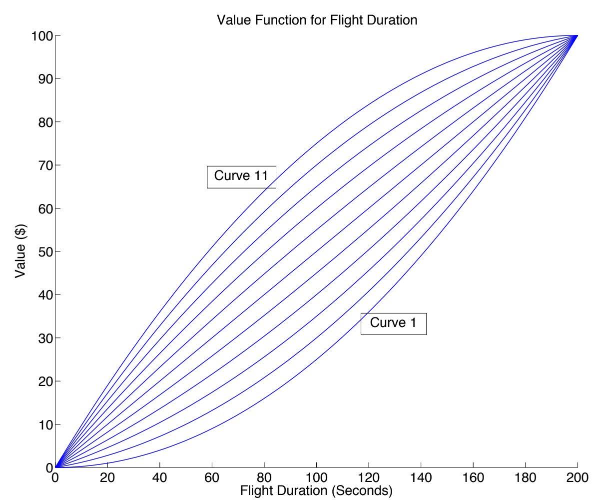


Figure 3.15: Value Functions for Flight Duration

The re-rank ordering of the rockets for each of the possible value curves can be seen in Table 3.5.

Table 3.5: Rank Ordering for Flight Duration Value Function

<table>
<tr><th>Curve 1</th><th>Curve 2</th><th>Curve 3</th><th>Curve 4</th><th>Curve 5</th><th>Curve 6</th><th>Curve 7</th><th>Curve 8</th><th>Curve 9</th><th>Curve 10</th><th>Curve 11</th></tr>
<tr><td colspan="2">21</td><td colspan="9">20</td></tr>
<tr><td colspan="2">20</td><td colspan="6">21</td><td colspan="3">19</td></tr>
<tr><td colspan="8">19</td><td colspan="3">21</td></tr>
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<tr><td colspan="11">8</td></tr>
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<tr><td colspan="7">10</td><td colspan="4">1</td></tr>
<tr><td colspan="9">9</td><td colspan="2">11</td></tr>
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<tr><td>7</td><td colspan="10">13</td></tr>
<tr><td>13</td><td colspan="10">7</td></tr>
<tr><td colspan="3">2</td><td colspan="8">16</td></tr>
<tr><td colspan="3">16</td><td colspan="8">2</td></tr>
<tr><td colspan="11">17</td></tr>
<tr><td colspan="11">3</td></tr>
</table>

Manipulating the value function for the flight duration performance attribute had a larger effect on the rank ordering than the height at apogee. The effect is noticeable when looking at the highest three ranked rockets for each of the different curves. The three highest ranked rockets all remain the same, but the ordering changes as the curves change. The first two curves have rocket 21 ranked the highest, with rocket 20 being ranked the highest after that. In the last three curves rocket 21 is even ranked behind rocket 19. This is due to the performance of these rockets and how the curves associate value to the performance. The first two curves greatly reward rockets with long flight times, because the value drops quickly further away from the maximum. Rocket 21 has the longest flight time and the change in value is large enough to rank rocket 21 ahead of rocket 20. On the other end of the spectrum, the final three curves all have value of $90 for any flight over 140 seconds. This allows rocket 19 to become ranked higher than rocket 21 because it outperforms it in both stability and payload size. The value increase for increased flight duration above a certain point does not pay large dividends.

The third performance attribute, non-dimensional stability, is a “nominal is better” attribute. The non-dimensional stability is calculated by taking the length difference between the center of pressure and the center of gravity and dividing that by the reference diameter of the rocket. An acceptable range for the stability is between 1 and 2. A stability number of two indicates a very stable rocket, with numbers larger than two starting to cause problems, leading to an over stable rocket. Over stable rockets have a tendency to weather vane into the wind, becoming dangerous. The value functions were constructed using 2 as the optimal value with the value falling off quickly after 2. The functions can be seen in Figure 3.16.

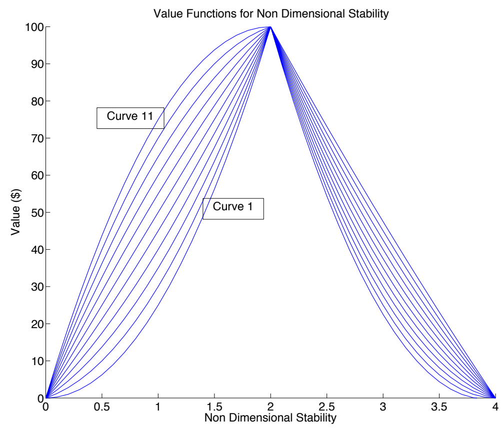

Figure 3.16: Stability Value Functions

The rank ordering of the rockets for each of the value functions in Figure 3.16 can be seen in Table 3.6.

Table 3.6: Rank Ordering for Stability Value Function

<table>
<tr><th>Curve 1</th><th>Curve 2</th><th>Curve 3</th><th>Curve 4</th><th>Curve 5</th><th>Curve 6</th><th>Curve 7</th><th>Curve 8</th><th>Curve 9</th><th>Curve 10</th><th>Curve 11</th></tr>
<tr><td colspan="8">20</td><td colspan="3">21</td></tr>
<tr><td colspan="2">19</td><td colspan="6">21</td><td colspan="3">20</td></tr>
<tr><td colspan="2">21</td><td colspan="9">19</td></tr>
<tr><td>18</td><td colspan="10">15</td></tr>
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<tr><td colspan="7">12</td><td colspan="2">6</td><td>14</td><td>12</td></tr>
<tr><td colspan="2">8</td><td colspan="7">14</td><td colspan="2">6</td></tr>
<tr><td colspan="2">14</td><td colspan="4">8</td><td colspan="5">1</td></tr>
<tr><td colspan="2">10</td><td colspan="4">1</td><td>8</td><td colspan="4">10</td></tr>
<tr><td colspan="2">1</td><td colspan="5">10</td><td colspan="4">8</td></tr>
<tr><td colspan="7">9</td><td colspan="2">11</td><td colspan="2">4</td></tr>
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<tr><td>13</td><td colspan="9">7</td><td>17</td></tr>
<tr><td colspan="7">16</td><td colspan="3">17</td><td>7</td></tr>
<tr><td colspan="6">2</td><td>17</td><td colspan="3">16</td><td>2</td></tr>
<tr><td colspan="6">17</td><td colspan="4">2</td><td>16</td></tr>
<tr><td colspan="11">3</td></tr>
</table>

Similar to the flight duration performance attribute, there are changes in the rank ordering of the top 3 rockets as the different curves are tested. Rocket 20 is the most stable rocket with a stability rating of 1.97. That is why it remains the highest value rocket until the final three curves. In the final three curves, the difference in value between rocket 20's stability (1.97) and rocket 21's stability (1.49) becomes small enough to allow rocket 21 to have a higher value. Rocket 21 has both a higher max apogee and longer flight time than rocket 20, but does not have a higher value until the difference in value due to stability is small enough. There are also a large number of changes to the medium and low-end designs as well as the different curves are used.

The fourth performance attribute, payload size, is a more is better function but is best set up as a step function due to how the payload sizes were set up in the problem statement. The payload size of the rocket is broken down into 5 potential sizes of scientific devices that can be placed into the top of the rocket. The sizes of the payload are broken down in Table 3.7. The larger the payload the more scientific data it can collect, which equates to a higher monetary value.

Table 3.7: Payload Sizes for Model Rocket

Payload Level	Minimum Area Needed (m^2)	Rocket Diameter (m)
Level 0	0	0.028
Level 1	0.001	0.0356
Level 2	0.002	0.05
Level 3	0.003	0.0618
Level 4	0.004	0.0714

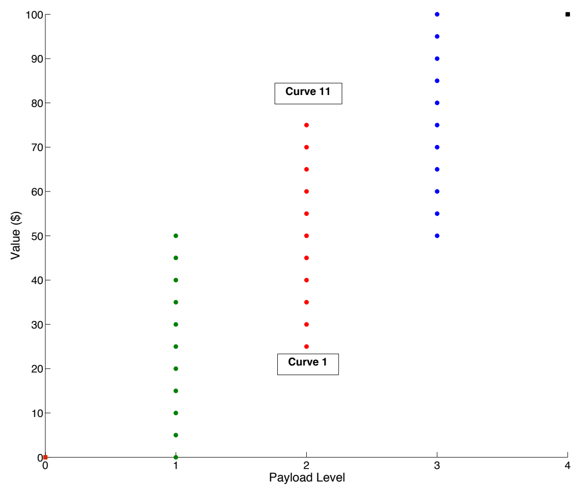

Figure 3.17: Payload Level Value Functions

Table 3.8: Rank Ordering for Payload Value Function

<table>
<tr><th>Curve 1</th><th>Curve 2</th><th>Curve 3</th><th>Curve 4</th><th>Curve 5</th><th>Curve 6</th><th>Curve 7</th><th>Curve 8</th><th>Curve 9</th><th>Curve 10</th><th>Curve 11</th></tr>
<tr><td colspan="4">21</td><td colspan="7">20</td></tr>
<tr><td colspan="4">20</td><td colspan="3">21</td><td colspan="4">19</td></tr>
<tr><td colspan="7">19</td><td colspan="4">21</td></tr>
<tr><td colspan="7">15</td><td colspan="4">18</td></tr>
<tr><td colspan="7">18</td><td colspan="4">15</td></tr>
<tr><td colspan="8">5</td><td colspan="3">6</td></tr>
<tr><td colspan="5">12</td><td colspan="3">6</td><td colspan="2">5</td><td>14</td></tr>
<tr><td colspan="5">6</td><td colspan="2">12</td><td colspan="3">14</td><td>5</td></tr>
<tr><td colspan="2">10</td><td colspan="5">14</td><td colspan="3">12</td><td>8</td></tr>
<tr><td colspan="2">14</td><td colspan="3">10</td><td colspan="5">8</td><td>1</td></tr>
<tr><td colspan="5">8</td><td colspan="5">1</td><td>12</td></tr>
<tr><td colspan="5">1</td><td colspan="6">10</td></tr>
<tr><td colspan="11">9</td></tr>
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<tr><td colspan="5">17</td><td colspan="6">2</td></tr>
<tr><td colspan="5">16</td><td colspan="6">17</td></tr>
<tr><td colspan="11">3</td></tr>
</table>

As with the previous three performance attributes, changes in the rank ordering are seen as the study progresses through the different curves. Design 21, which is unable to carry a payload, has the highest value for the first four curves, as those curves give lower than standard value to designs with payloads. Design 20 has the highest value for every curve after this due to it being able to carry a level 1 payload. Similar to the stability performance attribute, the payload attribute changes the rank ordering considerably for the mid-tier rockets, with rockets 12 and 14 changing four spots in the rank ordering from the first curve to the last curve. Rocket 12 loses the most value as the value functions change as it is able to carry the largest payload size and gets maximum value from the beginning. As the curves progress the value given to lower payloads is increased though, which minimizes rocket 12's advantage.

Looking at the changes that uncertainty in the four different performance attributes created it is clear that designs 19, 20, and 21 are the best three designs. They are the top three designs in each of the studies. The three designs are of a similar structure with designs 19 and 20 being the minimum size to carry a level 1 payload and rocket 21 having the smallest allowable diameter and carrying no payload. Each of the rockets also has a long thin nose cone, which reduces drag and allows for higher flights and longer flight durations. Since the performance attributes were weighted equally in this study the designs that flew higher and thus had longer flight times outperformed designs that focused on carrying the largest payload possible. The three best designs also had the same structure for the material of each of the pieces of the rocket. The fins and tube body were made with the lighter material option with the nose cone using the heavier material option. Having the heavier material on the nose cone allowed the rocket to stay shorter and reduce weight while still keeping the center of gravity far enough ahead of the center of pressure to ensure good stability.

As these results show, value functions used can have a very large effect on the rank ordering of the design. In each of the different performance attributes, the value functions were altered while keeping the same general trend. Changing the value functions for each of the different performance attributes affected the rank ordering in a different but predictable way that was easily explainable by looking at the performance of the designs.

3.3.2.2 Aggregation Structure Uncertainty

In this section, the effects of uncertainty in the aggregation structure are explored for the model rocket problem. The approach is slightly different than in the propane tank problem due to increased complexity of having four attributes as opposed to two. With two attributes, testing a full range of attribute weighting was fairly straightforward. In order to get a complete understanding of how the individual weights affect the rank ordering of the twenty-one model rockets a randomized approach was used. The approach can be seen in Figure 3.18, which is a flow chart of the process for creating the weight percentage for each of the performance attributes.

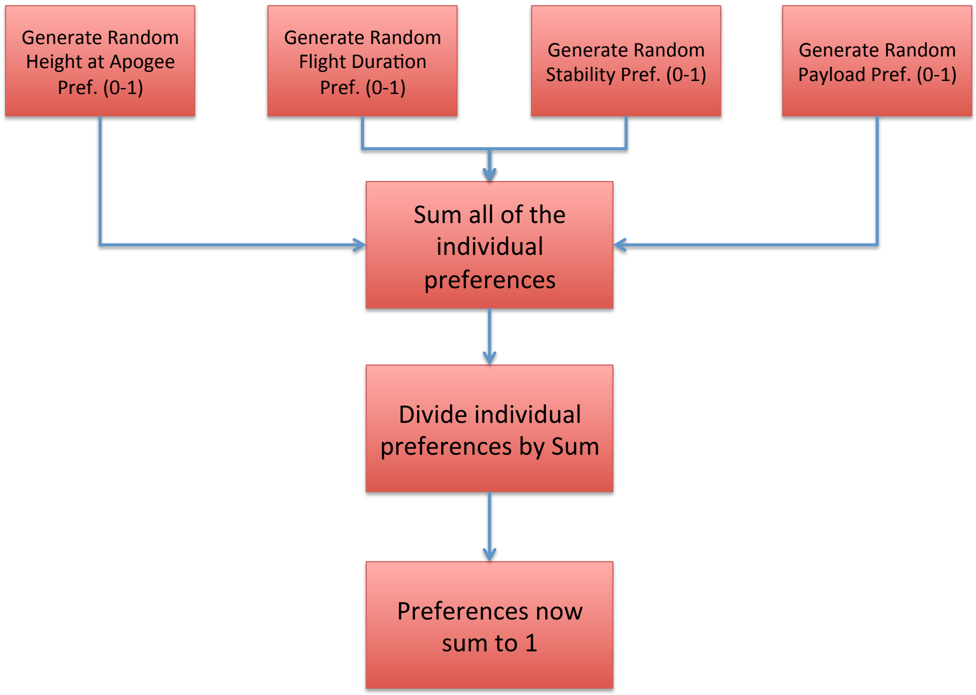

Figure 3.18: Uncertain Weight Generation

The process for creating the randomized aggregation structure was repeated 10,000 times to capture a sufficiently large proportion of the possibilities. When using a randomization process like this it is possible that the random weight will all be located in the very center of the space. Figure 3.19 plots the weights generated, and shows that while many of the aggregations structures are in the center of the space, the corners of the space are also represented.

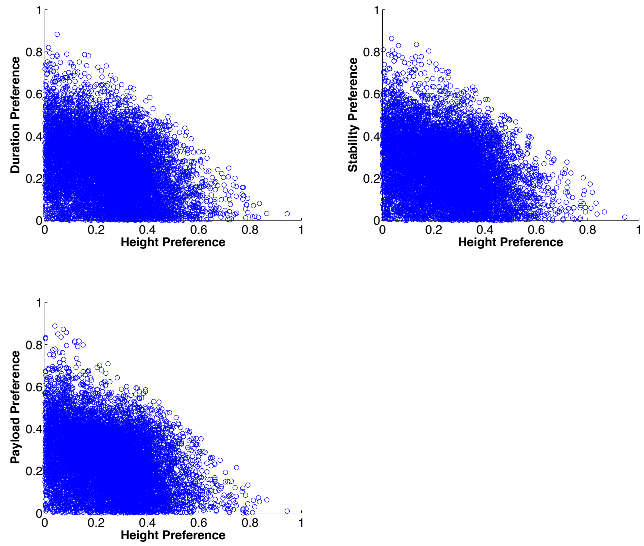

Figure 3.19: Aggregation Structure Sampling

As each weight structure was created, the model rockets were evaluated and rank ordered based on their value. The value functions were kept the same in each of the simulations to ensure that only changes to the weight structure would affect the value of the rocket. The linear forms of the value functions were used for simplicity. Each of the 10,000 simulations tested to see which of the twenty-one rockets finished first, second, and third in overall value. The results are shown below in pie chart and bar graph form.

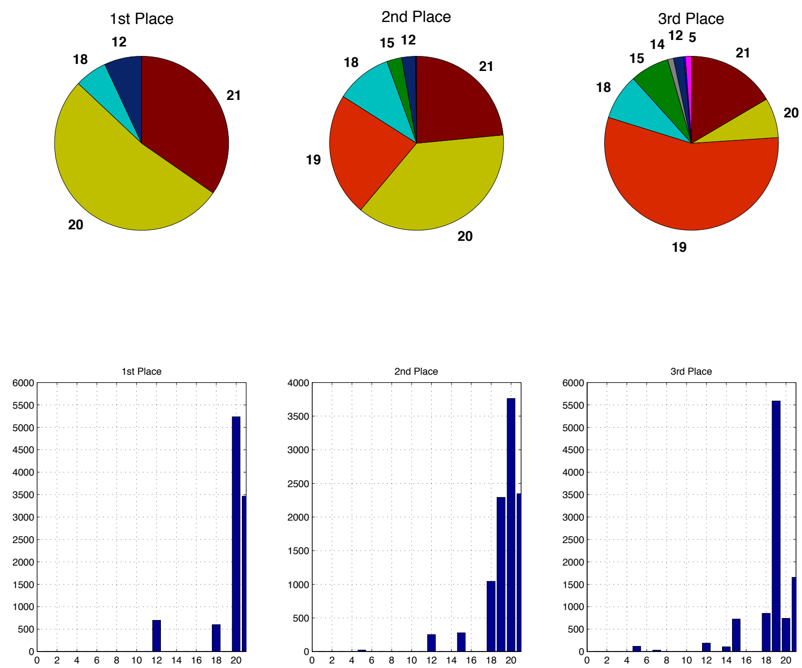

Figure 3.20: Results of Value Ranking for Weight Manipulation

The figure shows that of the 10,000 random attribute weight structures, design 20 is the optimum design more often than any of the other designs. Design 20 is the optimal design 5,240 times, followed by design 21 winning 3,470 times. It is interesting to note that only four of the designs were ever determined to be optimal. As Figure 3.20 shows, the only designs that win are designs 20, 21,12, and 18. It is interesting that design 19, which was in the top three designs in every study in the previous section, did not win in any of the simulations. This is due to how similar design 19 is to design 20. Both of the designs have a level 1 payload, but design 20 outperforms design 19 in every other category. The winning designs are different and excel in different performance attributes. The performance of each of the designs is presented in Table 3.9.

Table 3.9: Performance of Highest Value Rockets

Attribute	Design 12	Design 18	Design 20	Design 21
Height (m)	287	354	641	745
Duration (s)	67.9	77.1	146	187
Stability	0.2818	1.689	1.97	1.49
Payload level	4	3	1	0
Cost ($)	27.17	29.17	22.89	20.75

It is interesting to note the differences between the four winning designs, and what stands out about each of them allowing them to be the highest ranked. Design 12 is very poor comparatively in height, duration, and stability but is the only of the four to be able to carry the level 4 payload. Design 18 is only able to hold the level 3 payload, but has a much better stability rating and mid-level height and duration performance. These two designs can be separated from the other two designs based on general shape and performance characteristics. Designs 12 and 18 can be characterized as large payload designs with larger drag profiles, causing a decrease in the height and flight duration. Design 18 wins less often than design 12 but is the highest ranked design under certain circumstances. The circumstances that lead to design 18 winning are when payload level is the highest weighted performance attribute and stability is the second highest weighted. Design 18 vastly outperforms design 12 in stability, which gives it the advantage in this scenario. Unlike designs 12 and 18, designs 20 and 21 have much drag friendlier profiles, allowing the rockets to go to much higher and have longer flight durations. Design 20 is the most dominant of the designs, ranked as the most optimal design in 52.4% of the simulations. Design 20 outperforms design 21 by being able to carry the smallest payload, as opposed to no payload, and having a nearly perfect stability rating. However, design 21 is the second most successful design, winning in 34.7% of the simulations. Design 21 is able to be successful despite not being able to carry any payload due to its dominance in both height and flight duration. Design 21 has the highest height at apogee and longest flight duration of any of the rocket designs. When looking at the preference structures, it was found that when the combined height and duration were weighted at 60% or higher design 21 was always the winning design.

3.4 Results

The results from this chapter indicate that altering either the value functions or value model preference structure can have a large effect on the optimum design of a system. This result is understandable as the value model controls which performance attributes are desired, thus altering the designs to meet these needs. It was found that using different value functions can lead to a larger number of optimum designs as they have the ability to slightly change designs, where as changing the preference structure can greatly change the form of the system. The results answer the first research question and show that yes; uncertainty in the value model does have an effect on the optimum solution. The results also show that the way in which the optimum design changes can also be predicted based on changes to the value model. The amount of change is not ascertainable from the results of this study, but they do show that general trends can be found to help a designer if changes are made to the value model.

Chapter 4: Designing Under Value Model Uncertainty

4.1 Motivation

The previous chapter demonstrated that the optimum solution changes with variations in value model and value function formulation. As discussed in Chapters 1 and 2, value functions and models are constructed using economic data and design team preferences. Chapter 3 showed that the optimum solution of a system changes when there are large changes to the value model and value functions. However, such large changes may be unrealistic in true application, as the value model and functions will be somewhat known by the designers. The motivation of this chapter is to test a more realistic level of uncertainty in a value model. This study gives a better understanding of how potential slight variations in a value model affect the optimum design and helps to uncover strategies for managing this uncertainty.

4.2 General Methodology

In this study, a value model is created for a system, and individual value functions are created for each of the performance attributes. This value model is the baseline for the system; with uncertainty added to each of the value functions. Uncertainty in the value functions is introduced using the mean location of the attribute range. The value of the mean point is subjected to a normal distribution, using the baseline value function as the center of the distribution. An optimization on the design is then performed using a multi-objective genetic algorithm (MOGA). The objectives of the MOGA are maximizing mean value and minimizing standard deviation of value. During the optimization, the impact of uncertainty in a value function is explored using a Monte-Carlo simulation. In most design problems, Monte-Carlo simulations are used to change the parameters of a design based on a probability density function (PDF). In this method, a Monte-Carlo simulation is used to understand the role of uncertainty in the value functions that make up the value model. The overall process used in this work is shown in Figure 4.1.

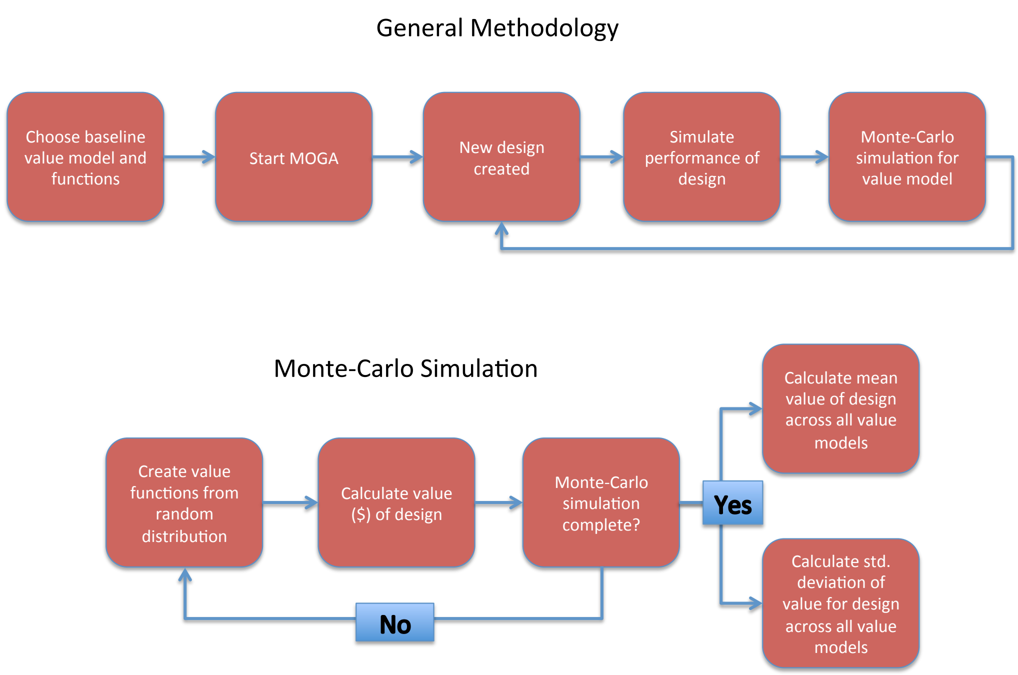

Figure 4.1: Methodology Flow Chart

Each of the steps shown in Figure 4.1 is further explained in the following sections.

4.2.1 Choosing a Baseline Value Model and Functions

In this method the value model is built with each of the performance attributes having equal weight in the aggregation structure. This section will detail the process for setting up a generic value function. The performance attribute used is generic and does not represent any of the performance attributes used in the case study.

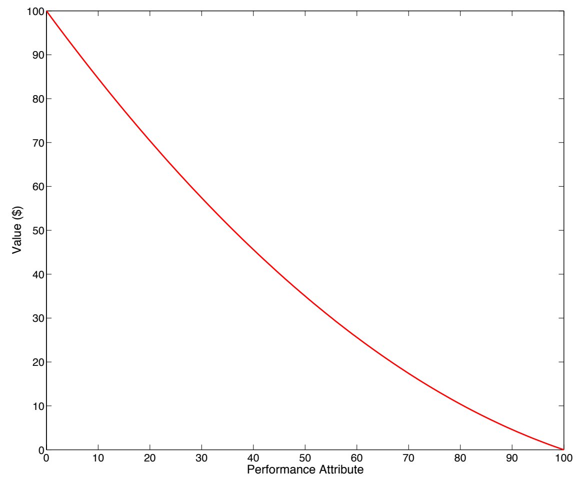

Figure 4.2: Generic Baseline Value Function

This baseline value function is a generic function that would represent a performance attribute where the value is increased as the attribute is minimized, with maximum value occurring when the attribute is 0. For this example the mean of this performance attribute is located at 50 and the baseline value corresponding to this location is $35. The maximum and minimum for the performance attribute are known and using this information a polynomial is fit to the data. This polynomial is the value function for one of the performance attributes. The process is completed for each of the performance attributes that make up the value model.

4.2.2 MOGA

Once the MOGA is started, it works to create designs to optimize the design objectives. The design objectives used are maximizing average value and minimizing standard deviation of value. Both of the objectives are potential design extremes when faced with uncertainty in the value model. A designer can choose to make decisions that create a system that has the highest mean value, or a system whose value varies the least. Each of the designs created by the MOGA is simulated to find the performance, which can be used to find the value. After the performance of the design is found it is fed into a Monte-Carlo simulation.

4.2.3 Monte-Carlo Simulation

Value function uncertainty is introduced using probability density functions. The PDF for each of the performance attributes is stored within the Monte-Carlo simulation. For example, the probability density function for the generic performance attribute is created by using the baseline \$35 and applying a normal distribution around this point with a standard deviation that represents the level of uncertainty in the function. This work assumes that a normal distribution is an accurate representation of the uncertainty, though other distribution forms could be applied. For this methodology, a standard deviation of \$5 has been applied. A standard deviation of \$5 was chosen because it allows for 10% of the total value range to be within plus or minus one standard deviation. This allows for some uncertainty in the value function, without drastically changing the form of the value function. Figure 4.3 shows the PDF for the generic value function and a histogram of possible mean point values.

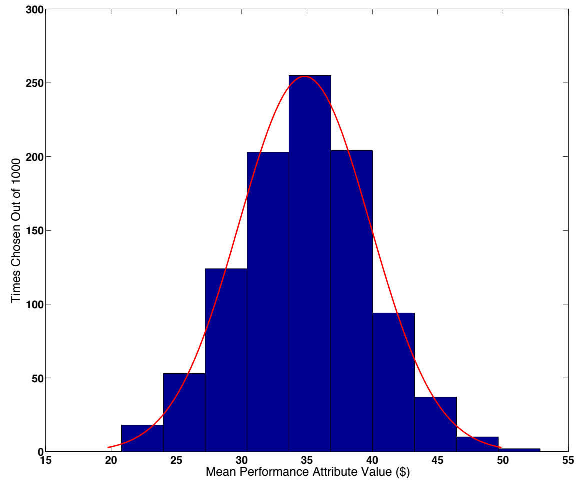

Figure 4.3: Generic Probability Density Function

During the Monte-Carlo simulation the mean value point is found from the PDF and then used with the minimum and maximum points to create the value functions. Figure 4.4 shows 20 instances of the generic value function when created using the PDF. Here, twenty was chosen solely to give a graphical representation of the effect.

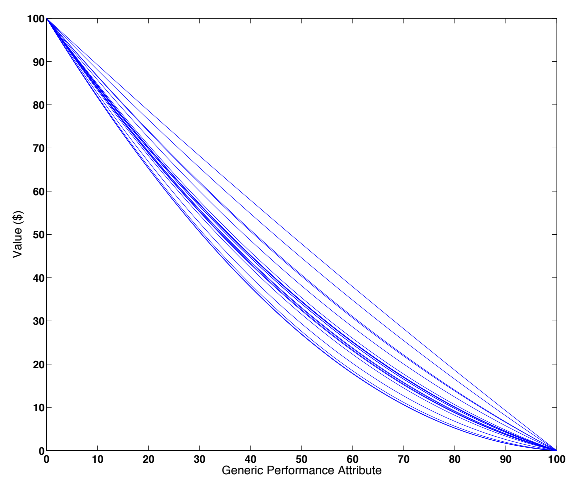

Figure 4.4: Generated Value Functions for Generic Case

As the Monte-Carlo simulations are run, the performance of the design is used to find the value for each of the value functions created using the PDF. When the Monte-Carlo simulation is completed, the mean average and standard deviation of value are found for the design. The MOGA then creates another design, repeating the process and finding the optimum designs. In the rest of this chapter, this methodology is applied to the design of a model rocket.

4.3 Case Study: Model Rocket

To test the method discussed in the previous section, a case study was performed on the design of a model rocket. A model rocket was used for the case study of this method because it allows for a complex design with four performance attributes to be viewed within the framework of VDD. The model rocket simulation was created using equations from [59] and [60]. The rocket model simulator is similar to OpenRocket, with simplified conditions in order to increase simulation speed. Figure 4.5 shows a flow chart for how the rocket simulator works.

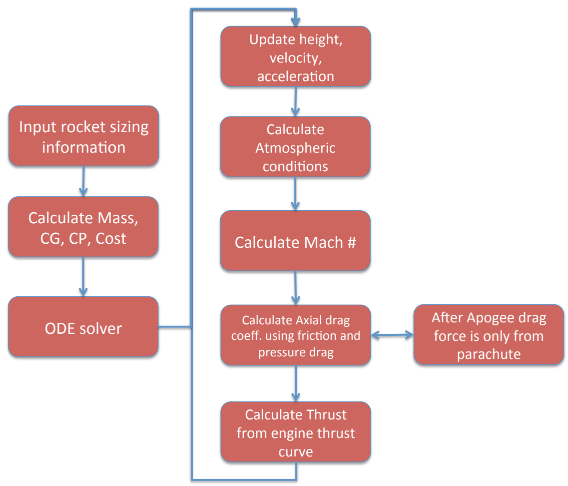

Figure 4.5: Rocket Simulator Flow Chart

As Figure 4.5 shows, the simulator undergoes the following steps:

1. Start with rocket sizing information for the nose cone, tube body, and stabilizing fins.
2. Calculate the mass, center of gravity, center of pressure, and cost of the system.
3. Use an ODE solver to estimate the height, velocity, and acceleration of the rocket.
4. Calculate the atmospheric conditions (temperature, density, pressure, speed of sound) using the height.
5. Calculate the axial drag coefficient using the Mach number and atmospheric conditions. The axial drag coefficient is then used to find the axial drag.

6. Calculate the current acceleration using the thrust (found using engine specific thrust curve), drag and weight. Repeat this process until the rocket reaches apogee.
7. After the rocket reaches apogee, the drag coefficient is strictly based on the deployed parachute. The simulator continues like this until the rocket reaches the ground again.

Conditions used to simplify the simulation include excluding wind, and assuming that the parachute deploys instantly at apogee.

4.3.1 Model Rocket Methodology Application

In this section, it will be shown how the general methodology from Section 4.2 was applied to a model rocket. The section will detail how the baseline value functions were chosen for each of the performance attributes and the probability density functions. A sample of the generated value curves will also be shown for each of the performance attributes. For the model rocket, the same performance attributes are being used as in Section 3.3.2: height at apogee, flight duration, non-dimensional stability, and payload level.

As a first step, the performance space was sampled to find the realistic ranges for the height at apogee and flight duration performance attributes. This step is optional, as it is expected that the designer would have a realistic idea of what the bounds for the rocket's performance is. To find the bounds and understand the performance space of the two performance attributes, 10,000 random rockets were created and their performance simulated. The performance from these rockets showed that the height at apogee ranged from 0 to 1100 meters and the flight duration ranged from 0 to 260 seconds. The average performance of the attributes was also found during the sampling. Using this information the following sub-sections will detail how the baseline value functions were created.

4.3.1.1 Height at Apogee Performance Attribute

The height of the rocket at the apogee of its flight is the first performance attribute that is explored. As described in Section 4.3.1, the range for this attribute is from 0 to 1100 meters. The random sampling also showed that the average height at apogee was 330 meters. A histogram of the rockets sampled is shown in Figure 4.6, showing how the randomized rockets performed in the height at apogee performance attribute.

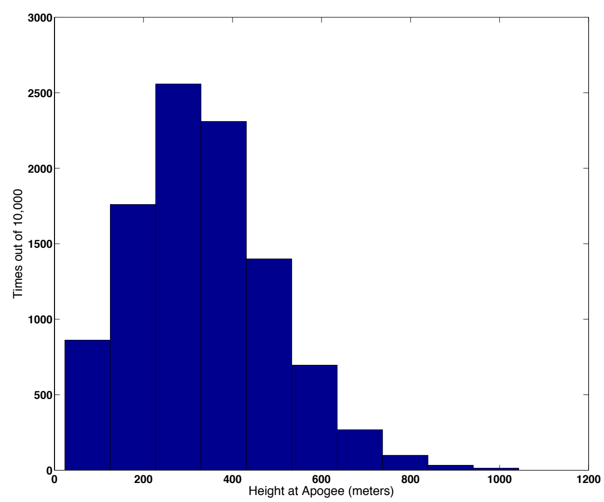

Figure 4.6: Histogram of Height at Apogee Performance

The average height was used with the minimum and maximum heights to produce the value function. To do this, the value for minimum, maximum, and average performance had to be assigned. For this attribute, the minimum and maximum value is set at \$0 and \$100 respectively. The value for the average height was chosen to be \$40. This decision was made to represent how the designer felt the baseline value function should look. The value function was created using these three points, and applying a 2nd order polynomial fit. The resultant value function is shown below in Figure 4.7. The equation for the baseline height at apogee value function is shown in Equation 4.1.

$$Value_{height} = (-3.94E - 5) * h^2 + (0.1342) * h \tag{4.1}$$

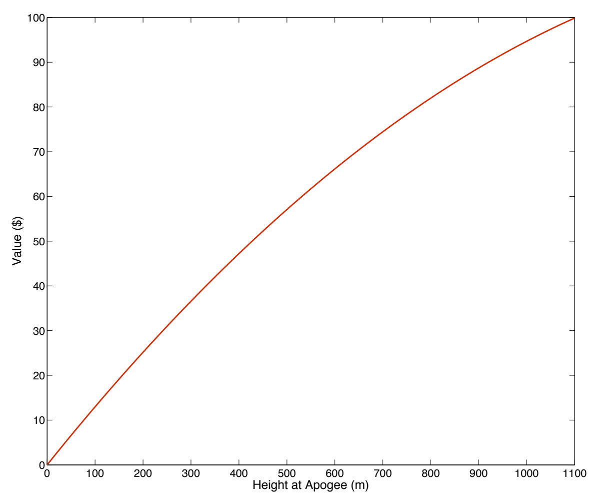

Figure 4.7: Baseline Value Function for Height at Apogee

After the baseline value function was created, the probability density function for the value at the mean height was then created. This was done using a normal distribution around the average performance value of \$40 with a standard deviation of \$5. As described in

Section 4.2.3, a standard deviation of \$5 was used as it allows for 10% of the value range to be within one standard deviation. The PDF for the height at apogee can be seen in Figure 4.8.

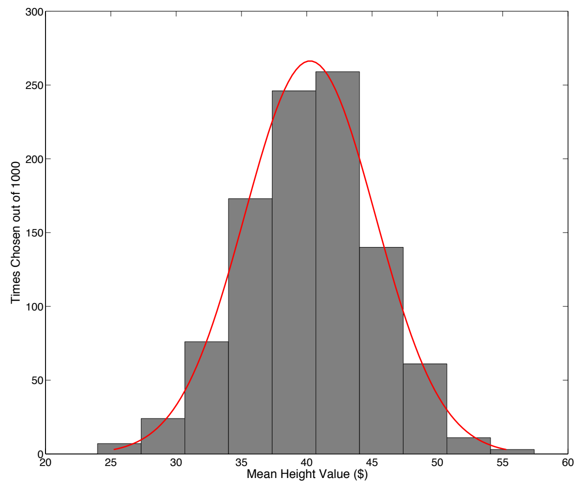

Figure 4.8: PDF for Height Value Function

The height value function is then used with the probability density function to create the possible value functions. A sampling of twenty possible value functions is shown below. Each of the value functions is created like the baseline functions. The minimum and maximum points are set and the value at the average point is then subject to the PDF. The value function is then created using a 2^{nd} order polynomial fit.

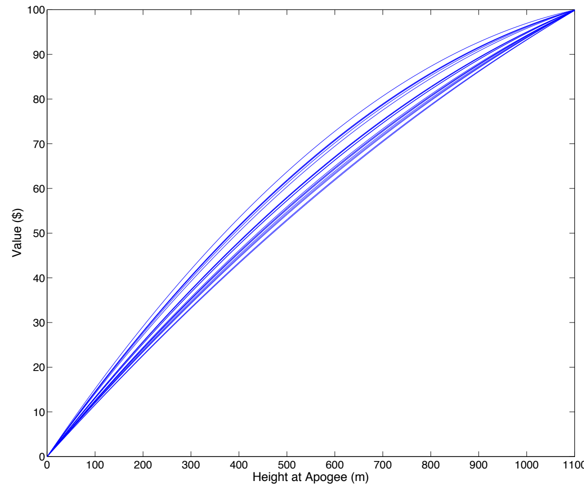

Figure 4.9: Monte-Carlo Generated Height Value Functions

Figure 4.9 shows some of the possible value functions that are generated for the height at apogee performance attribute. During the Monte-Carlo simulation a curve similar to one shown in Figure 4.9 is generated and the rocket's value found. The next performance attribute is the flight duration, which is very similar in nature to the height at apogee.

4.3.1.2 Flight Duration Performance Attribute

The flight duration was the second performance attribute studied. In the performance space sampling, the maximum flight duration was found to be 260 seconds with a mean flight time of 60 seconds. Figure 4.10 shows a histogram of the performance space sampling for the flight duration attribute. The histogram shows a left skewed distribution for the flight duration. The value for the mean performance is set lower than $50 due to the severity of the left skewed distribution.

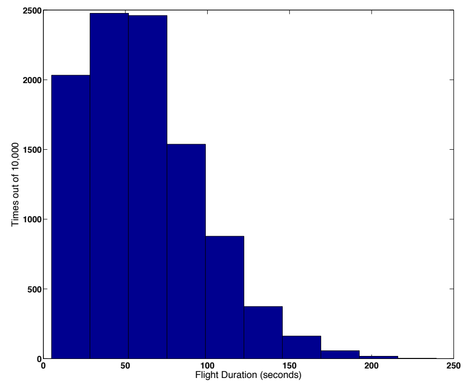

Figure 4.10: Histogram of Flight Duration Performance

The baseline value function for the flight duration performance attribute was created similarly to the height at apogee value function. The minimum and maximum points were assigned \$0 and \$100 of value respectively. The average flight time of 60 seconds was assigned \$30 of value. Thirty dollars was chosen in order to create the proper amount of risk averseness for the performance attribute. The three points were then used to find the value function by fitting a second order polynomial. Figure 4.11 below shows the baseline function for the flight duration attribute. The equation for the baseline duration value function is shown in Equation 4.2.

$$Value_{duration} = (-5.77E-3) * d^2 + (0.535) * d \tag{4.2}$$

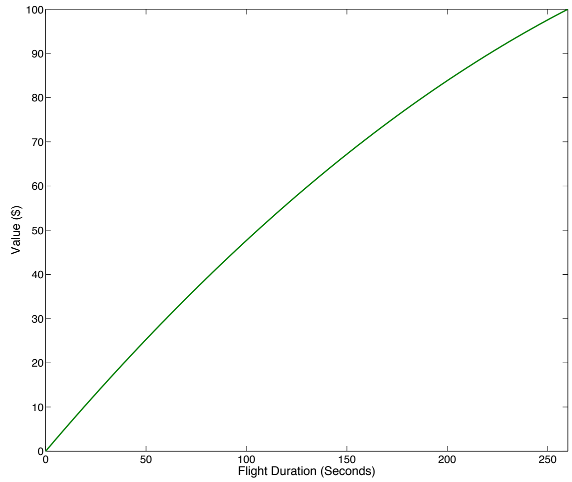

Figure 4.11: Flight Duration Baseline Value Function

After creating the baseline value function, the probability density function for the flight duration was created. The PDF for the flight duration was created using a normal distribution around the value of the average flight time, which is $30. A standard deviation of $5 was used in the PDF as it represents 10% of the total possible value within a standard deviation. A histogram overlaid with the exact PDF for the flight duration performance attribute can be seen in Figure 4.12 below.

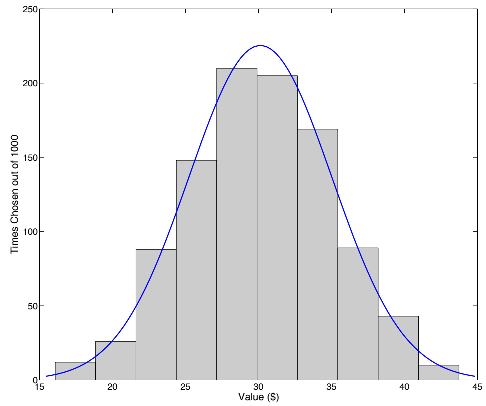

Figure 4.12: PDF for Flight Duration Value Function

The baseline flight duration function is then combined with the PDF in the Monte-Carlo simulation during each iteration of the MOGA. A sample of the twenty randomly generated flight duration value functions is shown in Figure 4.13 below.

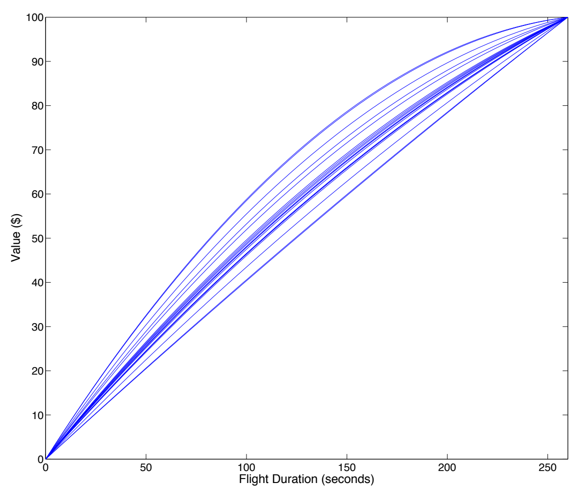

Figure 4.13: Monte-Carlo Generated Flight Duration Value Functions

The different value functions show a higher concentration located around the baseline with the lower concentrations still being visible at the extremes. This figure represents the uncertainty in this value function, and is used in the MOGA to test the performance of rocket designs. The third performance attribute, non-dimensional stability is different in nature from the first two because the objective is a nominal value as opposed to maximization.

4.3.1.3 Non-dimensional Stability Performance Attribute

Non-dimensional stability is the third performance attribute that was used in the evaluation of the model rockets. This performance attribute is different than the previous two in that there is a set range of good numbers for this attribute. A typical range that is considered acceptable for a rocket is for the non-dimensional stability to be between 1 and 2. A non-dimensional stability less than 1 creates an under-stable rocket and more than 2 creates an over-stable rocket that will have a tendency to weathervane into the wind. The baseline value function was created with this in mind and uses a parabola with five points of interest. The maximum value point is located at a stability of 1.5, with minimum values of $0 at non-dimensional stability numbers of 0 and 3. To ensure that the proper value is given for stability scores between 1 and 2, values of $75 are assigned to these points. The baseline stability value function is shown below in Figure 4.14. The equation for the baseline stability value function is shown in Equation 4.3.

$$Value_{Stability} = (-42.38) * s^2 + (127.4) * s - 1.0 \tag{4.3}$$

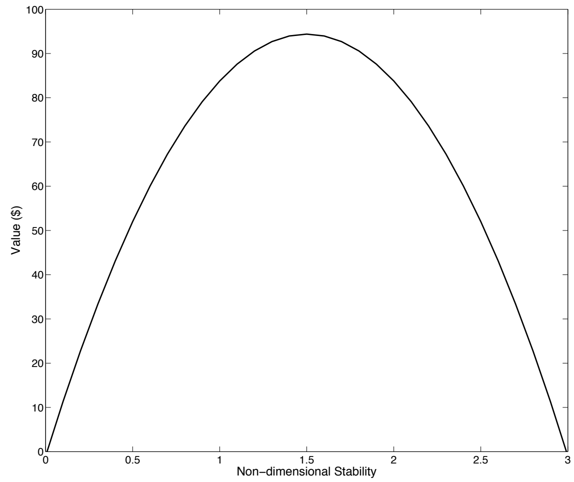

Figure 4.14: Baseline Stability Value Function

Since there are five points of interest in this value function, each of them are allowed to move subject to their own normal distributions focused around the baseline. The main point of interest is the maximum value point, which occurs at a stability of 1.5 in the baseline value function. This point is allowed to move within a standard deviation of 0.25. This ensures that maximum value occurs within the important range of 1-2, but allows for uncertainty. The points of $75 value are pinned to plus or minus 0.5 from the maximum value point to keep the parabolic shape. The stability points of 0 and 3 have $0 in the baseline value function. Uncertainty is introduced to these points by allowing the stability points of 0 and 3 to move within standard deviations of 0.1 around the baseline. The end result is that it creates slight variations from the baseline. This is not the only method for introducing the uncertainty for a nominal is better performance attribute. It was chosen because it allowed for variations from the baseline without significantly altering the form of the value function. A sampling of twenty randomly generated variations of the stability value function are shown in Figure 4.15.

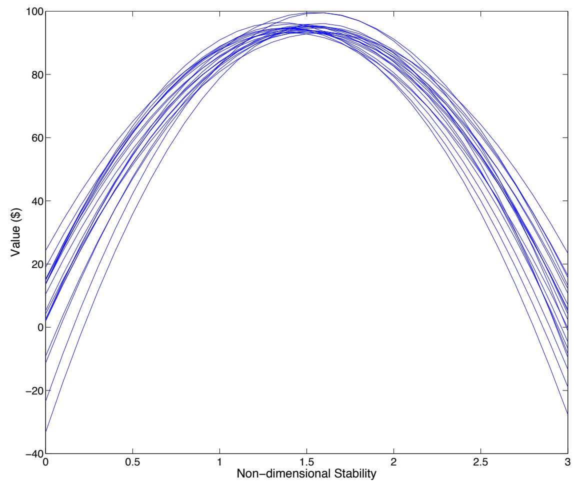

Figure 4.15: Monte-Carlo Generated Stability Value Functions

Figure 4.15 shows uncertainty in the stability value function. The important point to notice is in each of the value functions, the highest value is given for stability scores between 1 and 2. The uncertainty in the function comes from which stability score creates the maximum value and how low the value is for stability scores outside of the acceptable range. The fourth performance attribute is the payload level, which is different than any of the previous three due to its piece-wise nature.

4.3.1.4 Payload Level Performance Attribute

The payload level performance attribute is set up as a measurement of which of the five possible payloads the model rocket could carry. The levels are broken down into either no payload, or level 1 - 4. Levels 1 – 4 are based on the area at the top of the tube body. Each successive level in payload also increases in weight. Table 4.1 details the payload levels and what that means in terms of area at the top of the tube body and the weight of the payload.

Table 4.1: Payload Level Rocket Sizing

Payload Level	Minimum Area Needed (m^2)	Rocket Diameter (m)	Mass (kg)
Level 0	0	0.0	0.0
Level 1	0.001	0.0356	0.002
Level 2	0.002	0.05	0.004
Level 3	0.003	0.0618	0.006
Level 4	0.004	0.0714	0.008

The baseline value function for the payload levels is a piece-wise stepping function shown below in Figure 4.16.

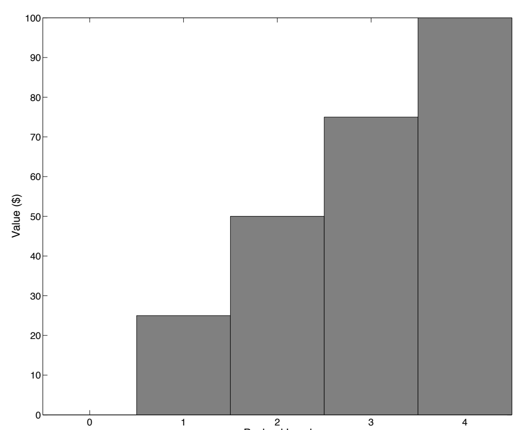

Figure 4.16: Baseline Payload Value Function

To create the uncertainty in the payload value function, a probability density function of the value for each of the payload levels was created. The baseline values for levels 0 – 4 are $0, $25, $50, $75, and $100 respectively. The PDFs are then created for each level by creating a normal distribution around the baseline value with a standard deviation of $5. Figure 4.17 shows the PDFs for each of the payload levels.

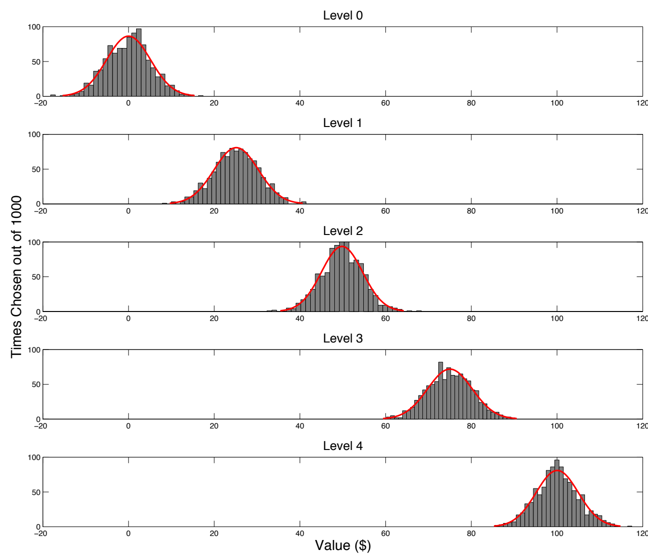

Figure 4.17: PDF for Value of Payload Levels

Each of the individual value functions and their corresponding PDFs are implemented within the Monte-Carlo simulation to create the different value models the model rocket is scored using. The Monte-Carlo simulation is worked into each step of the MOGA and then and optimization on mean value and standard deviation of value is performed. The set up of the optimization problem and the results from this experiment are detailed in the following sections.

4.4 Optimization of Model Rocket Value Under Uncertainty

The model rocket case study for optimizing value under uncertainty is a multi-objective optimization problem. Using a multi-objective approach in VDD is normally considered counter to the basic idea of using a single metric – value – to make design decisions. This approach does not go against this idea however, because the goal is to explore how best to make design decisions when the value model is uncertain. The two metrics explored are the maximization of mean value and the minimization of the standard deviation of value. Maximizing the mean of value across the uncertain value model will find a design that blends the preferences of the different models and outputs a best overall design. Minimizing the standard deviation of value is a different approach that looks at the possibility of the design that changes value the least across the different models being the design best equipped to deal with the uncertainty. The mathematical formulation for the problem is the following.

$$Value(\$) = \sum_{i=1}^{4} W_i * Value_i\,(X) - Cost(X) \tag{4.4}$$

$$W_{1-4} = 0.25 \tag{4.5}$$

$$Value_{1-4} = Value\ of\ each\ performance\ attribute \tag{4.6}$$

$$minimize\text{:}\ -mean\_value \tag{4.7}$$

$$minimize\text{:} \sqrt{\frac{1}{n}\sum_{j=1}^{n}(Value_j - mean\_value)^2} \tag{4.8}$$

In finding the Pareto frontier, 10,000 Monte-Carlo simulations are performed for each design. The MOGA uses a population size of 50, with other options being standard in

Matlab. The standard options include using rank ordering, tournament selection, random initial population, and constraint tolerance of 1e-6. The model rocket simulator uses 11 variables, which are detailed in Table 4.2 below.

Table 4.2: Model Rocket Variable Bounds for MOGA

Variable	Rocket Dimension	Lower Bound	Upper Bound
X1	Diameter	0.028 m	0.08 m
X2	NC Length	0.01 m	0.2 m
X3	NC Thickness	0.002 m	0.008 m
X4	NC Material	1	2
X5	Body Length	0.1 m	1.0 m
X6	Body Thickness	0.002 m	0.008 m
X7	Body Material	1	2
X8	Fin Length	0.01 m	0.2 m
X9	Fin Width	0.01 m	0.07 m
X10	Fin Thickness	0.002 m	0.008 m
X11	Fin Material	1	2

4.5 Pareto Frontier Exploration

The MOGA produced a Pareto frontier showing the tradeoffs necessary between maximizing mean value and minimizing standard deviation of value. Figure 4.18 below shows that the maximum mean value occurs at $47.4 and the minimum standard deviation of value is $1.35. The following sections will highlight certain areas of this figure and discuss the nature of the rocket designs that exist in these areas.

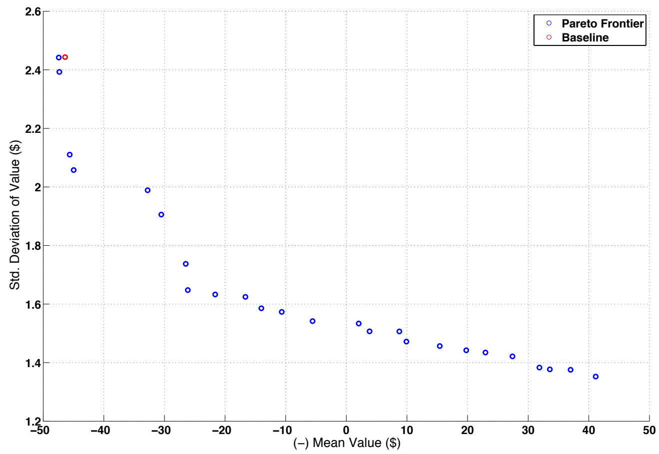

Figure 4.18: Mean Value vs. Standard Deviation of Value

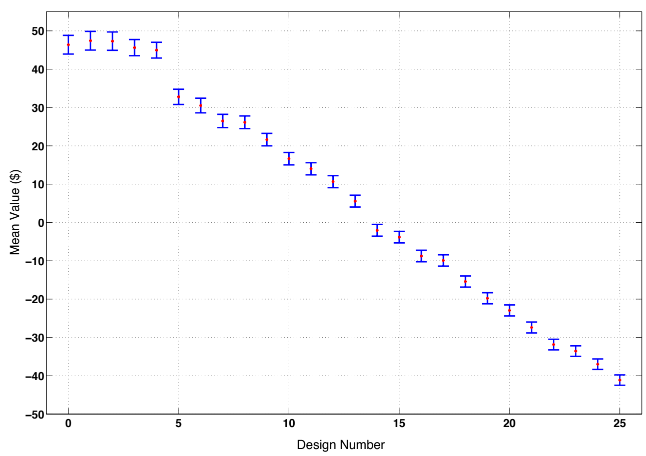

Figure 4.19: Pareto Frontier Designs

Figure 4.19 shows the designs from the Pareto Frontier organized in an easier to read format that also labels the designs 0-25. Design 0 is the optimum design found using the baseline value function. The figure show the design number along the x-axis with the mean value on the y-axis and the standard deviation of value shown with blue range bars around the design points.

It is important to explore what the optimum design is for the baseline value model and how the designs on the Pareto frontier compare. The optimum design for the baseline value model can be seen in the top left of Figure 4.18, and is denoted in red.

Table 4.3: Baseline Optimum Design

Design #	Mean Value	Std. Dev.	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
Baseline	46.2	2.44	0.036	0.197	0.004	1	0.20	0.0026	2	0.030	0.048	0.0023	2

This design is very close to being Pareto optimal – it has the same standard deviation of value as the design at the top left of the frontier, but a slightly lower mean value.

Table 4.4: Performance of Baseline Optimum Rocket

Rocket	Baseline
Height (m)	747.2
Duration (sec)	166.84
Stability	1.53
Payload	1
Cost ($)	21.6

The first designs that will be discussed and examined are the ones that fall on the upper left side of the Pareto frontier. These designs attempt to maximize mean value. The discussion will focus on the two designs that have the highest mean value and standard deviation of value. The two rockets are designs 1 and 2 on Figure 4.19. The parameters for the designs are shown in the table below.

Table 4.5: Highest Mean Value Designs

Design #	Mean Value	Std. Dev.	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
1	47.43	2.44	0.0359	0.188	0.004	1	0.191	0.0024	2	0.0229	0.0481	0.0023	2
2	47.32	2.39	0.0359	0.188	0.004	1	0.191	0.0026	2	0.0229	0.0481	0.0023	2

It can be seen that rocket designs 1 and 2 are nearly identical in design. The only difference in the designs is in design variable six, which is the tube body thickness. The difference is very small, being only a change of 0.2 millimeters in the tube body thickness making Rocket 2 weight slightly more. The two rocket's performance is also similar and is shown below.

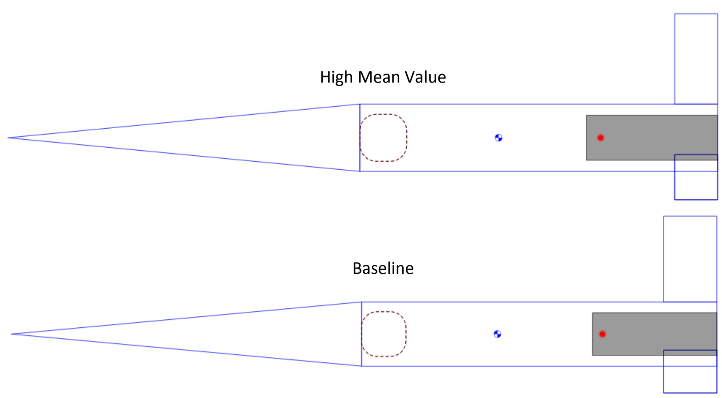

Figure 4.20: Baseline and High Mean Value Rockets

Table 4.6: Best Mean Value Rocket Performance

Rocket	1	2
Height (m)	763.88	763.13
Duration (sec)	171.4	171.5
Stability	1.454	1.434
Payload	1	1
Cost ($)	21.24	21.35

Table 4.6 shows that the two rockets are very similar in their performance; with Rocket 1 performing slightly better in height and stability. It is interesting to note that the extra weight added to the tube body in Rocket 2 shows up as an increase in cost. Other designs that are of interest are the ones that are at the other end of the Pareto frontier. These designs have the smallest standard deviation in value and are more immune to the uncertainty in the value models. The two designs selected from the right side of the Pareto frontier are shown below, followed by their performance scores. The two designs with the smallest standard deviation, Rockets 24 and 25 are shown in Table 4.7. The performance of these three designs are shown in Table 4.8.

Table 4.7: Smallest Standard Deviation Designs

Design #	Mean Value	Std. Dev.	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
24	-36.9	1.38	0.0743	0.018	0.0073	1	0.624	0.0075	1	0.074	0.067	0.0043	2
25	-41.1	1.35	0.0746	0.017	0.0079	1	0.625	0.0077	1	0.075	0.069	0.0075	2

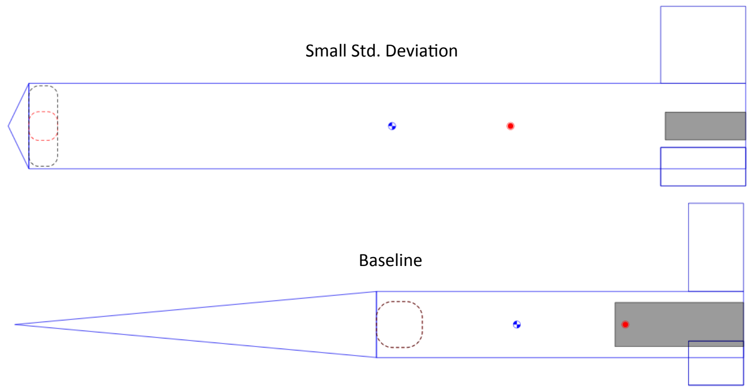

Figure 4.21: Baseline and Small Std. Dev. Rockets

Table 4.8: Performance of Smallest Std. Dev. Designs

Rocket	24	25
Height (m)	65.8	60.13
Duration (sec)	9.43	8.85
Stability	1.46	1.52
Payload	4	4
Cost	89.27	93.17

It becomes immediately obvious that the rockets with the smallest standard deviation have very poor performance in comparison with the designs that maximize mean value. The rockets with the smallest standard deviations have negative value, implicating that it costs more to make the rocket than they produce with their performance. The two designs are slightly different, but share a similar body size and have the ability to carry the level 4 payload. The main difference between the performances of the two rockets is in the height and duration attribute. These two designs also cost much more to make than the designs that have high mean value. The increased cost is due to having a tube body with a much larger diameter to accommodate the level 4 payload. The data shows that the designs that have the smallest standard deviation are the designs that perform poorly. This trend makes sense as the designs that perform poorly have small value to begin with and are thus less influenced by uncertainty in the value functions.

It is also important to look at the designs that fall in the middle of the Pareto frontier. The designs that are of interest are Rockets 7, 8, 9. These three rockets show designs that exist between mean values of $20 and $30. The three designs in question are highlighted in Figure 4.22.

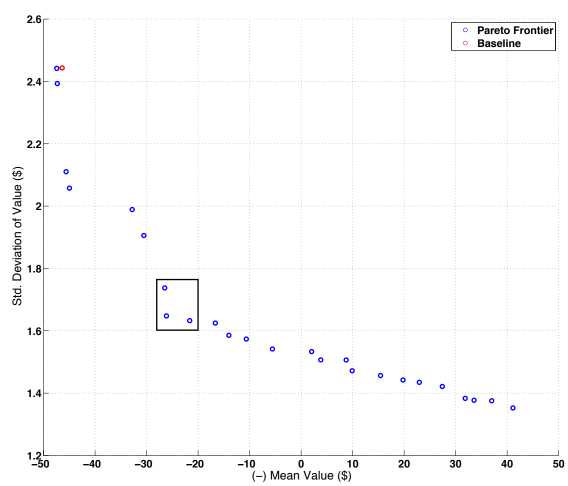

Figure 4.22: Middle of Pareto Frontier

Table 4.9: Middle of Frontier Designs

Design #	Mean Value	Std. Dev.	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
7	26.49	1.73	0.0719	0.027	0.0079	1	0.536	0.0027	2	0.065	0.062	0.004	2
8	26.14	1.65	0.0734	0.021	0.0066	1	0.589	0.0023	2	0.069	0.066	0.0034	2
9	21.62	1.63	0.0748	0.020	0.007	1	0.575	0.0032	2	0.067	0.064	0.0045	2

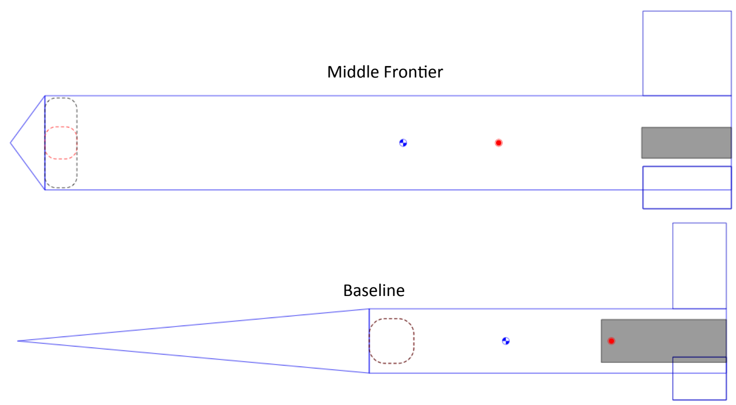

Figure 4.23: Baseline and Middle Frontier Rockets

Table 4.10: Middle of Frontier Performance

Rocket	7	8	9
Height (m)	166.77	146.17	143.23
Duration (sec)	34.82	31.33	30.0
Stability	1.48	1.53	1.42
Payload	4	4	4
Cost	32.2	31.5	35.65

As the tables show, the three rockets in the middle of the frontier are very similar in boy shape and performance. It is interesting to note that all of the designs carry a level 4 payload, which is the same as the designs that have the smallest standard deviations of value. The designs located in the middle of the frontier resemble the designs with small standard deviations more than they resemble the designs with high average value.

Another interesting point to investigate is the groupings that exist on the Pareto frontier in Figure 4.24. There exist four tiers of mean value where the solutions plateau and show variations in standard deviation while having the similar mean value. The performance from tiers two and three will be compared to observe any patterns or trends that exist causing the solution to plateau. The rockets in tier 1 were already considered when looking at the designs with the highest mean value and tier 4 rockets were considered as the middle of the frontier rockets.

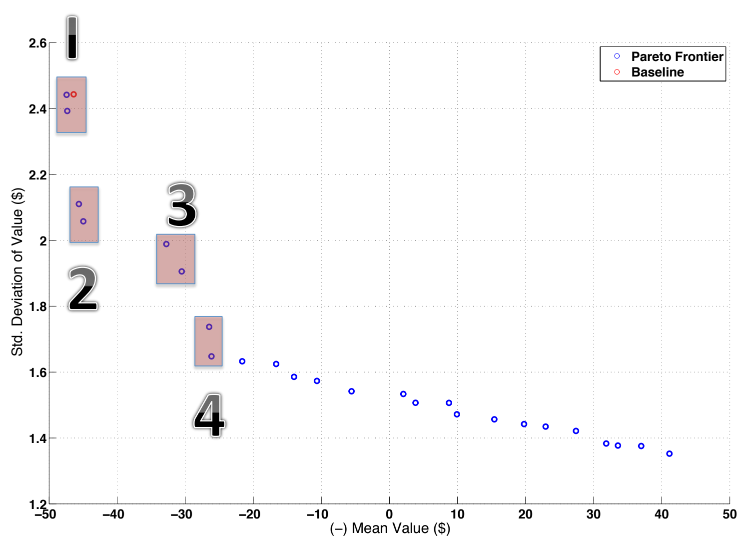

Figure 4.24: MOGA Design Tiers

The performance of the rockets in tier 2 and tier 3 is shown in Table 4.11 and Table 4.12 respectively. The rockets in tier two have mean values around $45 and are Rockets 3 and 4. The tier 3 rockets have mean values around $31 and are Rockets 5 and 6.

Table 4.11: Performance of Tier 2 Rockets

Rocket	3	4
Height (m)	852.84	863.73
Duration (sec)	200.6	202.4
Stability	1.67	1.71
Payload	0	0
Cost	20.48	21.23

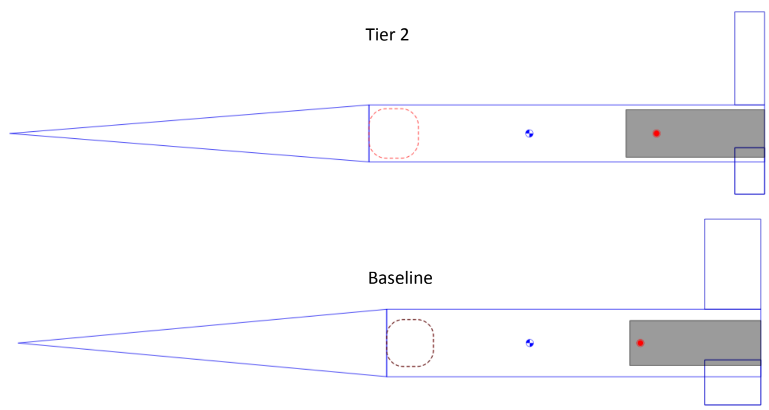

Figure 4.25: Baseline and Tier 2 Rockets

Table 4.11 shows that each of the rockets has very similar performance and cost values. The rockets each have the same body size as well, which is the smallest allowed that can hold the rocket motor. Neither of the two rockets are able to carry a payload, but are able to fly significantly higher due to the decrease in weight and drag. The rockets similar nature is not surprising given their mean values. However, it is surprising how close the two rockets are in average value to Rocket 1 and 2 while having significantly lower standard deviations. The standard deviation of value for Rocket 3 and 4 is \$2.11 and \$2.06 respectively. This compares to Rocket 1 and 2 having standard deviations of \$2.44 and \$2.39. The difference seems inconsequential with the prices associated with the building of a model rocket, but when scaled to the price of a full rocket can become very important.

Table 4.12: Performance of Tier 3 Rockets

Rocket	5	6
Height (m)	237.7	214.7
Duration (sec)	48.21	44.01
Stability	1.39	1.62
Payload	4	4
Cost	29.52	30.58

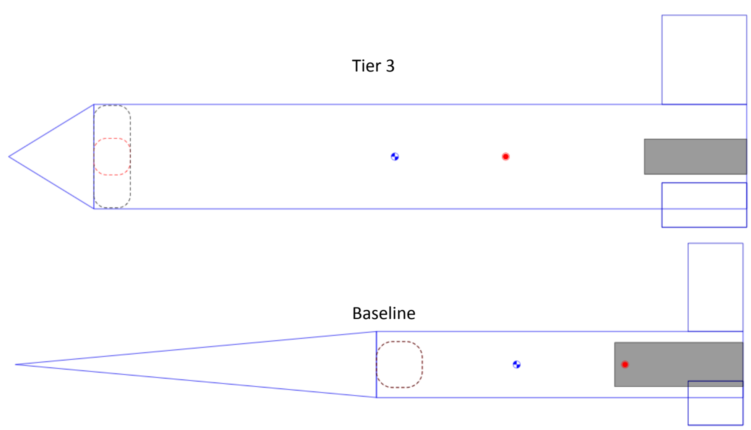

Figure 4.26: Baseline and Tier 3 Rockets

The tier 3 table shows that the designs along that plateau are similar in performance like the tier 2 rockets. The two tables and Pareto frontier plot show that these plateaus of mean value exist because certain designs become the only solutions to fill in that portion of the frontier. The difference in standard deviation is best explained by the random nature of the creation of the value functions. It is interesting to note that each of the designs in tier three have level 4 payloads unlike the tier two rockets. Every design after design 4 has the same body type, with the capacity to carry the level 4 payload. This can be explained by the ease at which value can be gained by simply making the rocket larger in diameter. The height and duration performance attributes are more difficult to achieve and thus only a small portion of the rockets get the majority of their value from them. Payload size is a simpler attribute to increase, but it does come with the caveat of increasing base cost. This increase in cost is the reason none of the rockets with a level 4 payload are able to achieve average values as high as the rockets with the lower payloads.

4.6 Results

The methodology in this chapter was developed in order to explore value from two different perspectives for designing when faced with uncertainty in a value model. The metrics tested were maximum mean average or minimum standard deviation of value. The methodology was applied to the design of a model rocket with four performance objectives. The results of the experiment show that the use of value models allows for designs that perform very well in each of the metrics or designs that fall somewhere in the middle. When looking at the performance of the rocket designs that excel in one of the metrics it becomes clear that designs with small standard deviations vastly underperform compared to designs that maximize mean value. In order for designs to become minimized in standard deviation of value, the algorithm pushes the design towards poor performance. The poor performance gives a low overall value, which is then not as subject to variance in the value model. On the other end of the spectrum are the designs that have high mean value. The rocket designs with higher mean value are more subject to uncertainty in the value model. As the value model fluctuates, the value associated with better performance changes more dramatically than it does for poor performance. These results lead to the conclusion that maximum mean value can be an effective way to design when there is uncertainty in a value model, with minimizing the standard deviation of value a secondary goal.

With respects to the design of the rocket, the results show that certain trade-offs must be made. Value is awarded to the design of the rocket by either having a smaller design that can fly high and stay in the air a long time or by having a larger rocket that is able to carry the maximum payload. Unfortunately, it is not possible to create a rocket that does both. It is surprising that no designs with level 2 or level 3 payloads were on the design frontier. It is believed that this is due to the objective of minimizing standard deviation of value. The easiest way to have a guarantee of value is to make the rocket large enough to carry the level 4 payload. The designs with level 4 payloads have worse performance in the height and duration performance attributes, which leads them to being near the beginning of the respective value functions. The model becomes most uncertain in the middle of the value function, so the designs are much less impacted by the uncertainty. The data shows that the best designs in terms of value come from the smaller rockets though. It is clear that in order to maximize the value and create the best possible design that the rocket needs to be large enough to hold a level 1 payload. This rocket design allows for very good performance in both the height and duration attributes, but also gains some value for holding a payload. It is the best compromise to make for the design of this model rocket.

A final summary of the designs from the baseline, tier 1, tier 2, tier 3, tier 4, and smallest standard deviation is shown in Table 4.13. This is followed by figures of the designs in order to show a final comparison of the possible frontier designs.

Table 4.13: Frontier Rocket Comparison

Design #	Mean Value	Std. Dev.	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
Baseline	46.2	2.44	0.036	0.197	0.004	1	0.20	0.0026	2	0.030	0.048	0.0023	2
Tier 1	47.43	2.44	0.0359	0.188	0.004	1	0.191	0.0024	2	0.0229	0.0481	0.0023	2
Tier 2	44.93	2.056	0.0288	0.182	0.004	1	0.20	0.0045	2	0.0151	0.0478	0.0023	2
Tier 3	32.78	1.98	0.0714	0.058	0.007	1	0.45	0.0024	2	0.0581	0.061	0.0027	2
Tier 4	26.14	1.65	0.0734	0.021	0.0066	1	0.589	0.0023	2	0.069	0.066	0.0034	2
Low-Std.	-41.1	1.35	0.0746	0.017	0.0079	1	0.625	0.0077	1	0.075	0.069	0.0075	2

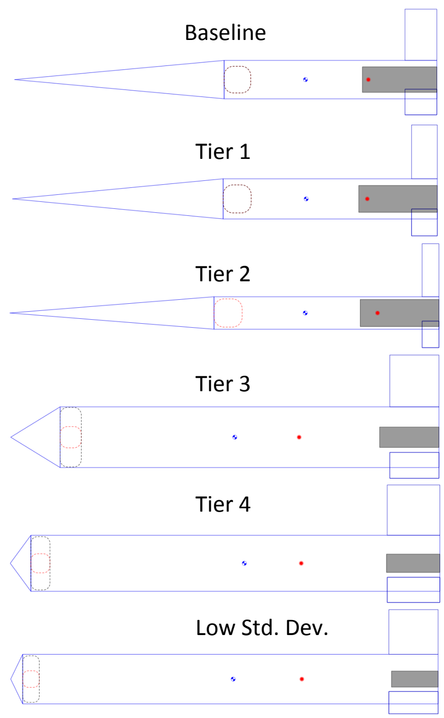

Figure 4.27: Frontier Rockets Comparison

Table 4.13 and Figure 4.27 show the designs moving from the top left of the frontier down to the bottom right. The baseline design is very close to the tier 1 design, but has slightly larger fins, which increases weight while decreasing performance and value. The tier 2 design is the design that is not able to take a payload due to it small diameter. Tier 2 designs are just large enough to hold the rocket motor. After tier 2 there is a very large increase in diameter, allowing all of the further designs to carry a level 4 payload. Moving further along the frontier it can be seen that in order to decrease the standard deviation, the most effective method is shortening the nose cone. This increases the drag and reduces performance, which makes the rocket more immune to the uncertainty.

The very different levels also suggest a possibility for creating rocket platforms. With only three different body sizes, it is possible to create any of the designs on the frontier. The platforms could be built around having a body just large enough to hold the motor, large enough for a level 1 payload, and large enough for a level 4 payload. With these platforms it is possible to make adjustments to the nose cone and fins in order to create a design on the frontier.

Chapter 5: Conclusions and Future Work

5.1 Thesis Review

In the previous chapters, the effects of uncertainty and methods for assessing uncertainty in value driven design were explored. The first chapter introduced the motivation for researching methods in system design to improve the design process. An example of the potential pitfalls of using requirement driven design was shown followed by the introduction of value driven design to help solve these problems. The hierarchical nature of VDD was shown detailing the relationship between the system value model, subsystem value, and value functions. The difficulty in correctly creating the system value model and value functions was shown as a potential area of research. Next, the two research questions were presented. The first research question aimed to explore how significant changes to the value model and value functions affected the optimum solution of the system being designed. The goal of the second question was to look at different methods for assessing value under realistic uncertainty conditions within the value model.

The second chapter provided background information on work that was related to the area of research. The first section focused on work that was done leading up to the introduction of VDD. This included work from the fields of economy, design theory, and probability. A progression of design engineering was shown starting from utility theory by von Neumann to the introduction of VDD by Collopy et al. The second section focused on recent and current research within the field of VDD. This includes the application of VDD toward the design of a large number of system types. The third sections introduced research within the field of uncertainty in design. Within this section methods for designing with uncertainty in the state variables or precision were explored. The third chapter explored the first research question. Two case study problems consisting of a pressure vessel and a model rocket were used to do this. The first case study problem, the pressure vessel, was a simpler problem consisting of two performance attributes within the value model. The second case study, the model rocket, was a more complicated problem consisting of four performance attributes. Each of the case studies explored how large changes to the value model impacted the optimum solution.

The fourth chapter explored the second research question. This time, only one case study was used. The design of a model rocket was used to explore the different ways of assessing value under realistic levels of uncertainty in the value model. Multiple methods for assessing value with uncertainty were explored leading to a Pareto frontier of potential designs.

This chapter summarizes the results of this thesis. In the next section, the identified research questions will be revisited. The results from chapters 3 and 4 will be applied to answer the questions. After revisiting the research questions, further areas of research stemming from this thesis and concluding remarks will be discussed.

5.2 Addressing the Research Questions

In this section, the research questions from chapter 1 are revisited. The following sections will show how thoroughly each of the questions was answered within this thesis. Each of the questions will be answered separately below.

5.2.1 Research Question #1:

How sensitive is the solution from a Value Driven Design analysis, and how predictable are expected changes when changes are made to the underlying value models?

To address research question 1, chapter 3 used two different case studies. The first case study was a pressure vessel, which used two performance attributes in its value model. To answer the question, the impact of changes to the value functions and the weights in the aggregation structure was explored. The pressure vessel case study showed that the optimum solution is sensitive to changes in both the value functions and the weights in the aggregation structure. Specifically for changes to the value functions, it was observed that the changes could lead to 21 distinct optimum solutions. During this study, trends could be found by grouping the type of value functions used into different designer types. Observing the different designer types showed that certain combinations of value functions would always lead to certain types of designs. Examples of this include multiple designer types leading to designs where it is smarter to not build the vessel. Other designer types had the capability of creating a large number of distinct designs. The next study looked at how changing the weights in the aggregation structure impacted the solution. The results of this study showed that this also had a very large effect on the solution. Changing the weights led to less optimum designs (8 distinct designs) than changing the value functions, but still impacted the design.

The second case study used the design of a model rocket to help answer the research question. The case study looked at how changing the value model and value functions impacted the rank ordering of rocket designs. The results in this case study show that the rank ordering of designs can be impacted by changes to either the aggregation structure or the value functions. Similar to the pressure vessel case study, it was shown that trends could be found in order to predict what would happen as changes to the value model were made.

To summarize, it was shown that large changes to either the value functions or the aggregation structure have a significant impact on the solution. It was found that changing the value functions made smaller changes to the design or rank ordering than changing the aggregation structure. Changing the aggregations structure caused large-scale changes as the focus of the design was shifted to different performance attributes. Changing the value functions allowed for smaller changes, as the impact was on the value in a specific attribute.

5.2.2 Research Question #2:

When faced with uncertainty in the value model, how might the best design – or set of best designs – be determined?

To address research question 2, chapter 4 used a case study exploring the design of a model rocket. In this case study a multi-objective genetic algorithm was used to observe different methods for assessing value when there is uncertainty in the value model. This was done with the goal of finding techniques that allow designers to use VDD under uncertainty.

The methods used for assessing value under uncertainty were mean value and standard deviation of value. Testing each of the methods allowed two of the possible methods of dealing with uncertainty in VDD to be explored. Creating a design with a small standard deviation served to make rocket designs that were less impacted by the uncertainty. On the other end of the spectrum was trying to create designs with maximum mean value. These designs followed the idea inherent to VDD of maximizing value and were more susceptible to changes in the value model.

It was shown that designs on the Pareto frontier that had small standard deviations also had smaller mean values. The designs with the lowest standard deviations were the designs with negative value. These designs had poor performance and ended up costing more than the monetary value they created. Designs on the other end of the Pareto frontier that had large mean values were shown to also have large standard deviations of value. This was shown to happen due to the nature of designs with better performance. Designs whose performance was higher in value became more susceptible to the changes due to uncertainty in the value functions. It was also shown that using the baseline value functions and optimizing the design for the highest possible value, without introducing uncertainty creates a design that falls on the Pareto frontier and is very similar to the designs found to have the highest mean value.

To summarize, the results indicated that designing under uncertainty in the value model is possible and there are multiple ways to approach the problem depending on the designer's goals. If the goal is to create designs that are not as susceptible to the uncertainty, then minimizing standard deviation of value can be used, but the performance of the system will decrease. If the goal of the designer is to create one with the best performance, then maximizing mean value will work but the designs value will become more susceptible to uncertainty.

5.3 Future Work

This thesis is a preliminary look at the effects of uncertainty within VDD. In order to better understand VDD and how it can function under uncertainty further avenues of research need to be explored. Some of these avenues are discussed in further detail in this section.

5.3.1 Different Distribution Types

As discussed earlier, this thesis assumed that a normal distribution accurately modeled the uncertainty in a value function. However, this may not be the case as a normal distribution assumes the starting point the most likely answer. It is possible that the baseline function is not the most likely answer or that there are more than one most likely answer. In order to test this, different distribution types could be used for the PDF.

A list of possible different distributions that could be used includes, a uniform distribution or one of the many forms of a beta or logit-normal distribution. Using one of these different distributions within the probability density function could allow designers to map the uncertainty to a more accurate representation.

5.3.2 Real Life Problem

In each of the case studies in this thesis, the problems were made up to test how uncertainty would impact the designs. Since the focus of the thesis was on exploring the impact of uncertainty, the value functions used do not accurately show the relationship between the performance attribute and monetary value. In order to further test the questions asked in this thesis, a real problem needs to be solved next. This would need to involve the help of a company with real data about how the performance of a system produces money. Using experts in the field to help create the baseline value functions would also improve the accuracy of the results. If experts in the field are used it would also give a better idea of how large the range of uncertainty is between the different designers. This would also show the best type of distribution to use for futures uses.

5.4 Concluding Remarks

The work presented in this thesis was done with the goal of improving knowledge within the field of value driven design. Exploring the effects of uncertainty in value driven design allows the designer to know how a solution will be affected when it is necessary to make a change to the value model. This research shows that making changes to a value model will have an impact on the solution of a design, but that it can be possible to predict how the change will propagate. This research also shows how two different methods can be used to assess the value of a system when the value model is uncertain. Finally, the research shows that uncertainty can have an impact on a system within VDD and the exact impact needs to be an area of further research.

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Appendices

Appendix A: Functions for the Propane Tank Value Functions

Value Functions for Volume:

$$Value_V = 10.0 * V \quad \text{(A.1)}$$

$$Value_V = 0.4 * V^2 + 6.0 * V \quad \text{(A.2)}$$

$$Value_V = 0.8 * V^2 + 2.0 * V \quad \text{(A.3)}$$

$$Value_V = 1.0 * V^2 \quad \text{(A.4)}$$

$$Value_V = -0.4 * V^2 + 14.0 * V \quad \text{(A.5)}$$

$$Value_V = -0.8 * V^2 + 18.0 * V \quad \text{(A.6)}$$

$$Value_V = -V^2 + 20.0 * V \quad \text{(A.7)}$$

$$Value_V = e^{0.46*V} \quad \text{(A.8)}$$

$$Value_V = 31.5 * \sqrt{V} \quad \text{(A.9)}$$

$$Value_V = 41.5 * \ln(x + 1.0) \quad \text{(A.10)}$$

Value Functions for Weight:

$$Value_W = -1.25 * W + 100.0 \quad \text{(A.11)}$$

$$Value_W = 0.0062 * W^2 - 1.75 * V + 100.0 \quad \text{(A.12)}$$

$$Value_W = 0.0125 * W^2 - 2.25 * V + 100.0 \quad \text{(A.13)}$$

$$Value_W = 0.0156 * W^2 - 2.5 * V + 100.0 \quad \text{(A.14)}$$

$$Value_W = -0.0063 * W^2 - 0.75 * V + 100.0 \quad \text{(A.15)}$$

$$Value_W = -0.0125 * W^2 - 0.25 * V + 100.0 \quad \text{(A.16)}$$

$$Value_W = -0.0156 * W^2 + 100.0 \quad \text{(A.17)}$$

$$Value_W = 100.0 * e^{-0.09*W} \quad \text{(A.18)}$$

$$Value_W = 100.0 * e^{-0.05*W} \tag{A.19}$$

$$Value_W = \frac{500.0}{W-85.0} + 105.0 \tag{A.20}$$

Appendix B: Rocket Designs for Section 3.3.2

Rocket Design Number
[Rocket Diameter]
[Length, Thickness, Material]: Nose Cone
[Length, Thickness, Material]: Tube Body
[Chord Length, Height, Thickness, Material]: Fins
Generated image of rocket design

*Note: Material 1 is cardboard; Material 2 is Blue XPS foam
All lengths given in meters

Rocket 1
[0.05]
[0.15 , 0.002 , 1]
[0.5 , 0.002 , 1]
[0.07 , 0.05 , 0.002 , 1]

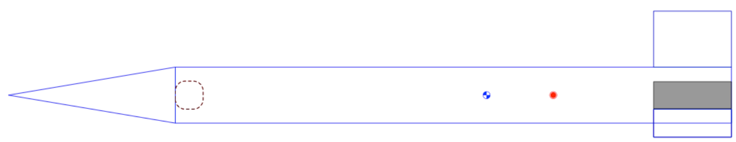

Figure B.1: Rocket 1

Rocket 2
[0.08]
[0.2 , 0.002 , 1]
[0.8, 0.002 , 1]
[0.1 , 0.05 , 0.002 , 1]

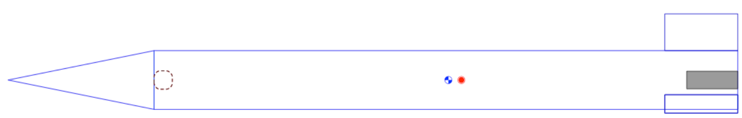

Figure B.2: Rocket 2

Rocket 3
[0.11]
[0.3 , 0.002 , 1]
[1.0 , 0.002 , 1]
[0.2 , 0.1 , 0.002 , 1]

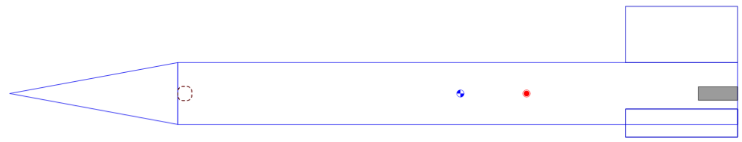

Figure B.3: Rocket 3

Rocket 4
[0.06]
[0.3 , 0.002 , 1]
[0.6 , 0.002 , 1]
[0.1 , 0.05 , 0.002 , 1]

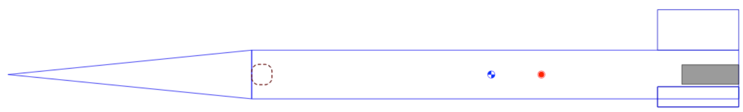

Figure B.4: Rocket 4

Rocket 5
[0.03]
[0.1 , 0.002 , 1]
[0.3 , 0.002 , 1]
[0.05 , 0.03 , 0.002 , 1]

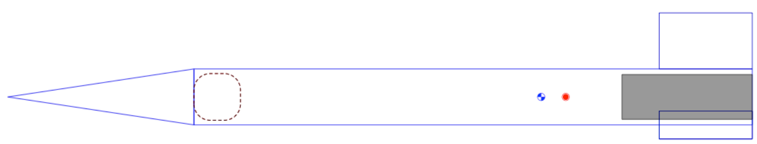

Figure B.5: Rocket 5

Rocket 6
[0.04]
[0.12 , 0.002 , 1]
[0.7 , 0.002 , 1]
[0.8 , 0.04 , 0.002 , 1]

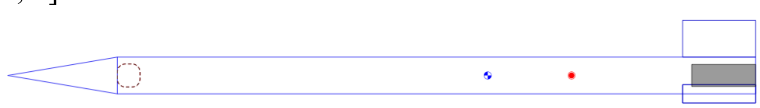

Figure B.6: Rocket 6

Rocket 7
[0.07]
[0.05 , 0.002 , 1]
[0.2 , 0.002 , 1]
[0.05 , 0.05 , 0.002 , 1]

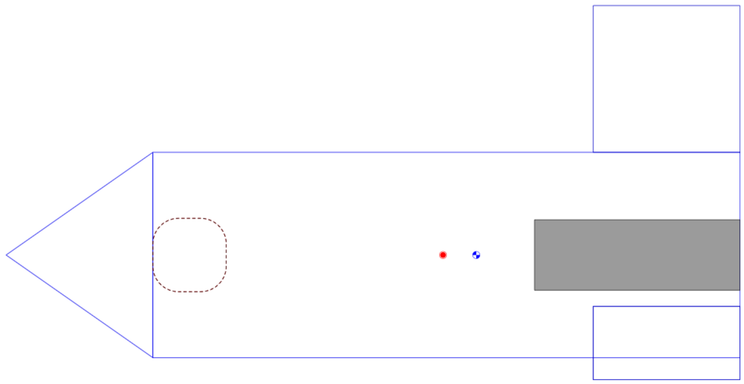

Figure B.7: Rocket 7

Rocket 8
[0.05]
[0.2 , 0.002 , 1]
[0.1 , 0.002 , 1]
[0.04 , 0.05 , 0.002 , 1]

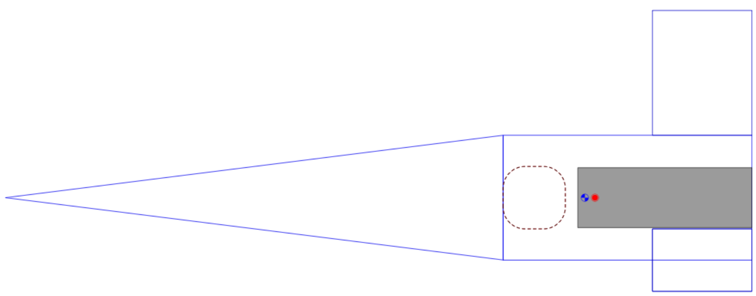

Figure B.8: Rocket 8

Rocket 9
[0.06]
[0.3 , 0.002 , 1]
[0.7 , 0.002 , 1]
[0.08 , 0.07 , 0.002 , 1]

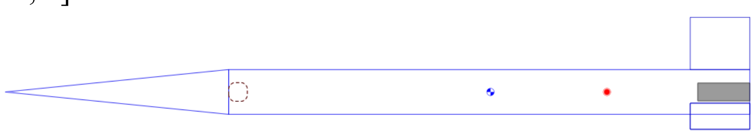

Figure B.9: Rocket 9

Rocket 10
[0.03]
[0.1 , 0.002 , 1]
[1.0 , 0.002 , 1]

[0.07 , 0.021 , 0.002 , 1]

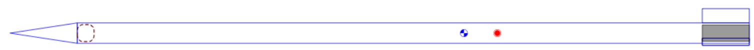

Figure B.10: Rocket 10

Rocket 11
[0.05]
[0.1 , 0.004 , 2]
[0.6 , 0.004 , 2]
[0.07 , 0.065 , 0.003 , 2]

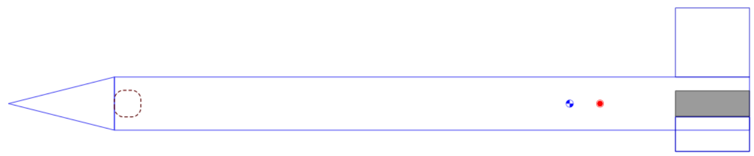

Figure B.11: Rocket 11

Rocket 12
[0.072]
[0.1 , 0.004 , 1]
[0.2 , 0.004 , 2]
[0.06 , 0.05 , 0.003 , 2]

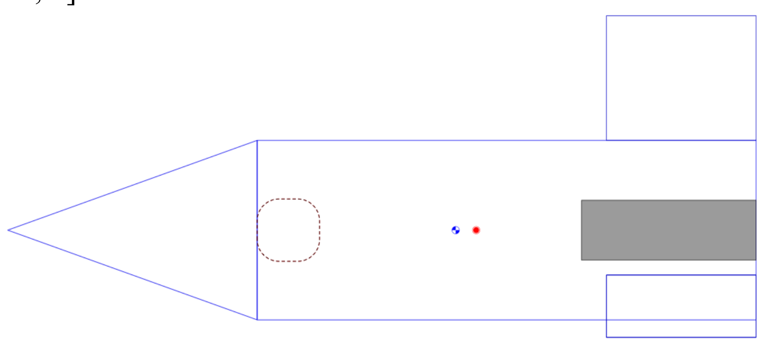

Figure B.12: Rocket 12

Rocket 13
[0.06]
[0.01 , 0.002 , 1]
[0.4 , 0.004 , 2]
[0.08 , 0.06 , 0.003 , 2]

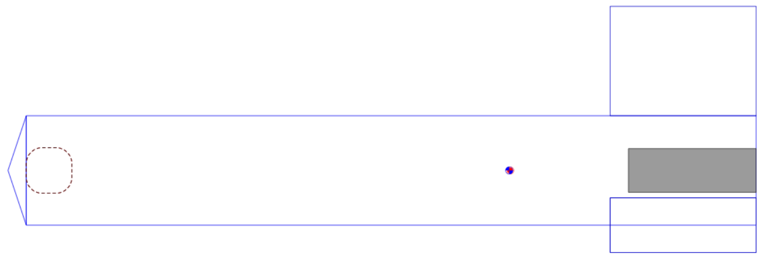

Figure B.13: Rocket 13

Rocket 14
[0.065]
[0.5 , 0.004 , 1]
[0.3 , 0.004 , 2]
[0.1 , 0.05 , 0.003 , 1]

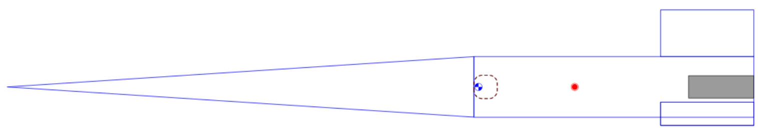

Figure B.14: Rocket 14

Rocket 15
[0.03]
[0.2 , 0.004 , 1]
[0.15 , 0.004 , 1]
[0.03 , 0.05 , 0.003 , 2]

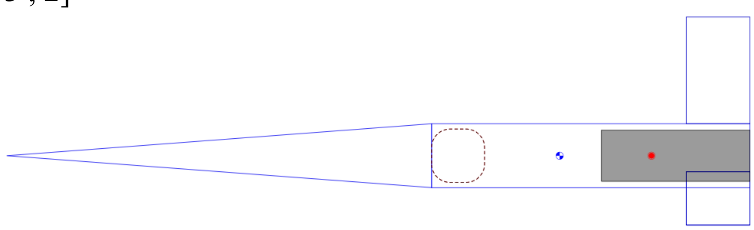

Figure B.15: Rocket 15

Rocket 16
[0.0475]
[0.001 , 0.002 , 1]
[0.35 , 0.004 , 1]
[0.1 , 0.04 , 0.003 , 2]

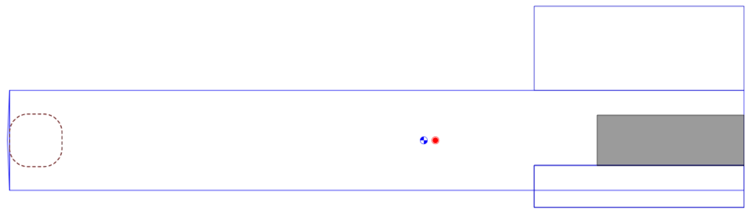

Figure B.16: Rocket 16

Rocket 17
[0.09]
[0.25 , 0.006 , 1]
[0.5 , 0.004 , 2]
[0.2 , 0.08 , 0.003 , 1]

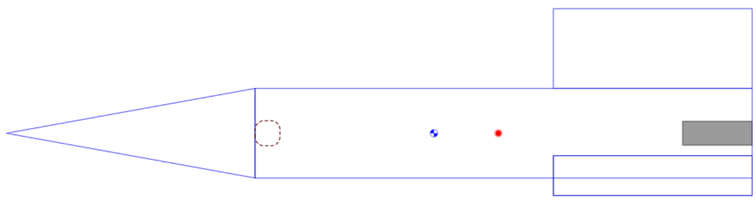

Figure B.17: Rocket 17

Rocket 18
[0.062]
[0.19 , 0.0036 , 1]
[0.4268 , 0.0027 , 2]
[0.0224 , 0.07 , 0.002 , 2]

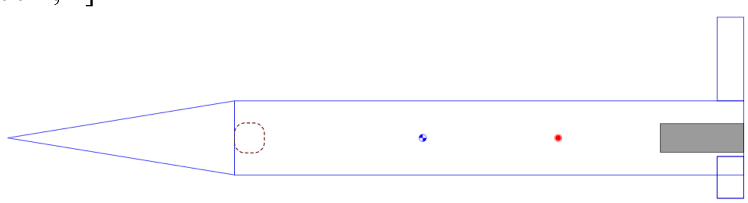

Figure B.18: Rocket 18

Rocket 19
[0.036]
[0.2 , 0.004 , 1]
[0.25 , 0.003 , 2]
[0.018 , 0.05 , 0.0025 , 2]

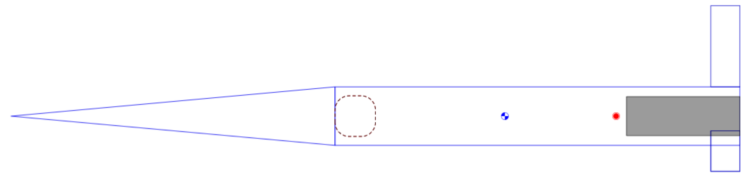

Figure B.19: Rocket 19

Rocket 20
[0.0357]
[0.2 , 0.008 , 1]
[0.189 , 0.004 , 2]
[0.015 , 0.05 , 0.002 , 2]

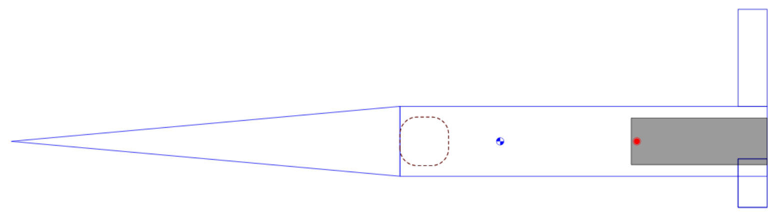

Figure B.20: Rocket 20

Rocket 21
[0.0286]
[0.2 , 0.008 , 1]
[0.14 , 0.002 , 2]
[0.016 , 0.033 , 0.002 , 2]

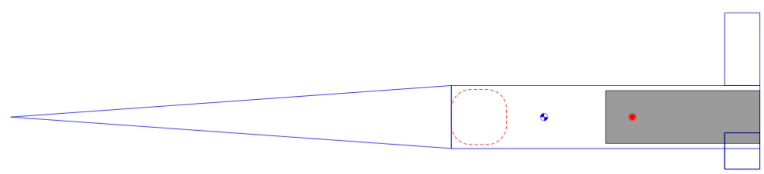

Figure B.21: Rocket 21