MANAGING UNCERTAINTY IN SPACE SYSTEMS CONCEPTUAL DESIGN USING PORTFOLIO THEORY

By
Myles Alexander Walton

Bachelor of Science Mechanical Engineering, Worcester Polytechnic Institute, 1997
Master of Science Aeronautics and Astronautics, Massachusetts Instituite of Technology, 1999

Submitted to the Department of Aeronautics/Astronautics
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy
in AERONAUTICS and ASTRONAUTICS
at the
MASSACHUSETTS INSTITUTE OF TECHNOLOGY
June, 2002

Author...
Department of Aeronautics/Astronautics

Certified by...
Daniel Hastings, Professor of of Aeronautics and Astronautics and Engineering Systems
Associate Director of Engineering Systems Division, Thesis Supervisor
Director, MIT Technology and Policy Program

Certified by...
Edward Crawley, Professor of of Aeronautics and Astronautics and Engineering Systems
Department Head, Aeronautics and Astronautics, Thesis Committee Member

Certified by...
Earll Murman, Professor of of Aeronautics and Astronautics and Engineering Systems
Ford Professor of Engineering, Thesis Committee Member

Certified by...
Joyce Warmkessel, Senior Lecturer, Department of Aeronautics and Astronautics
Thesis Committee Member

Accepted by...
Wallace Vander Velde, Professor Emeritus of Aeronautics and Astronautics
Chairman, Department Graduate Committee

MANAGING UNCERTAINTY IN SPACE SYSTEMS CONCEPTUAL DESIGN USING PORTFOLIO THEORY

by

Myles Alexander Walton

Submitted to the Department of Aeronautics and Astronautics in
partial fulfillment of the requirements for the degree of
Doctor of Philosophy in Aeronautics and Astronautics

Abstract

One of the most significant challenges in conceptual design is managing the tradespace of potential architectures—choosing which design to pursue aggressively, which to keep on the table and which to leave behind. This thesis provides a framework for managing a tradespace of architectures not through traditional effectiveness measures like cost and performance, but instead through a quantitative analysis of the embedded uncertainty in each potential space system architecture. Cost and performance in this approach remain central themes in decision making, but uncertainty serves as the focal lense to identify potentially powerful combinations of architectures to explore concurrently in further design phases.

Presented is an approach to identify, assess, and quantify uncertainty in space system architectures, as well as a means to manage it using portfolio theory and optimization. Perhaps best known to economists and investors, portfolio theory is based around the objective of maximizing return subject to a decision maker's risk aversion. This simple concept, as well as the theoretical rigor that has evolved the theory to practice, is presented as one means of exploring the tradespace of potential architectures around the central theme of uncertainty.

The approach presented relies upon previous work to model space system architectures using simulations that capture attributes of performance and cost. The first step in the approach is an analysis of the tradespace of potential architectures, including the bounding of architectural concepts that will be evaluated and the potential uncertainties and scenarios that will be investigated. The second step is to adjust the simulation models to include sources of uncertainty. The third step is to quantify the impact of the uncertainties on the evaluation criteria for each architecture through propagation techniques. Finally, portfolio theory is incorporated as an approach to manage uncertainty effectively.

Illustrative cases present the changing shape of the decision process with uncertainty as a focal point. The three cases, a military space based radar mission, a commercial broadband system, and an scientific observing mission, illustrate the this new approach on tradespace exploration and highlight some of the intuitive and non-intuitive characteristics that can be discovered about the tradespace.

Thesis Supervisor: **Professor Daniel Hastings**
Professor of Aeronautics and Astronautics and Engineering Systems
Associate Director of Engineering Systems Division, Thesis Supervisor
Director, MIT Technology and Policy Program

ACKNOWLEDGMENTS

I'd first like to acknowledge my advisor, Professor Daniel Hastings. In his capacity as my research supervisor and doctoral committee chair, Prof. Hastings afforded me the freedom to explore my interests in cross-disciplinary techniques that served as the basis for this research. His continuous support and encouragement made the conceptual blockbusting possible.

The rest of my doctoral committee deserves a great deal of credit for the work presented in this thesis. Prof. Earll Murman's generosity in bringing me into interesting and exciting projects outside of the narrow scope of my research broadened my experience here at MIT and allowed me to step back from the thesis from time to time. Dr. Joyce Warmkessel, my Master's Thesis advisor, provided me with the ever-important practical perspective of the industry expectations of research. Professor Ed Crawley served me with the amazing ability to wrap his mind around a problem quickly and an uncanny gift to craft effective messages of the research for communication. Professor Andreas Schulz's initial class in operations research served as some of the original impetus to this work.

Other faculty members who have contributed to this work through insightful feedback and review include Hugh McManus, David Miller and Olivier de Weck. I'd also like to acknowledge those organizations and individuals in industry who hosted site visits for me during the initial stages of the research and provided valuable feedback as it matured.

MIT has been my home for the past five years and it has been the amazing people here that have made the stay a wonderful experience, most notably, my graduate student colleagues in the Lean Aerospace Initiative (LAI) [Josh Bernstein, Carmen Carrera, Jim Chase, Rob Dare, Heidi Davidz, Jason Derleth, Bobeck Ferdowsi, Chris Forseth, Cory Hallam, Sean Hitchings, Brian Ippolito, Sandra Kassin-Deardorff, Aaron Kirtley, Jacob Markish, Michelle McVey, Rich Millard, Jeff Munson, Matthew Nuffort, Nirav Shah, Larry Siegel, Alexis Stanke, Dave Tonaszuck, Mandy Vaughn], the Space Systems Lab (SSL) [Cyrus Jilla and John Enright], and the Space Systems Policy and Architecture Research Consortium (SSPARC) [Adam Ross, Nathan Diller, Satwick Seshasai.].

Also, researchers from Prof. Hastings's research group have each provided insightful feedback on the work as it has evolved, notably Elisabeth Lamassoure, Roshanak Nilchiani, Peter Panetta, Chris Roberts and Joseph Saleh.

Living near my family has afforded me the luxury of staying in close contact with my parents, Steven and Evelyn Walton, and siblings [Vicky and Robert, Cindy and Jörg, Neal and Lynne, David and Jen, Tam and Steve, and Clint] whose constant encouragement and love made the PhD journey much easier. I'd also like to thank the family I married into [Arthur and Lillian Weigel and John] for welcoming me in as one of their own.

I've heard stories that getting a PhD can be an isolating experience. For me, it was anything but isolated. I had the unique advantage of a loving wife, Annalisa, going through the PhD process at the same time. A constant role model for me in research and life, Annalisa was and is my greatest source of support and inspiration.

The author gratefully acknowledges the financial support for this research from the Space Systems Policy and Architecture Research Consortium (SSPARC), a joint research program funded by the U.S. government involving the Massachusetts Institute of Technology, the California Institute of Technology, and Stanford University.

TABLE OF CONTENTS

CHAPTER 10

APPENDIX A

LIST OF FIGURES

LIST OF TABLES

Number *Page*

GLOSSARY

A glossary is presented to familiarize the reader with some of the terminology that is repeatedly used throughout the course of this work. Most of these terms are consistent with the literature, *where the literature itself is consistent.*

Architecture. 1.) Level of segmentation for analysis that represents overall project form and function; 2.) Term used in the Generalized Information Network Analysis (GINA) approach to describe individual design alternatives.[1] Note these design alternatives may differ only in subsystem characteristics. On the other hand, individual architectures could be very different such as large monolithic single satellite systems compared with distributed constellations of small satellites.

Asset. A measurable investment vehicle. An asset in space systems design can be an actual operational system, or the design from which an operational system could result.

Conceptual Design. Segment of the product development process charged with identifying customer needs, developing possible concepts to explore, and selecting concepts for more detailed design.

Customer. Individual(s) or organization(s) that procure a system.

Decision Maker. Individual(s) or organization(s) having power to direct allocation of resources.

Design Vector. Vector that represents tradable elements of architectural concepts. These might include altitude; satellite power, orbital characteristics and level of autonomy for example.

Diversification. Method of allocating resources among assets to avoid specific uncertainty.

Downside. The value distribution represents adverse outcomes of a statistical distribution, also known as "risk" if an outcome is in the distribution.

Efficient Frontier. The definable region of the tradespace where all efficient portfolios exist in the value vs. uncertainty tradespace.

Efficient Portfolio. A portfolio whose return cannot be increased without accepting more uncertainty.

Embedded uncertainty. Architecture characteristic that is neither obvious nor able to be isolated within the architecture and results from exposure to uncertainty from various sources and levels.

End User. Eventual user of the developed system.

---

1 Although we classify an individual combination of design variables as an architecture, in some case the differences between one combination and another may suggest that the GINA process is simply doing parameter design and not system architecting. This is the topic of ongoing debate, but to remain consistent with the terminology first developed with GINA, each combination of the design vector will be called an individual architecture.

Engineering Systems Design. The construction of solutions that satisfy complex technological and social issues using a systems level perspective with explicit engineering principles

Generalized Information Network Analysis. Method of conducting space systems analysis that provides for an "apples to apples" comparison of different architectural concepts.

Market Place. Economic boundary for investment.

Portfolio. The set of selected investments for which resources will be allocated.

Optimization. The maximization (minimization) of an objective subject to defined constraints.

Risk. A measure of negative consequences of investment and their likelihood.

Semi-Variance. Measure of uncertainty, can be either upside or downside of uncertainty

Specific Uncertainty. Uncertainty that is unique to some assets and can be decreased through diversification. This type of uncertainty might include individual technology specific to one design.

Stakeholder. In the broadest sense, stakeholders are those individuals or groups who affect or are affected by a system. In a perhaps narrower sense, a stakeholder is a constituent for whom value must be considered. This includes, customers, users, supplier, etc.

Systematic Uncertainty. Uncertainty that exists in all assets and cannot be decreased through diversification. This type of uncertainty affects all architectures equally such as cost estimation uncertainties.

System. Level of decomposition that is inclusive of a major architectural element and is semi-independent from the rest of the architecture. This could include a satellite, or ground segment or a launch vehicle.

Subsystem. The level of decomposition that is inclusive of parts and components that combined perform a portion of the overall system functionality.

Tradespace. The defined boundaries of potential design solutions that will be evaluated. The boundaries are typically defined through a design vector. In portfolio theory applied to space systems, the architectural tradespace becomes the metaphorical marketplace.

Uncertainty. Inability to quantify precisely; a distribution that reflects potential outcome.

Upside. The value distribution that exceeds positive outcomes, or the "reward" in the distribution if an outcome is defined.

Utility. Measure of worth from the perspective of the decision maker.

Value. Measure of worth inclusive of utility and any elements of disutility, i.e. cost, schedule; E.g. Function/Cost.

Chapter 1

INTRODUCTION

Too often, the existence of uncertainty in life is ignored. We avoid stating assumptions and the uncertainty associated with them, we anticipate the future based on little deviation from previous experience, we accept (and sometimes embrace) the idea of unquantifiable complexity, and seek out certainty as though it is more powerful than the uncertainty being faced. The bottom line is people hate being indecisive, inexperienced, and incorrect and all of these traits are too often associated with uncertainty. However, history has shown that it is not the simple existence of uncertainty, but instead the lack of identifying and understanding it that results in failure. Indeed, uncertainty can have a positive influence. Without it, there would be no room for advancement, there would be no capitalism, and there would be no religion, no freethinking or debate. Uncertainty therefore should not be ignored or enter into the decision making process as an afterthought. It should be a motivating central theme to any decision making process. The goal of this thesis is to portray uncertainty as a central concept in space systems design and to develop an uncertainty analysis framework that is approachable, quantifiable and useful in directing a project from concept to delivery. This document presents select methods of uncertainty analysis from a number of disciplines brought together in a single constructive framework that can be used in the early conceptual design of space systems.

For centuries, religion and the role of the gods dictated the fate of individuals and the outcomes of decisions; decision makers had a natural shield for the negative results of their actions. Not until the contradiction to the belief that man had little control over results, did full accountability become realized by many of the world's decision makers. Ironically, this was occurring at the same time, brilliant scientists, inventors, mathematicians and philosophers were making breakthroughs in their respective fields. Ideas of uncertainty and risk would only be seriously studied (e.g. mathematically) in the age of the Renaissance. Instead of blindly accepting fate and the will of deities, society started to realize that uncertainty was something that could be understood and incorporated into decision making, and further that decision makers should indeed be held accountable for their informed or misinformed actions and the resultant outcomes. The Greeks flirted with ideas of uncertainty and risk, but were unable to instill the notions into a culture that relied so heavily on the absolute truth and reality. This reliance obstructed the extension of mere philosophy and thinking to practice.[2]

Today in engineering systems design, designers and decision makers face much the same conflict that decision makers faced prior to the Renaissance. The precise behavior of these systems is so complex, that any attempt to understand and model them in detail is consistent with the role of oracles. Therefore, people do their best to understand what they can about the problem and its solution, but at the same time, the expectations for uncertainty analysis inclusion are minimal. If there is one challenge that the reader takes away after reading this thesis, it should be: *Engineering systems conceptual design needs to move toward more informed decision making through explicit inclusion of uncertainty as a criteria and in doing so return accountability to decision makers.*

The Renaissance gave rise to investigation into concepts of uncertainty, but the efforts were by and large focused on the negative effects of uncertainty, in the form of risk. To this day, most of the research continues to focus on the adverse consequences, or downside, of uncertainty, despite the maturing of qualitative and quantitative methods that could shed equal light on ideas of upside uncertainty. The method presented herein captures and distinguishes the upside and downside of uncertainty and presents alternatives to presenting uncertainty and managing it.

Like decision makers in all other fields of study, space systems decision makers are constantly confronted by the truism that "the only certainty is uncertainty." This should be the mantra that complex products systems development organizations adopt. Aerospace as an industry, with development lasting in some cases longer than a decade should be at the forefront of this adoption. However, all too often designers and decision makers convince themselves of the stability of the environment and the quality of their solutions and decisions. Unfortunately these convictions have a habit of blowing up in our faces (often quite literally). This is particularly the case in conceptual design where decisions are so far separated from the consequences of the decisions, but the impact of decisions is great, as shown in Figure 1. Because of the significant impact of decisions made in early

---

[2] Bernstein, P. (1998). Against the gods: The remarkable story of risk. New York, Wiley and Sons.

conceptual design and because of the inflexibility of phases of design, this research specifically targeted that phase as a segment of contribution.

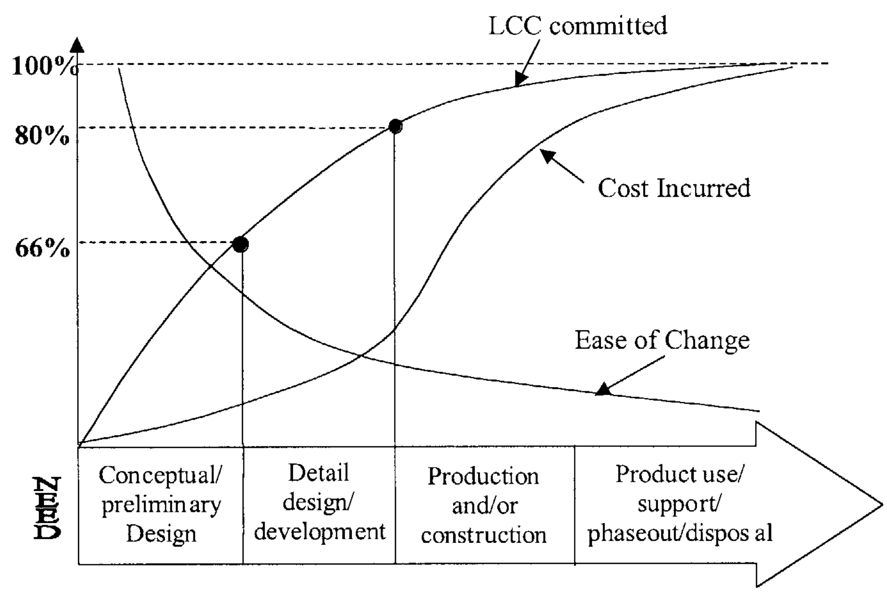


Figure 1: Lifecycle cost committal versus incurrence[3]

Part of the solution to finding better designs is to intelligently explore more of them. Advances in conceptual design methods for evaluating space systems architectures, specifically the Generalized Information Network Analysis (GINA) approach, provided a means of exploring conceptual tradespaces rather than just conceptual point solutions.[4] By modeling some space systems around the central assertion that these systems are in fact information transfer networks and aspects of information theory could be directly applied, the GINA approach was created. The greatest benefit of GINA was that it enabled a structured analysis, assessment and exploration of large tradespaces using simulation models that effectively segmented the problem of designing space systems. These simulation models are used to predict system behavior in terms of cost and various performance characteristics, such as system capacity over its lifetime and can be used to predict behavior of thousands of potential architectures simultaneously.

---

[3] Adapted from Fabrycky, W. (1991). Life Cycle Costs and Economics. NJ, Prentice Hall.

This thesis asserts that a simple deterministic prediction, as is the case in GINA and other modeling techniques, is not enough. This research extends the current thinking with regards to the GINA methodology, and other design techniques, such that architectures in the tradespace are further distinguishable by the *embedded uncertainty* in each. Traditionally, architectural designs are represented in a design tradespace, such as those in the GINA framework, as expected values in dimensions of utility and cost. But in fact, the architectures have little in the way of static existence and instead have associated with them embedded uncertainty. The term "embedded" implies that this characteristic is neither obvious nor can it be isolated within the architecture. Embedded uncertainty is lifeblood that runs through every aspect of the architecture and while its characterization can't be isolated to any architectural characteristic, it can be aggregated and described in a way that is helpful to the decision maker. Further, this uncertainty can in fact represent either risk or as less often realized—reward.

This research began with an exploration of how decisions were committing resources early in the conceptual development process. From this preliminary work, insights were gained into the inevitable trade-off between speed and flexibility: the trade-off between comfort and anxiety: the trade-off between certainty and change. Prompting the further investigation of modeling and understanding of the architectural uncertainty in the conceptual design process.[5] The improvement of uncertainty information and uncertainty trade-offs was a natural direction to pursue for making a contribution.

1.1 Problem Statement and Approach

Uncertainty and risk analysis in conceptual design at present can be characterized as qualitative, expert driven and point based. Moreover, uncertainties are evaluated individually, assessed and addressed as unique and any calculations of these uncertainties are typically a posteriori and are not embedded in the end model. This research addresses each of these issues. The presented method provides an approach that is both quantitative and tractable. Further, this approach provides the strategy necessary to differentiate among potential architectures and manage uncertainty in a tradespace.

---

[4] Shaw, G., D. Miller, and D. Hastings (2001). "Development of the Quantitative Generalized Information Network Analysis (GINA) Methodology for Satellite Systems." Journal of Spacecraft and Rockets 38(2): 257-269.

[5] Walton, M. (2000). Striving toward a Lean Clean Sheet Design of Space Systems. AIAA Space 2000, Los Angeles, CA, AIAA, #2001_4573.

Another perspective of engineering systems development explored in this research suggests that mental models of running from uncertainty or denying its existence can in fact be replaced by mental models of leveraging uncertainties that have reward potentials and understanding how to work with uncertainties that are likely to put project success at risk. These concepts are brought to bear through the application of financial risk management and, more specifically, the application of portfolio theory.

This thesis began as an exploration in the broad issue of improving the design and development of space systems. It evolved to a focus on the front end of conceptual design, because of the high impact per dollar spent of that phase of development and the significance of the decisions made there on the eventual success or failure of the developed system, as illustrated in Figure 1. So given the influence of decisions in the conceptual design phase, how can the information and/or the process by which decisions are made be improved? It is at this junction of the improvement of information and process that the thesis began to mature. By looking at all the criteria by which decisions are made, ideas of improved uncertainty quantification and uncertainty management stood out. The problem statement evolved from the broad question of: *How can design and development of space systems be improved in terms of cost, schedule and quality?* to *How can uncertainty of architectural choices be quantified and presented to designers and decision makers as to improve the overall design process in terms of cost, schedule and quality?*

Once a problem statement was defined and an initial literature review was completed, semi-structured interviews were conducted at four major space system design organizations to develop an overall perspective of the state of uncertainty analysis in industry and to collect challenges that could be addressed through this research. Some of the most significant challenges were 1.) developing a method that incorporates different stakeholders viewpoints and preferences toward uncertainty and value, 2.) addressing uncertainties from sources outside of the narrow scope of solely technical uncertainty, and 3.) developing a method that is both tractable and approachable to designers and decision makers. Overall the dominant theme echoed at the interviews was a desire to understand uncertainty at a level that would be useful as decision criteria and able to be traded in early conceptual design. Too often, it was pointed out, uncertainty analysis and corresponding risk analysis are an afterthought in early conceptual design, where modelers and designers are pushed to deliver the desired outcome behavior and decision makers are pressed to pick something to move forward to preliminary design, so as to not appear indecisive.

In order to treat uncertainty as decision criteria, quantitative methods of uncertainty analysis are used and an approach is developed to quantify the embedded uncertainty in each architecture considered. To do this, pre-existing quantitative methods were synthesized to create an adaptable approach that could be tailored to different sources of uncertainty and modeling methods. Primarily, the uncertainty analysis incorporates statistical uncertainty measurement, uncertainty propagation techniques and elements of probabilistic risk assessment and multi-attribute utility theory.

Realizing that individual uncertainty measurements would not be as useful to a decision maker as a method by which he/she could trade this information among potential architectures, portfolio theory and optimization is introduced as potential organizing method to manage uncertainty and guide decision makers as to what the raw uncertainty data suggests in terms of action.

Finally, all these contributed to a cohesive uncertainty analysis approach that was developed and demonstrated on three space systems case studies.

1.2 Structure of Document

Chapter 2 presents the potential that could arise from treating uncertainty as a central decision criteria in the design of space systems. The chapter presents the vision of why this research is important and the overarching principles that come out of the work. Part I describes the foundation on which the approach was conceived as well as a detailed description of the uncertainty analysis approach developed. Chapter 3 sets the stage for the current practice of uncertainty analysis in industry, while Chapter 4 highlights the literature on uncertainty quantification and management with respect to space systems design. Chapter 5 presents the first of two chapters describing the approach derived in this thesis. This chapter addresses the quantification of uncertainty in architectures, while Chapter 6 describes the application of portfolio theory to space systems design as a useful framework to managing uncertainty. Part II describes case studies used to demonstrate the applicability and potential of the uncertainty analysis framework. Chapter 7 describes the application of the uncertainty framework to a Space Based Radar Mission. Chapter 8 describes the same framework, but in the context of a Commercial Broadband Communications Space System. Chapter 9 describes the approach applied to a Scientific Earth Observing Space System. Each of the three cases highlights different elements of the uncertainty analysis and provides practical implementation examples.

Chapter 10 summarizes the conclusions found in the case studies and the generalizability of those conclusions, as well as suggestions for further research. Finally, an implementation tutorial is included in Appendix A as a step-by-step description for applying the approach.

Chapter 2

UNCERTAINTY AS A DECISION CRITERIA IN DESIGN

The purpose of this chapter is to present a vision of the potential benefit that could come from the use of uncertainty as a decision criteria in design. The application of portfolio theory to the design of space systems is briefly introduced, while an illustration of how decisions and the decision process in conceptual design would be altered within the approach set forth in the thesis. The chapter also introduces three principles of uncertainty in space systems conceptual design that have evolved from the work that serve to align the reader for the remainder of the thesis.

Consistent with the complexities of a space system, the conceptual design is plagued with uncertainties from sources both identifiable and concealed. It is the job of those involved in conceptual design to wade through the uncertainty that define the problem and arrive at decisions and architectures that, within the current level of available information, reflect the better alternative. It's clear that in uncertain environments, optimality is something of a myth. This of course is why design is part art in addition to part science. The simplistic assumptions of certainty of conditions, even at the embryonic stages of design, can yield detrimental conclusions. Often intractable problems, due in large part to uncertainty in the system and its the environment, are relegated to abstractions of the real problem that rely on the accuracy of current estimates. This research lays the framework for a new way of looking at the process of exploring potential architectures through the lens of uncertainty, that has the potential to change the way people think about early conceptual design and the selection of designs to pursue.

Decision criteria such as cost, performance and schedule are the standard when it comes to decision making in space systems design. These measures, quantified using anything from back of the envelope estimation to expert opinion to intense computation and modeling, typically serve as the basis of the information provided to the decision maker. The mechanism to calculate information, like cost, schedule and performance, has been taught in a number of books on the design of space systems in addition to the industrial practice exercised at each contractor and continues to be the subject of a large body of research.[6] In contrast, methods of accounting for uncertainty in predictions in space systems design have been far less published. No method has been presented, as of yet, that aggregates the types and sources of uncertainty that are typical of a space system and demonstrates an approach to manage such information. This thesis presents such an approach and goes further to develop a framework in which to explore the implications of uncertainty in different architectures.

Using uncertainty as decision criteria in design is not new. Typically, uncertainties in potential space system architectures are highlighted early as potential sources of risks. These risks are then discussed in terms of probability and likelihood. Individual risks on any given architecture are aggregated qualitatively to judge the architectural risk that is present. This allows in part for the relative comparison of risks among architectures. [As design moves beyond conceptual design, risk management takes on a more significant role with risk management specialists developing fault trees and conducting failure modes and effect analysis and more detailed probabilistic risk assessment.]

It is risk, rather than uncertainty that is the more common concept that currently pervades space systems design. This of course is not without reason; human psychology dictates that the downside of uncertainty is generally more important to decision makers than any upside benefits. Typical of conservatism is the immediate connection of uncertainty to risk. Although the connection between uncertainty and risk is clear, the distinctions are often buried. This thesis proposes uncertainty as a more general and powerful concept around which to develop a method to manage uncertainties and the potential risks that result.

It is shown that it is not just the information about uncertainty in any single architecture in isolation that provides the most benefit to the decision making process. Instead, it is with the collective uncertainty information of all the architectures in the tradespace from which real benefits and innovative solutions can be found. When the collective uncertainty information is known, relationships among architectures can be further discerned. For example, some of the most important

---

[6] Larson, W. a. J. W., Ed. (1992). Space Mission Analysis and Design. Torrance, CA, Microcosm., Wertz, J. a. W. L., Ed. (1996). Reducing Space Mission Cost. Torrance, CA, Microcosm., Gordon, G. a. W. M. (1993). Principles of Communications Satellites. New York, John Wiley & Sons, Inc.

information that can be gained is the relative dependence of architectures with respect to their expected outcomes under conditions of uncertainty. A decision maker must not only be aware of the uncertainty of the architectures she is considering, but also how carrying more than one architecture at the conceptual design phase might mitigate her exposure to total uncertainty; this is where portfolio theory and optimization become helpful. Simply investing resources in designs that have different levels of uncertainty will not do as much good as investing in designs that have equivalent uncertainty, but which have a relatively low correlation to each other in terms of outcome behavior under conditions of uncertainty. In fact, such correlation-blind investment might simply dilute the available resources for development.

2.1 Simple illustration of the impact of uncertainty included as a decision criteria.

It's easy to see the impact that uncertainty information could have on a decision making process. Although the increased information about uncertainty introduces complexity to the decision making process, it also highlights the realities that exist and are so important to decisions at the front end of product development, as they prescribe so much of the downstream project performance. Judging an architecture based on static interpretations leaves the decision maker with finality and an ability to make fairly clean tradeoffs amongst architectures. However, seldom is architectural behavior known to the point where outcome measures fully distinguish one architecture from another, as shown in Figure 2. The lack of clarity is due to the embedded uncertainty in each architecture. In the figure, a central point represents the expected value for a single architecture, while an ellipse represents the standard deviation about the expectation in the two key performance criteria. The first criterion is lifecycle cost and the other is total utility. The concept of "utility" will be explained in more detail in Chapter 4, but for now utility can be interpreted as the relative performance of an architecture with respect to accomplishing the desired mission. In this case, introduced in Chapter 9 as ATOS, the desired mission is to map the characteristics of the earth's ionosphere. A set of 30 architectural outcomes is illustrated graphically in Figure 2.

Rather than focusing on an architecture's expected performance, with the inclusion of uncertainty information, designers can begin to focus on the range of behavior that it could achieve. The decision of selecting the "best" architecture becomes less clear, how should judgments be made? On the basis of expectation? On the basis of uncertainty? On some combination of the two? Ideas of portfolio theory are used as the foundation from which to answer these questions.

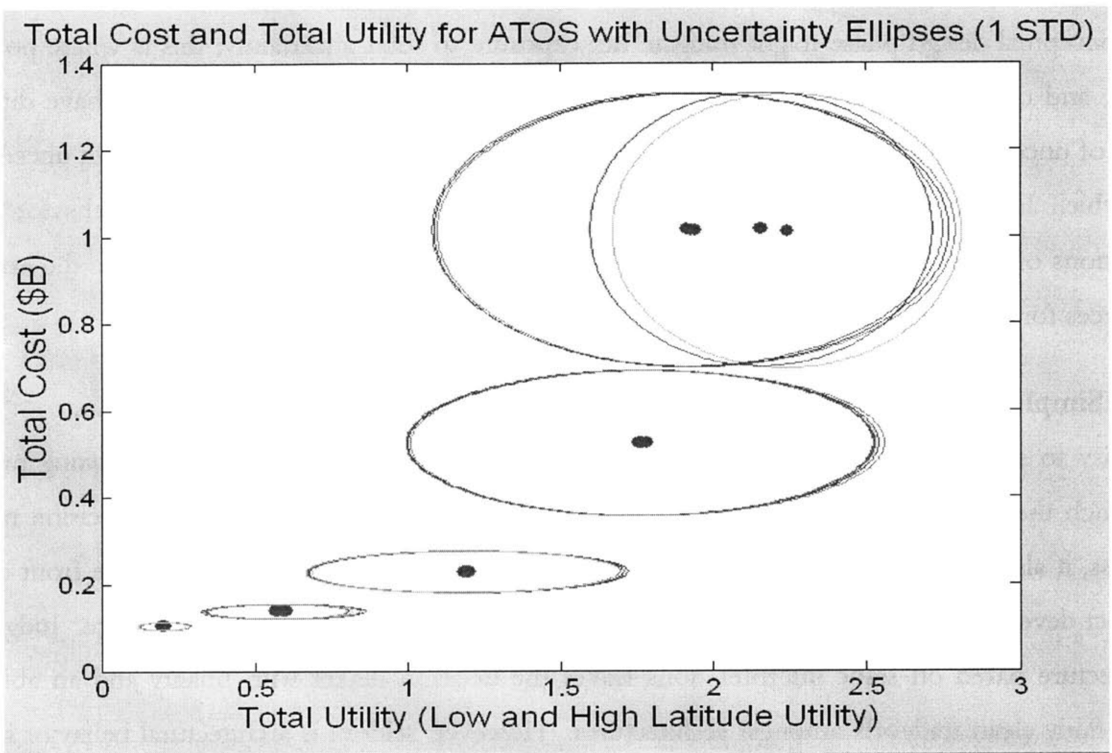


Figure 2: Example of Uncertainties in Cost and Utility

Portfolio theory is a corner stone of this thesis and is presented as a viable approach to manage the embedded architectural uncertainties that confront decision makers, as in Figure 2. Portfolio theory has deep roots in the fields of economics and finance; in fact, the creator of modern portfolio theory received a Nobel Prize in economics for his work on the subject.[7] Table 1 describes the metaphor this thesis constructs between the investment in financial instruments and investment in space system architecture designs. The similarities are striking and, as will be demonstrated, hold up in practice.

[7] Markowitz, H. (1952). "Portfolio Selection." Journal of Finance **7**(1): 77-91.

Table 1: Portfolio Theory Applied to Finance and Space Systems

	Financial Portfolio Theory	Portfolio Applied to Space Systems
Who Invests	Individuals/groups with capital resources	Decision makers who are committing resources
What are the investments	Financial instruments such as stocks, bonds, treasuries	Space system architecture designs
What is the choice space	Those vehicles that are available at a given time and within the constraints of a given investor	Those designs that are within the scope of the project and included in the tradespace
What is the objective	Maximize returns while considering the investors willingness to accept risk	Maximize expected value of the project while considering the decision maker's aversion to risk

Portfolio theory enables formal trade-offs to take place in a value vs. uncertainty tradespace, such as the one presented in Figure 3. This figure displays the same architectures as Figure 2, but allows for the selection of synergistic combinations of architectures rather than any single point design. The points represent the expectations in terms of utility/$ and uncertainty for each individual architecture, while the concave line represents the efficient frontier along which all optimal portfolio investment strategies lie. That is, the efficient frontier includes all portfolios, or sets of architecture designs, whose value cannot be improved without accepting more uncertainty.

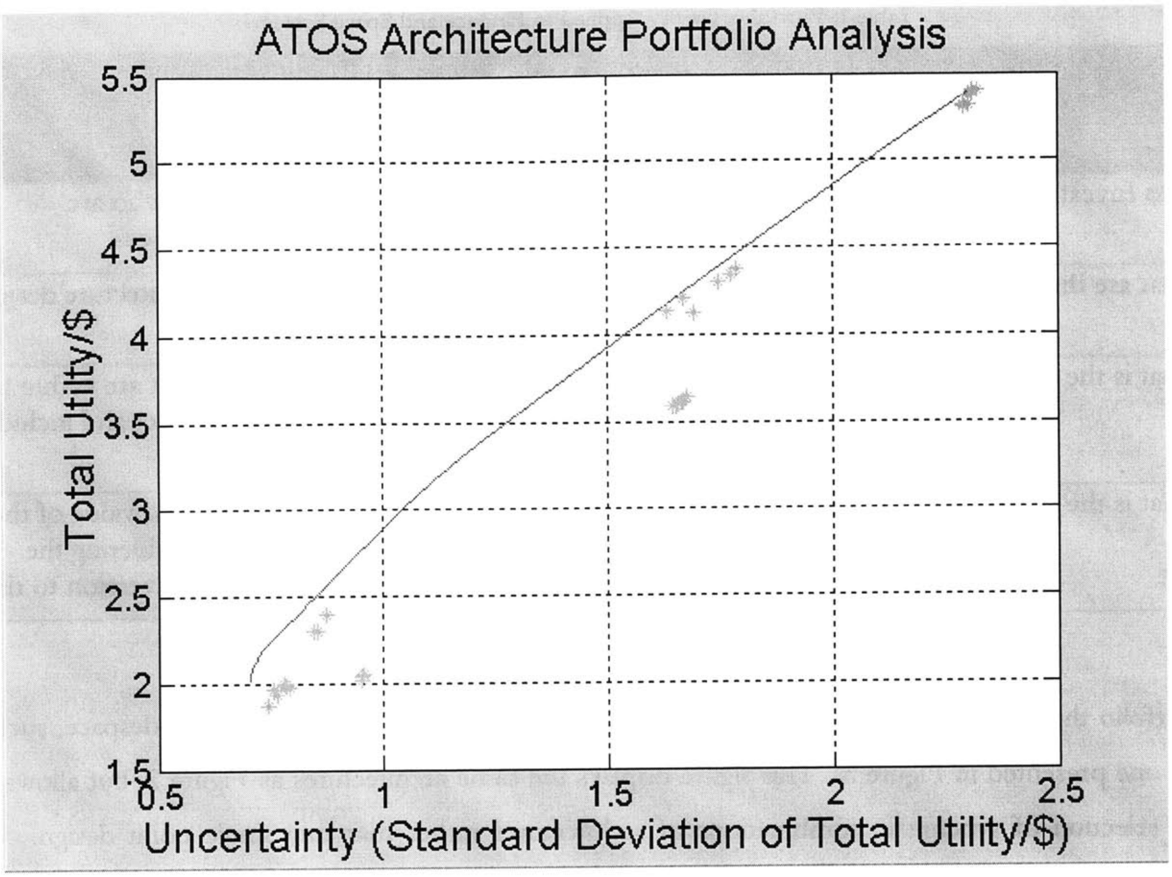


Figure 3: Example of a portfolio tradespace

Portfolio theory also provides for the inclusion of the decision maker's aversion to risk in the analysis, thus allowing an optimal strategy to be found, as shown in Figure 4. Notice that the optimal portfolio exceeds any individual architecture in terms of value for a given level of uncertainty. This non-intuitive result is achieved through diversification. Portfolio theory brings to the uncertainty analysis discussion not just the absolute measure of uncertainty in an architecture, but also how different architectures behave under conditions of uncertainty. Differences in behavior open the door for this type of diversification. In much the same way bonds and stocks move differently with respect to uncertainty, so too can architectural designs. In the example provided in Figure 4, the two architectures in the portfolio are achieving utility using different technical approaches and are therefore sensitive to different kinds of uncertainty. By carrying both, the total exposure to uncertainty is lowered because the outcome behavior of each with respect to uncertainty has a low correlation, thus providing an opportunity for diversification.

The details of the foundation, approach, assumptions and results follow, but before getting into the details a vision for uncertainty analysis in the context of space systems is presented as well as the overarching principles that are be extracted from the thesis.

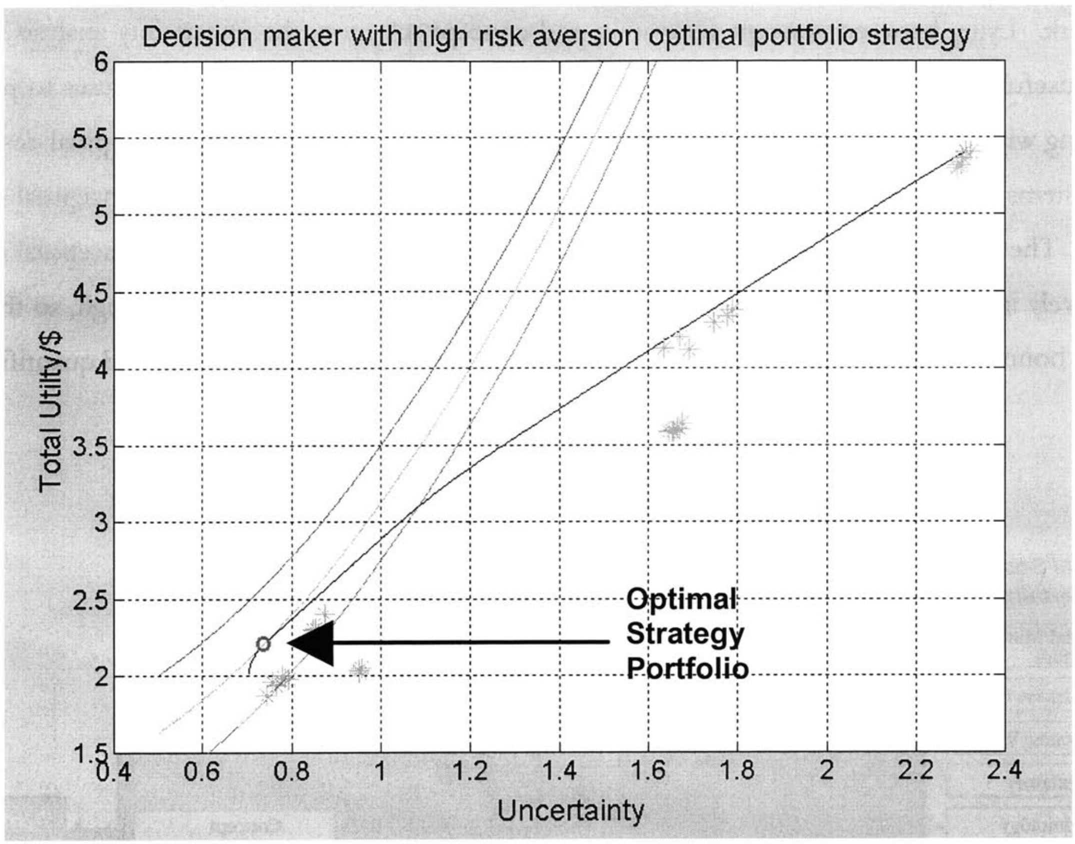


Figure 4: Example of optimal portfolio identification

2.2 Vision for Uncertainty Analysis in Space Systems Conceptual Design

Uncertainty becomes a formal and central decision criterion in the conceptual design of space systems.

This statement summarizes the overarching vision of the research presented in this thesis. Far too often uncertainty is treated as a supplemental piece of information that is considered usually after decisions have been made. Instead, this thesis asserts that uncertainty must be treated with the same attention as other decision criteria, like performance and cost, to avoid unexpected rework that contributes to extended schedules and overrun budgets. Therefore it is the mission of this research to develop an approach and techniques that enable the assessment, quantification, and management of uncertainty in the conceptual design of space systems.

Figure 5 presents a conceptual design flow with the inclusion of the proposed uncertainty analysis framework. Lying between concept generation and concept selection, the uncertainty analysis would provide useful information to the decision maker in preparation for selecting architectures to pursue. Coinciding with the vision for uncertainty to be a central decision criterion in the conceptual design of space systems, so too must the uncertainty analysis be a central component of the conceptual design process. The uncertainty analysis location, as described, would be early enough in conceptual design to positively influence decisions, while at the same time its location would be late enough, so that the problem boundaries are drawn and sources of uncertainty can be identified, assessed and quantified.

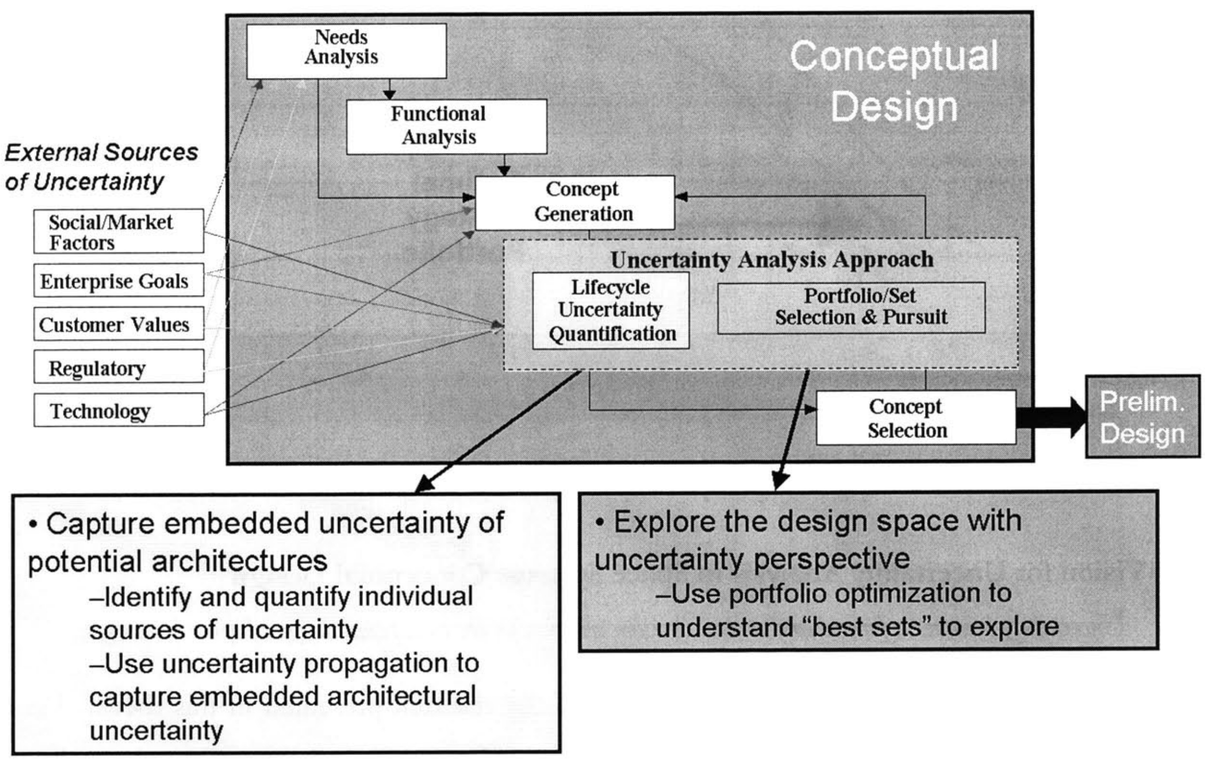


Figure 5: Insertion of the uncertainty analysis approach in conceptual design

2.3 Three Principles of Uncertainty Analysis in Space Systems Conceptual Design

Presented are three engineering principles on the subject of uncertainty. Each of the three principles is developed throughout the course of the thesis and they serve as touchstones for the reader to the overarching themes of the research.

Principle 1: Irreducible uncertainty exists in all space systems architectures

Perhaps a trivial statement, but in fact this principle above all other principles can lead to shifting the current mental models away from deterministic thinking about space systems conceptual design. Without accepting the unpredictable dynamics of the behavior of space system architectures in the face uncertainty, there will be little motivation for improving the way uncertainty is managed in the conceptual design process of space systems.

Principle 2: Space systems architectures can be characterized by their embedded uncertainty

Every space system architecture has associated with it an embedded uncertainty. This characteristic can be quantified, managed, diversified and reduced. Just like other characteristics of the space system architecture, though, embedded uncertainty is impossible to precisely quantify. However, its approximation can be readily achieved and incorporated into an uncertainty analysis approach, such as the one presented here.

Principle 3: A portfolio of architectures can be systematically used to adjust overall exposure to uncertainty

Carrying a set of architectures through design that respond differently to different types and levels of uncertainty can in fact reduce a project's overall exposure to uncertainty. Although there is generally an added cost to carrying more than a single point design, this thesis shows that this cost-benefit can be quantified.

PART I: AN APPROACH TO QUANTIFY AND MANAGE UNCERTAINTY IN SPACE SYSTEMS CONCEPTUAL DESIGN

This section describes the details of the proposed uncertainty analysis approach. Chapter 3 focuses on the current state of the art in industrial practice of uncertainty quantification and management in conceptual design, while Chapter 4 focuses more on the current state of art in the literature. Building on the foundation laid in the previous two chapters, Chapter 5 and 6 define the proposed uncertainty analysis approach. Chapter 5 is focused on the quantification of embedded architectural uncertainty, while Chapter 6 describes the application of portfolio theory and optimization to the field of space systems conceptual design. Although Chapter 5 and Chapter 6 together comprise the uncertainty analysis approach defined in this thesis, they are in fact separable and could be incorporated in isolation of one another.

Chapter 3

CURRENT STATE OF UNCERTAINTY ANALYSIS IN SPACE SYSTEMS DESIGN AT FOUR MAJOR SPACE SYSTEMS DEVELOPERS

3.1 Introduction:

The significance and presence of uncertainty is something that developers of space systems cannot escape. This chapter explores this fact. How indeed do designers in industry deal with the presence of uncertainty in early conceptual design? Four sites were investigated that represent a cross section of the space systems development industrial base as seen in Figure 6. Confidentiality agreements require the masking of organization names, but those interviewed serve commercial, civil and military customers and represent a cross-section of the space systems design industrial base. 26 individuals were interviewed in total at the sites whose functions were tied directly to conceptual design (conceptual designers, directors for advanced development) and were intimately aware of the role of uncertainty in conceptual design (risk practioners and project management).

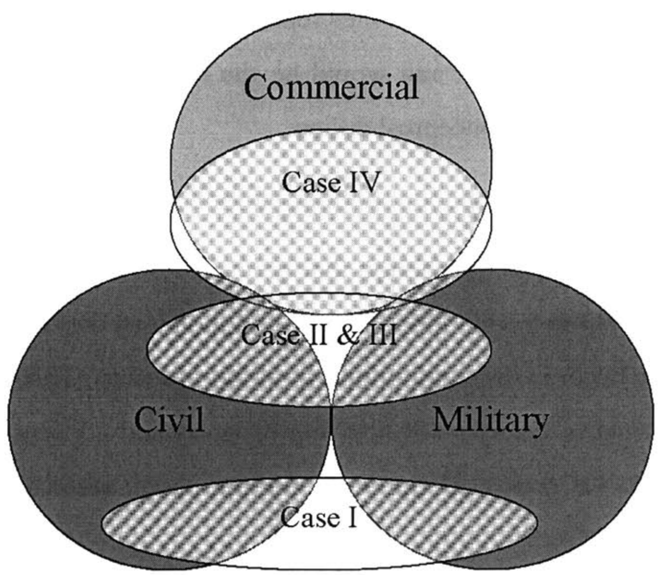


Figure 6: Cases along sector lines

While the research presented in this thesis extends far beyond the current state and suggests innovative ways to manage uncertainty in conceptual design, it is important as researchers to fully understand the real-world application environment where research must have impact. It is therefore the purpose of this chapter to not only highlight the current treatment of uncertainty in conceptual design, but also to bring out implementation issues that will arise from any proposals of this research.

The presence of uncertainty has classically been treated as the necessary evil that is embedded in the margins of design and has been done so through predominantly qualitative means. The results of this process have created the possibility of problems creeping up in the later design stages. It therefore leads to the research question: Can the architectural uncertainties that exist be better understood in early conceptual design? The answer that this thesis provides is a definitive yes. But as much as the answer may be yes, how should such an approach be implemented? Guidance for these questions was found from the structured interviews conducted within the following four cases.

A final note is that the qualitative analysis presented here results in findings that are, in general, local and contextually bound. Multiple perceptions of the same events are expected and acceptable, which can often be difficult for schools of natural science that seek single generalizable suggestions.[8] Nonetheless, the overarching themes and challenges observed are of significance and direct relevance to the overall success of this research as these sites represent a significant fraction of the organizations focused on space systems development and would be the direct beneficiaries of any improvements that could be made to space system conceptual design.

3.2 Case 1 [6 Interviewees-Group]

The first case was conducted at an organization that specializes in conceptual design studies for both military and civil space system projects. These conceptual design studies are done using dynamic real-time techniques that have become more common across the industry. Through the use of collocation of experts, the customer and a team leader, amazing progress and consensus on conceptual designs have been demonstrated. Of course all the work for the design studies are not completed in the

[8] Krathwohl, D. (1997). Methods of Educational & Social Science Research: An Integrated Approach. New York, NY, Addison Wesley Longman, Inc.

collocated team collaborative sessions, but instead a great deal of upfront model building, planning and discussions with the customer enable the sessions.

The conceptual design approach adopted by this site leads to some interesting aspects of design concurrency and customer feedback that can be achieved. There were two distinguishing features of this site that should be brought out and explained that differentiate it from the other cases.

1. Close involvement with the customer - the continual feedback and presence of the customer is an attribute that isn't found at the other sites. With this continuous informal contact, customer acceptance/aversion of uncertainties can be understood and explored more effectively.

2. This site specializes in the study phase of conceptual design – very early stage of design- and is characterized by uncertainty in everything including what the customer wants.

The conceptual design work that is conducted in this environment suffers from the most uncertainty due to its very early position in the overall design process. However, it also during this early study phase of conceptual design when architectural decisions will have a significant impact on the end result of product development. This site has demonstrated the ability to study in depth as many as twelve architectures for any given customer in an effort to explore the tradespace. This exploration is only limited by the capability of the tools and time that the customers and designers have to expend.

At this stage of development, the customer is often not sure what they value and what they need. This uncertainty in requirements can be the most deadly because it overrides all else in the design. An architecture free of all uncertainty other than that of customer requirements will still be a very difficult system to develop. In contrast, interviewees pointed out that the development of systems with little customer uncertainty, but uncertainties arising from other sources, such as technical uncertainties, could be managed much more effectively.

With regards to uncertainty analysis in early conceptual design, most analysis is done on a qualitative basis. Through a method that resembles an ad-hoc uncertainty assessment, each subsystem and system engineer reports to the customer what are the greatest sources of uncertainty in their purview, including some estimate of a likelihood and impact. This gives the customer some sense of the overall risk in the architectures considered. From these individual sources of uncertainty, the highest area(s) are sometimes brought to the discussion of architecture evaluation and pursuit. It is clear that there's no formal responsibility for the system/interface level uncertainties in the design, and further there is no means of aggregating individually identified uncertainties. This leaves the customer in the unenviable position of assessing not only the importance of the uncertainty information presented to him, but also the way he should combine it with other decision criteria he may be considering.

Although the technical uncertainties are dealt with in this non-aggregate, individual way, the cost uncertainty is approached from a different perspective because it is handled by one individual's responsibility. Because statistical models provide the costing for the system, the team can quickly identify the historical uncertainty of previously developed systems from the approximation curve fit statistical model they are using to cost the proposed system. In this way a quantitative estimate of uncertainty can be given to the customer in terms of cost. The estimates of cost are generally calculated using mass and power properties of spacecraft, estimations of software complexity guidelines of code cost estimations. As a rule of thumb, the 50th percentile of the cost distribution is presented to the customer.

The evaluation of multiple concepts (as many as twelve) for customers is unique with respect to other sites. This is not to say that other sites don't explore the tradespace, as will be discussed. Instead it shows that the exploration was one in which the customer was not involved, in general.

Ideas of any formal risk management process in early conceptual design don't exist at this site. Instead, at this stage of the study the process of uncovering uncertainties and risks are the main focus. A further hindrance to any risk management is the over-the-wall handoff that is typical of this study phase in aerospace conceptual design. Once studies and conceptual designs have been explored at this site, the end product is generally a report of some sort that brings out the conclusions of the analysis, the trades that were made, and the recommendations of the team. The majority of the analysis and models are not available, however, following the conclusion of studies. The post-study relationship becomes one that is primarily contextual in assisting any downstream realization of the project.

From discussions with individuals at the site, it is clear that they would welcome methods for looking at uncertainty more holistically in early conceptual design. One interviewee imagined a "risk station" could be incorporated into the concurrent designing environment to fit in with the current process.

3.3 Case 2 [6 Interviewees-Group]

The second case explored included an organization that in contrast to the previous case was under contract to design and build the conceptual designs they worked toward. This was a fundamental difference that distinguishes some of the characteristics and the interests of the second (and remaining) case over the first. This fact puts uncertainties into the economics of the company and therefore one could argue that they should be more visible in the end analysis.

Primarily a defense and civil space systems development contractor, the programs that are found at this location tended to be very unique, advanced, high cost and having lengthy development times. The effect of uncertainties on programs from the company perspective were definitive in terms of their prioritized impact on schedule, cost and technical aspects of the program. It was clear that although this is the predominant priority, the order might switch depending on stakeholder perspectives.

Individuals at this organization found that uncertainty analysis in early conceptual design would be a very useful in the pre-proposal and proposal phase as the trade space is being explored. The largest source, according to the consensus of interviewees at this site, were those arising from requirements instability-the ability to understand what the system needs to do. From this, they see a challenge to not only understand the uncertainty in a system that is developed under constant requirements, but also one that exists in a more dynamic customer environment. It has therefore become a major challenge for them to achieve a forward looking/anticipatory strategy that enables real foresight into potential outcomes in an uncertain environment in addition to the current approach of dealing with uncertainties as they arise.

Facing this dynamic environment of evolving requirements, it appears parallel path development would be common. This is more the exception than the rule as it applies to design though. One example of parallel design paths explored was given as it applied to a major component design.

During one development project three hydro pumps were carried through design until prototypes had been developed and tested and the uncertainty had been reduced to a level acceptable to make a decision on which variety to choose.

3.4 Case 3 [9 Interviewees-Individual]

The third case looks at conceptual design at an organization that works predominantly with government customers-military and civil- to design and develop space systems. This site, much like that in case two is focused on "one-off", highly advanced space systems that have cycle times that are generally much longer than that of commercial systems.

Like the space systems developed in the previous cases, the systems that are designed at this site represent some of the most advanced technology. There were two main groups that were interviewed at this site, those working on military systems and those working on civil programs. Although the two reside at the same location, it was clear that the treatment of uncertainty for the different customers did differ. The military programs suffered greatly from requirements creep and the uncertainty of operational issues that require real-time support and information delivery to the warfighter. In contrast, the civil programs were hampered by the risk aversion of the customer due to the high visibility of space missions.

Closely related to the topic of uncertainty was the notion of value about which information is uncertain. Utility and value were brought up in nearly all interviews as being a key aspect of understanding how early conceptual design was carried out and how uncertainties were thought of. One example was the case of a proposal for an advanced system whose design tradespace was fairly well understood, but the customers definition of value, or "best value", was not well known

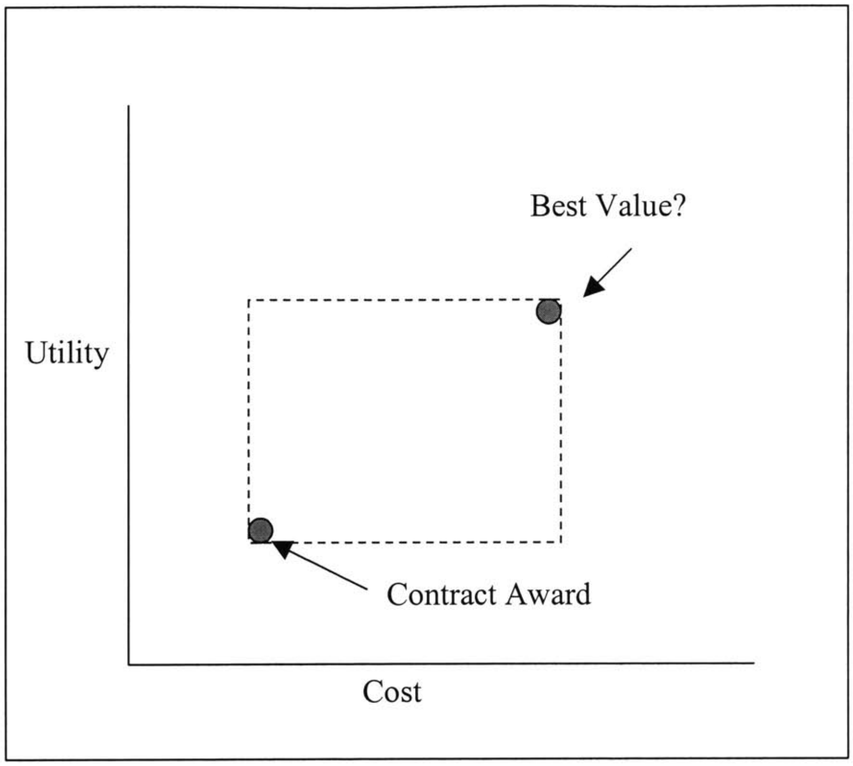


Figure 7: Government Contractor Perspective of Best Value

Figure 2 is used to represent this situation. The dashed line represents the envelope that the contractor believed the design should fall within and further believed from the customer that the "best value" design in this program's case was maximizing utility of the mission given a capped budget. They later found out after the award was given to a competitor that the customer was far more concerned with minimizing cost and just meeting minimum utility levels. It was the interviewee's belief that the customer could do a better job to make those types of trades more explicit and increase the possibility for dialogue. He did cite that the customer communication was dependent on the different customers. For example, on the DII mission it was clear that the Air Force was seeking the highest utility for a $400M budget.

Pre-proposal and proposal efforts at this site have "cost the company 10s of millions of dollars if not hundreds and can be as long as a two year effort." During this time the trade space is explored and the customers' perception of value is extracted along with the criteria for proposal selection might be. Uncertainty analysis during this stage of design is used to place margins on different characteristics of the architectures. One program manager believed that telling the truth about the uncertainties of the system actually led his organization to lose to a competitor whose proposal they viewed as a paper study without adequate margins. This places uncertainty analysis in a juxtaposition where the analysis may in fact work against winning a proposal.

When discussing the issue of pursuing parallel options, one interviewer cited that he did know of instance where a customer did retain multiple system level designs because they were attracted by a advanced technology system but were not comfortable with it as a single path so they carried another contract with a less advanced concept as well. However, he added that in terms of one contractor offering options customers adopted the position that "we didn't allow you to propose options". Instead of this position, the interviewee shared that his ideal proposal would include options in much the same way as automobiles carry options packages where "the customer can choose the barebones option or accept all the bells and whistles or anything in between".

Sources of uncertainty can come from anywhere and at this site many of those commonly overlooked were brought out including uncertainties associated with critical skills resources and the supplier base. The consequences of both can be significant, for example drawing out the schedule and technical risks in the case of lack of critical skills.

The relationships that different job functions have with respect to uncertainty are significant to discuss. There were some different interpretations of the interaction between concept designers, risk practioners (systems engineer whose primary focus was risk management) and program/project management and uncertainty. However, the differences can best be characterized as follows: conceptual designers are generally focused on subsystem margins to cover uncertainties but have the greatest knowledge of where internal uncertainties arise; risk practioners are interested on abstracting to the higher level of the architecture and typically address the uncertainties at the interfaces; program managers have a system level focus, like the risk practioners, but are also factoring in the external uncertainties and at the same time trying to managing the margins built in by designers and the respective systems level budgets of mass and power.

The greatest sources of uncertainty at this particular site were found to be uncertainties in requirements, technical issues, funding, and critical skills. It was pointed out that the requirements uncertainty arises not just from the customer though, the internal requirements flowdown of customer requirements provided as much of the uncertainty in the end.

Table 2: Military and Civil Sources of Uncertainty in Conceptual Design

Source of Uncertainty	Number of Interviewees citing the Source in Top 3
Requirements	8
Technical	6
Funding	4
Produciblity/Supplier	3
Critical Skills	1
System Integration	1
Political	1
Schedule	1

The formal risk management process of this site is primarily qualitative, but appears to be the most formal of the approaches seen elsewhere. A rule of thumb of 8.5% of the development cost was given that is typical in budgeting risk management and mitigation. This information serves as a useful jumping off point in justifying savings that risk management can result in.

3.5 Case 4 [5 Interviewees-Individual]

The final case bridges the gap to a predominantly commercial space systems design and development operation. The interesting distinction between commercial and government approaches to space systems development and the role of uncertainty in early conceptual design is brought out in this case.

This site is a leading developer of commercial space systems and the culture in place is far more acclimated to the commercial customer than that of the military customer. For the most part, the space systems that are sold from this site are direct derivatives of previous developments. Common bus platforms are used to lower costs and speed up delivery time to the customer. From a commercial standpoint this is a very effective approach, as most communication satellite are not pushing the envelope of performance, instead the customers are in general satisfied by the evolutionary advancement of the technology. This is in sharp contrast to the cultures of the first three cases that rely heavily on military and civil customers who are often looking to advance the state of the art.

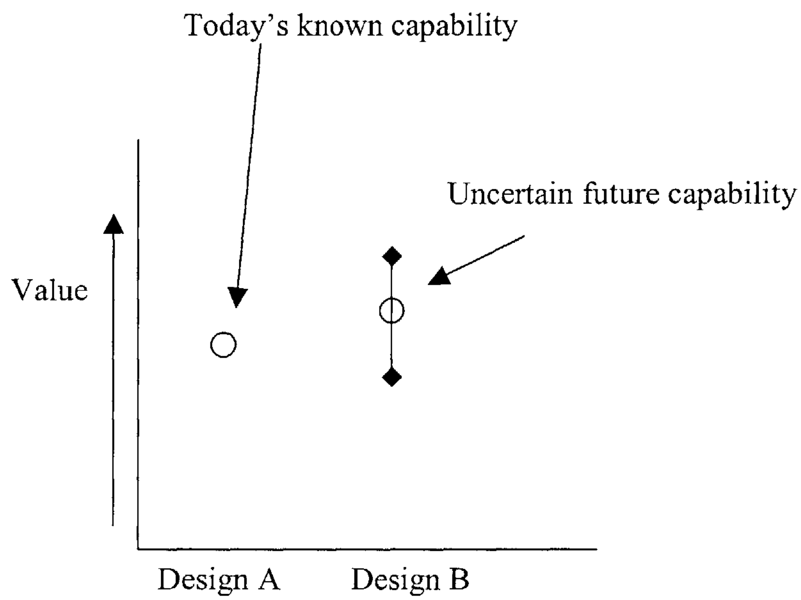


Figure 8: Commercial Contractor Perspective of Best Value

Figure 8 shows the common perspective of commercial goals in space systems. In general, there is no urgency to jump to the next uncertain future capability if today's capability is well known and satisfies the needs of the customer. This perspective results in two things. First a much slower evolution of space systems in the commercial environment and second a conceptual design effort that is much faster and involves little trade space exploration.

With this condition, it became readily apparent that the amount of individual satellite conceptual design for each customer's satellite is far less than efforts for government customers. Having said this, it also becomes clear that the role of uncertainty on the commercial customer programs is not as significant as on brand new space system developments. Of course there are areas of the system that carry some uncertainty, like new components or the stability of the customers cash flow or the integration of a payload with the platform bus. Instead of focusing on the current platforms development and sales, the area of the site that deals with new platform development serves as a jumping off point for investigating uncertainties in early conceptual design.

Developing a new communication bus platform is of comparable complexity to many of the government programs observed at the other sites. Further the uncertainties that exist in launching a new platform are substantial, as the designers are developing platforms that will not satisfy one customer, but many customers and that will serve as a backbone of sales and will be competitive with other companies' platforms for some period of time.

An insight that arose from this site was the use of, what is referred to as, *handover books*. These books are created during proposal phases of development and are used to document the rationale of the decisions involved in the proposal. As is often the case, those who work on the proposal may not be involved in the later phases of design and usually their tacit knowledge is not captured. With handover books, risks and uncertainties are documented for the design team. The motivation for the books was experiences with "unexpected" surprises that would arise in later stages of design after the proposal team had moved to other projects.

Table 3: Commercial Sources of Uncertainty in Conceptual Design

Source of Uncertainty	Number of Interviewees citing the Source in Top 3
Requirements	3
Schedule	2
Producibliity/Supplier	2
Critical Skills	2
System Integration	1
Technical	1
Inadequate Review	1

The observation that requirements uncertainty are at the top of the list for sources of uncertainty for both of the cases at which a survey was conducted is consistent with the literature that stresses the significant costs that come from rework due to uncertainty in requirements. Figure 9 presents just one example of the impact of requirements uncertainty in the complex systems product developments process. It is of no surprise that requirements uncertainty is of the most concern to the industrial sites, as it seems to one major sources of unplanned rework. Other research by Panetta reiterates these same conclusions[9] and a detailed survey of DoD program managers illustrates the same issues can be found outside of just space systems, as shown in Figure 10.

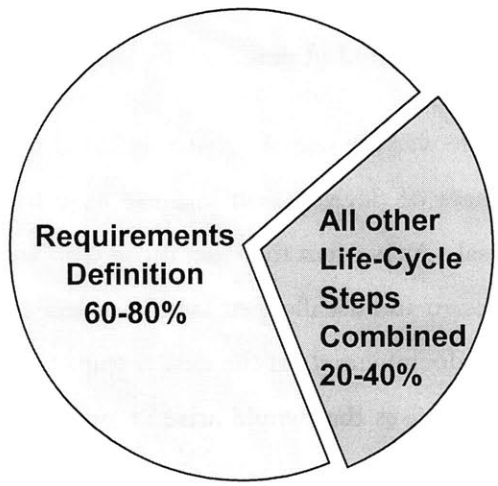


Figure 9: Source of System "Errors"[10]

Walton presented nine high level issues that serve as major sources of uncertainty in the generation of systems level requirements: expedited tradespace exploration, the challenge of bounding the tradespace without driving a point solution, changes in technology, changes in funding, changes in customer needs, changes in the world environment, ambiguous and unclear requirements communication, disconnect in user and producer knowledge, and the mistiming of requirements freeze.[11] Individuals at each of the case study visits echoed these same sources.

---

9 Panetta, P. a. D. H. (2002). "Managing Programmatic Risk for Complex Space System Development." International Journal of Aerospace Management **1**(4): 303-313.

10 Boar, B. (1984). Application Prototyping: A Requirements Definition Strategy for the 80's. New York, NY, Wiley & Sons, Inc.

11 Walton, M. (1999). Identifying the Impact of Modeling and Simulation in the Generation of System Level Requirements. Aeronautics and Astronautics. Cambridge, MA, Massachusetts Institute of Technology, SM.

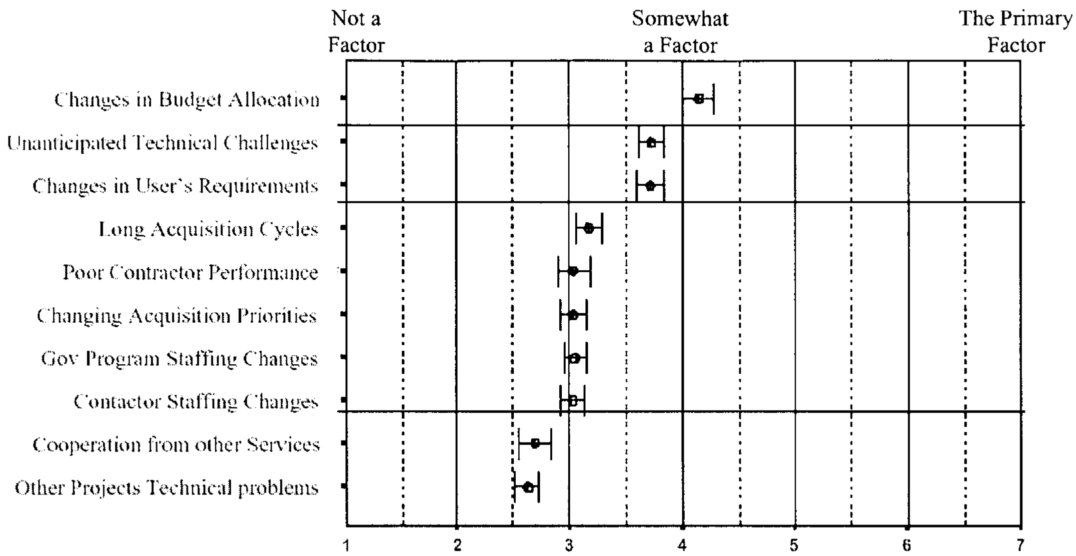


Figure 10: Causes of Program Instability on DoD Acquisition Programs (N=245, Mean +/- 1 SE)[12]

3.6 Overarching Themes and Challenges

This section summarizes some of the crosscutting themes and insights that have been uncovered from the cases. The themes represent important implications as research evolves and contributions are made to improve the conceptual design effort and the quality of knowledge that is gained from the effort.

- ***The Role of the Customer:*** The role that the customer plays in the conceptual design process can have a profound impact on the conceptual design process and more specifically the uncertainty analysis that is conducted. Although no absolute distinctions exist among the three types of customers (commercial, civil, and military), there are common characteristics in each of the three groups. All three groups were interested with uncertainty and more specifically risk, but typically for three distinct reasons. The civil community was averse to loss because of public visibility and the possibility of future funding loss, the commercial customer was averse to loss because it would have impact on business performance and the military customer was averse to loss because it would reduce their future warfighting capability.

[12] McNutt, R. (1998). Reducing DoD Product Development Time: The Role of the Schedule Development Process, Ph.D. Dissertation

Although the motivations were different, the levels of risk aversion were very contextual and no global ordering of aversion could be produced.

- ***Uncertainty in Conceptual Design:*** This is perhaps the most significant of the themes as it applies to contribution of any research that might be conducted. From the four cases it's clear that the role of uncertainty in conceptual design is significant; it can guide decisions or it can be punishing if not identified. The ever-present existence of uncertainty makes the topic very difficult to capture even qualitatively, but deep interest is present in the industry for evolving perspectives on how identification and even quantification might be done more easily.

- ***Risk Assessment/Management:*** This phrase best reflects the immediate thoughts and implications of uncertainty in the industry. Risk assessment and uncertainty analysis are indeed closely related, and therefore the analysis would be remiss to exclude the risk assessment/management that is being carried out, if any, during conceptual design. From the four sites, it became clear that the role of risk assessment/management is not a major effort in conceptual design and by and large does not enter the effort until later stages of design.

- ***Dynamics of Decisions:*** The concept of decisions being made on uncertain information is driving this theme. It is clear from previous research that a great deal, up to 80%, of the space system costs are being committed early in conceptual design with very uncertain information. Therefore, the current process of decision making is important to the overall impact that this or any research on uncertainty in conceptual design could have.

- ***Barriers to Change:*** This theme is important to discuss as it guides how research may or may not be accepted in different organizational cultures or processes. It can provide a great deal of guidance on the how and when question of implementation of the research, i.e. how uncertainty information should be represented, when the analysis might fit best into the conceptual design process at different sites.

3.6.1 Challenges taken up by the research

1. Develop an approach that can be used for a variety of perspectives and stakeholders. The challenge is perhaps self evident by the diversity of the cases that the approach would have to

be robust to organization implementation and to the types of projects that uncertainty analysis methods could be used.

2. A need was recognized for the characterization of uncertainties early in conceptual design and any practical approaches that could be developed would be of great utility.

3. Research must explore uncertainties beyond the myopic views of technical risk only; it would be beneficial if other ancillary functions (legal, finance, and market) that are sources of uncertainty could be embedded in the analysis.

3.6.2 Challenges posed to future research from the site visits

1. One of the major sources of uncertainty cited at the sites was the role of software in the overall conceptual design. This is an area of great concern amongst the sites visited, but the particular task of developing new methods to deal with uncertainty associated with the development of software in space systems is beyond the scope of this research.

2. Improve the proposal process that has been seen as a barrier to more effective treatments of uncertainty and the improvement to the quality of information that can be obtained early in conceptual design. Further, the post proposal debriefs and feedback on proposal should be more structured. Some interviewees sighted the benefits that might have come from a dialogue debrief, rather than a written response to proposal losses.

Chapter 4

CURRENT APPROACHES TO ASSESSING UNCERTAINTY AND RISK IN SPACE SYSTEMS CONCEPTUAL DESIGN

4.1 Introduction

In this chapter the relevant literature that applies to assessing uncertainty and risk in the conceptual design of space systems is reviewed for the purpose of motivating the uncertainty analysis approach provided in this thesis. The discussion evolves from qualitative to semi-quantitative to quantitative techniques of assessing uncertainty and risk in conceptual design. Limitations of methods in the literature are discussed and serve as motivation for the thesis.

Since the *Theory of Games and Economics Behavior* [13] and *Risk, Uncertainty and Profit* [14], publications and research into ideas of risk and uncertainty analysis have been continuous, yet the area continues to be a fertile ground for exploration and results. The main reason behind the breadth of the research on uncertainty and risk is its broad applicability to so many disciplines. From finance to policy and from natural science to applied science, risk and uncertainties tend to be drivers of system behavior. Table 4 presents some of the formal quantitative methods for evaluating uncertainty and risk.

---

[13] Von Neumann, J. a. O. M. (1944). Theory of Games and Economic Behavior. New York, John Wiley and Sons.

[14] Knight, F. H. (1965). Risk, uncertainty and profit. New York,, Harper & Row.

Table 4: Methods of Uncertainty and Risk Assessment

Methods to Approach Uncertainty and Risk Assessment	
Arbitrage Pricing Method	Financial Systems
Capital Asset Pricing Model	Financial Systems
Real Options	Financial Systems
Probabilistic Risk Assessment	Engineering Systems
Utility Theory	Engineering Systems
Reliability Theory/Markov Modeling	Engineering Systems
Technology Readiness Levels	Engineering Systems
Earned Value Management	Engineering/Organizational
Task Based Risk Assessment	Organizational Systems
Organizational Risk Management	Organizational Systems
Cost-Benefit Analysis	Political Systems
Monte Carlo Simulation/Uncertainty Propagation	All
Historical Trending	All
Sensitivity Analysis	All

This research leverages work being conducted in the area of uncertainty and risk outside the development of space systems, including the methods discussed above. The approaches that are looked into most closely in this work are financial risk assessment, probabilistic risk assessment, uncertainty propagation as well as some ideas of utility theory.

Before describing the literature, a context is provided for those familiar with traditional risk management in space systems. Risk management, as described by the DoD, is composed of four major subcomponents, as shown in Figure 11. The most relevant portion of the risk management framework to this work is the risk assessment process. Although, these subcomponents apply to the downside of uncertainty, risk, they can in fact be generalized to include upside potential as well.

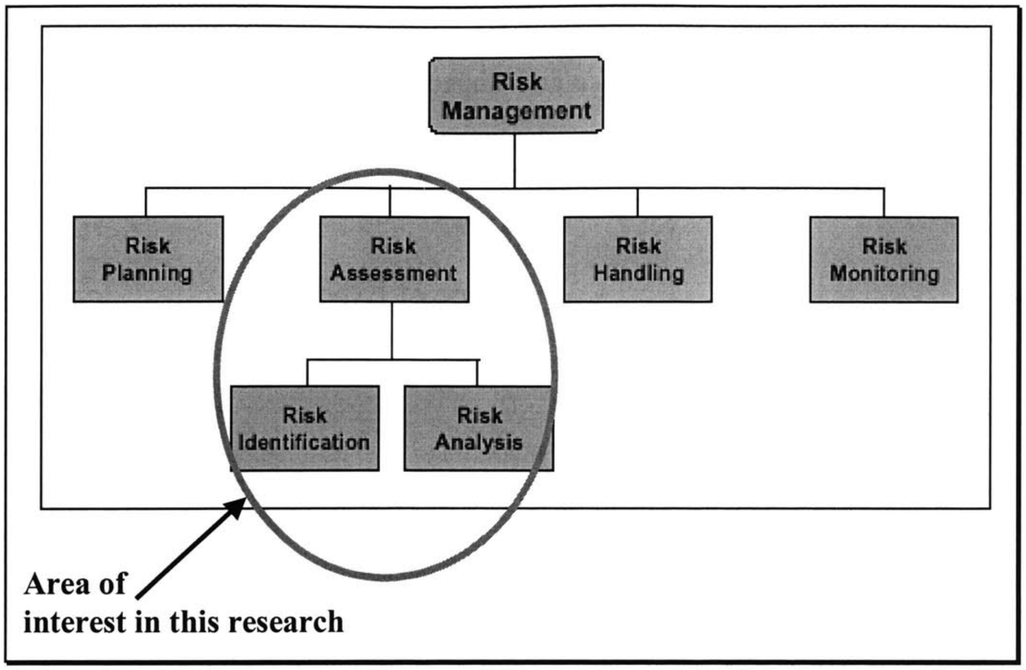


Figure 11: DoD framework for risk management[15]

4.2 Literature on qualitative techniques to managing uncertainty and risk

Qualitative methods of uncertainty and risk analysis in conceptual design are the most common in practice, because of the relative ease of use and the fact that most organizations that use semi-quantitative and quantitative methods also rely on qualitative approaches as inputs to their analysis. The goal of the qualitative methods in managing uncertainty and risk is to estimate the sources of uncertainty that provide the greatest exposure of risk to the program. Qualitative approaches typically rely on expert opinion or organizational knowledge, for example organizational experience with similar systems.

4.2.1 Risk Exposure Analysis

The most common type of qualitative analysis used is through the use of exposure charts, such as the one presented in Figure 12. Traditionally, more attention is paid to the left side of the chart that applies to only the risk that the system may be exposed to. However, it may be equally important to consider the high reward events that could be managed to maximize the likelihood of their occurrence.

[15] Risk Management Guide for Acquisition, Third Edition, January 2000.

To use the exposure chart, sources of uncertainty are identified and plotted individually on the chart according to their probability of occurrence and impact of consequence. Designers and decision makers can then focus the majority of their attention on the "area of anxiety" as called out in the figure.

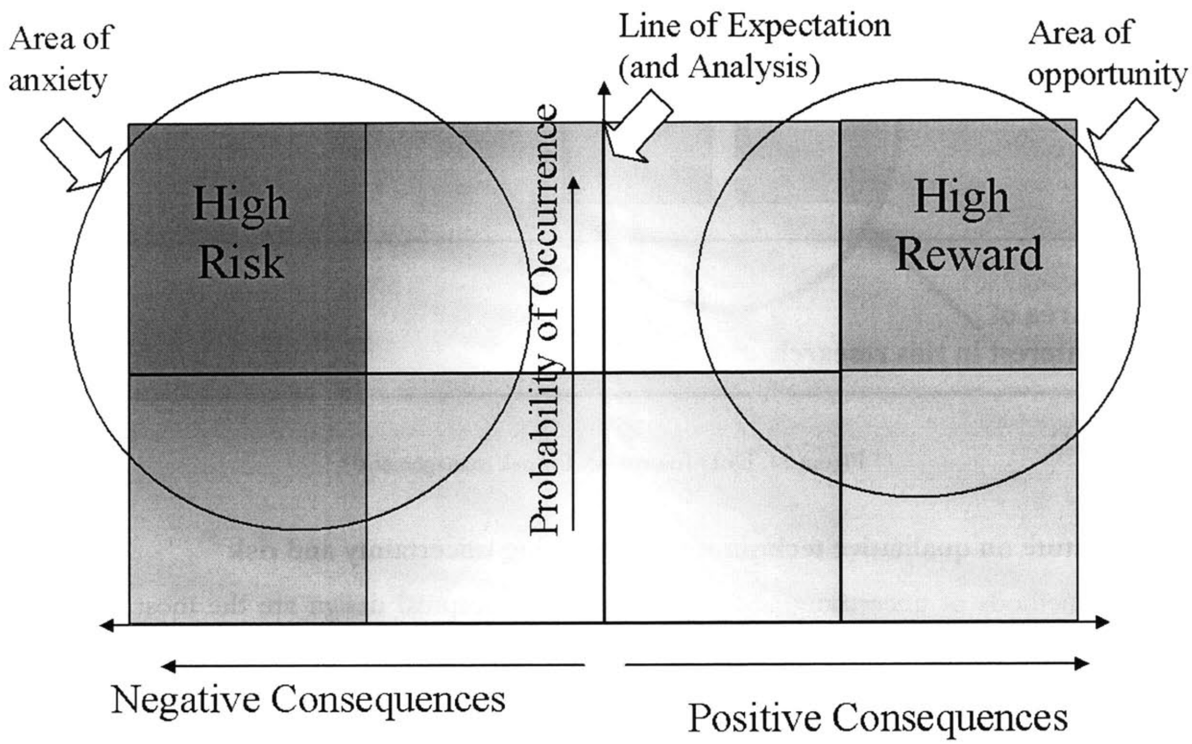


Figure 12: Probability and Consequence Exposure Chart

Roberts suggested relevant extensions to the classical risk exposure approach by using the exposure chart as a tool to focus on sources of uncertainty and risk that should be considered for more detailed analysis techniques.[16] These more detailed techniques would include some of the semi-quantitative and quantitative techniques that are presented here.

---

[16] Roberts, B. (2000). Risk Management Doesn't Save Money, It Saves Programs. Risk Management 2000: Lessons for the Millennium, McLean, VA.

4.3 Literature on semi-quantitative techniques to managing uncertainty and risk

Semi-quantitative approaches to uncertainty and risk management are those that generally include techniques of both qualitative and quantitative means. For example, expert opinion might be used to determine the technology readiness levels (TRLs) of certain technology, but more quantitative approaches are used to model the impact of these technology readiness levels on the overall program. Used extensively in NASA, TRLs serve as a method to quantify the effect of technology maturity on predictions of cost. Table 5 presents the TRL information typically used as a standard by NASA. These technology readiness levels are most often used in judging the technology maturity of subsystems or components, rather than at the system or architecture level.

Table 5: Technology Readiness Classification[17]

Technology Readiness Level	Definition	Relative Risk Level	Standard Deviation about Most Likely Estimate (%)
1	Basic principles observed	High	>25
2	Conceptual design formulated	High	>25
3	Concept design tested analytically or experimentally	Moderate	20-25
4	Critical function/characteristic demonstrated	Moderate	15-20
5	Component or breadboard tested in relevant environment	Moderate	10-15
6	Prototype/engineering model tested in relevant environment	Low	<10
7	Engineering model tested in space	Low	<10
8	Full operational capability	Low	<10

[17] Larson, W. a. J. W., Ed. (1992). Space Mission Analysis and Design. Torrance, CA, Microcosm.

4.4 Literature on quantitative techniques to managing uncertainty and risk

This section focuses on techniques that have been developed to address uncertainty and risk in the conceptual design of space systems that rely on predominantly quantitative techniques. A number of approaches are investigated ranging from statistical measures of uncertainty of the future based on historical experience to advanced uncertainty management techniques using fuzzy sets and finally probabilistic risk assessment is described as a technique that has been used extensively to manage risk in space systems.

4.4.1 Statistical Techniques of Measuring Uncertainty

Common statistical measures of uncertainty in space systems design include estimation errors around cost estimating relationships and parametric design rules of thumb. To create these relationships, historical data is collected and regressions are conducted to develop equations that can be used in the conceptual design of space systems. An example of a cost estimating relationship (CER) is the relation between satellite bus dry mass and the cost of the satellite bus in FY00$K as expressed by Eq. 1, where X is the dry mass of the proposed satellite bus. The standard error around this estimation is $3696 in $FY00K. Such cost estimating relationships and their associated uncertainties are common and have been segmented for a number of different space mission classes as well, from the Air Force unmanned space vehicle cost model[18] to the small satellite cost model developed by Bearden.[19]

$$Sat\_Bus\_Cost = 781 + 26.1X^{1.261}$$

Eq. 1

A second statistical approach of measuring uncertainty employs the use of TRLs as initial statistical errors for propagation. The ROSETTA model has been developed as a software platform in which TRLs can be incorporated into the system simulation analysis.[20] By allowing different subsystem features to be modeled using statistical measures of uncertainty based on the TRLs, the method allows for uncertainty in outcome figures of merit to be better understood. The ROSETTA model serves as

[18] Space and Missile System Center, D. o. C., Los Angeles AFB, CA (1994). Unmanned Space Vehicle Cost Model. Los Angeles AFB, CA, Space and Missile System Center.

[19] Bearden, D. E. (1996). Cost Modeling. Reducing Space Mission Cost. J. a. W. L. Wertz. Torrance, CA, Microcosm Press.

[20] Crocker, A., A.C. Charania, and John R. Olds (2001). An Introduction to the ROSETTA Modeling Process for Advanced Space Transportation Investment. Space 2001 Conference and Exposition, Albuquerque, NM.

a foundation on which to propagate the effects of components with different technology readiness through to the system behavior. The model has specifically been applied to the design of 2nd and 3rd generation reusable launch vehicles as a way to generate probabilistic predictions of performance under a variety of technology uncertainty conditions.

4.4.2 Fuzzy Logic applied to managing uncertainty in space systems

Anotonnson and Otto provide an approach to managing uncertainties in design through the use of fuzzy logic applied to design. Antonnson and Otto coined the term "imprecision" to define a specific class of uncertainty and the Method of Imprecision (MoI) as an approach from which to base decisions during the preliminary design stage.[21] They use the MoI to provide one of the first quantitative methods to look at creating input ranges to set based design. More specifically, they develop an approach to determine what design characteristics it would be beneficial to delay decisions on due to uncertainty in the system.

Maglaras presented the application of fuzzy sets to the design process and how results differ from results obtained using probabilistic techniques.[22] His specific application was to the design of a truss structure with dampers where the damper characteristics are the main source of uncertainty. He demonstrates that probabilistic optimization resulted in a better design than the resultant design from fuzzy set optimization. The fuzzy set approach neglected to consider the ease of controlling different sources of uncertainty, while probabilistic optimization allowed for that.

4.4.3 Probabilistic Risk Assessment

The field of probabilistic risk analysis has evolved into a standard of systems analysis. The most common implementation of PRA is through fault trees and hazard (failure) modes and effects analysis. Like a lot of systems concepts, PRA had its first implementation during the era of complex systems in the 1950s and 60s. The first program that used the method extensively was the Minuteman Missile program. The main focus on the Minuteman was to prevent accidental warhead detonation or missile launch.

---

[21] Antonsson, E. a. K. O. (1995). "Imprecision in Engineering Design." ASME Journal of Mechanical Design **117B**.

[22] Maglaras, G. (1995). Experimental Comparison of Probabilistic Methods and Fuzzy Sets for Designing Under Uncertainty. Dept. of Aerospace Engineering. Blacksburg, VA, Virginia Polytechnic Institute.Ph.D. Dissertation.

First serving the needs of the aerospace industry in terms of risk analysis, the method was in fact abandoned by NASA following bad experience with the Apollo program and probability estimates.[23] The departure from the space program would last two decades. Following the Challenger accident, a push for probabilistic risk assessment brought the technique back to the forefront of risk analysis.

The process of conducting probabilistic risk analysis is contained in Figure 13. The main strengths of PRA are: it has been successfully implemented in systems development, it has a quantitative foundation and wealth of research, it is generally accepted in practice as a method of assessing risk and it is good in decomposable, sequential systems analysis. There are weakness of course, these are: a complete set of failures is not definable, independence of modes can not be generally achieved, there are high sensitivities to probability assumptions, it is difficult dealing with inconsistent outcomes, i.e. dollars and lives, and the method is best suited for looking in detail at a single point design analysis.

---

[23] Hughes, A. a. T. H. (2000). Systems Experts and Computers: The Systems Approach in Management and Engineering World War II and After. Cambridge, MA, MIT Press.

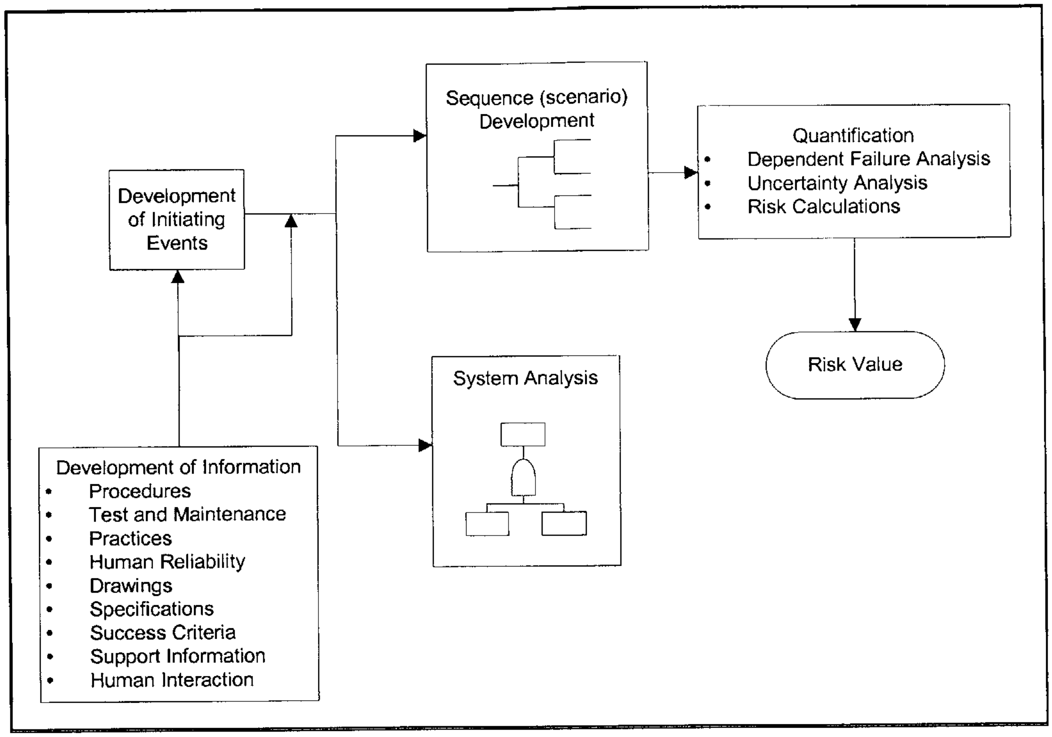


Figure 13: The PRA Process[24]

4.4.3.1 Utility Theory

Utility theory is introduced as a method sometimes employed in probabilistic risk assessment to deal with inconsistent outcomes in PRA by the normalizing consequences of events so that individual event risks can be understood on an "apples-to-apples" comparison. Utility theory provides a means to map relative preference to an attribute at different levels, thus defining a trade-off curve of worth of achieving an attribute in a number of different states. Original research in unidimensional utility

[24] Modarres, M., M. Kaminskiy, et al. (1999). Reliability engineering and risk analysis. New York, Marcel Dekker.

theory by von Neumann and Morgenstern[25], Schlaifer[26], Arrow[27], Pratt[28], and Meyer[29] was later extended to the multi-dimensional problem by Keeney and Raiffa[30].

4.4.3.2 Relevant Extensions of PRA

Dillon's work provided the advanced probabilistic assessment model (APRAM) to address the technical and management risks that potential architectures face. The fundamental question that APRAM addresses is how much to spend to maximize the technical reliability of a system vs. how much to hold in reserves to solve unforeseen problems or errors in the development phase with the final goal of minimizing the overall probability of project failure.[31]

APRAM provides a great deal of insight into single objective risk optimization of a static concept and slight modifications thereof. However, it's weakness lies in the single objective of minimization of probability of failure and the intractability of such a method for evaluating over the entire trade space of a set of architectures.

4.4.4 Other relevant methods of uncertainty analysis in conceptual design

Browning developed a method for quantifying product development uncertainty through activity-based modeling. In his work, he developed a causal model for product development uncertainty through the literature and data collection at aerospace companies. He further constructed an approach to understand the connection between iterations in design and the overall project risk that could be expected.[32] This work provided a significant step forward in probabilistically modeling the design processes quantitatively through the use of design structure matrices.

---

25 Von Neumann, J. a. O. M. (1944). Theory of Games and Economic Behavior. New York, John Wiley and Sons.

26 Schlaifer, R. O. (1969). Analysis of Decisions under Uncertainty. New York, McGraw-Hill.

27 Arrow, K. J. (1965). Aspects of the Theory of Risk-Bearing. Helsinki, Yrjo Hahnsson Foundation.

28 Pratt, J. W. (1964). "Risk Aversion in the Small and in the Large." Econometrica **32**: 122-36.

29 Meyer, R. F. a. J. W. P. (1968). "The consistent assessment of preference functions." IEEE Systems Science and Cybernetics **SSC-4**: 270-278.

30 Keeney, R. a. H. R. (1976). Decisions with Multiple Objectives. New York, Wiley and Sons.

31 Dillon, R. a. E. P.-C. (To Appear 2000). "APRAM: Advanced Programmatic Risk Analysis Method." International Journal of Technology, Policy and Management. and Pate-Cornell, E. a. R. D. (1999). Advanced Programmatic Risk Analysis For NASA's Faster-Better-Cheaper Mission and Programs, Stanford University.

32 Browning, T. (1998). Modeling the impact of process architecture on cost and schedule risk in product development. Technology Management and Policy. Cambridge, MA, MIT. Ph.D. Dissertation

Another relevant extension of uncertainty assessment can be found through research on the abstraction of the aerospace systems design process as a control system problem. This thesis provides an analogy of investing in space systems as that of investing in financial instruments. Another group of researcher took the analogy that the aerospace system design process could be modeled as a control system problem.[33] By using control theory, methods to quantify design process robustness and sensitivities to uncertainty were obtained through feedback and error models.

4.5 Limitations of methods for current methods for managing uncertainty and risk

As was seen in Chapter 3 from the site visits, most industry organizations use elements of the methods described above. Typically using the qualitative methods in very early conceptual design and as the design matures, other methods are applied like the semi-quantitative and quantitative methods described above. The literature and current approaches to manage uncertainty fall short in three main areas.

- There is little understanding of methods to quantify the uncertainty in the tradespace of potential architectures to pursue as opposed to the uncertainty and risk in a specific point design.

- There is no method to provide trade-offs of different architectures reacting differently under conditions of uncertainty; instead current methods are focused on how to manage uncertainty within the context of a single design or the more general design process.

- There is no method in the literature that quantifies the potential value of carrying multiple potential architectures in design, let alone the cost of carrying those designs.

---

[33] DeLaurentis, D. a. D. M. (2000). A New Model for the Aerospace Design Process Based on a Control System Analogy. 8th AIAA/USAF/NASA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, Long Beach, CA, AIAA. and DeLaurentis, D. a. D. M. (2000). Uncertainty Modeling and Management in Multidisciplinary Analysis and Synthesis. 38th Aerospace Sciences Meeting & Exhibit, Reno, NV.

Each of these three issues is addressed by the approach presented in Chapter 5 and 6. Further the uncertainty analysis approach that is presented is inclusive of the some of the techniques outlined above, thus providing a unified framework to address the problem of managing uncertainty in the early conceptual design of space systems.

Chapter 5

QUANTIFICATION OF EMBEDDED LIFECYCLE UNCERTAINTY

The previous two chapters discussed the current state of uncertainty analysis in the development of space systems at industrial sites and in the literature. This chapter introduces the first segment of the uncertainty analysis approach put forth in this thesis. This chapter introduces the means to calculate the embedded lifecycle uncertainty in each of the potential architectures in the tradespace. The method includes identification, assessment, quantification and visualization of uncertainty in the tradespace of architectures. The next chapter will present the second segment of the uncertainty analysis approach using portfolio theory as a unifying concept to manage uncertainty in the tradespace.

5.1 Defining Embedded Uncertainty

It is not trivial that this paper's content is focused on uncertainty, rather than risk. Uncertainty in this thesis is defined as the inability to quantify precisely an architecture's value to the stakeholders of the systems, i.e. company, customer, shareholders, etc. This is in contrast to the term risk that always reflects a negative consequence of the probability of loss or injury. The delineation is important, as it opens the research to aspects of uncertainty that may in fact be positive.

The first step in this method is to develop a holistic view of uncertainties of potential architectures that enumerates all of the primary sources of risk over the lifecycle of the space system. The uncertainty structure that was developed is presented in Table 6. This characterization helps to both encompass the various types of uncertainty but also serves as a framework for discussion with industry.

Table 6: Uncertainty Categorization

Development Uncertainty	Operational Uncertainty
Political Uncertainty- uncertainty of development funding instability	Political Uncertainty- uncertainty of operational funding instability
Requirements Uncertainty- uncertainty of requirements stability	Lifetime Uncertainty - uncertainty of performing to requirements in a given lifetime
Development Cost Uncertainty- uncertainty of developing within a given budget	Obsolescence Uncertainty – uncertainty of performing to evolving expectation in a given lifetime
Development Schedule Uncertainty- uncertainty of developing within a given schedule profile	Integration Uncertainty – uncertainty of operating within other necessary systems
Development Technology Uncertainty- uncertainty of technology to provide performance benefits	Operations Cost Uncertainty – uncertainty of meeting operations cost targets
	Market Uncertainty-uncertainty in meeting demands of an unknown market
Model Uncertainty	

From an aerospace perspective, the life-cycle view is important because a space system's operational existence often incurs a significantly higher degree of cost than its development. One of the reasons this is typically overlooked is that the contractors and buyers are imminently interested in delivery of the product within time and fiscal constraints. The operational context therefore often follows as a secondary priority. However, this framework provides the opportunity to focus on the uncertainty of the system's life-cycle value.

5.2 Quantifying Embedded Uncertainty in Space System Architectures

Risk and uncertainty are major decision criteria in the pursuit of space system design, and yet the ability to quantify and provide uncertainty information is not satisfactory, as was discussed in Chapter 3 and 4. Uncertainty and risk analysis in conceptual design at present can be characterized as qualitative, expert driven and point based. Moreover, uncertainties are evaluated individually, assessed and addressed as unique and any calculations of these uncertainties are not embedded in the simulation models of conceptual design. A more complete approach to design would provide for enabling the quantification and aggregation of uncertainty, as well as the ability to integrate that information into the simulation models. This chapter provides such a method.

First a description of how to identify individual sources of uncertainty and the how to quantify them is presented. Next the modeling framework with which potential space system architectures are explored is described. [The modeling framework used was the generalized information network analysis (GINA) framework, however, any method that provides for analyzing system outcome behavior could be used, thus making the uncertainty analysis approach available to organizations that use other system simulation tools.] The next step is to use the modeling framework as a platform to propagate the effects of individual uncertainties on the outcome criteria (i.e. cost, performance, etc.) of potential architectures.

5.2.1 Developing the boundaries for uncertainty

Identifying the right uncertainties is part art and part science, much like the rest of conceptual design. Far more important than identifying ***all*** the sources of uncertainty in conceptual design is identifying the ***right*** sources of uncertainty in conceptual design. The right sources will have at least one of the following characteristics. First, the uncertainty has a major impact on the expected behavior of the architecture. This major impact could be caused by a low probability event but significant implications (either positive or negative) or by a higher probability event with less significant implications. What is a high or low probability event and what is a significant impact are where the art of design enters. The second characteristic of an uncertainty that should be included in the analysis is one that differentiates one architecture from another. An example of this second characteristic can be found in a tradespace of architectures that don't rely on the same technology. For example, assume a GEO communication spacecraft could be developed using current technology for solar cell power delivery, but the LEO architectures in the tradespace would require successful development of a higher efficiency solar cell or delivery system. Technology is just one source of differentiating uncertainty, policy, market conditions or manufacturing capability are others.

5.2.2 Quantifying Individual Sources of Uncertainty

In order to achieve a characterization of architectural uncertainty, the designer must not only identify, but also quantify the individual sources of uncertainty that contribute to the architectural uncertainty. This results in a bottoms-up approach to uncertainty assessment, as opposed to a top-down approach that looks to directly identify uncertainty at the architectural level. Using the bottoms-up approach, the designer typically has greater insight into the component, subsystem and even system level uncertainties and their outcomes.

Once the relevant sources of uncertainty have been identified, the next step is to attribute some level of probability and impact to them and quantify them on an individual basis. A relative notion of how significant the uncertainties are will be determined in the identification stage, but in this step more resolution in needed so that it can be incorporated into the simulation models. Some individual uncertainties can be very straightforward to quantify. For example, if the cost model being used is based on historical data, a typical standard deviation about the most likely value can be used, as was pointed out in Chapter 4. Other estimating relationships have comparable standard error measures that can be found in the literature[34] or in company specific databases. Examples of these technologies might include payload sizing estimation or other scaling factors for mass or power.

Other uncertainties might not be so straightforward to quantify. These could arise from market conditions, policy uncertainty, new technology or novel architectural concepts. The quantification of these types of uncertainties is best done using one of two approaches. The first is to develop distribution profiles over which outcomes exist, e.g. market-capture probability density function in Figure 14. The figure presents likelihood of achieving a range of different values of market capture for a given system. In Chapter 8, a commercial space system case study is used to illustrate the significance of market uncertainty on interpreting the architectural tradespace.

[34] Larson, W. a. J. W., Ed. (1992). Space Mission Analysis and Design. Torrance, CA, Microcosm.

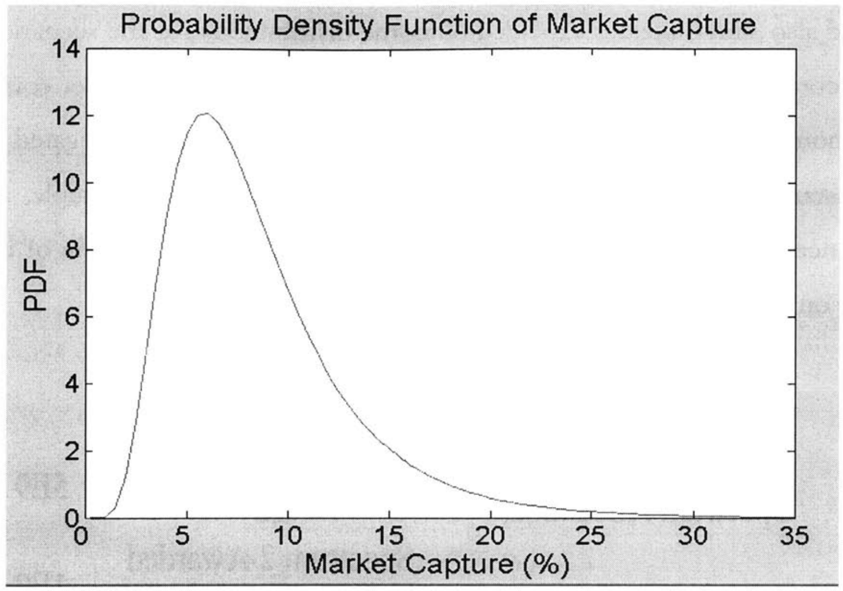


Figure 14: Probability Density Function of Market Capture for Broadband Space System

As significant as the uncertainties discussed above are, so too are uncertainties surrounding the various scenarios that are attributable to an architecture and that could result in significant impacts to the architecture design. One example of such a scenario would be the chance event of acquiring one of two frequencies from the regulatory commissions for transmissions.

Scenario analysis is conducted using a three-step process. The first is to identify the possible scenarios that would cause significant impact to the value of architectures in the tradespace. The second is to determine the outcomes of these scenarios and the probability of each outcome. The final step is to determine a distribution of outcomes and probabilities that can be incorporated into the simulation models for the purpose of uncertainty propagation. This approach is most useful when chance events can be isolated and quantified, for example a chance event of acquiring different transmission frequencies, as shown in Figure 15. In the figure, the chance event is the spectrum allocation for transmission, while the two outcomes are spectrum 1, with an allocation of 5E9Hz, and spectrum 2, with an allocation of 1E9Hz, with a probability of 0.4 and 0.6, respectively. This type of scenario could have a tremendous impact on the relative value of different architectures, perhaps making some architectures now infeasible. Other scenarios, such as technology fallback plans if one technology doesn't achieve operational readiness, can be modeled equally well using this approach. Using a software package like Decision Analysis by TreeAge® enables the quick development of these decision trees and also allows creates expected outcome distributions for the scenarios developed that can be quickly incorporate. Decision trees also serve as one method to consider correlated sources of uncertainty. Although the sources included in each of the three cases investigated are uncorrelated, there are circumstances where uncertainty correlations may exist. For example, an uncertainty in battery performance, i.e. Watts/kg, might depend upon the uncertain outcome of developing a new battery or relying on heritage components.

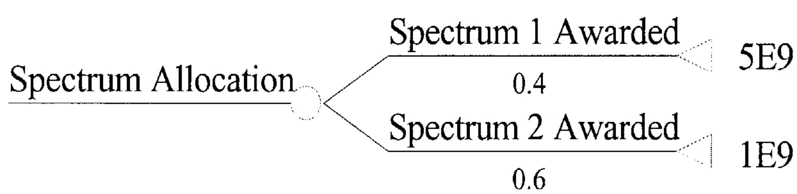


Figure 15: Spectrum Allocation Scenario

Another source of uncertainty arises from the designer's understanding of what is meant by value to the customer. One method of determining this value is through a utility analysis that attempts to uncover the preferences of customers. This utility information can then be modeled quantitatively and incorporated into the overall evaluation of the architectures and their performance.[35]

The uncertainties associated with the utility can be significant, as this can serve as the major decision criterion by which architectures are evaluated. The sources of uncertainty in utility can come from a number of causes including the selection of people involved in eliciting customer utility, and the time dynamics of changing utility. The case study in Chapter 9 incorporates the notion of utility and the uncertainty associated with it in the context of a scientific space mission.

5.2.3 GINA Design Approach

The assertion that most space systems are in fact information transfer networks involved in the collection and dissemination of data led to a significant breakthrough in space systems conceptual

[35] de Neufville, R. (1990). Applied Systems Analysis: Engineering Planning and Technology Management. New York, McGraw-Hill.

design. This assertion opened the door for the application of interdisciplinary techniques of design and evaluation to be applied from network theory onto the problem in space systems conceptual design. From the assertion, a framework was created, the generalized information network analysis (GINA) methodology, which has been applied to a number of space system development problems and been regarded with success.[36,37] By modeling a space system as an information network, common evaluation criteria are calculated. These criteria allow for the comparison of very different architectures on equal footing, as shown in Figure 16.

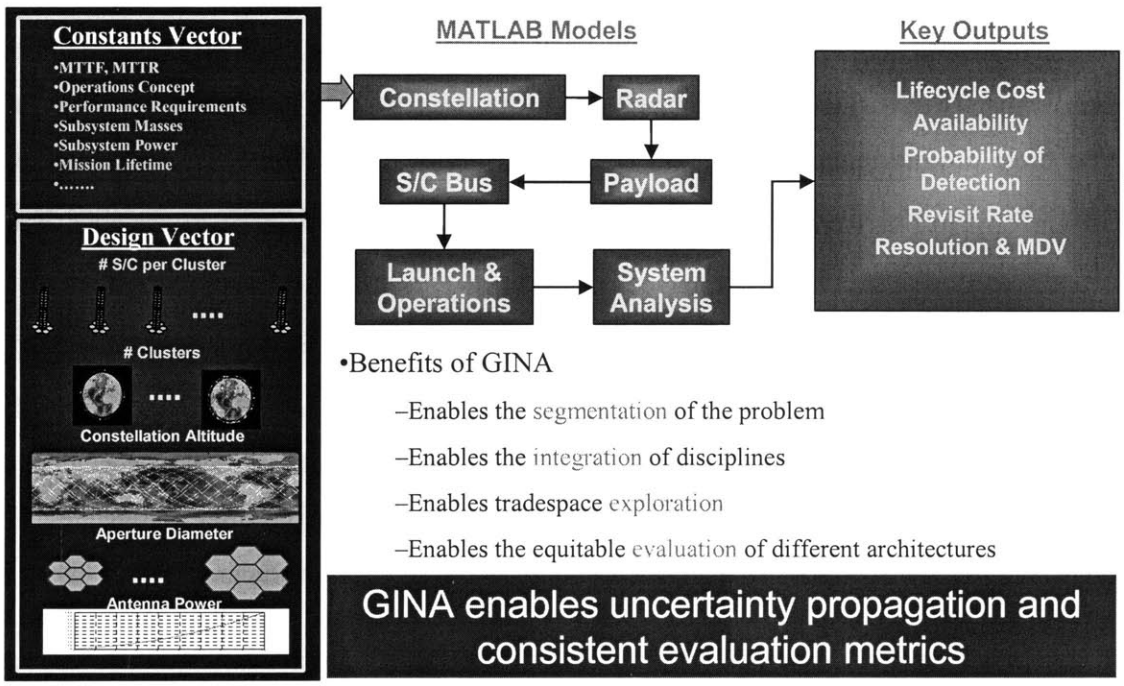


Figure 16: The Generalized Information Network Analysis Method[38]

Advances in conceptual design methods for evaluating space systems architectures, specifically the GINA method, provided a means of exploring conceptual trade spaces rather than just conceptual point solutions. This is the reason that GINA, or a system simulation approach like it, is so important

---

[36] Shaw, G., D. Miller, and D. Hastings (2001). "Development of the Quantitative Generalized Information Network Analysis (GINA) Methodology for Satellite Systems." Journal of Spacecraft and Rockets **38**(2): 257-269.

[37] Jilla, C. (2002). A Multiobjective, Multidisciplinary Design Optimization Methodology for the Conceptual Design of Distributed Satellite Systems. Aeronautics and Astronautics. Cambridge, MA, Massachusetts Institute of Technology. Ph.D. Dissertation

[38] Ibid.

to the full implementation of the uncertainty analysis framework presented here. GINA serves as the platform within which uncertainties from different sources can be incorporated into simulation models and propagated, thus developing distributions of outcomes for architectures in the tradespace.

5.2.4 Propagating Uncertainties

In order to understand an aggregate view of embedded uncertainty, an ability to simulate and propagate uncertainties of assumptions, components, and other modeled characteristics of architectures must exist. Because most space systems conceptual design is forward looking, the designers typical rely on historical statistics and future projections when establishing various component characteristics that are necessary to move forward and model an architecture. By definition these projections have uncertainties associated with them. Using the uncertainty sources previously identified and quantified and this model uncertainty, an uncertainty propagating technique is developed.

In the GINA methodology, most of the sources of uncertainty can be found in what is known as the *constants vector*. The constants vector contains architecture and environmental characteristics that are held constant for all architectures evaluated. Therefore the only variables changing across architectures are the key design variables known as the *design vector*, i.e. number of satellites, altitude, power, etc. and the intermediate variables calculated in each of the sub-modules.[39]

In the uncertainty analysis approach presented, not only are the uncertainties of the assumptions important, but more so are the implications of those assumptions on the decision criteria of the space system architectures in the trade space, such as performance and cost. Therefore, initial uncertainties are used as sources that are propagated in the simulation models to develop distributions of outcomes for each architecture in each decision criteria dimension.

Two implementation approaches can be used to capture the various ranges of probabilities of performance experienced by the system, either the extreme condition approach or the Monte Carlo simulation approach. The extreme condition approach has the benefit of being far less

[39] Although we classify an individual combination of design vector variables as an architecture, in some case the differences between one combination and another may suggest that the GINA process is simply doing parameter design and not system architecting. This is the topic of ongoing debate, but to remain consistent with the terminology first developed with GINA, each combination of the design vector will be called an individual architecture.

computationally intensive while the Monte Carlo simulation approach provides a greater confidence in the embedded architectural uncertainty based on the number of samples taken. The first case study in Chapter 7 employs the extreme condition approach, while the second and third cases in Chapter 8 and 9 present the implementation of the simulation approach. Du describes in detail some of the advantages and disadvantages of the two methods.[40]

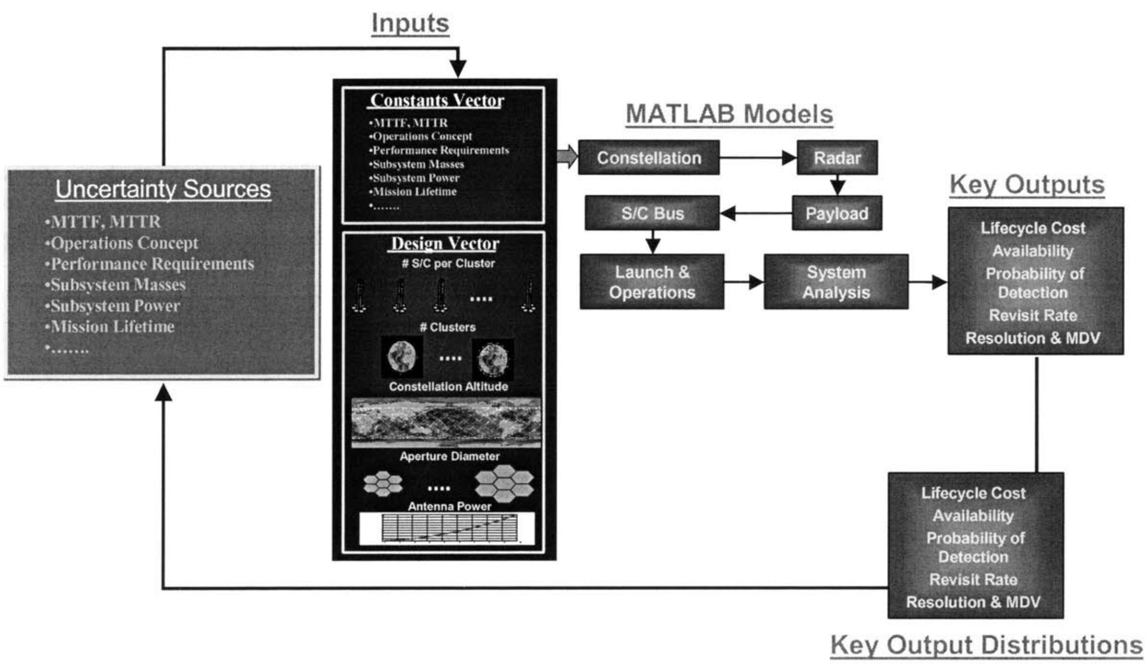


Figure 17: Uncertainty propagation within the GINA framework

Once the individual sources of uncertainty have been identified and quantified, the uncertainty propagation technique is applied to the GINA simulation model, as shown in Figure 17. The constants vector that contains all the sources of uncertainty is sampled. This sample is then held constant for the evaluation of each combination of the design vector using a GINA simulation call. This creates a single set of outcomes for each of the architectures in the tradespace. In order to create distributions of outcomes, the process is repeated with a new sampling of the constants vector. In the extreme approach, the number of iterations will be three, whereas in the Monte Carlo approach the number will vary, depending on the desired sample size. The number of samples that should be

[40] Du, X. a. W. C. (2000). "Methodology for Managing the Effect of Uncertainty in Simulation-Based Design." AIAA Journal **38**(8): 1471-1485.

conducted is not explicitly stated here, as it depends on the sources and levels of uncertainty that have been identified. For example, source uncertainties that have been characterized by continuous normal distributions will require fewer iterations in the uncertainty propagation approach than situations involving discrete scenario modeling that may require more iterations to fully develop satisfactory outcome distributions. Further there are various statistical measures that can be taken to verify a statistically significant population such as the approach developed by Morgan.

Morgan describes his technique for selecting the sample size as follows:[41]

Assume a Monte Carlo simulation has generated *m* random outputs, $(y_1, y_2, y_3, \ldots y_m)$. This distribution is then used to estimate the mean and standard deviation according to the following equations:

$$\bar{y} = \sum_{i=1}^{m} \frac{y_i}{m}$$

Eq. 2

$$s = \sqrt{\sum_{i=1}^{m} \frac{\left(y_i - \bar{y}\right)^2}{(m-1)}}$$

Eq. 3

Given a confidence, α, the confidence interval can be calculated from Eq. 4, where c is the deviation for the normal distribution enclosing probability α.

$$\left(\bar{y} - c\frac{s}{\sqrt{m}}, \bar{y} + c\frac{s}{\sqrt{m}}\right)$$

Eq. 4

In order to calculate a sample size, an interval width, *w*, is selected that will estimate the mean of y with confidence, α, as given by Eq. 5

[41] Morgan, M. G. a. M. H. (1990). Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk Policy Analysis. Cambridge, UK, Cambridge University Press.

$$2c\frac{s}{\sqrt{m}} < w$$

Eq. 5

In practice, to quantify a sample size, m, a small Monte Carlo simulation is initially run to estimate the variance. From this the appropriate sample size can be calculated.

5.3 Visualizing Architectural Uncertainty

Visualization of complex information, such as uncertainty, often provides valuable insight into underlying characteristics of the data that wouldn't otherwise be noticed. Visualization of data is a human-machine interface problem and often a useful representation to one person may not provide value to another. An ongoing body of research on uncertainty visualization provides direction as to the significant role that visually presenting uncertainty can play.[42] Most researchers agree that there is no "best" visualization technique for presenting uncertainty information, but a number of general guidelines are common. Three of these guidelines are 1.) deliver the information in a way that is consistent with the type of decisions upon which the data will be based, 2.) clearly separate the data from the uncertainty, and 3.) develop visualizations that are consistent with human intuition.[43]

Therefore, a menu of uncertainty visualization techniques is presented that may enable the designers to understand and convey characteristics of the embedded architectural uncertainties both individually and collectively in the tradespace.

5.3.1 Focusing on individual architectures

The first and most straightforward way to represent the outcome distributions for an individual architecture is to use a histogram that presents the predicted outcomes and their probability of occurrence, as shown in Figure 18. The figure is generated by "binning" potential outcomes and counting the number of observations that fall in each bin considered, thus generating a vertical bar chart. Further, if a normal distribution is expected, a normal expectation line can be overlaid onto the graph to visually judge relative fit of the data, as shown in the graph. The figure represents the output for an architecture whose mission is to map the earth's ionosphere that will be discussed later in

---

[42] Ibid.

[43] Mahoney, D. P. (Nov 1999). "The Picture of Uncertainty." Computer Graphics World.

Chapter 9. The prime decision criteria in the case of this architecture was total utility, which is a relative measure of worth by which all architectures could be judged.

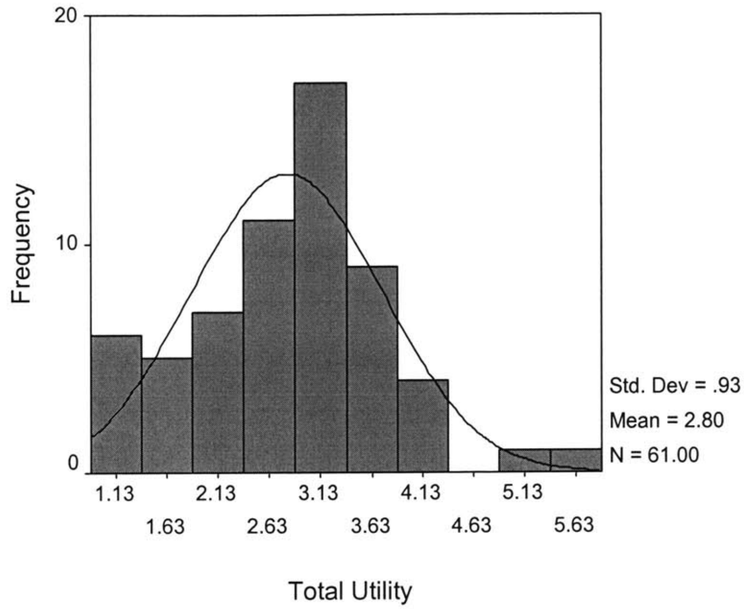


Figure 18: Example Histogram for Architectural Uncertainty[44]

The boxplot provides a snap shot view of the architectural uncertainty as it applies to a single outcome measures, as plotted for total utility in Figure 19. The box-plot gives information at a quick glance that all of the observations recorded fell within the bracketed figure with exception of outliers that are shown separately where they exist. The box represents the interquartile range that contains the 50% of values, while the solid black line represent the median.

[44] Although typical convention would normalize utility to 1, this example involved the aggregation of sub-utility functions resulting in ranges greater than 1

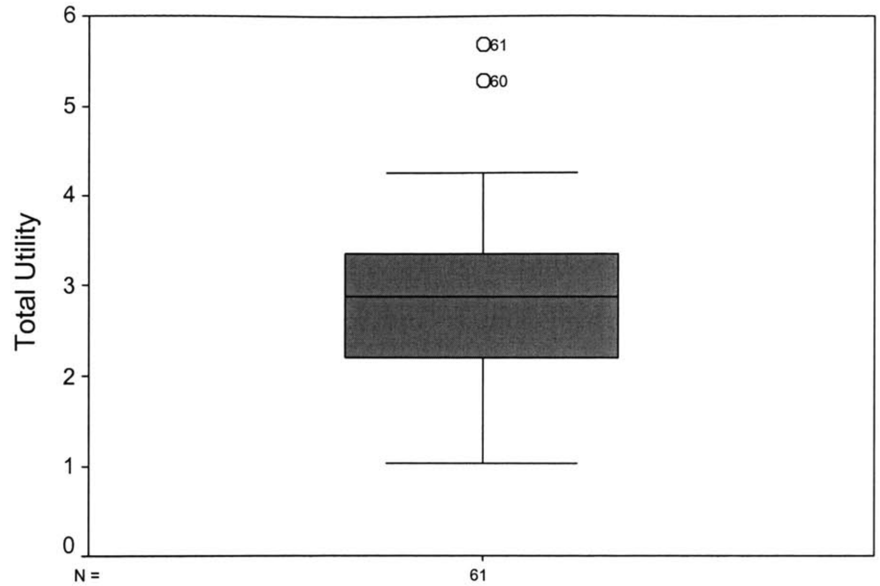


Figure 19: Example Box Plot for Architectural Uncertainty

There are as many dimensions of uncertainty as there are outcome measures that are trying to be predicted. The previous examples, and in fact much of the rest of the thesis is oriented around the most important one or two dimensions from which decisions are generally based. However, there can be a great deal of value in understanding the way other outcome measures move with respect to uncertainty. This information might not drive a decision, but it would more likely impact the overall development plan and concept of operations. For example, the uncertainty in expected customers of a broadband telecommunications system would directly impact the marketing and rollout plans for the new product.

In addition, by visualizing uncertainty in more than one dimension, the designer can see how outcomes in different dimensions move with each other. Figure 20 presents a two-dimensional histogram of low latitude mission utility and high latitude mission utility for the ionospheric mapping space system that is discussed in depth in Chapter 9. From this type of figure, the designer can quickly identify high and low likelihood scenarios as well as appreciate architectural characteristics that are not evident by looking at each dimension of uncertainty independently. For example, from this figure both high and low latitude utility can be seen to be right skewed distributions that are positively correlated. The right skewed behavior can be seen from the high degree of frequency in the upper right quadrant and the positive correlation is evident from the symmetry about the diagonal.

By looking back at the sources of uncertainty that effect these two dimensions of utility, the explanation becomes clear. Both dimensions are driven by the uncertainty in the user lifetime requirement of five years and the uncertainty in the reliability of the satellites in operation These uncertainty would effect both the high latitude and low latitude mission in the same manner. Although this is the case for the particular architecture modeled in Figure 20, it does not necessarily dictate that other architectures behave in a similar manner. The next section describes the role of comparative techniques in visualizing uncertainty in the tradespace rather than any single architecture.

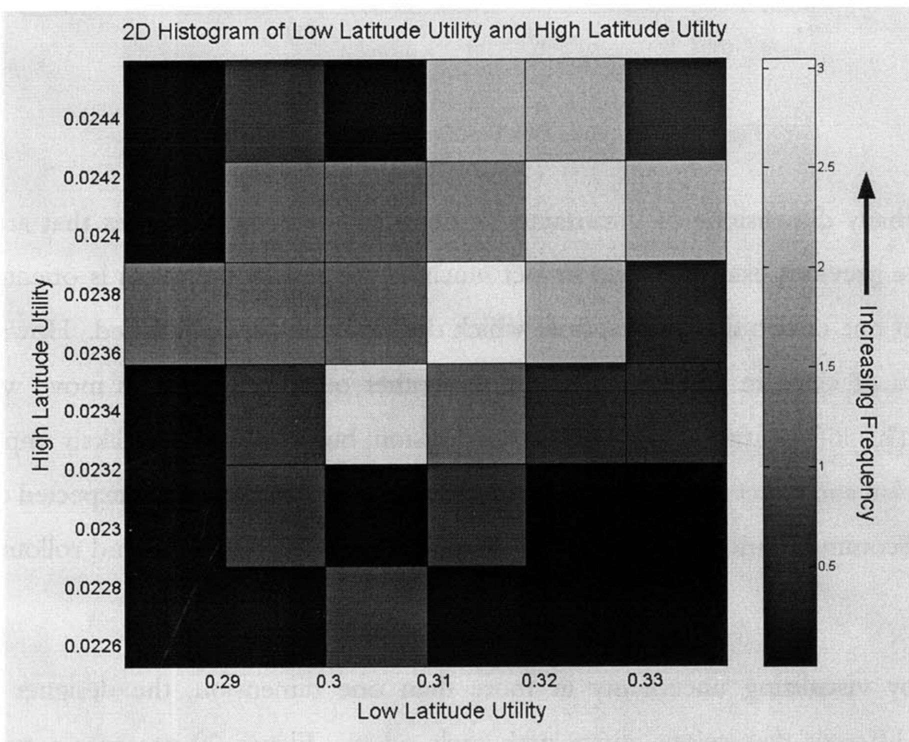


Figure 20: Visualizing Architectural Uncertainty in Two Dimensions

5.3.2 Comparative techniques

Visualizing the uncertainty of a single architecture is important, but in conceptual design it is perhaps more important to understand the uncertainty in the tradespace of exploration. A number of techniques to represent visually the embedded architectural uncertainty for a tradespace of architectures simultaneously is presented.

The first method suggested is the use of error bars in the tradespace analysis, as shown in Figure 21. This multi-dimension aspect might be better appreciated through the use of ellipses of uncertainty. In either case, one standard deviation from each outcome measure defines the edge of the error bar or ellipse. The ellipses are useful in visualizing overlap among architectures in terms of outcomes; however, the elliptical representation has some mathematical assumptions that the simple error bars escape. The ellipses with their shape imply a distribution to the uncertainty of an attribute that may or may not be correct.

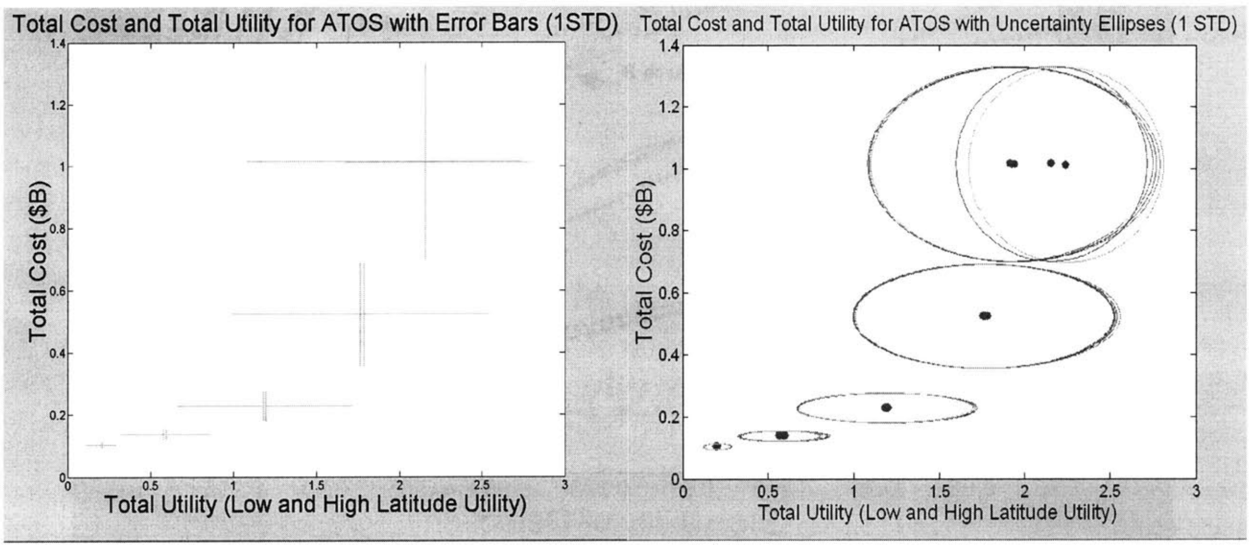


Figure 21: Uncertainty in a tradespace using error bars and uncertainty ellipses

The error bars and uncertainty ellipses allow the designer to see the relative uncertainty that exists among architectures, but it provides no insight into if these architectures react differently under different conditions of uncertainty. To address this, a method is introduced that captures the shifting outcomes of each architecture tied to different characteristics of uncertainty.

Suppose, the extreme approach is used to calculate the embedded architectural uncertainty and three conditions of uncertainty are simulated for each architecture. Figure 22 is developed by plotting the three outcomes for each architecture and connecting the outcomes with a line. As opposed to previous representations where points or ellipses represented a single architecture, a line defines an architecture in this framework. This particular visualization technique has not been used previously in the literature, but it provides some fundamental insights that the less complex ellipse and error bar charts don't provide.

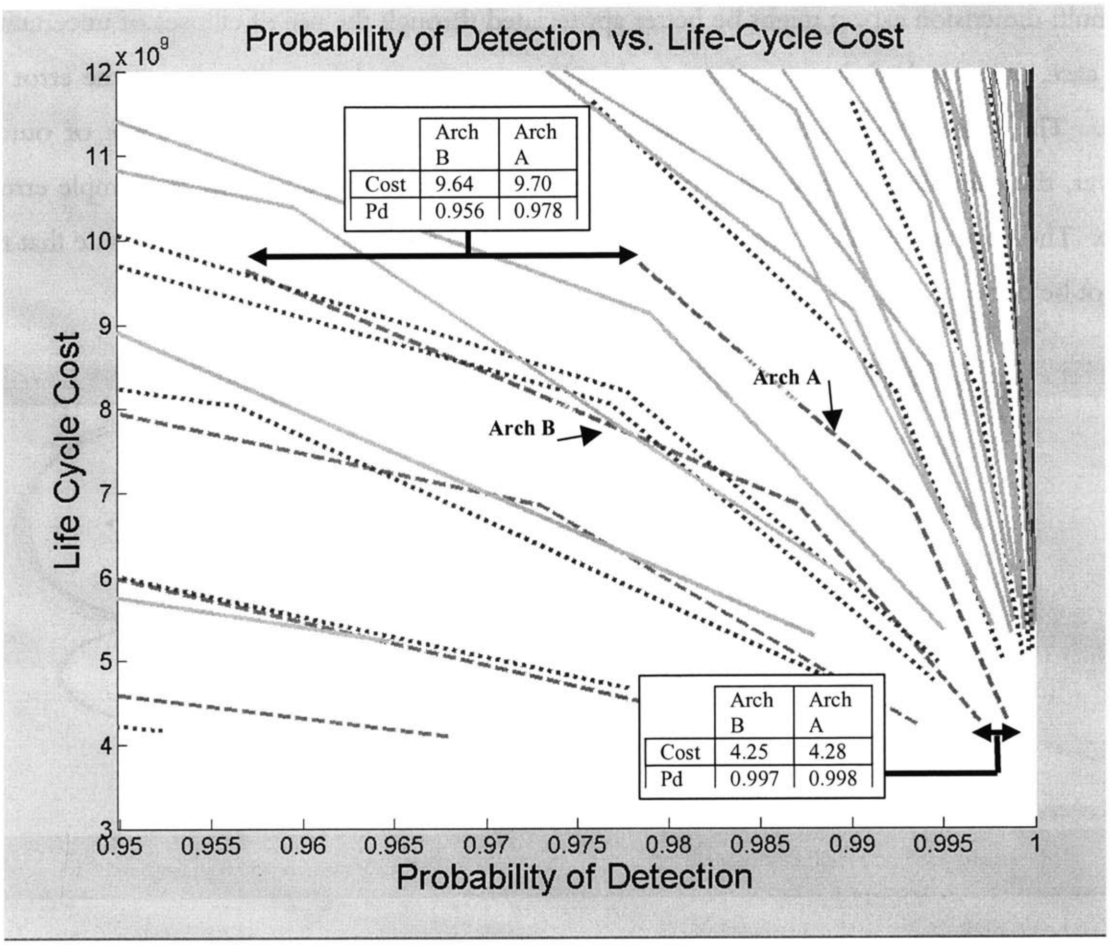


Figure 22: Characterizing embedded uncertainty under three scenarios

The first thing to notice from this chart is the relative sensitivity different architectures have with respect to the three scenarios of uncertainty conditions. The second thing to notice is that "good" architectures can quickly become "bad" architectures under some conditions of uncertainty. For example, Architecture A and B appear to both be good architectures under low levels of uncertainty. However, as the uncertainty increases so too does the separation distance between the two architectures in terms of Probability of Detection to as much as 2.2%. It appears that all the architectures move in the same general pattern, but it is the degree to which they move that can provide insight. Without this analysis, a decision maker who is presented with deterministic information might perceive the lower cost Architecture B to be a good choice and Architecture A to not be worth the \$3E7 in lifecycle cost for only $1/10^{th}$ of a percent improvement in Probability of Detection. This kind of visualization allows the immediate interpretation of relative sensitivities to uncertainty of the architectures in the tradespace.

Sometimes, shading is a more powerful visualization tool than geometric figures alone. Therefore a final method is presented for visualizing uncertainty in a tradespace based on a shaded contour plot. Figure 23 is generated in much the same way as the previous tradespace uncertainty figure; however, contours are used to describe the embedded architectural uncertainty that exists. Building on the example presented in Figure 21, a similar tradespace is presented representing the ionospheric mapping mission. Instead of presenting the two dimensions of uncertainty separately a single aggregate uncertainty is presented, the uncertainty in utility/cost. This chart shows that although the absolute uncertainty is increasing monotonically with cost and uncertainty, the relative uncertainty (uncertainty in the utility per cost dimension) actually has a turning point, as shown in the figure denoted by the light square at 1.2 utility and \$0.25B.

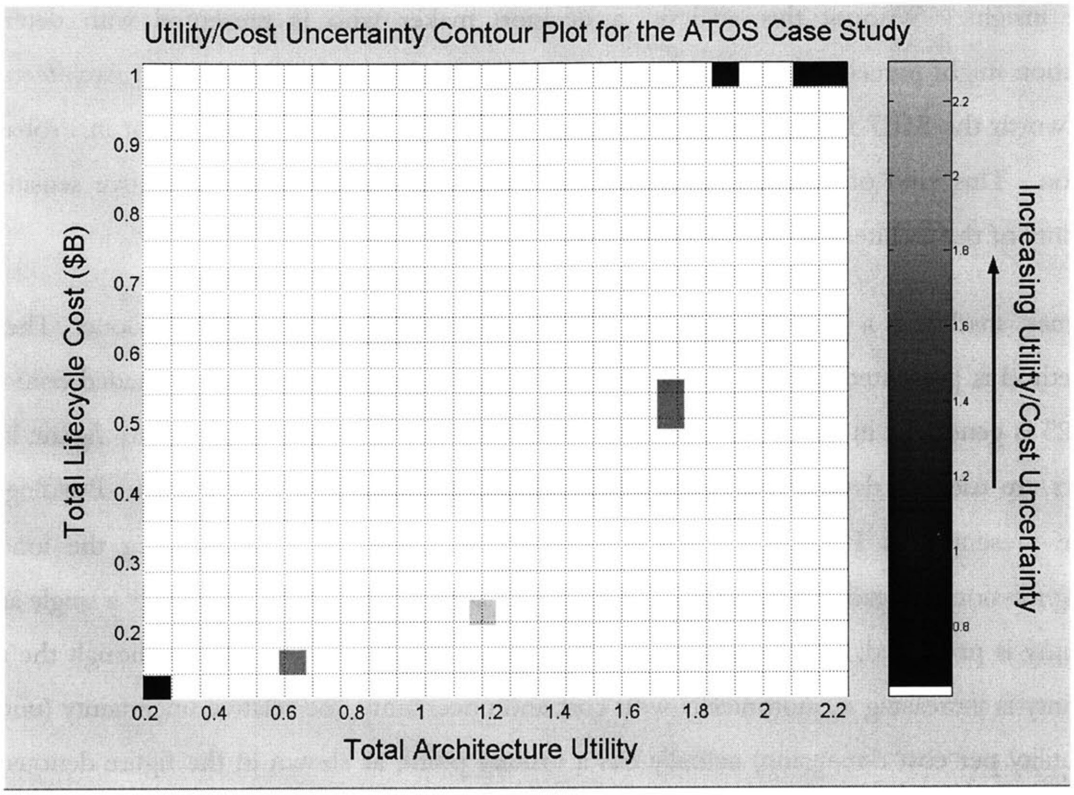


Figure 23: Embedded Uncertainty Contour Plot

Uncertainty quantification and uncertainty visualization can provide a great deal of insight into not only individual architectures and their relationship with uncertainty, but also the comparative relationship that different architectures share with respect to uncertainty. Although useful and insightful, this information provides the decision maker with no clearer strategy of how to proceed in conceptual design. A method has to be developed that incorporates the uncertainty information and codifies into a coherent strategy to suggest to the decision maker. In the next chapter a method is presented that satisfies this charge. Building on portfolio theory and optimization, an approach is developed that incorporates embedded architectural uncertainty information as well as decision maker aversion to risk to define sets of architectures whose returns are often greater than any single asset for a given exposure to uncertainty.

Chapter 6

PORTFOLIO THEORY APPLIED TO SPACE SYSTEMS CONCEPTUAL DESIGN

The previous chapter described the approach used in this thesis to quantify the embedded uncertainty in architectures that are being evaluated. This chapter presents a method to manage uncertainty information associated with each architecture after it has been collected. The method is based on portfolio theory and optimization. The foundations of portfolio theory are first presented, followed by the mathematics of portfolio optimization. An explanation of portfolio theory in both the financial, as well as the space system context is then presented. Methods for identifying decision maker risk aversion are then presented as essential to identify optimal portfolio strategies. Caveats to traditional portfolio theory applied in the field of space systems are then presented along with limitations of the approach in theory and practice.

6.1 Modern Portfolio Theory

Harry Markowitz revolutionized the way people manage investments with the introduction of portfolio theory in 1952.[45] The underlying goals of portfolio theory are to recommend investment strategies that balance the needs of an individual investor to 1.) achieve the maximum return for their investment and 2.) for this return to be subject to as little uncertainty as possible. Markowitz put it in the following way:

> *A good portfolio is more than a list of good stocks and bonds. It is a balanced whole, providing the investor with protections and opportunities with respect to a wide range of contingencies.*[46]

The mental leap from the context of this theory in finance to its usefulness in design is not that great—what decision maker would not be interested in developing a project with "protections and opportunities with respect to a wide range of contingencies?" This goes back to one of the key goals

---

[45] Markowitz, H. (1952). "Portfolio Selection." Journal of Finance **7**(1): 77-91.

[46] Markowitz, Harry M., (1991). Portfolio Selection, second edition, Blackwell, Cambridge, MA.

of this thesis: *To develop a method that creates portfolios of architectures to invest in during conceptual design which have inherent in them a level of robustness and flexibility to uncertainty*[47].

Portfolio theory assumes that for a given level of uncertainty, investors prefer higher returns to lower returns—a risk averse utility-maximizer decision maker. Similarly, for a given level of expected return, investors prefer less uncertainty to more uncertainty. It is standard to measure uncertainty in terms of the variance, or standard deviation, of return. Therefore, it can be assumed that investors would like to invest in an efficient portfolio -- one in which there is no other portfolio that offers a greater return with the same or less uncertainty (or less uncertainty with the same or greater expected return).

Portfolio Theory highlights a very important concept that is often overlooked and that is that the assets traded in the stock market do not move together in terms of return. For example, the overall market may be moving up, but at the same time there are stocks that are losing value. There are some stocks that tend to move together, and others that move in opposite directions, and others that seem to have no relation to one another. This tendency is measured mathematically by correlations and covariance. The covariance provides the variability or uncertainty in a portfolio, as well as a independence measure of each asset with respect to other assets in the portfolio.

In order to go beyond general principles of portfolio theory, optimization techniques are used to enable the search of the tradespace of architectures so that the decision maker arrives at an optimal set of architectures to pursue that maximize return while at the same time consider his aversion to risk. The specific class of optimization is quadratic optimization based on an appropriate weighting of risks and returns. These risks and returns are typically derived from historical movements of stock or asset movements, but in the case of space systems, the simulation models are relied upon to generate distributions of potential outcomes.

6.1.1 Mathematics of Portfolio Optimization

Two precursors to the portfolio optimization algorithm are the quantification of returns and uncertainty of players in the market. The methods to discover architectural uncertainties in conceptual design were previously explored in Chapter 5. From the measured responses of architectures in the GINA model under varying levels of uncertainty in the inputs and environment, a covariance matrix

---

[47] See Saleh, J. (2001). "Spacecraft Flexibility." Journal of Spacecraft and Rockets **Forthcoming**. for discussion of value of flexibility and its relationship to robustness.

can be obtained that describes not just the individual uncertainty of each asset in the tradespace, but also how each architecture's uncertainty moves with respect to another architecture. That is, how independent are the architectures in terms of the uncertainty that exists and how likely is diversification of the uncommon or specific uncertainty associated with individual architectures. Figure 24 portrays the diversification of specific uncertainty, and the remaining systematic uncertainty that can't be escaped.

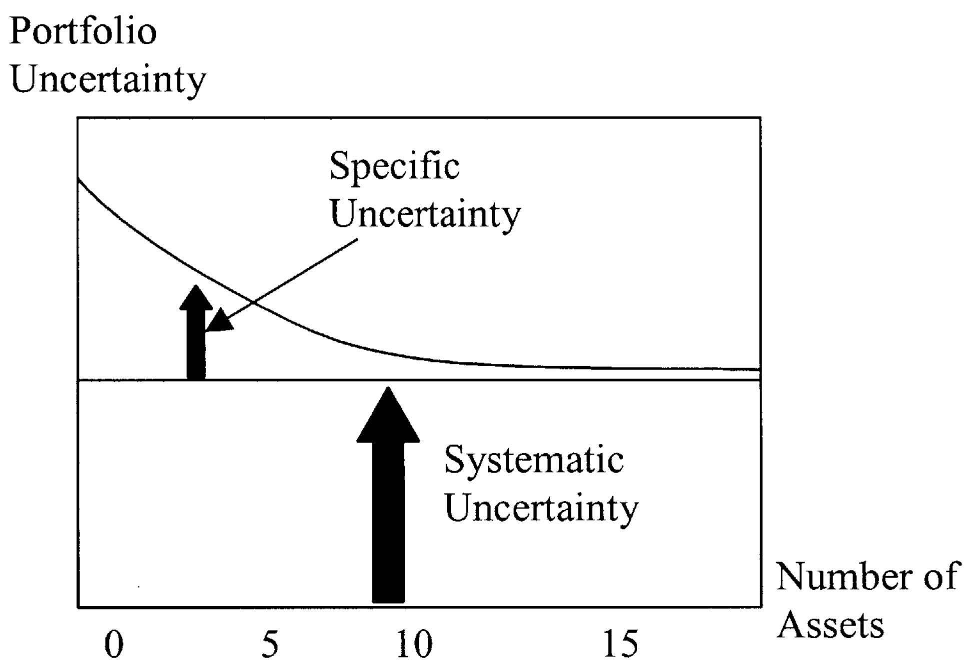


Figure 24: Power of Diversification[48]

6.1.1.1 Value

In order to define strategies for a given decision maker, the value that is desired from the system must be understood. Nearly everyone has an idea of what *value* means, so in that way it is a familiar concept; however, seldom are individual's ideas on value interchangeable. Take for example the same mission of delivering communications capability to the military and to the consumer marketplace. Although both seek the same basic service, the way each customer judges the service value will have striking differences. Typically security, availability, and performance will be at the top of the military customer

---

[48] Adapted from Brealey, Richard and Stewart Myers. (2000) Principles of Corporate Finance, sixth edition, McGraw-Hill, Boston.

list, while cost, carrier quality and latency may be at the top of the consumers' list of value desired from the system.

Researchers at MIT have taken a broader perspective to define value and in the process created a useful framework in which to think about how to identify, agree upon and deliver value to stakeholders, including the customer. They make the point that value is contextual, multi-dimensional and dynamic, but despite these qualities it can be identified, agreed upon and delivered. Termed the value creation framework, the construct provides a guidepost on how a multi-dimension, multi-decision maker value identification and agreement might come about. The first stage of the framework is the identification of what each stakeholder would like to get out of the system; the second step provides for the formal understanding of what the goal of the system is and how each stakeholder may derive value; while the third stage describes necessary approaches to execute on the agreed upon value proposition.[49] It is at the second stage of the framework where a value measures for a space system architecture might start to be considered.

To utilize portfolio optimization, a one-dimensional measure of value is created. Most of the literature suggests that this value is a function of cost, and the many attributes of utility that could exist. The exact relationship will be mission and customer specific, as previously discussed. However, methods to translate multi-attribute utility and cost into value is the subject of ongoing research, and although the third case study described in Chapter 9 uses the concept of utility based on multi-dimensional attributes, the most common value criterion remains a *function per cost* metric, such as "billable T1 hours/$ spent" as in commercial broadband case in Chapter 8 or "probability of detection/$ spent" as in the military case described in Chapter 7.

---

[49] Murman, E. e. a. (2001). Lean Enterprise Value. New York, NY, Palgrave Publishers, Ltd.

Once the value criterion is set, simulation models are used to capture the architecture outcome, as described in Chapter 5, under varying levels of uncertainty. Once *n* samples are collected, the sample mean, *m*, can calculated for architecture *x* with Eq. 6. This sample mean represents the expectation of value that will be derived for a given architecture and will be used in portfolio optimization as a measure of return on the asset.

$$m = \frac{\sum_{i=1}^{n} x_i}{n}$$

Eq. 6

6.1.1.2 *Uncertainty and Covariance*

To continue with the portfolio optimization, the individual uncertainty of each architecture, through its standard deviation from the mean, must be understood and also the covariance of each pair of assets must be determined. This information is necessary to create a covariance matrix, as shown in Figure 25, that describes the independence of assets in the tradespace with respect to uncertainty. Eq. 7 describes the calculation of covariance, $\sigma_{X1,X2}$, given standard deviation, σ_{X1} and σ_{X2}, and correlation coefficient, $\rho_{X1,X2}$, for two assets.

Assets	X_1	X_2	X_3	●	●	X_n
X_1	σ_1^2	$\rho_{12}\sigma_1\sigma_2$	$\rho_{13}\sigma_1\sigma_3$	●	●	●
X_2	$\rho_{12}\sigma_1\sigma_2$	σ_2^2	$\rho_{23}\sigma_2\sigma_3$	●	●	●
X_3	$\rho_{13}\sigma_1\sigma_3$	$\rho_{23}\sigma_2\sigma_3$	σ_3^2	●	●	●
●	●	●	●	●	●	●
●	●	●	●	●	●	●
X_n	●	●	●	●	●	●

Figure 25: The Covariance Matrix, *Q*

$$\sigma_{X_1,X_2} = \rho_{X_1,X_2}\sigma_{X_1}\sigma_{X_2}$$

Eq. 7

The most common method in finance to calculate the covariance matrix in Figure 25 is through the use of time samples of comparative variables. Following similar logic, in order to obtain the value in the covariance matrix for space systems, the distribution outcomes for each architecture under the same conditions of uncertainty are used. Each datum in the outcome distribution becomes a sample observation in the calculation of mean, covariance and variance for each architecture and pair of architectures by using the standard deviation equation, Eq. 8, and the covariance equation, Eq. 9, for two assets x and y. Substituting Eq. 8 and Eq. 9 into Eq. 7 yields the correlation coefficient for each pair of architectures in the tradespace.

$$\sigma_x = \sqrt{\frac{n\sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2}{n(n-1)}}$$

Eq. 8

$$\sigma_{x,y} = \frac{1}{n-1}\left(\sum_{i=1}^{n} x_i y_i - \frac{1}{n}\sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i\right)$$

Eq. 9

Figure 26 describes two one-dimensional optimization problems for managing investments. Variance can be either minimized such that it meets some fixed level of return for an investment or the return can be maximized subject to some maximum level of uncertainty a decision maker is willing to take. In these equations, *Q* is the covariance matrix of the assets as described in Figure 25, *r* is the expected returns and *w* is the selected weightings of assets.

Minimize Variance	Maximize Return
$\min \frac{1}{2} w^T Q w$	$\max \sum_{i=1}^{n} r_i w_i$
$S.T. \sum_{i=1}^{n} r_i w_i \geq r_*$	$S.T. \frac{1}{2} w^T Q w \leq \sigma_*^2$
$S.T. \sum_{i=1}^{n} w_i = 1$	$S.T. \sum_{i=1}^{n} w_i = 1$
$S.T. w \geq 0$	$S.T. w \geq 0$

Figure 26: Equations of Different Objectives

Portfolio optimization seeks to combine both of these important preferences into a single objective function to maximize, as shown in Eq. 10. This equation represents the basis for most applied portfolio theory that can be found in practice. In words, it seeks to maximize the returns that can be achieved given known uncertainties and returns of players in the market and also given a known level of aversion to uncertainty, *k*.

$$\max : r^T w - \frac{k}{2} w^T Q w$$
$$S.T. \sum_{i=1}^{n} w_i = 1$$
$$S.T. w \geq 0$$

Eq. 10

The application of portfolio theory has been shown to be effective in a number of applications and disciplines, including the modeling of a social welfare state[50], organizational restructuring and business acquisition strategy[51] and many others far from the original financial domain, but this work represents the first rigorous extension of portfolio theory to systems design.

Eq. 10 can be used to find the optimal portfolio based on returns and uncertainties of architectures for a decision maker, but random portfolios can also be calculated in terms of overall expected return and uncertainty. Eq. 11 and Eq. 12 describe the methods of calculating portfolio returns and variances, where R_P is the associated return, w_i is the investment in asset i.

$$E(R_P) = \sum_{i=1}^{n} w_i R_i$$

Eq. 11

$$Var(R_P) = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j (R_i - E(R_i))(R_j - E(R_j))$$

Eq. 12

50 Elton, E.J and M.J. Gruber. (1979) "Optimal Dynamic Consumption and Portfolio Planning in the Welfare State", TIMS Studies in the Management Sciences 11: 179-196.

51 Bergh, Donald. (1998) "Product-market uncertainty, portfolio restructuring, and performance: an information-processing and resource-based view." Journal of Management Mar/Apr 1998.

6.1.2 An example of financial portfolio analysis

A financial portfolio example is presented to develop the connection between applying portfolio theory in the context of finance and applying it in the context of space systems. Suppose a financial investor has $1000 dollars to invest. What are the best investment vehicles he/she can put the money into to gain the best return? Portfolio theory provides a framework to find an ideal mix of assets to put money into that will provide the most return for the risk their willing to take. To simplify this example, suppose this investor is limited by their retirement plan to invest in only three mutual funds. These funds have historical data from which an expected return and a standard deviation have been calculated. Using the historical data, the correlation coefficient for each pair wise combination of the three funds is presented. This information is presented in Table 7.

Table 7: Mutual fund options for sample investor

Mutual Fund Name	Expected Return (%)	Standard Deviation (%)	Correlation to Value	Correlation to Growth	Correlation to SmallCap
Value	11.77	7.18	1.000	0.1175	-0.1136
Growth	13.78	7.45	0.1175	1.000	0.0886
SmallCap	12.37	6.51	-0.1136	0.0886	1.0000

Using this information, an efficient frontier is calculated on which all optimal investment strategies will reside. This frontier is done by first calculating the maximum return portfolio possible and then calculating the minimum uncertainty portfolio possible. These two portfolios define the boundaries of the efficient frontier. The next step is find portfolios that represent the best return for a given level of uncertainty. Repeating this step generates the efficient frontier, as shown in Figure 27. The location of the individual mutual funds has been labeled in the figure as well. The composition of a portfolio on the efficient frontier can be seen on the right hand side of the chart. The point shown in the chart consists of 13% of the Value Fund, 54% of the Growth Fund, and 33% of the SmallCap Fund. If this was the optimal strategy for the example investor, it would mean he/she should put $130 in the Value

Fund, $540 in the Growth Fund, and $330 in the Small Cap Fund to achieve the highest return, in this case 13.1% for the risk his level of risk aversion allows, a standard deviation of 4.9% for this portfolio.

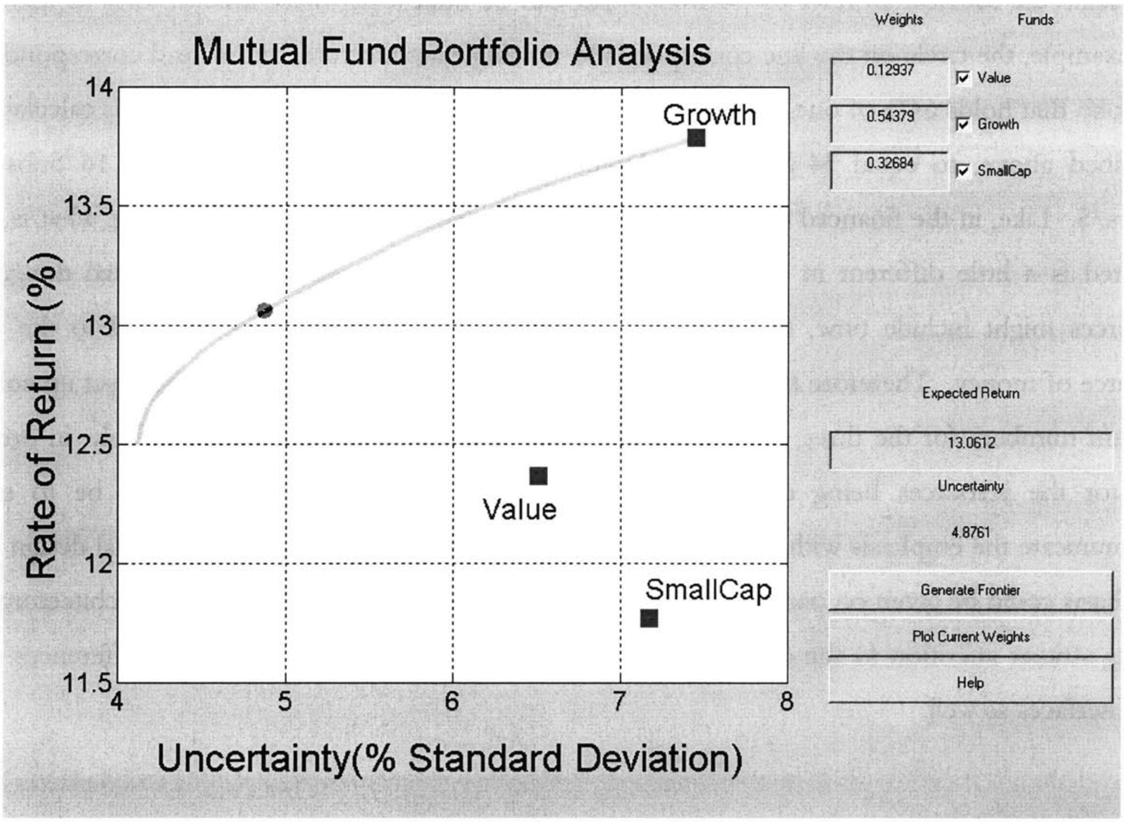


Figure 27: Mutual fund portfolio analysis example

There are two major points to take away from this example. First, a continuous set of investments has been established which the investor can choose from, as opposed to discrete assets. Second, notice that portfolios are available to the investor that provide more return at a lower level of uncertainty than any single mutual fund would have allowed. This comes from the uncorrelated behavior of these assets to situations of uncertainty. Keeping the financial example in mind, an example of portfolio theory applied to space systems conceptual design is presented.

6.1.3 An example of portfolio analysis applied to space systems

The typical end result of portfolio analysis is the formulation of an efficient front of portfolios, as was shown in the financial example. Portfolios that lie on the efficient frontier are those that maximize value for a given level of uncertainty, as shown in Figure 28. This figure represents work on a broadband system whose value is represented here subscriber hour per dollar and whose uncertainty is the standard deviation around the expected return. Individual architecture's subscriber hour/$ and uncertainty have been plotted and are marked with diamonds on the chart. The concave line represents the efficient frontier of portfolios that can be built using these architectures as members. For example, the circle on the line corresponds to no single architecture, but instead corresponds to a portfolio that holds 64% of one, 34% of another and 22% of still another. The return is calculated, as described above, to equal 34 Subscriber Hours/$ while the standard deviation is 16 Subscriber Hours/$. Like, in the financial example, this implies an investment strategy. However, what is being invested is a little different in conceptual design than it is in finance. In conceptual design, the resources might include time, money people, infrastructure support, etc as opposed to the single resource of money. Therefore this portfolio would direct a decision maker to perhaps set up contract account numbers for the three different architectures and allocate resources accordingly, in order to monitor the resources being expended on each asset. Another approach might be to simply communicate the emphasis with which the designs should be explored to the conceptual design team. Emphasis could be given on parallel designing the common features of the different architectures and paying stricter attention to the differences among the architectures and how those differences effect any interfaces as well.

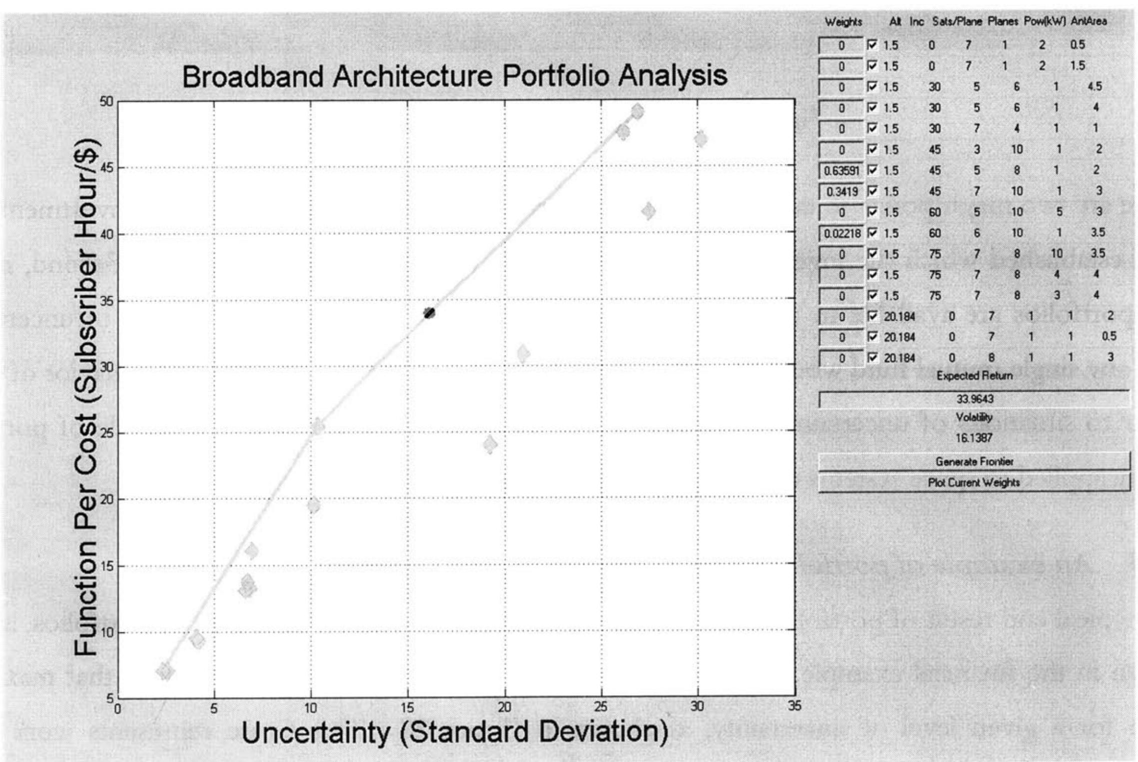


Figure 28: Sample Portfolio Analysis

Figure 28 helps transition to the next important question in portfolio analysis, which is where on the frontier of efficient portfolios does the decision maker's optimal strategy exist? The answer to that question lies in the decision maker's level of risk aversion.

6.2 Uncovering risk aversion in stakeholders

A method to quantify the efficient frontier has been presented, but further guidance as to where on the frontier looks most attractive must be found. This localization is one more step in focusing the efforts of design and condensing the tradespace based on available information. The available information in this case is the level of risk aversion of the decision maker.

Once an approach for calculating risk aversion is presented, the vision of formalizing uncertainty in the conceptual design of space systems becomes much more generalizable and actionable amongst a large group of stakeholders whose preferences need not align.

Some authors have made distinctions between uncertainty aversion and risk aversion in the past. For most, uncertainty aversion has meant the aversion to not knowing even the chances of an event occurring.[52] This is in contrast to the classic interpretation of risk aversion as the aversion of a decision maker to known probabilities, but uncertain outcomes.[53] Using a fair coin toss as an example to illustrate this difference. Uncertainty averse individuals concern themselves with not knowing how likely heads or tails may be. The risk averse individual is more concerned with the implications of the coin landing on heads or tails.

The point has been made previously that this thesis is focused on uncertainty rather than risk because uncertainty can be considered inclusive of risk. The use of the overarching concept of uncertainty is used in this analysis as well; however, aversion as is discussed in this thesis more closely relates to risk aversion, as described in the literature than to that of uncertainty aversion described above. This is because most decision makers in the case of space systems are more concerned with the implications of the negative outcomes than they are with the simple existence of uncertainty.

Understanding the level of aversion in stakeholders must be achieved in much the same way the utility analysis is conducted through direct interaction and structured dialogue with stakeholders. Two

---

[52] Epstein, L. (1997). Uncertainty Aversion. Toronto, Canada, University of Toronto and Hong Kong University of Science and Technology.

[53] Savage, M. F. a. L. P. (1948). "The Utility Analysis of Choices involving Risk." Journal of Political Economy **56**: 279-304.

methods for extracting the value of the risk aversion constant, *k*, are described for use in the portfolio optimization approach outlined above.

6.2.1 Methods of capturing uncertainty aversion

It is of course an oversimplification that a person's aversion can be described by one scalar value, but it allows for analysis that would otherwise be intractable. Financial markets have struggled with uncovering stakeholder risk aversion for investment purposes. These levels of aversion are often brought out by questions from experienced financial advisors or structured questionnaires that have proven effective in the past. Instead of questionnaires, two technique are presented: a quantitative method based on decision maker utility functions and a second, qualitative approach to qualify a decision maker's aversion through the use of indifference curves.

6.2.1.1 *Method 1: Using utility functions*

The capturing of a decision maker's utility is also an exercise in capturing their aversion to risk.[54] For example, a question that might be asked during a utility interview is: Given the following two options what would be the value of *p* for which you would be indifferent in the selection?

1. *Certainty Option*: Value X_i
2. *Uncertain Option*: Value X_0 with probability p and X_n with probability $1-p$, such that $U(X_0)<U(X_i)<U(X_n)$

A series of these types of questions will lead to utility function, as shown in Figure 29. This function illustrates the utility of a risk averse individual, through its characteristic concave function. Moreover, Figure 30 highlights the risk premium, π_Z, that a decision maker is willing to pay to avoid risk. A neutral individual equates no premium to having a sure thing and would therefore judge indifference based solely on expected value. In contrast, a risk prone decision maker would be characterized by a convex utility function signifying their proclivity toward uncertainty.

---

[54] Von Neumann, J. a. O. M. (1944). Theory of Games and Economic Behavior. New York, John Wiley and Sons.

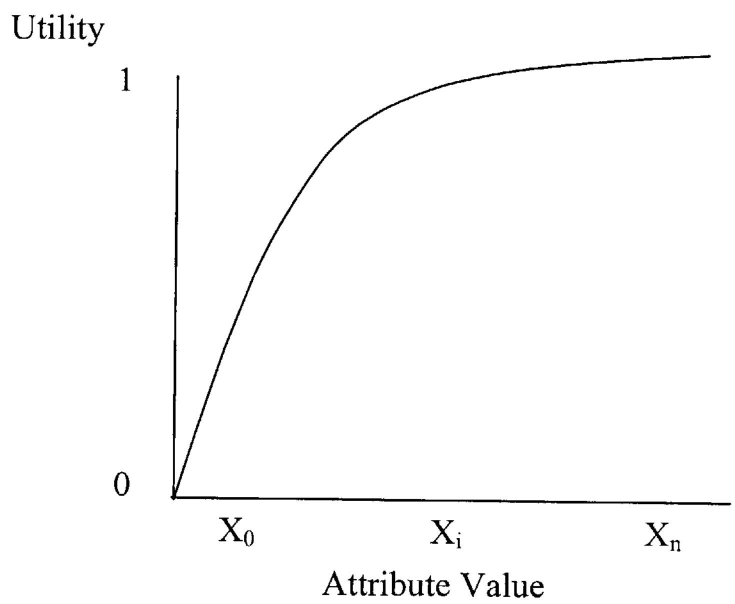


Figure 29: Sample Utility Function

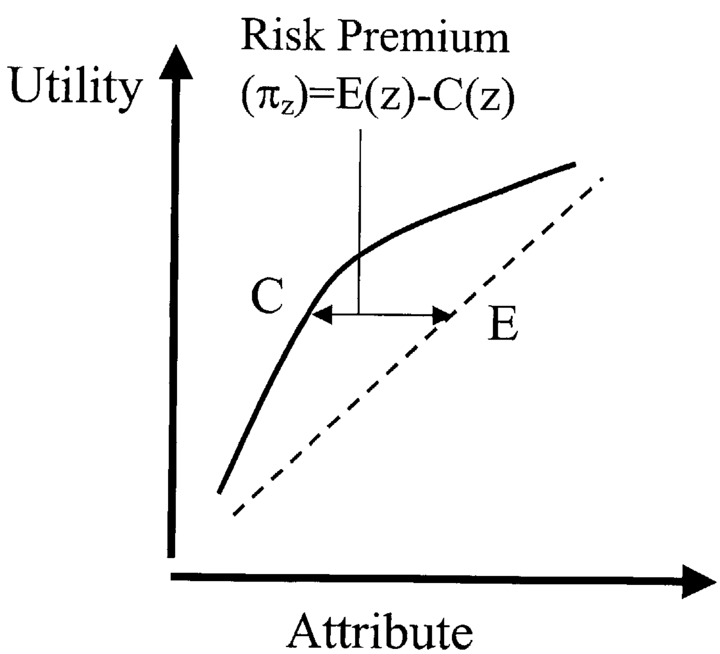


Figure 30: Measuring risk premiums

Eq. 13 presents a mathematical representation of risk aversion. The value known as absolute risk aversion (ARA) is obtained from information in the utility function, as developed above, in the form of the first and second derivative.[55,56]

$$s_u(x) = -\frac{u''(x)}{u'(x)}$$

Eq. 13

This factor will be positive for a risk averse individual and negative for a risk prone individual. The decreasing incremental rate of utility improvement is due to the decision maker's willingness to pay a premium in terms of a lower attribute value if it implies a decreased exposure to uncertainty.

An augmentation to this notion of absolute rate of risk aversion is relative risk aversion (RARA), which includes a provision for the current state of wealth of the decision maker. Research has been done to show that risk aversion may be subject to a number of conditions, including the present value of the decision maker's wealth. In order to address this concern, the present value of the wealth condition is included in the analysis, as shown in Eq. 14.[57,58]

$$S_u(x) = xs_u(x) = -x\frac{u''(x)}{u'(x)}$$

Eq. 14

6.2.1.2 Method 2: Using graphical approaches

A graphical approach can be employed to augment or stand-alone as a measure of risk aversion. This graphical approach is aimed at directly interacting with the decision maker to address the preferences of risk aversion. Using this approach a relative value for the decision maker's risk aversion factor can be determined that can be used directly in the portfolio optimization approach. This number provides the "weighting" of uncertainty, *k*, in the maximization of returns subject to uncertainty, as shown in Eq. 10.

---

[55] Pratt, J. W. (1964). "Risk Aversion in the Small and in the Large." Econometrica **32**: 122-36.

[56] Arrow, K. J. (1965). Aspects of the Theory of Risk-Bearing. Helsinki, Yrjo Hahnsson Foundation.

[57] Pratt, J. W. (1964). "Risk Aversion in the Small and in the Large." Econometrica **32**: 122-36.

[58] Arrow, K. J. (1965). Aspects of the Theory of Risk-Bearing. Helsinki, Yrjo Hahnsson Foundation.

This approach works when a stakeholder is available for consultation or the approach was built into the front end of the process. Using a series of indifference curves, such as those in Figure 31, a decision maker can be polled as to the amount of uncertainty they are willing to except for increased return. Figure 31 presents the indifference curve for three different decision makers with *k* values of 1, 2 and 3.

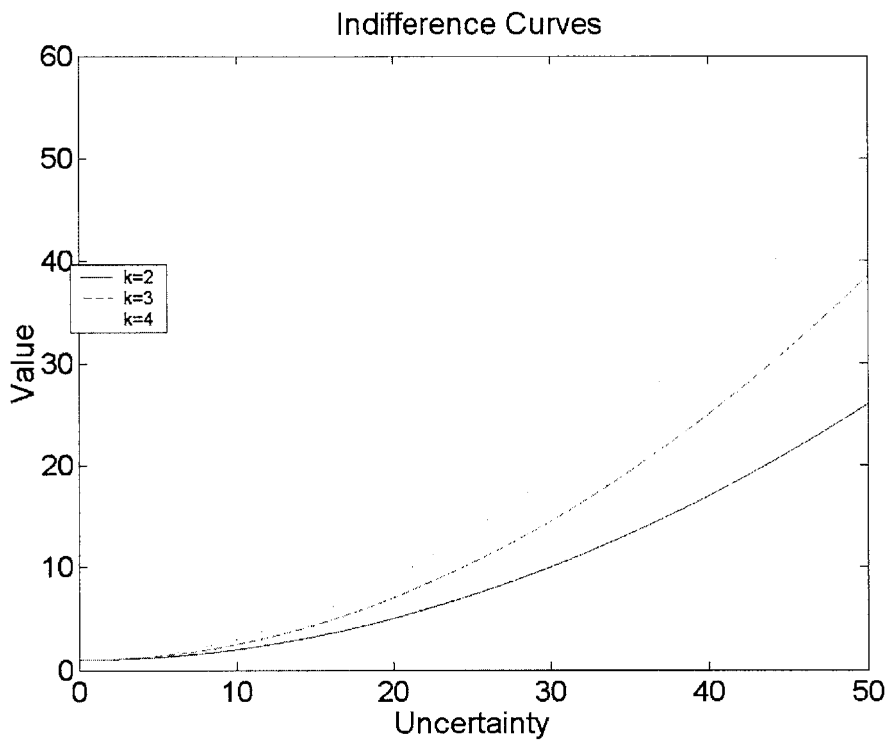


Figure 31: Indifference Curves for Decision Makers, Varying Risk Aversion Factors

After a *k* is chosen using the indifference curves, a family of Iso-utility contours is created as shown in Figure 32. From this information and the previously calculated efficient frontier of portfolios, a recommendation can be made on what specific portfolio to pursue. The tangent point of the highest iso-utility line and the efficient frontier denotes the optimal portfolio, as shown in Figure 33.

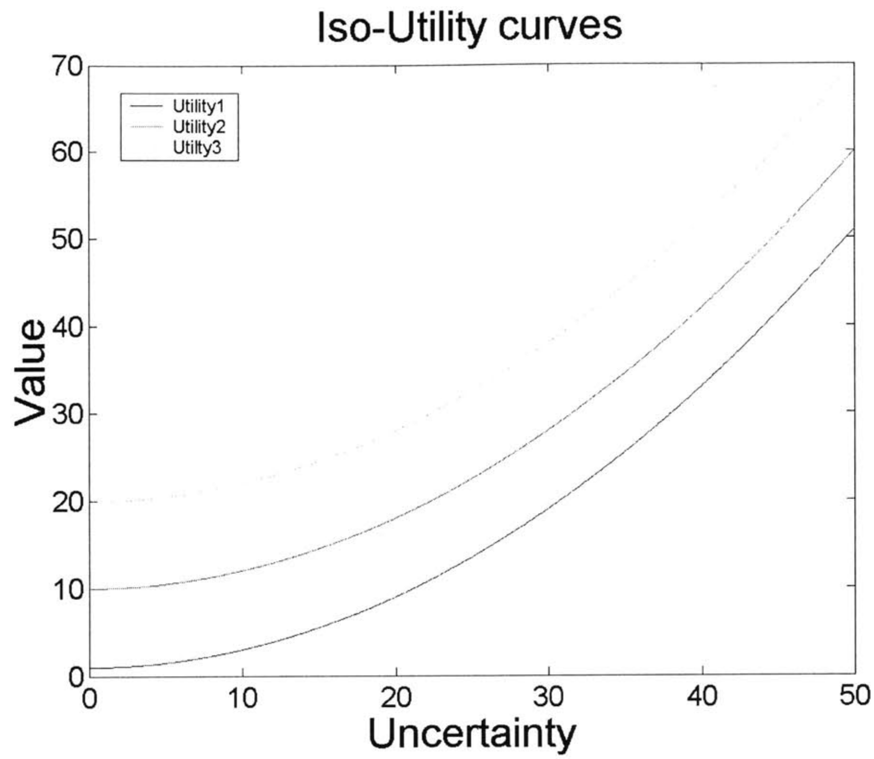


Figure 32: Iso-Utility Curves for a Decision Maker

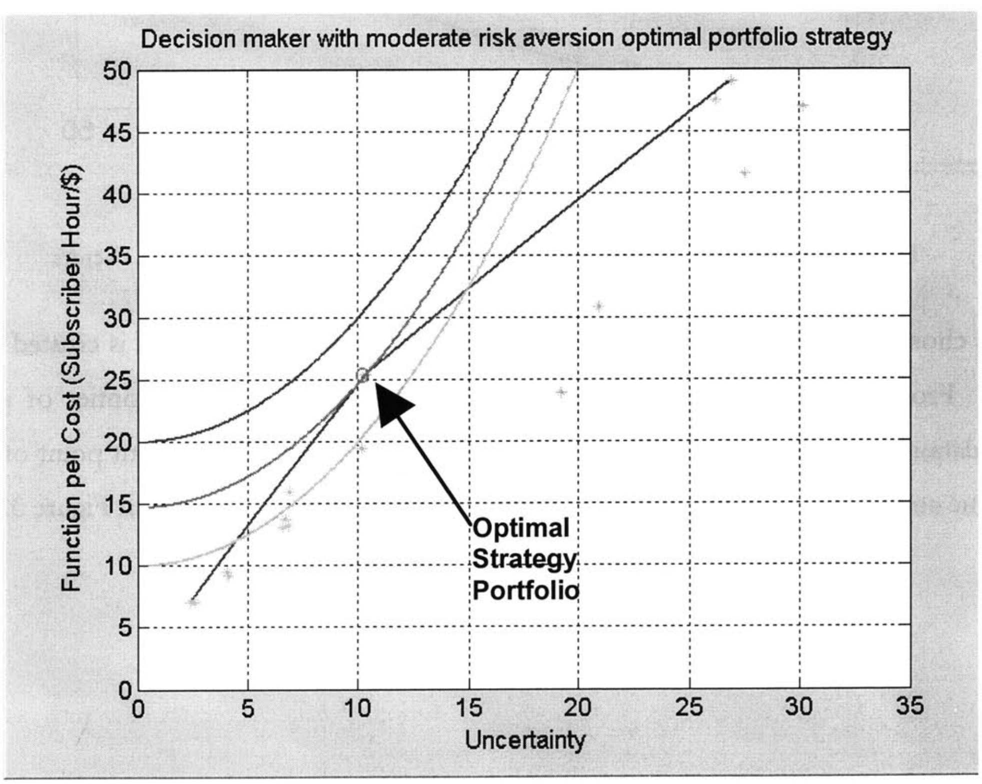


Figure 33: The portfolio tradespace with aversion criteria overlaid

6.3 Extensions of portfolio theory to space system design

There are a number of assumptions from traditional financial portfolio theory that are challenged when investigating real assets, like space systems. These assumptions include: customers are driven by the risks and place no value in upside potential of systems, uncertainty is represented by normal distributions of outcomes, and there is no cost in holding an asset in the portfolio. This section addresses the extensions that can be made to traditional portfolio theory as to overcome some of these assumptions.

6.3.1 Accounting for upside potential from uncertainty

One of the fundamental assumptions that Markowitz made in the development of portfolio theory was that investors were risk-averse. While it is true of space system designers as well, an approach is investigated to value the upside of uncertainty that is so often neglected in traditional uncertainty and risk assessment. The value of such upside potential of uncertainty has been discussed extensively in the area of Options and Real Options. However, it is the downside of uncertainty that dominates most research and practical analysis, and perhaps rightfully so considering the level of risk aversion pervasive in the aerospace industry. The following analysis tries to capture the importance of understanding the risk in the assets and at the same time determine a method to separate it from the upside potential.

To separate the upside and the downside of uncertainty, the concept of semi-variance, both s_{upside} and $s_{downside,}$ are introduced as measures of one-sided uncertainty.[59] Assume 10 likely values for a space systems architecture value to the customer are represented by r={1 4 2 10 9 7 3 4 8 1}. To calculate semi-variance, two companion set of outcomes are created, r^+={4.9 4.9 4.9 10 9 7 4.9 4.9 8 4.9} and r^- ={1 4 2 4.9 4.9 4.9 3 4 4.9 1} and companion deviations around the expectation, as shown in Eq. 15 and Eq. 16.

$$(r_i - E(r))^+ = \begin{bmatrix} 0 \text{ if } r_i \leq 0 \\ (r_i \text{ - E(r)) if } r_i > 0 \end{bmatrix}$$

Eq. 15

$$(r_i - E(r))^- = \begin{bmatrix} (r_i \text{ - E(r)) if } r_i \leq 0 \\ 0 \text{ if } r_i > 0 \end{bmatrix}$$

[59] Markowitz, H. (1991). Portfolio Selection: Efficient Diversification of Investments. Cambridge, MA, Basil Blackwell. . describes a possible extension of the mean-variance portfolio selection approach that incorporates the idea of down-sided semi-variance.

Eq. 16

From these equations $(r-E(r))^+ = \{0\ 0\ 0\ 5.1\ 4.1\ 2.1\ 0\ 0\ 3.1\ 0\}$ and $(r-E(r))^- = \{-3.9\ -0.9\ -2.9\ 0\ 0\ 0\ -1.9\ -0.9\ 0\ -3.9\}$. The upside and downside semi-variances can be found $s_{upside} = E([(r-E(r))^+]^2) = 5.684$ and $s_{downside} = E([(r-E(r))^-]^2) = 4.406$. This difference in the upside and downside semi-variance illustrates the lack of normality in the distribution of r. Portfolio theory was originally based on the premise of random motion of stocks in the form of volatility that could indeed be modeled by normal variables having upside and downside semi-variance that are in fact equal. The same cannot necessarily be assumed in space systems, as many of the probability distribution functions that describe things like market uncertainty or events of decision tree analysis are not gaussian. Using the semi-variance information, two covariance matrices, Q_{upside} and $Q_{downside}$ are constructed. Once these matrices are constructed, the portfolio optimization formulation can be expressed in the form of Eq. 19 and Eq. 20. The objective function in Eq. 19 reflects a decision maker who is very concerned with the true downside of uncertainty and sees no reason to reflect any upside benefit due to uncertainty. While the objective function of Eq. 20 incorporates the negative aspects of the downside of uncertainty as well as the upside potential the uncertainty might present.

$$Q_{Upside} = \begin{bmatrix} S_{u1}^2 & \rho_{2,1} S_{u2} S_{u1} & \rho_{3,1} S_{u3} S_{u1} & \bullet & \rho_{n,1} S_{un} S_{u1} \\ \rho_{1,2} S_{u1} S_{u2} & S_{u2}^2 & \rho_{3,1} S_{u3} S_{u1} & \bullet & \rho_{n,2} S_{un} S_{u2} \\ \rho_{1,3} S_{u1} S_{u3} & \rho_{2,3} S_{u2} S_{u3} & S_{u3}^2 & \bullet & \rho_{n,3} S_{un} S_{u3} \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \rho_{1,n} S_{u1} S_{un} & \rho_{2,n} S_{u2} S_{un} & \rho_{3,n} S_{u3} S_{un} & \bullet & S_{un}^2 \end{bmatrix}$$

Eq. 17

$$Q_{Downside} = \begin{bmatrix} S_{d1}^2 & \rho_{2,1} S_{d2} S_{d1} & \rho_{3,1} S_{d3} S_{d1} & \bullet & \rho_{n,1} S_{dn} S_{d1} \\ \rho_{1,2} S_{d1} S_{d2} & S_{d2}^2 & \rho_{3,1} S_{d3} S_{d1} & \bullet & \rho_{n,2} S_{dn} S_{d2} \\ \rho_{1,3} S_{d1} S_{d3} & \rho_{2,3} S_{d2} S_{d3} & S_{d3}^2 & \bullet & \rho_{n,3} S_{dn} S_{d3} \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \rho_{1,n} S_{d1} S_{dn} & \rho_{2,n} S_{d2} S_{dn} & \rho_{3,n} S_{d3} S_{dn} & \bullet & S_{dn}^2 \end{bmatrix}$$

Eq. 18

$$\max : E(r)w - \frac{k}{2} w' Q_{Downside} w$$
$$\text{s.t.} : \sum_{i=1}^{n} w_i = 1$$
$$\text{s.t.} : \mathrm{w} \geq 0$$

Eq. 19

$$\max : E(r)w + \frac{1}{2} w' Q_{upside} w - \frac{k}{2} w' Q_{Downside} w$$
$$\text{s.t.} : \sum_{i=1}^{n} w_i = 1$$
$$\text{s.t.} : \mathrm{w} \geq 0$$

Eq. 20

6.3.2 Cost of Diversification

In finance, portfolios are composed of assets whose growth is not driven by contributions by the asset holder. This is not the case in the space systems, where the outcome value of each asset in the portfolio is driven by the asset holder's continued contribution to the design, through people's time, testing resources, money, etc. For this reason, there is an added cost to the portfolio owner having more than one asset in a portfolio over and above the single design cost. Unlike in finance, the question remains, "What is the cost of diversification?"

One method for quantifying the cost of diversification derived here is based on the correlation of assets. Rather than derive new information from the architectures, current information can be used in the form of correlation coefficients that are easily obtainable from the covariance matrix previously calculated.

$$\rho_{ij} = \frac{\sigma_{ij}}{\sigma_i \sigma_j}$$

Eq. 21

Using the correlation coefficient as a relative measure of marginal cost increase for pursuing multiple portfolios, a relative cost penalty for diversification can be obtained that illustrates the diversification penalty. Knowing that as the correlation coefficient of two architectures approaches one, the architectures represent decreasing marginal cost to include both in the portfolio. It is also true then that as the correlation coefficient approaches zero, the architectures represent more dissimilar designs and will have greater marginal costs to include in the portfolio. The cost of diversification would therefore approach zero as the correlation coefficient approach one and approach the full cost of an additional architecture as the correlation coefficient goes to zero. The cost of diversification, C_D, is characterized in Eq. 22, where C_{NonRec} is the nonrecurring cost of design for architecture i, w_{max} is the maximum fractional investment in any of the architectures in the tradespace, w_i is the fractional investment in asset i, n is the number of assets in the portfolio and ρ_{ij} is the correlation coefficient between asset i and j:

$$C_D = \sum_{i=w>0} \sum_{j=w>0} \frac{w_i}{w_{\max}} C_{Non\,Rec_i} \frac{(1-\rho_{ij})}{n}$$

Eq. 22

6.4 Putting it together

The classic portfolio optimization problem has been extended to encompass many of the real world situations that are encountered in space systems. The new formulation of this problem is presented in Eq. 23 and Eq. 24.

$$\begin{aligned}
&\max: E(r)w - \frac{k}{2} w' Q_{Downside} w \\
&\text{s.t.}: \sum_{i=1}^{n} w_i = 1 \\
&\text{s.t.}: C_D < C_{Avail} \\
&\text{s.t.}: \mathrm{w} \geq 0
\end{aligned}$$

Eq. 23

$$\begin{aligned}
&\max: E(r)w + \frac{1}{2} w' Q_{upside} w - \frac{k}{2} w' Q_{Downside} w \\
&\text{s.t.}: \sum_{i=1}^{n} w_i = 1 \\
&\text{s.t.}: C_D < C_{Avail} \\
&\text{s.t.}: \mathrm{w} \geq 0
\end{aligned}$$

Eq. 24

Similar to traditional portfolio theory, the objective seeks to maximize expected returns from the underlying assets subject to acceptable uncertainty, but here it is only looking to minimize the exposure to the downside of uncertainty (and also seeking to maximize the portfolio exposure to upside effects of uncertainty in the case of Eq. 24). Finally, the "cost" of diversification involved in exploring sets of architectures in conceptual design is addressed by placing an available cost to diversify constraint on the optimization.

6.5 Implementing the Algorithm

Matlab® was used as a programming platform from which to implement the portfolio analysis. This has the benefit of leveraging ongoing work with algorithms in the Matlab® language as well as maintaining a common platform with the simulation software that is used to model the space system architectures. This avoids the difficulties that come with interoperability of programs and computer systems. Further, because Matlab® is a common engineering software platform, there is relatively little burden on implementers of the uncertainty analysis approach to learn or procure a new software tool.

The portfolio optimization algorithm, as described in Eq. 10 is a non-linear optimization problem, more specifically a quadratic optimization program. Luckily there is a good deal of research on solving quadratic optimization problems and those optimization problems specifically tied to portfolio theory as well. Because quadratic optimization and specifically portfolio theory has been of such interest to researchers, there are a number of methods that could employed to address the algorithm outlined in Eq. 10 and then tailored to address the needs of the modified portfolio optimization applied to space systems conceptual design.

There are a number of methods to attack quadratic optimization problems, but one of the most common optimization routines is done using line search methods, notably conjugate-gradient and Newton steepest descent search methods. These approaches have been employed in a number of commercial products including the Matlab® Optimization Toolbox, Excel Add-ins and stand-alone portfolio optimization programs. This thesis relied heavily on the use of the Matlab® Optimization toolbox to remain consistent with the platform of the simulation models. The Matlab® quadratic optimization routine defines a problem as either large scale or medium scale and then implements a tailored algorithm to appropriately deal with the complexity of the problem. The quadratic optimization algorithm in Matlab® uses the Newton's steepest descent line search algorithm that from an initial feasible starting point calculates the steepest gradient in any direction, still within the feasible space, and moves in that one direction the maximum amount. This is then continued until no feasible direction provides a better solution than the current solution. There are subtleties to the algorithm that ensure no cycling and the algorithm is also based on the assumption that the Q matrix is positive semi-definite, thus making the optimization problem convex. In the next section, the convexity assumption provides some issues when implementing the suggested add-ons to the classic portfolio theory approach.

6.6 Where the portfolio theory breaks down in space systems design

Of course, the portfolio approach presented here has limitations like any methodology and it is often as significant to understand the relative weaknesses of an approach, as it is to understand its strengths. The modes of failure for the approach fall into two distinct categories, practical limitations and theoretical limitations. Practical limitations are those that although, consistent mathematically or theoretically, they hold relatively little value for the decision maker or the analyst, whereas theoretical limitations are those that come with applying the portfolio theory rigorously to the problem of space systems.

6.6.1 Practical Limitations

Determining uncertainty distributions for each architecture in the potential tradespace can be computationally intensive and intractable. Therefore, the scope of the architectures is limited by both the precision of the architectural distribution, i.e. how many outcome samples for each architecture, as well as the total number of architectures considered.

Further, the outcome of the portfolio analysis provides the decision maker with an optimal strategy that suggests which architecture should be assigned resources for further development. When portfolio solutions present a decision maker with portfolio that recommends a very small investment in an architecture, it's questionable if this is a reasonable strategy to employ in practice. For example, a portfolio that recommends investment of 46% in a LEO satellite systems, 52% in a MEO satellite system and 2% in a GEO satellite system should probably be looked closely at to justify the 2% investment in the GEO architecture. It is most likely the case that such a small investment would not overcome the threshold to make any progress on further design. In that case, the portfolio should be adjusted to reflect relative investment in the LEO and MEO architectures only.

Moreover, the relative investment that is derived using portfolio theory should not be seen as absolute. It is easy to distinguish 46% of cash to invest, but it is more difficult to gain such precision in the allocation of design resources. Instead, the optimal portfolio should be seen more as a relative guide to direct the decision makers thinking than an absolute position.

6.6.2 Theoretical Limitations

There are a few mathematical assumptions that serve as limitations in some instances of applying the portfolio optimization framework proposed herein. The first assumption is that the outcome distributions are normal distributions. This is why variance is used in the Markowitz portfolio theory implementation. In the case of a normal distribution the scaled semi-variance would provide the same information as the variance. Therefore the mathematical complication of calculating semi-variance can be avoided. Normality of outcomes can be tested using statistical tests and software such Statistical Package for the Social Science (SPSS®). However, seldom do assets have true normal outcome distributions. Therefore, one way to address a non-normal distribution is to use semi-variance in the portfolio optimization implementation, as opposed to variance. This would address the issue of skewed distributions. However, there are potential outcome distributions whose behavior simply cannot be captured under portfolio theory. In these cases, even if the portfolio analysis provided little guidance, the uncertainty quantification would at the very least provide decision makers of the embedded architectural uncertainty. The existence of these cases doesn't invalidate the results of the portfolio analysis, but at the same time, when they appear, portfolio theory might not be providing the complete set of uncertainty information to the decision maker.

The second assumption in the portfolio theory algorithm is that the covariance matrix is semi-positive definite. In mathematical terms, this indicates that the eigenvalues for the matrix are non-negative, or more practically, a portfolio can't have uncertainty less than zero. Typically, this is not an issue and the traditional portfolio optimization method with the algorithms previously described works efficiently. However, when using both upside and downside semi-variance in conjunction, the modified Q matrix may very well not be positive definite, i.e. right skewed distributions. The options in this case are to consider the two sides of uncertainty independently or heuristic methods can be employed on the problem to search the solution space.[60]

The third assumption of the algorithms shown was a condition of linear constraints. However, the cost of diversification constraint is non-linear. Therefore, there are two options in the case of employing the cost-to-diversify extension. The first is to use heuristic search methods but run the risk of poor solutions or second post-process the results on the efficient frontier and deliver only those that satisfy the constraint as feasible portfolios to pursue.

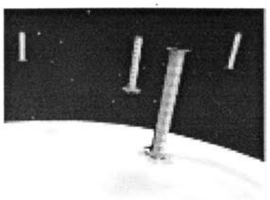
---

[60] See Masini, R. a. M. G. S. (1996). "Heuristic algorithms for the portfolio selection problem with minimum transaction lots." European Journal of Operational Research **114**(2): 219-233. and Winker, P. (2000). Optimization Heuristics in Econometrics: Applications of Threshold Accepting. New York, Wiley.

PART II: CASE STUDIES AND RESULTS

The goal of the following case studies is to demonstrate the implementation, applicability and worth of the uncertainty analysis approach presented in Part I. There are three cases investigated, a space based radar space system, a space based broadband communications systems, and a space based ionospheric mapping mission. These three cases represent the three overarching segments of space systems, namely military, commercial and civil (science) missions, as shown in Figure 34. Further, the technology and conceptual architecture in each of the architectures differs significantly. These differences provide complementary implementation scenarios for the uncertainty analysis approach that provide the reader with a broader vision of how the approach could work in practice.

Each case is structured identically for ease of reading. The first section in each case describes the overall mission as well as the conceptual design model description. The next section focuses on quantifying the architectural uncertainty embedded in each architecture, while the third section describes the application of portfolio theory to the individual case. Finally each case is closed with insights and conclusions that each provided about the specific mission as well as the uncertainty analysis approach. The primary purpose of each case is not to describe the individual mission and modeling approach of each in depth. For this information, references have been provided. Instead, it is the focus of these chapters to demonstrate the applicability of the uncertainty analysis approach to the broad class of problems that each case represents.



Mission Name: TechSat 21 (Military)

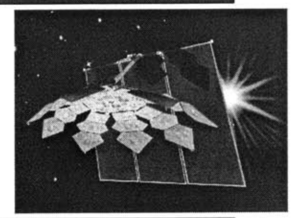
Value Measure: Probability of Detection/$

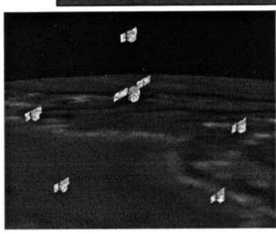
Uncertainty Measure: StdDev(Pd/$)

Mission Name: Broadband System (Commercial)

Value Measure: Billable Hour/$

Uncertainty Measure: StdDev(BH/$)





Mission Name: ATOS (Science)

Value Measure: Total Utility/$

Uncertainty Measure: StdDev(TU/$)

Figure 34: Three case studies summary

Chapter 7

TECHSAT 21: CUTTING EDGE DESIGN INTRODUCES UNCERTAINTY

7.1 Mission and Model Description

TechSat 21, short for Technology Satellite of the 21st Century, is a program aimed at pushing the boundaries on the current approach to satellite systems development. Its novelty lies in concepts at both the architectural, system, subsystem and component level. The most obvious feature of the TechSat 21 architecture is the departure from the traditional monolithic satellite designs of the Milstar and Defense Support Program satellites. Unlike those systems, TechSat 21 employs collaborate clusters of satellites in what is hoped to be a more flexible, extensible, better performing and less costly architecture. Using a cluster of formation flying satellites, a synthetic aperture can be created whose properties for a variety of missions ranging from space based radar to ground moving target indication. Of course because this is a non-traditional architecture there is significant uncertainty associated with many aspects of the concepts proposed. It therefore provides a good example of the uncertainty analysis approach applied to a highly complex, high technology, and envelope-pushing problem.

The TechSat 21 mission is envisioned to push the current thinking on how industry designs space systems as generally monolithic, inflexible and costly systems. Through the use of sets of clusters of satellites, it's expected that space systems could be developed for lower lifecycle cost, better performance, improved reliability and adaptability. These benefits would arise from a number of the features of the formation flying clusters, including larger numbers of smaller satellites and therefore opportunities for economies of scale and wider availability to inexpensive launch vehicles. The improved mission performance would come from the now unrestricted effective aperture and the multi-mission possibilities that such a constellation could provide. The satellite cluster design would have the potential to improve the overall system reliability in certain cases and would also provide for an adaptable system that could be upgraded through the installation of more satellites

To conduct a systems analysis of the potential architectures that could be employed to accomplish the TechSat 21 mission, boundaries were established as to what concepts would be evaluated. The different architectural characteristics that were considered are presented in Table 8. In the GINA terminology, these characteristics are called the design vector and a combination of the six design variables constitutes a separate architecture. For example, one architecture evaluated was a 500km satellite constellation, having 4 satellites, existing in one cluster, on 2 planes, with an antenna power of 100W and an antenna area of $0.5m^2$.

Table 8: Design vector for the TechSat21 Satellite System

Name	Description	Potential Values
Altitude	The operating altitude of the TechSat21 constellation	500-1500km
Number of Satellites	The number of satellites in each cluster/swarm	4-16
Number of Cluster	The number of cluster/swarms that comprise the constellation	2-100
Number of Planes	The number of orbital planes occupied by the constellation	2-10
Antenna Power	Antenna Transmission Power	100-1kW
Antenna Diameter	Antenna Aperture Diameter	0.5-3m

The goal of this case study is to demonstrate the applicability of a formal uncertainty analysis framework that includes both the quantification of uncertainties in individual architectures, but also a portfolio based approach to pursuing a set of the potential architectures to minimize decision maker's exposure to uncertainty. The case study is used as a way to introduce the reader to the approach presented in the previous chapters. In this case, the primary sources of uncertainty are due to technology and the designer's ability to model a non-traditional architecture.

7.1.1 GINA Model

The TechSat 21 GINA model developed in the MIT Space Systems Lab was essential to completing this case study.[61] The model developed over a number of years and involving many researchers has allowed systems analysis and architecture trade-offs to be made on a significantly large design tradespace. The broad architectural concept for TechSat 21 consists of a set of collaborative,

[61] Jilla, C. (2002). A Multiobjective, Multidisciplinary Design Optimization Methodology for the Conceptual Design of Distributed Satellite Systems. Aeronautics and Astronautics. Cambridge, MA, Massachusetts Institute of Technology. PhD.

formation flying spacecraft in low earth orbit that could perform multiple missions ranging from synthetic aperture radar to ground moving target indication to signal interception. The abstraction of a space system to a series of computer simulation models is something of an art. Defining interfaces, segmenting the problem and capturing outcome measures are all techniques that are not typically taught in aerospace curriculum, but are essential to generating results and crafting observations and conclusions that are of use to the decision maker. The segmentation of the TechSat 21 GINA model is presented in Figure 35. The initial modules of the simulation model are the input of the Design Vector, as previously described, and the Constants Vector. The Constants Vector represents those variables that for the enumeration of the tradespace are held constant. By doing so, architectures can be equitably compared. Examples of constants can range from orbital constants like the radius of the earth, to performance constants such as the probability of failure of an individual spacecraft, to operational constants like how many ground stations will be necessary.

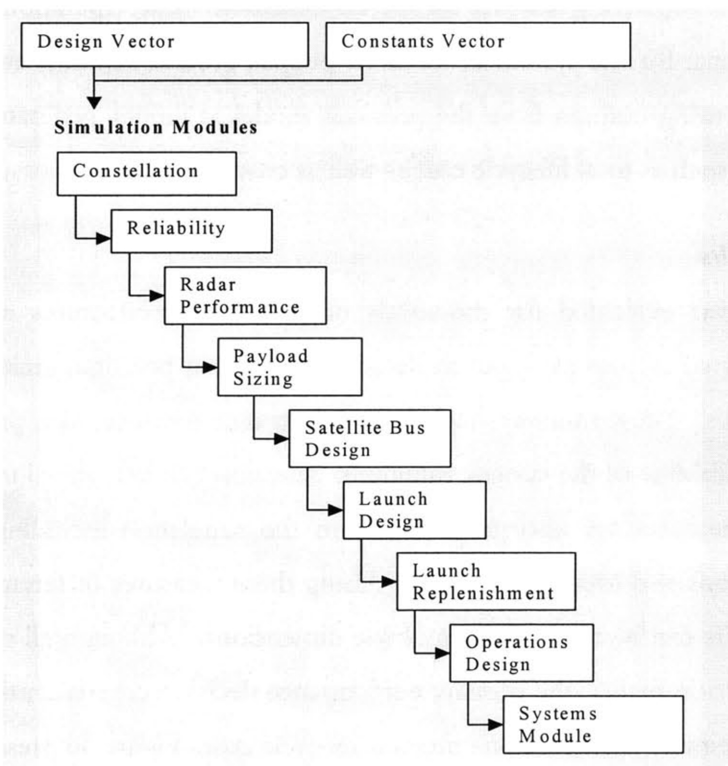


Figure 35: GINA Model Flow Chart

Once the Design Vector and the Constants Vector have been initialized, the simulation proceeds with the Constellation Module. This module produces the orbital characteristics for the space segment that make it possible to later assess the performance of the architecture. The Reliability Module is used to assess the overall architecture reliability and performance degradation based on the reliabilities of individual spacecraft. The Radar Module quantifies the various technical performance measures in a radar context. These include: probability of detection, minimum detectable velocity of a ground target, and area search rate. The Payload Sizing module uses the inputs of the Design and Constants Vector to model an appropriate payload antenna for a given architecture. Using the Payload Module output, the Satellite Bus Module designs an appropriate configuration and sizes all subsystems to satisfy the payload requirements in terms of power and mass, as well as other conditions of the Design and Constants Vector. Once the satellites and their payloads have been modeled, the launch sequence is determined by the Launch Module. The Launch Replenishment Module using the previous reliability assessment designs a repopulating scheme for the constellation. The Operations Module defines the operational requirements for the system in terms of people, ground stations, etc. The final module, the Systems Module, using outputs from the previous model as inputs, generates outcome measures for each architecture, such as total lifecycle cost as well as cost per function measures.[62,63]

7.1.2 Model Results

The GINA model was evaluated for thousands of potential architectures and various outcome measures were generated to provide input to decision makers on potential architectures to pursue in further design exercises. These measures included performance measures like: probability of detecting a given target, the availability of the system, minimum detection velocity, signal to noise ratio, and area search rate. Cost measures are also generated from the simulation including launch, design and development, operations and total lifecycle cost. Using these measures different architectures can be analyzed and trade-offs can be made along multiple dimensions. Although all outcome measures are of interest to the decision maker, the primary performance decision criteria chosen was probability of detection, while the primary cost decision criteria is lifecycle cost. Figure 36 presents the model results

---

62 Shaw, G. B. (1999). The generalized information network analysis methodology for distributed satellite systems. Aeronautics/Astronautics. Cambridge, MA, Massachusetts Institute of Technology. ScD.

63 Jilla, C. (2002). A Multiobjective, Multidisciplinary Design Optimization Methodology for the Conceptual Design of Distributed Satellite Systems. Aeronautics and Astronautics. Cambridge, MA, Massachusetts Institute of Technology. PhD.

for 3000 architectures in the TechSat 21 tradespace. Each point in the chart represents a single architecture whose composition is defined by a unique design vector, i.e. altitude=800km, number of satellites per cluster=4, number of clusters=42, number of planes=6, antenna power=800, and antenna diameter=2.5m^2. The target region for the best architecture would be of minimum cost, with maximum probability of detection.

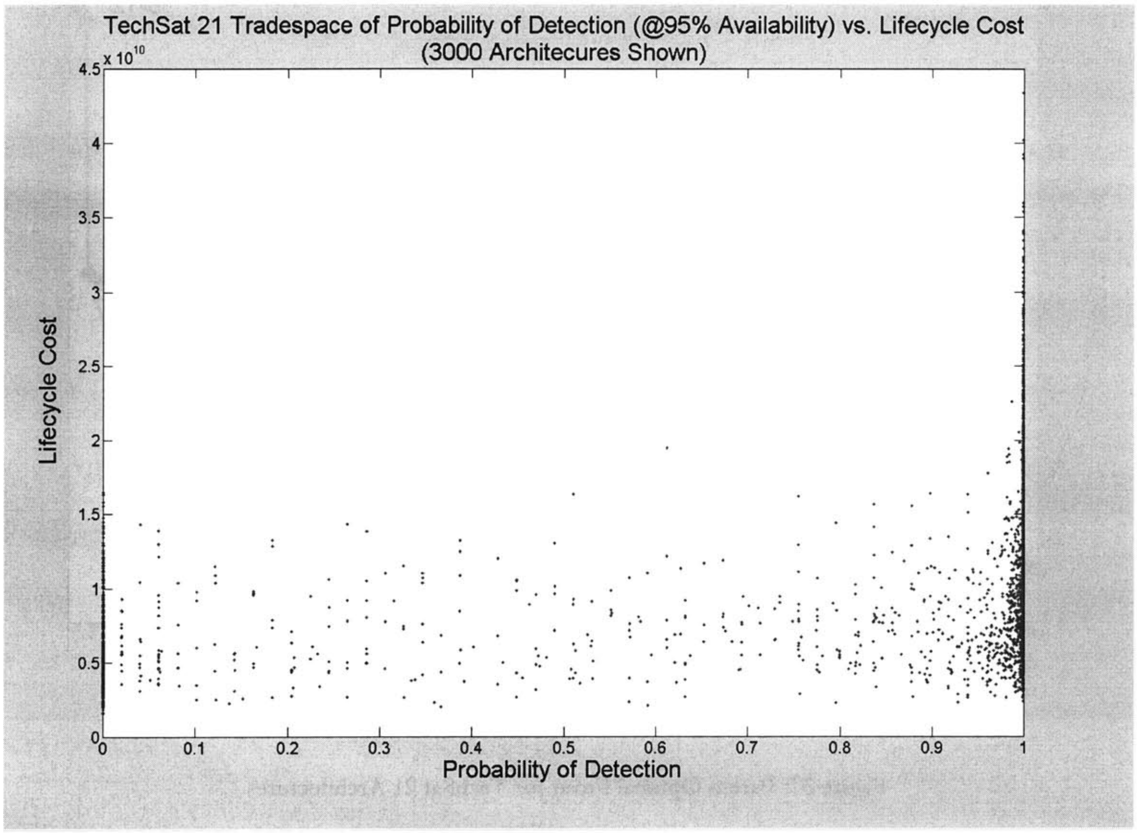


Figure 36: TechSat 21 Tradespace

Knowing the primary decision criteria as Probability of Detection and Lifecycle Cost, the Pareto optimal front can be found for the tradespace by identifying non-dominated architectures. A non-dominated architecture is one whose performance cannot be surpassed without higher costs. Figure 37 presents the Pareto optimal front, as calculated by Jilla using heuristic search methods.[64] The

[64] Ibid.

Pareto optimal design vector values are shown in Table 9. All the architectures in the table had an altitude of 800km, 6 planes and 42 clusters of spacecraft each having 4 satellites.

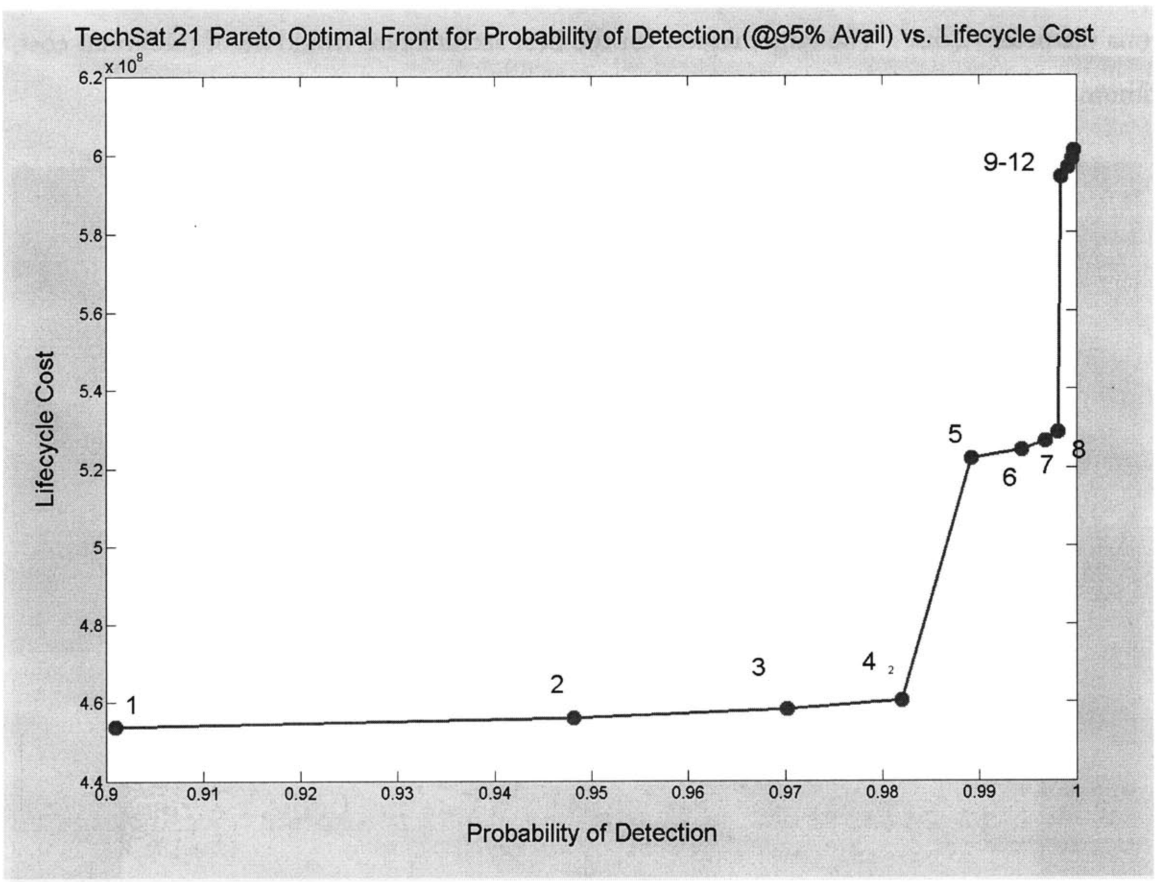


Figure 37: Pareto Optimal Front for TechSat 21 Architectures

Table 9: TechSat 21 Pareto Optimal Architectures and Outcome Measures

Architecture	1	2	3	4	5	6	7	8	9-12
Ant Diam	2.5	2.5	2.5	2.5	3.0	3.0	3.0	3.0	3.5
Ant Pow	700	800	900	1000	700	800	900	1000	700-1000
P(d)	90.0%	95.0%	97.0%	98.2%	98.9%	99.4%	99.7%	99.8%	99.8%-99.9%
Lifecycle Cost ($B)	4.57	4.59	4.61	4.64	5.18	5.20	5.22	5.24	6.00-6.07

The results presented above were made using deterministic assumptions and calculations, but what kind of uncertainty is associated with each architecture selection and what is an appropriate means by which uncertainty can be managed and quantitative trade-offs can be made? By applying the uncertainty analysis approach from Chapter 5 and Chapter 6, it is shown that there is a considerable amount of uncertainty associated with each architecture, that it can be quantified and that portfolio theory provides a central framework in which the uncertainty of the tradespace can be managed.

7.2 Uncertainty Quantification

The first phase in the uncertainty analysis approach is the quantification of embedded uncertainty in each of the architectures under consideration. The necessary initial step will be to focus on the TechSat 21 tradespace, models and environment and identify the relevant individual sources of uncertainty. Once the sources are identified, each source has to be assessed for inclusion in the analysis and if included, quantified as previously in Chapter 5. After the identification, assessment and quantification of individual sources of uncertainty, the same GINA simulation models previously developed are used to quantify embedded architectural uncertainty through uncertainty propagation. This propagation provides one means of aggregating the individual sources of uncertainty and a method to identify contributions of individual sources to the final embedded architectural uncertainty.

In this section, the effect of uncertainty on individual architectures is presented. In the next section, through the use of portfolio theory and optimization, the implications of uncertainty to the whole tradespace are discussed as well as the effective management of these uncertainties for various types of decision makers.

7.2.1 Sources of uncertainty

TechSat 21 represents a revolution in the development of space systems. The program is incorporating a number of unproven technologies, architectural and operational concepts. It is truly a case of pushing the envelope. That being said, it is not surprising that the TechSat 21 has a good deal of uncertainty associated with it. Table 10 presents the attributes and value ranges that were used as potential sources of uncertainty. These uncertainties were chosen from the constants vector and represent both technical uncertainty, i.e. achievable false alarm rate and model uncertainty, i.e. tram cost density for the TechSat 21 mission.

Table 10: TechSat 21 Modeled Sources of Uncertainty[65]

Attribute	Best Value	Expected Value	Worst Value
Mission Lifetime	9 years	10 years	11 years
Radar Freq.	10.2E9 Hz	10E9 Hz	9.8E9 Hz
Ant Trans. Duty Cyc.	0.045	0.05	0.055
Radar Cross Section	10.2 m^2	10 m^2	9.8 m^2
Required Range Res.	240m	250m	260m
Tram Mass Dens.	8 kg/m^2	6 kg/m^2	4 kg/m^2
Tram Elec. Dens.	7 kg/m^2	5 kg/m^2	3 kg/m^2
Tram Cost Dens	1.25E6 $\$/m^2$	1E6 $\$/m^2$	0.75E6 $\$/m^2$
Tram Elec. Cost Dens.	1.25E6 $\$/m^2$	1E6 $\$/m^2$	0.75E6 $\$/m^2$
Stowed Depth	0.6 m	0.5 m	0.4 m
# PrimexPPT	6	4	3
Mass Primex PPT	2 kg	1.5 kg	1 kg
Pow. Primex PPT	20 W	1 W	1 W
#Micro PPT	12	10	8
Mass Micro PPT	0.5 kg	0.2 kg	0.2 kg
Pow Micro PPT	10 W	0.5 W	0.4 W
Star Sens. Mass	2.5 kg	0.7 kg	0.5 kg
Star Sens. Pow	20 W	4 W	4 W
Magnometer Mass	1.2 kg	0.13 kg	0.13 kg
Mangonmeter Pow	1 W	0.5 W	0.5 W
# Torque Rods	4	3	2
Mass Torque Rods	0.6 kg	0.45 kg	0.4 kg
Power Torque Rods	2 W	1.3 W	1 W
MB per Chip	48 MB	64 MB	96 MB
Mass per Chip	1 kg	0.5 kg	0.5 kg
Bat. Power Density	45 W hr/kg	51 W hr/kg	60 W hr/kg
Operators per Satellite	1.2	1.1	1
MTTF	450 months	498 months	550 months
MTTR	2 months	3 months	4 months

65 Best and worst cases were obtained by using univariate analysis to determine the direction of goodness for each individual variable.

7.2.2 Embedded architectural uncertainty

After the individual sources of uncertainty have been identified and quantified, the next step is to develop distributions of outcomes for each of the architectures. Through uncertainty propagation in the model and simulations of the architectures under varying levels of uncertainty, resultant distributions can be obtained for each of the architectures in the tradespace. These resultant distributions are necessary to proceed to the next step in the uncertainty analysis, portfolio selection.

In this case the extreme method of uncertainty propagation was used. The first step in the technique is to list the extreme possibilities as was done in Table 10. A single state-best, worst or expected- is selected and incorporate the results into the constants vector. This vector is then used for each of the architectural simulations programmed and results are captured in an outcome vector for each architectures that includes characteristics such as performance measures such as probabilities of detection, coverage and cost measures such as development, operating and total life cycle cost. It also includes system architecture characteristics, such as mass, power, launch vehicles used and other high-level design characteristics.

Next, a new state is chosen-best, worst, expected and the simulation is repeated for each of the architectures that are being investigated and the outcome vector is saved. This process of selecting a constants vector is repeated until outcome measures have been generated for all states.

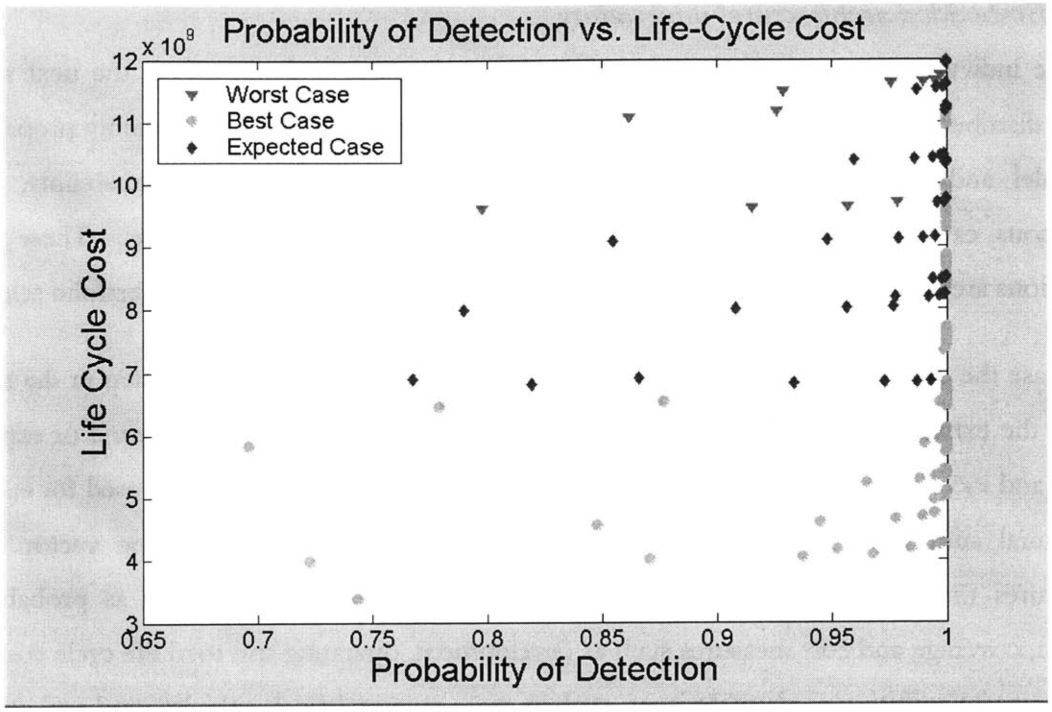


Figure 38: TechSat 21 Architectural Tradespace Under Uncertainty

This uncertainty quantification can be done for each of the architectures in the tradespace, or as suggested here, an efficient tradespace preprocessor can be used to develop a substantially smaller set of architectures from which to conduct uncertainty analysis. This efficient tradespace preprocessor allows for improved distributions in the embedded uncertainty of each architecture. It also allows for a more tractable overall conceptual design. Figure 38 presented the outcomes of the uncertainty analysis using the extreme approach and Figure 39 presents the subset of those results constituting only the Pareto optimal front architectures. The spread of the worst case from the expected case is noticeably larger than that of the spread of the best case from the expected case. This is true in the dimensions of cost and probability of detection. This shows that the uncertainty distributions for the tradespace are left skewed meaning there is more downside than upside in the architectures being considering.

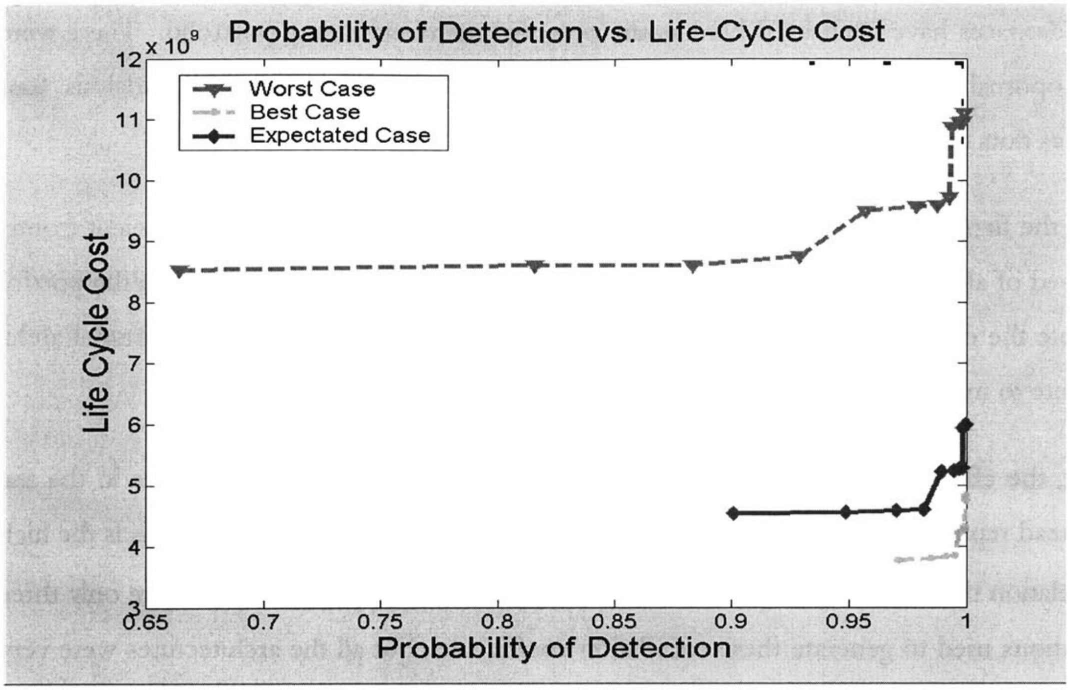


Figure 39: Pareto Front for Three Cases of Uncertainty

7.3 Portfolio Analysis

The previous section described the quantification of embedded architectural uncertainty. Knowing the architectural uncertainty can help decision makers in a number of circumstances, such as developing a mitigation plan once an architecture has been selected. Embedded uncertainty, along with correlation measures of how architectures behave under conditions of uncertainty, can provide the decision maker with even more potential. Using portfolio theory, the decision maker can create accurate trade-offs and begin to manage not the uncertainty in an *individual architecture*, but instead manage the uncertainty in a *tradespace of potential architectures*. This section describes the application of the portfolio optimization technique described in detail in Chapter 6. The results of the TechSat 21 uncertainty quantification are used to generate an efficient frontier of portfolios that represent optimal strategies for a decision maker to pursue in order to maximize his expected value of the project while considering his/her aversion toward risk.

Figure 40 shows the general characteristics of the TechSat 21 value vs. uncertainty tradespace. The Pareto optimal architectures that were determined in the traditional concept exploration of utility vs.

cost tradespaces have been used here as the potential members in any portfolio. There were twelve Pareto optimal architectures in all that were evaluated using the uncertainty analysis framework, plotted as dots in Figure 40.

One of the first insights seen from the value/uncertainty tradespace is that the efficient frontier is not composed of all the Pareto optimal architectures. Instead, only a few contribute to the portfolios that constitute the efficient frontier. In all, only three of the original twelve Pareto optimal architectures contribute to membership along the efficient frontier.

Further, the efficient frontier does not extend beyond any individual architectures in the tradespace and instead represents a linear combination of only three assets. The reason for this is the high degree of correlation the architectures being considered share, i.e. all $\rho_i \geq 0.998$. There were only three sets of observations used to generate these correlation coefficients, but all the architectures were very similar differing in only antenna diameter and power.

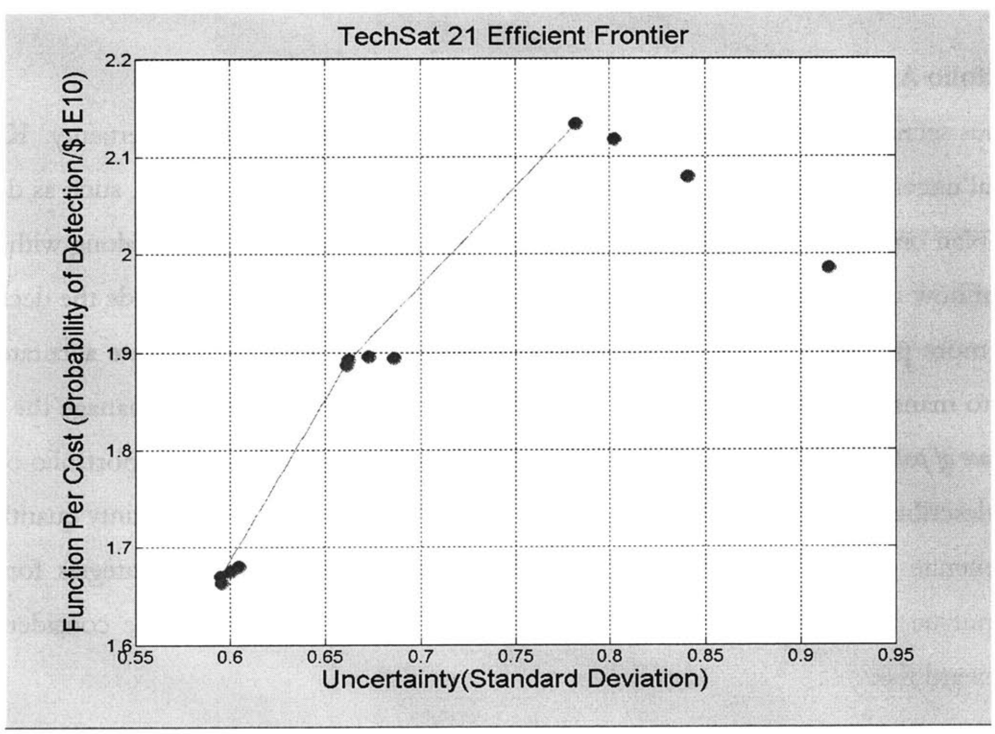


Figure 40: TechSat 21 Portfolio Analysis

7.3.1 Quantifying Decision Maker Risk Aversion

Once the efficient frontier has been calculated, the next logical next step is to determine where the optimal strategy is for a given decision maker. As discussed in Chapter 6, capturing decision maker risk aversion can be relatively straightforward through the use of indifference curves and iso-utility lines. By interacting directly with the customer with this graphical technique, preferences of the decision maker can be captured and incorporated into the portfolio optimization. As previously seen, the level of aversion of the decision maker can greatly affect the optimal strategy and this is also true in this case study. There are a total of 3 architectures that constitute membership in a portfolio somewhere on the efficient frontier and there are many combinations of those possible.

The highly risk averse individual would find himself looking at portfolio in the lower left corner of the efficient frontier, while the more risk prone decision makers would have preferences leading to strategies in the upper right corner. Rather than chose a single decision makers aversion, two decision makers who represent these extremes as well as a more moderate decision maker are presented as well as their optimal portfolio strategy that would come from the uncertainty analysis. By using three representative decision makers, the overall sensitivities of the portfolio can be observed and outcomes compared to demonstrate the adaptability of the uncertainty analysis approach to a large range of decision makers who become involved in the development of space systems.

Assume that Figure 41 represents the three-decision maker's indifference curves for the value/uncertainty trade. The lines represent k values of 0.5, 2 and 3. Using this information an optimal investment strategy can be developed based on the portfolio optimization. As one might expect, the decision maker with a low level of risk aversion will accept far more uncertainty for a given increase in value than the decision makers with moderate and high levels of risk aversion. Notice that a completely risk averse individual would have a indifference curve that is represented by a vertical line, while a horizontal line would represent a risk neutral decision maker.

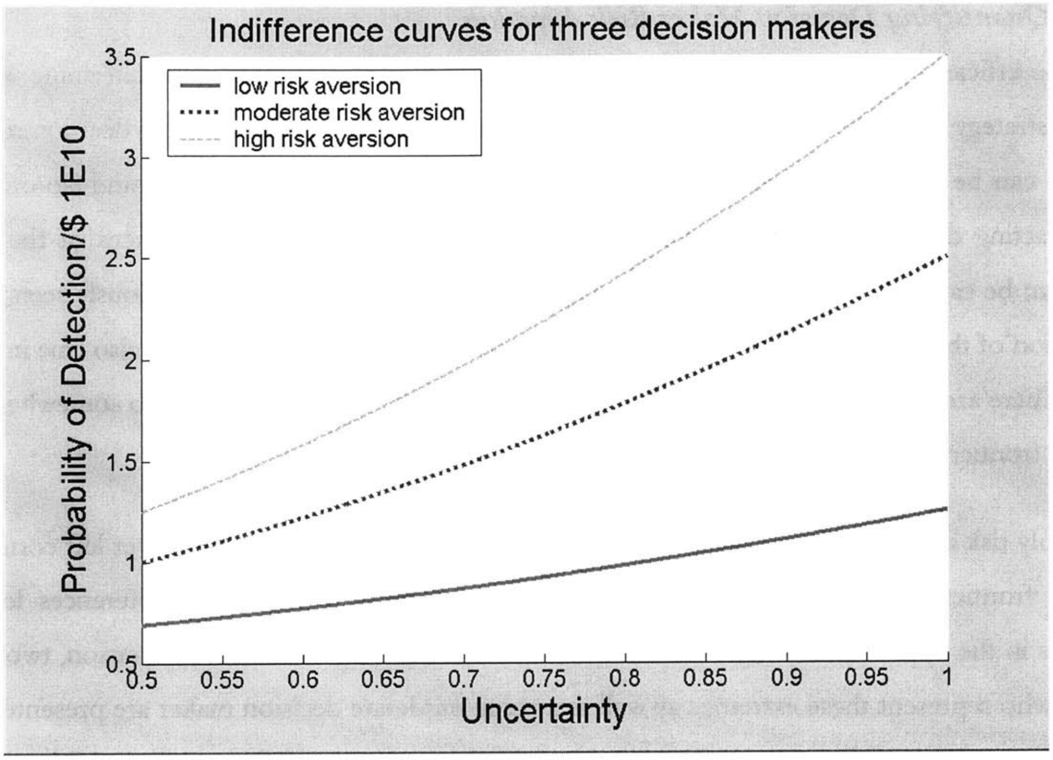


Figure 41: Indifference curves for three decision makers

7.3.1.1 *Decision maker with high risk aversion optimal portfolio strategy*

The first decision maker looked at has a risk aversion coefficient of 3. The iso-utility lines for this decision maker have been overlaid on the efficient frontier in Figure 42. The optimum portfolio for this decision maker resides in the lower left corner of the efficient frontier and consists of only a single architecture. Notice that the optimal strategy portfolio resides at the tangent point of the efficient frontier and the maximum utility iso-utility line. This type of figure will be used repeatedly in this chapter and the next two to illustrate optimal strategies for specific decision makers.

The composition of this portfolio is shown in Table 11 and consists of a single architecture that is a constellation consisting of 42 clusters each having 4 satellites that have an antenna power of 1kw and a diameter of 2.5m^2. The entire constellation resides at 800km and occupies six orbital planes. Although portfolios can suggest sets of assets to pursue, it can also suggest single assets, when the individual asset lies on the efficient frontier and is tangent to the maximum iso-utility line, as in this case.

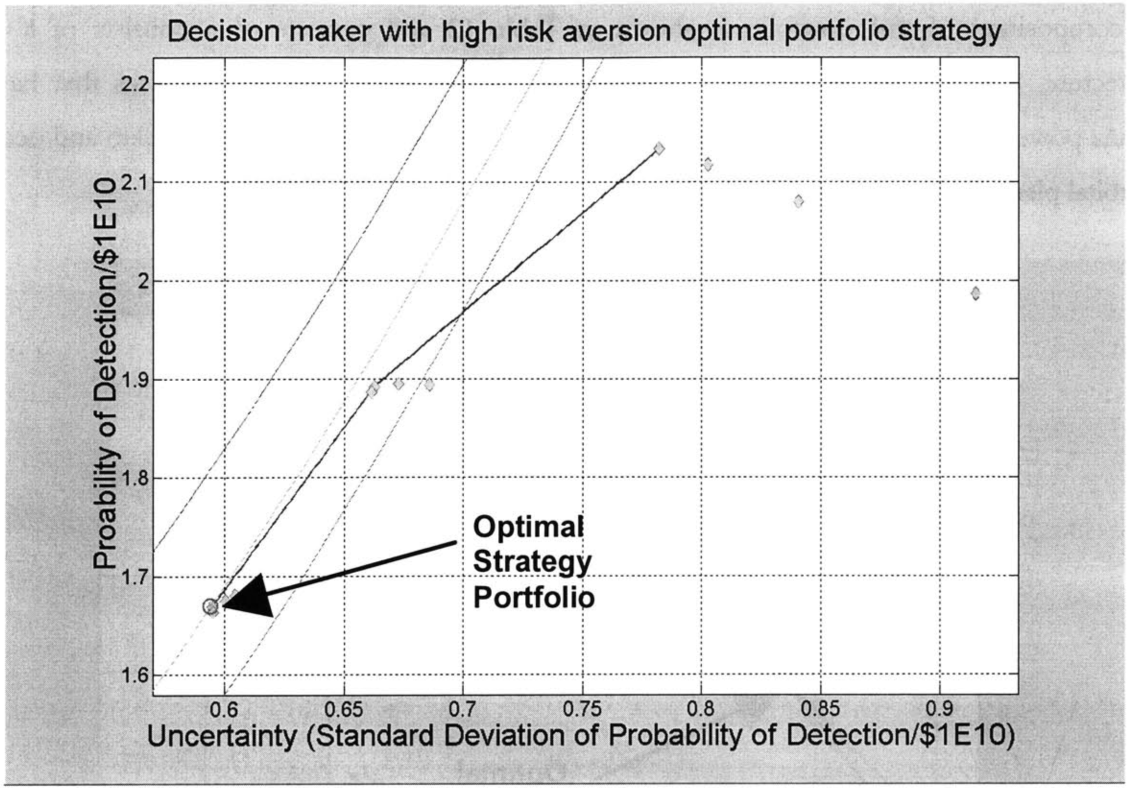


Figure 42: Optimal investment strategy for high risk aversion decision maker

Table 11: Composition of TechSat 21 high risk aversion decision maker strategy

	Percentage of Portfolio	Architecture Design Vector {alt,sats/clustr,#clustr,#planes,ant pow,ant_diam}	Total Utility/$	Uncertainty
	100%	{800, 4, 42, 6, 1000, 2.5}	1.67	0.59
	100%	Complete Portfolio Value and Uncertainty	1.67	0.59

7.3.1.2 Decision maker with moderate risk aversion optimal portfolio strategy

A second decision maker that was considered was one that had a moderate risk aversion, k=2. This decision maker's optimum portfolio strategy as shown in Figure 43: Optimal investment strategy for moderate risk aversion decision maker resides in the middle of the efficient frontier. As was the case in the high risk aversion decision makers, this portfolio consists of only a single asset.

The composition of this portfolio is shown in Table 12 and consists of a consists of a single architecture, that is a constellation consisting of 42 clusters each having 4 satellites that have an antenna power of 1kw and a diameter of $3m^2$. The entire constellation resides at 900km and occupies six orbital planes.

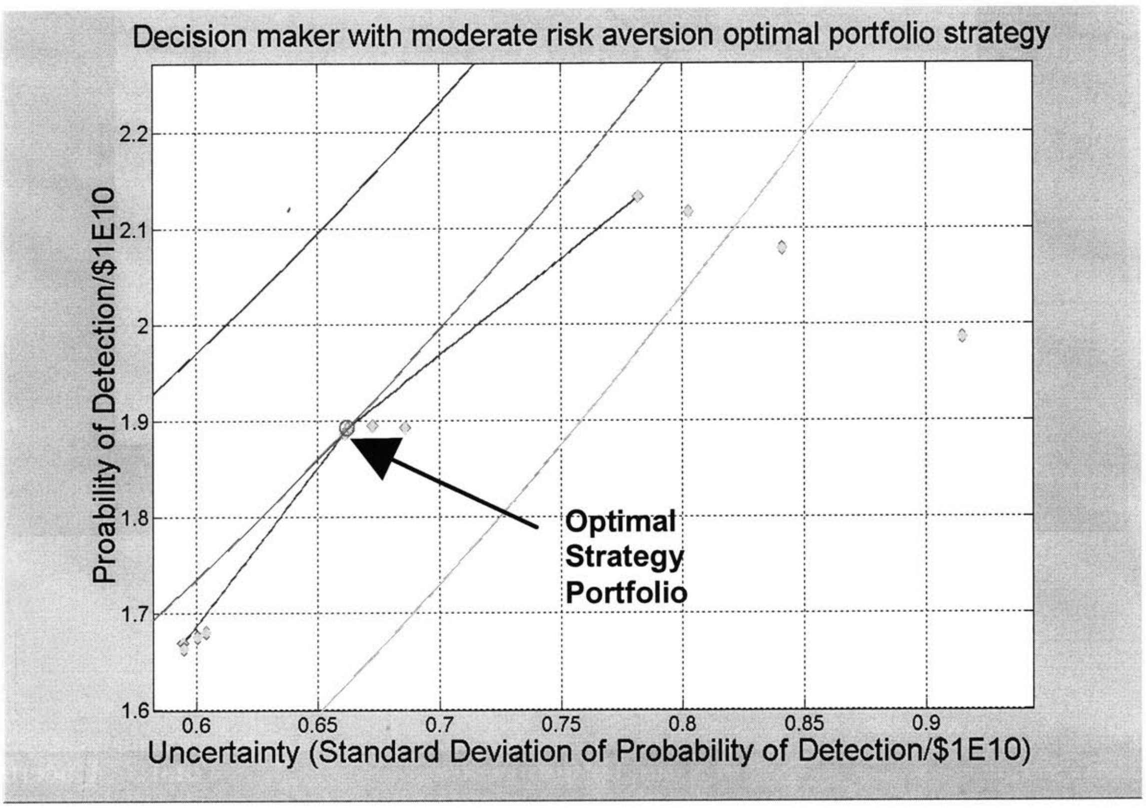


Figure 43: Optimal investment strategy for moderate risk aversion decision maker

Table 12: Composition of TechSat 21 moderate risk aversion decision maker strategy

Percentage of Portfolio	Architecture Design Vector {alt,sats/clustr,#clustr,#planes,ant pow,ant_diam}	Total Utility/$	Uncertainty
100%	{800,4,42,6,900,3}	1.89	0.66
100%	Complete Portfolio Value and Uncertainty	1.89	0.66

7.3.1.3 *Decision maker with low risk aversion optimal portfolio strategy*

The relatively low risk aversion decision maker has an optimal portfolio strategy in the upper right corner of the efficient frontier again consisting of only a single architecture.

The composition of the low risk aversion decision maker is shown in Table 13. The portfolio contains a single asset, specifically a satellite constellation of 42 clusters each having 4 satellites at 800km covering 6 planes and each satellite having a transmission power of 900W and an antenna diameter of 3.5m^2.

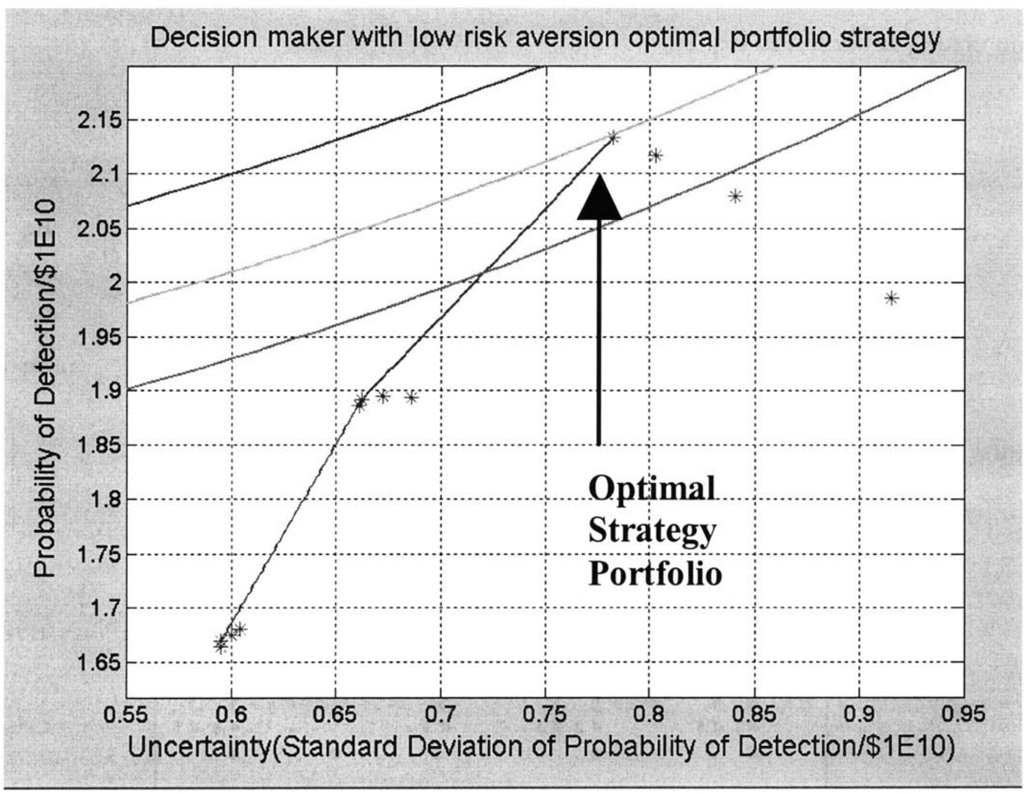


Figure 44: Optimal investment strategy portfolio for low risk aversion decision maker

Table 13: Composition of low risk averse optimal portfolio strategy

	Percentage of Portfolio	Architecture Design Vector {alt,sats/clustr,#clustr,#planes,ant pow,ant_diam}	Total Utility/$	Uncertainty
	100%	{800,4,42,6,900,3.5}	2.13	0.78
	100%	Complete Portfolio Value and Uncertainty	2.13	0.78

7.3.2 *Implications of incorporating the extensions to portfolio theory*

7.3.2.1 Differentiating risk from uncertainty

Presented above was the implementation of portfolio theory using uncertainty as a surrogate for risk. Here, the impact of separating the upside and downside of uncertainty is explored within a reapplication of portfolio optimization to discover any new insights. The first step is to differentiate the risk from the uncertainty in the distribution. The risk can be found by focusing on the downside semi-variance, as previously discussed in Chapter 6. To do so, first adjust the variance of individual observations around the expectation as shown in Eq. 25. Then, calculate the variance of these new observation errors, as shown in Eq. 26.

$$(r_i - E(r))^- = \begin{bmatrix} (r_i \text{ - E(r)) if } r_i \leq 0 \\ 0 \text{ if } r_i > 0 \end{bmatrix}$$

Eq. 25

$$S_{Downside} = 2 * E\left[\sum (r - E(r))^2\right]$$

Eq. 26

Thus creating a downside covariance matrix as shown in Eq. 27.

$$Q_{Downside} = \begin{bmatrix} S_{d1}^2 & \rho_{2,1} S_{d2} S_{d1} & \rho_{3,1} S_{d3} S_{d1} & \bullet & \rho_{n,1} S_{dn} S_{d1} \\ \rho_{1,2} S_{d1} S_{d2} & S_{d2}^2 & \rho_{3,1} S_{d3} S_{d1} & \bullet & \rho_{n,2} S_{dn} S_{d2} \\ \rho_{1,3} S_{d1} S_{d3} & \rho_{2,3} S_{d2} S_{d3} & S_{d3}^2 & \bullet & \rho_{n,3} S_{dn} S_{d3} \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \rho_{1,n} S_{d1} S_{dn} & \rho_{2,n} S_{d2} S_{dn} & \rho_{3,n} S_{d3} S_{dn} & \bullet & S_{dn}^2 \end{bmatrix}$$

Eq. 27

Finally the portfolio algorithm is implemented in the similar manner to traditional portfolio theory, only substituting $Q_{donwside}$ for Q, as shown in Eq. 28.

$$\max: E(r)w - \frac{k}{2} w' Q_{Downside} w$$

$$\text{s.t.}: \sum_{i=1}^{n} w_i = 1$$

$$\text{s.t.}: \mathrm{w} \geq 0$$

Eq. 28

Using this algorithm, an efficient frontier can be calculated in the same manner performed earlier in the case. The tradespace of uncertainty and probability of detection is shown in Figure 45. The efficient frontier for both the full uncertainty portfolio analysis, as well as the semi-variance analysis is shown in the figure. The most interesting insight to take away from this chart is that there is more risk in the tradespace than would be perceived if uncertainty were used as a surrogate for risk. Another thing to observe is that the relative position of the architectures with respect to one another has not changed and instead, the result from the semi-variance analysis is a simple shift to the right.

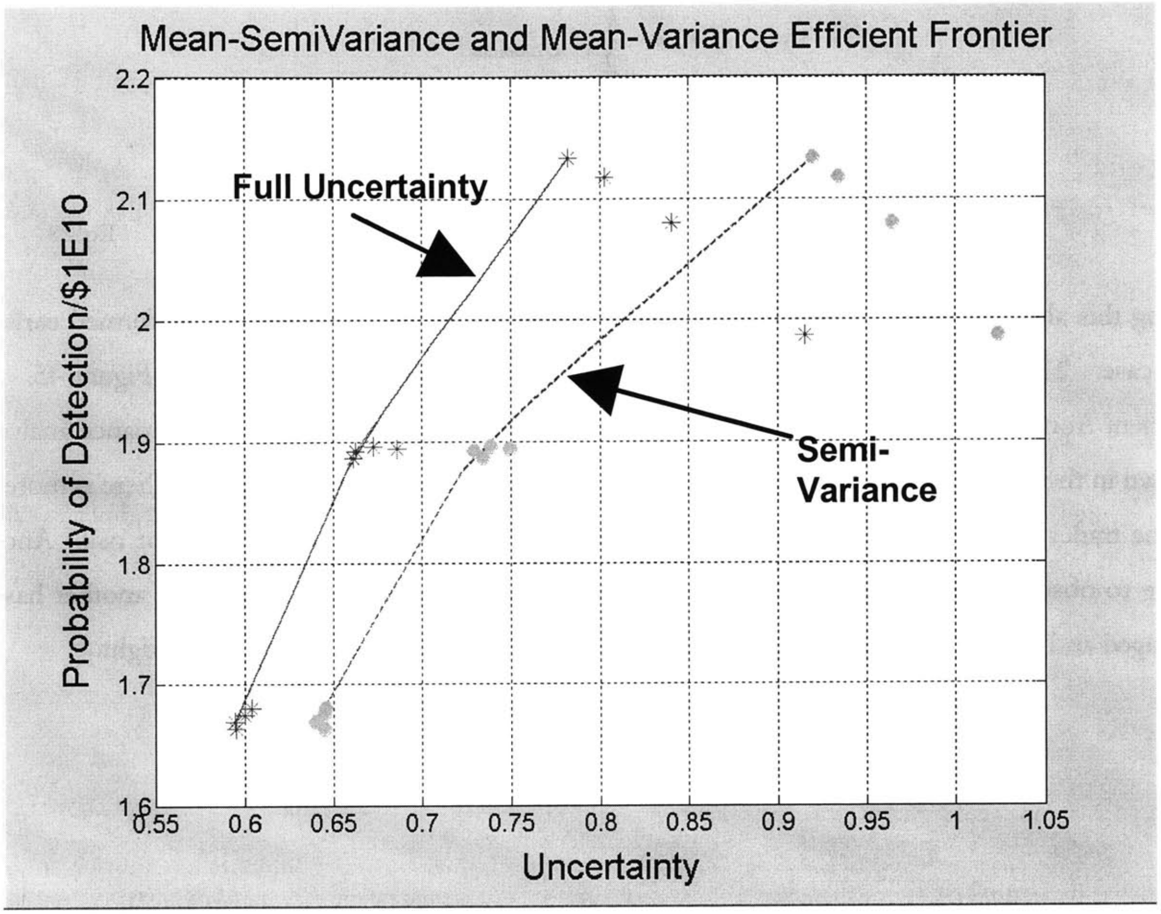


Figure 45: TechSat 21 Portfolio Analysis with full uncertainty and semi-variance

Now that there is a different efficient frontier, it is conceivable that decision makers should choose different optimal portfolio strategies. Using the same decision makers previously used, the low, moderate and high risk aversion, the effects that this extension provides to classical portfolio analysis are described.

The first decision maker was the high risk aversion decision maker. Under the efficient frontier using semi-variance, his optimal portfolio strategy has remained the same as previously found, as shown in Figure 46 and Table 14. This is reasonable because there are no less uncertain architectures to pursue even though there is a higher degree of risk in the tradespace.

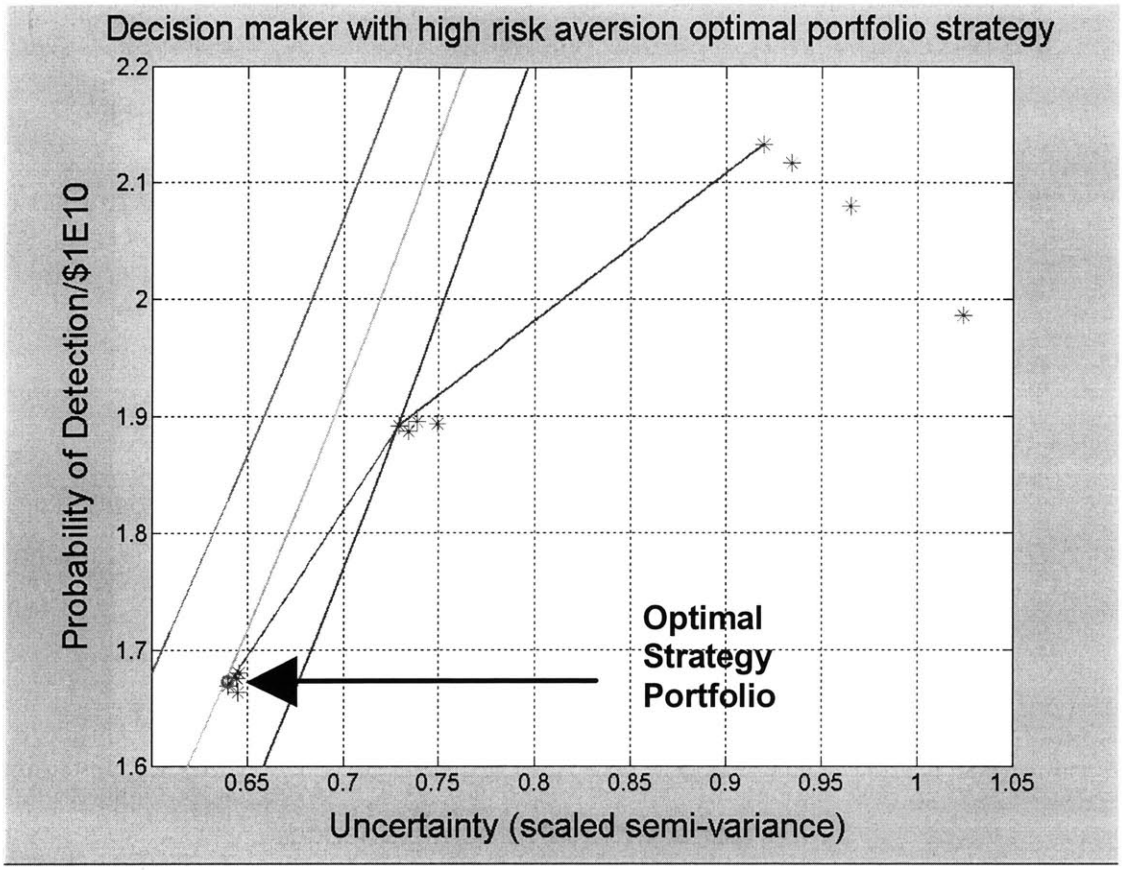


Figure 46: Optimal investment strategy for high risk aversion decision maker using semi-variance

Table 14: Composition of high risk averse optimal portfolio strategy using semi-variance

	Percentage of Portfolio	Architecture Design Vector {alt,sats/clustr,#clustr,#planes,ant pow,ant_diam}	Total Utility/$	Uncertainty
	100%	{800, 4, 42, 6, 1000, 2.5}	1.67	0.64
	100%	Complete Portfolio Value and Uncertainty	1.67	0.64

The moderate decision maker does have a shift in his portfolio. The optimal portfolio and composition are shown in Figure 47 and Table 15. He has shifted to the same single asset portfolio strategy as the high risk aversion decision maker. It is interesting to notice that this decision maker's iso-utility line is nearly parallel to the part of the efficient frontier between his previous portfolio single asset and his new portfolio single asset.

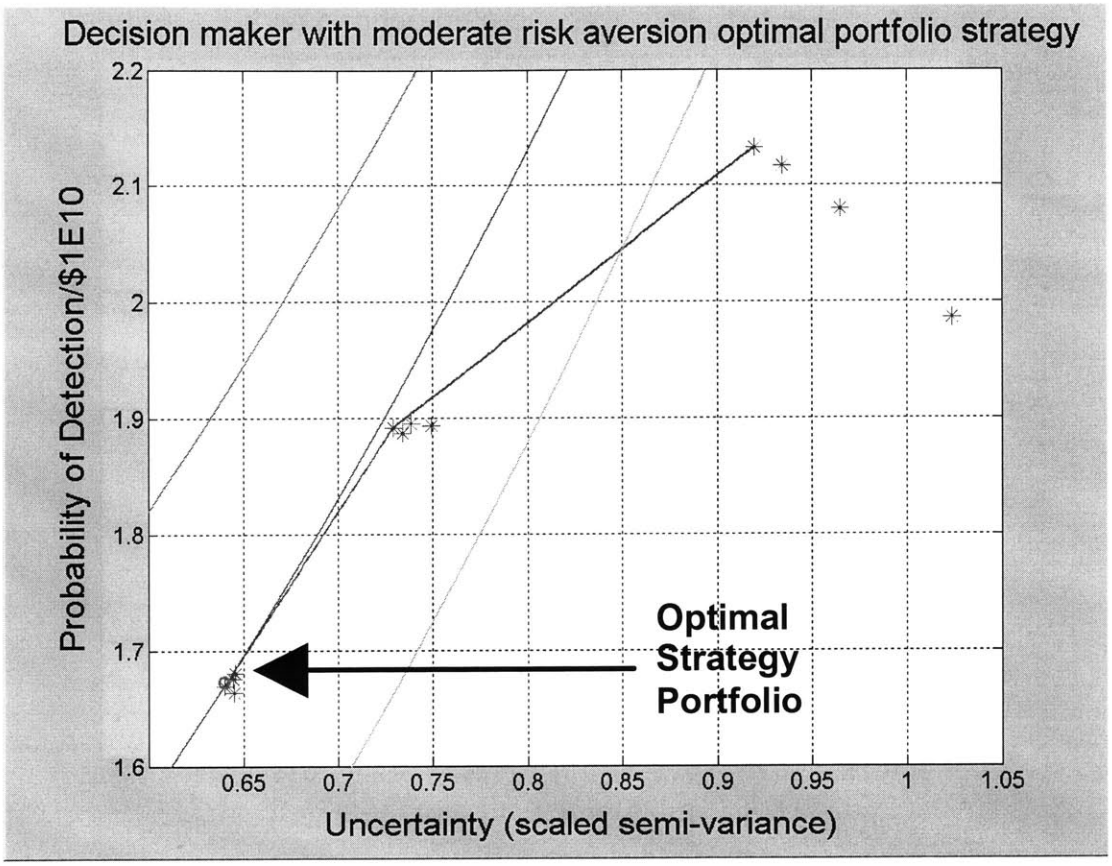


Figure 47: Optimal investment strategy for moderate risk aversion decision maker using semi-variance

Table 15: Composition of moderate risk averse optimal portfolio strategy using semi-variance

	Percentage of Portfolio	Architecture Design Vector {alt,sats/clustr,#clustr,#planes,ant pow,ant_diam}	Total Utility/$	Uncertainty
	100%	{800, 4, 42, 6, 1000, 2.5}	1.67	0.64
	100%	Complete Portfolio Value and Uncertainty	1.67	0.64

The low decision maker's optimal portfolio strategy has remained in the upper right corner of the efficient frontier, as shown in Figure 48 and Table 16. The increased uncertainty that he is now exposed to is still not enough to adjust the low risk aversion decision maker.

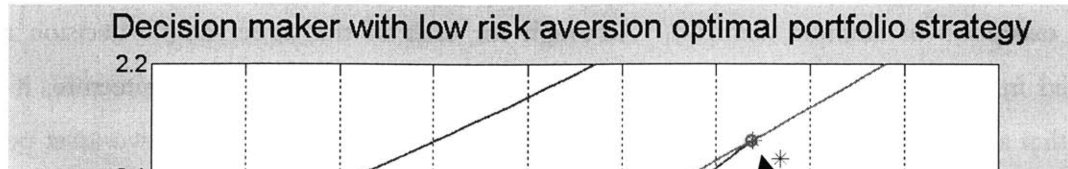


Figure 48: Optimal investment strategy for low risk aversion decision maker using semi-variance

Table 16: Composition of low risk averse optimal portfolio strategy using semi-variance

	Percentage of Portfolio	Architecture Design Vector {alt,sats/clustr,#clustr,#planes,ant pow,ant_diam}	Total Utility/$	Uncertainty
	100%	{800,4,42,6,900,3.5}	2.13	0.92
	100%	Complete Portfolio Value and Uncertainty	2.13	0.92

7.3.2.2 Cost of diversification

Because the efficient frontier in the case of TechSat 21 is comprised of a relatively few number of architectures, three, and the maximum number of architectures in any portfolio along the efficient frontier is 2, there is a relatively small cost to diversify and it would likely not exceed any decision makers available funds for development, as all the architectures have much the same characteristics with the exception of antenna diameter. Although for each of the three sample decision makers highlighted in this case, the optimal portfolio strategy consisted of a single architecture, it is still possible that a decision maker's strategy contain more than one architecture. The two-asset portfolio would represent very minimal cost though, with the architectures differing in antenna diameter by only 0.5 m^2.

7.4 Conclusions

This case provided an illustration of the uncertainty analysis approach applied to a very advanced military space system. The level of uncertainty in the tradespace was considerable and yet, the optimal portfolio strategies for three decision makers were comprised of single architectures. Of the architectures evaluated, there was simply not enough independence of architectures with respect to uncertainty for diversification possibilities to come about. In the other cases presented, diversification does show up as an optimal strategy; however, this case points out that not all tradespaces contain complementary architectures, that when combined yield more than any single asset, thus making the teaching point that optimal portfolio strategies sometimes consist of single architectures.

The inclusion of uncertainty analysis did illustrate the large amount of uncertainty associated with each architecture in the tradespace, thus allowing the decision maker to base decisions, not on deterministic predictions, but ones that are cautioned by some level of uncertainty. The uncertainty analysis further illustrated the ability to compare architectures in the tradespace and understand the relative sensitivities and trace those sensitivities back to sources of uncertainty. This traceability allows designers to concentrate on either modeling with more resolution or building in enough margins in their designs to accommodate the resultant possibilities. The impact that separating the upside and downside consequences of uncertainty can have on a decision maker's optimal portfolio strategy was also presented.

Chapter 8

COMMERCIAL BROADBAND SATELLITE SYSTEM: MARKET UNCERTAINTIES MAKE OR BREAK THE BUSINESS MODEL

8.1 Mission and Model Description

The struggle of delivering broadband infrastructure has been the focus of a number of recent commercial endeavors, ranging in implementation concepts from wired options like cable and DSL to wireless delivery options either through ground, air or space based sources. The most successful implementations thus far have been through ground-based systems; however, there are also companies seriously exploring the capabilities a space-based platform provides. The primary benefits of a space broadband system over that of any ground based system is that space systems have less reliance on any preexisting ground infrastructure and can serve changing and/or rapidly growing markets more effectively through repositioning satellites and adding more capacity to the systems through increasing the complement of space assets or satellite upgrades. Locations where satellite based services have advantages over land-based systems include economically developing nations with little pre-existing infrastructure, sea based platforms and air based platforms, and remote locations that have little access to land based systems. Space based broadband systems also have the potential to compete even in markets where infrastructure is widespread and competitors already serve customers. This phenomenon can be seen in the satellite TV industry where satellite based TV broadcast customers represent a significant share of the overall market. Through competitive pricing strategies and product differentiation, DirecTV and others have proven that space based systems are viable competitors with other platforms.

This case study explores the systems analysis of such a space based broadband architecture. This commercial venture allows the demonstration of the uncertainty analysis framework in a context that includes aspects of market uncertainty. Numerous examples of the effects of market uncertainty can be seen on the space industry, ranging from uncertainties in launch vehicle capacity to meet the evolving needs of low earth satellite delivery to market uncertainties that defined bankruptcies in the case of Iridium and GlobalStar space systems. Where the major decision criteria for a complex system is market driven, market uncertainties should always be considered

The goal of the systems analysis is to explore the tradespace of potential architectures that satisfy a recognized need for a broadband communications infrastructure. The major feature of the architectural concept consists of a satellite network complemented by ground stations. While a space system has been chosen to service this market, the details of the architecture have not been defined and instead have been left open for defining the tradespace. Six tradable parameters define the boundaries of the tradespace. These are altitude, inclination, satellites per plane, number of orbital planes, payload power, and the area of the phased array antenna. These characteristics and their possible values are given in Table 17.

Table 17: Design vector for the Broadband Communication Satellite System

Name	Description	Potential Values
Altitude	Altitude for a defined circular orbit	LEO(1500km), MEO(20184km), GEO(35786km)
Inclination	The inclination of the circular orbits.	0-90°
Satellites per Plane	The number of satellites in each of the occupied planes	1-8
Number of Planes	The number of orbital planes that the satellite constellation occupies	1-10
Payload Power	Downlink power from an individual satellite	1kW-10kW
Phased Array Area	Area in square meters of the total phased array antenna area	1-5m^2

8.1.1 GINA Model

Figure 49 describes the simulation flow that was employed in this case study, based on work by Kashitani.[66] The model initiates with the definition of a constants vector that contains parameters of the designs that remain constant across all of the architectures that are being evaluated. Examples of constants in the Broadband model are scientific constants, such as the earth's radius, and conversion factors. Other constants that are included in the Broadband model are market constants such as market size and distribution, satellite sizing ratios, and launch vehicle performance.

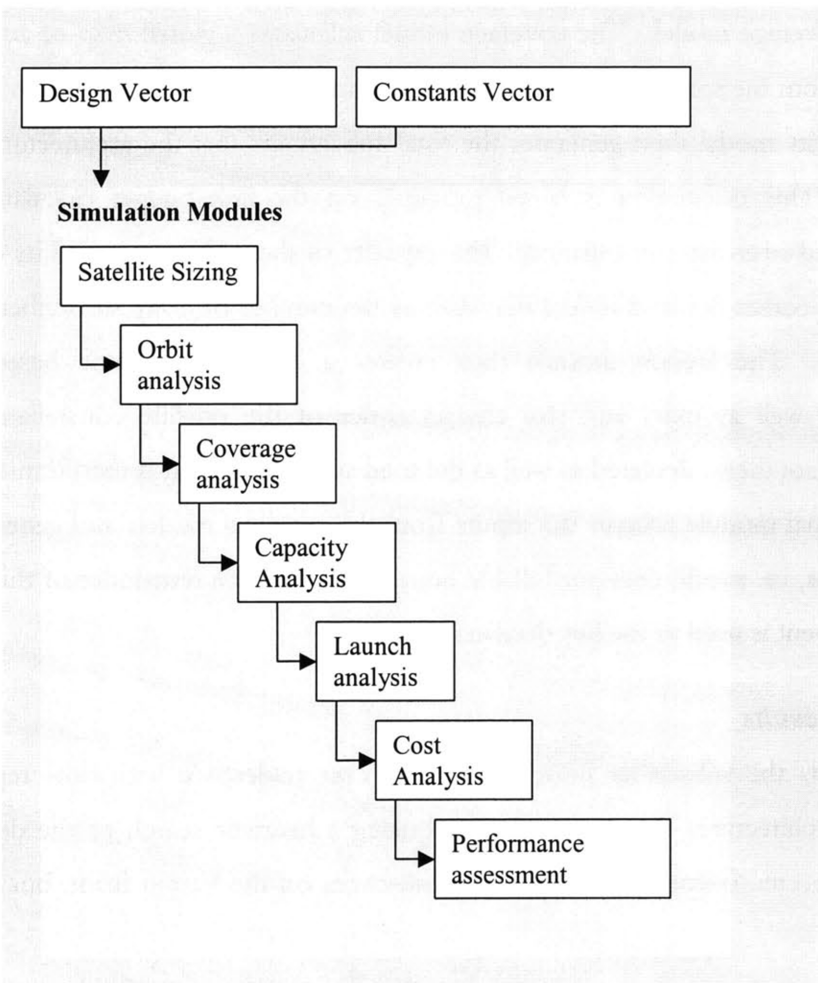


Figure 49: Systems Simulation Flow

---

[66] Kashitani, T. (2002). Development and Application of an Analysis Methodology for Satellite Broadband Network Architectures. Proceedings of the 20th AIAA International Communications Satellite Systems Conference, Montreal, Canada.

The simulation is relatively course in system design detail, but serves as a good case for analysis because of the use of market models that exemplify circumstances where market uncertainty can have the driving effects on outcomes. The flow of the model begins with a relative sizing of the spacecraft based on rules of thumb and the design vector inputs. For example, from the antenna power and antenna size, the relative mass and size of the spacecraft can be determined from sizing relationships commonly used in conceptual design.[67] After the relative size of the spacecraft is calculated, Satellite Tool Kit® is used to propagate the satellites in their individual orbits and capture ephemeris that can be used in the coverage model. The coverage model calculates a global map of acceptable coverage that is achieved from the space segment of the architecture, based on probabilities of satellites in view. The system capacity model then generates the total subscribers that the architecture being evaluated could support. This calculation is based primarily on the link budget calculation of individual spacecraft summed over the constellation. The capacity of the architecture and its coverage are then compared with a market demand model that defines the number of likely subscribers over the course of a given year. The launch module then creates a launching scheme based on the orbital characteristics, as well as mass and size characteristics of the satellite constellation. The system component costs are then calculated as well as the total system cost that is then transformed to present valuation. The final module accepts the inputs from the previous models and generates a number of outcome measures, i.e. profit, cost-per-billable hour, etc.[68] For the remainder of this case the billable hour-per dollar spent is used as the key decision criteria.

8.1.2 Model Results

Figure 50 presents the subscriber hour and system cost tradespace with dots representing the 13 Pareto optimal architectures that were calculated using a heuristic search of the design tradespace.[69] These are the expected outcomes for the 13 architectures on the Pareto front, but of course there is

---

[67] For more detail on sizing relationships see Larson, W. a. J. W., Ed. (1992). Space Mission Analysis and Design. Torrence, CA, Microcosm.

[68] Kashitani, T. (2002). Development and Application of an Analysis Methodology for Satellite Broadband Network Architectures. Proceedings of the 20th AIAA International Communications Satellite Systems Conference, Montreal, Canada.

[69] Jilla, C. (2002). A Multiobjective, Multidisciplinary Design Optimization Methodology for the Conceptual Design of Distributed Satellite Systems. Aeronautics and Astronautics. Cambridge, MA, Massachusetts Institute of Technology.

uncertainty that surrounds each expectation that will be addressed in the next section.[70] From this tradespace of total subscriber hours generated by the space system and the system cost, a billable hour per dollar-invested metric (subscriber hour/$) is developed that is used later as the single measure of value for the decision maker.

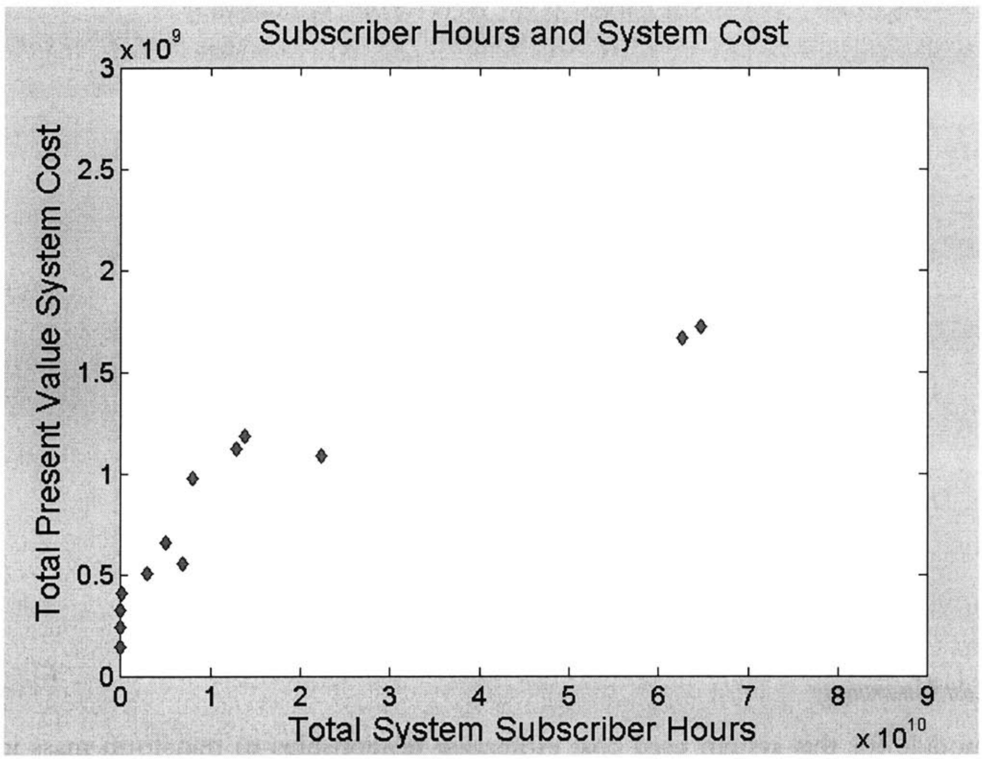


Figure 50: Commercial Broadband System Pareto Optimal Front

8.2 Uncertainty Quantification

Once the baseline GINA model was developed, the uncertainty quantification approach was initiated. The first step in the process was to identify the potential sources of uncertainty in architectures being investigated. Once the initial sources were identified and quantified the Monte Carlo uncertainty propagation technique was used to develop the embedded uncertainty for each architecture.

70 A total of 17 Pareto optimal architectures were initially found; however 4 of these became infeasible under the inclusion of uncertainty and were excluded from further consideration. The infeasibility was caused by launch vehicle constraints on mass that were violated for these architectures.

8.2.1 Sources of uncertainty

Table 18 presents the various sources of uncertainty that were considered in the Broadband case study. Because the Broadband GINA model is relatively coarse, a good deal of the uncertainty being quantified arises from the rules of thumb being used in the model simulation to generate results. However, because of the commercial nature of the case, market uncertainties are also introduced.

Table 18: Sources of Uncertainty considered in Broadband Case

Total Market Size
Market Capture
Payload Power per Unit Mass
Mass Fraction of the Payload with respect to Dry Mass
Fraction of Dry Mass in Wet mass
Density of Satellite
Discount Rate
Theoretical First Unit Cost per Kilogram

8.2.1.1 Cost Uncertainty

The cost module for this system used cost estimating relationships to transform mass into cost for development of the spacecraft. This served as one source of cost uncertainty. For example, The historical rule of thumb for Theoretical First Unit Cost per Kilogram is $84,000. A normal distribution centered around $84k with a standard deviation of $10k was used in the simulation models to capture the expectation and uncertainty associated with the cost estimating relationship.

8.2.1.2 Market Uncertainty

The broadband system analysis affords the opportunity to introduce market uncertainty into application. Specifically this market uncertainty is arising from the estimation of three main parameters: 1.) total market size of broadband customers, 2.) percent market capture for this project, and 3.) the discount rate used in the cash flow analysis. These three sources of market uncertainty serve as representative examples of market uncertainty. Others could have been included such as uncertainty in market geographic distribution or competition scenarios. Kelic investigated a number of market uncertainties that include those listed above in her analysis of potential space based broadband delivery systems.[71]

Uncertainty in total market size is modeled using a lognormal distribution that is consistent with pervious market analysis of the broadband market potential. A lognormal distribution is used for the obvious reasons that the market has a lower bound of zero, but a more uncertain upper bound. Figure 51 represents the market distribution that was used in the analysis. The expected market size was calculated on an annual basis with a six year projection.

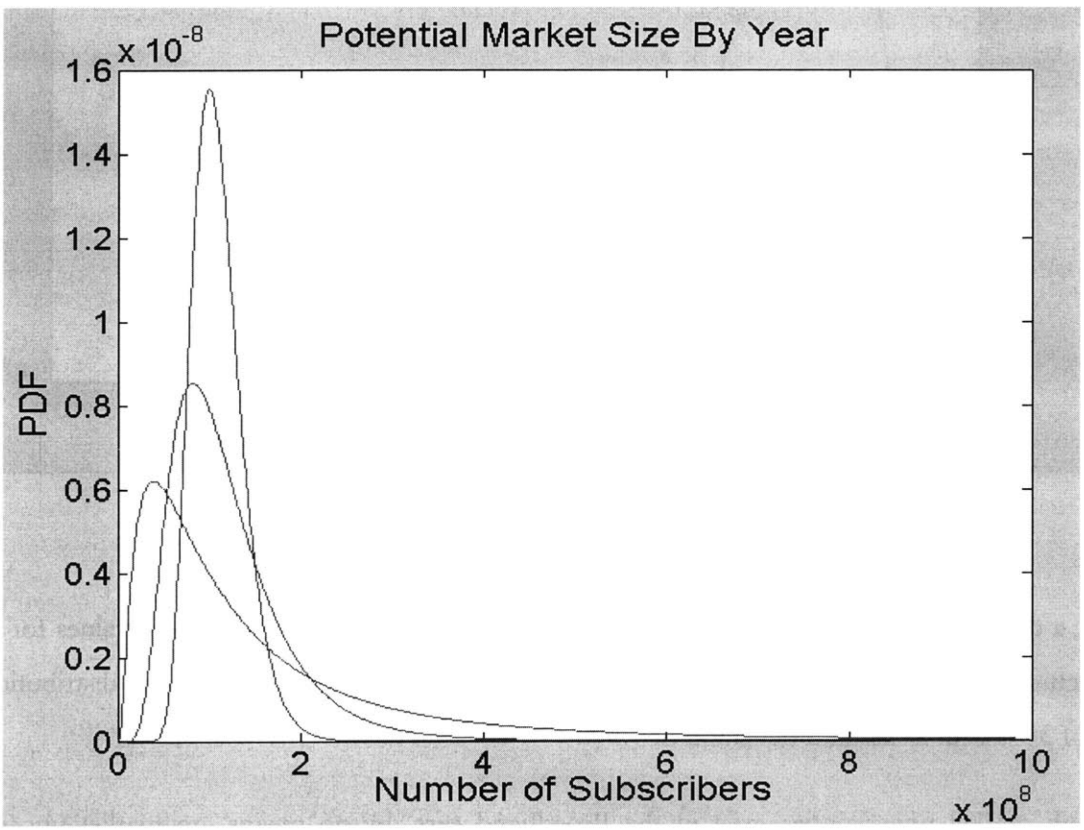


Figure 51: Broadband Market Size by Year

The percent market capture is another source of uncertainty. Even with a precise market, there is no way to know what competitors you'll have and what customers will prefer. Again a lognormal

---

71 Kelic, A. (1998). Assessing the Technical and Financial Viability of Broadband Satellite Systems Using a Cost per T1 Minute Metric. Aeronautics and Astronautics. Cambridge, MA, Massachusetts Institute of Technology, SM.

distribution is used here to represent an expected market capture of 7.5% and the distribution around that, as shown in Figure 52.

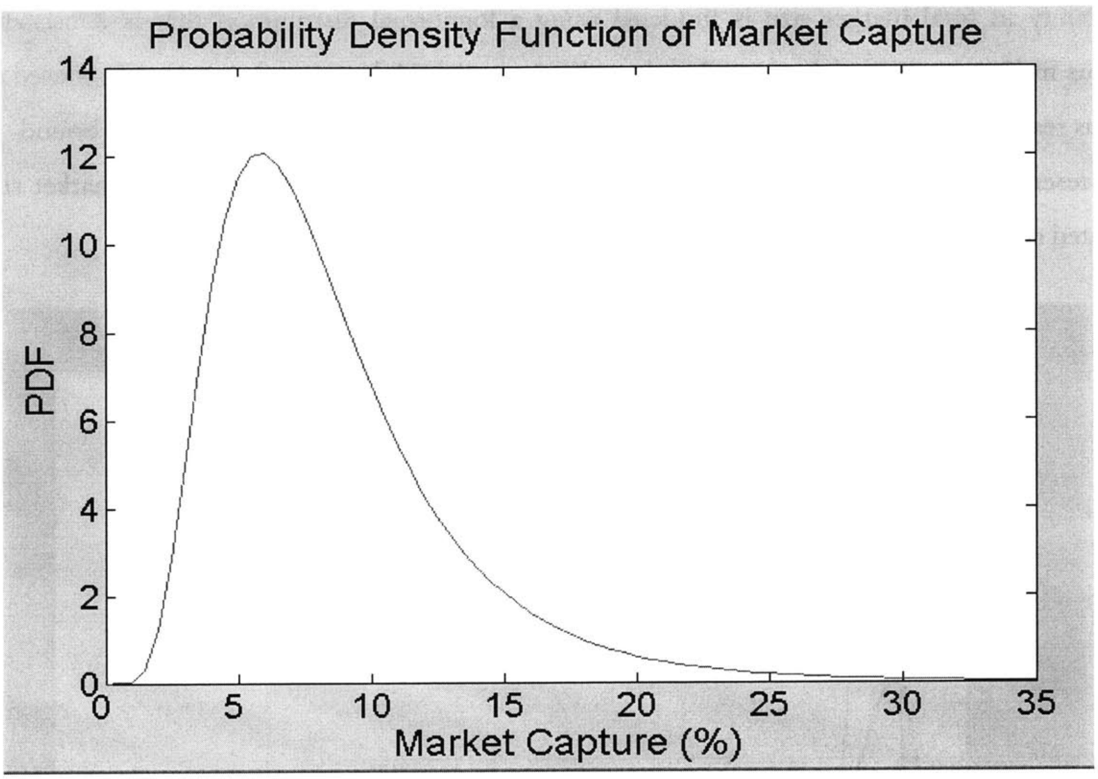


Figure 52: Broadband Percent Market Capture Year over Year

Finally, a discount rate was used in some of the calculations to generate net present values for various architecture outcomes. The discount rate uncertainty was represented by a normal distribution with mean of 30% with a standard deviation of 7.5%.

Although market uncertainties exist in the Broadband case, by no means are market uncertainties isolated to commercial ventures. Military and civil systems also suffer from market uncertainties in a number of ways, ranging from competition to demand for the system.

8.2.1.3 Model Uncertainty

Because, the simulation model was relatively course, there were a number of design rules of thumb used to size features of the architectures. These rules of thumb are based on historical trends and the hope is that the previous design trends will hold for the current system. Most of these rules of thumb have associated with them an expected scaling factor and a standard error.[72] The model uncertainties that were considered in this case were the sizing relationships for payload power per unit mass, mass fraction of the payload with respect to dry mass, fraction of dry mass in wet mass, and the density of the satellite.

8.2.2 Embedded Architectural Uncertainty

To calculate the embedded uncertainty in each architecture, the set of individual sources of uncertainty is built into the constants vector. The first step is to sample the constants vector under conditions of uncertainty, as shown in Figure 53. For example, a % market capture will be randomly selected from the possible distribution, a single number of potential subscribers for each year of operation will be randomly selected, a satellite density value will be randomly chosen from the potential values it could take on, etc. Once the constants vector is initialized, this vector is the used for each of the potential design vector combinations under consideration and results in an outcome vector for each architecture considered.

Next, a new constants vector is selected from the distribution of possible constants vectors. The simulation for each design vector combination under consideration is repeated, resulting in a second set of outcome observations for each architecture evaluated. This process of selecting a constants vector is repeated many times until a populated distribution of outcome measures can be generated. The number of runs is only limited by the computation required and time allowed, as many simulation models for every design vector combination can take 5-10minutes.

---

72 Larson, W. a. J. W., Ed. (1992). Space Mission Analysis and Design. Torrance, CA, Microcosm.

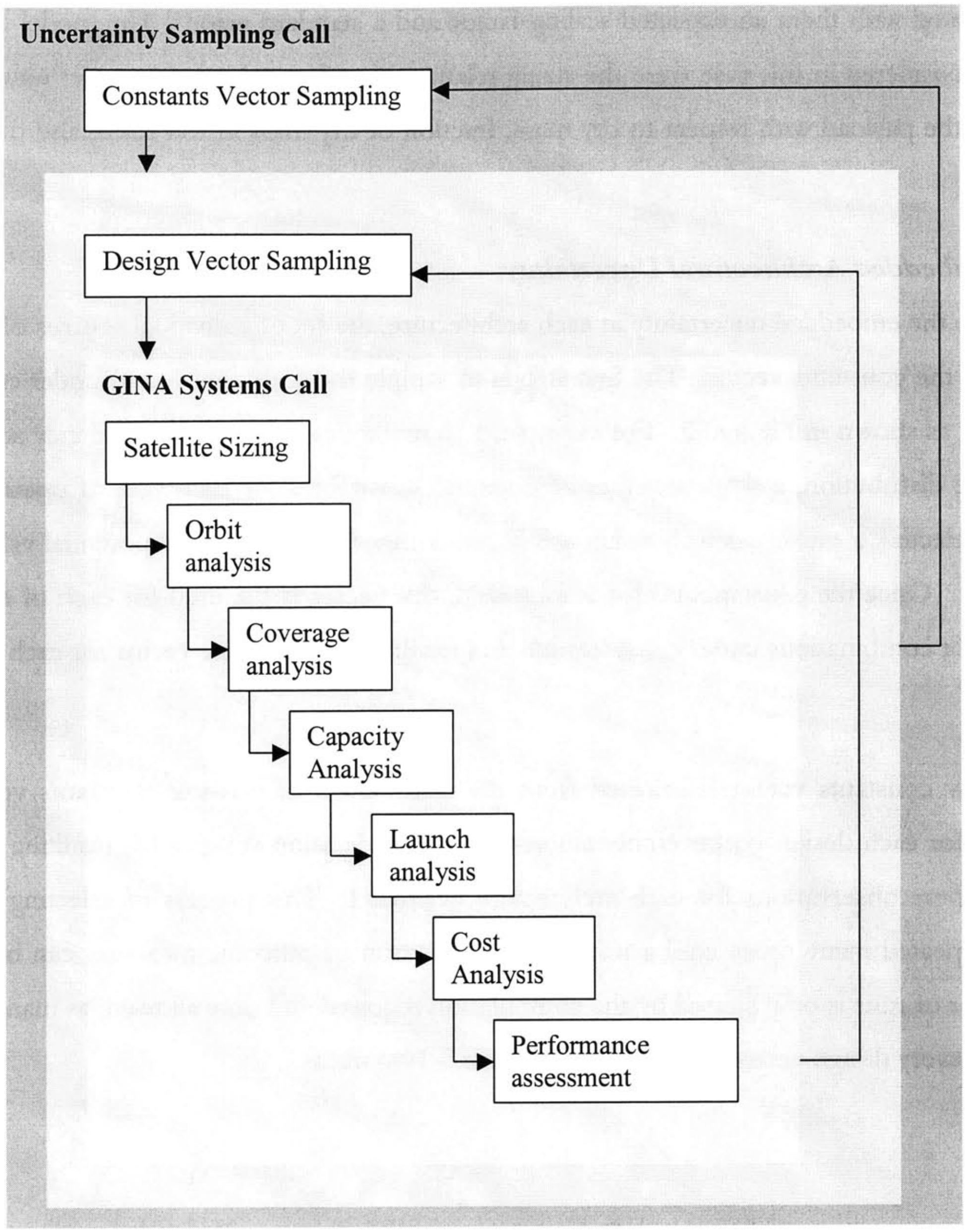


Figure 53: Creating distributions of architectural outcomes

The end result of the uncertainty propagation is an ordered set of outcomes for every architecture considered. This data can be used to create statistical measures of uncertainty for a single architecture and also the pair-wise correlation coefficients that are necessary in portfolio optimization. Figure 54 presents a snapshot of the embedded uncertainty that was calculated for each architecture on the Pareto optimal front. The diamonds represent the expected value of the architecture in terms of system cost and total subscriber hours, while the ellipses represent the uncertainty of each architecture in both dimensions.

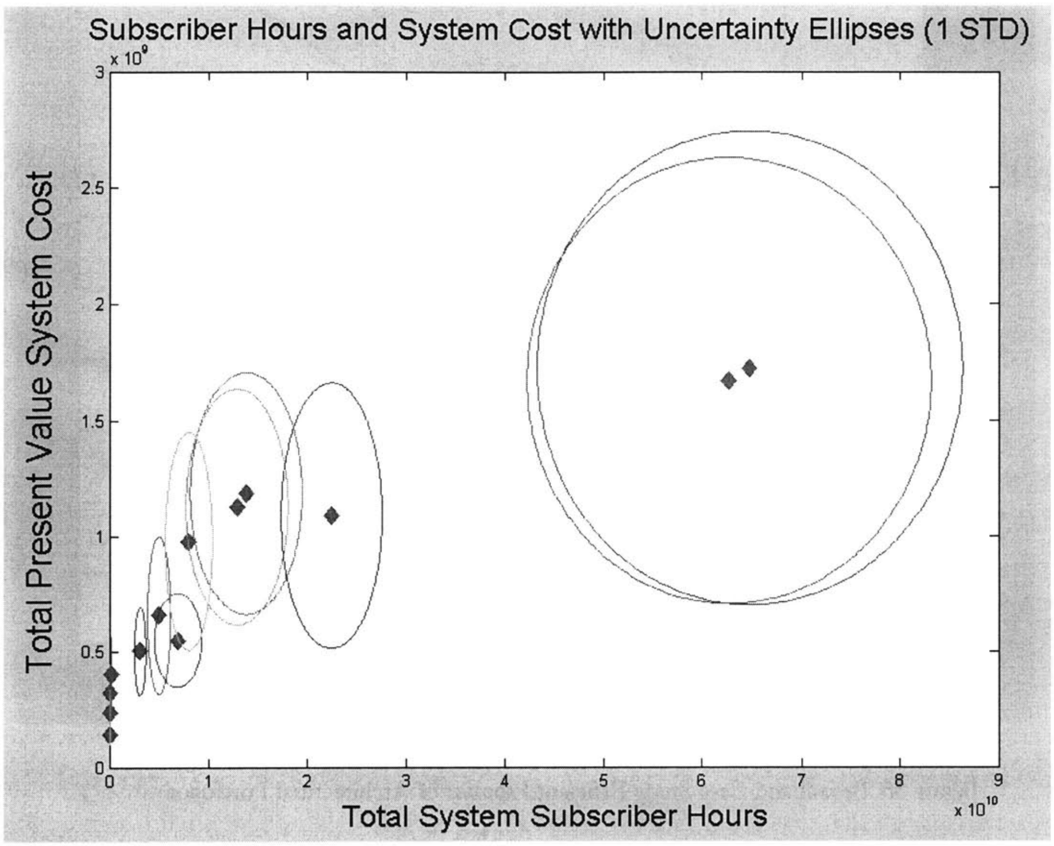


Figure 54: Broadband tradespace with the inclusion of uncertainty

8.3 Portfolio Assessment

Once the embedded architectural uncertainties have been calculated, the portfolio assessment, as described in detail in Chapter 6, can be applied. The portfolio assessment will be useful in helping the designer to assess and manage the uncertainty in the architectural trade space and not just single point designs. The portfolio assessment also provide a context in which trade-offs of uncertainty and value, subscriber hour/$, can be made. Using an expected return and covariance matrix based on 100 observations of 13 architectures, the portfolio optimization algorithm was applied to generate the efficient frontier. Figure 55 presents the broadband efficient frontier, as derived under the classis portfolio optimization algorithm in Eq. 10.

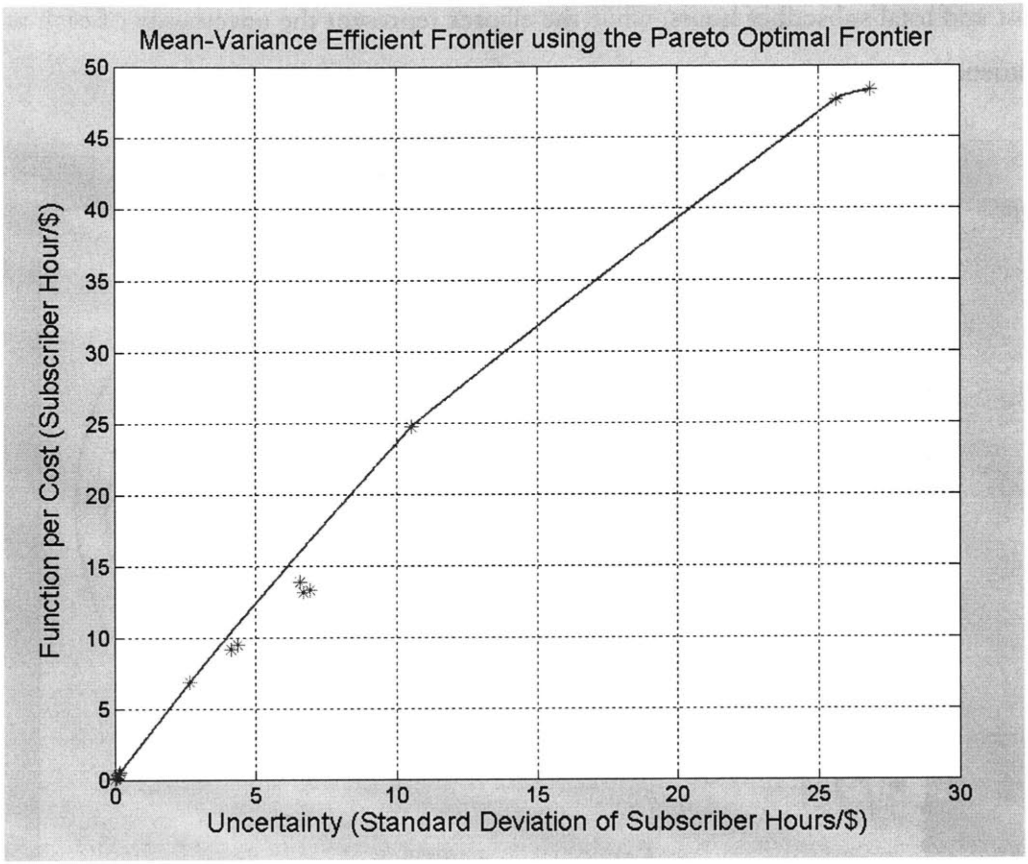


Figure 55: Broadband Case Study Efficient Frontier of Architectural Portfolios

Using an architecture portfolio analysis flight simulator, the designer and decision maker can dynamically explore trade-offs between uncertainty and function-per-cost. Figure 56 provides a screen shot of the flight simulator. The dot indicates the current portfolio, while the weight of each architecture in the portfolio is listed on the right hand side along with the expectation of function-per-cost and uncertainty. For example, the dot on the efficient frontier represents a portfolio consisting of two architectures, both LEO and equivalent antenna size and power levels, but having different numbers of spacecraft in the constellation and different orbital configuration. An immediate observation from the portfolio tradespace is the clear demarcation of GEO, MEO and LEO architectures along measures of value and uncertainty.

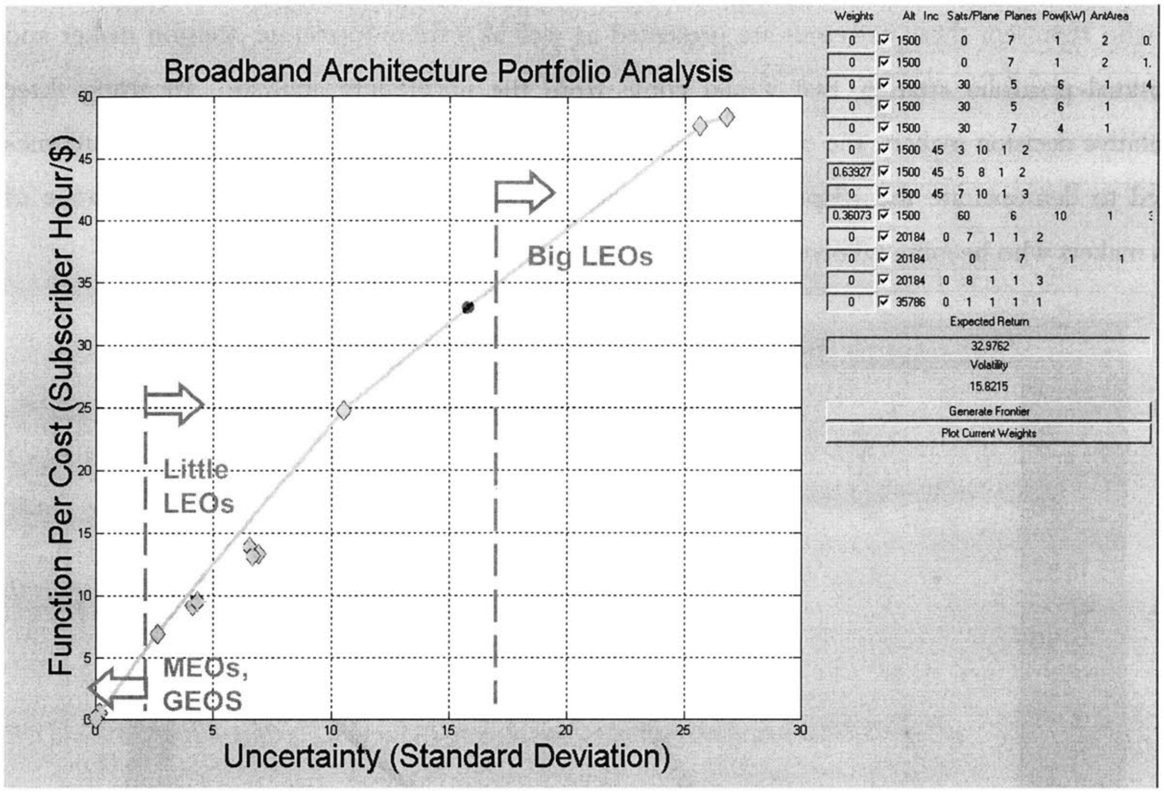


Figure 56: Snapshot of the Architecture Portfolio Flight Simulator

8.3.1 Quantifying Decision Maker Risk Aversion

Once the efficient frontier has been calculated, the next logical next step is to determine where what the optimal strategy is for a given decision maker. As discussed in Chapter 6, capturing decision maker risk aversion can be relatively straightforward through the use of indifference curves and iso-utility lines. By interacting directly with the customer with this graphical technique, preferences of the decision maker can be captured and incorporated into the portfolio optimization. As was previously seen, the level of aversion of the decision maker can greatly affect the optimal strategy and this is also true in this case study. There are a total of 7 architectures that constitute membership in a portfolio somewhere on the efficient frontier and there are many combinations of those possible.

The highly risk averse individual would find himself looking at portfolio in the lower left corner of the efficient frontier, while the lower risk averse decision makers would have preferences leading to strategies in the upper right corner. Rather than chose a single decision makers aversion, two decision makers who represent these extremes are presented as well as a more moderate decision maker and their optimal portfolio strategy that would come from the uncertainty analysis. By using three representative decision makers, the overall sensitivities of the portfolio can be observed and outcomes compared to demonstrate the adaptability of the uncertainty analysis approach to a large range of decision makers who become involved in the development of space systems.

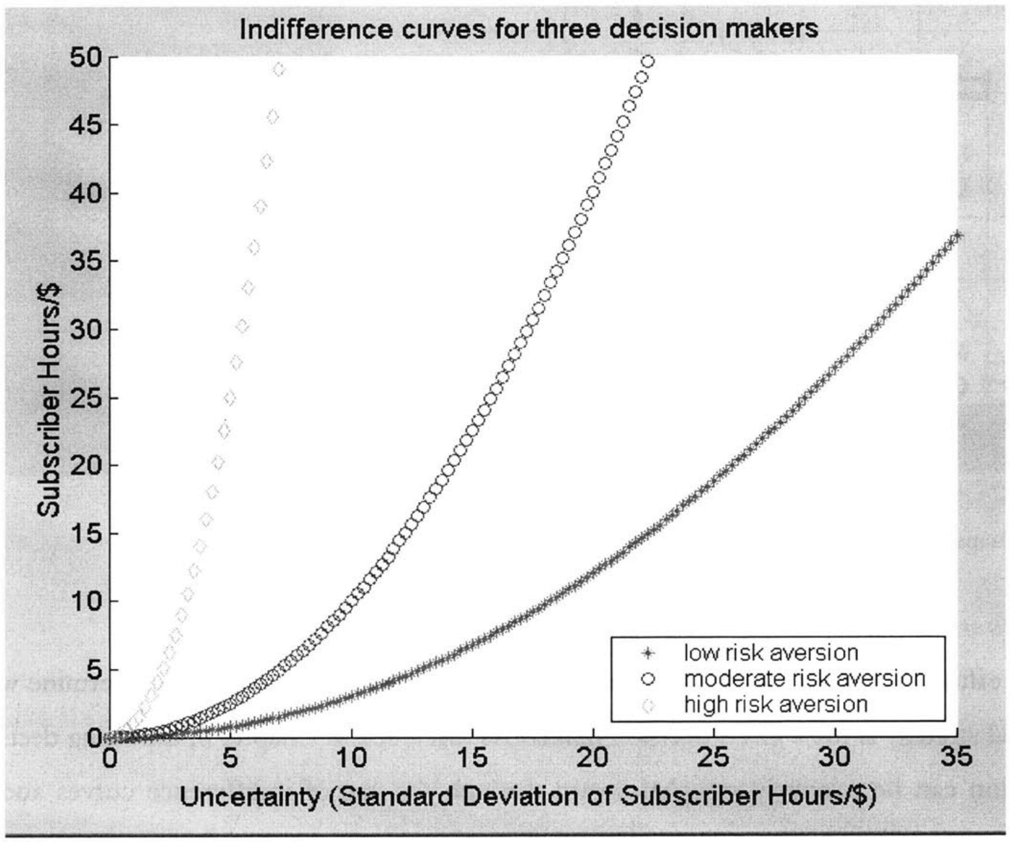


Figure 57: Indifference curves for three decision makers

Assume that Figure 57 represents the three-decision maker's indifference curves for the value/uncertainty trade. Using this information an optimal investment strategy can be developed based on the portfolio optimization. As one might expect, the decision maker with a low level of risk aversion will accept far more uncertainty for a given increase in value than the decision makers with moderate and high levels of risk aversion. Notice that a completely risk averse individual would have an indifference curve that is represented by a vertical line, while a horizontal line would represent a risk neutral decision maker.

The k values representing the three decision makers looked at in this case are 0.03, 0.1, and 1. These are relatively low k values, thus indicating decision makers who are closer to being risk neutral. This set of k values was chosen to span the portfolio space. This range suggests that the efficient frontier has relatively high levels of uncertainty and little offering to the highly risk averse individuals.

8.3.1.1 Decision maker with high risk aversion optimal portfolio strategy

The first decision maker looked at was the highly risk averse decision maker with a k value of 1. A highly risk averse decision maker would expect to find themselves in the lower left hand corner of the efficient frontier and that is exactly what is shown in Figure 58. The efficient frontier, the concave line, as well as three iso-utility lines have been plotted for the decision maker. An optimal investment strategy where the highest iso-utility curve becomes tangent to the frontier is shown in the figure.

The composition of the optimal strategy is defined in Table 19. This portfolio contains both a MEO architecture and a LEO architecture. There were lower risk assets for which the decision maker could have invested, such as the one GEO architecture on the Pareto optimal front, but this decision maker desired more return that the lower risk architectures could provide.

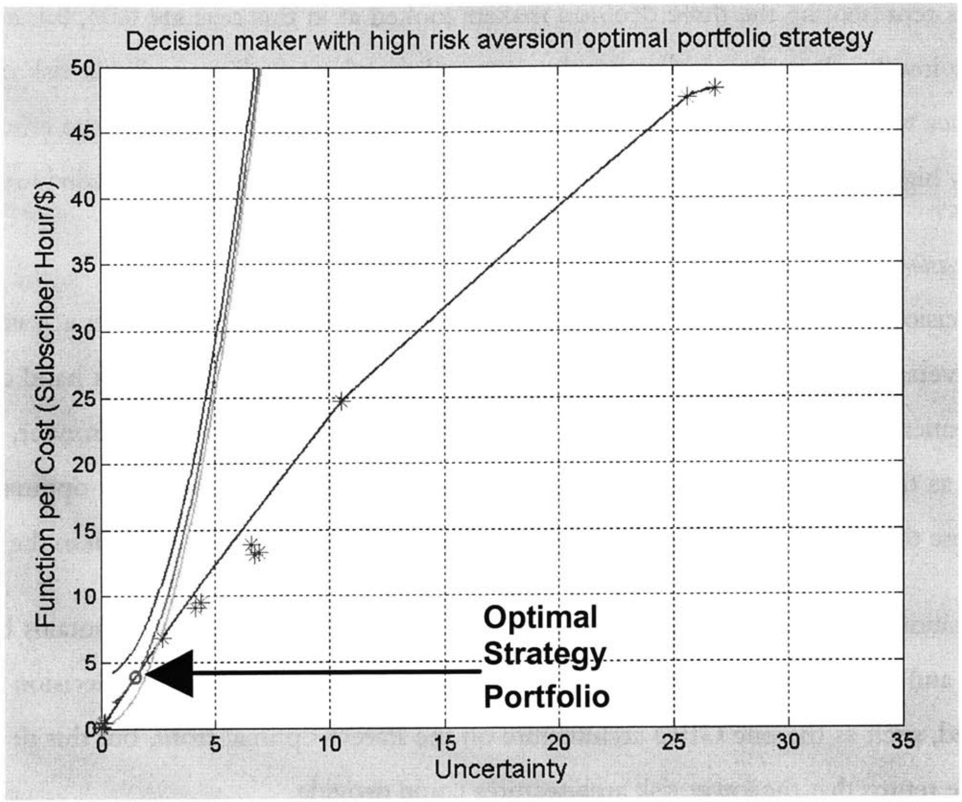


Figure 58: Optimal investment strategy for high risk aversion decision maker

Table 19: Composition of Broadband high risk aversion decision maker strategy

	Percentage of Portfolio	Architecture Design Vector {alt, inc, sats/plane, planes, pow, ant area}	Subscriber Hour/$	Uncertainty
	55%	{MEO, 0, 8, 1, 1, 3}	0.5	0.2
	45%	{LEO, 0, 7, 1, 2, 0.5}	6.9	2.7
	100%	Portfolio Value and Uncertainty	3.4	1.3

8.3.1.2 Decision maker with moderate risk aversion optimal portfolio strategy

The second decision maker investigated has a k value equal to 0.1. In most cases this value would not be considered a "moderate" level of risk aversion, but the phrase is used here to show the relative preference to uncertainty of three decision makers. The optimal investment strategy for the moderate risk aversion decision maker is shown in Figure 59.

The composition of this portfolio lies at a single architecture, a LEO architecture consisting of 40 satellite constellation each with a 2 m^2 antenna and 1 kW power. It appears that implementation of portfolio theory failed to create a multi-asset portfolio for the decision maker as an optimal strategy. However, it is not the goal of portfolio theory to create a portfolio for the sake of increasing the number of investments. Instead the goal is to use different assets where possible to diversify away some level of uncertainty. In the case of this tradespace, the architectures considered, the models used and the uncertainty sources quantified produced architectural outcomes whose behaviors were highly correlated. In cases where tradespaces lack this type of diversity, there will always exist portfolios that contain a single asset because the efficient frontier will closely resemble a linear combination of assets.

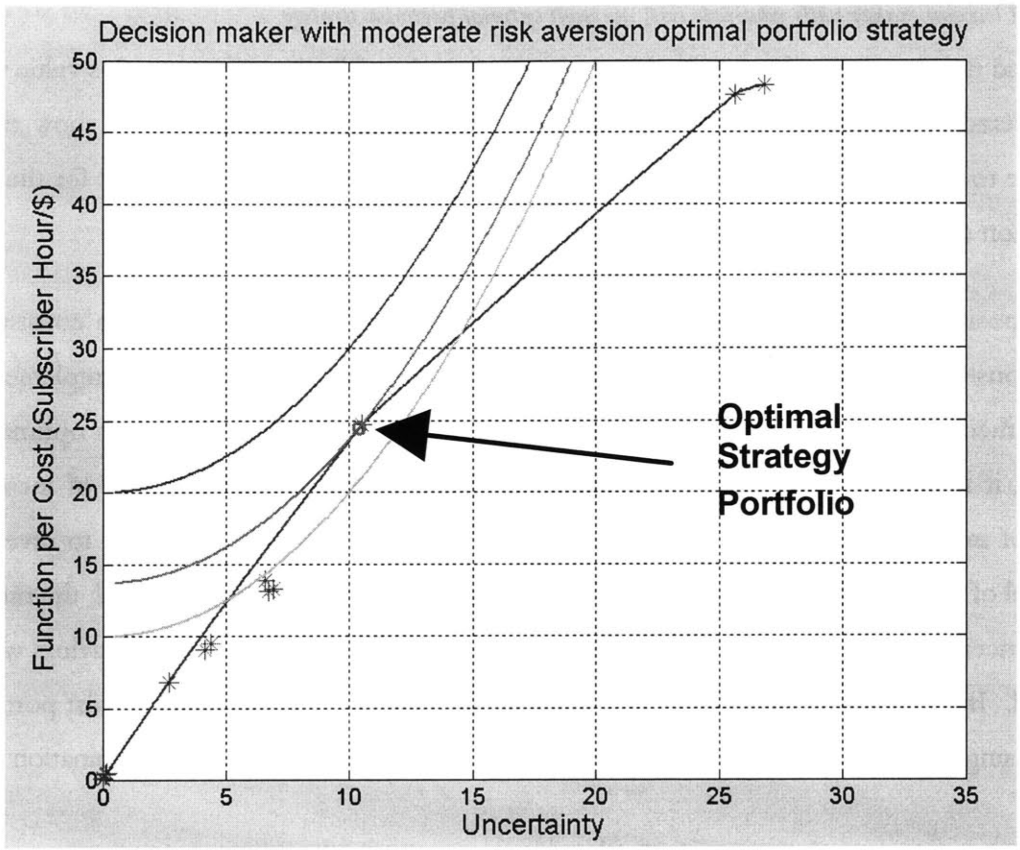


Figure 59: Optimal Investment strategy for moderate risk aversion decision maker

Table 20: Composition of Broadband moderate risk aversion decision maker strategy

	Percentage of Portfolio	Architecture Design Vector {alt, inc, sats/plane, planes, pow, ant area}	Subscriber Hour/$	Uncertainty
	100%	{LEO, 45, 5, 8, 1, 2}	24.7	10.5
	100%	Portfolio Value and Uncertainty	24.7	10.5

8.3.1.3 Decision maker with low risk aversion optimal portfolio strategy

The third decision maker has a very low level of risk aversion, k=0.03. The optimal strategy for this decision maker is shown in Figure 60 and as one might expect, it resides in the upper right corner of the efficient frontier. This strategy is indeed taking on a good deal of uncertainty with expected value of 45.5 Hours/$ and a standard deviation of over half that.

The composition of the portfolio is described in detail in Table 21. There are three assets in the portfolio, all LEO architectures. The reason for large LEO architectures dominating this portfolio is that the larger the constellation of satellites and the more capacity a system has to achieve subscriber hours if the market conditions are good. However, under adverse market conditions, the system won't achieve the subscribers expected and it will have required a significant capital investment to construct it. Notice that one of the assets suggested is only 2% of the portfolio. In practice 2% of an architectural investment would most likely not be enough to produce tangible benefits, so this percentage might best be distributed amongst the other two assets.

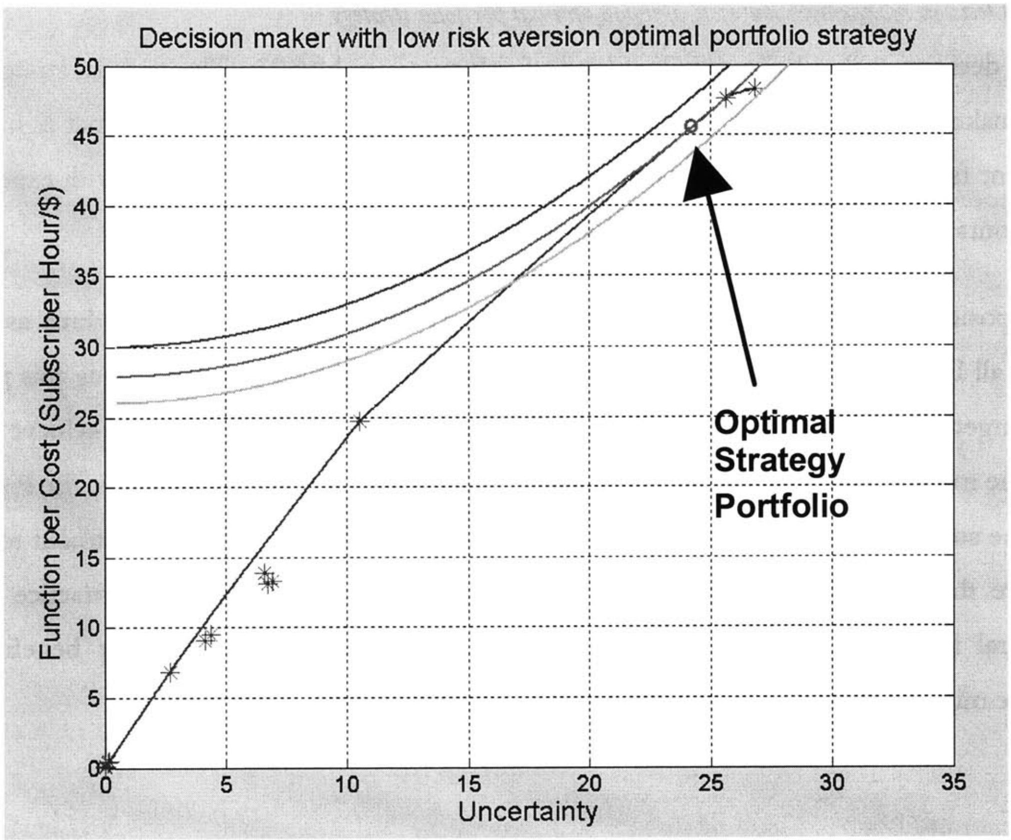


Figure 60: Optimal strategy portfolio for low risk aversion decision maker

Table 21: Composition of Broadband low risk aversion decision maker strategy

	Percentage of Portfolio	Architecture Design Vector {alt, inc, sats/plane, planes, pow, ant area}	Subscriber Hour/$	Uncertainty
	9%	{LEO, 45, 5, 8, 1, 2}	24.7	10.5
	2%	{LEO, 45, 7, 10, 1, 3}	48.3	26.8
	89%	{LEO, 60, 6, 10, 1, 3.5}	47.6	25.6
	100%	Portfolio Value and Uncertainty	45.5	24.2

8.3.2 Implications of incorporating the extensions to portfolio theory

The classical implementation of portfolio theory has been presented using uncertainty as a surrogate for risk, but in fact, the two can be separated, as shown below through the use of semi-variance. The low risk aversion decision maker has a suggested optimal portfolio that consists of more than one asset. What is the extra cost of that portfolio and how should a cost benefit trade be made? To find the answer, the correlation coefficient of the portfolio members is used as a starting point.

8.3.2.1 Differentiating risk from uncertainty

The first step to differentiate the risk from the uncertainty in the distribution can be found by focusing on the downside semi-variance, as previously discussed in Chapter 6. To do so, first adjust the variance of individual observations around the expectation as shown in Eq. 29. The variance of these new observation errors is then calculated, as shown in Eq. 30.

$$(r_i - E(r))^- = \begin{bmatrix} (r_i \text{ - E(r)) if } r_i \leq 0 \\ 0 \text{ if } r_i > 0 \end{bmatrix}$$

Eq. 29

$$S_{Downside} = 2 * E\left[\sum (r - E(r))^2\right]$$

Eq. 30

Thus creating a downside covariance matrix as shown in Eq. 31.

$$Q_{Downside} = \begin{bmatrix} S_{d1}^2 & \rho_{2,1} S_{d2} S_{d1} & \rho_{3,1} S_{d3} S_{d1} & \bullet & \rho_{n,1} S_{dn} S_{d1} \\ \rho_{1,2} S_{d1} S_{d2} & S_{d2}^2 & \rho_{3,1} S_{d3} S_{d1} & \bullet & \rho_{n,2} S_{dn} S_{d2} \\ \rho_{1,3} S_{d1} S_{d3} & \rho_{2,3} S_{d2} S_{d3} & S_{d3}^2 & \bullet & \rho_{n,3} S_{dn} S_{d3} \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \rho_{1,n} S_{d1} S_{dn} & \rho_{2,n} S_{d2} S_{dn} & \rho_{3,n} S_{d3} S_{dn} & \bullet & S_{dn}^2 \end{bmatrix}$$

Eq. 31

Finally, implement the portfolio algorithm in the similar manner to traditional portfolio theory, only substituting $Q_{donwside}$ for Q, as shown in Eq. 32.

$$\max : E(r)w - \frac{k}{2} w' Q_{Downside} w$$
$$\text{s.t.} : \sum_{i=1}^{n} w_i = 1$$
$$\text{s.t.} : \mathrm{w} \geq 0$$

Eq. 32

Using this algorithm, an efficient frontier can be calculated in the same manner performed earlier in the case. The tradespace of risk and function per cost is shown in Figure 61. The efficient frontier for both the full uncertainty portfolio analysis, as well as the semi-variance analysis is shown in the figure. The most interesting insight to take away from this chart is that there is less risk in the tradespace than would be perceived if uncertainty were used as a surrogate for risk. Another thing to observe is that the relative position of the architectures with respect to one another has not changed and instead, the result from the semi-variance analysis is a simple shift to the right. Also the relative separation between the two frontiers is not constant and suggests that the architectures in the upper right have a greater relative upside than those in the lower left hand corner of the efficient frontier.

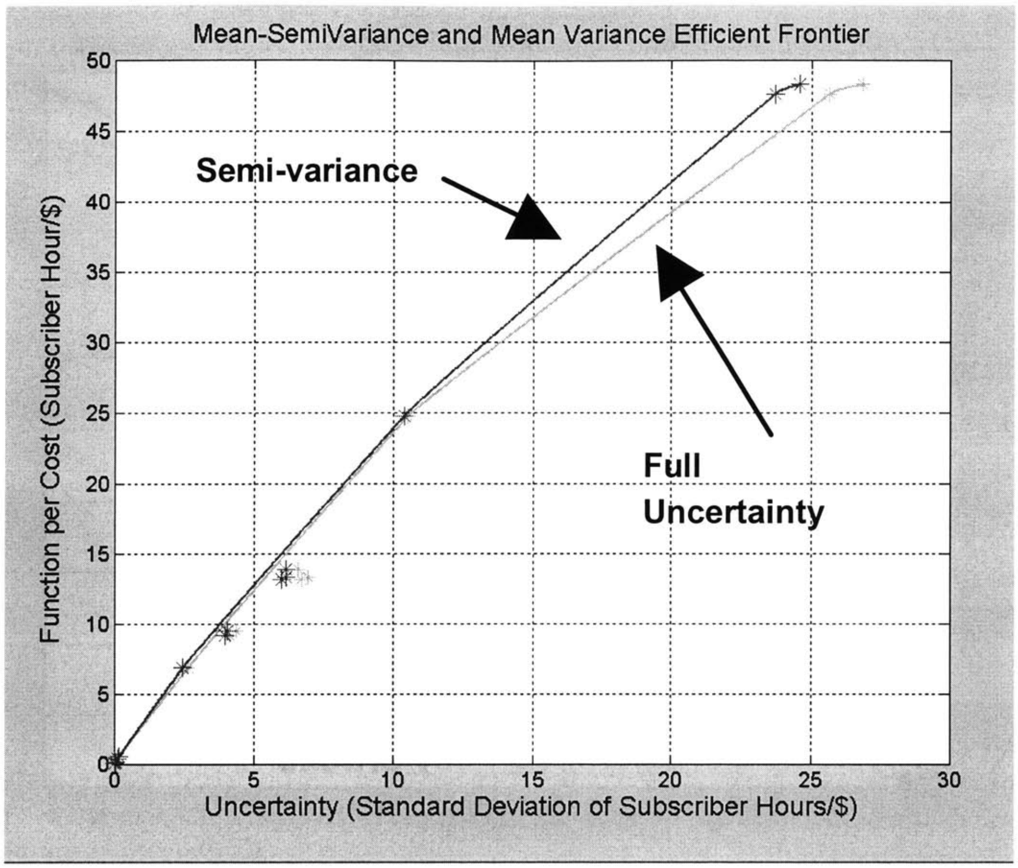


Figure 61: Broadband portfolio analysis with full uncertainty and semi-variance

With a different efficient frontier, it is conceivable that decision makers should choose different optimal portfolio strategies. Using the same decision makers previously used, the low, moderate and high risk aversion, the effects that this extension to classical portfolio analysis would provide are discussed.

The first decision maker was the high risk aversion decision maker. Under the efficient frontier using semi-variance, his optimal portfolio strategy has remained the same as was previously found, as shown in Figure 62 and Table 22.

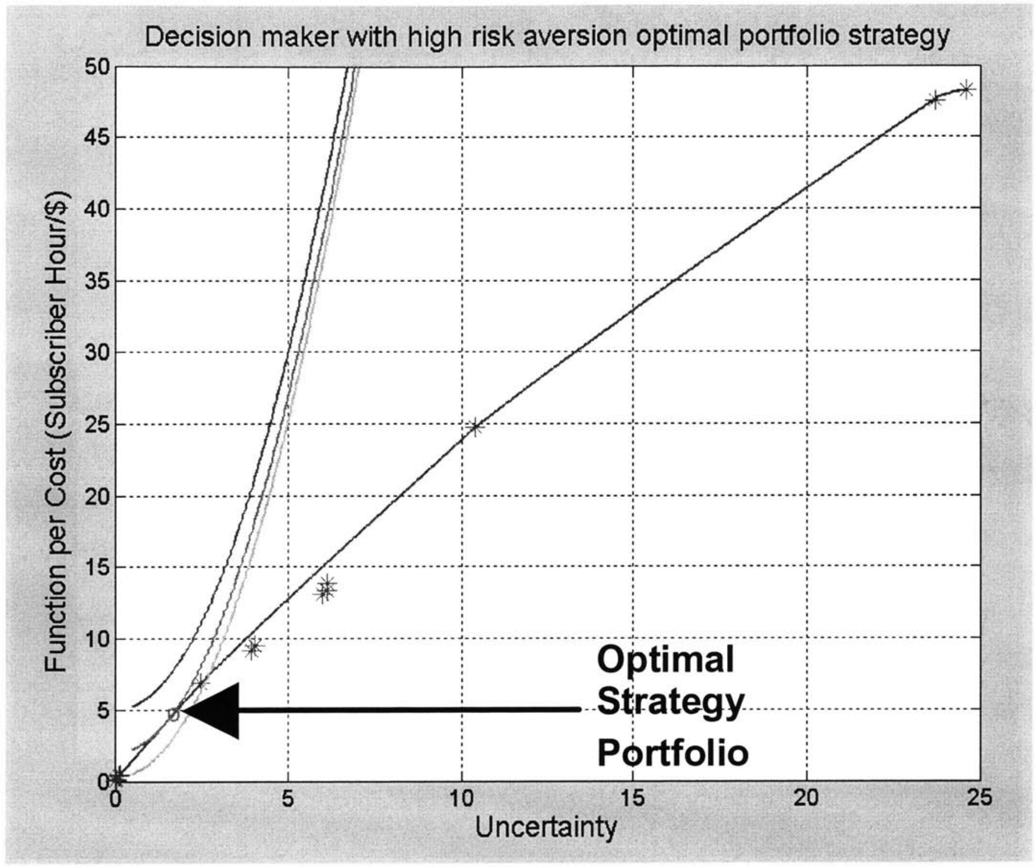


Figure 62: Optimal investment strategy for high risk averse decision maker

Table 22: Composition of Broadband high risk aversion decision maker strategy

	Percentage of Portfolio	Architecture Design Vector {alt, inc, sats/plane, planes, pow, ant area}	Subscriber Hour/$	Uncertainty
	49%	{MEO, 0, 8, 1, 1, 3}	6.9	1.1
	2%	{LEO, 0, 7, 1, 2, 0.5}	13.3	2.6
	49%	{LEO, 30, 5, 6, 1, 4}	0.5	0.08
	100%	Portfolio Value and Uncertainty	3.9	0.63

The moderate risk aversion decision maker has seen no shift in his optimal portfolio strategy. Although there is less perceived risk in the tradespace under the semi-variance calculation, the same architecture is still retained.

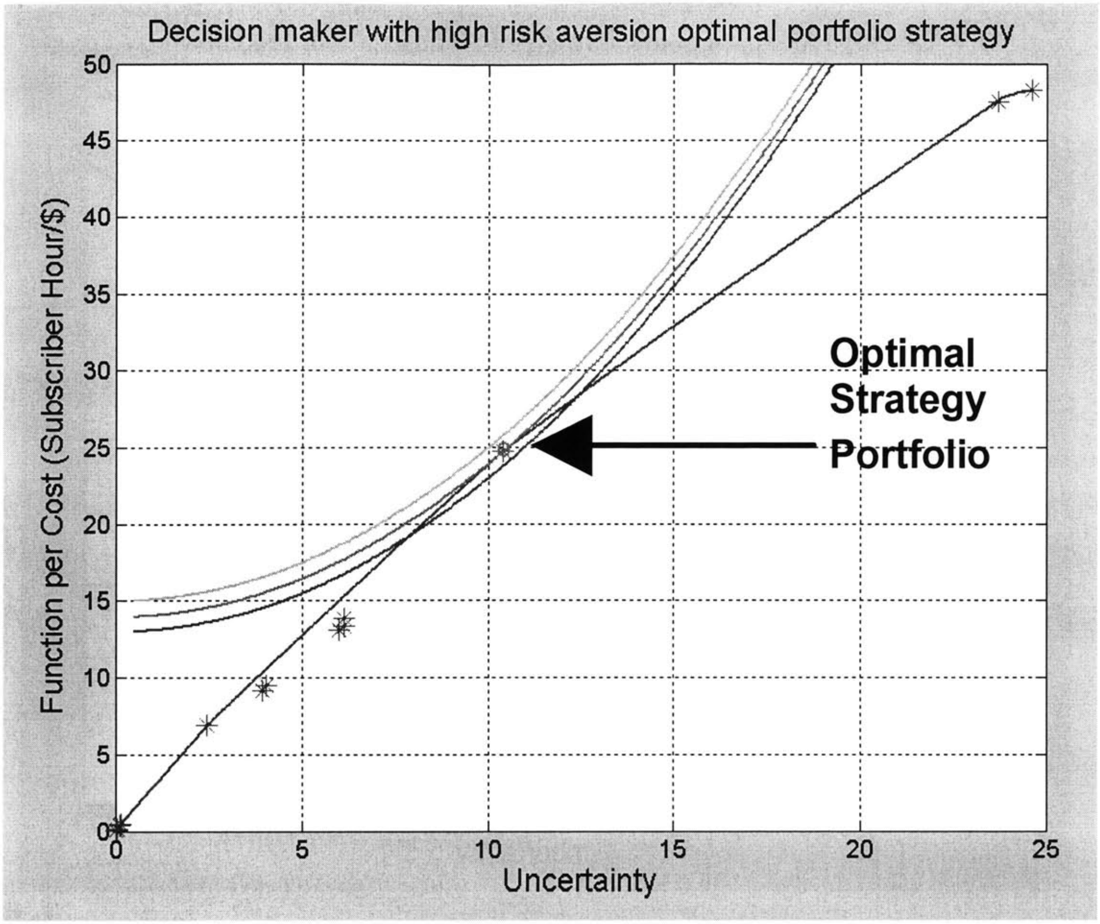


Figure 63: Optimal investment strategy for moderate risk averse decision maker

Table 23: Composition of Broadband moderate risk aversion decision maker strategy

Percentage of Portfolio	Architecture Design Vector {alt, inc, sats/plane, planes, pow, ant area}	Subscriber Hour/$	Uncertainty
100%	{LEO, 45, 5, 8, 1, 2}	24.7	10.5
100%	Portfolio Value and Uncertainty	24.7	10.5

The low risk averse decision maker has seen a shift in strategy. He previously had a portfolio of three assets as an optimal portfolio strategy, but now has two, namely the architectures that had the highest values, as shown in Figure 64 and Table 24.

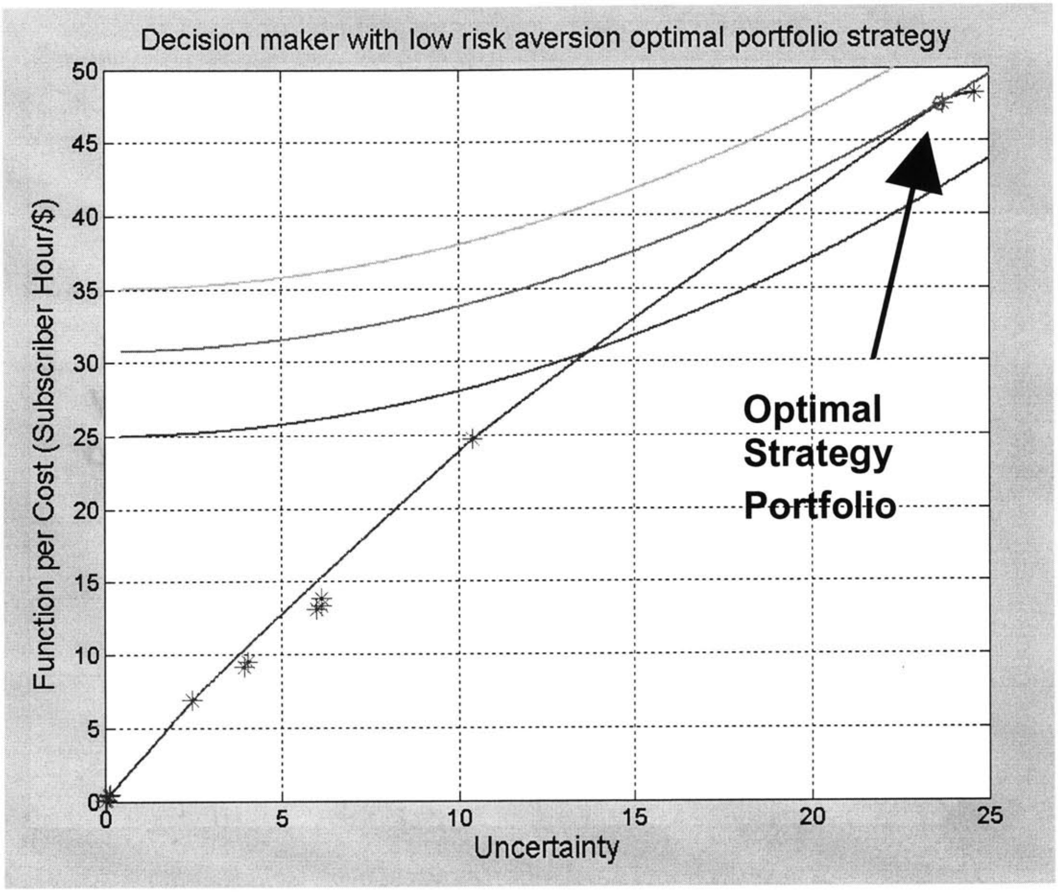


Figure 64: Optimal investment strategy for low risk averse decision maker

Table 24: Composition of Broadband low risk aversion decision maker strategy

Percentage of Portfolio	Architecture Design Vector {alt, inc, sats/plane, planes, pow, ant area}	Subscriber Hour/$	Uncertainty
24%	{LEO, 45, 7, 10, 1, 3}	48.3	10.4
76%	{LEO, 60, 6, 10, 1, 3.5}	47.6	9.9
100%	Portfolio Value and Uncertainty	47.7	9.9

8.3.2.2 Cost of diversification

Some of the optimal portfolio strategies that have been found in this case have included more than one asset and therefore more than one architecture to pursue in design. In order to calculate the exact cost to diversify into a portfolio, the individual assets should be closely looked at by the designers and decision makers. For example, two LEO architectures with 45°inclination operating at 1kW and $2m^2$ antennas and having only a small difference in the number of satellites in slightly different planes will probably not incur twice the design cost of a single architecture because of the commonality between the two architectures. In contrast, a two asset portfolio with a very large LEO architecture requiring many ground stations and a two satellite GEO architecture might represent a significantly higher cost to develop than either of the two individually.

A relative measure of the cost of diversification is used to judge the relative extra cost of carrying a portfolio based on the correlation of assets in the portfolio, as described in Chapter 6. For an example, the low risk aversion decision maker under the full uncertainty distribution would have a cost to diversify equal to 0.5% of the cost to design the architecture with the design vector {LEO, 45, 5, 8, 1, 2} plus 0.1% of the cost to design the architecture with the design vector {LEO, 45, 7, 10, 1, 3}. Therefore the total cost to proceed with the portfolio would be the cost of designing the majority constituent in the three-architecture portfolio plus this additional cost to diversify. This type of calculation can provide the basis for additional consideration by the decision maker on whether or not to proceed with the portfolio strategy. Again the cost to diversify calculated here is a figure of merit and represents a relative estimate on what the cost could be. The actual cost to diversify will be case specific and should be looked at carefully by the designers and decision makers.

8.4 Conclusions

This case demonstrated the applicability of the uncertainty analysis approach to space based broadband communications architecture. Market and model uncertainty were explored as primary sources of uncertainty and the case demonstrated how significant these sources could be to the overall value of a given architecture, with some architectures maintaining 50% uncertainty. The role of downside semi-variance focus was also demonstrated, in contrast to a full uncertainty, and the impact that such separation would have on the decision maker's optimal strategy with the same level of risk aversion was shown.

The intuitive observations that comes from the analysis such as LEO architectures having predominantly greater uncertainty than MEO and GEO architectures is reinforcing to current speculations, but the case provides a quantitative base for exploring the intuition in more detail.

Moreover, an interesting final note on this case is how real world systems are acting with respect to the efficient frontier that was developed. The Teledesic Space System has been in development for some time. Initially conceived as a very large, LEO constellation of satellites, the system would provide global broadband capability with very low latency and at a reasonable price. The original concept was released in 1994 as having 840 satellites at development cost of $6.3B and total life cycle cost of $17.8B.

In 1998, Teledesic went through a dramatic redesign from 840 satellites in LEO to 288 satellites. As was shown in the analysis, this shift to fewer spacecraft lowered the potential market capture of the system, but also lowered the exposure to risk that the system would have from the upfront development cost investment.

In February 2002, a Teledesic architecture redesign was publicly released consisting of 12 satellites in MEO at a development cost of $1B and 18 more MEO satellites deployed at a later date to supplement coverage to achieve global capacity. Again, this is a downward movement on the efficient frontier, opting for less capacity and subscriber hours/$, but at a significantly lower cost than the LEO systems. Had Teledesic taken a portfolio perspective on design, would they have made more progress on becoming operational? Possibly, but with the analysis presented here, they definitely would have realized where they were heading a lot sooner.

Chapter 9

TOP SIDE SOUNDING IONOSPHERIC MAPPING MISSION: UNCERTAINTIES IN UTILITY

9.1 Mission and Model Description

The ATOS Mission (short for the first iteration, A, in a series of Terrestrial Observing Swarms missions) has the primary objective of collecting and disseminating fine measurements of the ionosphere. This data would be used by the science customer as inputs to a simulation model used for describing the behavior for the ionosphere. An understanding of the ionosphere's composition at fine detail would allow for more accurate prediction and mitigation of errors in communication and location measurement. Potential tactical benefits of a detailed mapping of the ionosphere begin to paint a clear picture of the potential value of such a mission beyond the pure science of ionospheric mapping.

9.1.1 The Ionosphere

The ionosphere makes up just a fraction of the total mass of the atmosphere, but has a great deal of significance to the space community because of its influence on the propagation of RF transmissions through it. The influence is caused by the presence of charged particles that acts as conductors and interfere with the transmission of radio waves.

The ionosphere is divided into four main layers from 50km to 1000km altitude, as shown in Figure 65. The first layer, including altitudes 50km to 90km, is the D-region. The E-region extends higher to about 150km where it meets the F region. This region, sometimes divided into the F1 and F2 region, has the most significant concentration of charged particles and contributes the most in the way of interference to the transmission of radio waves. The F2 stops around 600km and joins what is known as the topside of the ionosphere.

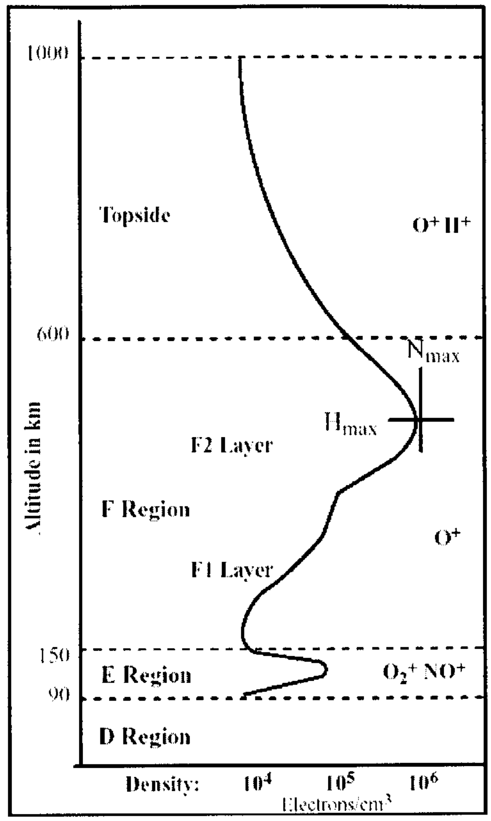


Figure 65: Ionospheric characteristics[73]

In addition to altitude distinctions in the ionosphere, other spatial characteristics exist. Characteristics are nearly identical in the longitudinal directions, but have substantive differences along lines of latitude. Specifically, the ionosphere forms two major bands of interest. The first occurs in the equatorial-low latitude region and the second in the high latitude region, greater than 60° latitude.

Not only does the ionosphere change by location, the makeup also varies in terms of concentration and composition in both predictable and unpredictable time scales. Figure 66 provides a rough estimate of the ionosphere's electron concentration as a function of altitude for both nighttime and daytime conditions under solar-max and solar-min conditions. Notice the dramatic bulge between 200 and 400 km, known as the F-layer. The F-layer is typically of the most interest to the scientists as it causes the most interference with RF transmissions. In addition, daytime measurements are typically more beneficial to the scientists as this is the time when concentrations are at their highest levels.

[73] Anderson, D. a. T. F.-R. (1999). Space Environment Topics: The Ionosphere. Boulder, CO, Space Environment Center, SE-14.

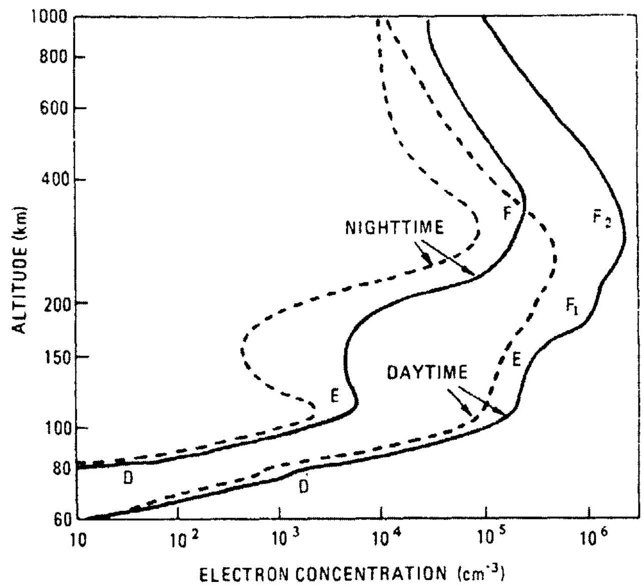


Figure 66: Ionosphere Concentration vs. Altitude for Daytime and Nighttime[74]

9.1.2 Ionospheric Influence

Figure 67 graphically illustrates the influence of ionospheric effects known as scintillation on the transmission of a radio wave signal. Notice the considerable spike in the noise that lasts approximately 40 seconds. The greater the amplitude of this spike the more significant the impact on any communications. This signal degradation is caused by small-scale structures in the ionosphere whose presence is typically associated with certain bands of latitude, specifically a low latitude band, <20°, and a high latitude band, >60°. The low latitude occurrences tend to be associated with times just after sunset, while the high latitude turbulence can be present day or night.

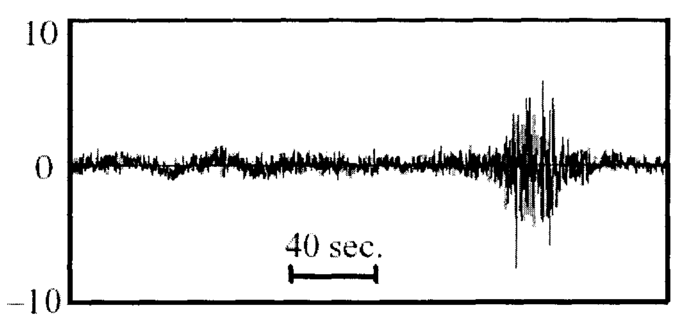


Figure 67: Signal is interrupted due to scintillation[75]

---

[74] Tascione, T. F. (1988). Introduction to the space environment. Malabar, Fla., Orbit Book Co.

9.1.3 The ATOS Mission

Given the significant impact of the ionosphere and its variability on communications and navigation, the science- and even broader space-community are interested in the accurate modeling and prediction of ionospheric dynamics. The overarching goal of the ATOS mission was to design a space system that captured both the large scale and time-scale aspects of the ionosphere, as well as the detailed, small time-scale fluctuations that are so unpredictable.

One of the most interesting features of the ATOS model is the use of utility measures to define "goodness" in the tradespace of architectures. Instead of using a set of performance measures, such as usable bytes delivered or resolution and accuracy, a non-traditional approach, utility theory, was applied to the problem of balancing the many sets of customer needs that were involved in the program.

Utility theory allows the designer to capture the preference of customers and decision makers in mathematical equations that provide for customer-in-the-loop trade-offs. This is in contrast to the customer-in-loop approach used in at the first case study site in Chapter 3. At that site, Case 1, the customer was physically present during the trade-offs process of conceptual design. In contrast, utility theory allows the customer preferences to be present during trade-offs but not necessarily require their physical presence. There are of course good and bad aspects to each of these approaches. One of the greatest advantages of utility theory is having the customer explicitly define their preferences through the use of utility interviews. Many customers have a broad vision for what they want in a system, but few have taken the vision and broken it down to the relative system attributes and how important each of those attributes are. Utility theory enables that process. In contrast, the physical collocation of the customer can be clarifying and perhaps more accurate and adaptive to unforeseen circumstances, but take a toll on the customer in terms of time invested in the project.

Five concepts to accomplishing the ATOS mission were investigated, as shown in Figure 68. The ionosphere is represented by the dotted patterns in each of the five charts, while the boxes represent the notional satellites that are part of the overall space system. The first concept, UV Sensing would provide for the passive measurement of the ionosphere characteristics based on the reflections of UV rays off the ionosphere and complex ground processing to back out useful science data. By using a

---

[75] Anderson, D. a. T. F.-R. (1999). Space Environment Topics: The Ionosphere. Boulder, CO, Space Environment Center, SE-14.

swarm of satellites, rather than one satellite, the accuracy of the science data would be greatly improved. This concept has the benefit of being fairly straightforward in design and technology as well as requiring relatively little power and mass in the passive sensor payload; however, it's hampered by taking passive measurement whose accuracy is less than direct measurement and the required post-processing to obtain useful measurement information.

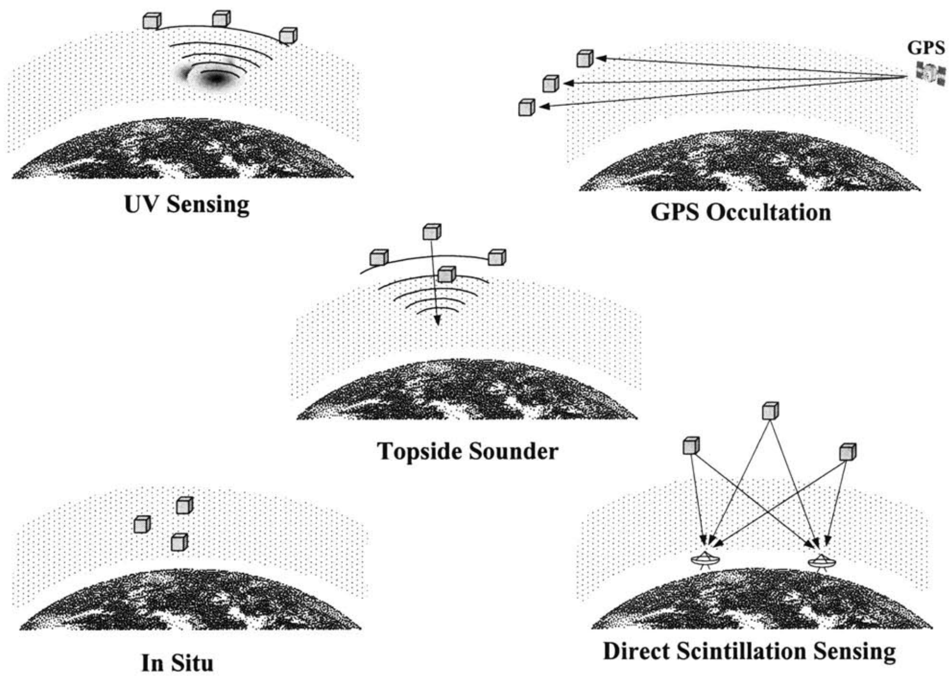


Figure 68: Approaches to Measuring Ionosphere Characteristics

The second possible measurement was another passive technique, GPS Occultation. Again, by acquiring a signal, in this case the GPS transmission, and measuring the effect of the ionosphere on the transmission of the signal through it, models can be developed that back out the expected composition. Using a swarm of satellites, relative differences in GPS signal reception could be used to gain better insight into the small-scale characteristics of the ionosphere.

The third possible approach would be the use of a top-side sounder. By using an active payload that sends pulses from the topside of the atmosphere downward, certain characteristics can be obtained about the ionosphere including charged particle concentration. Further, because most disturbances in the ionosphere occur above the maximum density region, the most compelling ionospheric data could be collected.

The fourth approach, direct scintillation sensing relies a good deal more on the ground segment to measure variability in the ionosphere. By using simple communication schemes from multiple satellite payloads to ground stations, direct scintillation measurements can be taken and then be used to characterize the ionosphere's characteristics.

The fifth approach was the one that was employed in the ATOS architecture. Perhaps the easiest to conceive of all the possible measurement schemes, the in situ approach would rely on direct measurement of ionospheric conditions as the individual satellites passed through it. The payload would be a passive payload consisting primarily of Planar Langmuir Probes (PLPs) to record charged particles densities. This approach has the benefits of having a relatively simple passive payload that requires little power, mass and records data that needs little post-processing to arrive at useful information for the customer. To move further in the conceptual design process, there needed to be a shared understanding of the relative worth of the different attributes of the mission that the customer wanted the systems to achieve.

9.1.4 Derived Utility Function

The utility was derived from the architecture's ability to satisfy three distinct sub-missions. The first, the low latitude survey mission, was an equatorial region survey that would identify unstable regions of the ionosphere near the equator. The second mission, the low latitude snapshot mission, would require the space system to initiate an extensive data collection of an unstable region once the first mission identified a instability. The third mission was to perform a high latitude survey that would accurately measure relative ionospheric density correlated with GPS-to-ground data.

The low latitude survey mission was to measures the low latitude characteristics of the ionosphere at a sampling rate of approximately 1Hz, as shown in Figure 69. From this information, the customer's model could be populated with the large-scale characteristics of the ionosphere.

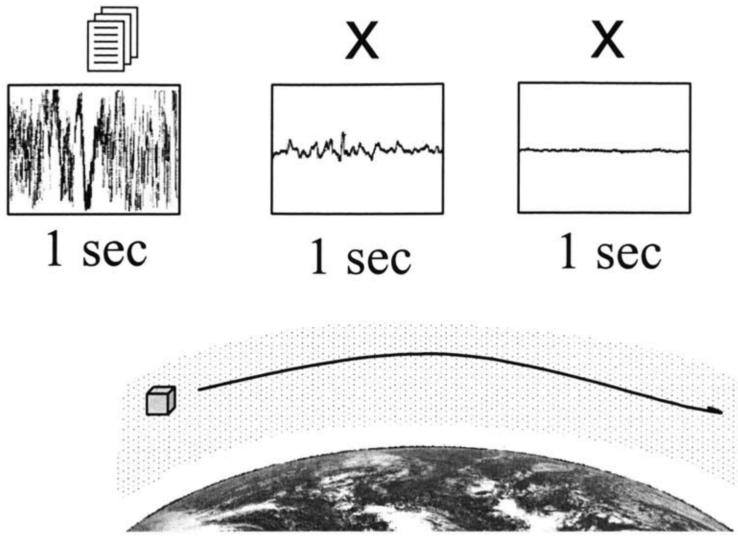


Figure 69: ATOS Low Latitude Survey Mission

The low latitude snapshot sub-mission would be important once the survey mission identified a ionosphere disturbance. Using a swarm of satellites, fine-scale measurements of the anomaly would be collected. As shown in Figure 70, satellites at different separation distances are useful to the customer, because at large separation distances the overall shape and characteristics of the disturbance would be captured, while small separation distances would provide more baseline measurements of variability within the disturbance. All this data would feed into the customer's model and provide better predictability for future communications outage planning.

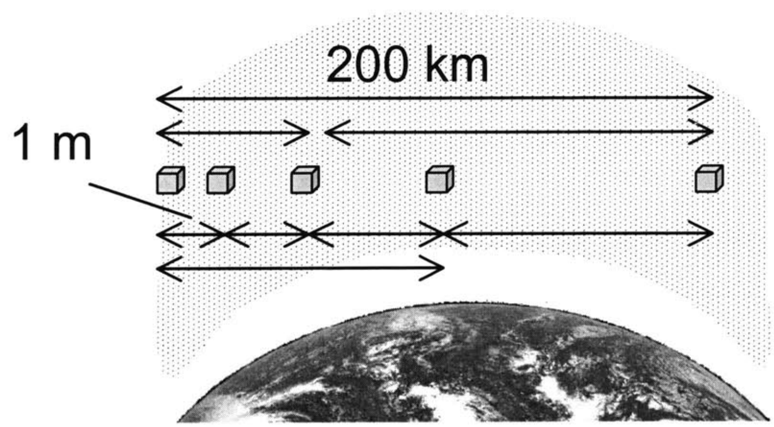


Figure 70: ATOS Low Latitude Snapshot Mission

The last sub-mission is a high latitude survey. As mentioned earlier, the major charged particle concentration in the ionosphere is centered about the equatorial band and the high latitude region. Although not as significant a sub-mission as the low latitude missions, the high latitude mission would provide further population of the science communities global ionospheric model and prediction ability. Typically, the high latitude region is less turbulent than the low latitude region and therefore, the science community is only interested in the survey mission as opposed to the survey and snapshot mission. Figure 71 represents the notional space segment that could accommodate the high latitude mission. The desirable separation among satellites in this mission is about 75km in the direction of longitude and latitude and 20km in the direction of altitude. In the low latitude region, the ionosphere is fairly constant with altitude, this assumption does not hold with the high latitude mission. Further, there would be added value to the science community if GPS occultation measurements could be taken as well to correlate the data produced by in-situ measurements of the swarm.

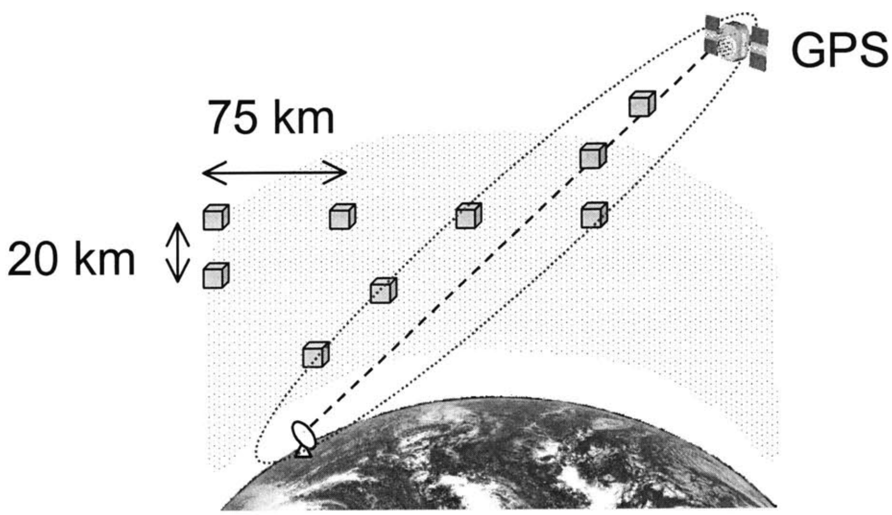


Figure 71: ATOS High Latitude Survey Mission

From the above missions, utility functions were calculated for each of the missions, as a function of each mission's attributes, as notionally shown in Eq. 33, Eq. 34, and Eq. 35. For example, the low latitude survey mission was a function of individual sample observations and the location and time of day of each measurement.

$$U(Low\_Surv) = f(X_1, X_2, ..., X_m) \quad \text{Eq. 33}$$

$$U(Low\_Snap) = g(Y_1, Y_2, ..., Y_m)$$

Eq. 34

$$U(High\_Surv) = h(Z_1, Z_2, ..., Z_n)$$

Eq. 35

Additionally, a total architecture utility variable was defined as a weighted sum of the two separate mission utilities, as shown in Eq. 36. Although this is a simple linear aggregation of the multiple elements of utility it provided a first look at how ideas of utility could be incorporated into the space systems conceptual design process. Considerable progress has been made on subsequent design iterations that exploit the full potential of multi-attribute utility theory.[76]

$$U(Total) = U(High\_Surv) / U_{max}(High\_Surv) + 2 * (U(Low\_Surv) + U(Low\_Snap)) / (U(Low\_Surv) + U(Low\_Snap))_{max}$$

Eq. 36

The design vector that was developed to define the tradespace of architectures that would be investigated is presented in Table 25 and graphically in Figure 72. The design vector consisted mainly of orbital parameters, as the mission was driven by the in-situ locations of individual satellites throughout the mission lifetime.

Table 25: Design vector for the ATOS Satellite System

Name	Description
Altitude	Altitude of the satellite swarm
Subplanes per Swarm	Number of subplanes in swarm
Satellites per Swarm	Number of satellite in swarm
Suborbits per Swarm	The number of concentric orbits in swarm
Subplane Yaw	The yaw angle of the swarm with respect to nadir
Separation Distance	The maximum along track separation

[76] Diller, N., Qi Dong, Carole Joppin, and S. K. Sandra Jo Kassin-Deardorff, Dan Kirk, Michelle McVey, Brian Peck, Adam Ross, Brandon Wood (2001). B-TOS Architecture Study:Second Iteration of the Terrestrial Observer Swarm Architecture. Cambridge, MA, Massachusetts Institute of Technology.

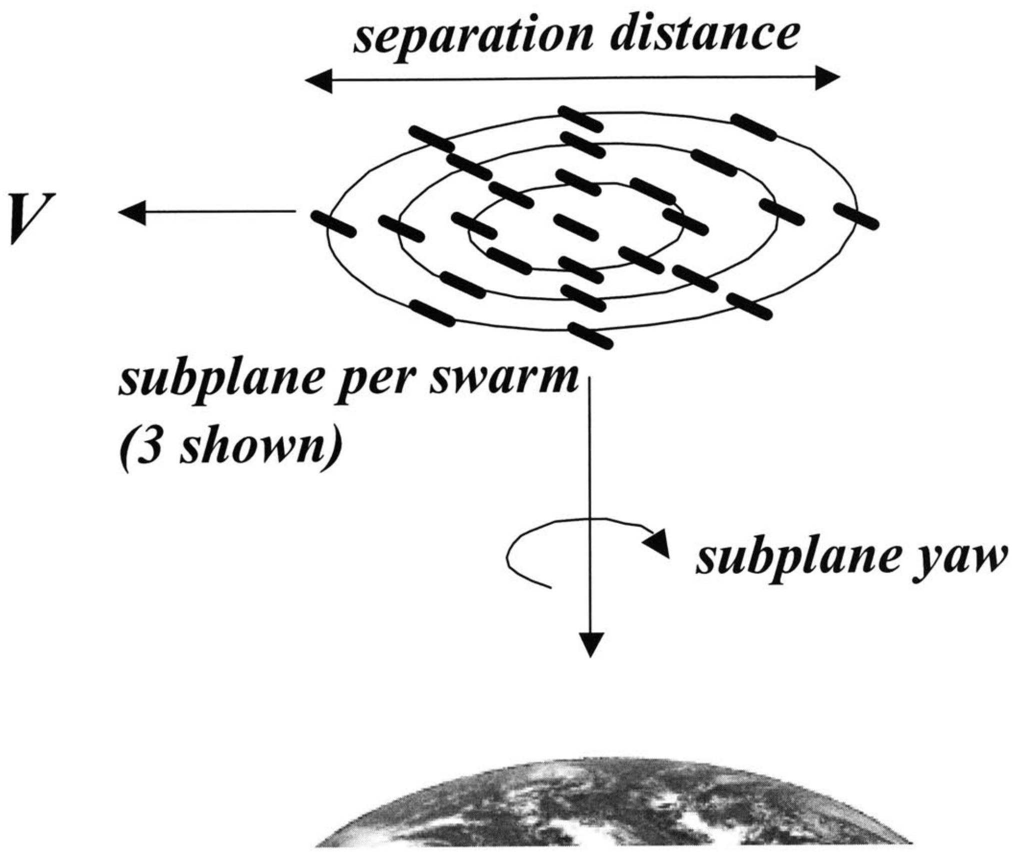


Figure 72: Graphical representation of ATOS Design Vector

9.1.5 GINA/Utility Model

The conceptual design simulation models developed during the ATOS design effort were based on the GINA heritage, but actually went beyond the original approach by applying utility theory to capture the preferences of the customer in the simulation. Instead, utility theory was applied as described earlier and incorporated into the system simulation, as presented in Figure 73 to generate outcome measures that would enable informed trade-offs of potential architectures.

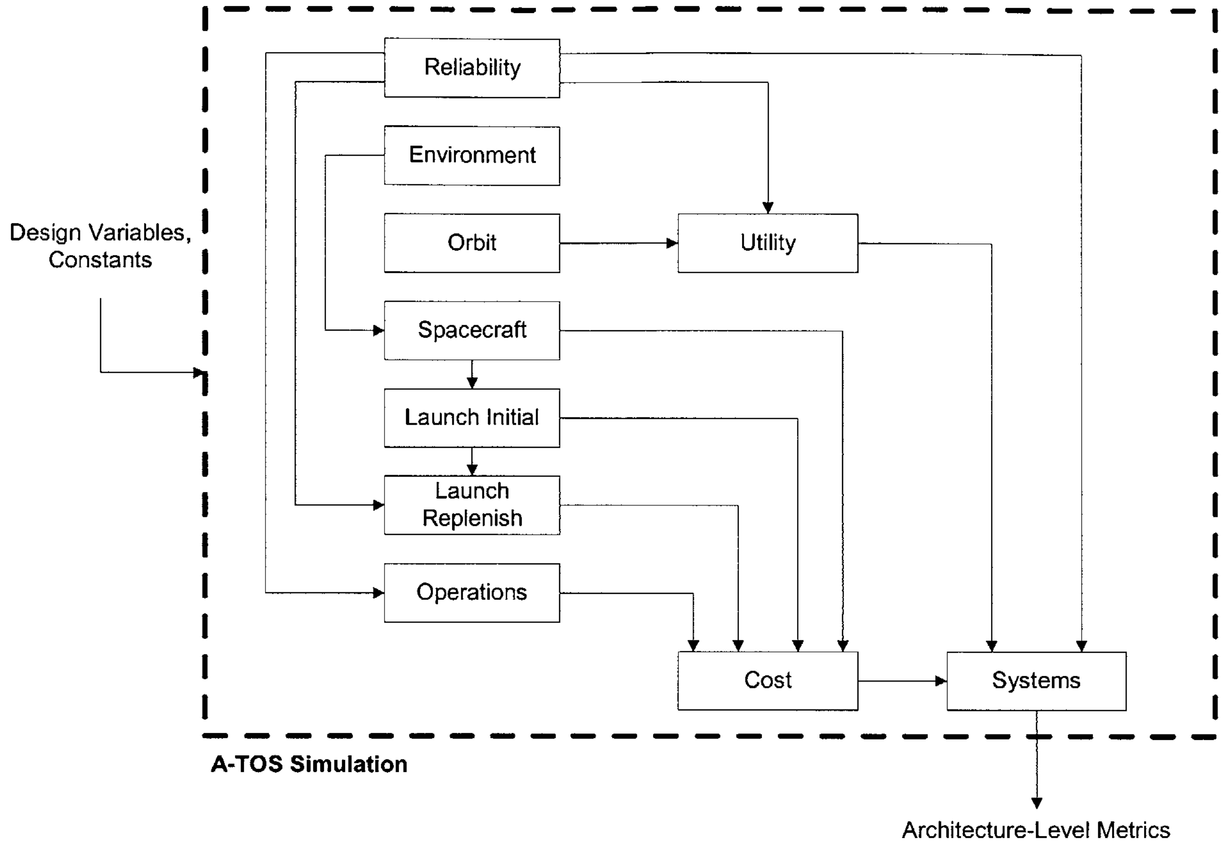


Figure 73: ATOS GINA Model Module Flow Diagram

The ATOS mission used the GINA method as a way of conceptualizing the structure of the simulation model, but strayed from the strict application of information theory and instead implemented a methodology summarized in Table 26. By identifying the customer very early in the process and by capturing their input with a formal utility approach, design trade off were carried out more effectively than would have otherwise been possible to with only performance measures.

Table 26: ATOS Methodology

Collect stakeholder needs
Develop program goals and priorities
Describe and scope the system functionally
Define the solution space based on available technologies and constraints
Develop the mission utility function
Develop a simulation model
Explore the architecture trade space with respect to the utility function
Revisit and verify the stakeholders needs were captured

9.1.6 Model Results

Over four thousand architectures were evaluated using the simulation model described in the previous section. After calculating the expected outcomes for these thousands of potential architectures, the tradespace was explored along the fundamental utility and cost measures developed in the early problem formulation. Figure 74 gives the first look at how the tradespace took shape in terms of low latitude utility, high latitude utility and cost. Each shaded square in the chart represents at least one specific architecture concept, as defined by a unique design vector. In the figure, the two dimensions of customer utility have been plotted and the shaded squares represent the life-cycle cost of a given architecture. The first intuitive conclusion that can be drawn from this tradespace is that utility increases with increasing cost. It is further evident though that there are some relatively inexpensive architectures that accomplish the low latitude mission quite well, but don't perform very well in the high latitude mission. These types of multi-dimensional utility plots can be used with the customer to revisit the relative importance of individual missions.

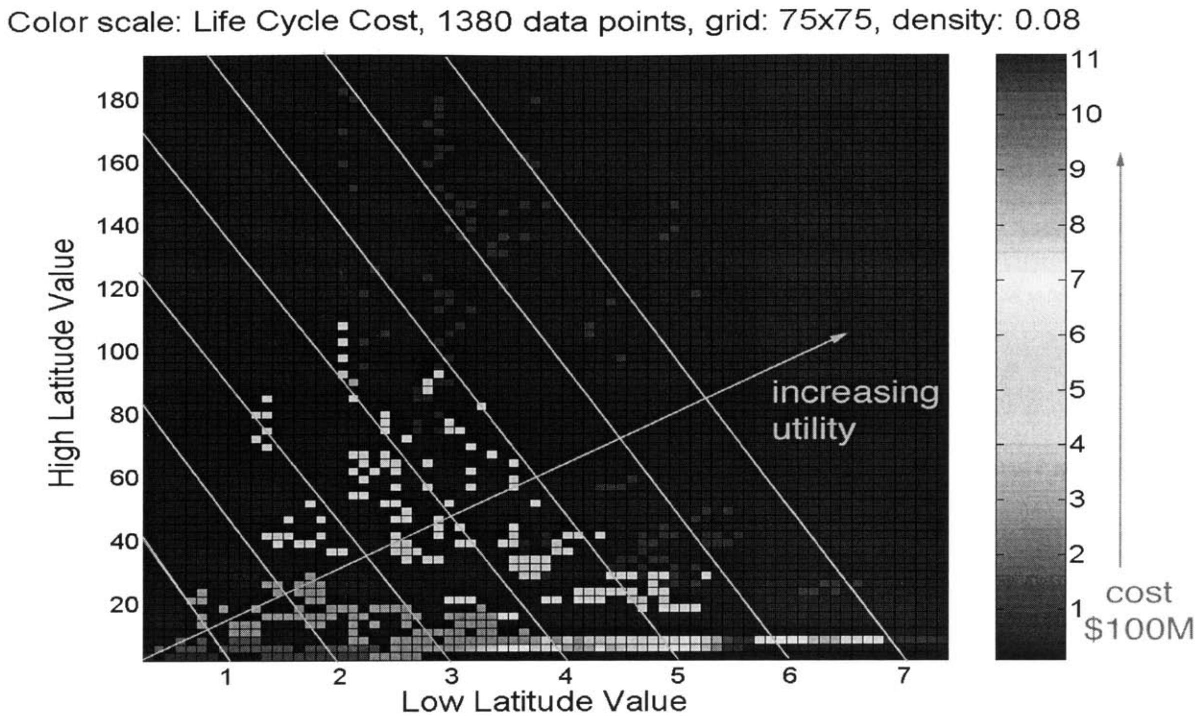


Figure 74: Low and High Utility Tradespace

Exploring the tradespace further, the individual points can be identified by what architecture they represent, as well as what characteristics drive the performance outcomes. Figure 75 represents the total utility and cost predicted outcomes for 1380 designs, which are represented as diamonds in the plot. By using the total utility function in Eq. 36, overall architectural preferences can begin to be observed. For example the highest utility-per-dollar or the highest total utility architecture can be found, as shown in the figure. Interesting to notice is that the highest utility-per-dollar architecture is separated from a "bad" design by only a few design characteristics changing.

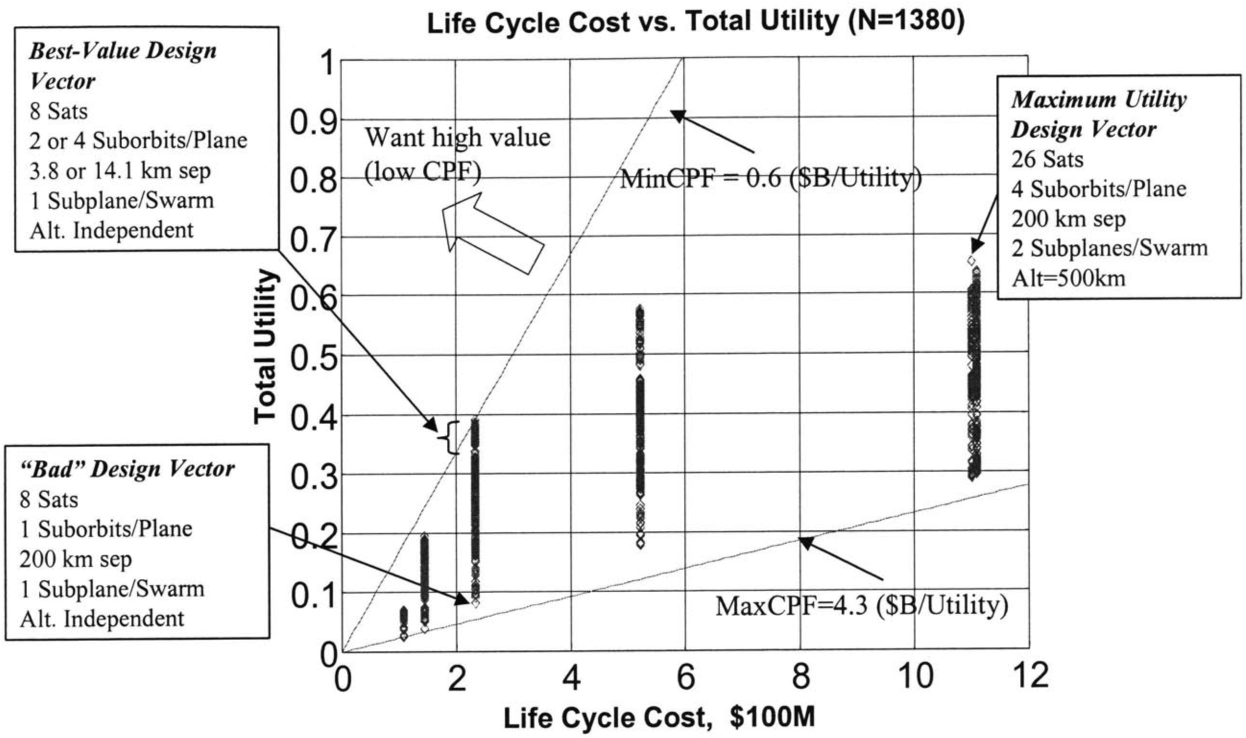


Figure 75: ATOS Cost and Utility Tradespace

One of the most important things to notice is that this is a fairly large tradespace with varying outcome measures and that there are some very good designs, but there are also some less desirable outcome designs. The vertical bands that are being formed are due to the number of satellites in the swarms that drive the lifecycle cost of the mission. Other dimensions of the design vector drive the outcome value for total utility.

As was done in the previous case, uncertainty investigation is limited to the Pareto optimal front of architectures in the tradespace, primarily for the reason of computational efficiency. The true Pareto optimal architectures in the ATOS tradespace consist of only 6 architectures, however. Therefore to increase the pool of potential architectures to draw upon in the portfolio analysis, and because of no computational limitations, 30 near Pareto optimal architectures were chosen to use in the uncertainty analysis approach. These 30 architectures are graphed in Figure 76. The next section addresses the question of: what is the embedded uncertainty in each of these architectures being evaluated?

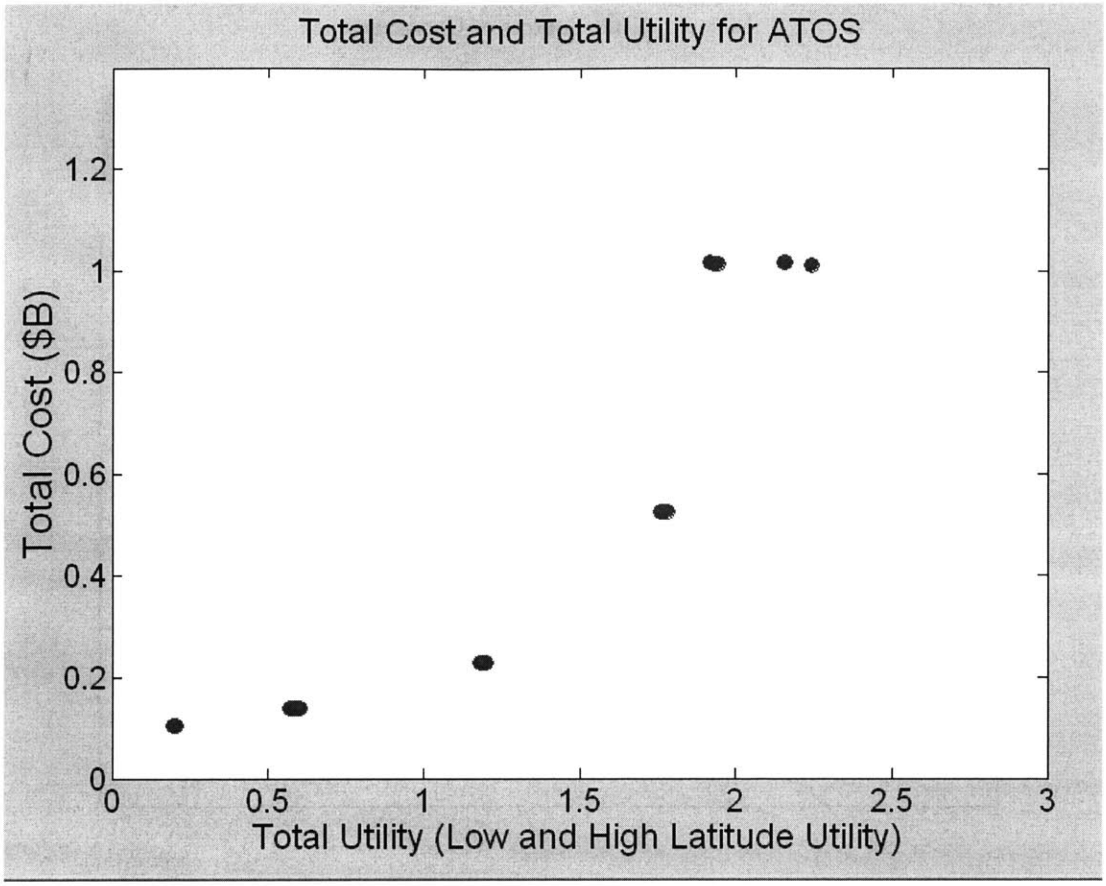


Figure 76: (Near) Pareto Optimal Front for the ATOS Architectural Tradespace

9.2 Uncertainty Quantification

The first step in quantifying embedded architectural uncertainty is to bound the sources of uncertainty appropriately. The possible sources of uncertainty that affect the architecture outcomes must first be identified and the designer must decide which will be included in the analysis. There are two primary reasons to not include all sources of uncertainty in practice. The first is that the analysis would quickly become intractable and the second reason is that there are some sources of uncertainty whose effects would be either very difficult to model or have little impact on the architectural uncertainties.

9.2.1 Sources of uncertainty

The uncertainty quantification in ATOS included technical, cost, modeling and utility uncertainty. Table 27 lists the uncertainties that were included in the case.

Table 27: ATOS Sources of Uncertainty

Sources of Uncertainty for ATOS
Mean Time to Failure per Satellite
Cost Estimating Relationships for Satellite Bus
Payload Cost Uncertainty
Number of Controllers Required per Satellite
Cost of Ground System (Software and Hardware)
Low Latitude Mission Utility Relative to High Latitude Mission Utility
Satellite Density

9.2.1.1 *Technical Uncertainty*

The major technical uncertainty that was included came from the mean time to failure (MTTF) for a single satellite in the constellation. Because the mean time to failure is a representative reliability of the entire satellite, it is a very difficult number to measure. Small satellites such as those presented have previously used 500 months as the mean time to failure. However, there are not a lot of these distributed satellite systems in operation, so the reliability warranted the inclusion of uncertainty bounds. A normal distribution with a standard deviation of 50 months, as shown in Figure 77, was used to represent the uncertainty in MTTF.

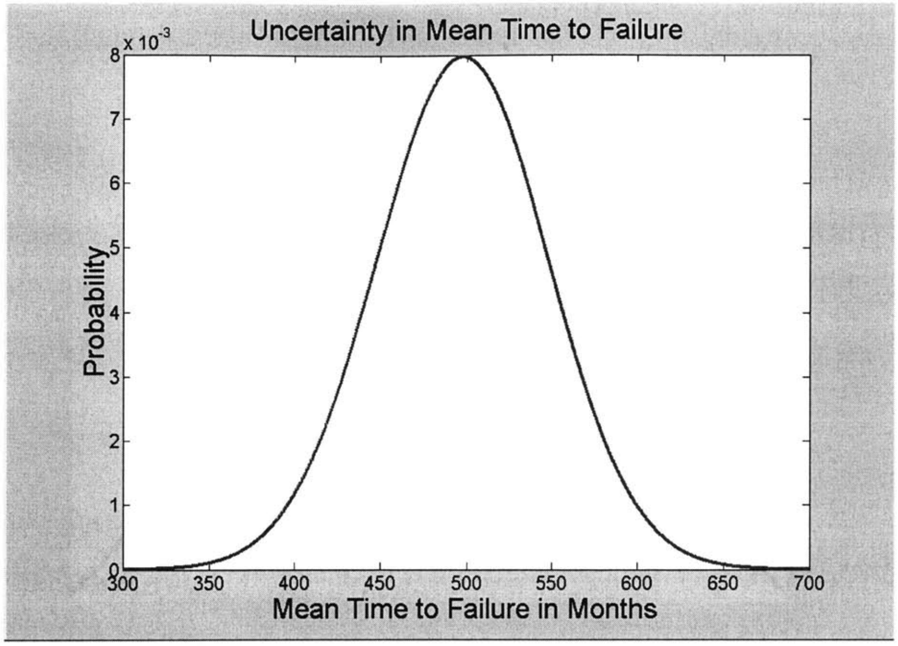


Figure 77: Uncertainty in the Mean Time to Failure for a single satellite

9.2.1.2 Cost Uncertainty

The cost uncertainty arose from both cost to develop and the cost of operations. The uncertainty in the cost of development of the satellite bus was captured using the standard error in the historical cost estimating relationships used in the simulation models. The development cost uncertainty for the payload was also included. The operations cost uncertainty arose from uncertainty in the estimation of the individual sources that contribute, such as the number of engineers and operators required for maintaining the system and the uncertainty in the cost of ground software and equipment.

9.2.1.3 Utility Uncertainty

Because this case relied on utility as the key decision criteria, an element of utility uncertainty was included in the analysis. The combined low latitude mission and high latitude mission were difficult for the customer to distinguish in terms of precise relative value, so a nominal value of 2:1 was used as the utility ratio of the combined low utility mission to the high utility mission as was shown in Eq. 36. Instead of using this ratio, the relative worth of the high latitude mission over the low latitude mission was modeled as a probabilistic density function, as shown in Figure 78 with a mean of 2 and a standard deviation of 1.

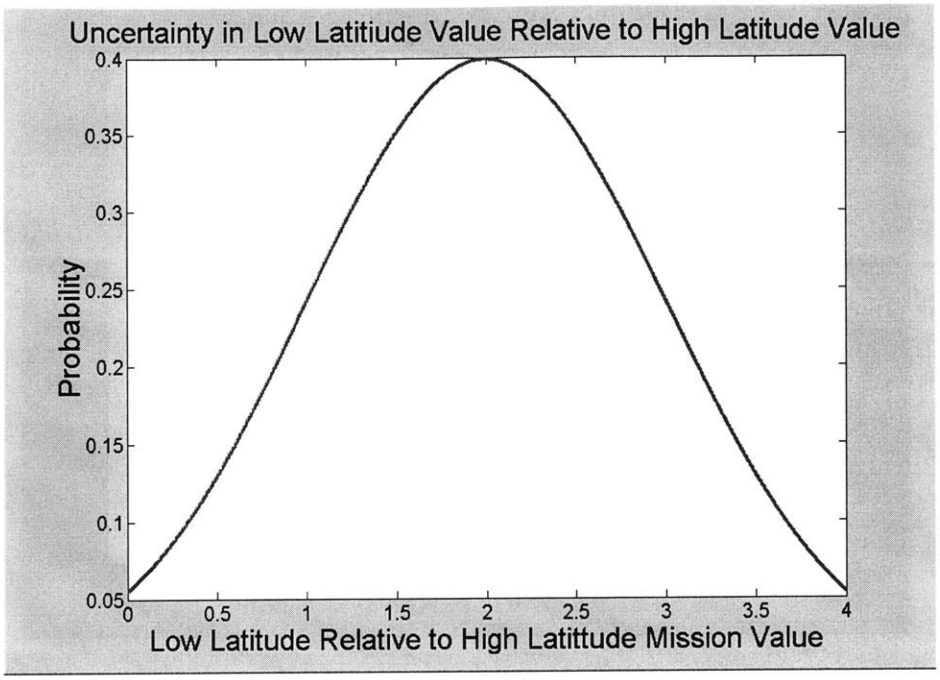


Figure 78: Uncertainty in Low Latitude Value Relative to High Latitude Value

9.2.1.4 *Model Uncertainty*

The model uncertainty in the ATOS case study arose from the designers in ability to precisely quantify different aspects of the system through mathematical formulation. Instead, design rules of thumb or parametric relationships are used that are based on historical observations. Two model uncertainties in the case of ATOS were the satellite density, which is used to calculate the derived mass and overall structure within the model, and the learning curve used to estimate production costs for more than one satellite.

9.2.2 *Embedded Architectural Uncertainty*

Once the sources of uncertainty have been identified and each has been quantified and inserted into the constants vector, a Monte Carlo sampling routine is conducted with the goal of developing distributions of outcomes for each of the architectures evaluated, as shown in Figure 79. These distributions characterize the embedded architectural uncertainty and are used to compare architectures and their responses to the various sources of uncertainty.

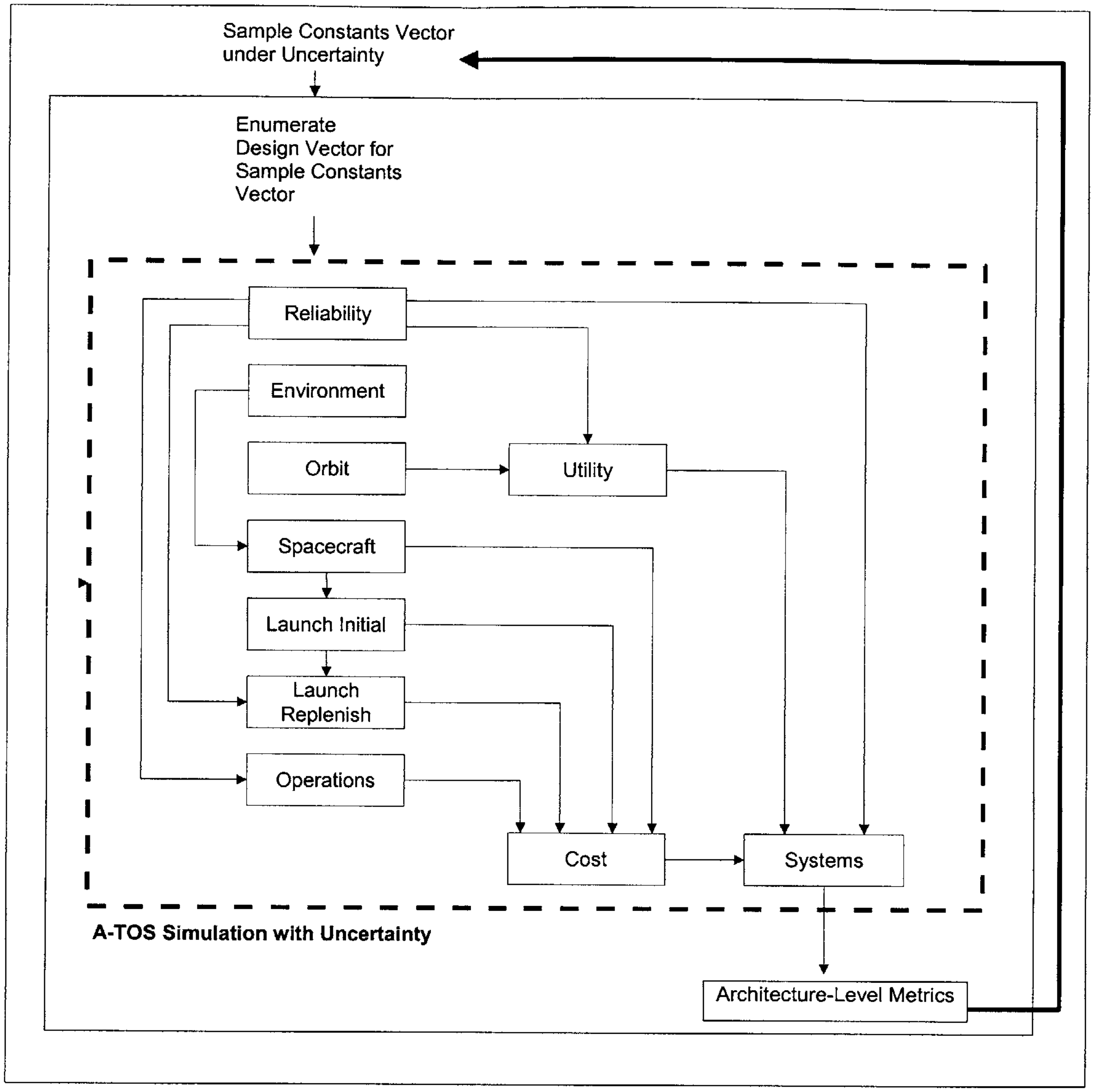
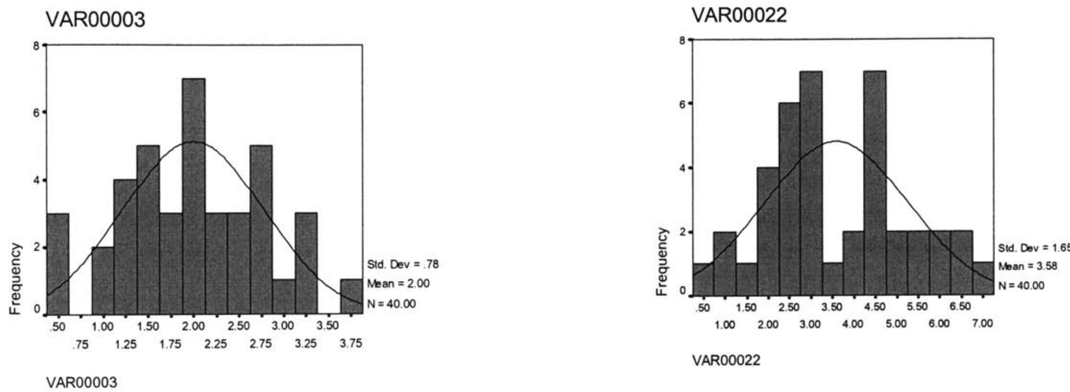


Figure 79: ATOS Simulation Flow with Uncertainty

9.2.2.1 Normality in Architectural Distributions

Once the outcome distributions have been calculated, they can be plotted in histograms such as those in Figure 80. Portfolio theory and optimization abstracts uncertainty characteristics to simple measures of expectation and variance that are consistent with gaussian distribution. The individual architecture uncertainty distributions should be investigated to satisfy this assumption that the characteristics of the uncertainty distribution can indeed be captured by these simple measures. Normality can be tested using statistical measures such as skewness and kurtosis as well as graphical techniques. Using the Shpiro-Wilk test for normality, the hypothesis for normality could not be rejected for any of the architectural distributions created.



DesignVector=>2,300,3.8,1,1,30 ***DesignVector=>16,700,14.1,3,1,0***

Figure 80: Representative Architectural Uncertainty Distributions

The end result of the uncertainty propagation is an ordered set of outcomes for every architecture considered. This data can be used to create statistical measures of uncertainty for a single architecture and also the pair-wise correlation coefficients that are necessary in portfolio optimization. Figure 81 presents a snapshot of the embedded uncertainty that was calculated for each architecture on the Pareto optimal front. The points represent the expected value of the architecture in terms of cost and total utility, while the ellipses represent the uncertainty of each architecture in both dimensions.

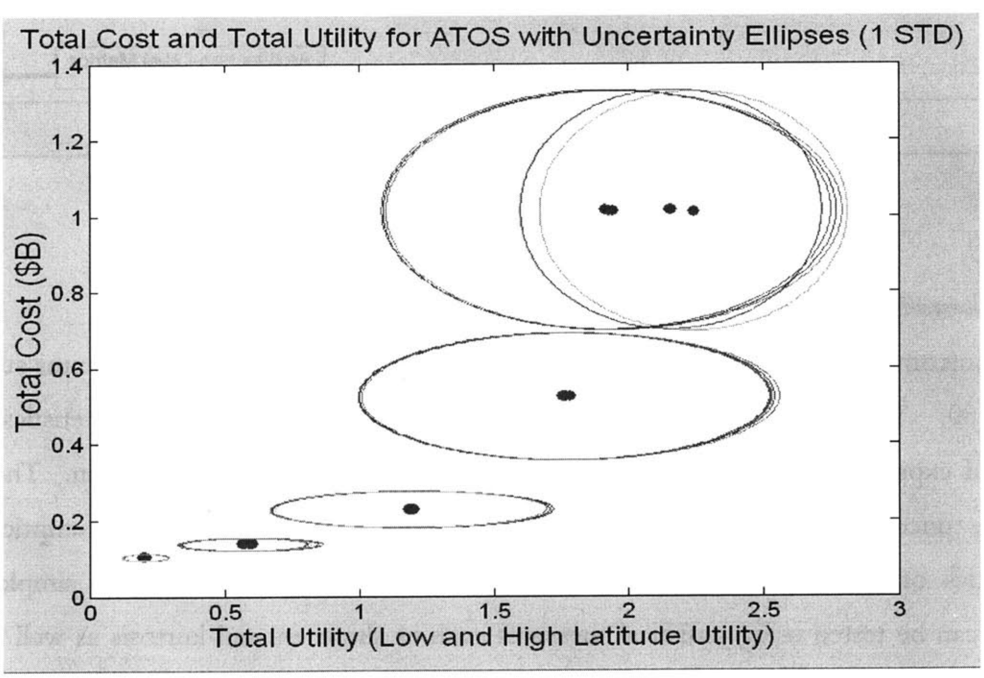


Figure 81: ATOS Utility and Cost Tradespace with Uncertainty Ellipses

9.3 Portfolio Assessment

Using the quantified uncertainty for each architecture, and knowing the correlation of outcomes, the portfolio analysis technique was applied, as described in Chapter 6. Using an expected return and covariance matrix based on 60 observations of 30 architectures, the portfolio optimization algorithm was applied to generate the efficient frontier.

Figure 82 presents the ATOS efficient frontier, as derived under the classic portfolio optimization algorithm in Eq. 10. Although this efficient frontier appears very similar to frontiers seen in the previous cases, it has a very interesting quality. The efficient frontier extends beyond the performance achieved by any single architecture, as shown in Figure 83. This is an important finding as it shows that portfolio theory can provide more potential to the decision maker than would otherwise be possible with a single asset. The reason for the extension beyond any single architecture can be traced back to Figure 74. Notice that some architectures achieve a very high level of low latitude value at low cost but perform the high latitude mission poorly, whereas others perform well in both low and high latitude missions. Because of these two different approaches to achieving total value, there arises a chance to diversify uncertainty. The amount diversified is not enormous, but it is measurable and presents one of the first illustration that portfolio assessment in space systems can help decision makers achieve higher returns for a given level of uncertainty than they otherwise could with single assets.

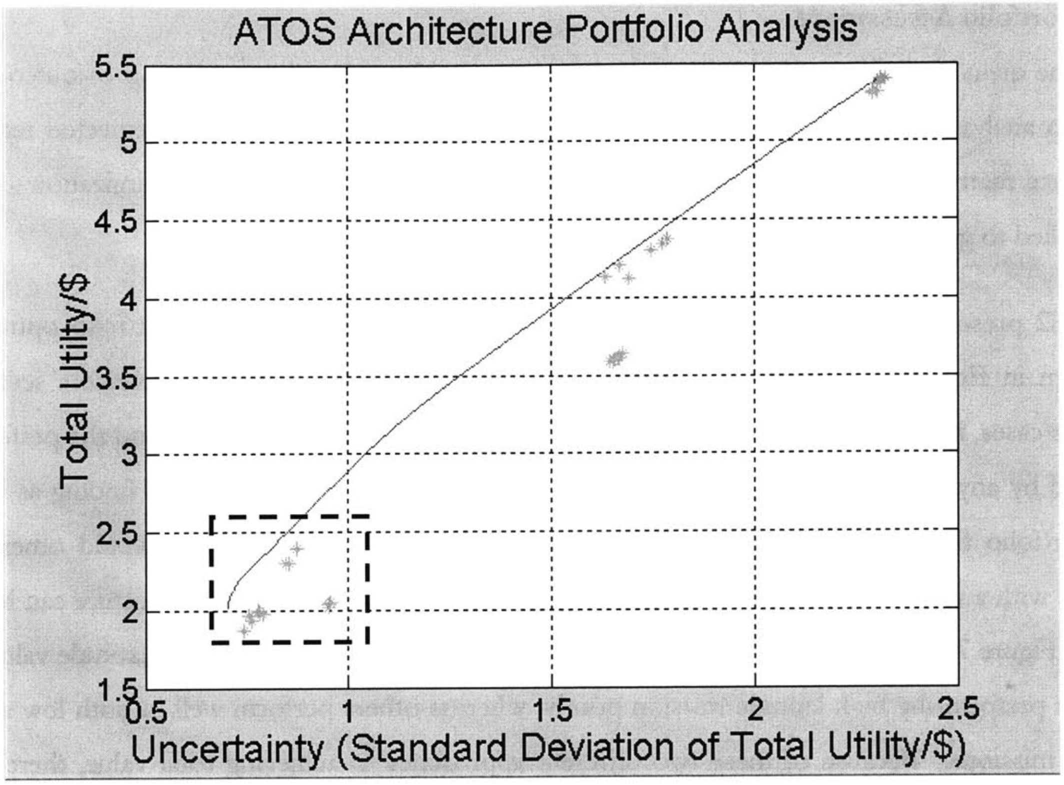


Figure 82: Efficient Frontier in the ATOS tradespace

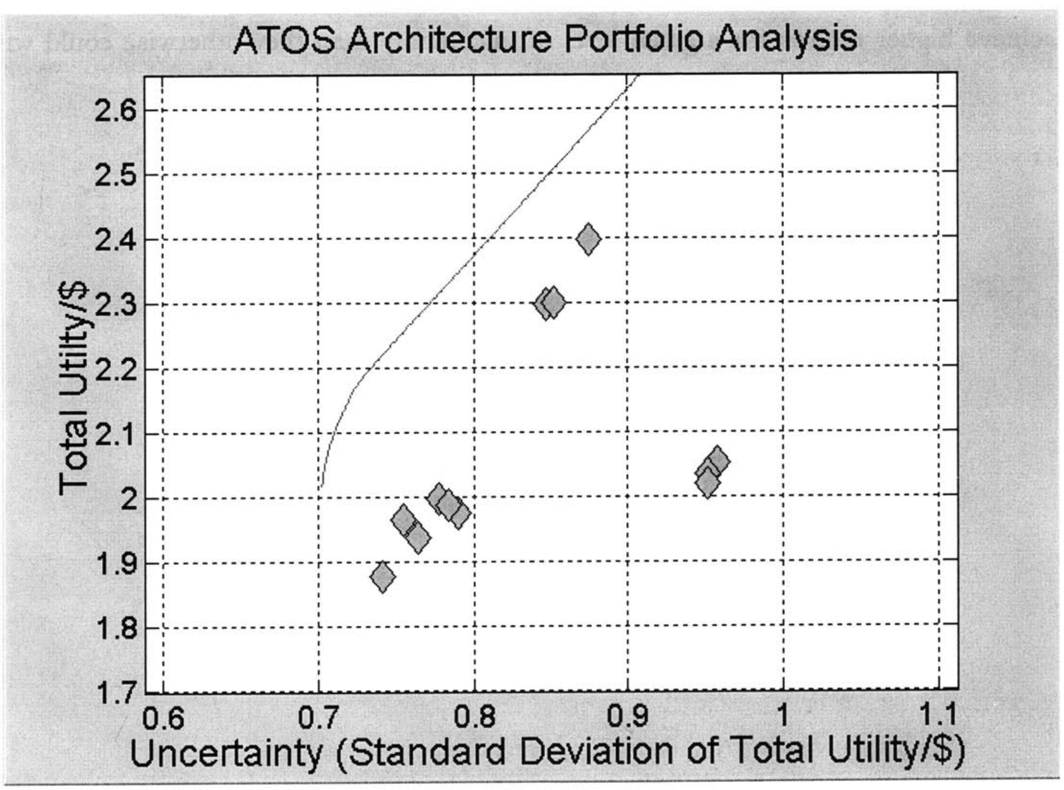


Figure 83: Closer Look at the ATOS Efficient Frontier

Using the flight simulator shown in Figure 84, the designer can dynamically explore the portfolios that lie along the efficient frontier. Notice for example the dot highlights a portfolio of composition architecture 2 and architecture 25. This combined portfolio provides for an expected return of 0.88 Total Utility/$ and an uncertainty of 0.3 Total Utility/$. Using this approach, the decision maker can quickly identify the changing characteristics of portfolios along the efficient frontier.

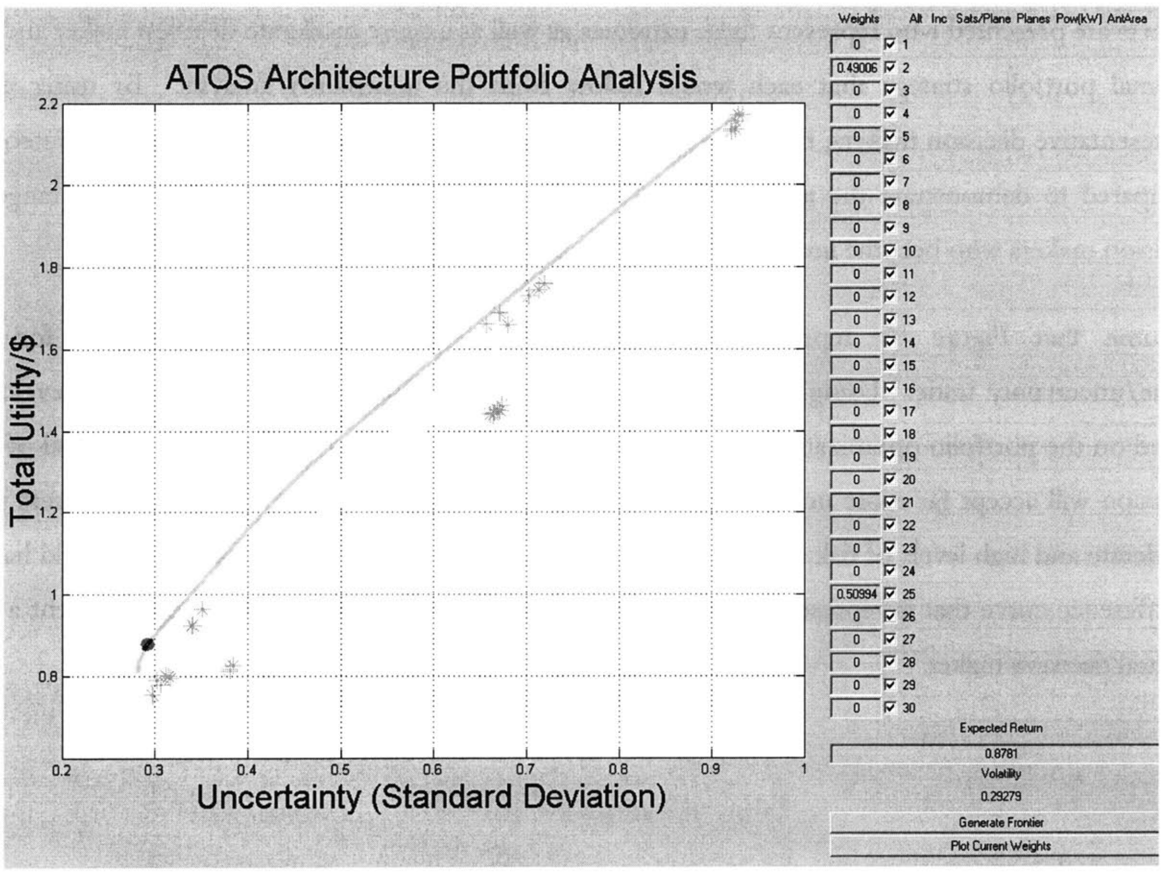


Figure 84: Flight Simulator for the ATOS Architectural Portfolio Analysis

9.3.1 Quantifying Decision Maker Risk Aversion

Once the efficient frontier has been calculated, the next logical next step is to determine where what the optimal strategy is for a given decision maker. As discussed in Chapter 6, capturing decision maker risk aversion can be relatively straightforward through the use of indifference curves and iso-utility lines. By interacting directly with the customer with this graphical technique, preferences of the decision maker can be captured and incorporated into the portfolio optimization. As was previously seen, the level of risk aversion of the decision maker can greatly affect the optimal strategy and this is also true in this case study. There are a total of 7 architectures that constitute membership in a portfolio somewhere on the efficient frontier and there are many combinations of those possible.

The highly risk averse individual would find himself looking at portfolios in the lower left corner of the efficient frontier, while the low risk aversion decision makers would have preferences leading to strategies in the upper right corner. Rather than chose a single decision makers aversion, two decision makers are presented who represent these extremes as well as a more moderate decision maker and the optimal portfolio strategy that each would follow from the uncertainty analysis. By using three representative decision makers, the overall sensitivities of the portfolio can be observed and outcomes compared to demonstrate the adaptability of the uncertainty analysis approach to a large range of decision makers who become involved in the development of space systems.

Assume that Figure 85 represents the three-decision maker's indifference curves for the value/uncertainty trade. Using this information an optimal investment strategy can be developed based on the portfolio optimization. As one might expect, the decision maker with a low level of risk aversion will accept far more uncertainty for a given increase in value than the decision makers with moderate and high levels of risk aversion. Notice that a completely risk averse individual would have a indifference curve that is represented by a vertical line, while a horizontal line would represent a risk neutral decision maker.

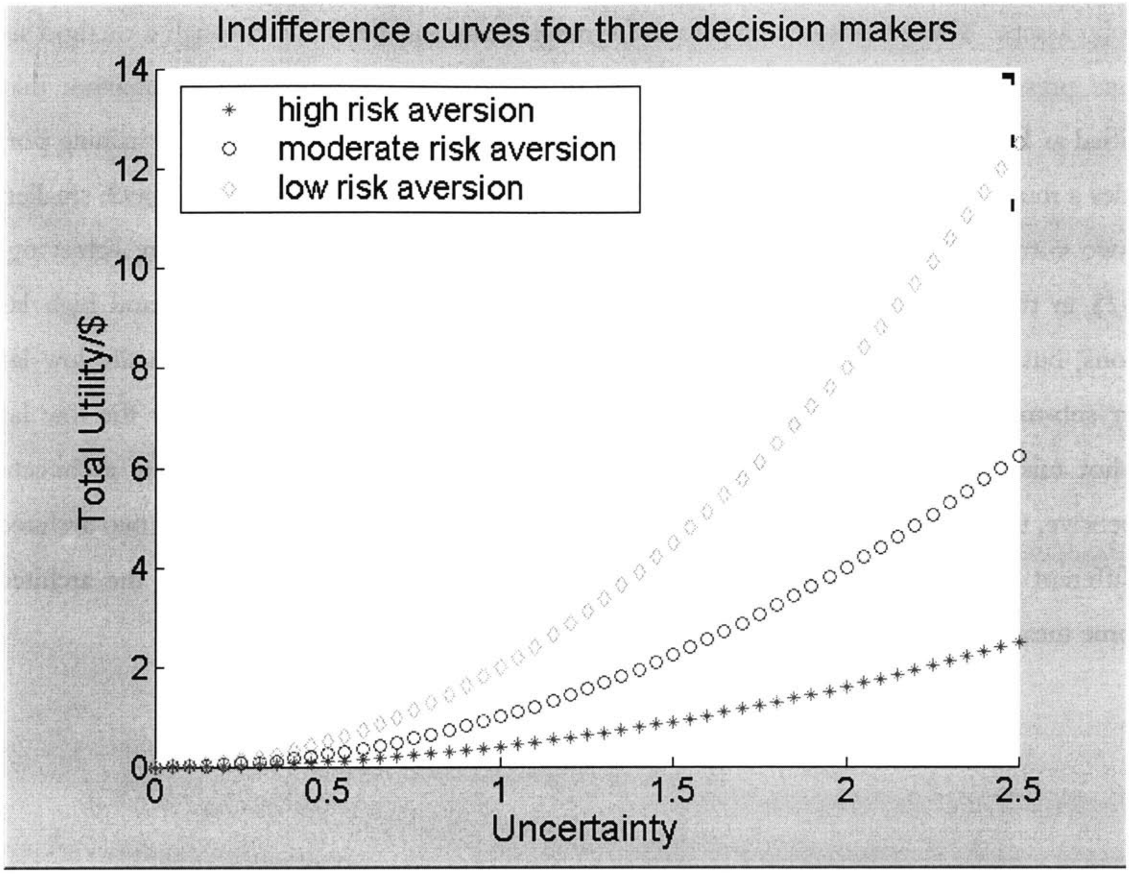


Figure 85: Indifference curves for three decision makers

9.3.1.1 *Decision maker with high risk aversion optimal portfolio strategy*

The first decision maker looked at has a risk aversion coefficient, *k*, equal to 2. This is a relatively high degree of risk aversion and so it is expected that this decision maker's optimal portfolio strategy reside in the lower left corner of the efficient frontier, and that is exactly what Figure 86 shows. To identify this point, the efficient frontier is plotted and then overlaid with iso-utility curves for a given decision makers aversion level. The three convex curves represent the iso-utility curves for a decision maker, each increasing in utility as they move to the upper left. Therefore the optimal portfolio investment strategy would lie at the tangent point of the iso-utility curves and the efficient frontier, as show in Figure 86.

The composition of the optimal portfolio for this decision maker is 48% of one architecture and 52% of another, as shown in Table 28. The two architectures that have been selected behave differently enough to move the curve beyond a simple linear combination of the two and provide measurable value through diversification. A strategy has been created that has less uncertainty than either of the portfolio assets. These kinds of non-intuitive synergies can only be found through a method such as the one presented here. The majority of the portfolio is occupied by the architecture that was identified as having the maximum utility in the tradespace in Figure 75, while the remaining portfolio includes a much smaller architecture of only 2 satellites, compared to 26, and has a much smaller cost. The two combine synergistically in this portfolio because the two architectures are achieving total utility/$ in two ways. The 26 satellites architectures is achieving both the low and high latitude missions, but at a high price. The 2 satellite mission is achieving good results on the low latitude survey sub-mission, but doesn't have enough satellites to do a good job at either the low latitude snapshot mission or the high latitude survey. On the other hand, the 2 satellite architecture is inexpensive, thus it achieves a good total utility/$. Because the approaches that the two architectures are different with respect to total utility/$, the effects of uncertainty on each of the architectures outcome measure have been different.

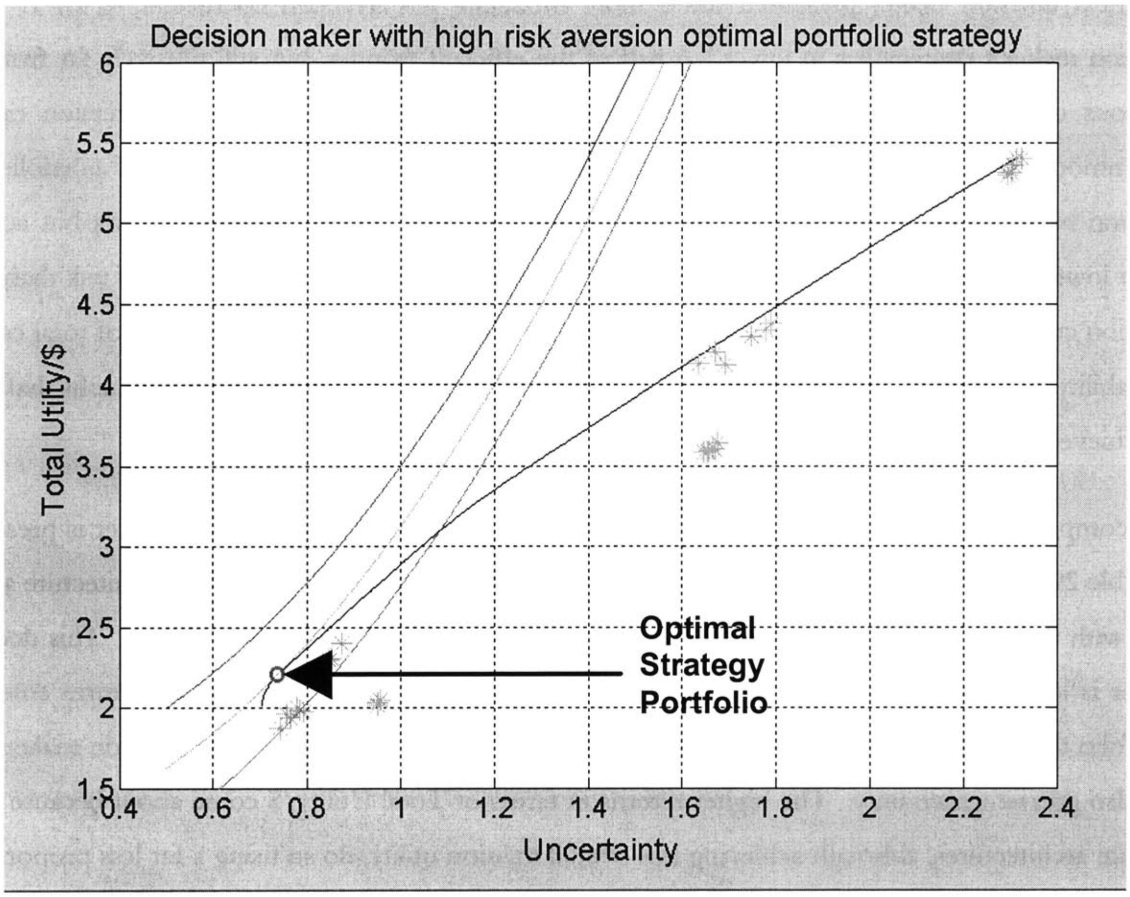


Figure 86: Optimal investment strategy for high risk aversion decision maker

Table 28: Composition of ATOS high risk aversion decision maker strategy

	Percentage of Portfolio	Architecture Design Vector {sats/swarm, suborbs,size,yaw,subplanes,alt}	Total Utility/$	Uncertainty
	52%	{26,4,14.1,60,2,700}	2.4	0.9
	48%	{2,1,3.8,30,1,300}	1.9	0.8
	100%	Portfolio Value and Uncertainty	2.2	0.7

9.3.1.2 Decision maker with moderate risk aversion optimal portfolio strategy

The next decision maker presented has a more moderate risk aversion coefficient, *k*, of 1. This decision maker's strategy lies in lower left half of the efficient frontier, but still relatively far from the previous decision maker. Notice that a decision maker with this level of risk aversion can be accommodated in the portfolio analysis technique. However, without the creation of portfolio, the decision maker would have to settle for single assets that meet his risk aversion criteria but achieve much lower total utility/$, or the decision maker would need to accept a higher level of risk than their aversion coefficient would predict them to be comfortable with to achieve a high level of total cost/$. The ability of portfolio theory to create continuous investment strategies is another benefit that can't be achieved with single assets.

The composition of the optimal portfolio is for the moderate risk averse decision maker is presented in Table 29. Once again, the majority of the portfolio is occupied by the 26 satellite architecture as was seen with the previous decision maker. The rest of the portfolio has changed though. This decision maker is looking to get more return and willing to accept more risk, so two architectures enter the portfolio that have greater returns than the architectures in the highly risk averse decision maker case, but also greater uncertainty. The higher returns in terms of Total Utility/$ come about because the 4 satellite architectures, although achieving less overall mission utility, do so using a far less proportional cost.

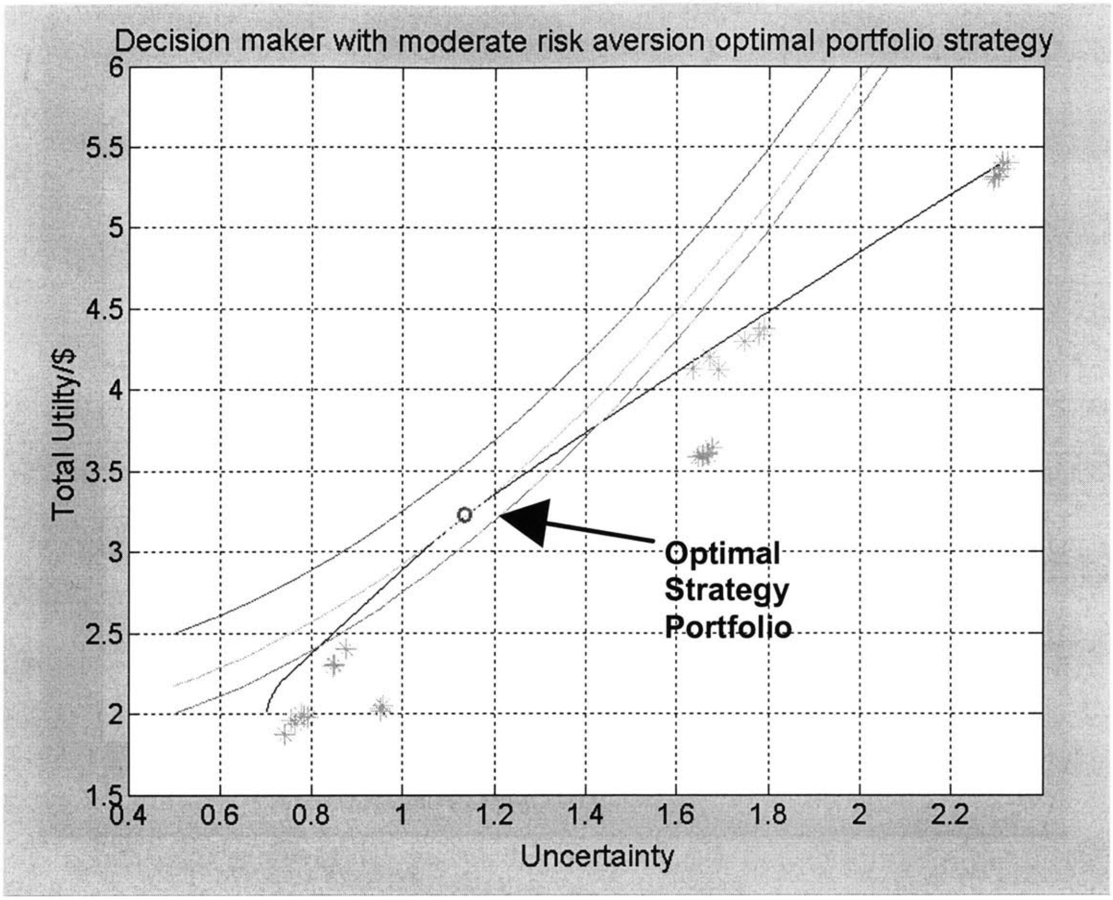


Figure 87: Optimal Investment strategy for moderate risk aversion decision maker

Table 29: Composition of ATOS moderate risk averse decision maker strategy

Percentage of Portfolio	Architecture Design Vector {sats/swarm, suborbs,size,yaw,subplanes,alt}	Total Utility/$	Uncertainty
57%	{26,4,14.1,60,2,700}	2.4	0.9
28%	{4,2,3.8,30,1,500}	4.2	1.7
15%	{4,1,14.1,0,1,700}	4.1	1.6
100%	Portfolio Value and Uncertainty	3.2	1.1

9.3.1.3 Decision maker with low risk aversion optimal portfolio strategy

Finally, a decision maker who has a relatively low risk aversion coefficient, *k*, of 0.4 is investigated. The optimal portfolio strategy, as shown in Figure 88, lies in the upper right corner of the efficient frontier. With a relatively low level of risk aversion, this type of decision maker is trying to get the most value out of the system with relatively little worry about the risk that the solution might carry.

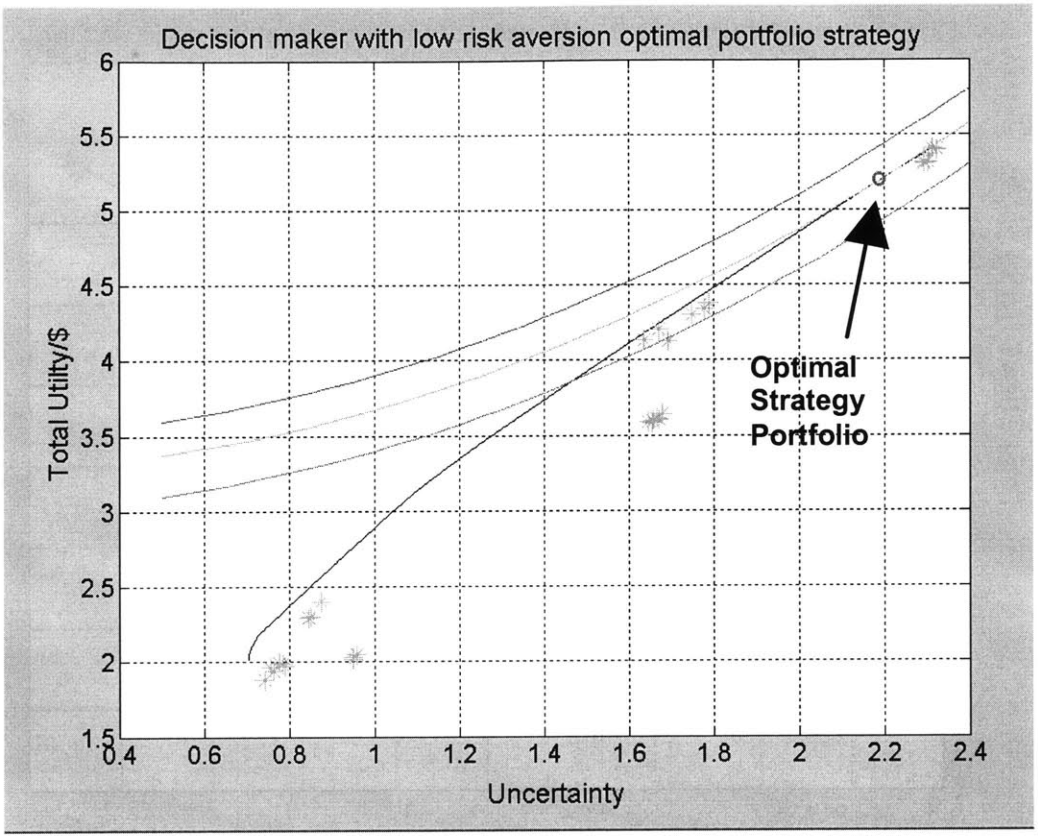


Figure 88: Optimal strategy portfolio for low risk aversion decision maker

The composition of the optimal portfolio is presented in Table 30. Notice one architecture from the moderate risk averse decision maker is kept, but a new architecture has been added as well. This architecture should be familiar, as it was called out in Figure 75 as the best value design. Indeed, this architecture did have the highest total utility/$, but it also had the highest level of uncertainty for any of the architectures.

Table 30: Composition of ATOS low risk averse decision maker strategy

	Percentage of Portfolio	Architecture Design Vector {sats/swarm, suborbs,size,yaw,subplanes,alt}	Total Utility/$	Uncertainty
13	83%	{8,4,14.1,30,1,700}	5.4	2.3
11	17%	{4,2,3.8,30,1,500}	4.2	1.7
	100%	Portfolio Value and Uncertainty	5.2	2.2

9.3.2 Implications of incorporating the extensions to portfolio theory

Although classic portfolio techniques were used above, the extensions to portfolio theory, as presented in Chapter 6, could also be applied to glean any new information. The first extension that can be made is separating the risk from the uncertainty previously used. This separation can be useful to illustrate to decision makers that architectures are more or less risky than their uncertainty distributions might lead to one to believe. The second extension that is used is to quantify the cost of carrying a portfolio of architectures, rather than any single asset.

9.3.2.1 Differentiating risk from uncertainty

The first step to differentiate the risk from the uncertainty in the distribution can be found by focusing on the downside semi-variance, as previously discussed in Chapter 6. First adjust the variance of individual observations around the expectation as shown in Eq. 37. Then simply calculate the variance of these new observation errors, as shown in Eq. 38.

$$(r_i - E(r))^- = \begin{bmatrix} (r_i \text{ - E(r)) if } r_i \leq 0 \\ 0 \text{ if } r_i > 0 \end{bmatrix}$$

Eq. 37

$$S_{Downside} = 2 * E\left[\sum (r - E(r))^2\right]$$

Eq. 38

Thus creating a downside covariance matrix as shown in Eq. 39.

$$Q_{Downside} = \begin{bmatrix} S_{d1}^2 & \rho_{2,1} S_{d2} S_{d1} & \rho_{3,1} S_{d3} S_{d1} & \bullet & \rho_{n,1} S_{dn} S_{d1} \\ \rho_{1,2} S_{d1} S_{d2} & S_{d2}^2 & \rho_{3,1} S_{d3} S_{d1} & \bullet & \rho_{n,2} S_{dn} S_{d2} \\ \rho_{1,3} S_{d1} S_{d3} & \rho_{2,3} S_{d2} S_{d3} & S_{d3}^2 & \bullet & \rho_{n,3} S_{dn} S_{d3} \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \rho_{1,n} S_{d1} S_{dn} & \rho_{2,n} S_{d2} S_{dn} & \rho_{3,n} S_{d3} S_{dn} & \bullet & S_{dn}^2 \end{bmatrix}$$

Eq. 39

Finally implement the portfolio algorithm in the similar manner to traditional portfolio theory, only substituting $Q_{donwside}$ for Q, as shown in Eq. 40.

$$\max : E(r)w - \frac{k}{2} w' Q_{Downside} w$$
$$\text{s.t.} : \sum_{i=1}^{n} w_i = 1$$
$$\text{s.t.} : \text{w} \geq 0$$

Eq. 40

Using this algorithm, calculate an efficient frontier in the same manner performed earlier in the case. The tradespace of risk and function per cost is shown in Figure 89.

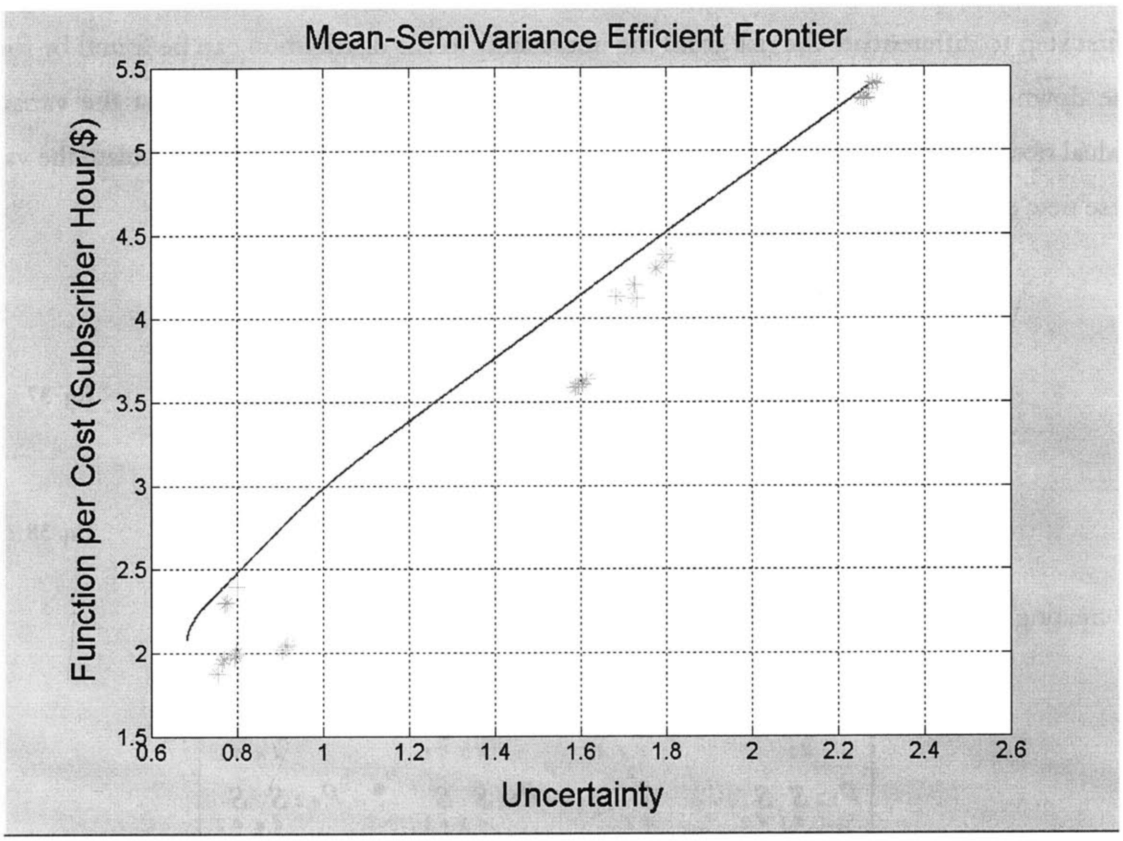


Figure 89: ATOS portfolio analysis with semi-variance

The semi-variance scaled efficient frontier with the full uncertainty distribution efficient frontier is shown in Figure 90. The efficient frontier for both the full uncertainty portfolio analysis, as well as the semi-variance analysis is shown in the figure. The most interesting insight to take away from this chart is that there is about the same level of risk in the tradespace that would be perceived if uncertainty were used as a surrogate for risk.

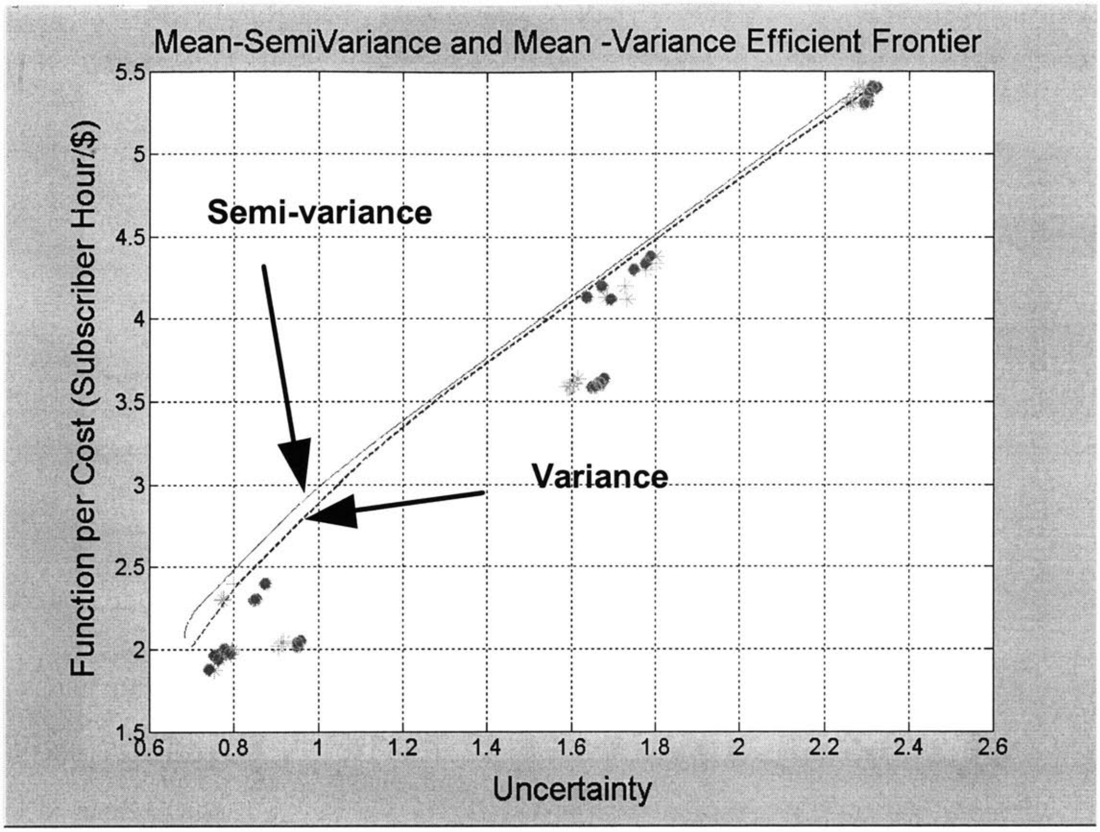


Figure 90: ATOS portfolio analysis with full uncertainty and semi-variance

With a different efficient frontier, it is conceivable that decision makers should choose different optimal portfolio strategies. Using the same decision makers previously used, the low, moderate and high risk aversion, the effects that this extension to classical portfolio analysis would provide are discussed.

The first decision maker was the high risk aversion decision maker. Under the efficient frontier using semi-variance, his optimal portfolio strategy has changed only in percentage investment in each of the assets in his portfolio, as shown in Figure 91 and Table 31. The optimal portfolio now has a higher degree of emphasis on the higher return/higher risk asset.

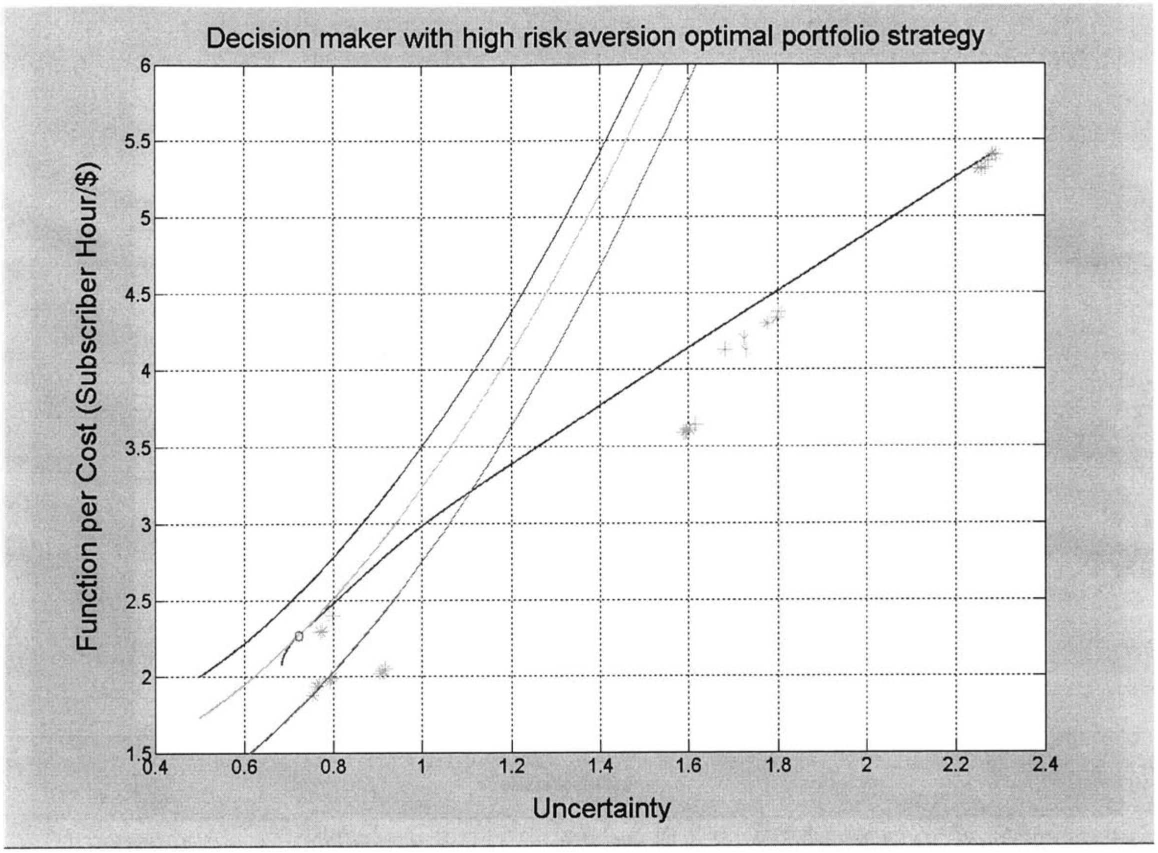


Figure 91: Optimal investment strategy for high risk averse decision maker

Table 31: Composition of ATOS high risk aversion decision maker strategy using semi-variance

	Percentage of Portfolio	Architecture Design Vector {sats/swarm, suborbs,size,yaw,subplanes,alt}	Total Utility/$	Uncertainty
	64%	{26,4,14.1,60,2,700}	2.4	0.8
	36%	{2,1,3.8,30,1,300}	2.0	0.8
	100%	Portfolio Value and Uncertainty	2.3	0.7

The moderate decision maker has kept two of the previous three asset portfolio. There is also an overall greater percentage investment in the higher return/higher risk asset.

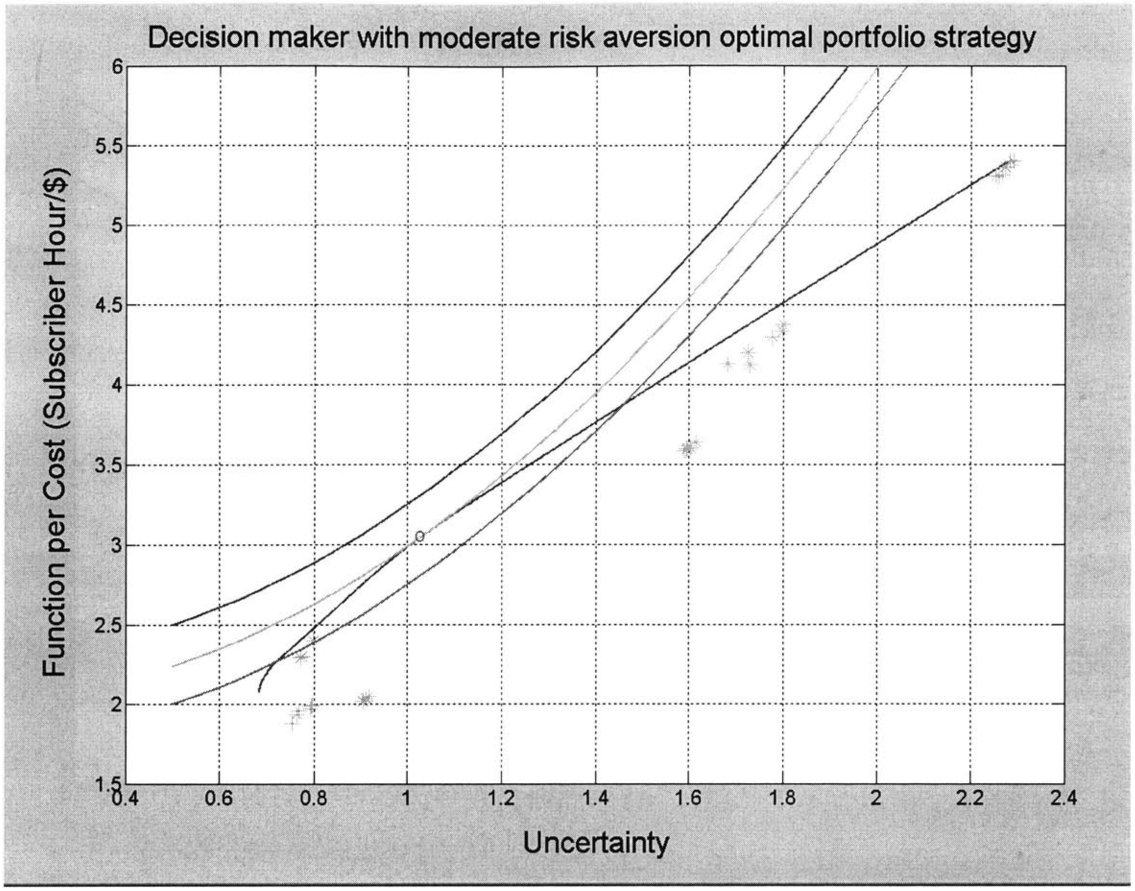


Figure 92: Optimal investment strategy for moderate risk averse decision maker

Table 32: Composition of ATOS moderate risk aversion decision maker strategy using semi-variance

	Percentage of Portfolio	Architecture Design Vector {sats/swarm, suborbs,size,yaw,subplanes,alt}	Total Utility/$	Uncertainty
	65%	{26,4,14.1,60,2,700}	2.4	0.8
	35%	{4,2,3.8,30,1,500}	4.3	1.8
	100%	Portfolio Value and Uncertainty	3.1	1.0

The low risk aversion decision maker has moved his optimal strategy to a one-asset portfolio. Although there did not appear to be a large degree of shift in the efficient frontier using semi-variance in place of full uncertainty, there was enough to move 17% investment of another architecture out of this portfolio, so that 100% of the resources could be devoted to the highest value system.

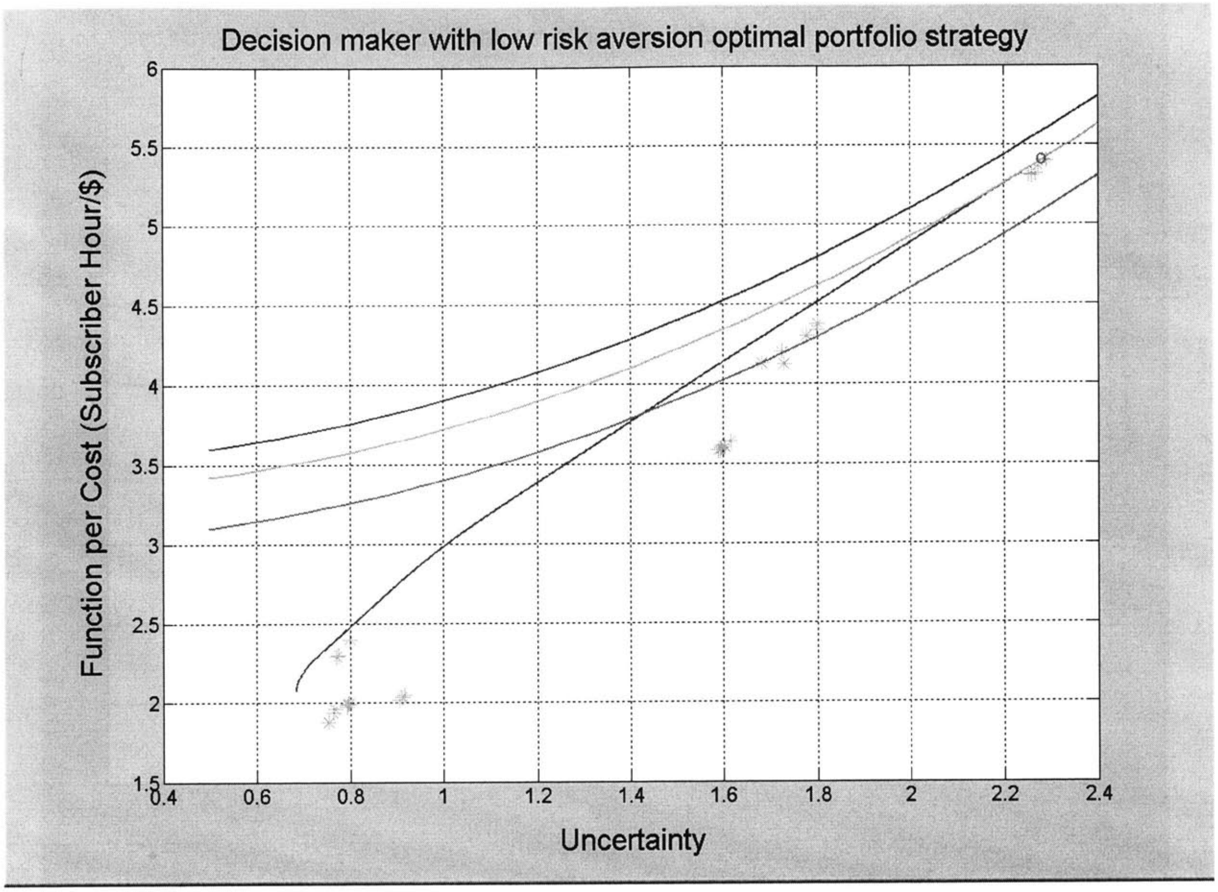


Figure 93: Optimal investment strategy for low risk averse decision maker

Table 33: Composition of ATOS low risk aversion decision maker strategy using semi-variance

	Percentage of Portfolio	Architecture Design Vector {sats/swarm, suborbs,size,yaw,subplanes,alt}	Total Utility/$	Uncertainty
	100%	{8,4,14.1,30,1,700}	5.4	2.3
	100%	Portfolio Value and Uncertainty	5.4	2.3

9.3.2.2 Cost of diversification

Some of the optimal portfolio strategies suggested in this case have included more than one asset and therefore more than one architecture to pursue in design. In order to calculate the exact cost to diversify using a portfolio, the individual assets should be investigated by the designers and decision makers. For example, two 4 satellite architectures with similar characteristics differing only in altitude by 200km will probably not incur twice the design cost of a single architecture because many of the similarities in each architecture can be design for both. In contrast, a two-asset portfolio with a 26 satellite architecture at very large separation distance and a two satellite swarm at very small separation distance architecture might represent a significantly higher cost to develop than either of the two individually.

A measure of the cost of diversification can be used to judge the relative extra cost of carrying a portfolio based on the correlation of assets in the portfolio, as described in Chapter 6. For example, the high risk aversion decision maker under the full uncertainty distribution would have a cost to diversify equal to 33% of the cost to design the 2 satellite architecture. This high cost to diversify is based on the low correlation that exists between the two assets, 0.598. In contrast the cost to diversify of the low risk averse decision maker would be only 3.5% of the cost to design the 4 satellite architecture in the portfolio. This lower additional cost is due to the higher degree of correlation that exists, 0.965.

9.4 Conclusions

This case provided an opportunity to implement the uncertainty analysis approach in the context of a space system whose primary mission was science. Unlike the previous two cases that focused on a direct function per cost metric, like probability of detection per dollar or subscriber hour per dollar, the ATOS case study demonstrated the use of the uncertainty analysis method in a system exploration that centered around utility/$ as a fundamental decision criteria.

This case also presented the benefit that portfolio analysis can provide to a decision maker by creating investment strategies for design that achieve higher value for lower uncertainty than would be possible with any single asset. Illustrated by the high risk averse decision maker whose optimal portfolio consisted of architectures that achieved value through different approaches and therefore reacted differently to uncertainty. Finally the focus on downside of uncertainty was shown to have impact on the optimal investment strategy of different decision makers.

Chapter 10

CONCLUSIONS AND RECOMMENDATIONS

The uncertainty analysis approach presented here represents not only a new way of looking at uncertainty in the conceptual design of space systems, but also a new of doing space systems conceptual design in general. Its implementation has been demonstrated on three distinct cases each representing teaching lessons on the potential this uncertainty analysis approach provides. Beyond the approach itself, numerous observations have been made on the conceptual design process and the role that uncertainty plays. By establishing a framework in which to identify, assess, quantify, propagate and manage uncertainty, formal trade-offs involving uncertainty can begin to take place. These kind of trade-offs can lead to better guidance in choosing an architecture or set of architectures in the conceptual design phase and along with that reduce the cost and cycle time due to unplanned rework.

In this chapter, the collective observations of the case studies and approach are reviewed, this thesis' contribution to the state of the art are revisited and directions of future research that build on the foundations of this research are suggested.

10.1 Collective Observations from Three Case Studies

Three different case studies were used to illustrate the potential of the uncertainty analysis approach presented in this thesis. This section revisits the observations gained by the individual cases and the overarching themes that evolve from them.

10.1.1 Level of diversity with respect to uncertainty can be observed

The level of diversity in the architectural tradespace can be observed through the covariance matrix and the overall behavior of the portfolio tradespace. The more diverse a population of assets in the tradespace, as in the ATOS case, the closer the correlation coefficients will be to zero and in turn the more potential opportunities for diversification of uncertainty. This level of diversity can generally be seen in the portfolio tradespace, the more diverse tradespace of architectures will have an efficient frontier that extends beyond the uncertainty and value of any individual asset.

Diversity among a tradespace of architectures is not readily visible from the design parameters alone. Instead, the diversity of the tradespace with respect to uncertainty is emergent once the approach has been executed. This is another reason why the term *embedded uncertainty* is used to describe the characteristic uncertainty in each architecture.

10.1.2 Portfolio assets may differ at the architecture, system, subsystem or component level

This is an important observation because it goes back to what a portfolio is, as the term is used in this thesis. The portfolio is a set of assets that a decision maker invests in to achieve a return. In the case of the TechSat 21 case, examples of portfolios were presented whose assets would potentially differ by only the power and size of the transmission antenna illustrating only component and perhaps subsystem differences. In the broadband case study, there were portfolios whose composition included MEO and LEO satellites—substantially different systems, and in varying architectural configurations. Likewise in the ATOS example, substantial differences were observed at the architectural level, with the high risk aversion decision maker having an optimal investment strategy of two very distinct concepts, one very large swarm having 26 satellites at 700km and another much smaller 2 satellite swarm at 300km.

Because of the variety of differences that distinguish assets in the portfolio, the implementation of portfolio strategies will be different. For example, it may be difficult to convince a decision maker to invest in three or four architectures at first. However, the different assets may only be pointing out very specific features of the overall concept that should be held open.

10.1.3 Total tradespace uncertainty analysis can be more cumbersome than valuable...using a subset of the tradespace for uncertainty analysis is more effective

Developing distributions of outcomes for architectures can be a computationally intensive task. The detail and run-time of the design simulation model will largely dictate the extent to which uncertainty analysis can be applied to the entire tradespace. This thesis presented the uncertainty analysis approach applied to the Pareto optimal architectures that were found in exploring the traditional cost and utility tradespaces. By focusing on the subset of best architectures under consideration, statistically significant distributions of outcomes can be calculated for each architecture under evaluation. As more effective computation schemes are researched or more computation power becomes available, the tradespace can be broadened to include more dominated solutions that might add to the decision maker's options.

10.1.4 Pareto optimal architectures don't necessarily lie on the efficient frontier of the uncertainty/value tradespace.

Although Pareto optimal architectures were used as inputs to the uncertainty analysis approach, the cases showed that Pareto optimality in the cost and utility tradespace doesn't dictate their existence in the efficient frontier of portfolios. This suggests that those Pareto optimal architectures would never be part of an investment strategy identified by the portfolio analysis and further that the architectures are therefore candidates for removal from the set under consideration.

10.1.5 Upside and downside of uncertainties can be separated, as risk and reward.

Indeed the uncertainty in the traditional portfolio theory commingles the upside and downside of uncertainty, but it is fairly straightforward to separate the two. The separation can present the decision maker with different optimal strategies than would otherwise be considered under the total uncertainty implementation of portfolio optimization. This distinction between portfolios under full uncertainty and downside uncertainty arises from the outcome distributions not being truly normal. For example, a set of architectures with right skewed distributions might move the efficient frontier to the left in the portfolio tradespace, thus allowing more risk averse decision makers, portfolio strategies with higher returns.

10.1.6 Distribution rather than the extreme approach provides better confidence, but requires more computation.

The extreme approach to uncertainty propagation is far less computationally intensive; however, the level of precision in the distribution is not nearly as good as the Monte Carlo distribution technique of uncertainty propagation. The choice between the two will be a question of computational resources and the number of architectures that are to be looked at.

The extreme approach is best suited to reach initial best/worst case uncertainties, as was seen in the TechSat 21 example, or to identify architecture behavior under very specific instances of uncertainty. The approach is also best suited to exploring many architectures at once, because it requires far less computation time than the Monte Carlo simulation technique. In some cases, in may be best to perform an extreme approach assessment of the entire tradespace to ensure the "right" architectures are being included in the uncertainty analysis framework and then the Monte Carlo simulation technique could be used with the subset of architectures identified from the extreme approach to develop outcome distributions from which more confident portfolio investment strategies could be established.

10.1.7 Sources of uncertainty other than technical can often drive portfolio strategies

The presence of market uncertainty in the broadband case study is a simple, yet powerful example of the role that a non-technical uncertainty can play in defining embedded architectural uncertainty and optimal portfolio strategies. In the case of the broadband system, uncertainty in the overall potential market and the market that the system would capture created a significant amount of uncertainty for large LEO systems that although having significant returns, also had considerably more uncertainty

It was also shown that other uncertainties, such as those in the utility functions of missions, as in the ATOS example, have significant impact on optimal strategies to pursue. In this case, the total utility of the mission was comprised of achieving a low latitude mission component and a high latitude utility component. The uncertainty of the relative importance of each was a source included in the analysis. There are of course many other non-technical sources of uncertainty as shown in Table 34 and every effort should be made to include as many sources as are applicable.

10.1.8 When the Pareto optimal architectures are relatively few, more dominated solutions can be included in the analysis.

Although, it was found that all Pareto optimal architectures are often found to not exist on the efficient frontier of the portfolio tradespace, it was also shown that non-Pareto optimal architectures can. This was demonstrated in the ATOS example, where a relatively small set of architectures occupied the Pareto optimal front, 6, and additional architectures were added to the analysis to provide a broader pool of potential assets to draw from. In the end, seven architectures were found to exist in portfolio along the efficient frontier. Given availability of computation power, or a small set of Pareto optimal architectures, it may serve the designer to investigate a larger collection of architectures from the initial tradespace.

10.2 Contribution to the State of the Art

This research breaks new ground in a number of areas and furthers the research of others in a number of ways. By building on the foundation of current uncertainty assessment in space systems design and applying the interdisciplinary concept of portfolio theory, this thesis extends the state of the art of conceptual design and the way uncertainty can be identified, assessed, quantified and managed.

10.2.1 Developed an approach to quantify and understand embedded architectural uncertainty

The idea that architectures have associated with them a distinguishing characteristic in embedded uncertainty and that this characteristic can and should be used in trade-offs and decision making throughout design is a fundamental insight that comes directly from this work. Without the inclusion of uncertainty analysis, designers aren't pressed to question their assumptions and the decision makers are without valuable information that could prevent future rework.

In addition to quantification techniques of embedded architectural uncertainty were a suite of visualization techniques that provide necessary communication vehicles of architectural and tradespace uncertainty. Single dimension, multi-dimensional single architecture techniques as well as methods for visualizing multiple architectures' uncertainties simultaneously were presented.

10.2.2 Applied portfolio theory to the design of space systems thus making uncertainty trade-offs possible

The interdisciplinary application of portfolio theory to space systems provides a new approach to managing uncertainty in the conceptual design tradespace. The approach provides for strategies to form around the basis of decision maker's aversion to uncertainty and risk and takes into account the non-intuitive aspects of tradespace uncertainty, specifically covariance.

10.2.3 Developed an approach that is adaptable for different stakeholders and systems

The uncertainty analysis approach includes preferences of decision makers in suggesting optimal strategies, thus making the approach adaptable for organizations that deal with many customers. As was pointed out through the case studies in Chapter 3, there are a number of different customers that are being served and a single adaptable framework provides the best hope for adoption in practice.

10.2.4 Contributed ideas of upsides and downsides of uncertainty

This thesis established emphasized and demonstrated the difference between risk and uncertainty and illustrated that uncertainty is not always to the detriment of the system. By using semi-variance techniques to bisect an outcome distribution about its mean, the negative consequences of uncertainty and the positive consequences of uncertainty could be quantified and incorporated into the portfolio optimization to produce investment strategies that are driven by risk, rather than total uncertainty.

10.2.5 Produced case studies that illustrate lessons learned from uncertainty analysis

The three case studies that were used in this thesis serve as a basis for future implementations of the uncertainty analysis framework in cases of similar characteristics. They illustrate different potential outcomes that might be observed in practice and serve as guides to practitioners of the uncertainty analysis method.

10.2.6 Developed overarching principles of uncertainty in the design of space systems

As stated in chapter 3, there were three engineering principles on the subject of uncertainty proposed from this work.

> *Principle 1: Irreducible uncertainty exists in all space systems architectures* – Sources of uncertainty in conceptual design can be reduced but never extinguished. Because of the interaction of humans, technology and an open system environment where markets and politics come into play, uncertainty can be guaranteed.

Principle 2: Space system architectures can be characterized by their embedded uncertainty – In the same way that an architecture can be characterized by its cost and performance, so too can it be characterized by it embedded uncertainty. Trade-offs can be made with uncertainty and other architectural features and decisions can be influenced by uncertainty as a distinguishing characteristic.

Principle 3: A portfolio of architectures can be systematically used to adjust overall exposure to uncertainty – There were two ways portfolio theory can adjust the overall exposure to uncertainty. First, portfolio theory provides for continuous investment opportunities for any level of risk aversion, unlike discrete assets. Second, portfolio theory provides a means of diversifying uncertainty through combinations of different architectures on the basis of covariance.

10.3 Recommendations for Further Research

Like most research, there is still much work to be done. Although a unified approach has been presented and demonstrated through practical examples, there is a great deal of opportunity to extend, implement and refine the approach upon which this thesis is based. The true benefits of this research won't be exploited until, "actual" programs experiment with the method as part of their conceptual design process.

There are of course other issues that although not directly discussed in this work, arose as potential areas of further research. These include: the implementation of multi-period portfolio analysis, implementation of the approach in more "real world" case studies, investigation into different representations of uncertainty on which to base the portfolio analysis, broadening the method to incorporate sources of uncertainty that weren't investigated in this thesis, the implementation of the approach on a more formal multi-attribute utility case study, the implementation of the approach at the multi-program enterprise level and the implementation of the uncertainty analysis approach on engineering systems outside of the field of space systems design.

10.3.1 Multi-Period Portfolio Analysis

The approach presented in this thesis is based around a single time period analysis of the tradespace of potential architectures. Naturally the question arises, how do I adjust my portfolio as uncertainties change? One potential answer would be through a multi-period assessment of the tradespace of potential architectures. Taking the starting portfolio as the tradespace of exploration, a second analysis could be done on the subset of architectures until an eventual architecture is chosen. The time step for analysis would depend on the timing of information about uncertainty. For example, a second portfolio analysis could be initiated for a space system after one of its key technologies was further along and the performance/cost of the technology were more certain.

This multi-period portfolio analysis would continue until the optimal portfolio consists of a single architectural design. The initial portfolio is meant as a starting position in concept selection, a jumping off point from which to assign resources in pursuit of an operational design. It is expected that once the portfolio is chosen, the operational system will be one of the current members of the portfolio. There is of course a possibility for unknown unknowns to "pop-up" that could require the decision maker to open up the portfolio to new designs; however, every attempt should be made to minimize the possibility for these unknown unknowns to not be modeled in the original uncertainty analysis. No approach will ever be perfect in terms of eliminating any unplanned rework, but the hope is that the approach presented in this thesis, minimizes the exposure of the decision maker to the effects of unplanned rework due to both known and unknown uncertainties.

There is no real way to know at what period of analysis the portfolio will evolve to a single design asset. For instance, the period of analysis at which a single design emerges is highly dependent on the initial tradespace that was explored and the level of diversity of the assets in the portfolio. It is also highly dependent on the decision maker and their level of risk aversion, as well as their willingness to pay for a portfolio of designs to be developed. The multi-period approach would define methods to reduce the portfolio, as well as adjust the optimal investment strategies as information changes.

10.3.2 Suggested Cases of Implementation

The cases presented in this thesis provided implementation examples in the three major classes of space systems today: military, commercial and science. However, these examples were just that, examples. The real test of any approach comes when it is implemented "in the field" on a development program. There is no doubt that this type of implementation will teach very important lessons that were not yet uncovered in the course of this research. Possible teachings that would come from these implementations would be more realistic/practical estimations of different sources of uncertainty. The uncertainty quantification presented in this thesis was based on literature and engineering judgment; however, it's certainly possible that satellite design organizations, such as those interviewed in Chapter 3, could have more precise estimations of uncertainty for their individual organizations.

Other results of real world implementation could include valuable feedback on how to structure results for the most benefit to the decision maker or how to best overcome current mental models of jumping to point designs early in conceptual design. These are some of the major cultural issues that would arise from real world implementations of the approach. Other findings could include sources of uncertainty that weren't included in this research, but are significant drivers in different organizations. The next suggestion for future work builds on this thought and would provide an opportunity to incorporate more fully sources of uncertainty into the approach.

10.3.3 Incorporating Other Sources of Uncertainty

Various sources of uncertainty were uncovered as contributing to the embedded uncertainty in space system architecture designs. However, not all of those sources of uncertainties were included in the example cases presented in this thesis. Significant further research is still needed to incorporate uncertainties whose individual quantification is quite difficult. These types of uncertainties would include various sources of potential political uncertainty, as well as obsolescence uncertainty, lifetime uncertainty, and integration uncertainty. Table 34 illustrates the different sources of uncertainty affecting space systems conceptual design and highlights the broad categories of uncertainties that were not fully developed in this thesis. For example, Weigel showed policy and uncertainties associated with them can have significant impact on the evaluation of an architectural tradespace.[77]

[77] Weigel, A. (2002). Bringing Policy into Space Systems Conceptual Design: Quantitative and Qualitative Methods. Technology Management and Policy. Cambridge, MA, Massachusetts Institute of Technology. Ph.D. Dissertation

Table 34: Sources of uncertainty included in this research

Development Uncertainty	Operational Uncertainty
Political Uncertainty- uncertainty of development funding instability	Political Uncertainty- uncertainty of operational funding instability
Requirements Uncertainty- uncertainty of requirements stability	Lifetime Uncertainty - uncertainty of performing to requirements in a given lifetime
Development Cost Uncertainty- uncertainty of developing within a given budget	Obsolescence Uncertainty – uncertainty of performing to evolving expectation in a given lifetime
Development Schedule Uncertainty- uncertainty of developing within a given schedule profile	Integration Uncertainty – uncertainty of operating within other necessary systems
Development Technology Uncertainty- uncertainty of technology to provide performance benefits	Operations Cost Uncertainty – uncertainty of meeting operations cost targets
	Market Uncertainty-uncertainty in meeting demands of an unknown market
Model Uncertainty	

10.3.4 Other Representations of Uncertainty in Portfolio Optimization

In the approach presented in this thesis, the number representing a standard deviation from the expected outcome value represented uncertainty in the portfolio optimization approach. There are other uncertainty measures that could be used in the production of the value/uncertainty tradespace. For example, a typical measure in finance is representing value as a percentage expected return on an investment and the uncertainty as a % deviation from the expected return. This kind of approach would have immediate applicability to the Broadband case, for example, where the system profit and investment could be transformed into an expected rate of return and percentage differences around that expectation would immediately fall out. In the end, the designer should strive to put analysis in front of the decision maker that is the most applicable and other representations than those presented in this thesis may be more appropriate for some decision makers.

10.3.5 Uncertainty Analysis Approach on a More Formal Multi-Attribute Utility Case

The ATOS case study represented an initial attempt at applying utility theory to the design of space systems; however, the technique and quality of the application have been improved by ongoing research at MIT.[78] There is a great deal of promise in applying portfolio theory with multi-attribute utility as the primary measure of value, as it would represent all attributes important to the customer in a single dimension. Further, risk aversion could be explicitly extracted from utility functions, as was discussed in Chapter 6.

10.3.6 Multi-Program Enterprise Uncertainty Analysis

The approach presented in this thesis is focused on enabling the effective development of a single operational system. That is, from the portfolio of *n* architectures, it is envisioned that only one of these architectures will be fully developed and return operational value to the decision maker. There is potential, however, to generalize the uncertainty approach presented here to a set of operational systems. This could be implemented at the level of program management, where an optimal investment strategy for resources would arise from the analysis of prospective programs and there expected returns and uncertainties.

One timely example of this implementation would be in developing a Mars Program that consists of multiple projects that each has individual returns and individual uncertainty, but in the end maximize the total return of the Mars Program. In fact most program already think in a portfolio mindset, and simply need the formal approach to go along with it. There are a number of pitfalls that can happen with simply applying a portfolio mentality in putting together a set of programs. A overly simplistic view of portfolio theory might lead decision makers to simply assemble a set of low, medium and high uncertainty programs, rather than understand the sources of the uncertainties in the designs and how they behave relative to one another. This would give rise to not only the single point failure scenarios, and therefore mitigate any benefit gained from a portfolio of projects, but it might also not be the optimal strategy in terms of allocating resources. It is conceivable that the decision maker is simply diluting their resources by spreading them over a number of programs whose uncertainty (and

---

[78] Diller, N., Qi Dong, Carole Joppin, and S. K. Sandra Jo Kassin-Deardorff, Dan Kirk, Michelle McVey, Brian Peck, Adam Ross, Brandon Wood (2001). B-TOS Architecture Study: Second Iteration of the Terrestrial Observer Swarm Architecture. Cambridge, MA, Massachusetts Institute of Technology.

therefore risk) are not clearly understood. Interesting work by Guikema on minimizing risk among a group of projects competing for fixed resources could be start for applying uncertainty analysis in this context.[79]

10.3.7 Uncertainty analysis in other areas of engineering systems

Although all the examples presented in this thesis are in the field of space systems, there is significant potential to carry the approach over to other disciplines in engineering systems. The obstacles to carry over the research to other disciplines would be fairly small in terms of theory, but instead the majority of issues would arise in the identification of the classes of uncertainty that most directly affect whatever discipline is investigated. For example, in aircraft or automotive design, desired styling in terms of product form will be a much larger source uncertainty as opposed to space systems design. In space systems, very few customers care about the satellite system looks. The same cannot be said of customers of aircraft and automobiles. At first glance, the uncertainty analysis framework could hold up quite well in other disciplines of engineering systems, but it will be the goal of future research to demonstrate its applicability.

---

[79] Guikema, S. a. E. P.-C. (2001). The Danger of Myopic Conservatism in Risk Analysis: The Problem of Time Allocation For The Deep Space Network. AIAA Space 2001, Albuquerque, NM, AIAA, 2001-4518.

Risk Management Guide for Acquisition, Third Edition, January 2000.

Amram, M. a. N. K. (1999). Real Options: Managing Strategic Investment in an Uncertain World. Boston, MA, Harvard Business School Press.

Anderson, D. a. T. F.-R. (1999). Space Environment Topics: The Ionosphere. Boulder, CO, Space Environment Center.

Antonsson, E. a. K. O. (1995). "Imprecision in Engineering Design." ASME Journal of Mechanical Design **117B**.

Arrow, K. J. (1963). Social choice and individual values. New Haven, Yale University Press.

Arrow, K. J. (1965). Aspects of the Theory of Risk-Bearing. Helsinki, Yrjo Hahnsson Foundation.

Bacharach, M. a. S. H. (1991). Foundations of Decision Theory. Cambridge, MA, Basil Blackwell.

Baldwin, C. a. K. C. (2000). Design Rules: The Power of Modularity. Cambridge, MA, MIT Press.

Bearden, D. E. (1996). Cost Modeling. Reducing Space Mission Cost. J. a. W. L. Wertz. Torrance, CA, Microcosm Press.

Bernstein, J. I. (1998). Design methods in the aerospace industry: looking for evidence of set-based practices. SM

Bernstein, P. (1998). Against the gods: The remarkable story of risk. New York, Wiley and Sons.

Boar, B. (1984). Application Prototyping: A Requirements Definition Strategy for the 80's. New York, NY, Wiley & Sons, Inc.

Book, S. (2000). Tutorial: Earned Value Management: What we can and cannot learn by tracking earned value. Risk Management 2000: Lessons for the Millennium, McLean, VA.

Boppe, C. (1998). Aerospace Product Development Course Notes. Cambridge, MA.

Brealey, R. a. S. M. (1996). Principles of Corporate Finance. New York, McGraw-Hill.

Browning, T. (1998). Modeling the impact of process architecture on cost and schedule risk in product development. Technology Management and Policy. Cambridge, MA, Massachusetts Institute of Technology. PhD

Crocker, A., A.C. Charania, and John R. Olds (2001). An Introduction to the ROSETTA Modeling Process for Advanced Space Transportation Investment. Space 2001 Conference and Exposition, Albuquerque, NM.

Culpitt, I. (1999). Social Policy and Risk. London, Sage.

de Neufville, R. (1990). Applied Systems Analysis: Engineering Planning and Technology Management. New York, McGraw-Hill.

DeLaurentis, D. a. D. M. (2000). A New Model for the Aerospace Design Process Based on a Control System Analogy. 8th AIAA/USAF/NASA/ISSMO

Symposium on Multidisciplinary Analysis and Optimization, Long Beach, CA, AIAA.

DeLaurentis, D. a. D. M. (2000). Uncertainty Modeling and Management in Multidisciplinary Analysis and Synthesis. 38th Aerospace Sciences Meeting & Exhibit, Reno, NV.

Diller, N., Qi Dong, Carole Joppin, and S. K. Sandra Jo Kassin-Deardorff, Dan Kirk, Michelle McVey, Brian Peck, Adam Ross, Brandon Wood (2001). B-TOS Architecture Study: Second Iteration of the Terrestrial Observer Swarm Architecture. Cambridge, MA, Massachusetts Institute of Technology.

Dillon, R. a. E. P.-C. (To Appear). "APRAM: Advanced Programmatic Risk Analysis Method." International Journal of Technology, Policy and Management.

Drake, A. (1967). Fundamentals of Applied Probability Theory. New York, McGraw-Hill.

Du, X. a. W. C. (2000). "Methodology for Managing the Effect of Uncertainty in Simulation-Based Design." AIAA Journal **38**(8): 1471-1485.

Dunn, C. P. a. B. K. B. (1996). "Stakeholder Interests and Community Groups: A New View." International Association for Business and Society Annual Meetings.

Epstein, L. (1997). Uncertainty Aversion. Toronto, Canada, University of Toronto and Hong Kong University of Science and Technology.

Fabozzi, F. a. J. G. (2000). Value Based Metrics Foundations and Practice. New Hope, PA, Fabozzi Associates.

Fabrycky, W. (1991). Life Cycle Costs and Economics. NJ, Prentice Hall.

Farrell, J. (1997). Portfolio Management: Theory and Application. New York, McGraw-Hill.

Fishburn, P. (1964). Decision and Value Theory. New York, Wiley and Sons.

Fleisher, G. (1975). Risk and Uncertainty: Non-Deterministic Decision Making in Engineering Economy. Norcross, GA, American Institute of Industrial Engineers Inc.

Freeman, R. E. (1984). Strategic Management: A stakeholder perspective. Boston, Pittman.

Gordon, G. a. W. M. (1993). Principles of Communications Satellites. New York, John Wiley & Sons, Inc.

Guikema, S. a. E. P.-C. (2001). The Danger of Myopic Conservatism in Risk Analysis: The Problem of Time Allocation For The Deep Space Network. AIAA Space 2001, Albuquerque, NM, AIAA.

Haddawy, P. (1994). Representing plans under uncertainty: a logic of time, chance and action. Berlin ; New York, Springer-Verlag.

Highsmith III, J. (1999). Adaptive Software Development: A Collaborative Approach to Managing Complex Systems. New York, Dorset House Publishing.

Hirshleifer, J. (1989). Time, uncertainty, and information. Oxford, UK; New York, NY, B. Blackwell.

Horn, J. a. N. N. (1993). Multi-Objective Optimization Using the Niched Pareto Genetic Algorithm. Urbana, Il, University of Illinois at Urbana-Champaign.

Hughes, A. a. T. H. (2000). Systems Experts and Computers: The Systems Approach in

Management and Engineering World War II and After. Cambridge, MA, MIT Press.

Hughston, L. (1999). Options: Classic Approaches to Pricing and Modeling. London, Haymarket House.

Hunter, A. and S. Parsons (1998). Applications of uncertainty formalisms. Berlin; New York, Springer.

Jacoby, H. a. D. L. (1990). Uncertainty, Information and Project Evaluation. Cambridge, MA, MIT.

Jensen, M. (2001). Value Maximization, Stakeholder Theory, and the Corporate Objective Function. Cambridge, MA, Harvard Business School.

Jilla, C. (2002). A Multiobjective, Multidisciplinary Design Optimization Methodology for the Conceptual Design of Distributed Satellite Systems. Aeronautics and Astronautics. Cambridge, MA, Massachusetts Institute of Technology. PhD

Jilla, C. D. (1999). The Multidisciplinary Design Optimization Methodology For Distributed Satellite Systems, Ph.D. Proposal.

Jilla, C. D. (1999). Separated spacecraft interferometry: system architecture design and optimization. Aeronautics/Astronautics. Cambridge, MA, Massachusetts Institute of Technology. SM

Jilla, C. D., D.W. Miller, R. J. Sedwick (2000). "Application of Multidisciplinary Design Optimization Techniques to Distributed Satellite Systems." Journal of Spacecraft and Rockets **37**(4): 481-490.

Jilla, C. D. a. D. W. M. (2000). Assessing the Performance of a Heuristic Simulated Annealing Algorithm for the Design of Distributed Satellite Systems. 51st International Astronautical Congress, Rio de Janeiro, Brazil.

Kashitani, T. (2002). Development and Application of an Analysis Methodology for Satellite Broadband Network Architectures. Proceedings of the 20th AIAA International Communications Satellite Systems Conference, Montreal, Canada.

Katzan, H. (1992). Managing uncertainty: a pragmatic approach. New York, Van Nostrand Reinhold.

Keeney, R. a. H. R. (1976). Decisions with Multiple Objectives. New York, Wiley and Sons.

Kelic, A. (1998). Assessing the Technical and Financial Viability of Broadband Satellite Systems Using a Cost per T1 Minute Metric. Aeronautics and Astronautics. Cambridge, MA, Massachusetts Institute of Technology. SM

Kelic, A., Shaw, G. B., and Hastings, D. E. (1998). "Metric for Systems Evaluation and Design of Satellite-Based Internet Links." Journal of Spacecraft and Rockets **35**(1): 73-81.

Klir, G. J. and M. J. Wierman (1998). Uncertainty-based information: elements of generalized information theory. New York, Physica-Verlag.

Knight, F. H. (1965). Risk, uncertainty and profit. New York, Harper & Row.

Knight, J. (1998). Value Based Management. New York, McGraw-Hill.

Krathwohl, D. (1997). Methods of Educational & Social Science Research: An Integrated Approach. New York, NY, Addison Wesley Longman, Inc.

Lamassoure, E. a. D. H. (2000). Generalized Metrics for Optimization of Space Systems Cost-Effectiveness. AIAA Space 2000, Long Beach, CA, AIAA.

Larson, W. a. J. W., Ed. (1992). Space Mission Analysis and Design. Torrance, CA, Microcosm.

Leisman, G. e. a. (1999). Analysis and Preliminary Design of On-Orbit Servicing Architectures for the GPS Constellation. Space Technology Conference & Exposition, Albuquerque, New Mexico.

Luhmann, M. (1993). Risk: A Sociological Theory. Berlin, de Gruyter & Co.

Maglaras, G. (1995). Experimental Comparison of Probabilistic Methods and Fuzzy Sets for Designing Under Uncertainty. Dept. of Aerospace Engineering. Blacksburg, VA, Virginia Polytechnic Institute. Ph.D.

Mahoney, D. P. (Nov 1999). "The Picture of Uncertainty." Computer Graphics World.

Markowitz, H. (1952). "Portfolio Selection." Journal of Finance **7**(1): 77-91.

Markowitz, H. (1991). "Foundations of Portfolio Theory." Journal of Finance **46**(2): 469-477.

Markowitz, H. (1991). Portfolio Selection: Efficient Diversification of Investments. Cambridge, MA, Basil Blackwell.

Masini, R. a. M. G. S. (1996). "Heuristic algorithms for the portfolio selection problem with minimum transaction lots." European Journal of Operational Research **114**(2): 219-233.

McNutt, R. (1998). Reducing DoD Product Development Time: The Role of the Schedule Development Process. Aeronautics and Astronautics. Cambridge, MA, Massachusetts Institute of Technology. PhD

Meyer, R. F. a. J. W. P. (1968). "The consistent assessment of preference functions." IEEE Systems Science and Cybernetics **SSC-4**: 270-278.

Modarres, M. (1993). What Every Engineer Should Know About Reliability and Risk Analysis. New York, Marcel Dekker, Inc.

Modarres, M., M. Kaminskiy, et al. (1999). Reliability engineering and risk analysis. New York, Marcel Dekker.

Morgan, M. G. a. M. H. (1990). Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk Policy Analysis. Cambridge, UK, Cambridge University Press.

Murman, E., M. Walton, E. Rebentisch (2000). "Challenges in the Better, Faster, Cheaper Era of Aeronautical Design, Engineering and Manufacturing." The Aeronautical Journal **104**(1040): 481-489.

Murman, E. e. a. (2001). Lean Enterprise Value. New York, NY, Palgrave Publishers, Ltd.

Neely, J. a. R. d. N. (Yet to Be Published). "Hybrid Real Options Valuation of Risky Product Development Projects." International Journal of Technology, Policy and Management.

NRC (1996). Understanding Risk: Informing Decisions in a Democratic Society. Washington, D.C., National Academy Press.

Oberampf, W. a. J. H. (2001). Mathematical Representation of Uncertainty. Non-Deterministic Approaches Forum, Seattle, WA, American Institute of Aeronautics and Astronautics.

Panetta, P. a. D. H. (2002). "Managing Programmatic Risk for Complex Space System Development." International Journal of Aerospace Management **1**(4): 303-313.

Pate-Cornell, E. a. R. D. (1999). Advanced Programmatic Risk Analysis For NASA's Faster-Better-Cheaper Mission and Programs, Stanford University.

Pratt, J. W. (1964). "Risk Aversion in the Small and in the Large." Econometrica **32**: 122-36.

Risk, P. s. T. F. C. o. P. P. a. (1983). Engineering Risk. Wellington, New Zealand, Institution of Professional Engineers New Zealand.

Rivett, P. (1994). The Craft of Decision Modeling. New York, Wiley and Sons.

Roberts, B. (2000). Risk Management Doesn't Save Money, It Saves Programs. Risk Management 2000: Lessons for the Millennium, McLean, VA.

Saleh, J. (2002). "Spacecraft Flexibility." Journal of Spacecraft and Rockets **Forthcoming**.

Sarfield, L. (2000). The Application of Best Practices to Unmanned Spacecraft Development. Washington, D.C., RAND.

Savage, M. F. a. L. P. (1948). "The Utility Analysis of Choices involving Risk." Journal of Political Economy **56**: 279-304.

Schlaifer, R. O. (1969). Analysis of Decisions under Uncertainty. New York, McGraw-Hill.

Shaw, G., D. Miller, and D. Hastings (2000). "Generalized Characteristics of Communications, Sensing and Navigation Satellite Systems." Journal of Spacecraft and Rockets **37**(6): 801-811.

Shaw, G., D. Miller, and D. Hastings (2001). "Development of the Quantitative Generalized Information Network Analysis (GINA) Methodology for Satellite Systems." Journal of Spacecraft and Rockets **38**(2): 257-269.

Shaw, G. B. (1999). The generalized information network analysis methodology for distributed satellite systems. Aeronautics/Astronautics. Cambridge, MA, Massachusetts Institute of Technology. ScD

Soler Ramos, J., Kim Staking, et.al. (2000). Financial Risk Management: A Practical Approach for Emerging Markets. Washington, D.C., Johns Hopkins University Press.

Space and Missile System Center, D. o. C., Los Angeles AFB, CA (1994). Unmanned Space Vehicle Cost Model. Los Angeles AFB, CA, Space and Missile System Center.

Ulrich, L. a. S. E. (1995). Product Design and Development. New York, McGraw-Hill.

Utterback, J. (1994). Mastering the Dynamics of Innovation. Boston, Harvard Business School Press.

Von Furstenberg, G. M. (1990). Acting under uncertainty : multidisciplinary conceptions. Boston, Kluwer Academic Publishers.

Von Neumann, J. a. O. M. (1944). Theory of Games and Economic Behavior. New York, John Wiley and Sons.

Vonortas, N. S. (1997). Cooperation in research and development. Boston, Kluwer Academic Publishers.

Walton, M. (1999). Identifying the Impact of Modeling and Simulation in the Generation of System Level Requirements. Aeronautics/Astronautics. Cambridge, MA, Massachusetts Institute of Technology. SM

Walton, M. (2000). Striving toward a Lean Clean Sheet Design of Space Systems. AIAA Space 2000, Los Angeles, CA, AIAA.

Walton, M. (2001). Dynamic Space Systems Conceptual Development Through Management Of Decisions And Uncertainty. IAF 2001, Toulouse, France.

Ward, A., Jeffrey Liker, John Christiano, Durward Sobek (1995). "The Second Toyota Paradox: How Delaying Decisions Can Make Better Cars Faster." Sloan Management Review **36**(3): 43-61.

Weigel, A. (2002). Bringing Policy into Space Systems Conceptual Design: Quantitative and Qualitative Methods. Technology Management and Policy. Cambridge, MA, Massachusetts Institute of Technology. PhD

Wertz, J. a. W. L., Ed. (1996). Reducing Space Mission Cost. Torrance, CA, Microcosm.

Appendix A

FORMALIZING UNCERTAINTY IN SPACE SYSTEMS DESIGN: AN IMPLEMENTATION TUTORIAL

To enable implementation of the framework described in this thesis, a tutorial is included that provides a step-by-step description of its application. It is the hope that this research will be adopted and experimented with during "real world" conceptual design projects.

Step 1. Developing the boundaries for uncertainty

> *When one admits that nothing is certain one must, I think, also add that some things are more nearly certain than others.* -Bertrand Russell

Uncertainty is so pervasive in conceptual design, that a near infinite source list could be developed that in some way or another contribute to actual behavior that is different than predicted. Therefore, a designer could become absorbed and bogged down in the intractable problem of discovering ***all*** the myriad of uncertainties in an architectural concept. This, of course, is not a desirable outcome.

Identifying the right uncertainties is part art and part science, much like the rest of conceptual design. Far more important than identifying ***all*** the sources of uncertainty in conceptual design is identifying the ***right*** sources of uncertainty in conceptual design. The right sources will have at least one of the following characteristics. First, the uncertainty has a major impact on the expected behavior of the architecture. This major impact could be caused by a low probability event but significant implications (either positive or negative) or by a higher probability event with less significant implications or by a higher probability event and significant implications. What is a high or low probability event and what is a significant impact are where the art of design enters. The second characteristic of an uncertainty that should be included in the analysis is one that differentiates one architecture from another. An example of this second characteristic can be found in a tradespace of architectures that don't rely on the same technology. For example, assume a GEO communication spacecraft could be developed using current technology for solar cell power delivery, but the LEO architectures in the tradespace would require successful development of a higher efficiency solar cell or delivery system. Technology is just one source of differentiating uncertainty, policy, market conditions or manufacturing capability are others.

Step 2. Quantifying Individual Uncertainties

If you cannot measure .... your knowledge is of an unsatisfactory kind -Lord Kelvin

Once the relevant sources of uncertainty have been defined, the next step is to apply some level of probability and impact to them. A relative notion of how significant the uncertainties are has already been determined in step 1, but in this step more resolution needs to be provided so that it can be built into the design models in the next step. Some individual uncertainties can be very straightforward to quantify. For example, if the cost model being used is based on historical data, these models typically have standard deviations that can be included as cost modeling uncertainty. Other estimating relationships have comparable standard error measures that can be found in the literature[80] or in company specific databases. Examples of these technologies, might include payload sizing estimation or other scaling factors for mass or power.

Other uncertainties might not be so straightforward to quantify. These could arise from market conditions, policy uncertainty, new technology or novel architectural concepts. The quantification of these types of uncertainties is best done using one of two approaches. The first is to develop distribution profiles over which outcomes exist, e.g. market-capture probability density function in Figure 95. The second approach is to generate scenarios with outcomes using a decision tree approach. This approach is most useful when chance events can be isolated and quantified, for example a chance event on acquiring a necessary slice of spectrum and the impact of being awarded different outcomes, as shown in Figure 94. Other scenarios, such as technology fallback plans if one technology doesn't achieve operational readiness, can be modeled equally well using this approach. Using a software package like Decision Analysis by TreeAge® enables the quick development of these decision trees and also develops expected outcome distributions within the program.

---

[80] Larson, W. a. J. W., Ed. (1992). Space Mission Analysis and Design. Torrence, CA, Microcosm.

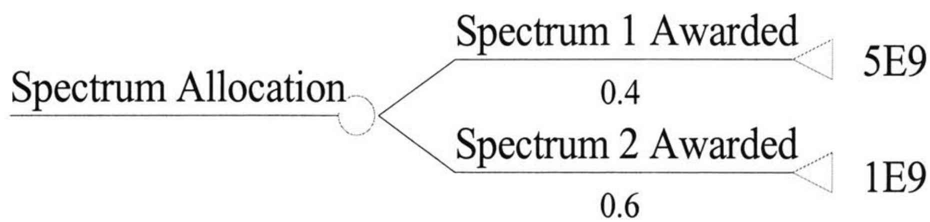


Figure 94: Sample Decision Tree Scenario

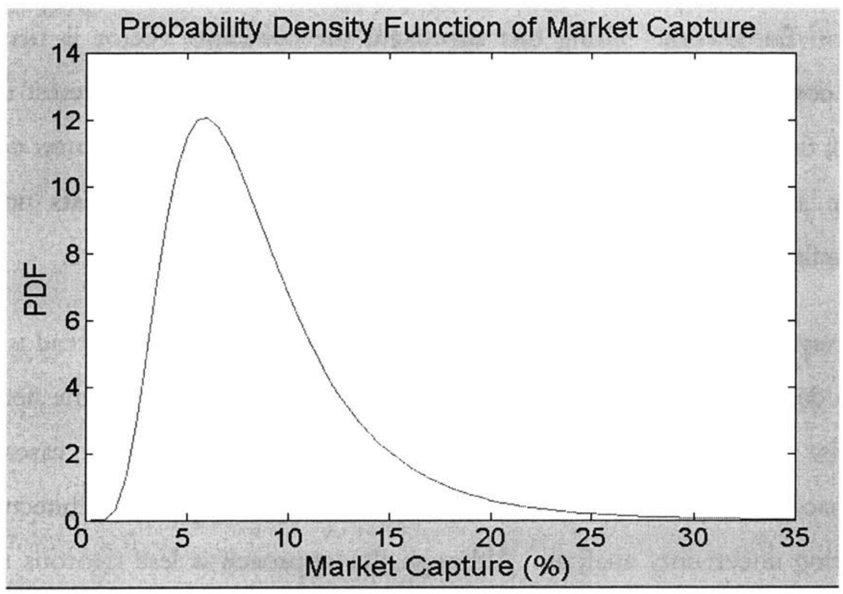


Figure 95: Probability Density Function of Market Capture for Broadband Space System

Step 3. Accounting for uncertainties in the design models

> *... we cannot "ask" an electron where it is without changing its position. Social systems have Heisenberg principles all over the place, for we cannot predict the future without changing it.*
>
> \- Kenneth Ewert Boulding

Design models will be different with design location or organization; therefore a general approach is suggested to integrate the uncertainty information calculated in steps 1 and 2 with the major design models. The purpose of this step is to integrate uncertainty into the design models, such that the effects of uncertainties can be observed in the behavior of the architectures and the outcome measures/decision criteria.

To predict the behavior of the architectures and outcome measures, non-deterministic simulation models of the architectural systems and their environment are run multiple times subjected to previously quantified individual sources of uncertainty. Integration of the individual sources of uncertainty as identified in step 1 and quantified in step 2 can be done in a number of ways and will be very dependent on the types of uncertainty that need to be included. For example, most of the uncertainties in the cases presented in this thesis were able to be included in the constants vector of a systems simulation framework. Using this approach, the constants vector is first sampled. This creates an initial condition that is used to evaluate all the architectures of interest in the uncertainty analysis. Once all the architectures are evaluated under this static condition, a new constants vector is sampled and the architectures are evaluated using it. This process repeats until a satisfactory distribution of results has been developed for each architecture in the tradespace.

The number of runs necessary to develop distributions is not defined; but instead is constrained only by the resolution desired in the behavior distributions and the computation time necessary to run the simulation models. Further, computation time may be so prohibitive in some cases, that a subset of the entire tradespace is analyzed. In the cases in this thesis, Pareto optimal architectures were defined prior to introducing uncertainty analysis. Although this approach is less rigorous than applying the uncertainty analysis to the entire tradespace, tractability became an overriding implementation concern and experiments predicted little additional information was to be gained from a full tradespace uncertainty analysis.

While building the decision criteria distributions from the uncertainty analysis, care should be taken to ensure trial numbers are noted for each distribution element. This is important for calculating the correlation coefficient among space system architectures. The correlation coefficients allow the analyst to develop covariance matrices that enable the use of portfolio theory as a mechanism to manage uncertainty.

Step 4: Postprocessing the Results

Once the distributions of decision criteria have been developed for each architecture, the data will need to be post processed to feed the next step in the approach, portfolio theory. At this point statistics of each distribution should be calculated. This includes standard measures of expected value and standard deviation or variance.

In addition to these measures, other features of the distribution should also be looked at. For example, features like tail behavior and bifurcation of the distribution could be of interest and might be clouded by the broad statistical measures. These other features could bring out characteristics that might not be fully captured in the portfolio theory application, but would be of interest to the decision maker. More important than those features is perhaps the explanation of why the analysis provided such results. Typical reasons would be that one or two scenarios dominate the expectation outcome and the outcomes have very different results, which could explain bifurcations. Long tails in the distribution would be explained by very low probability outcomes that have significantly different outcomes than the expectation. Both of these reasons could be very significant to a particular decision maker and should be treated as valuable pieces of information that are considered alongside the portfolio strategy suggested.

Once individual distributions have been investigated, the set of distributions also needs to be post-processed to develop the covariance matrices for use in implementing the portfolio optimization. The covariance matrix represents the relative independence of the architectures, as well as the uncertainty of the architectures. The matrix is created, as shown in Figure 96, by placing the variance of assets on the diagonal and using pair-wise covariance, as calculated in Eq. 41, on the off-diagonals.

$$\sigma_{X_1,X_2} = \rho_{X_1,X_2}\sigma_{X_1}\sigma_{X_2} \qquad \text{Eq. 41}$$

Assets	X_1	X_2	X_3	●	●	X_n
X_1	σ_1^2	$\rho_{12}\sigma_1\sigma_2$	$\rho_{13}\sigma_1\sigma_3$	●	●	●
X_2	$\rho_{12}\sigma_1\sigma_2$	σ_2^2	$\rho_{23}\sigma_2\sigma_3$	●	●	●
X_3	$\rho_{13}\sigma_1\sigma_3$	$\rho_{23}\sigma_2\sigma_3$	σ_3^2	●	●	●
●	●	●	●	●	●	●
●	●	●	●	●	●	●
X_n	●	●	●	●	●	●

Figure 96: The Covariance Matrix, *Q*

Step 5: Implementing Portfolio Theory

> *An investor who knew future returns with certainty would invest in only one security, namely the one with the highest future return…But diversification is a common and reasonable investment practice. Why? To reduce uncertainty!* -Harry Markowitz

Modern portfolio had its origin in economics and finance, so the application of the approach in space systems design can seem abstract, but the metaphor and mathematics have a near one for one correlation with the goals and constraints of investing and design. At the highest level, the ultimate goal of portfolio theory is to provide an optimal investment strategy that maximizes returns with subject to the aversion of the decision maker to the downside of uncertainty and its consequences. In applying this thinking to space systems, an analogy is employed of providing an "optimal" investment strategy to decision makers that suggests exploring a portfolio of architectures. This strategy will maximize the expected reward from the development effort while taking into considerations the decision makers willingness to take on risk.

The analogy can be further developed to who is investing and what is being invested in and what is the range of investment opportunities. In the financial world, the investor would represent any individual or group of individuals that has resources they are willing to exchange for an opportunity to create value with the explicit understanding of the uncertainties and consequences associated with any investment. That is, return more wealth to the individual than would otherwise be realized without investment while taking into consideration his/her acceptance of risk. Investment vehicles for these individuals and groups are typically financial instruments such as stocks, bonds, options and others. However, the scope of the marketplace of financial instruments is continuously expanding with more and more firms creating new vehicles of investment.

In space systems, decision makers have resources in the form of money, people and time, which they too would like to exchange for an opportunity to create value. In the financial investment case, investors have an explicit understanding of the associated uncertainties and consequences of actions, likewise, decision makers in the space systems context must have an explicit statement of aversion to risk. Investment vehicles in the case of space systems are the actual space system designs. These designs would be carried in a portfolio, much like that of the financial investor and the portfolio would reap benefits by diversifying the exposure of the investor to overall uncertainty while at the same time maximizing the expected return by retaining perhaps promising, but untested designs. Finally, the choices that are available to the decision maker to keep in his/her portfolio are based solely on the concept generation phase and what is willing to be considered in the tradespace of potential architectures for development.

In the case of space systems, return might be profit (NPV) or some other measure of value in terms of a function per cost, such as billable minutes per dollar in the case of a commercial communication system or images per dollar in the case of observing missions. Of course other measures of value could be used like a multi-attribute measure of utility that encompasses costs and various attributes of utility.[81]

The application of portfolio theory can not only be expressed qualitatively, as described above, but also in mathematics as was developed first by Harry Markowitz in 1952.[82] He formulated the problem as an optimization in which, the decision maker is seeking to maximize the overall return of the portfolio based on the individual assets and their expected return while discounting any aversion a decision maker has toward risk and the associated risk in each of the assets. Embedded in the

---

[81] de Neufville, R. (1990). Applied Systems Analysis: Engineering Planning and Technology Management. New York, McGraw-Hill.

[82] Markowitz, Harry M., (1991). Portfolio Selection, second edition, Blackwell, Cambridge, MA.

problem formulation was an elegant way to not only a method to consider the uncertainty of assets, but also a way to consider the relative movements of assets with respect to different uncertain conditions. This elegant solution allows for the inherent rewarding of assets in the portfolio that moves in different ways with respect to uncertainty and discounts those that compound uncertainty because of their high correlation. The modern portfolio algorithm is shown in Eq. 42 and represents the foundation of many of today's investment strategies. In the equation, E(r) represents the expected returns of the assets, Q represents the covariance matrix of the tradespace of architectures (as was calculated in Step 4), k is the measure of risk aversion of the decision maker (which will be calculated in the Step 6) and w reflects the weightings of the individual assets in the tradespace that have been selected for investment. The sum total of all w_i must naturally equal one as w_i is a measure of relative composition of asset *i* in the portfolio.

$$
\begin{aligned}
&\max : E(r)w - \frac{k}{2} w' Q w \\
&\text{s.t.} : \sum_{i=1}^{n} w_i = 1 \\
&\text{s.t.} : \mathrm{w} \geq 0
\end{aligned}
$$

Eq. 42

This formulation would provide a single optimal strategy to follow, but the overall behavior of what is known as the efficient frontier is also of interest to the decision maker. This information can be calculated by plotting a "portfolio tradespace" of uncertainty versus expected return, as shown in Figure 97. The points in this tradespace represent potential portfolio to invest in and are calculated using Eq. 43 and Eq. 44 for return and uncertainty, respectively.

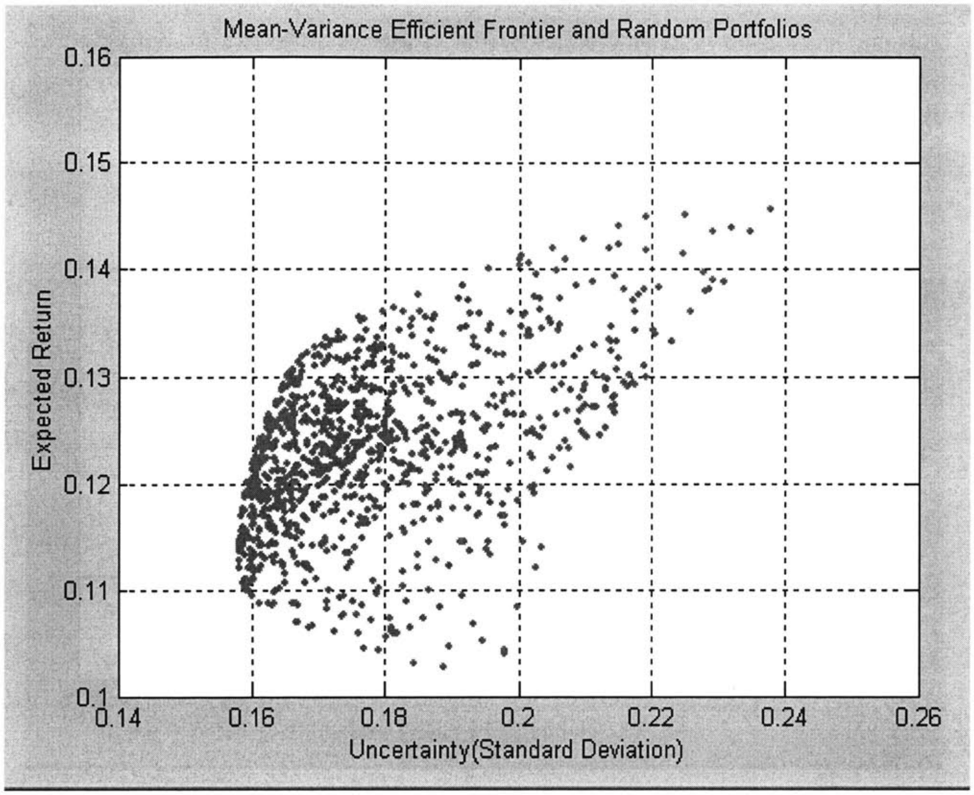


Figure 97: Sample portfolio tradespace

$$E(r) = \sum_{i=1}^{n} w_i r$$

Eq. 43

$$Unc = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j (r_i - E(r_i))(r_j - E(r_j))$$

Eq. 44

From this tradespace an efficient frontier can be determined that contains all the optimal strategies for any level of risk aversion, as shown by the blue line in Figure 98. A portfolio on the efficient frontier represents a collection of assets whose total return cannot be improved by changing any assets in the portfolio without increasing the current portfolio uncertainty.

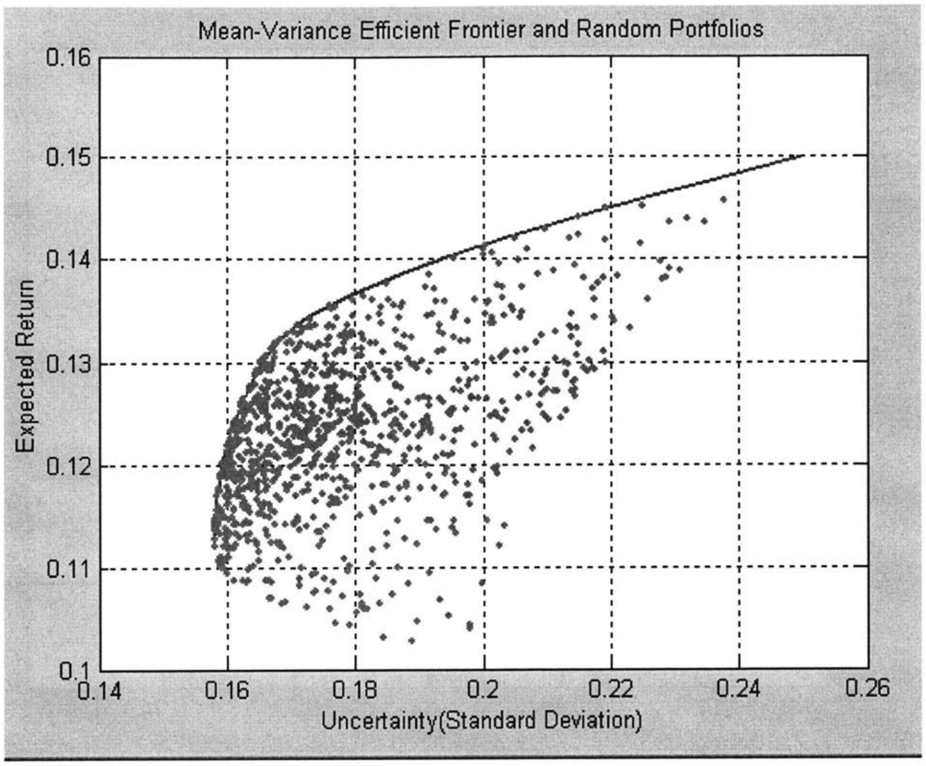


Figure 98: Sample portfolio tradespace with efficient frontier

Much like design tradespaces, a great deal of information is contained in a portfolio tradespace of uncertainty and return. The visualization of the portfolio tradespace, like that of traditional cost and utility tradespaces, highlights trends and properties of the overall set of solutions that enable a focus on the 10% of the data that is really interesting while not wasting time exploring the other 90%. First, the shape of the frontier gives a general feel for the types of architectures that are available to a decision maker. For example, its slope and concavity can provide information on where optimal portfolios of individuals with different levels of risk aversion will be found on the frontier.

It is also useful to overlap the portfolio tradespace with the expected return and uncertainty of the single design assets in the tradespace, as shown in Figure 99. This enables the decision maker to visualize the potential that portfolios provide over single assets. Further, the plotting allows the decision maker to quickly understand the relative uncertainty of different single architectures, which is helpful if he/she chooses not to pursue a portfolio of designs.

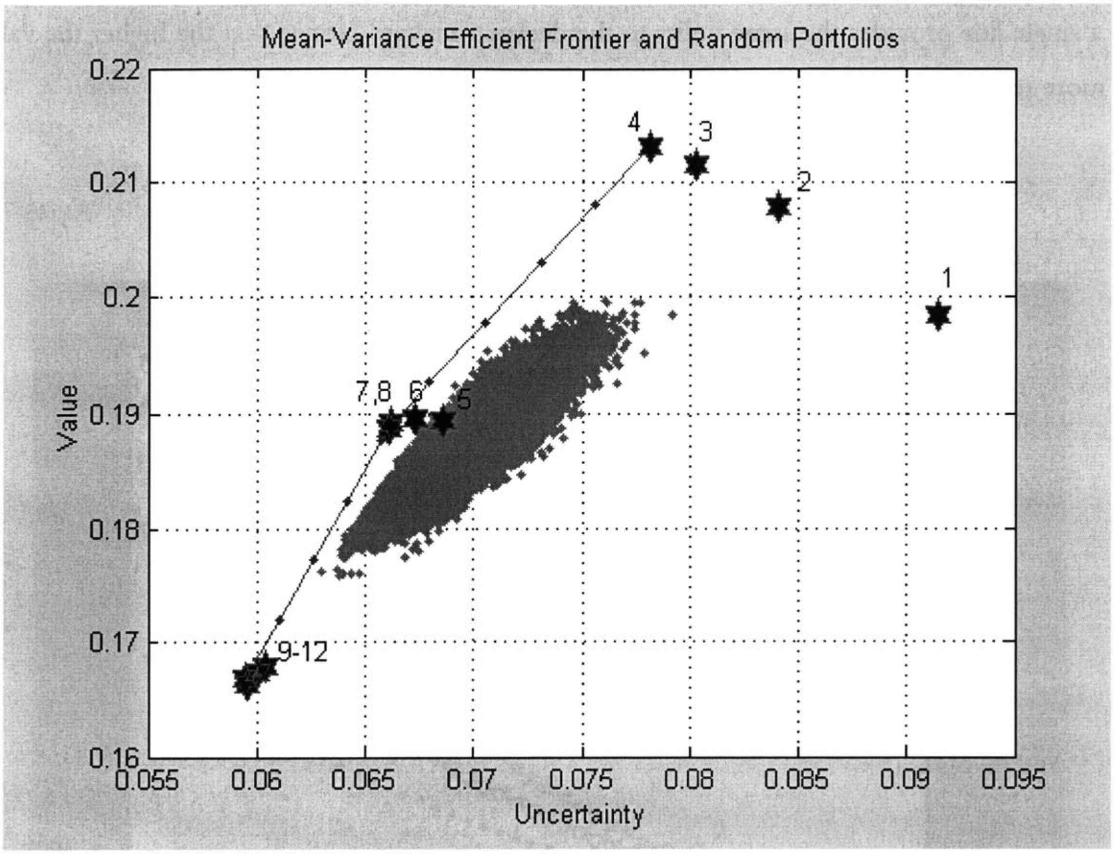


Figure 99: Portfolio Tradespace with Individual Assets Mapped

Step 6: Determining Decision Maker Uncertainty Aversion

One man's risk is another man's pleasure -Anonymous

In Step 5, the portfolio theory algorithm is developed and a portfolio tradespace is designed that shows the set of solutions on the efficient frontier from which an optimal solution should be chosen. In order to determine where a decision maker's optimal strategy lies, their level of aversion to uncertainty must be quantified. The most straightforward method of calculating a decision maker's aversion is to find an indifference curve in the value and uncertainty tradespace that accurately reflects his/her interests. Indifference curves typically take on the mathematical form shown in Eq. 45 and graphically in Figure 100. v in Eq. 45 represents the expected return or value of the system while σ^2 is the uncertainty in a portfolio. The lines in Figure 100 represent 3 different levels of risk aversion, values of *k*, and reflect a decision makers indifference to lie anywhere on the curve. That is, anywhere along a single line provides the same utility to the decision maker. Notice that the higher the value for *k* the more return is required to tolerate the same level of uncertainty.

$$U = v - k\sigma^2$$

Eq. 45

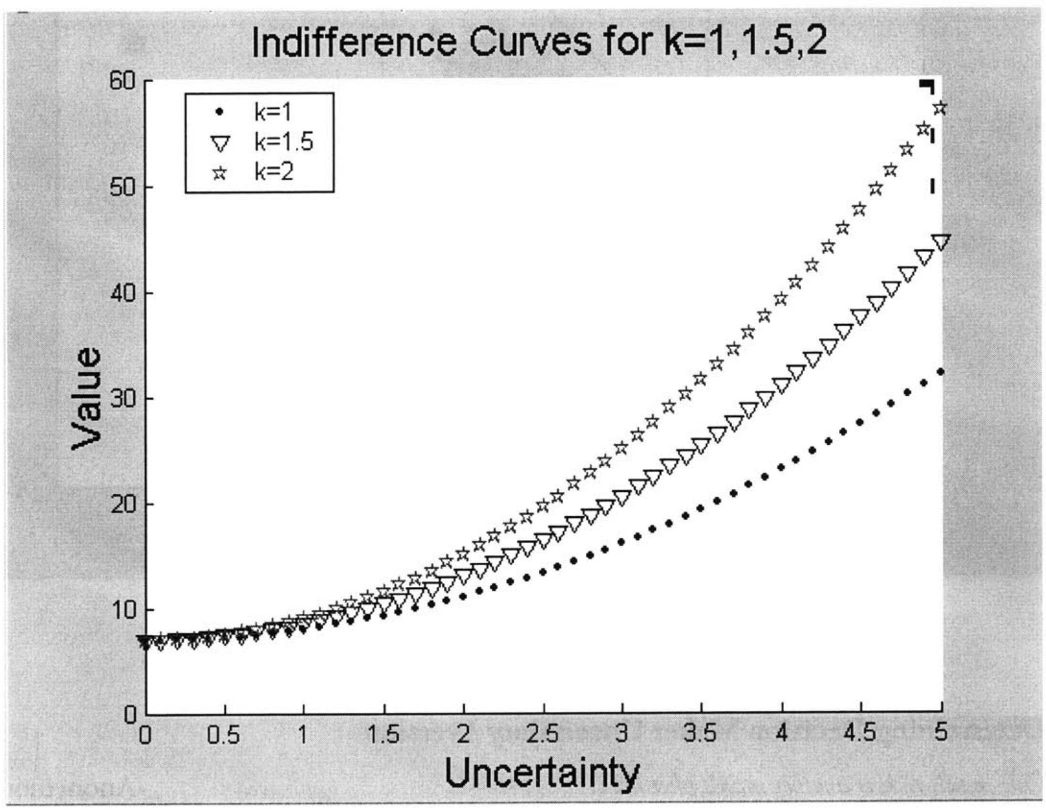


Figure 100: Indifference Curves for Decision Makers, Varying Risk Aversion Factors

Using this kind of visualization, the analyst can interview the decision maker to determine his/her *k* value.[83]

[83] There are other quantitative measures of aversion that can be used and are discussed in Chapter 6 of this thesis.

Step 7: Determining the optimal investment strategy

With uncertainty present, doing things, the actual execution of activity, becomes in a real sense a secondary part of life; the primary problem or function is deciding what to do and how to do it.

-Frank Knight

Once the aversion of the decision maker has been captured and the full portfolio tradespace has been defined, an optimal strategy can be determined by combining the two pieces of information. The optimal strategy can be found graphically or through the portfolio optimization algorithm as shown in Eq. 42. Graphically it can be seen that an optimal portfolio for a decision maker will be found at the tangent point of the decision maker's iso-utility curves and the portfolio tradespace of value and uncertainty. First calculate iso-utility curves for a decision maker's level of aversion as shown in Figure 101. Notice that utility increases as the iso-utility curves move toward the upper left hand corner, maximizing value and minimizing uncertainty.

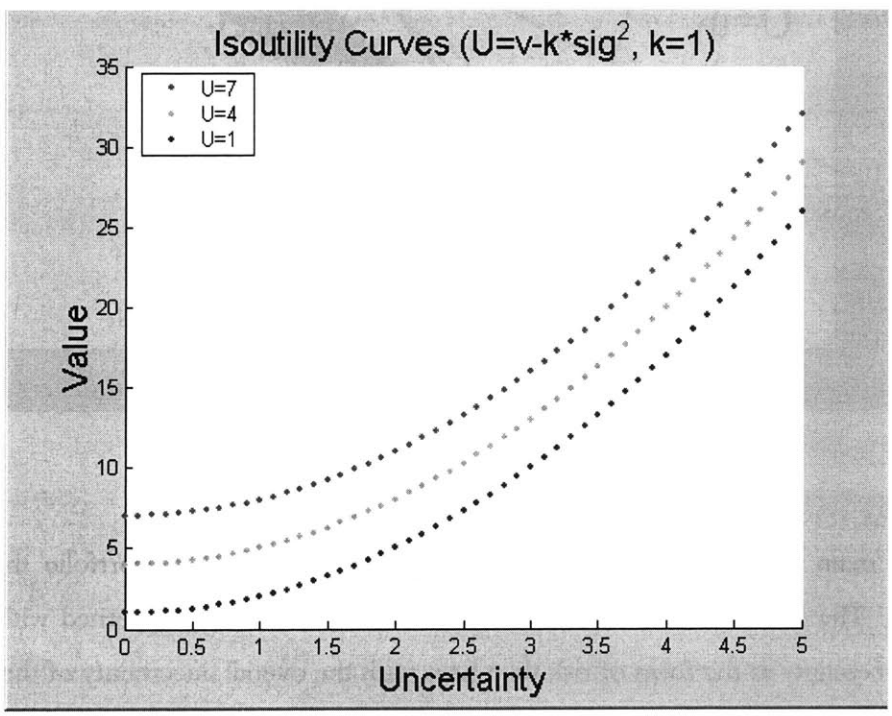


Figure 101: Isoutility lines for a given uncertainty aversion

Next plot the portfolio tradespace over the aversion curves. Find the tangent point of the two curves and determine the composition of the portfolio at that point. This portfolio represents the optimal strategy for a decision maker to pursue. Of course there are other factors to consider in deciding this is the optimal portfolio to go with. Traditional portfolio theory would expect the decision maker to accept the portfolio given, but with complex systems design, it shouldn't be quite so deterministic.

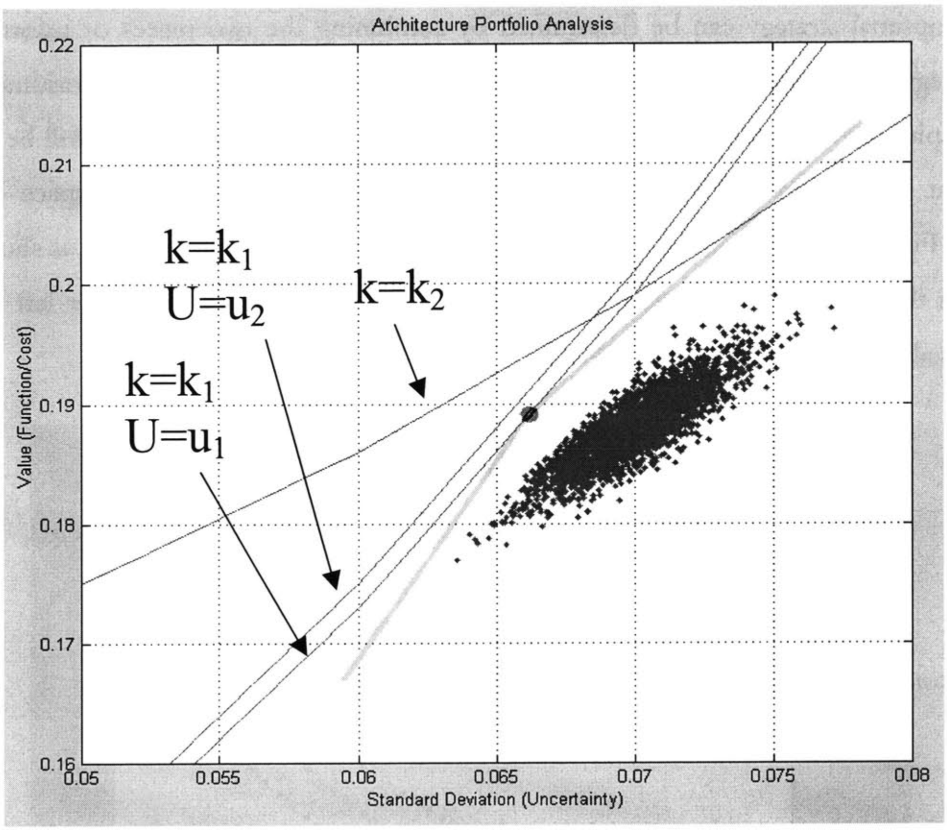


Figure 102: Illustration of aversion in the portfolio tradespace

There are two main complexities that have not yet been considered, as portfolio theory applies to space systems. The first is that the decision maker is probably more concerned with the downside exposure to uncertainty in the form of risk than he is with the overall uncertainty of the outcome. For example, traditional portfolio theory takes into account the uncertainty that will be experienced over the entire range of expectations. This is inclusive of both the upside and downside of uncertainty. A graphical example to illustrate what this data could be hiding is presented in Figure 103 and Figure 104. Although, these two distributions are quite different, they would be represented the same way under traditional portfolio theory, that is their variance and expected return would be equal. Seeing the distributions, though, it is clear that Figure 103 represents a significantly larger downside than does Figure 104.

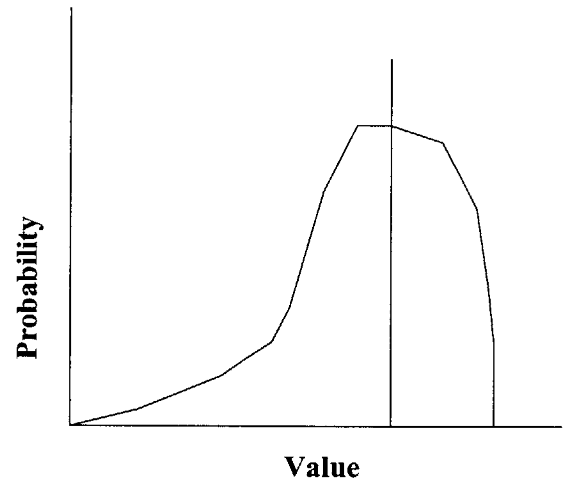


Figure 103: Left Skewed Outcome Distribution Example

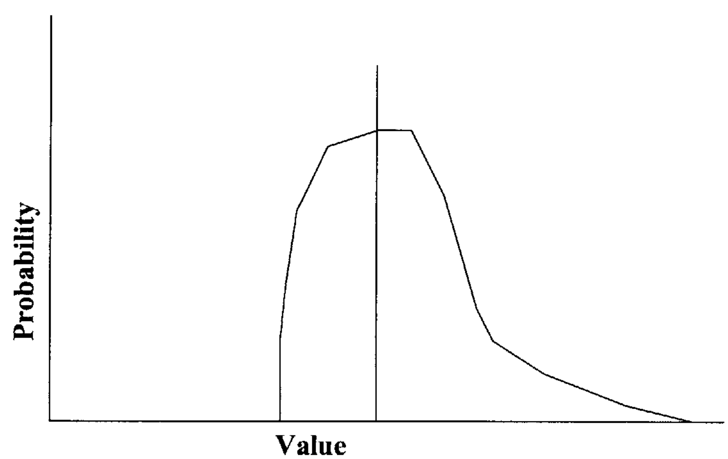


Figure 104: Right Skewed Outcome Distribution Example

To overcome this problem, use semi-variance, as opposed to variance, to distinguish the upside potential from the downside risk. Semi-variance is the average of the squared deviations below (or above) the expected return. The concept of semi-variance, both s_{upside} and $s_{downside,}$ is introduced as a measure of one-sided uncertainty.[84] Assume 10 likely values for a space systems architecture value to the customer, represented by r={1 4 2 10 9 7 3 4 8 1} have been calculated. To calculate semi-variance, two companion set of outcomes are created, r^+={4.9 4.9 4.9 10 9 7 4.9 4.9 8 4.9} and r^-={1 4 2 4.9 4.9 4.9 3 4 4.9 1} and companion deviations around the expectation, as shown in Eq. 46 and Eq. 47.

$$(r_i - E(r))^+ = \begin{bmatrix} 0 \text{ if } r_i \leq 0 \\ (r_i - \text{E(r)}) \text{ if } r_i > 0 \end{bmatrix}$$

Eq. 46

$$(r_i - E(r))^- = \begin{bmatrix} (r_i - \text{E(r)}) \text{ if } r_i \leq 0 \\ 0 \text{ if } r_i > 0 \end{bmatrix}$$

Eq. 47

From this $(r-E(r))^+$ = {0 0 0 5.1 4.1 2.1 0 0 3.1 0} and $(r-E(r))^-$ = {-3.9 -0.9 -2.9 0 0 0 -1.9 -0.9 0 -3.9}. Then the upside and downside semi-variances can be found s_{upside}= $E([(r-E(r))^+]^2)$ = 5.684 and $s_{downside}$= $E([(r-E(r))^-]^2)$ = 4.406. This difference in the upside and downside semi-variance illustrate the lack of normality in the distribution of r. Portfolio theory was originally based on the premise of random motion of stocks in the form of volatility that could indeed be modeled by normal variables having upside and downside semi-variance that are in fact equal. The same cannot necessarily be assumed in space systems, as many of the probability distribution functions that describe things like market uncertainty or events of decision tree analysis are not gaussian. Using the semi-variance information, two covariance matrices, Q_{upside} and $Q_{downside}$ are constructed.

[84] Markowitz, H. (1991). Portfolio Selection: Efficient Diversification of Investments. Cambridge, MA, Basil Blackwell.. describes a possible extension of the mean-variance portfolio selection approach that incorporates the idea of down-sided semi-variance.

$$Q_{Upside} = \begin{bmatrix} \sigma_{u1}^2 & \rho_{2,1}\sigma_{u2}\sigma_{u1} & \rho_{3,1}\sigma_{u3}\sigma_{u1} & \bullet & \rho_{n,1}\sigma_{un}\sigma_{u1} \\ \rho_{1,2}\sigma_{u1}\sigma_{u2} & \sigma_{u2}^2 & \rho_{3,1}\sigma_{u3}\sigma_{u1} & \bullet & \rho_{n,2}\sigma_{un}\sigma_{u2} \\ \rho_{1,3}\sigma_{u1}\sigma_{u3} & \rho_{2,3}\sigma_{u2}\sigma_{u3} & \sigma_{u3}^2 & \bullet & \rho_{n,3}\sigma_{un}\sigma_{u3} \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \rho_{1,n}\sigma_{u1}\sigma_{un} & \rho_{2,n}\sigma_{u2}\sigma_{un} & \rho_{3,n}\sigma_{u3}\sigma_{un} & \bullet & \sigma_{un}^2 \end{bmatrix}$$

Eq. 48

$$Q_{Downside} = \begin{bmatrix} \sigma_{d1}^2 & \rho_{2,1}\sigma_{d2}\sigma_{d1} & \rho_{3,1}\sigma_{d3}\sigma_{d1} & \bullet & \rho_{n,1}\sigma_{dn}\sigma_{d1} \\ \rho_{1,2}\sigma_{d1}\sigma_{d2} & \sigma_{d2}^2 & \rho_{3,1}\sigma_{d3}\sigma_{d1} & \bullet & \rho_{n,2}\sigma_{dn}\sigma_{d2} \\ \rho_{1,3}\sigma_{d1}\sigma_{d3} & \rho_{2,3}\sigma_{d2}\sigma_{d3} & \sigma_{d3}^2 & \bullet & \rho_{n,3}\sigma_{dn}\sigma_{d3} \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \rho_{1,n}\sigma_{d1}\sigma_{dn} & \rho_{2,n}\sigma_{d2}\sigma_{dn} & \rho_{3,n}\sigma_{d3}\sigma_{dn} & \bullet & \sigma_{dn}^2 \end{bmatrix}$$

Eq. 49

With these two semi-variance matrices, the traditional portfolio theory is adjusted to reflect the changing considerations. First, if the decision maker is concerned solely with the downside of uncertainty, then he can simply substitute Q_{Downside} into the traditional portfolio theory algorithm, as shown in Eq. 50. However, if the decision maker would also like to consider the upside potential of architecture, then both the upside benefit, Q_{Upside}, and the downside risk, Q_{Downside}, can be implemented together in the portfolio theory algorithm, as shown in Eq. 51.

$$\begin{aligned} &\max : E(r)w - \frac{k}{2} w' Q_{Downside} w \\ &\text{s.t.} : \sum_{i=1}^{n} w_i = 1 \\ &\text{s.t.} : \mathrm{w} \geq 0 \end{aligned}$$

Eq. 50

$$\max : E(r)w + \frac{1}{2} w'(Q_{upside} - kQ_{Downside})w$$
$$\text{s.t.} : \sum_{i=1}^{n} w_i = 1$$
$$\text{s.t.} : \mathrm{w} \geq 0$$

Eq. 51

One last extension that can be made to traditional portfolio theory for use in space systems is a cost of carrying on a portfolio of designs. In the financial approach to portfolio theory, there is no assumption of recurring investment in the collection of assets in the portfolio. This is not the case in space systems, where resources must be assigned and used on designs to refine and test them. Therefore the size of the portfolio or the total diversity of the portfolio might be constrained by available resources. For example, even if a twenty-asset portfolio of designs is suggested by the analysis, it is unlikely that adequate resources would be available to make this a viable opportunity.

A constraint is placed on the portfolio optimization algorithm that takes into consideration the cost of diversification and bounds the feasibility of solutions that exceed available resources. Using this approach, the optimal number of architectures to carry forward is not defined, but rather that number would be suggested from the analysis and the constraints on available resources. The algorithm for the cost of diversification is shown in Eq. 52. C_D considers the average correlation of the asset to the rest of the portfolio as a measure of additional resources that will have to be invested for this asset to belong in the set. It also takes into consideration, the relative estimated nonrecurring cost to design the asset and the proportion of assets in the portfolio.

$$C_D = \sum_{i=w>0} \sum_{j=w>0} \frac{w_i}{w_{\max}} C_{Non\,Rec\,i} \frac{(1-\rho_{ij})}{n}$$

Eq. 52

Using cost of diversification as a constraint, the following portfolio theory implementation is developed, as shown in Eq. 53. Of all the algorithms shown, the analyst should decide which is best suited for their situation in terms of decision maker considerations, problem tractability and resource constraints.

$$
\begin{aligned}
&\max: E(r)w + \frac{1}{2}w'(Q_{upside} - kQ_{Downside})w \\
&\text{s.t.}: \sum_{i=1}^{n} w_i = 1 \\
&\text{s.t.}: \sum_{i=w>0} \sum_{j=w>0} \frac{w_i}{w_{\max}} C_{Non\,Rec\,i} \frac{(1-\rho_{ij})}{n} < C_{Avail} \\
&\text{s.t.}: \mathrm{w} \geq 0
\end{aligned}
$$

Eq. 53

Step 8: Analyze optimal portfolio and overall trends in the uncertainty/value tradespace

Whichever portfolio optimization algorithm was used, you now have a set of assets that represents the optimal investment strategy for the decision maker. The resultant portfolio suggests not only what assets should be maintained in the portfolio but also what percentage of the portfolio each asset should occupy.

A reality check should be done at this stage to not only verify that the portfolio is doable, but also to investigate the surrounding architectures in the portfolio tradespace and run some sensitivities on the decision makers aversion factor. The portfolio tradespace should also be analyzed for overall trends and identifying the driving uncertainties in the tradespace. This will help the designers remain vigilant on the elements that contribute the most uncertainty and impact to the overall system value. The information on dominant uncertainty contains necessary data to understand what changes in conditions warrant a reduction in the portfolio of designs. When the major uncertainties have been reduced, the analyst should recompute the efficient frontier of the portfolio tradespace. The portfolio approach discussed herein should not be implemented as a one-time analysis, but instead should be performed as more information is gained on the sources and amount of uncertainty in the tradespace and its architectures. The goal in the end is to develop a single system that delivers the best value to the customer and this portfolio approach will provide a path along which to proceed.

3231- 50